Storm Surges, Informational Shocks, and the Price of Urban Real Estate: An Application to the Case of Hurricane Sandy*

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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 quantify the effects of these shocks on property values for dry (non-flooded) properties in New York City for Hurricane Sandy. The average effect of a 1 mile positive "surprise" (i.e., for properties where the storm surge distance is greater than the distance to the flood zones distance) is approximately 7.5% higher house prices, while the corresponding 1 mile negative "surprise" effect is roughly 17.2% lower prices, on average. But the effect of a surprise on sale prices is not statistically significantly different for "negative" shocks than for "positive" ones. "Neutral" (i.e., small) shocks have no significant impact on sale prices.

Key words: Hurricane Sandy, Storm Surges, New York City, Real Estate Prices
JEL Classification: R3

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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.[1] 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

[1] For Harvey see: https://www.nytimes.com/interactive/2017/09/01/us/houston-damaged-buildings-in-fema-flood-zones.html?mcubz=1&_r=1.

(CNN, 2013). Estimates of total losses for New York City alone were about $19 billion, and $33 billion for the entire state.[2]

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 relative beliefs or expectations about future surges, by focusing on changes in real estate prices for those properties not directly flooded.

We focus our analysis on how the Sandy storm surge locations compared with insurance flood zone delineations. The flood zones 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).[3]

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[2] For New York City see:
http://www.nyc.gov/html/sirr/downloads/pdf/final_report/Ch_1_SandyImpacts_FINAL_singles.pdf.

[3] Note that as of June 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).

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, by 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. More specifically, we break up the estimation samples into three subsamples – properties experiencing "negative" shocks (i.e., properties that are closer to the storm surge than the FEMA flood maps predicted), those with "positive" shocks (i.e., being further from the storm surge than expected based on the FEMA flood zone), and "neutral" shocks (i.e., those properties where the storm surge is very close to the FEMA flood zone, either in the positive or negative direction).

We find that, on average, both the positive and negative shocks have a statistically significant effect on property values. While the magnitudes of the negative shocks are approximately double the magnitudes of the positive shocks, their magnitudes are not statistically significantly different from each other. Also, for neutral shocks (i.e., very small positive or negative shocks), we find no statistically significant effect on house prices. 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 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.

2. 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%.[4] [5]

[4] 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.

[5] 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.

With these studies in mind, our research considers both positive and negative shocks or surprises due to storm 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.

3. 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. *A priori*, however, the effects of a storm on the dry side of the storm surge can be unclear. Our main identification strategy is to look at the informational shock that occurred based on the FEMA floodplain maps used to assess insurance premiums. In short, our variable of interest is the difference between the closest distance of a property to the FEMA floodplain relative to the closest distance to the storm surge.

That is, we aim to estimate:

$$lnP_i = \theta shock_i + X_i\zeta + \varepsilon_i$$

where

$$shock_i = surge\ distance_i - FEMA\ floodplain\ distance_i$$

for $i = 1, \ldots, N$, non-flooded properties, and where X_i are control variables 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 shock value. Below we denote $surge\ distance$ to a property as *Sandy*, and

$FEMA\ floodplain\ distance_i$ to a property as $FEMA$. As well, for simplicity, the difference between Sandy distance and FEMA distance is denoted *Sandy-FEMA*.

We consider three separate “zones” – one where the shock is negative and is less than -1/8 mile; another where the shock is positive and greater than 1/8 mile; and a “neutral” zone where the value of the shock is between -1/8 mile and +1/8 mile (-660 feet and 660 feet, respectively). We demonstrate in the appendix that the results are robust to changes in these 1/8-mile cutoffs. We also allow for a “buffer” of 0.03 mile (or approximately 158 feet, or more than half the length of a football field) between each property and the storm surge location, so that we ensure the immediate neighborhood is not substantially impacted by the flood. Our empirical results are robust to decreasing this buffer to 0.02 miles or 0.01 miles (where 0.01 miles is approximately 52 feet)).[6] 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 after the storm (between the date of the storm – October 29, 2012 – and the end of 2013).

