No Shelter from the Storm?

Hurricanes and Commercial Real Estate Values

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Abstract

We study how investors price hurricane risk based on micro-level data from the $8 trillion US commercial real estate market. Using Hurricane Sandy as a natural experiment, we find that properties exposed to hurricane risk experience 4 to 10 percent lower price appreciation post-Sandy as compared to their pre-Sandy counterparts matched on hurricane risk. This price effect dissipates over time but, in the cross-section, it extends beyond areas immediately affected by the disaster to similar locations that have not yet experienced a hurricane strike. We also document that the price effect of hurricane risk operates through income, vacancy rates, and risk premia. Lastly, we present evidence for contagion effects from locally important occupiers adversely affected by Sandy to the value of unrelated properties nearby. Our results contribute to the debate about how investors price the exposure of real assets to physical risks associated with climate change, an area of particular concern among regulators and market participants.

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1 Introduction

Regulators and markets worry about the effect of climate change on asset values (Carney, 2016). Concerns notably include pricing the exposure of real assets to climate change-related physical risks, such as natural disasters. The pricing of these risks has potentially profound implications for insurers, financial stability and the economy (Carney, 2015). As a result, it is important to understand how markets price climate change-related risks to different assets.

Extreme weather events, such as hurricanes, are among the primary physical risk factors associated with climate change. The frequency, duration and intensity of hurricanes have increased over recent decades, as have global temperatures (Mann and Emanuel, 2006). Average hurricane intensity and destructiveness are projected to increase further as the climate continues to warm (Emanuel, 2005). At the same time, the intensity of any given impending storm is forecasted to become less predictable, making it harder to prepare for landfall and thus contributing to the potential damage caused (Emanuel, 2017).

Moreover, the geographic pattern of hurricanes has changed. Hurricane risk used to be confined to tropical and subtropical regions. However, over recent decades the path of hurricanes has shifted north (Kossin, Emanuel, and Vecchi, 2014). Hurricane risk has thus expanded to a set of new locations, all along the US east coast, that were previously considered immune (Reed et al., 2015). Some of these new locations have already been hit. For instance, record-breaking Hurricane Sandy unexpectedly hit New York in 2012:Q4. Similar locations, such as Boston, have thus far been spared. However, Sandy is viewed as an example of the type of event in store for the region (Baldini et al., 2016).

We focus on the effect of hurricane risk on the value of real property. The economic damage to these assets caused by hurricanes is significant. Any fallout from hurricanes in terms of injury and loss of life is tragic. However, the economic magnitude of damage to real property by far exceeds total death risk, especially in wealthy nations such as the US (Kahn, 2005). For instance, the economic toll of the hurricane season 2017 amounts to an estimated $206.6 billion, the costliest since records began in 1871.[1]

Within real property, we focus on commercial real estate. The economic damage of hurricanes is naturally concentrated in densely populated areas, i.e. cities. Hurricane Sandy reportedly cost New York $19 billion.[2] Commercial real estate is at the core of any urban economic activity.[3] The severe damage inflicted by hurricanes on real property in urban areas, and the possibly ensuing toll on local economic activity exerted by this damage, means that correctly pricing hurricane risk in commercial real estate assets is an economically important challenge.

The second reason why we focus our study on real property is that much of it, notably buildings, is fixed in location. Therefore, the exposure of those assets to hurricane risk, which is largely a function of location-specific characteristics, is difficult to mitigate (Bunten and Kahn, 2014). At the same time, location-specific geographic and atmospheric characteristics allow us to develop an exogenous measure of *ex ante* hurricane risk. With this measure, we can assess the price of hurricane risk even in locations that have not actually been hit yet.

[1] See USA Today, November 29, 2017, Nightmarish, destructive 2017 hurricane season comes to an end, https://www.usatoday.com/story/weather/2017/11/29/nightmarish-destructive-2017-hurricane-season-comes-end/906185001/.

[2] See DNA Info, November 26, 2012, Hurricane Sandy Cost City $19 Billion, Bloomberg Says, https://www.dnainfo.com/new-york/20121126/new-york-city/bloomberg-says-hurricane-sandy-cost-city-19-billion.

[3] Commercial real estate also accounts for a substantial fraction of US wealth (Plazzi, Torous, and Valkanov, 2010). Savill's, a leading global real estate brokerage firm, estimates the value of US commercial real estate in 2016 to be about $8 trillion, or almost 20% of the US stock market, see http://www.savills.co.uk/blog/article/219340/international-property/the-10-most-valuable-real-estate-markets-in-the-world.aspx.

Of course, hurricane damage to the physical structure of buildings from flooding as well as disruption to business operations can be insured. Nonetheless, there are at least three reasons to expect an impact of hurricane risk on property prices: Widespread under-insurance, possible spikes in flood risk insurance premiums following hurricane strikes, and the significant and lasting impact of storm surge on the coastal environment far beyond the immediate physical damage to buildings, potentially disrupting normal economic activity.[4]

Hurricane risk is primarily a function of proximity to the coastline and low elevation – essentially an oceanfront location. The central identification challenge is thus to isolate the impact of hurricane risk from that of the environmental amenity value of oceanfront property. We first filter transaction prices for value-relevant hedonics to obtain residual prices. We then focus on the unexpected strike of Hurricane Sandy in New York in 2012. We match residual prices of properties sold after Sandy with those sold before Sandy based on their distance to the coastline and elevation. We argue that a shift in the pricing of those characteristics after Sandy captures the new information about hurricane risk revealed by Hurricane Sandy.

Overall, we find that a 1 mile reduction in distance to the coastline results in a 4.3 percent reduction in differential residual prices across properties sold after Sandy relative to those sold before Sandy. Given that the unconditional residual price differential in our sample was 46 percent, the estimated effect amounts to a relative slowdown in appreciation of almost 10 percent. A reduction in elevation by 10 feet results in a 1.7 percent reduction in relative appreciation, or almost 4 percent as compared to the unconditional mean of 43 percent.

[4]For evidence on underinsurance and the changes to flood insurance markets following Hurricane Sandy in New York, see Dixon, Clancy, Bender, Kofner, Manheim, and Zakaras (2013).

In terms of timing, we find that the price impact of distance to the coastline persists from 2012 until the end of our study period in 2017. However, we find that the price impact of elevation begins to dissipate in 2014, consistent with the strike of Hurricane Sandy becoming an increasingly distant memory over time. In the cross-section of locations, we find that the price effect of distance to the coast is exclusive to the New York Metro Area. However, our estimates suggest that the price effect of elevation is also significant in the Boston metro area, which is now theoretically at risk of hurricane strikes, but has thus far been spared. Our results are consistent with information about hurricane risk revealed by Sandy traveling beyond the area immediately affected by the storm. However, our results also suggest that in locations further afield, the price effects of hurricane risk begin to dissipate earlier. As for the channel through which hurricane risk affects property values, a sub-sample analysis suggests that it operates through lower income, higher vacancy rates and higher cap rates, reflecting an increased risk premium for properties exposed to hurricane risk. We also document contagion effects from locally important occupiers adversely affected by Hurricane Sandy on the properties surrounding their premises. Placebo tests using data from Chicago, located by Lake Michigan but far from the coast, confirm our results.

Our results are important for at least three reasons. First, we contribute to the literature on the costs of climate change and the potential benefits of mitigation policies (Barro, 2015; Becker, Murphy, and Topel, 2011; Deshpande and Greenstone, 2011; Gollier, 2016; Nakamura, Steinsson, Barro, and Ursúa, 2013; Nordhaus, 2007; Stern, 2007; Weitzman, 2012). We provide novel evidence on the pricing of climate-change related physical risks to real assets, an area of particular concern among regulators and market participants (Carney, 2015, 2016).

Second, prior research has explored the effect of natural disasters and climate change on the value of agricultural land (Deschênes and Greenstone, 2007) and house prices (Atreya and Czajkowski, 2014; Bernstein, Gustafson, and Lewis, 2017; Boustan, Kahn, Rhode, and Yanguas, 2017; Ortega and Taspinar, 2016). Our study is the first to address hurricane risk, a primary physical risk factor associated with climate change, on commercial property values, an asset class at the core of any economic activity in the densely populated urban centers where hurricane damage is typically concentrated.

Third, Daniel, Litterman, and Wagner (2016) and Giglio, Maggiori, Stroebel, and Weber (2015) show how efficient market pricing of climate change-related risks could inform policy. However, there is little evidence on whether markets price climate change-related risks, with notable exceptions. Bansal, Kiku, and Ochoa (2016) show that risks associated with rising temperatures are priced in the stock market. On the other hand, Hong, Li, and Xu (2016) show that the stock market under-reacts to drought risk, due to a lack of experience with this risk. We show that commercial real estate markets price hurricane risk after experiencing the event and, to some extent, already after observing the event elsewhere, suggesting that market participants are able to overcome any potential lack of experience.

We proceed as follows. Section 2 presents evidence on the relationship between rising temperatures, a primary indicator of climate change, and hurricane patterns in the US. Section 3 outlines our empirical approach. The data used in this study is presented in Section 4. Section 5 discusses our empirical results. Section 6 presents the placebo tests and other robustness checks. Section 7 concludes.

