Where, When, and How Do Investors Respond to Flood Risk?*

Piet Eichholtz[†]
Maastricht University

Eva Steiner[‡]
Cornell University

Erkan Yönder[§]
Concordia University

This Draft: February 2019

Abstract

While the empirical evidence on the pricing of flood risk exposure in residential real estate held by uninformed households is mixed, this study shows that sophisticated investors in commercial real estate markets respond to heightened flood risk by bidding down the prices of exposed assets. Using a novel micro-level database on commercial real estate transactions completed in New York, Boston, and Chicago before and after the shift in the salience of flood risk caused by Hurricane Sandy, we document that properties exposed to flood risk experience 9% slower price appreciation after the storm than equivalent unexposed properties. We further show that: the price effect is not driven by local damage incurred from Hurricane Sandy in New York, nor by concurrent unrelated pricing trends for waterfront property; it persists through time; it is driven by higher risk premiums for exposed properties, not weaker operating performance of those assets; and that the price effect is exacerbated by contagion from locally important occupiers.

Keywords: Climate change, asset prices, real estate
JEL Classification: G14, Q54, R33

*We thank Sumit Agarwal, Robert Connolly, Moussa Diop, Andra Ghent, Barney Hartman-Glaser, Nils Kok, Sam Kruger, David Ling, Gonzalo Maturana, Sati Mehmet Özsoy, Juan Palacios, Gary Pivo, Tim Riddiough, Shane Sherlund, Christophe Spaenjers, Joseph Tracy, as well as seminar participants at Bilkent University, Cornell University, Maastricht University, the University of Wisconsin at Madison, the AREUEA National Conference, UNC Chapel Hill Real Estate Symposium, Alliance for Research on Corporate Sustainability Conference, Western Economic Association Conference, and the Joint Federal Reserve Bank of Atlanta–Georgia State University Real Estate Finance Conference.

[†]School of Business and Economics, Maastricht University, P.O. Box 616, 6200MD Maastricht, Netherlands. p.eichholtz@maastrichtuniversity.nl

[‡]Cornell SC Johnson College of Business, 465B Statler Hall, Ithaca, NY 14853. ems457@cornell.edu

[§]John Molson School of Business, Concordia University, 1455 de Maisonneuve West, Montréal, Québec H3G 1M8, Canada. erkan.yonder@concordia.ca

1 Introduction

Regulators and market participants worry about the effect of environmental risks on real asset values (Carney, 2015, 2016). The risk to coastal real estate from flooding is at the center of these concerns but empirical evidence on associated value effects is mixed. Murfin and Spiegel (2018) document that coastal property prices are insensitive to flood risk from sea-level rise. In contrast, Bernstein et al. (2018) show that properties exposed to sea-level rise trade at a discount relative to equivalent unexposed properties. Baldauf et al. (2018) find that the price effect of flood risk exposure depends on buyer beliefs about climate change. However, these studies focus on flood risk in residential properties owned by uninformed households primarily for the purpose of housing consumption. We complement prior work by estimating the price effects of flood risk exposure for commercial properties held by sophisticated agents for investment purposes.

The U.S. commercial real estate market is worth \$8.8 trillion, 55% of which is equity-financed and 45% of which is commercial real estate debt (Ling and Archer, 2018). Of the equity share, 60% is held by public and private institutional investors; the remaining 40% is held by other professional investors. Given the penetration of the U.S. commercial real estate market by investment professionals, the marginal buyer is likely a sophisticated agent with the skills and resources required to evaluate investment risk. As a result, this market is a useful laboratory for testing the hypothesis that environmental risk is capitalized into real estate values.

To capture a shift in the salience of flood risk, we focus on Hurricane Sandy. Hurricane-related flood risk has always been present along the southern parts of the U.S. East Coast but a gradual northward shift in hurricane patterns puts new locations at risk (Kossin et al., 2014; Reed et al., 2015). Hurricane Sandy hit New York in 2012:Q4 but spared locations further north, such as Boston. Nonetheless, Sandy is viewed as an example of the type of event in store for the entire region. Importantly, it represents a discrete and unexpected event that has increased the salience of flood risk in U.S. East Coast locations previously considered immune to this type of disaster (Baldini et al., 2016). In our empirical design, we use Hurricane Sandy to document where, when, and through which channels flood risk affects commercial real estate values.

To show how Hurricane Sandy has influenced the effect of flood risk on real estate prices, we obtain a proprietary set of commercial real estate transactions over the 2001–2017 period from Costar, a leading commercial real estate data provider. Flood risk is a function of proximity to the coast and low elevation. The identification challenge is to isolate the impact of flood risk from the environmental amenity value of waterfront property. In Costar, we observe transaction dates and values as well as a rich set of property characteristics. To this dataset we apply a matched pairs analysis. We first filter transaction prices for value-relevant hedonics to obtain residual prices for the pre-Sandy period. In these hedonic regressions we also account for distance to the coast and elevation. The results suggest little environmental amenity value associated with these characteristics for the commercial properties in our pre-Sandy sample. We then match estimated residual prices of properties sold after Sandy in 2012:Q3 with those sold before Sandy based on their building quality and zip code. We regress the residual price difference on our hurricane risk measure, which is a combination of a property's distance to the coast and elevation.

Do investors capitalize information about hurricane risk into real estate values? If so, where? We study three locations: New York, which used to be considered immune to hurricane risk but has experienced a severe storm (Hurricane Sandy); Boston, which is now also considered exposed to hurricane risk but has not yet experienced major damage; and Chicago, which is also located on the waterfront but is not exposed to hurricane risk and serves as a placebo test.

We estimate that a one-mile reduction in distance to the coast results in a 9% slowdown in price appreciation for New York properties sold in the pre- versus post-Sandy period. Of course, New York suffered property damage from Hurricane Sandy, and our results may reflect that. To avoid confounding effects of damages incurred, we estimate the same regressions for commercial property in Boston. Our estimates suggest that a reduction in distance to the coast by one mile in Boston also results in a 9% slowdown in price appreciation across matched pre- versus post-Sandy transactions. Our results are consistent with Hurricane Sandy affecting the capitalization of hurricane risk factors into real estate values in the area hit by the storm but also beyond, in previously unaffected locations. Placebo tests in Chicago over the same period are insignificant, confirming that our results are not driven by concurrent unrelated price trends for waterfront property.

We then turn to the question over what timeframe hurricane risk affects property prices in New York and Boston after Hurricane Sandy struck in 2012. We document that the price effect of hurricane risk exposure remains constant until the end of our sample period in both locations. Our results suggest that the negative price effects of hurricane risk exposure are persistent through time. We find no evidence that such value effects decay as time passes and the disaster becomes a more distant memory.

Next, we analyze the channels through which hurricane risk affects property prices. A sub-sample analysis suggests that hurricane risk exposure affects property values through higher capitalization rates, which reflect higher risk premia. We document no significant effects on vacancy rates, suggesting that operating income, as driven by the occupancy of a property by rent-paying tenants, is unaffected by hurricane risk exposure. Our findings imply that agents in the property investment market respond to hurricane risk more than the actual users of space in buildings at risk of hurricane damage.

Lastly, we document contagion from local corporate occupiers to unrelated properties surrounding their headquarters. Our results suggest that there is a persistent decline in the prices of properties that are close to the headquarters of public firms whose stock prices are negatively affected by Hurricane Sandy, irrespective of their location being exposed to the storm.