As a hypothetical example, consider two identical houses, A and B, where each is 900 feet from the closest FEMA floodplain boundary line. For house A, suppose the flood approached within 2000 feet, for a $shock = 2000 - 900 = 1100$ (so that any value above 660 feet is “good news” or a positive shock). In the case of house B, suppose the flood came to within 200 feet of the house, for a $shock = 200 - 900 = -700$; thus house B experienced a negative shock. In this case, we would expect house B to lose value, relative to house A. This would then suggest that in general we would expect $\theta > 0$, for both house A and house B, where θ is the effect of a one-mile

[6] Going from a 0.03-mile buffer to a 0.01-mile buffer raises the sample size by less than 2 percent.

(or equivalently, a 5280 foot) shock on the housing price change. Note that the shock (Sandy distance – FEMA distance) variable is measured in miles in our analysis below.

4. Hurricane Sandy

4.1 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 after the storm, which is our main sample for the OLS regressions. Information about additional control variables are provided in the Appendix.

{Table 1 about here: Desc stats. }

Because our analysis focuses on the shock after the storm, we provide statistics for residential properties that were within one mile (but outside of) the storm surge boundary and sold after Hurricane Sandy (October 29, 2013) and through 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%) are in the borough of Queens. The next largest fraction is in Brooklyn (27%). Less than 5% of sales were in Manhattan. There are 10,208 residential property sales that satisfy the filters described above. The average property in this sample sold for slightly over $1 million, was nearly 74 years old, had 2.38 floors and sold for a price per square foot of approximately $267 with slightly less than 4,600 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.

4.2 Hedonic Regression Results

Distance is measured from the centroid of the property. So, if the distance to the Sandy flood minus the distance to the FEMA floodplain, *Sandy-FEMA*, is positive, it means that the FEMA floodplain was closer to the property than the storm (a positive shock). A negative value for *Sandy-FEMA* means the storm was closer to the property than the FEMA floodplain (a negative shock). We hypothesize that the coefficient for the *Sandy-FEMA* regressor would be positive—the lower the negative shock, the lower the housing price; or the greater the positive shock, the greater the housing price.[7]

[7] Note our regressions use levels for *Sandy-FEMA*, but we also ran regressions with *ln(Sandy)-ln(FEMA)*; results for the latter are given in the Appendix, and give qualitatively similar results.

Table 2, Column (1) presents results for a regression of the log of sale price per square foot against a constant and *Sandy-FEMA*, including year-quarter dummies, and census tract fixed-effects. This sample includes residential properties that sold between the date of Sandy (October 29, 2012) and the end of 2013. The parameter estimate on the *Sandy-FEMA* variable is 0.080 (with t-stat = 2.18), which suggests that with each mile shock prices adjusted by 8.0%, 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 *Sandy-FEMA* regressor is slightly smaller in this specification, equal to 0.0686(with t-stat = 2.91). 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: OLS Regs 1-mile up 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. 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 the *Sandy-FEMA* regressor rises to

0.0972 (with t-stat = 4.48). This implies that for every mile closer the storm surge came relative to what was expected, residential sale prices per square foot were approximately 9.7% lower.

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 *Sandy-FEMA* variable, they are much smaller by more than 50%, and only significant in one specification. This suggests that by the end of 2013 the shock effect began to dissipate, meaning that after about a year, things began to return to normal in terms of the perceptions of home buyers. Because the shock appears to have a dissipated after 2013, we proceed by retaining the end-date of 2013 in the remaining regressions.

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

Table 4 shows the coefficient estimates from when we divide the sample into three subsamples—those with larger positive shocks (Column (1)), those with large negative shocks (Column (2)) and those with little to no or little shocks (Column (3)). Here we define a property as having a "large" shock when the absolute value of the distance to the Sandy flood zone minus the distance to the FEMA floodplain is greater than 0.125 miles (we show in the Appendix that the results are not sensitive to small changes of this cut off).

More specifically, a large positive shock is one where *Sandy-FEMA>0.125 miles*; a large negative one is where *Sandy-FEMA<-0.125 miles;* and a neutral shock is one between the range of *0.125 miles and -0.125 miles*. Figure 1 maps out all of the residential property sales between the date of Sandy and the end of 2013, where a yellow dot is a neutral shock, a dark blue dot is a positive shock, a red dot is a negative shock, and the light blue region is the area flooded by the storm (but we focus exclusively on non-flooded properties in our analysis).