2 Rising Temperatures and Hurricanes

Although not the focus of our study, we begin by exploring the relationship between rising sea surface temperatures, a primary indicator of climate change[5] identified by the EPA, and hurricane patterns in the US for the period 1965-2015.

[Figures 1 and 2 about here]

Panel (a) of Figure 1 plots the number of years since the most recent hurricane in the US, along with a linear trend line fitted to the data, against annual global sea surface temperatures. The data suggest a rising trend in sea surface temperatures. According to the EPA, sea surface temperatures have been consistently higher during the past three decades than at any other time since reliable observations began in the late 1800s. Along with rising temperatures, the incidence of hurricanes has increased, as illustrated by the declining trend in the number of years since the most recent hurricane in the US.

Panel (b) of Figure 1 plots the average duration (in days) of hurricanes in the US, along with a linear trend line, against sea surface temperatures. The data suggest that increasing temperatures coincide with a positive trend in the average duration of hurricanes in the US.

Panel (a) of Figure 2 presents the time series evolution of total hurricane damage to property in the US, along with a linear trend line fitted to the data, against annual global sea surface temperatures. The positive trend in the severity of hurricanes is primarily driven by the period from 1992 onward. The most severe (category 5) hurricane strikes with the largest amount of

[5] See: `https://www.epa.gov/climate-indicators`

property damage are Hurricane Andrew in 1992, Hurricane Ivan in 2004, and four hurricanes of category 5 in the 2005 season (Emily, Katrina, Rita and Wilma). The 2012 Atlantic hurricane season did not see any category 5 storms but two highly destructive category 3 storms, Michael and especially Sandy. Overall, the data suggest a positive correlation between sea surface temperatures and the severity of hurricanes.

Panel (b) of Figure 2 lists the states on the east coast of the US sorted from south to north and the total number of hurricanes experienced in these states by decade. The Figure shows that prior to 1986, no coastal state north of Florida experienced more than one or two hurricanes per 10-year period. Over the period 1986-1995, coastal states as far north as New York began experiencing a higher number of hurricanes, such as North Carolina (three hurricanes over 1986-1995), Maryland (four) or New York (three). Over the subsequent 10-year period 1996-2005, coastal states even north of New York, such as Massachusetts and New Hampshire, began experiencing higher numbers of hurricanes. Our data is consistent with climate-scientific studies suggesting a northward migration of hurricanes along the US east coast, putting numerous densely populated centers of economic activity at risk.

3 Method

3.1 Identification Strategy

To identify the effect of hurricane risk on observed property prices, we require variation in the exposure of properties to hurricane risk. Climate-scientific research suggests that hurricane risk is primarily a function of geographic and atmospheric conditions in a given location, most prominently distance to the coastline and elevation, which are easy to measure.

However, using these location characteristics to measure hurricane risk poses an identification challenge. Proximity to the coastline and low elevation may influence property prices for reasons other than hurricane risk, such as the amenity value of oceanfront property (Albouy, Graf, Kellogg, and Wolff, 2016; Chay and Greenstone, 2005). Cross-sectional regressions of property prices on these metrics are thus insufficient to identify the price of hurricane risk.

We focus our analysis on the unexpected strike of Hurricane Sandy in New York in 2012:Q4. The city was believed to be immune to hurricane risk because of its location north of the tropical and sub-tropical regions where hurricanes typically occur. Prior to Sandy, the price of proximity to the coastline and elevation in New York thus arguably reflects amenity value, not hurricane risk. However, Sandy produced new information about local hurricane risk.[6] Therefore, a shift in the pricing of distance to the coastline and elevation after Sandy plausibly captures this new information about hurricane risk. However, we see no reason for the amenity value of oceanfront property to shift at the same time.

3.2 Measuring Ex Ante Hurricane Risk

The National Hurricane Center concludes that storm surge poses the greatest hurricane-related threat to coastal property, illustrated in Figure 3.[7] Therefore, our *ex ante* measure of hurricane risk will be based on exposure to storm surge risk.

[Figures 3 and 4 about here]

[6] Sandy was a significant enough event to alter the objective level of hurricane risk scientifically determined for the area. Flood data about Sandy entered into the revision of the Federal Emergency Management Agency (FEMA) flood maps for New York in 2013. See `http://www.nytimes.com/2013/01/29/nyregion/homes-in-flood-zone-doubles-in-new-fema-map.html`.

[7] Storm surge is an abnormal rise of sea water generated by a storm's winds, which can reach heights well over 20 feet, span hundreds of miles of coastline, and travel several miles inland. See `http://www.nhc.noaa.gov/prepare/hazards.php`.

Research suggests that distance to the coastline and elevation increase storm surge risk. Other geographic and atmospheric location characteristics, e.g. distance to the tropical line, sea surface temperature, average sea level, and wind speed on the nearest coastline, further contribute to this risk.[8] We focus on distance to the coastline and elevation as the two main risk factors and measure asset-specific *ex ante* hurricane risk for each property on this basis.

In order to assess the suitability of our measure of hurricane risk, we regress actual *ex post* hurricane damage on *ex ante* hurricane risk. If our risk measure is a meaningful predictor of damage, then it represents relevant information that investors are able to incorporate into their valuations. The smallest geographic unit for which we are able to obtain damage data is the county. We thus aggregate the *ex ante* hurricane risk measures to the county level by calculating the average exposure of the sample properties in a county. We then estimate the following OLS regression:

$$\ln Damage_{i,t} = \beta_0 + \beta_1 Risk_i + \beta_2 CTRL_{i,t} + u_{i,t} \tag{1}$$

where ln *Damage* is the natural logarithm of damage for county (i) and disaster (t) and *Risk* measures *ex ante* hurricane risk for county (i), based on average distance to the coastline and elevation. $CTRL$ contains covariates for county-level population. We also control for year, month, as well as state fixed effects, and cluster standard errors by county. We expect a negative coefficient β_1 on the *Risk* variables in Equation (1), indicating that proximity to the coastline and lower elevation increase hurricane exposure risk.

[8]See: `https://www.nasa.gov/vision/earth/environment/HURRICANE_RECIPE.html`.

3.3 Property Prices and Hurricane Risk

3.3.1 Filtering Transaction Values

The price of commercial real estate is largely a function of observable property characteristics. Thus, we begin by filtering transaction values for the effect of these characteristics, using the following hedonic pricing model for all sample transactions prior to Sandy:

$$\ln P_{i,t} = \beta_0 + \beta_1 Hedonics_{i,t} + u_{i,t} \tag{2}$$

where $\ln P_{i,t}$ is the natural logarithm of the transaction prices per square foot for property (i) at time (t), as properties may sell multiple times, and $Hedonics_{i,t}$ contains covariates for property size (natural logarithm of square footage), age, age squared, number of floors, building class, quality rating, year-quarter and state fixed effects. In alternative specifications, we also include each property's distance to the coastline and elevation. The resulting coefficient estimates provide an indication of the price of property and location characteristics before any shift in hurricane risk perception caused by Hurricane Sandy. The estimates for location characteristics are thus more likely to reflect the amenity value of an oceanfront location.

3.3.2 Price Impact Analysis of Hurricane Sandy

Recall that we have calculated distance to the coastline and elevation for each sample property. For each transaction after Sandy, we identify the nearest match of transactions before Sandy, based on those location features. We calculate the difference between the residual price for post-Sandy transactions and the residual price of the nearest match of pre-Sandy transactions, where residual prices are based on the coefficient estimates from Equation (2). If several properties qualify as the nearest match, we take the average of their residual prices. We then regress the difference in residual prices across transactions post- versus pre-Sandy on the *ex ante* measures of hurricane risk for the property in the post-Sandy transaction:

$$\Delta ResidualPrice_{i,t} = \beta_0 + \beta_1 Risk_i + \beta_2 CTRL_{i,t} + u_{i,t} \tag{3}$$

where $\Delta ResidualPrice_{i,t}$ ($\Delta \hat{u}_{i,t}$ obtained from Equation (2)) is the difference in residual prices between each post-Sandy transaction and its pre-Sandy match, and $Risk_i$ is distance to the coastline or elevation for each property transacted after Sandy. $CTRL_{i,t}$ includes an indicator whether the property was built after Sandy. Properties constructed after Sandy may incorporate advanced building technology that may be more resilient to hurricane strikes. Also, building codes may have evolved to require more features that make a building resilient to hurricanes.

We further include information about objective changes in hurricane-related flood risk in the control variables for the regression in Equation (3). Specifically, Hurricane Sandy influenced the way in which New York flood maps were revised in 2013. As a result, a number of properties were reclassified as located in a flood zone in the revised maps, as compared to the previous version of the maps from 2007. These revised maps were first released in 2015. In order to account for the new information about flood risk that became available to market participants through the new maps in 2015, we include an indicator whether a property was reclassified from not being in a flood zone as per the 2007 maps to being in a flood zone in the 2015 maps. This variable essentially captures the objective change in a property's hurricane exposure risk after Sandy. We also include fixed effects for year and zip code.