Our results relate to the broad literature on the drivers of investment demand and performance in real estate (see, e.g. Ghent (2018); Sagi (2018)). Specifically, our study contributes to the debate on the effect of environmental risks on real estate values. On the one hand, Harrison et al. (2001), Bin and Landry (2013), Atreya et al. (2013), Atreya and Ferreira (2015), and Murfin and Spiegel (2018) find little evidence that flood risk has a lasting negative impact on property prices. Flood risk also does not seem to outweigh the amenity value of waterfront property (Atreya and Czajkowski, 2014). On the other hand, Keenan et al. (2018) show that properties at risk of inundation experience slower price appreciation, while Bernstein et al. (2018) document that such properties sell at a discount relative to equivalent unexposed properties.[1]

[1]Related evidence explores the impact of flooding and flood risk on local economic growth and output (Boustan et al., 2017; Deschênes and Greenstone, 2007; Novkov and Tol, 2018) as well as the impact of hurricane mitigation features on home prices (Gatzlaff et al., 2018).

There are at least two possible explanations for these conflicting results. First, existing work commonly focuses on the value of residential property largely held by uninformed households for the purpose of housing consumption. Bernstein et al. (2018) acknowledge that the price effects they document may be driven by the more sophisticated households in their sample. Second, prior studies focus on flood risk emanating from sea-level rise, a slow and gradual process. Murfin and Spiegel (2018) and Giglio et al. (2018) point out that price effects may be stronger when the salience of environmental risk shifts. In this study, we document significant price effects of flood risk in a sample of commercial properties held by sophisticated professional and institutional agents for investment purposes. Our results suggest that investor sophistication influences the pricing of environmental risk factors. We also focus on the pricing of property characteristics associated with flood risk exposure before and after Hurricane Sandy, a discrete event that has increased the salience of hurricane risk along large parts of the U.S. East Coast that were previously considered immune. Our findings suggest that the salience of environmental risks is a significant determinant of the extent to which they are capitalized into asset values.

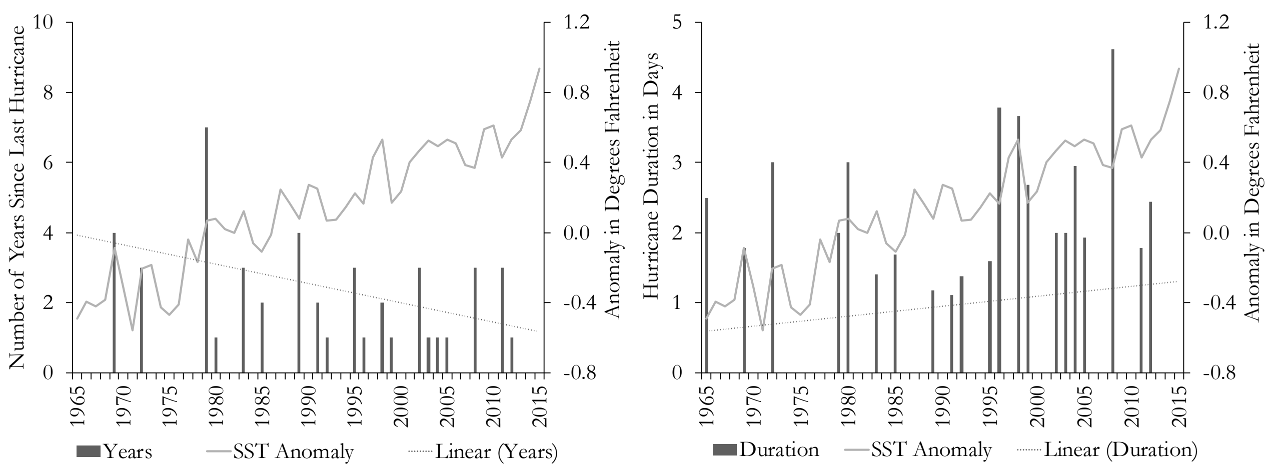
Barr et al. (2017), Ortega and Taspinar (2016) and Gibson et al. (2017) also study Hurricane Sandy but focus on the New York housing market alone. We provide evidence for commercial property held for investment purposes and document the impact of Hurricane Sandy in locations further afield, beyond those directly damaged by the storm. Our results show that investors do not necessarily need to experience a disaster locally in order to respond to it by incorporating the relevant risk factors into asset valuations. In this respect, our findings also relate to Hong et al. (2017), who show that the stock market under-reacts to drought risk, due to a lack of experience with this risk. We further expand on prior work by identifying economic channels (vacancy, capitalization rates, contagion from locally important occupiers) through which flood risk influences property values.

We proceed as follows. Section 2 describes stylized facts about hurricane patterns in the U.S. The data used in this study are presented in Section 3. Section 4 outlines our methodology. Section 5 discusses the empirical results. Section 6 presents robustness tests. Section 7 concludes.

2 Hurricane Patterns in the U.S.

We begin by exploring hurricane patterns in the U.S. for the period 1965–2015. Figures 1 and 2 graphically show the development of the sea surface temperature anomaly, as a primary indicator of global climate conditions, against different measures of hurricane incidence and severity.[2]

Panel A of Figure 1 depicts hurricane incidence in the U.S. against annual global sea surface temperatures. A bar indicates that at least one hurricane struck the U.S. in that year, with the length of the bar indicating the number of years that passed since the last hurricane. We also fit a trend line through these bars. 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 storm. Panel B of Figure 1 shows the average duration of hurricanes in the U.S., 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 U.S.

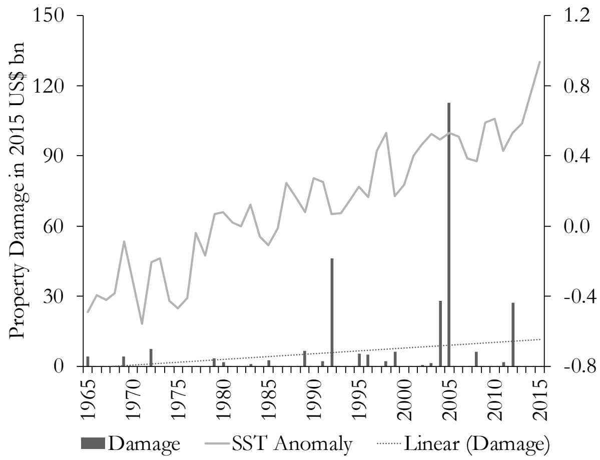


(A) Frequency of Hurricanes

(B) Duration of Hurricanes

Figure 1. Sea Surface Temperatures and Hurricanes in the U.S., 1965–2015. The figure depicts the relationship between the sea surface temperature (SST) anomaly and hurricanes in the U.S. Panel (A) shows the time series evolution of the number of years since the most recent hurricane in the U.S., along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies. Panel (B) shows the average duration (in days) of hurricanes in the U.S., along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies. This graph uses the 1971–2000 global sea surface temperature average as a baseline for measuring temperature anomalies. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.

[2]Sea surface temperature is the temperature of the upper millimeter of the ocean's surface. The temperature anomaly is the departure from the average temperature between 1971 and 2000. See United States Environmental Protection Agency on Climate Change Indicators in the United States.



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

(A) Severity of Hurricanes

(B) Northward Migration of Hurricanes

Figure 2. Hurricane Patterns in the U.S., 1965–2015. The figure depicts hurricane patterns in the U.S. Panel (A) shows the time series evolution of total hurricane damage to property in the U.S., along with a linear trend line fitted to the data, against annual global sea surface temperature (SST) 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 U.S. 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 experienced in a state in a given decade increases. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.