{Figure 1 about here: Map}

The results form Table 4 suggest that, on average, there was no relationship between the shock size and housing prices for neutral shocks. Though the coefficient is negative it is statistically insignificant, with a p-value of 0.61. On the other hand, we also see evidence that the magnitudes of price changes from a large negative shock were not statistically different than a large positive shock; a Chi-squared test for the null hypothesis that the q are equal in the regressions for the negative shock and the positive shock has a p-value =0.17, implying we cannot fully reject the null hypothesis of equality of the two values of q. The coefficient estimate for the negative shock was 0.172, as compared to the point estimate for the positive shock of 0.075. The coefficients on both the positive and negative shocks are highly statistically significant. Neutral (or small) shocks had no significant impact on house prices (t-statistic = 0.56).

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

This suggests that both positive and negative shocks are important, and from a statistical standpoint, home buyers are no more (or less) concerned with large negative flood risk shocks than large positive shocks. Properties where the storm surge came a mile closer than expected, experienced a 17.2% reduction in sale prices per square foot, ceteris paribus. On the other hand, for every mile further away the storm surge was relative to what was expected from the flood maps, property prices per square foot rose by approximately 7.5% after controlling for other factors. Also, small (or neutral) shocks are not of concern to homebuyers in terms of their willingness-to-pay for residential properties.

5. Additional Tests

To confirm that the results are, in fact, picking up a true shock, we performed two additional tests. 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 close to zero (and 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. Though the lower bands tend to be below zero, we can see that in 2012Q3, the lower band is much lower (close to -0.4).

{Table 5 about here: regression for 2011 only}

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 our measure for the shock to be statistically insignificant prior to the storm. Table 5 recreates the regressions for Table 2 but only for the year in 2011. In short, across specifications, the coefficient estimate for Sandy-FEMA is statistically insignificant, thus providing evidence that storm was a true shock.

6. Conclusion

This paper estimates the effects that a major hurricane has on properties that are not flooded by the storm. Specifically, our approach examines how prices are affected by the distance to the flood zone relative to the distance of the FEMA floodplain. 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 after Hurricane Sandy, within one mile of the storm surge but at least 0.03 miles (158 feet) from the surge. We separate the sample into those that had large positive, large negative, and "neutral" shocks to explore for the possibility that the effects of the surge are different for each category. The parameter estimate for the negative shock is more than twice as large as the parameter estimate for the positive shock. But we cannot reject the hypothesis that the positive and negative shocks are equal in magnitude (at conventional statistical significance levels, i.e., with p-value < 0.10; for this test we find that the p-value = 0.17). Neutral (i.e., small positive or negative) shocks have no statistically significant impact on property values.

Interestingly, our estimate of the effect of a negative shock on property values (17.2% decrease for a 1 mile shock) is at the lower bound of 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. Given that the average property in our sample sold for approximately $1 million, the impacts of a 1-mile negative shock result in prices that are approximately $172,000 lower. 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 also find direct evidence that the impact of the shocks dissipate quickly. By the middle of the 2014, about 1.5 years after the storm, the effects appear to have disappeared altogether. Since the FEMA floodplain maps have not changed again during this timeframe, for example, this suggests that in the minds of buyers the impacts of shocks are quickly discounted. Future work needs to better explore the reasons why the market tends to "forget" these shock in relatively short order, given that such damaging hurricanes appeared again in other cities not much longer after Sandy.

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Tables

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	#Obs.
Sale price ($)	1,035,043	4,247,757	37,500	252,000,000	10208
Bldg. area	4,549	15,337	428	509,090	10208
Price per sq. ft.	267.5	125.9	30.2	664.9	10208
Sandy-FEMA Dist. (miles)	-0.11	0.28	-1.09	0.883	10208
Total Units	4.64	16.31	1	550	10208
Lot area (sq. ft.)	3,444	4,834	353	273,600	10208
Building age	74.0	29.2	0	213	10207
# floors	2.38	1.16	0	35	10208
Manhattan	0.046	0.210	0	1	10208
Bronx	0.153	0.360	0	1	10208
Brooklyn	0.274	0.446	0	1	10208
Queens	0.334	0.472	0	1	10208
Staten Island	0.192	0.394	0	1	10208

Notes: Statistics given for residential properties sold between October 29, 2012 and end of 2013, within one mile of Sandy flood zone (on dry side), but more than 0.03 miles from the flood. Information about additional variables used in regressions is given in the Appendix.