The commercial property market in the US expanded strongly after the Great Recession.[9] Thus, we expect property prices to appreciate overall from the pre-Sandy period to the post-Sandy period. However, we expect this positive general trend to differ significantly across properties with differential exposure to hurricane risk. In other words, we expect that the coefficients on distance to the coast and elevation in Equation (3) are positive and significant. Such a result would indicate that properties with lower hurricane risk exposure, i.e. those further away from the coastline or with higher elevation, experience stronger price appreciation from the pre-Sandy period to the post-Sandy period than those with higher hurricane risk, i.e. those located closer to the coastline or with lower elevation.

4 Data

First, we require property transaction data. We obtain this data from Costar. Costar has tracked commercial property transactions in the US since 1987. Costar relies on data sources including press releases, news reports, SEC filings, public records, and listing services. As of 2017, the Costar database includes a total of more than 3.2 million US-based commercial real estate deals, or an estimated 83 percent of the total CRE market by value. Each record in the database contains both property- and transaction-specific information. Costar covers transactions on numerous types of commercial property, including office, retail, and industrial properties. We focus on offices.

We obtain data on office transactions from 2001:Q1 to 2017:Q4 in New York, Boston and Chicago. We focus on New York because it is a major commercial property market, which

[9] The property research firm Real Capital Analytics reports, based on their Commercial Property Price Index (CPPI), that commercial property values have increased by 28 percent between 2007 and 2017.

was unexpectedly and severely hit by Hurricane Sandy. We add data from Boston because much like New York, it is now also at risk of hurricane strikes as these storms have shifted their path northwards but unlike New York, Boston has thus far been spared major damage. We add data from Chicago because it is also located on the shore of a major body of water, Lake Michigan, but unlike an oceanfront location, property near an enclosed inland body of water is not affected by hurricane risk or sea-level rise.

Next, we require property-specific data on hurricane risk. We use the property addresses supplied in the Costar data to geocode the location of the properties, producing an exact longitude/latitude position for each of them. For each property location, we measure distance to the coastline and elevation, using topological modeling and GIS software.[10]

The final data set we require is data on actual hurricane damage to properties to test the relevance of our *ex ante* location-based risk measure. Here, we use data provided by the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[11] The database covers the period from January 1960 to December 2015.

Table 1 presents descriptive statistics for all of the data in our sample.

[Table 1 about here.]

[10]We obtain shape files for US counties and coastline from the US Census Bureau and US Geological Survey. The US Board on Geographic Names provides primary feature attributes including elevation. See: `https://geonames.usgs.gov/domestic/download_data.htm`. To calculate elevation, we take the average of the elevation data for primary features in each county. We obtain shape files for the 2007 and 2013 versions of the New York flood maps from the New York Department of Environmental Protection. We obtain elevation of each property with coordinates using Elevation API from Bing Maps REST Services.

[11]SHELDUS is a county-level hazard data set for the US and covers natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornadoes as well as perils such as flash floods, heavy rainfall, etc. It contains information on the date of an event, affected location (county and state) and the direct losses caused by the event including damage to physical property in US$. Data and maps are compiled and geo-referenced at the University of South Carolina.

5 Results

5.1 Testing the Ex Ante Measures of Hurricane Risk

Table 2 presents regression results for county-level hurricane damage, as a function of the geographic variables we use to measure hurricane risk. We find that closer proximity to the coastline and lower elevation are associated with significantly higher levels of damage. A one standard deviation increase in distance to the coastline (elevation) reduces county-level hurricane damage by $875,000 ($523,000). When including both measures in the same regression, the effect of proximity to the coastline dominates that of elevation. Overall, our results suggest that these location features contain information about *ex ante* hurricane risk.

[Table 2 about here.]

5.2 The Hedonic Pricing Model

Table 3 presents the hedonic pricing models for the pre-Sandy period. Column (1) shows the specification based on which we calculate residual prices for the price impact analysis. Columns (2) to (7) show the results for the New York, Boston, and Chicago metro areas. We find that the coefficient on distance to the coastline is insignificant in New York but property prices increase between 1.7 percent (in Boston) and 2.5 percent (in Chicago) for being located 1 mile closer to the waterfront. Conversely, the coefficient on elevation is significantly negative in New York (0.9 percent price reduction per 10 feet elevation increase) and Boston (1.3 percent price reduction) but insignificant in Chicago. Our findings suggest that, in the period prior to Hurricane Sandy, proximity to the coast and low elevation attract an environmental amenity premium in some locations.

[Table 3 about here.]

5.3 The Effect of Hurricane Risk on Property Prices

Table 4 presents the regression results for the main price impact analysis. The dependent variable is the difference between the log residual prices per sqft for post-Sandy transactions and the corresponding log residual prices for the matched pre-Sandy transactions. Columns (1) to (3) present the results for pre- and post-Sandy transactions matched on distance to the coastline. In Columns (4) to (6), transactions are matched based on elevation. The predictors of interest are distance to the coastline and elevation. Table 4 presents the results.

[Table 4 about here.]

We find that a larger distance to the coastline and higher elevation are associated with a significantly larger difference in residual prices between transactions after Sandy as compared to transactions before Sandy, all else equal (Columns (1) and (3)). In contrast to our earlier finding that proximity to the coastline and low elevation carry an amenity value premium in the pre-Sandy period, our results suggest that *ex ante* hurricane risk exposure attracts a negative price premium after the property markets in our study experience Hurricane Sandy.

Since the dependent variable is measured as the difference in log residual prices, we can interpret the coefficients approximately in percentage terms, given a unit change in the predictor. We estimate that a 1-mile reduction in a property's distance to the coastline results in a 4.3 percent reduction in price appreciation as compared to the pre-Sandy match, or almost 10 percent relative to the unconditional mean of differential residual prices (0.46). A reduction in elevation by 10 feet results in a 1.7 percent reduction in relative price appreciation, or almost 4 percent relative to the unconditional mean (0.43).

These estimates hold after controlling for the effect of a property being constructed after Sandy, which may incorporate more hurricane-resistant features as building technology advances and building codes evolve (Columns (2) and (5)). In fact, we find that the effect of a property being constructed after Sandy is largely insignificant, while the coefficients on distance to the coastline and elevation are very similar to the first specification.

The estimates on our *ex ante* hurricane risk measures are also robust to controlling for the effect of properties that were reclassified after Sandy as being located in a flood zone (Columns (3) and (6)). This variable essentially captures an expert's scientific assessment of changes in hurricane risk. This analysis is performed only for properties located in New York as revised flood maps are only available for New York. In these results, the coefficients on distance to the coastline and elevation are larger than for the broader sample, suggesting that the effect of Hurricane Sandy on property prices was more pronounced in New York. Consistent with expectations, a reclassification as flood zone is associated with a significantly smaller increase in residual prices post-Sandy relative to pre-Sandy. Our finding implies that properties that are now considered more sensitive to flood risk experience slower price appreciation over time. Given that our measures of hurricane risk remain significant after controlling for the change in a property's objective flood risk, our results suggest that the market in New York reacted more strongly to flood risk perceptions after Hurricane Sandy than what was warranted by a scientific evaluation of the newly revealed information about a property's flood risk exposure.

5.4 Dissecting the Price Effect of Hurricane Risk

We expand on the main results above to address a set of related questions. First, we assess the evolution of any value effect of hurricane risk exposure over time. It is possible that market participants initially react to Hurricane Sandy but that the effect decays over time as the event becomes an increasingly distant memory. We assess the evidence for this hypothesis by augmenting Equation (3) with interaction terms between our hurricane risk measures and each year after Sandy. Table 5 presents the results.

[Table 5 about here.]

We find that closer proximity to the coastline is associated with 4.8 percent lower price appreciation over pre-Sandy sales. The effects over the period 2013 to 2017 are indistinguishable from this baseline impact. Further, we estimate that lower elevation is associated with 2.9 percent lower price appreciation. From 2014 onwards, we find a gradual reversal in price appreciation trends. The negative coefficients on the interaction terms between elevation and the years 2014 to 2017 suggest that from 2014 onwards, the negative impact of low elevation on price appreciation dissipates. Between 2014 and 2017, we estimate that the negative price effect of lower elevation declines by 1.43 percent per year on average. This result seems to be driven largely by properties outside the New York metro area: we find that for properties in New York, the negative price effect of lower elevation only begins to dissipate in 2017.

Second, we assess the geographic radius of any value effect of hurricane risk. Here, we exploit the fact that the path of hurricanes has shifted northwards, now putting a range of new locations along the US east coast at risk. However, not all of those locations have experienced actual hurricane strikes yet. Boston, north of New York, has not yet experienced a severe storm such as Hurricane Sandy, but Sandy is viewed as an example of the type of event in store for the region (Baldini et al., 2016). Local investors in Boston thus have no first-hand experience of severe hurricane strikes yet but they were able to observe Sandy in New York, another location that was thought to be similarly immune in the past.