Panel A of Figure 2 presents the time series evolution of hurricane severity, measured as total damage to property, along with a linear trend line. 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 U.S. East Coast sorted from south to north and the total number of hurricanes experienced by state and decade. Prior to 1986, no coastal state north of Florida experienced more than one or two hurricanes per decade. Over the period 1986-1995, coastal states as far north as New York began experiencing a higher number of hurricanes. From 1996 to 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 a northward migration of hurricanes along the U.S. East Coast, putting numerous densely populated centers of economic activity at risk.

In all, the frequency, duration and intensity of hurricanes have increased over recent decades (Mann and Emanuel, 2006). By way of reference, the economic toll of the 2017 hurricane season exceeds \$200 billion, most of which is concentrated in real property.[3] Going forward, average hurricane intensity and destructiveness are projected to increase further (Emanuel, 2005).

[3]See USA Today, November 29, 2017: Nightmarish, Destructive 2017 Hurricane Season Comes to an End.

3 Data

We collect property transaction data from Costar, a leading commercial real estate data provider. To our knowledge, this is the first study employing Costar data to assess the price effects of flood risk on commercial property prices. Costar comprehensively tracks commercial property transactions in the U.S. based on public records, real estate listing services, press releases, SEC filings, and news reports. As of 2017, the Costar database covers more than 3.2 million U.S. commercial real estate deals, representing over 80% of the total market by transaction volume.

Each record in the database contains transaction-specific information, such as transaction date and price. Costar further provides a set of hedonics, including property type, size, age, number of stories, building class, and exact address location. The database covers transactions on all major types of commercial property. We focus on offices. This property type is highly redeployable as it is not very specific to the current owner or user, increasing the number of potential investors. By focusing on office space, we minimize the influence on price dynamics of thin markets, which may occur for more specialized property types, such as hotels, for instance.

We obtain data on office transactions from 2001:Q1 to 2017:Q4 in three major U.S. commercial real estate markets: New York (NY), Boston (MA), and Chicago (IL). From the initial sample, we discard properties built after Hurricane 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 buildings more resilient to hurricanes. We also restrict the sample to properties located within 20 miles of the coast, as flood risk becomes less relevant further inland. The final sample contains 12,192 transactions.[4]

We compile property-specific data on hurricane risk as follows. We use the property addresses provided in Costar 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 coast and elevation, using topological modeling and GIS software.[5]

[4]Our results are robust to including properties built after Hurricane Sandy and lifting the 20-mile restriction.

[5]We obtain shape files for U.S. counties and coast from the U.S. Census Bureau and U.S. Geological Survey. The U.S. 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

We obtain data on hurricane damage to properties from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[6] The database covers the period 1965 to 2015. The smallest geographical unit for which we observe damage is a U.S. county.

Table 1 presents descriptive statistics for the sample data. Panel A covers the county-level data over the 1965–2012 period. The county-level damage from an average hurricane is $56 million. Average distance to the coast of counties hit by hurricanes is 89 miles while elevation is 50 ft, on average. Average population of counties hit by a hurricane is 127,000.

Panel B of Table 1 shows descriptive statistics for property transactions that occurred before and after Hurricane Sandy. Properties sold after Sandy have a mean price per sqft of $396, higher than the mean of $289 before Sandy. This observation reflects that commercial real estate prices experienced a strong upward trend during the sample period. The property characteristics are comparable across the assets sold before versus after Hurricane Sandy, suggesting no significant changes in the composition of the traded real estate stock over the sample period. Properties sold before and after Hurricane Sandy have a similar mean distance to the coast of 7 miles and mean elevation of 60 ft. The mean building size of transactions prior to Hurricane Sandy is 102,000 sqft, compared to approximately 94,000 sqft after Hurricane Sandy. The mean age of properties transacted age prior to Hurricane Sandy is 61 years, compared to 69 after Hurricane Sandy. The number of stories in buildings transacted before and after Hurricane Sandy is the same at seven. The distribution of building quality class, ranging from A (highest quality) to C (lowest quality) is similar across transactions completed before and after Hurricane Sandy. The distribution of properties across the three markets; namely, New York (NY), Boston (MA), and Chicago (IL), is also comparable in the sub-samples of transactions completed before versus after Hurricane Sandy.

[Table 1 about here.]

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 property elevation with coordinates using Elevation API from Bing Maps REST Services.

[6]SHELDUS is a county-level hazard data set for the U.S. 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 U.S.$. Data and maps are compiled and geo-referenced at the University of South Carolina. The database is commonly used in studies on natural hazards and the damage caused, see, e.g. Cutter and Emrich (2005) or Arkema et al. (2013).

4 Method

4.1 Identification Strategy

To identify the effect of hurricane risk on observed property prices, we require variation in the exposure of properties to hurricane risk. Hurricane risk is a function of atmospheric and geographical conditions in a given location, primarily distance to the coast and elevation. These location-specific characteristics are easy to measure, even on the micro-level of individual properties. However, proximity to the coast and low elevation may influence property prices for reasons other than hurricane risk, such as the amenity value of waterfront property (Albouy et al., 2016; Chay and Greenstone, 2005). Cross-sectional regressions of property prices on these metrics are thus insufficient to identify any price impact of hurricane risk. We additionally require variation in the salience of hurricane risk over time.

We obtain such time-series variation from the unexpected strike of Hurricane Sandy in New York in October 2012. New York was believed to be immune to hurricane risk because of its location north of the (sub-) tropical regions where hurricanes typically occur. This belief was unanchored when Hurricane Sandy struck. Moreover, given the changing geographical patterns of hurricanes, Hurricane Sandy is an example of the kind of event now in store for cities all along the U.S. East Coast (Baldini et al., 2016).

Hurricane Sandy caused significant damage to properties in New York. An analysis of property prices before and after Hurricane Sandy in New York alone would inadvertently confound the effect of damage and the potential price impact of exposure to future hurricane risk. To address this issue, we analyze not only properties in New York but also, separately, in Boston. Boston is located even further north than New York and has thus far been spared major hurricane damage. However, the experience of Hurricane Sandy in New York has raised the salience of hurricane risk along the entire U.S. East Coast, including Boston. Further, to ensure that our analysis captures the impact of hurricane risk and not any other price dynamics specific to waterfront property, we also analyze property prices in Chicago. Chicago is situated on a major body of water (Lake Michigan) but due to its inland location it is insensitive to hurricane risk.

4.2 Measuring Hurricane Risk

The National Hurricane Center concludes that flooding from storm surge poses the greatest hurricane-related threat to coastal property.[7] Therefore, our measure of hurricane-related flood risk is based on exposure to storm surge risk. The most important property-location characteristics determining exposure to storm surge risk are distance to the coast and elevation.[8] We use these two location variables as proxies to measure hurricane risk exposure on the property-level.

Based on each property's distance to the coast and elevation, we construct a hurricane risk score. We first create categories of distance to the coast and, separately, elevation, for the sample properties. We then assign hurricane risk scores ranging from one to four, with a higher number indicating greater risk exposure. We assign scores as follows. Distance to the coast is divided into three categories: properties located less than one mile from the coast; those located between one and five miles from the coast; and those located more than five miles from the coast. Elevation is also divided into three categories: properties located below 100 ft of elevation; those located between 100 and 200 ft; and those located above 200 ft.[9] Properties in the category closest to the coast (less than 1 mile), which are also in the lowest elevation category (less than 100 ft), receive the highest risk score with a value of four. Properties in the lowest elevation category but the middle or closest distance category, as well as properties in the closest distance category but the middle and lowest elevation category, receive a score of three. Properties with a combination of middle and closest (lowest) categories of distance (elevation), receive a score of two. Properties in the category furthest from the coast and with the highest elevation receive the lowest risk score with a value of one.