Table 2: After Sandy within 1 mile. Dep. Var.: Ln(Price per square foot)

Variable	(1)	(2)	(3)
Sandy-FEMA	0.0803*	0.0686**	0.0972**
	(2.18)	(2.91)	(4.48)
ln(units)		0.140***	0.375***
		(6.28)	(7.85)
ln(land area)		0.244***	0.187***
		(25.25)	(9.11)
ln(age)		-0.0671***	-0.0883***
		(6.66)	(7.00)
ln(building area)		-0.549***	-0.632***
		(24.45)	(55.12)
ln(floors)		0.0817	0.0378
		(1.92)	(0.82)
Constant	5.424***	7.830***	7.488***
	(568.70)	(32.02)	(57.14)
Year Dummies	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes
N	10208	10165	10165
R-sq	0.506	0.592	0.615
adj. R-sq	0.438	0.535	0.559
AIC	8757.8	6790.7	6217.4
BIC	8786.7	6819.6	6246.3

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.

Table 3: After Sandy within 1 mile but up to 2014. Dep. Var.: Ln(Price per square foot)

Variable	(1)	(2)	(3)
Sandy-FEMA	0.0454	0.0381	0.0582*
	(1.38)	(1.92)	(2.49)
ln(units)		0.138***	0.351***
		(4.81)	(5.56)
ln(land area)		0.253***	0.188***
		(20.12)	(15.24)
ln(age)		-0.0650***	-0.0846***
		(6.15)	(8.28)
ln(building area)		-0.528***	-0.605***
		(23.38)	(36.06)
ln(floors)		0.0867*	0.0343
		(2.17)	(1.02)
Constant	5.406***	7.587***	9.023***
	(296.57)	(26.28)	(57.01)
Year Dummies	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes
N	18981	18877	18877
R-sq	0.469	0.554	0.579
adj. R-sq	0.43	0.521	0.546
AIC	17391.9	14052.9	12991.5
BIC	17423.3	14084.3	13022.8

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.

Table 4: After Sandy within 1 mile, by shock type. Dep. Var.: Ln(Price per square foot)

	Pos. Shock	Neg. Shock	Neutral Shock
Variable	**(1)**	**(2)**	**(3)**
Sandy-FEMA	0.0746***	0.172*	-0.11
	(8.43)	(2.47)	(0.56)
ln(units)	0.423**	0.544**	0.336***
	(3.25)	(3.54)	(6.83)
ln(land area)	0.198***	0.197***	0.179***
	(26.63)	(10.41)	(4.87)
ln(age)	-0.0747***	-0.0468	-0.0953***
	(7.52)	(2.10)	(5.82)
ln(building area)	-0.638***	-0.707***	-0.617***
	(26.21)	(24.24)	(22.53)
ln(floors)	-0.0533	0.112*	0.0342
	(0.72)	(2.33)	(0.70)
Constant	8.725***	9.450***	7.646***
	(25.64)	(53.15)	(44.01)
Year Dummies	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes
N	819	3004	6342
R-sq	0.613	0.600	0.640
adj. R-sq	0.54	0.527	0.577
AIC	144.7	1783.2	3882.9
BIC	158.8	1807.2	3909.9

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.