We assess the extent to which hurricane risk is priced in locations that are theoretically at risk but have not been exposed to a major hurricane strike yet by conditioning the regression in Equation (3) on a property's location in the states corresponding to the New York versus Boston metro areas. The results are shown in Table 6.

[Table 6 about here.]

We find that the price effect of proximity to the coastline is exclusive to NY, where it persists through time, while the price effect of lower elevation is significant in NY, MA and NH. Specifically, properties in New York experience 3.6 percent lower price appreciation per 10 feet of lower elevation, 2.5 percent lower appreciation in MA and 4.1 percent lower appreciation in NH. While we estimate that the price effect of low elevation in NY does not begin to dissipate until 2017, it seems to reverse from 2015 in NH, and 2016 in MA. Our findings suggest that market participants do not need to experience a disaster locally to price the associated *ex ante* risk indicators. The information about hurricane risk revealed by Sandy hitting New York seems to travel to locations further afield that are now theoretically also at risk but have thus far been spared. However, in those locations the price effect of hurricane risk exposure seems taper off earlier than in areas that have been hit.

Next, we assess the channel through which hurricane risk affects property values. Commercial property values are fundamentally a function of the cash flows they produce in the form of income, which is the product of rental values and vacancy rates, and the yield applied to capitalize the stream of future rental cash flows, which incorporates a risk premium for the property (capitalization or cap rate).

For a sub-set of the Costar transaction records, we have data on cap rate, net income per square foot, and vacancy rates. We thus replace the dependent variable in Equation (3) with the differences in cap rate, net income, and vacancy across matched transactions.[12]

[Table 7 about here.]

As shown in Table 7, we find that a location within the lowest decile of distance to the coastline is associated with a an increase in cap rates across post- versus pre-Sandy transactions of 5.3 basis points (corresponding to more than five times the unconditional mean), consistent with increased hurricane risk associated with proximity to the coastline. This effect begins to reverse in 2015. We also find that a shorter distance to the coastline is associated with a positive net income differential across post- versus pre-Sandy transactions in 2012:Q4 but this is followed by significant negative effects in 2013, and then from 2015 onwards (average reduction of $29.78 per year, or 2.5 times the unconditional mean). Note that lease contracts govern rental payments. As a result, it is not surprising that the negative impact of our

[12]The smaller number of observations available on cap rate, net income, and vacancy reduces the number of achievable matches by distance and elevation. Thus, we match properties across the pre- and post-Sandy periods based on their county, as an alternative measure of location, and building quality class. We further replace the continuous predictors of interest, distance to the coastline and elevation, with indicators whether a post-Sandy transaction occurred in a property located in the decile with the shortest distance to the coastline or with the lowest elevation of all post-Sandy transactions.

hurricane risk measures on net income turns significant with a time delay. We find that the effect of elevation is concentrated in vacancy rates, with a positive differential of 17.66 percentage points in 2012:Q4, or almost 7 times the unconditional mean, which reverses from 2013 onwards. With the caveat that the cap rate and net income regressions are based on comparatively smaller sample sizes, we conclude that hurricane risk can affect property values through the channels of income, vacancy rates and capitalization rates.

We further assess the notion of contagion, where an economically important occupier in a local area being adversely affected by Hurricane Sandy impacts the value of surrounding properties. We first identify those sample properties that have the headquarters of a listed firm located within a 0.5 mile or 1 mile radius. We calculate cumulative abnormal returns for those listed firms during a 5-day period from October 22, 2012 to October 26, 2012.[13] We then define an indicator that takes the value of 1 for those properties in our sample that are located within 0.5 miles or 1 mile of a listed firm that experienced a negative CAR on those dates around Sandy.[14] Table 8 presents the results.

[Table 8 about here.]

We find that properties located close to firms that were adversely affected by Sandy experience slower price appreciation against their pre-Sandy match by zip code and building quality class. This effect is more pronounced for properties within 0.5 miles of the headquarters of

[13] We estimate normal returns based on the CAPM from May 1, 2012 (Day -120) until October 19, 2012 (last trading day before Sandy). We start to calculate abnormal returns on October 22, 2012 (Day 0) when Sandy first developed into a tropical storm in the Caribbean Sea. We cumulate abnormal returns until October 26, 2012 (Day 4) when New York State declared a state of emergency. See `https://edition.cnn.com/2013/07/13/world/americas/hurricane-sandy-fast-facts/index.html`.

[14] In the interest of sample size, we match properties based on zip code and building quality class.

an affected firm (5.3 times slower appreciation) and becomes less pronounced, but remains significant, for properties within a 1 mile radius (3.4 times slower appreciation). We find that these effects are concentrated in the first year after Hurricane Sandy. Our results suggest that the economic toll of Hurricane Sandy was not limited to the immediate physical damage to properties and the potentially ensuing disruption to operations. Rather, our findings suggest that there are further-reaching, economically important effects stemming from the adverse impact of Sandy on individual large occupiers in a given local area.

6 Robustness Tests

We assess the robustness of our results by conducting a placebo test using data from Chicago. Chicago is also located on the shore of a substantial body of water, Lake Michigan, but the lake is fully enclosed, so property on its shore is not subject to hurricane risk. Lakefront property is also insensitive to other climate-change related risks to oceanfront property, such as sea-level rise (Bernstein, Gustafson, and Lewis, 2017). We use the contrast with transactions from Chicago in two ways. First, we repeat the analysis from Equation 3 for properties in Chicago, where we measure their distance to the lakefront and elevation analogous to the main sample in the New York and Boston metro areas. The elevation of properties located in Chicago is measured relative to the elevation of Lake Michigan, which is around 574 feet. The results in Table 9 show that proximity to the waterfront in Chicago generally attracts a price premium in more recent transactions as compared to their earlier matches. We find no significant results for elevation in Chicago.[15] We conclude from this test that, as expected,

[15] The significant coefficient for the interaction between elevation and 2013 is entirely due to a small sub-set of transactions of class B buildings and vanishes when we exclude the < 100 transactions concerned.

hurricane risk does not seem to factor into pricing properties near the waterfront in Chicago.

[Table 9 about here.]

Next, instead of matching post-Sandy transactions to their pre-Sandy counterparts in the same location and estimating the impact of hurricane risk on the differential residual price, we match the transactions from New York and Boston to those in Chicago, based on distance to the waterfront and elevation. We then estimate the impact of these location features on the differential residual price, before and after Sandy. Table 10 presents the results.

[Table 10 about here.]

This test allows us to hold constant (at zero) climate change-related risks to waterfront property in the Chicago transactions against which we compare the residual prices of the New York and Boston properties. The results are consistent with our prior findings. Closer proximity to the waterfront and lower elevation in New York and Boston are associated with lower residual price differentials as compared to matched properties in Chicago. We further find that these effects become stronger after Hurricane Sandy.

We also consider that distance to the coastline and elevation combine to determine hurricane risk. Thus, we create a hurricane risk score for each property that takes into account both characteristics. We create terciles of distance to the coastline and, separately, elevation for the sample properties. We then assign a hurricane risk score ranging from 1 to 5, with a higher number indicating more risk.[16] To illustrate the combined hurricane risk measure,

[16]We assign scores as follows: Properties in the tercile of properties closest to the coastline, which are also in the tercile with

Figure 5 shows the location of each of our sample properties in The New York City Borough of Manhattan, shaded with reference to its hurricane risk ranging from 1 (low risk) to 5 (high risk). For the purpose of this robustness test, we match properties by zip code and building quality class in New York and Boston, and, for contrast, in Chicago, and measure the impact of hurricane risk scores on differential residual prices across transactions post- versus pre-Sandy.

[Figure 5 and Table 11 about here.]

Table 11 presents the results. We find that in New York and Boston, but not in Chicago, higher hurricane risk scores are monotonically associated with lower differential residual prices (Columns (1) and (2) for New York and Chicago versus Columns (4) and (5) for Chicago). Consistent with the pattern we document in our main results, we find that the negative price effect of hurricane risk for New York and Boston begins to dissipate from 2014 onwards. As expected, we generally find no significant results in Chicago.[17]

Lastly, we re-estimate Equation 3 but calculate the difference in residual prices between each property transaction that occurred after Sandy and the mean of residual prices observed for transactions in the same zip code and building class before Sandy. We have used this specification in some of our additional tests in the interest of obtaining a larger sample size. The added advantage is that it explicitly controls for building quality in the matching process,

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the lowest elevation, receive a score of 5. Properties in the lowest elevation tercile but the middle distance tercile, as well as properties in the closest distance tercile but the middle elevation tercile, receive a score of 4. Properties in the middle terciles of distance to the coastline and elevation receive a score of 3. Properties in the highest elevation tercile but the middle distance tercile, as well as properties in the furthest distance tercile but the middle elevation tercile, receive a score of 2. Properties in the Properties in the tercile of properties furthest from the coastline and with the highest elevation receive a score of 1.