To illustrate the hurricane risk score, Figure 3 shows the location of each of our sample properties in the New York Borough of Manhattan, shaded with reference to their hurricane risk score ranging from 1 (low risk) to 4 (high risk).

[7]Storm surge is an abnormal rise of sea water generated by a storm's winds, which can reach heights well over 20 ft, span hundreds of miles of coast, and travel several miles inland. See NOAA on Storm Surge Risk.

[8]See: NASA on Recipe for a Hurricane.

[9]Our results are robust to choosing alternative cut-offs for the categories of distance and elevation.

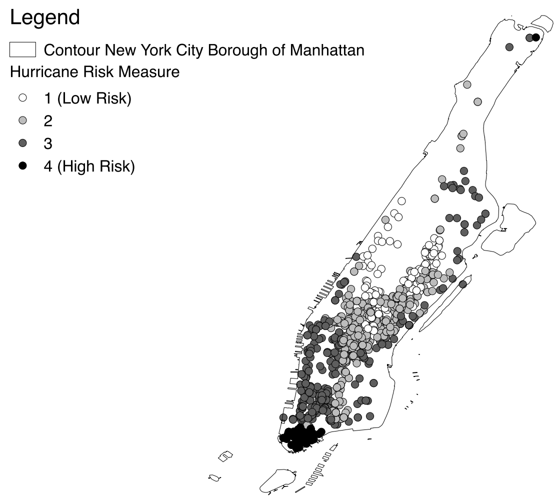


Figure 3. Hurricane Risk Score for Sample Properties in Manhattan. The map shows the geo-coded locations of our final sample properties in the New York Borough of Manhattan. Each property location is shaded to indicate its level of hurricane risk based on our hurricane risk score.

We assess the suitability of our hurricane risk score by regressing actual hurricane damage on its constituent components, distance to the coast and elevation. If these variables are related to actual damage, then they represent observable information about hurricane risk exposure that investors are able to incorporate into valuations. We estimate the following OLS regression:

$$Damage_{i,t} = \beta_0 + \beta_1 Risk_{m,i} + \beta_2 Population_{i,t} + \gamma_t + \theta_t + \delta_z + u_{i,t} \tag{1}$$

where $Damage_{i,t}$ is the natural logarithm of hurricane damage to properties in county i at time t, measured in 2015 \$ million. β_0 is a constant. $Risk_{m,i}$ denotes hurricane risk factor m in county i, where risk factors include county-level average distance to the coast and county-level average elevation. Recall that the smallest geographic unit for which we observe damage data is a U.S. county. We aggregate the components of our hurricane risk score to the county-level by calculating the average distance and elevation across the sample properties in a given county. $Population_{i,t}$ is the natural logarithm of population in county i at time t. γ_t are year fixed effects. θ_t are month fixed effects. δ_z are state fixed effects. $u_{i,t}$ is the residual. We cluster standard errors by county. We expect negative coefficients β_1 on $Risk_{m,i}$ in Eq. (1), indicating that closer proximity to the coast and lower elevation are associated with greater hurricane damage.

4.3 Hurricane Risk and Property Prices

Property prices are a function of observable building characteristics, location and time. We begin our price impact analysis by filtering transaction values for the effect of these observables, using the following hedonic pricing model for all sample transactions completed prior to Sandy:

$$Price_{i,t} = \beta_0 + \beta_1 \mathbf{Hedonics_{i,t}} + \gamma_t + \delta_z + u_{i,t} \tag{2}$$

where $Price_{i,t}$ is the natural logarithm of the transaction price per square foot for property i at time t. The subscript t reflects that property i may sell multiple times during our sample period. β_0 is a constant. $\mathbf{Hedonics_{i,t}}$ is a matrix of covariates; namely, property size (natural logarithm of square footage), age, age squared, number of stories, and building quality class. Building quality class is denoted by letters from A to C, with A (C) representing the highest (lowest) quality. γ_t are year-quarter fixed effects, and δ_z are zip code fixed effects. $u_{i,t}$ is the residual.

In an alternative specification, we add each property's distance to the coast and elevation to the model described in Eq. (2). The resulting coefficient estimates provide an indication of the price of such characteristics prior to any shift in hurricane risk perception caused by Hurricane Sandy. These estimates thus quantify the potential amenity value of waterfront property.

We conduct the price impact analysis of Hurricane Sandy using a matched-pairs approach. Hurricane Sandy hit New York in 2012:Q4 (October). For each property sold in a given market after Hurricane Sandy; that is, between 2013:Q1 until the end of our sample period in 2017:Q4, we identify the "best match" in that market among the properties sold before Hurricane Sandy; that is, properties sold between the start of our sample in 2001:Q1 and 2012:Q3. The "best match" is determined based on building quality class and zip code of the property transacted post-Sandy. We calculate the difference in residual prices across the properties matched in this way. Residual prices are obtained from the hedonic pricing model in Eq. (2), so the value effects of observable property characteristics are accounted for. If several properties qualify as the best match, we compute the average of their residual prices. If the same property is sold before Hurricane Sandy and after Hurricane Sandy, then its features are identical and it is picked as its own best match.

We regress the residual price difference across matched properties on our hurricane risk score:

$$Residual\ Price\ Difference_i = \beta_0 + \beta_1 Hurricane\ Risk\ Score_i + \gamma_t + \delta_z + u_i \tag{3}$$

where *Residual Price Difference*$_i$ is the difference in residual prices, obtained from Eq. (2), for pair i of post-Sandy versus pre-Sandy matched transactions. β_0 is a constant. *Hurricane Risk Score*$_i$ is the value of our hurricane risk score for the property in the pair that is transacted after Hurricane Sandy. γ_t are year fixed effects for the year of the post-Sandy transaction, and δ_z are zip code fixed effects. u_i is the residual. We expect β_1 in Eq. (3) to be negative and significant. Such a result indicates that properties with higher hurricane risk exposure, i.e. those closer to the coast or with lower elevation, experience weaker price appreciation from the pre-Sandy period to the post-Sandy period than those with lower hurricane risk exposure, i.e. properties located further away from the coast or with higher elevation.

5 Results

5.1 Testing the Ex Ante Measures of Hurricane Risk

Table 2 presents the regression results for county-level hurricane damage outlined in Eq. (1). The estimates in column (1) suggest that a one-standard deviation increase in distance to the coast reduces county-level hurricane damage on average by \$1.1 million. For elevation, the estimated effect is \$1.7 million for elevation (column (2)).[10] When including both measures in the same regression (column (3)), the effect of proximity to the coast dominates that of elevation. In all, these results suggests that the location features we use to construct our hurricane risk score contain relevant information about hurricane risk as reflected in property damage upon exposure to a storm.

[Table 2 about here.]

[10]The economic magnitudes of these effects are computed as follows. For *Distance*, coefficient –0.009 × standard deviation of *Distance* 97.18 = –0.09; the exponential of that value is approximately \$1.1 million. For *Elevation*, coefficient –0.075 × standard deviation of *Elevation* 6.97 = –0.52; the exponential of that value is approximately \$1.7 million.