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

Variable	(1)	(2)	(3)
Sandy-FEMA	-0.00785	0.0146	0.0423
	(0.09)	(0.17)	(0.48)
ln(units)		0.0967**	0.430***
		(3.71)	(8.28)
ln(land area)		0.250***	0.185***
		(11.69)	(9.59)
ln(age)		-0.0676***	-0.0858***
		(5.67)	(6.25)
ln(building area)		-0.555***	-0.601***
		(17.87)	(44.35)
ln(floors)		0.0729	0.0342
		(1.49)	(1.76)
Constant	5.403***	7.838***	7.643***
	(373.15)	(21.36)	(42.36)
Year Dummies	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes
N	6839	6809	6809
R-sq	0.526	0.609	0.629
adj. R-sq	0.432	0.531	0.551
AIC	5620.5	4304.5	3947.7
BIC	5647.8	4331.8	3975

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.

Figures

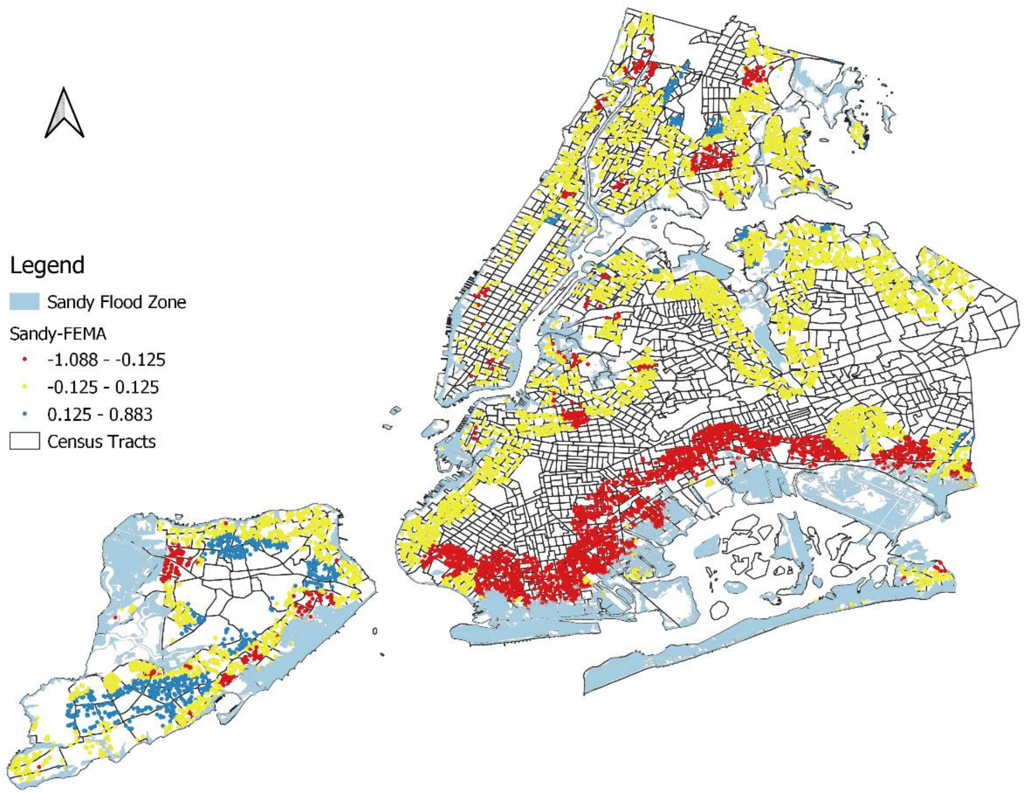

Figure 1: Shock values across NYC.