[17] As noted before, the significant coefficient for the interaction between elevation and 2013 is entirely due to a small sub-set of transactions of class B buildings and vanishes when we exclude the < 100 transactions concerned.

which we only account for in the first-stage hedonic models in our main analysis. Table 12 shows that the results are consistent with our prior findings.

[Table 12 about here.]

7 Conclusion

We explore the way in which commercial property investors price hurricane risk. We develop an *ex ante* measure of hurricane exposure based on the geographic characteristics associated with the location of each property in our sample. We test the suitability of our risk measure by using it to predict county-level hurricane damage. We then combine a classic hedonic pricing model with an analysis of transactions post- versus pre-Hurricane Sandy, where the cross-section is defined over several locations differentially exposed to the event.

We document the following main findings. Location features associated with an oceanfront location attract an environmental amenity premium in locations unaffected by hurricane risk. We also find evidence for this amenity premium in locations that are affected by hurricane risk but only after those markets experience Hurricane Sandy. After Hurricane Sandy hit, properties in closer proximity to the coast and at lower elevation experience significantly slower price appreciation over their pre-Sandy counterparts matched on those location features. Further, we find that the initial impact of hurricane risk on price appreciation dissipates as time passes after the event has occurred. We also find that, after Sandy, hurricane risk is not only priced in locations directly affected by the storm but also further afield, in other locations theoretically at risk but that have thus far been spared. Our evidence suggests, however, that the price impact of hurricane risk begins to decay faster in those locations not immediately affected by the storm. We also find that hurricane risk affects property values through lower income, higher vacancy and higher cap rates, suggesting a higher risk premium for those properties exposed to hurricane risk. Lastly, we find that locally important occupiers that were adversely affected by Sandy have contagion effects on the value of properties nearby. Placebo tests using data from Chicago, which also features a waterfront location but is insensitive to hurricane risk, confirm our results.

Our findings are significant because ours is the first study, to the best of our knowledge, that documents the price effects of hurricane exposure risk in real assets. Our results contribute to the debate whether markets efficiently price climate risks, even given a potential lack of experience among investors with the associated events.

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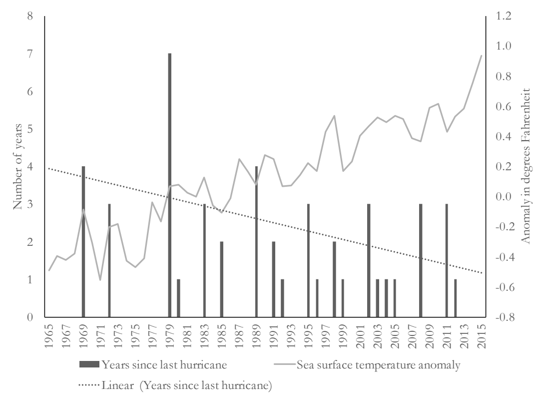
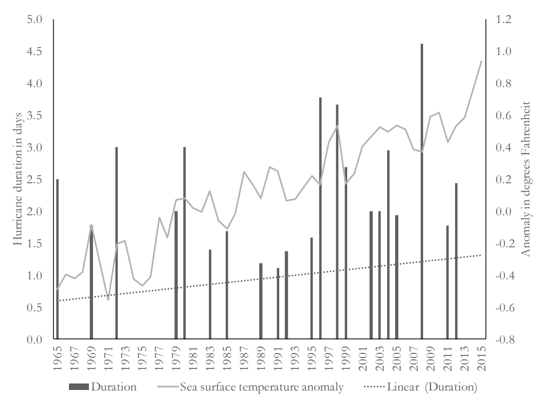
8 Figures and Tables

Sea Surface Temperatures and Hurricanes in the US, 1965-2015



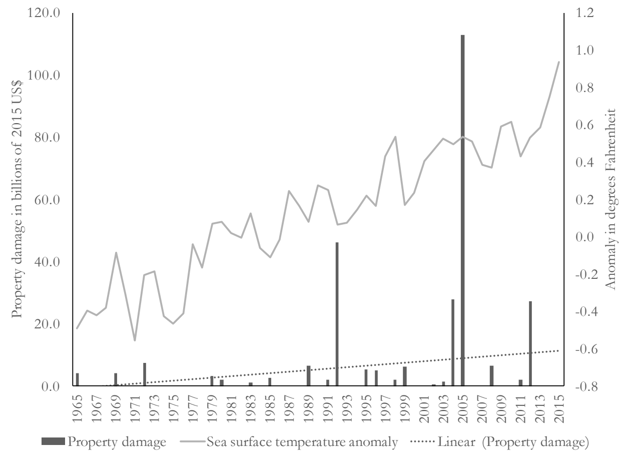
(a) *Sea Surface Temperatures and Frequency of Hurricanes*



(b) *Sea Surface Temperatures and Duration of Hurricanes*

Figure 1: *Panel (a) shows the time series evolution of the number of years since the most recent hurricane in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. Panel (b) shows the average duration (in days) of hurricanes in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. This graph uses the 1971-2000 global temperature average as a baseline for depicting temperature anomalies. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.*

Hurricane Patterns in the US, 1965-2015



(a) *Sea Surface Temperatures and Severity of Hurricanes*

East coast states south to north	1965-1975	1976-1985	1986-1995	1996-2005	2006-2015
Florida	3	1	2	4	2
Georgia	1	0	1	3	0
South Carolina	1	1	2	2	0
North Carolina	1	1	3	6	2
Virginia	2	1	2	6	2
Maryland	2	1	4	5	2
Delaware	1	1	0	3	1
New Jersey	1	1	1	4	2
New York	1	1	3	4	2
Connecticut	1	1	2	2	2
Rhode Island	1	1	2	2	2
Massachusetts	1	1	1	3	2
New Hampshire	1	1	2	3	1
Maine	0	1	1	2	0

(b) *Northward Migration of Hurricanes*

Figure 2: *Panel (a) shows the time series evolution of total hurricane damage to property in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. This graph uses the 1971-2000 global temperature average as a baseline for depicting temperature anomalies. Panel (b) shows the states on the east coast of the US sorted from south to north and the total number of hurricanes experienced in these states by decade. To illustrate geographic and time series patterns in hurricane exposure, the shading of the cells becomes darker as the number of hurricanes increases. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.*

Oceanfront Before and After Hurricane Ike on the Bolivar Peninsula, Texas, September 2008

Figure 3: *Photo published by the United States Geological Survey, obtained from NOAA.*

Storm Surge Damage

(a) *Beachfront Road and Boardwalk Damaged by Hurricane Jeanne (2004)*

(b) *Damaged Boats in a Marina*

Figure 4: *Panel (a) shows how currents created by tides combine with the waves to severely erode beaches and coastal highways. Buildings that survive hurricane winds can be damaged if their foundations are undermined and weakened by erosion. Photo published by FEMA, obtained from NOAA. Panel (b) shows how, in confined harbors, the combination of storm tides, waves, and currents can also severely damage marinas and boats. In estuaries and bayous, salt water intrusion endangers public health, kills vegetation, and can send animals, such as snakes and alligators, fleeing from flooded areas. Photo published by the United States Coast Guard Digital, obtained from NOAA.*

Hurricane Risk Score for Sample Properties in Manhattan

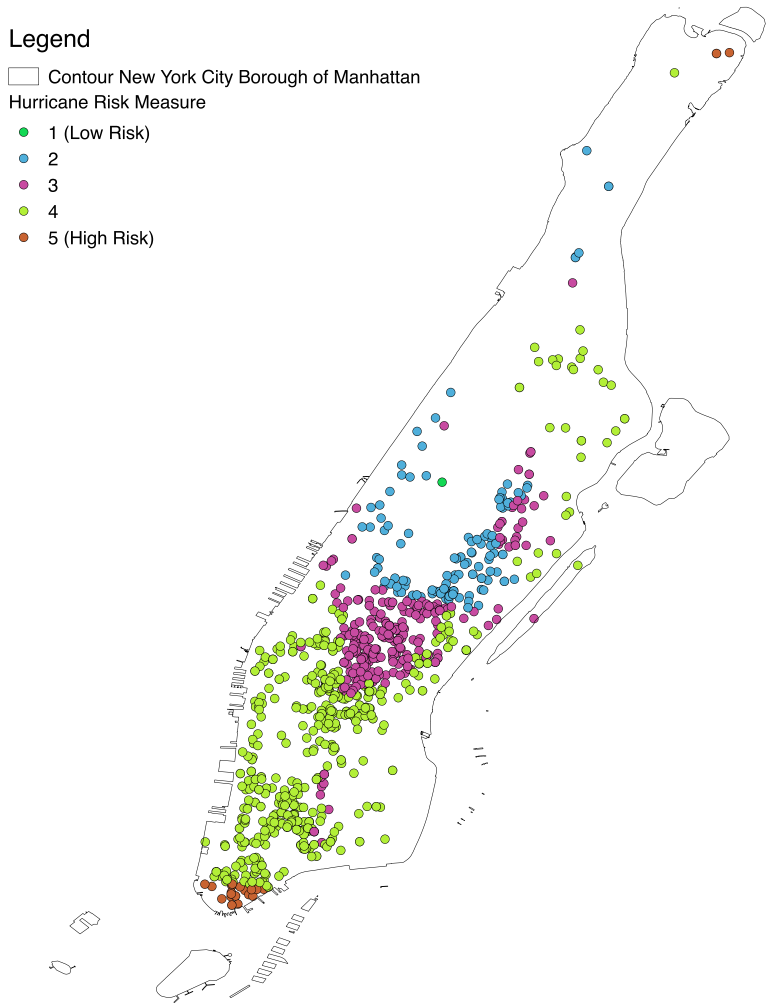


Figure 5: *The map shows the geo-coded locations of our final sample properties in the New York City Borough of Manhattan. Each property location is color-coded to indicate its level of hurricane risk based on the hurricane risk score, which we calculate as a combination of a property's distance to the coastline and elevation, where shorter distance and lower elevation are associated with higher hurricane risk.*