5.2 The Hedonic Pricing Model

Table 3 presents the hedonic pricing model from Eq. (2), estimated over the pre-Sandy period 2001:Q1 through 2012:Q3. Column (1) shows the specification based on which we calculate residual prices for the price impact analysis. Columns (2) and (3) show that property prices in New York are insensitive to distance to the coast and elevation. The estimates in columns (4) and (5) indicate that in Boston, property prices decline 3.3% for a one-mile increase in distance to the coast and are insensitive to elevation. The estimates in columns (6) and (7) suggest that property prices in Chicago drop by 5.2% for every one-mile increase in distance to the coast and are also insensitive to elevation. Our results suggest little amenity value associated with a waterfront location for the commercial properties in our sample.

[Table 3 about here.]

5.3 The Effect of Hurricane Risk on Property Prices

Table 4 presents the results of the price impact analysis described in Eq. (3). Columns (1) and (2) show the price impact regression results for New York. Columns (3) and (4) (respectively, (5) and (6)) present the corresponding estimates for Boston (Chicago).

[Table 4 about here.]

The estimates in column (1) suggest that a one-unit increase in the hurricane risk score is associated with 9% slower price appreciation between transactions completed in New York before versus after Hurricane Sandy. The results reported in column (2) show that the negative price effect of hurricane risk increases monotonically in risk exposure. The estimates suggest that a hurricane risk score of two is associated with 13.7% slower price appreciation; a score of three is associated with 19.1% slower appreciation; and price appreciation is 33.5% slower for properties with the highest hurricane risk score value of four. However, New York has experienced considerable damage during Hurricane Sandy, and our results here may partly reflect the economic cost of such damage. Thus, we also assess the extent to which hurricane risk is priced in Boston — a location that is at risk but has not yet been exposed to a major hurricane strike.

The results for Boston are shown in Columns (3) and (4) of Table 4. The estimates reported in column (3) suggest that a one-unit increase in the hurricane score is associated with 9.5% slower price appreciation between matched transactions before and after Hurricane Sandy, consistent with the magnitude of the effect in New York. The results in column (4) indicate that this overall effect is driven by properties with hurricane risk scores of one and two. Our results suggest that market participants price hurricane risk already after observing disaster strike elsewhere.

The placebo tests over the same period for Chicago (columns (5) and (6)) are insignificant, as hurricane risk is not present for property near an inland body of water. These estimates indicate that our results are not confounded by concurrent unrelated price trends in waterfront property.

5.4 Dissecting the Price Effect of Hurricane Risk

5.4.1 Price Impact of Hurricane Risk Over Time

Market participants may initially react to Hurricane Sandy but the effect may decay over time as the event becomes an increasingly distant memory. We assess the evidence for this hypothesis by augmenting the price impact analysis from Eq. (3) with interaction terms between our hurricane risk score and each year after Hurricane Sandy during which a transaction occurs.

[Table 5 about here.]

Table 5 presents the results. Columns (1) and (2) report the results for New York. Column (1) repeats the main effect of the hurricane risk score for reference. Column (2) presents the estimates by year following Hurricane Sandy. In this specification, the main effect of *Hurricane Risk Score* reflects the price effects of hurricane risk exposure in 2013, the first year after Hurricane Sandy. The results suggest that the initial effect of hurricane risk exposure persists over time, with no significant decay as time passes. Column (3) and (4) present the main price effect and, respectively, year-by-year effects of hurricane risk in Boston. The results suggest that the price impact of hurricane risk exposure persists in Boston as well. The placebo tests for Chicago, reported in columns (5) and (6), suggest no significant shifts in the pricing of distance to the waterfront and elevation in this location, where hurricane risk is not prevalent.

5.4.2 Channels of the Price Impact

Commercial property values are fundamentally a function of the cash flow they produce, which is driven by vacancy rates, and the yield applied to capitalize the expected stream of future cash flows, which incorporates a risk premium for the property (capitalization rate). For a sub-set of the Costar records, we observe capitalization rate and vacancy at the time of the transaction. We replace the dependent variable in Eq. (3) with the differences in capitalization rates and, alternatively, vacancy across matched transactions. We further replace the main independent variable with an indicator that takes the value of one when a post-Sandy transaction is located in the lowest decile; i.e., that with the shortest distance to the coast. In an alternative specification, we replace the main independent variable with an indicator that takes the value of one when a post-Sandy transaction has a *Hurricane Risk Score* of four (highest risk).

[Table 6 about here.]

Table 6 presents the results. The estimates in column (1) show that the difference in capitalization rates across pre- versus post-Sandy transactions for properties located closest to the coast increases by 68 basis points. The estimates in column (2) suggest that there is no discernible effect on vacancy. In column (3) we report estimates on the indicator for the highest hurricane risk exposure: the results suggest that the difference in capitalization rates across matched properties increases by 67 basis points between pre- versus post-Sandy matches, consistent with the findings in column (1). The results reported in column (4) again suggest no significant effect on vacancy.

Our results imply that the value effects of hurricane risk exposure we document are unlikely to be driven by a decline in operating performance for properties at risk, as we document no significant changes in vacancy rates. As a result, our findings indicate no decline in operating income from properties with greater exposure to hurricane risk due to tenant departures or delays to re-letting. By contrast, our results suggest that greater exposure to hurricane risk is associated with an increase in capitalization rates. Given our evidence that income is unaffected by hurricane risk exposure, this increase in capitalization rates must be due to an increase in risk premiums charged by investors for bearing exposure to hurricane risk.

5.4.3 Contagion Effects

Real estate values are affected by the composition of local occupiers. Corporate space users may be differentially affected by hurricane strikes due to their line of business. Those who are more affected may suffer economic losses and move away, or local real estate investors may attribute a higher likelihood to this possibility. Such dynamics may adversely affect local real estate values.

We use variation in the degree to which corporate space users were affected by Hurricane Sandy to test this local contagion hypothesis. We identify the publicly listed firms headquartered within a 0.5-mile or 1-mile radius of each of our sample properties. We estimate normal stock returns on those firms based on the capital asset pricing model from May 1, 2012 (Day –120) until October 19, 2012 (last trading day before Hurricane Sandy). We compute cumulative abnormal returns (CAR) during the 5-day period from October 22, 2012 (Day 0, when Hurricane Sandy first developed into a tropical storm in the Caribbean Sea) to October 26, 2012 (Day 4, when New York declared a state of emergency). We construct *Negative CAR* as a variable that takes the absolute value of negative CAR, or zero if a firm does not generate negative CAR during Sandy. If there are multiple headquarters in the vicinity of a sample property, we use the CAR of the closest firm. We then re-estimate Eq. (3) for the residual price difference across matched properties, using *Negative CAR* of the firm headquartered nearest the property sold post-Sandy as independent variable.

[Table 7 about here.]

Table 7 presents the results. The estimates in columns (1) through (4) of Panel (A) consistently suggest that properties located in the vicinity of firms that were adversely affected by Hurricane Sandy experience slower price appreciation against their pre-Sandy matches if the transaction was completed in 2013, the first year after Sandy. These effects are robust to variation in the size of the radius by which we define vicinity to sample properties and to different combinations of fixed effects. The results presented in columns (1) through (4) of Panel (B) show that the coefficients on the *Negative CAR* for transactions completed in the years after 2013 are small and not statistically significant, suggesting that contagion effects on local property values are concentrated in the first year after the disaster.

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 Hurricane Sandy on individual occupiers in a given area, indicating that there is also a decline in the value of real assets due to diminished local economic activity.