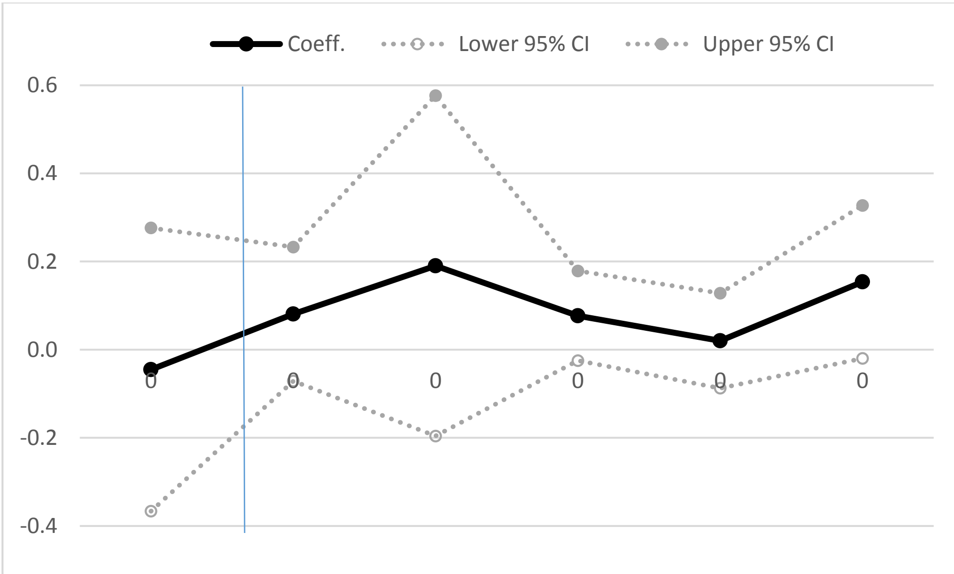

Figure 2: Sandy-FEMA coefficients for dry properties from individual quarter-by-quarter regressions (within one mile of Sandy flood zone). The storm occurred in 2012Q4. The blue line is the approximate date of the storm.

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.

2. 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, *Sandy-FEMA*. Full regression results are available upon request.

Table A.2: After Sandy 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)

	>0	**>0.05**	**>0.1**	**>0.125**	**>0.15**
Varible	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Sandy-FEMA	0.0990***	0.103***	0.109***	0.0746***	0.0736**
	(4.76)	(6.09)	(6.70)	(8.43)	(5.35)
N	3519	1306	939	819	746
R-sq	0.642	0.606	0.612	0.613	0.616
adj. R-sq	0.585	0.529	0.539	0.54	0.544
AIC	1596.9	352.9	212.4	144.7	124.2
BIC	1621.6	368.4	226.9	158.8	138.1

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: After Sandy 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)

	<0	**<-0.05**	**<-0.1**	**<-0.125**	**<-0.15**
Varible	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Sandy-FEMA	0.0683	0.0605	0.146	0.172*	0.171
	(0.99)	(0.78)	(1.93)	(2.47)	(2.12)
N	6646	4134	3198	3004	2876
R-sq	0.617	0.613	0.606	0.6	0.598
adj. R-sq	0.547	0.539	0.53	0.527	0.526
AIC	4281.9	2449.1	1848.3	1783.2	1728.4
BIC	4315.9	2474.4	1872.5	1807.2	1752.2

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.4: After Sandy within 0.5 miles (same categories at Table 3). Dep. Var.: Ln(Price per square foot)

	All	Pos.	Neg.	Neutral
	(1)	(2)	(3)	(4)
Sandy-FEMA	0.157**	0.0203	0.124	0.0567
	(2.96)	(1.17)	(1.54)	(0.22)
N	5722	178	1698	3846
R-sq	0.629	0.747	0.648	0.639
adj. R-sq	0.565	0.586	0.567	0.566
AIC	3387.9	-64.19	811.4	2354.1
BIC	3414.5	-57.83	833.2	2379.1

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.5 After Sandy within 1 mile, *Sandy and FEMA* variable in logs. Dep. Var.: Ln(Price per square foot)

	(1)	(2)	(3)
Ln(Sandy)-ln(FEMA)	0.0172	0.0124*	0.0185***
	(2.04)	(2.45)	(6.42)
N	10195	10152	10152
R-sq	0.506	0.593	0.615
adj. R-sq	0.438	0.536	0.559
AIC	8751	6783.3	6212.3
BIC	8779.9	6812.2	6241.2

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.6: After Sandy within 1 mile, by shock type, *Sandy and FEMA* variable in logs. Dep. Var.: Ln(Price per square foot)

	Pos.	Neg.	Neutral
	(1)	(2)	(3)
Ln(Sandy)-ln(FEMA)	0.0193	0.0285	-0.0057
	(2.29)	(1.24)	(0.35)
N	813	3004	6335
R-sq	0.617	0.6	0.64
adj. R-sq	0.544	0.527	0.578
AIC	139.8	1784.3	3877.3
BIC	153.9	1808.3	3904.3

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.