Descriptive Statistics

VARIABLES	N	Mean	SD	P25	Median	P75	Min	Max
Panel A - Transaction-Level Data								
	Before Sandy							
Price per Sqft	10,893	245.07	254.79	96.09	160.60	280.75	9.27	1,546.15
Property Size (1000 Sqft)	10,893	80.75	176.00	5.86	16.79	64.00	1.10	1,070.00
Property Age	10,893	55.90	37.93	24.00	48.00	86.00	0.00	294.00
Number of Stories	10,893	5.65	8.17	2.00	3.00	5.00	1.00	110.00
Building Class=A	10,893	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Building Class=B	10,893	0.41	0.49	0.00	0.00	1.00	0.00	1.00
Building Class=C	10,893	0.49	0.50	0.00	0.00	1.00	0.00	1.00
Building Class=F	10,893	0.00	0.03	0.00	0.00	0.00	0.00	1.00
Star Rating=1 Star	10,893	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Star Rating=2 Star	10,893	0.47	0.50	0.00	0.00	1.00	0.00	1.00
Star Rating=3 Star	10,893	0.39	0.49	0.00	0.00	1.00	0.00	1.00
Star Rating=4 Star	10,893	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Star Rating=5 Star	10,893	0.01	0.10	0.00	0.00	0.00	0.00	1.00
State=NY	10,893	0.32	0.46	0.00	0.00	1.00	0.00	1.00
State=MA	10,893	0.27	0.44	0.00	0.00	1.00	0.00	1.00
State=NJ	10,893	0.20	0.40	0.00	0.00	0.00	0.00	1.00
State=NH	10,893	0.02	0.14	0.00	0.00	0.00	0.00	1.00
Chicago Metro Area	10,893	0.19	0.39	0.00	0.00	0.00	0.00	1.00
	After Sandy							
Distance to Coastline (miles)	5,598	11.31	8.83	6.04	9.34	13.44	0.02	58.29
Elevation (10 feet)	5,598	9.86	11.21	2.95	5.91	12.14	0.00	101.38
Lowest-Decile Distance	5,598	0.11	0.32	0.00	0.00	0.00	0.00	1.00
Lowest-Decile Elevation	5,598	0.19	0.40	0.00	0.00	0.00	0.00	1.00
Hurricane Risk=2	5,,598	0.12	0.33	0.00	0.00	0.00	0.00	1.00
Hurricane Risk=3	5,598	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Hurricane Risk=4	5,598	0.27	0.44	0.00	0.00	1.00	0.00	1.00
Hurricane Risk=5	5,598	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Negative CAR around Sandy (1 mile)	2,492	0.01	0.03	0.00	0.00	0.01	0.00	0.13
Negative CAR around Sandy (0.5 mile)	1,878	0.01	0.03	0.00	0.00	0.01	0.00	0.13
Built after Sandy	5598	0.04	0.19	0.00	0.00	0.00	0.00	1.00
Reclassified as Flood Zone	2418	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Differential Residual Price, Net of								
Best Match by Distance	5,598	0.46	0.95	-0.05	0.46	1.01	-4.58	5.27
Best Match by Elevation	5,598	0.43	0.82	-0.04	0.46	0.99	-3.96	3.74
Mean by Zip Code, Building Class	5,598	0.43	0.75	0.04	0.47	0.90	-4.25	2.96
Differential Residual Cap Rate	460	0.01	0.49	-0.04	-0.02	0.01	-3.01	8.90
Differential Residual NI per Sqft	460	9.85	20.57	0.54	6.61	13.96	-32.05	193.27
Differential Residual Vacancy	1671	2.59	24.81	-12.05	-4.79	8.69	-45.71	94.06
Panel B - County-Level Data								
Damage (million $)	4,888	55.74	501.35	0.06	0.81	11.13	0.00	12,129.93
Distance to Coastline (miles)	4.888	89.26	97.18	9.03	58.12	144.18	0.00	605.78
Elevation (10 feet)	4,888	5.26	6.97	0.70	2.82	7.13	0.01	54.32
Population (1000)	4,888	127.00	260.00	18.81	41.50	110.00	0.04	3,980.00

Table 1: *Panel (A) presents the sample of Costar transactions for New York, Boston and Chicago metro areas, before Sandy (2001:Q1 to 2012:Q3) and after Sandy (2012:Q4 to 2017:Q4). Panel (B) presents the descriptive statistics on the variables used in the damage analysis to assess our* ex ante *hurricane measure.*

Hurricane Damage as a Function of Distance to the Coastline and Elevation

	ln(Property Damage)		
VARIABLES	(1)	(2)	(3)
Distance to Coastline (miles)	-0.009***		-0.009***
	(-16.872)		(-13.248)
Elevation (10 feet)		-0.075***	-0.000
		(-9.404)	(-0.022)
Population (in logs)	0.164***	0.173***	0.164***
	(4.881)	(4.767)	(4.893)
Constant	6.990***	6.185***	6.990***
	(13.103)	(11.228)	(13.128)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	4,888	4,888	4,888
Adj. R-squared	0.294	0.274	0.294

Table 2: *The table presents the regression results of county-level property damage in 2015 log US\$, conditional on a county being hit by a hurricane, as a function of some of the geographic variables that we will examine as potential components of our* ex ante *measure of hurricane risk. The sample includes 1,273 counties in US east coast states that were hit by a hurricane during the period 1965 to 2012. Heteroskedasticity robust standard errors are clustered by county and t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Hedonic Pricing Model

	ln(Price per sqft)						
VARIABLES	(1) All	(2) NY	(3) NY	(4) Boston	(5) Boston	(6) Chicago	(7) Chicago
Distance to Coastline (miles)		-0.002		-0.017***		-0.025***	
		(-0.765)		(-14.474)		(-6.627)	
Elevation (10 feet)			-0.009***		-0.013***		-0.004
			(-6.699)		(-13.249)		(-0.868)
ln(sqft)	-0.179***	-0.153***	-0.154***	-0.229***	-0.235***	-0.203***	-0.205***
	(-19.066)	(-10.699)	(-10.869)	(-15.123)	(-15.385)	(-9.874)	(-9.795)
Property Age	-0.001**	-0.003**	-0.003**	-0.004***	-0.004***	-0.012***	-0.012***
	(-2.087)	(-2.172)	(-2.281)	(-4.165)	(-4.397)	(-7.067)	(-6.782)
Property Age Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(4.894)	(4.367)	(4.357)	(3.993)	(4.121)	(6.314)	(6.820)
Number of Stories	0.025***	0.023***	0.022***	0.063***	0.064***	0.024***	0.026***
	(12.490)	(7.448)	(7.061)	(9.517)	(9.563)	(9.182)	(9.742)
Building Class=B	-0.109***	0.025	0.007	-0.257***	-0.273***	-0.157**	-0.156**
	(-3.029)	(0.411)	(0.112)	(-5.057)	(-5.290)	(-2.395)	(-2.347)
Building Class=C	-0.237***	-0.087	-0.112*	-0.426***	-0.440***	-0.196***	-0.201***
	(-6.002)	(-1.342)	(-1.718)	(-7.342)	(-7.528)	(-2.678)	(-2.729)
Building Class=F	-0.316	0.321	0.261	-1.770***	-1.782***	0.389	0.410
	(-1.056)	(1.171)	(0.953)	(-5.134)	(-5.193)	(1.610)	(1.432)
Star Rating=2 Star	0.188***	0.144***	0.138**	0.059	0.089*	0.472***	0.479***
	(4.972)	(2.587)	(2.519)	(1.200)	(1.836)	(3.080)	(3.071)
Star Rating=3 Star	0.420***	0.401***	0.386***	0.196***	0.231***	0.611***	0.639***
	(9.766)	(6.243)	(6.073)	(3.320)	(3.988)	(3.852)	(3.961)
Star Rating=4 Star	0.616***	0.609***	0.592***	0.364***	0.396***	0.849***	0.891***
	(9.912)	(6.200)	(6.052)	(3.844)	(4.169)	(4.798)	(4.951)
Star Rating=5 Star	0.745***	0.689***	0.679***	-0.220	-0.221	0.809***	0.840***
	(7.296)	(4.577)	(4.549)	(-0.746)	(-0.742)	(3.784)	(3.860)
Constant	5.938***	6.332***	6.418***	7.204***	7.099***	6.333***	6.187***
	(53.280)	(37.371)	(38.144)	(39.438)	(39.048)	(24.752)	(23.804)
Year/Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,893	5,656	5,656	3,148	3,148	2,089	2,089
Adj. R-squared	0.328	0.309	0.316	0.248	0.242	0.243	0.227