6 Robustness Tests

In our first robustness test, we control for flood risk classification, as hurricane risk may be covered by flood insurance. We collect data for flood insurance risk maps in New York and determine whether a property in our sample is located in a flood zone. This analysis is similar to Gibson et al. (2017). The original map applied before Hurricane Sandy was created in 2007 by the Federal Emergency Management Agency (FEMA). In 2015 FEMA published an updated map following the experience of Hurricane Sandy. We replicate our analysis for New York using these two maps. We run a hedonic model controlling for a Flood Zone indicator using the 2007 map to obtain residual prices. Then we regress the differential residual price on a Flood Zone indicator using the 2015 map in addition to distance to the coast as a major flood risk factor. The results presented in Table 8 suggest that the negative impact of distance to the coast remains significant after controlling for flood risk. These results imply that hurricane risk remains relevant for property prices even in the presence of flood insurance.

[Table 8 about here.]

In our final analysis, we investigate whether hurricane risk is priced separately from the risk relating to sea-level rise.[11] Our findings remain significant, indicating that investors price hurricane risk separately from an asset's exposure to sea-level rise. The results from this robustness test are available on request.

[11] Bernstein et al. (2018) document the impact of sea-level rise on house prices by focusing on a sample of properties within a distance of 0.25 miles to the coast. The critical level of exposure to sea-level rise is around 6 ft. We discard observations that are located less than 1 mile from the coast and with elevation of up to 6 ft to test whether the values of properties that are less likely to be exposed to sea-level rise are still affected by hurricane risk.

7 Conclusion

We examine whether sophisticated, well-informed real estate investors price flood risk. We develop a measure of flood risk 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 explain actual county-level flood damage. We then combine a hedonic pricing model with a matched-pairs analysis of transactions completed pre- versus post-Hurricane Sandy to estimate the price effect of flood risk after the shift in salience caused by Sandy.

We document that location features associated with waterfront property attract a small environmental amenity premium in some locations but only before Hurricane Sandy. After Hurricane Sandy, properties in closer proximity to the coast and at lower elevation experience significantly slower price appreciation over their pre-Sandy counterparts matched on building quality and zip code. We document significant price effects of Hurricane Sandy in New York, which has suffered damage to property from the event, but also in Boston. Given recent shifts in hurricane patterns, Boston is also at risk of future hurricane strikes but has thus far been spared major damage. The evidence we present on the significant price impact of hurricane risk on commercial property in Boston indicates that investors price hurricane exposure even after observing the effects of such disasters elsewhere. Further, we show that the impact of hurricane risk on price appreciation persists through time. Placebo tests in Chicago, also situated on a major body of water but immune to hurricane risk given the inland location, confirm our results.

We dig deeper into our findings to identify the channel through which hurricane risk affects real estate values. We show that hurricane risk affects property values through higher capitalization rates, reflecting higher risk premiums, while operating income as determined by vacancy rates is unaffected. We also study local contagion as a transmission channel. Here, we document that the local presence of corporate occupiers whose stocks performed poorly during Hurricane Sandy is associated with adverse value effects on properties nearby.

References

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff, 2016, Climate Amenities, Climate Change, and American Quality of Life, *Journal of the Association of Environmental and Resource Economists* 3, 205–246.

Arkema, Katie K, Greg Guannel, Gregory Verutes, Spencer A Wood, Anne Guerry, Mary Ruckelshaus, Peter Kareiva, Martin Lacayo, and Jessica M Silver, 2013, Coastal Habitats Shield People and Property from Sea-Level Rise and Storms, *Nature Climate Change* 3, 913.

Atreya, Ajita, and Jeffrey Czajkowski, 2014, Is Flood Risk Universally Sufficient to Offset the Strong Desire to Live Near the Water?, Technical Report, Risk Management and Decision Processes Center, The Wharton School of the University of Pennsylvania.

Atreya, Ajita, and Susana Ferreira, 2015, Seeing is Believing? Evidence from Property Prices in Inundated Areas, *Risk Analysis* 35, 828–848.

Atreya, Ajita, Susana Ferreira, and Warren Kriesel, 2013, Forgetting the Flood? An Analysis of the Flood Risk Discount Over Time, *Land Economics* 89, 577–596.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2018, Does Climate Change Affect Real Estate Prices? Only If You Believe in It, *Review of Financial Studies* Climate Finance Call, Conditionally Accepted.

Baldini, Lisa M., James U. L. Baldini, Jim N. McElwaine, Amy Benoit Frappier, Yemane Asmerom, Kam-Biu Liu, Keith M. Prufer, Harriet E. Ridley, Victor Polyak, Douglas J. Kennett, Colin G. Macpherson, Valorie V. Aquino, Jaime Awe, and Sebastian F. M. Breitenbach, 2016, Persistent Northward North Atlantic Tropical Cyclone Track Migration Over the Past Five Centuries, *Scientific Reports* 6.

Barr, Jason, Jeffrey Cohen, and Eon Kim, 2017, Storm Surges, Informational Shocks, and the Price of Urban Real Estate: An Application to the Case of Hurricane Sandy, Technical Report, Department of Economics, Rutgers University, Newark.

Bernstein, Asaf, Matthew Gustafson, and Ryan Lewis, 2018, Disaster on the Horizon: The Price Effect of Sea Level Rise, *Journal of Financial Economics* Forthcoming.

Bin, Okmyung, and Craig E. Landry, 2013, Changes in Implicit Flood Risk Premiums: Empirical Evidence from the Housing Market, *Journal of Environmental Economics and Management* 65, 361–376.

Boustan, Leah Platt, Matthew E. Kahn, Paul W. Rhode, and Maria Lucia Yanguas, 2017, The Effect of Natural Disasters on Economic Activity in U.S. Counties: A Century of Data, Technical Report 23410, National Bureau of Economic Research.

Carney, Mike, 2015, Breaking the Tragedy of the Horizon – Climate Change and Financial Stability, Speech at Lloyd's of London, 29 September.

Carney, Mike, 2016, Resolving the Climate Paradox, Speech at the Arthur Burns Memorial Lecture, Berlin, 22 September.

Chay, Kenneth, and Michael Greenstone, 2005, Does Air Quality Matter? Evidence from the Housing Market, *Journal of Political Economy* 113, 376–424.

Cutter, Susan L., and Christopher Emrich, 2005, Are Natural Hazards and Disaster Losses in the U.S. Increasing?, *EOS, Transactions American Geophysical Union* 86, 381–389.

Deschênes, Olivier, and Michael Greenstone, 2007, The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather, *American Economic Review* 97, 354–385.

Emanuel, Kerry, 2005, Increasing Destructiveness of Tropical Cyclones Over the Past 30 Years, *Nature* 436, 686–688.

Gatzlaff, Dean, Kathleen McCullough, Lorilee Medders, and Charles M. Nyce, 2018, The Impact of Hurricane Mitigation Features and Inspection Information on House Prices, *Journal of Real Estate Finance and Economics* 57, 566–591.

Ghent, Andra, 2018, What's Wrong with Pittsburgh? Investor Composition and Trade Frequency in U.S. Cities, Technical Report, University of Wisconsin-Madison.

Gibson, Matthew, Jamie T. Mullins, and Alison Hill, 2017, Climate Change, Flood Risk, and Property Values: Evidence from New York City, Working paper, University of Massachusetts-Amherst.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2018, Climate Change and Long-Run Discount Rates: Evidence from Real Estate, Technical Report 17-22, Chicago Booth.

Harrison, David M., Greg T. Smersh, and Arthur L. Schwartz, 2001, Environmental Determinants of Housing Prices: The Impact of Flood Zone Status, *Journal of Real Estate Research* 21, 3–20.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2017, Climate Risks and Market Efficiency, *Journal of Econometrics* Forthcoming.