Table 3: *The table shows the hedonic regressions on the logarithm of Price per sqft for New York, Boston, and Chicago metro areas for the sample period 2001:Q1 to 2012:Q3 (before Sandy). Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.*

Price Impact Analysis

	Differential Residual Price per sqft					
VARIABLES	(1) All	(2) All	(3) NY	(4) All	(5) All	(6) NY
	Net of Best Match by Distance			Net of Best Match by Elevation		
Distance to Coastline (miles)	0.043**	0.044**	0.210***			
	(2.310)	(2.321)	(3.587)			
Elevation (10 feet)				0.017***	0.017***	0.028***
				(4.610)	(4.588)	(3.840)
Built after Sandy		-0.047	-0.210*		0.094	0.027
		(-0.449)	(-1.897)		(1.209)	(0.325)
Reclassified as Flood Zone			-0.475***			-0.252*
			(-3.004)			(-1.770)
Constant	-0.498**	-0.500**	-1.821***	-0.185***	-0.185***	-0.112
	(-2.262)	(-2.268)	(-3.310)	(-3.062)	(-3.075)	(-1.194)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,598	5,598	2,418	5,598	5,598	2,418
Adj. R-squared	0.172	0.172	0.174	0.321	0.321	0.353

Table 4: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on distance to the coastline or elevation. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (3) show the results for properties matched based on distance to the coastline. Columns (4) to (6) show the results for properties matched based on elevation. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.*

Price Impact Analysis with Year Interactions

VARIABLES	(1) All	(2) All	(3) NY	(4) All	(5) All	(6) NY
	Differential Residual Price per sqft					
	Net of Best Match by Distance			Net of Best Match by Elevation		
Distance to Coastline (miles)	0.048**	0.049**	0.210***			
	(2.217)	(2.231)	(3.367)			
Elevation (10 feet)				0.029***	0.029***	0.036***
				(4.469)	(4.444)	(3.201)
× Year=2013	0.002	0.002	0.017	-0.005	-0.005	0.000
	(0.240)	(0.233)	(0.980)	(-0.850)	(-0.837)	(0.038)
× Year=2014	-0.004	-0.004	0.010	-0.011**	-0.011**	-0.007
	(-0.415)	(-0.422)	(0.637)	(-2.058)	(-2.044)	(-0.726)
× Year=2015	-0.009	-0.009	0.001	-0.014**	-0.014**	-0.015
	(-0.893)	(-0.900)	(0.075)	(-2.568)	(-2.553)	(-1.611)
× Year=2016	-0.010	-0.010	0.003	-0.016***	-0.016***	-0.007
	(-0.965)	(-0.967)	(0.209)	(-2.814)	(-2.806)	(-0.866)
× Year=2017	-0.004	-0.004	0.012	-0.016***	-0.016***	-0.016*
	(-0.349)	(-0.368)	(0.741)	(-2.772)	(-2.734)	(-1.855)
Built after Sandy		-0.047	-0.207*		0.090	0.022
		(-0.445)	(-1.868)		(1.171)	(0.269)
Reclassified as Flood Zone			-0.489***			-0.282**
			(-3.077)			(-1.980)
Constant	-0.553**	-0.556**	-1.828***	-0.300***	-0.300***	-0.169
	(-2.198)	(-2.208)	(-3.071)	(-3.827)	(-3.827)	(-1.515)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,598	5,598	2,418	5,598	5,598	2,418
Adj. R-squared	0.173	0.173	0.174	0.324	0.324	0.355

Table 5: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on distance to the coastline or elevation. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (3) show the results for properties matched based on distance to the coastline. Columns (4) to (6) show the results for properties matched based on elevation. In each set of columns we include interaction terms between the years 2013 to 2017 and distance to the coastline or elevation, respectively. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis with State Interactions

	Differential Residual Price per sqft							
VARIABLES	(1) NY	(2) NJ	(3) MA	(4) NH	(5) NY	(6) NJ	(7) MA	(8) NH
	Net of Best Match by Distance				Net of Best Match by Elevation			
Distance to Coastline (miles)	0.211***	0.019	0.044	-0.065				
	(3.369)	(0.423)	(1.452)	(-1.174)				
Elevation (10 feet)					0.036***	0.018	0.025***	0.041*
					(3.248)	(1.332)	(2.695)	(1.712)
× Year=2013	0.016	0.044	0.003	-0.012	0.000	-0.011	0.002	-0.033
	(0.966)	(1.562)	(0.155)	(-0.772)	(0.017)	(-0.807)	(0.212)	(-1.613)
× Year=2014	0.010	-0.002	-0.002	-0.016	-0.007	-0.021	-0.005	-0.032
	(0.623)	(-0.085)	(-0.112)	(-1.065)	(-0.735)	(-1.533)	(-0.640)	(-1.491)
× Year=2015	0.003	0.020	-0.011	-0.016	-0.014	-0.013	-0.008	-0.046**
	(0.199)	(0.742)	(-0.608)	(-0.919)	(-1.496)	(-0.970)	(-0.969)	(-2.183)
× Year=2016	0.006	0.015	-0.015	-0.014	-0.006	-0.023	-0.014*	-0.044**
	(0.364)	(0.530)	(-0.794)	(-0.742)	(-0.746)	(-1.614)	(-1.652)	(-2.266)
× Year=2017	0.014	0.024	-0.018	-0.008	-0.015*	-0.011	-0.012	-0.061*
	(0.849)	(0.892)	(-0.907)	(-0.342)	(-1.740)	(-0.783)	(-1.328)	(-1.734)
Built after Sandy	-0.220**	-0.020	0.724***		0.014	-0.133	0.597***	
	(-1.993)	(-0.047)	(3.080)		(0.176)	(-0.450)	(3.941)	
Constant	-1.832***	-0.229	-0.709*	1.083	-0.173	-0.257*	-0.403***	-0.847**
	(-3.073)	(-0.459)	(-1.794)	(0.951)	(-1.550)	(-1.734)	(-2.886)	(-2.085)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,418	1,169	1,771	240	2,418	1,169	1,771	240
Adj. R-squared	0.168	0.038	0.177	0.069	0.353	0.096	0.351	0.022

Table 6: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on distance to the coastline or elevation. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (4) show the results for properties matched based on distance to the coastline. Columns (5) to (8) show the results for properties matched based on elevation. Each column presents the results for one of the individual states in our sample, NY, NJ, MA and NH. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis for Discount Rate, Income and Vacancy Rate

	Residuals - Net of Mean by County, Building Class					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cap Rate	NI per sqft	Vacancy	Cap Rate	NI per sqft	Vacancy
Lowest-Decile Distance	0.053***	25.829**	10.686			
	(5.516)	(2.013)	(0.860)			
Lowest-Decile Elevation				-0.001	-1.392	17.664**
				(-0.051)	(-0.119)	(2.060)
× Year=2013	-0.030	-32.130**	-1.301	0.003	-11.604	-17.227*
	(-0.475)	(-2.176)	(-0.087)	(0.046)	(-0.914)	(-1.888)
× Year=2014	0.943	-19.469	-13.311	0.382	3.067	-23.654***
	(0.995)	(-1.260)	(-1.014)	(0.991)	(0.248)	(-2.652)
× Year=2015	-0.049**	-33.554**	-17.230	-0.008	1.927	-22.696**
	(-2.512)	(-2.554)	(-1.283)	(-0.346)	(0.157)	(-2.470)
× Year=2016	-0.060	-26.886**	-12.070	0.242	-0.018	-20.639**
	(-1.415)	(-1.965)	(-0.868)	(1.065)	(-0.001)	(-2.260)
× Year=2017	-0.013	-26.551**	-7.711	-0.005	-3.868	-21.246**
	(-0.935)	(-1.981)	(-0.560)	(-0.233)	(-0.310)	(-2.349)
Built after Sandy	-0.021	13.820***	-8.735***	-0.063	13.661***	-7.653***
	(-0.550)	(5.744)	(-7.624)	(-0.853)	(6.113)	(-5.725)
Constant	-0.003	-3.069	8.685***	0.003	0.507	6.579**
	(-0.399)	(-0.750)	(3.356)	(0.333)	(0.115)	(2.527)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	No	No	No	No	No	No
Observations	460	460	1,671	460	460	1,671
Adj. R-squared	0.057	0.014	0.012	0.013	0.013	0.017