Keenan, Jesse M, Thomas Hill, and Anurag Gumber, 2018, Climate Gentrification: From Theory to Empiricism in Miami-Dade County, Florida, *Environmental Research Letters* 13, 054001.

Kossin, James P, Kerry A Emanuel, and Gabriel A Vecchi, 2014, The Poleward Migration of the Location of Tropical Cyclone Maximum Intensity, *Nature* 509, 349–352.

Ling, David, and Wayne Archer, 2018, *Real Estate Principles: A Value Approach*, Fifth edition (McGraw-Hill Education).

Mann, Michael E., and Kerry A. Emanuel, 2006, Atlantic Hurricane Trends Linked to Climate Change, *Eos, Transactions American Geophysical Union* 87, 233–241.

Murfin, Justin, and Matthew Spiegel, 2018, Is the Risk of Sea Level Capitalized in Residential Real Estate?, *Review of Financial Studies* Climate Finance Call, Conditionally Accepted.

Novkov, Monika, and Richard S. J. Tol, 2018, Effects of Sea Level Rise on the Economy of the United States, *Journal of Environmental Economics and Policy* 7, 85–115.

Ortega, Francesc, and Süleyman Taspinar, 2016, Rising Sea Levels and Sinking Property Values: The Effects of Hurricane Sandy on New York's Housing Market, Technical Report 10374, IZA.

Reed, Andra J., Michael E. Mann, Kerry A. Emanuel, Ning Lin, Benjamin P. Horton, Andrew C. Kemp, and Jeffrey P. Donnelly, 2015, Increased Threat of Tropical Cyclones and Coastal Flooding to New York City During the Anthropogenic Era, *Proceedings of the National Academy of Sciences* 112, 12610–12615.

Sagi, Jacob, 2018, Asset-Level Risk and Return in Real Estate Investments, Technical Report, UNC Chapel-Hill.

Table 1. Descriptive Statistics

Can we show difference in means of property characteristics before/after Hurricane Sandy?

This table shows descriptive statistics for the main variables used in our empirical analyses. Panel (A) presents the descriptive statistics on the county-level variables used in the damage analysis. The sample includes 1,273 counties in U.S. East Coast states that were hit by a hurricane during the 1965–2012 period. *Damage* is county-level hurricane damage, measured in 2015 $ million. *Distance* is mean distance to the coast of the sample properties located in a given county, measured in miles. *Elevation* is mean elevation of the sample properties in a given county, measured in 10 ft. *Population* is county-level population, measured in '000 inhabitants. Panel (B) presents the sample of property transactions obtained from Costar by sub-period: before Hurricane Sandy (2001:Q1–2012:Q3) and after Hurricane Sandy (2013:Q1–2017:Q4). *Price* is property transaction price per sqft. *Distance* is a given property's distance to the coast, measured in miles. *Elevation* is a given property's elevation, measured in 10 ft. *Size* is property size, measured in '000 sqft. *Age* is property age, measured in years. *Stories* is the number of stories in a given property. *Building Class* indicates building quality and ranges from A (highest quality) to C (lowest quality). *Location* indicates property location and includes New York (NY), Boston (MA), and Chicago (IL).

	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
	Panel (A) County-Level Damage Data									
Damage	55.74	501.35	0.00	12,129.93	4,888					
Distance	89.26	97.18	0.00	605.78	4,888					
Elevation	5.26	6.97	0.01	54.32	4,888					
Population	127.00	260.00	0.04	3,980.00	4,888					
	Panel (B) Property-Level Transaction Data									
	Before Hurricane Sandy					After Hurricane Sandy				
Price	289.24	287.16	9.27	1,546.15	7,599	396.26	389.89	9.27	1,546.15	4,593
Distance	7.43	4.24	0.02	20.00	7,599	7.38	4.30	0.02	19.96	4,593
Elevation	5.72	5.16	0.00	43.96	7,599	5.88	5.45	0.00	41.67	4,593
Size	102.00	201.00	1.10	1,070.00	7,599	93.86	194.00	1.10	1,070.00	4,593
Age	60.80	37.66	0.00	259.00	7,599	69.04	37.95	2.00	274.00	4,593
Stories	7.06	9.27	1.00	110.00	7,599	6.84	8.95	1.00	110.00	4,593
Building Class										
A	0.12	0.32	0.00	1.00	7,599	0.10	0.30	0.00	1.00	4,593
B	0.42	0.49	0.00	1.00	7,599	0.44	0.50	0.00	1.00	4,593
C	0.46	0.50	0.00	1.00	7,599	0.46	0.50	0.00	1.00	4,593
Location										
New York	0.44	0.50	0.00	1.00	7,599	0.46	0.50	0.00	1.00	4,593
Boston	0.29	0.45	0.00	1.00	7,599	0.30	0.46	0.00	1.00	4,593
Chicago	0.27	0.44	0.00	1.00	7,599	0.24	0.43	0.00	1.00	4,593

Table 2. County-Level Hurricane Damage

General question: Do we want to show a constant in all regression models? It's hard to interpret and looks weird sometimes.

This table reports output from Eq. (1). The regression is estimated over the 1965–2012 period. The dependent variable is the natural logarithm of county-level hurricane damage to property, measured in 2015 $ million. *Distance* and *Elevation* are county-level hurricane risk factors, aggregated across the sample properties in a given county. *Distance* is mean distance to the coast of the sample properties located in a given county, measured in miles. *Elevation* is mean elevation of the sample properties in a given county, measured in 10 ft. *Population* is the natural logarithm of county-level population, measured in '000 inhabitants. Fixed effects are included as indicated. Standard errors are clustered by county. Heteroskedasticity-robust t-statistics are reported in parentheses.

	County-Level Damage		
	(1)	(2)	(3)
Distance	-0.009***		-0.009***
	(-16.872)		(-13.248)
Elevation		-0.075***	-0.000
		(-9.404)	(-0.022)
Population	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 Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Observations	4,888	4,888	4,888
Adj. R-squared	0.294	0.274	0.294

Statistical significance is indicated as follows:
* p <0.1; ** p <0.05; *** p <0.01.

Table 3. Hedonic Pricing Model

Need to present results for "All" (column (1)) including distance and elevation to show that these variables are not significant. Otherwise, leaving them out from the hedonic model means that model is mis-specified and our residual prices are wrong. Maybe drop the distance and elevation variables all together here? They are significant for some of the locations, raising questions about (i) should we use location-specific models to estimate residual prices, and (ii) is our hedonic model mis-specified? Coefficient estimates on the hedonics also vary across locations, raising the question whether it is correct to compute residual prices based on the model in column (1) across all locations. Are s.e. clustered? How can we have building class F here? It doesn't seem to be part of the sample described in Table 1?