Table 7: *The table shows the differential regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on county and building quality class. For each property, we obtain information on cap rate, net income (NI) per sqft, and vacancy rate. We calculate the difference in these variables between the matched properties. These differences are used dependent variable. The predictors of interest are indicator variables for whether a property is in the lowest decile of the sample distribution of distance to the coastline, or elevation, respectively. Columns (1) to (3) show the results for distance to the coastline. Columns (5) to (8) show the results for elevation. We also include interaction terms between these location characteristics and the years 2013 to 2017. Each column presents the results for one of the individual outcome variables, cap rate, net income, or vacancy. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis for Contagion Effects

	Net of Mean by Zip Code, Building Class			
	1st Year after Sandy		After 1st Year	
VARIABLES	(1) Within 1 mile	(2) Within 0.5 mile	(3) Within 1 mile	(4) Within 0.5 mile
Negative CAR around Sandy	-3.385**	-5.338***	-0.142	-0.315
	(-2.011)	(-2.595)	(-0.206)	(-0.439)
Built after Sandy	0.179	-0.006	-0.159	-0.219
	(0.925)	(-0.035)	(-1.224)	(-1.481)
Constant	0.116**	0.142**	0.698***	0.771***
	(1.970)	(2.282)	(16.534)	(15.240)
Year FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Observations	470	364	2,022	1,514
Adj. R-squared	0.310	0.353	0.199	0.195

Table 8: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on zip code and building quality class. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. The main predictor of interest is an indicator for whether the property is within 0.5 miles or 1 mile of the headquarters of a listed firm that experienced a negative cumulative abnormal return (CAR) around Sandy. Columns (1) and (2) show the results for properties sold within one year of Hurricane Sandy. Columns (3) and (4) show the results for properties sold thereafter. Each column presents the results for one of the radii considered, i.e. 0.5 miles or 1 mile. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis for Properties in Chicago

	Differential Residual Price per Sqft					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Net of Best Match by Distance			Net of Best Match by Elevation		
Distance to Coastline (miles)	-0.070*	-0.068*	-0.077			
	(-1.740)	(-1.683)	(-1.515)			
Elevation (10 feet)				-0.005	-0.005	-0.016
				(-0.270)	(-0.275)	(-0.539)
× Year=2013			0.037			0.056**
			(1.081)			(2.165)
× Year=2014			0.012			0.012
			(0.366)			(0.471)
× Year=2015			-0.017			0.021
			(-0.499)			(0.794)
× Year=2016			-0.035			-0.008
			(-1.030)			(-0.302)
× Year=2017			-0.001			-0.008
			(-0.015)			(-0.312)
Built after Sandy		0.756***	0.716***		0.725***	0.677***
		(3.460)	(3.239)		(3.009)	(2.810)
Constant	0.057	0.043	0.088	-0.225*	-0.226*	-0.184
	(0.255)	(0.194)	(0.349)	(-1.856)	(-1.864)	(-1.233)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,177	1,177	1,177	1,177	1,177	1,177
Adj. R-squared	0.204	0.209	0.218	0.323	0.331	0.340

Table 9: *The table shows the differential residual price regressions for the Chicago metro area. Each property sold after Sandy is matched with properties sold before Sandy, based on distance to the lakefront or elevation. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (3) show the results for properties matched based on distance to the coastline. Columns (4) to (6) show the results for properties matched based on elevation. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis Net of Best Match in Chicago

	Net of Best Match in Chicago by Distance		Net of Best Match in Chicago by Elevation	
VARIABLES	(1)	(2)	(3)	(4)
Distance to Coastline (miles)	0.032*	0.033*		
	(1.825)	(1.875)		
Elevation (10 feet)			0.021***	0.020***
			(4.482)	(4.391)
× Post-Sandy	0.015***		0.011**	
	(3.030)		(2.274)	
× Year=2013		0.044***		-0.007
		(4.530)		(-0.661)
× Year=2014		0.026***		0.013*
		(2.783)		(1.745)
× Year=2015		0.002		-0.006
		(0.171)		(-0.714)
× Year=2016		0.003		0.024***
		(0.355)		(2.584)
× Year=2017		0.011		0.039***
		(1.099)		(4.052)
Post-Sandy	-0.180**		-0.129*	
	(-2.021)		(-1.861)	
Built after Sandy	0.552***	0.542***	0.401***	0.408***
	(6.420)	(6.290)	(6.216)	(6.351)
Constant	-0.345**	-0.350**	-0.098**	-0.096**
	(-2.323)	(-2.363)	(-2.210)	(-2.165)
Year FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Observations	10,926	10,926	10,926	10,926
Adj. R-squared	0.317	0.318	0.308	0.310

Table 10: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold in New York or Boston is matched with properties in Chicago, based on distance to the waterfront or elevation. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) and (2) show the results for properties matched based on distance to the coastline. Columns (3) and (4) show the results for properties matched based on elevation. The main predictors of interest are the hurricane risk measures, an indicator for whether the transaction took place after Sandy, and interaction terms between the hurricane risk measures and the years 2013 to 2017. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis with Combined Hurricane Risk Score

	Net of Mean by Zip Code, Building Class					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	New York and Boston			Chicago		
Hurricane Risk=2	-0.051			-0.330		
	(-0.747)			(-0.814)		
Hurricane Risk=3	-0.215***			-0.201		
	(-2.746)			(-0.542)		
Hurricane Risk=4	-0.259***			0.070		
	(-2.986)			(0.181)		
Hurricane Risk=5	-0.315***			-0.014		
	(-3.383)			(-0.036)		
Hurricane Risk		-0.075***	-0.172***		0.081	0.121
		(-3.534)	(-4.630)		(1.165)	(1.246)
× Year=2013			0.042			-0.177**
			(1.192)			(-2.185)
× Year=2014			0.099***			-0.012
			(2.919)			(-0.158)
× Year=2015			0.127***			-0.017
			(3.814)			(-0.212)
× Year=2016			0.117***			0.046
			(3.423)			(0.572)
× Year=2017			0.115***			0.025
			(3.372)			(0.325)
Built after Sandy	0.009	0.005	-0.006	0.666***	0.668***	0.638***
	(0.111)	(0.065)	(-0.073)	(3.351)	(3.386)	(3.121)
Constant	0.168**	0.222***	0.520***	-0.211	-0.586**	-0.757*
	(2.358)	(2.985)	(4.425)	(-0.576)	(-1.971)	(-1.808)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,598	5,598	5,598	1,177	1,177	1,177
Adj. R-squared	0.234	0.233	0.237	0.268	0.266	0.279

Table 11: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on zip code and building quality class. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (3) show the results for properties matched based on distance to the coastline. Columns (4) to (6) show the results for properties matched based on elevation. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.*

Price Impact Analysis with Match by Zip Code and Building Class

	Net of Mean by Zip Code, Building Class					
VARIABLES	(1) All	(2) All	(3) NY	(4) All	(5) All	(6) NY
Distance to Coastline (miles)	0.062***	0.062***	0.149***			
	(4.013)	(3.999)	(3.310)			
Elevation (10 feet)				0.023***	0.023***	0.019**
				(3.994)	(3.995)	(2.559)
× Year=2013	-0.005	-0.005	0.016	-0.007	-0.007	-0.007
	(-0.714)	(-0.714)	(1.262)	(-1.308)	(-1.307)	(-0.963)
× Year=2014	-0.011*	-0.011*	0.001	-0.012**	-0.012**	-0.011*
	(-1.716)	(-1.715)	(0.067)	(-2.192)	(-2.191)	(-1.866)
× Year=2015	-0.016**	-0.016**	-0.008	-0.016***	-0.016***	-0.018***
	(-2.378)	(-2.378)	(-0.621)	(-3.020)	(-3.019)	(-2.724)
× Year=2016	-0.016**	-0.016**	-0.000	-0.017***	-0.017***	-0.009
	(-2.242)	(-2.241)	(-0.019)	(-3.114)	(-3.112)	(-1.594)
× Year=2017	-0.019***	-0.019***	-0.006	-0.017***	-0.017***	-0.017***
	(-2.790)	(-2.790)	(-0.543)	(-3.253)	(-3.253)	(-3.189)
Built after Sandy		-0.002	-0.089		0.003	-0.081
		(-0.030)	(-1.079)		(0.038)	(-0.976)
Reclassified as Flood Zone			-0.182			-0.174
			(-1.316)			(-1.255)
Constant	-0.701***	-0.702***	-1.289***	-0.234***	-0.234***	-0.046
	(-3.930)	(-3.921)	(-3.005)	(-3.364)	(-3.363)	(-0.488)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,598	5,598	2,418	5,598	5,598	2,418
Adj. R-squared	0.236	0.236	0.251	0.237	0.236	0.248

Table 12: *The table shows the differential residual price regressions for New York and Boston metro areas. Each property sold after Sandy is matched with properties sold before Sandy, based on zip code and building quality class. For each property, we obtain the residual price, measured as the natural logarithm of price per sqft, from the regression in Table 3, Column (1). We calculate the difference in these residual prices between the matched properties. This difference is the dependent variable. Columns (1) to (3) show the results for properties matched based on distance to the coastline. Columns (4) to (6) show the results for properties matched based on elevation. Heteroskedasticity robust t-statistics are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01*