This table reports output from Eq. (2). The regression is estimated over the sub-sample period prior to Hurricane Sandy; that is, 2001:Q1 through 2012:Q3. The dependent variable is the natural logarithm of property transaction price per sqft. Column (1) presents results across all locations; that is, New York (NY), Boston (MA), and Chicago (IL). Columns (2) and (3) present results for New York. Columns (4) and (5) present results for Boston. Columns (6) and (7) present results for Chicago. Across columns (2) through (7), even columns present results controlling for *Distance*, whilst odd columns present results accounting for *Elevation*. *Distance* is a given property's distance to the coast, measured in miles. *Elevation* is a given property's elevation, measured in 10 ft. *Size* is property size, measured in '000 sqft. *Age* is property age, measured in years. *Age*^{2} is the square of property age. *Stories* is the number of stories in a given property. *Building Class* indicates building quality and ranges from A (highest quality) to C (lowest quality). Building quality class A is the excluded category. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Property Transaction Price						
	(1) All	(2) New York	(3) New York	(4) Boston	(5) Boston	(6) Chicago	(7) Chicago
Distance		0.043		-0.033*		-0.052**	
		(0.873)		(-1.798)		(-2.296)	
Elevation			0.012		0.005		-0.000
			(1.504)		(1.187)		(-0.009)
Size	-0.196***	-0.174***	-0.171***	-0.208***	-0.207***	-0.208***	-0.210***
	(-22.525)	(-12.443)	(-12.327)	(-14.101)	(-14.045)	(-11.716)	(-11.864)
Age	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.010***	-0.010***
	(-9.572)	(-4.604)	(-4.723)	(-6.686)	(-6.519)	(-5.478)	(-5.423)
Age^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(7.712)	(4.185)	(4.251)	(5.645)	(5.552)	(4.202)	(4.222)
Stories	0.010***	0.007**	0.006**	0.024***	0.024***	0.015***	0.015***
	(6.384)	(2.464)	(2.345)	(6.024)	(5.992)	(5.681)	(5.744)
Building Class=B	-0.258***	-0.123**	-0.123**	-0.298***	-0.298***	-0.358***	-0.361***
	(-7.689)	(-2.130)	(-2.121)	(-5.603)	(-5.575)	(-5.787)	(-5.850)
Building Class=C	-0.400***	-0.307***	-0.303***	-0.436***	-0.435***	-0.422***	-0.426***
	(-10.212)	(-4.495)	(-4.436)	(-7.225)	(-7.183)	(-5.830)	(-5.902)
Building Class=F	-0.686***	-0.429**	-0.427**	-1.396***	-1.416***	-0.022	-0.037
	(-3.474)	(-1.977)	(-1.968)	(-3.774)	(-3.778)	(-0.076)	(-0.120)
Constant	7.336***	6.782***	7.062***	7.736***	7.412***	7.374***	7.137***
	(63.296)	(15.289)	(35.953)	(33.288)	(39.759)	(30.458)	(30.935)
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,599	3,329	3,329	2,215	2,215	2,055	2,055
Adj. R-squared	0.583	0.514	0.514	0.460	0.459	0.352	0.350

Statistical significance is indicated as follows: * p <0.1; ** p <0.05; *** p <0.01.

Table 4. Price Impact of Hurricane Risk by Location

Should transactions be matched on hurricane risk score? Wouldn't that be more logical? How are s.e. treated? Clustered? Column (4) shows that impact of hurricane risk is non-monotonic in Boston. That looks weird. I wonder if this is because of the deterministic cut-offs for distance and elevation in the construction of the hurricane risk score. Shouldn't it be relative and market-specific, i.e. the closest/lowest x% of the sample properties in a given market by distance/elevation get a risk score of 4 — rather than properties within x miles of the coast etc.? That would also mitigate the issue that there is currently no estimate for hurricane risk score of 4 in Chicago, which also looks weird. How can we account for gentrification of locations? Can we have combined zip code–year FE? That would cover it, presumably.

This table reports output from Eq. (3). The dependent variable is the difference in residual prices across matched transactions from the pre- and post-Sandy sub-periods. The pre-Sandy sub-period runs from the start of our sample in 2001:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2013:Q1 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (2), estimated for all transactions in the pre-Sandy period (see Table 3, column (1), for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on zip code and building quality class. Columns (1) and (2) present results for New York. Columns (3) and (4) (respectively, (5) and (6)) present results for Boston (Chicago). Odd columns report results for *Hurricane Risk Score* as a continuous variable. Even columns present results for indicator variables created from the four values *Hurricane Risk Score* is defined to take, where the lowest risk score (value of one) is the excluded category. *Hurricane Risk Score* is the hurricane risk measure constructed from property-level distance to the coast and elevation. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Residual Price Difference					
	(1) New York	(2) New York	(3) Boston	(4) Boston	(5) Chicago	(6) Chicago
Hurricane Risk Score	-0.099***		-0.095*		0.124	
	(-2.713)		(-1.800)		(1.331)	
Hurricane Risk Score=2		-0.137**		-0.311***		-0.237
		(-2.377)		(-3.135)		(-1.249)
Hurricane Risk Score=3		-0.191**		-0.295***		-0.169
		(-2.364)		(-2.673)		(-1.411)
Hurricane Risk Score=4		-0.335***		-0.560		
		(-2.936)		(-1.606)		
Constant	0.785***	0.699***	0.537***	0.567***	-0.241	0.291**
	(8.550)	(11.470)	(3.764)	(5.382)	(-0.884)	(2.336)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,110	2,110	1,358	1,358	1,125	1,125
Adj. R-squared	0.213	0.213	0.206	0.209	0.269	0.269

Statistical significance is indicated as follows: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 5. Price Impact of Hurricane Risk by Location and Year

How are s.e. treated? Clustered?

This table reports output from Eq. (3), augmented with interaction terms between hurricane risk and the year of the post-Sandy transaction. The dependent variable is the difference in residual prices across matched transactions from the pre- and post-Sandy sub-periods. The pre-Sandy sub-period runs from the start of our sample in 2001:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2013:Q1 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (2), estimated for all transactions in the pre-Sandy period (see Table 3, column (1), for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on zip code and building quality class. Columns (1) and (2) present results for New York. Columns (3) and (4) (respectively, (5) and (6)) present results for Boston (Chicago). Odd columns report results for *Hurricane Risk Score* as a continuous variable for reference. Even columns present results for *Hurricane Risk Score* as a continuous variable and interaction terms between this variable and indicators for the year of the post-Sandy transaction. The main effect of *Hurricane Risk Score* in the even columns reflects the price impact of hurricane risk exposure in 2013, the first year after Hurricane Sandy. *Hurricane Risk Score* is the hurricane risk measure constructed from property-level distance to the coast and elevation. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Residual Price Difference					
	(1) New York	(2) New York	(3) Boston	(4) Boston	(5) Chicago	(6) Chicago
Hurricane Risk Score	-0.099***	-0.096**	-0.095*	-0.186**	0.124	0.017
	(-2.713)	(-2.059)	(-1.800)	(-2.056)	(1.331)	(0.106)
× *Year=2014*		-0.010		0.096		0.048
		(-0.203)		(0.923)		(0.279)
× *Year=2015*		-0.009		0.152		0.031
		(-0.195)		(1.567)		(0.169)
× *Year=2016*		-0.016		0.142		0.290
		(-0.328)		(1.336)		(1.604)
× *Year=2017*		0.029		0.070		0.206
		(0.568)		(0.699)		(1.135)
Constant	0.785***	0.777***	0.537***	0.776***	-0.241	0.074
	(8.550)	(6.942)	(3.764)	(3.229)	(-0.884)	(0.158)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,110	2,110	1,358	1,358	1,125	1,125
Adj. R-squared	0.213	0.212	0.206	0.206	0.269	0.270

Statistical significance is indicated as follows: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6. Price Impact of Hurricane Risk by Performance Metric

For which markets are these regressions estimates? NY and Boston? Why do we have lowest decile distance here? And why only hurricane risk score of 4? These are breaks from prior methodology. Could we just have the continuous version of hurricane risk score and the breakdown between categories for consistency with prior tables? I understand sample size may be an issue here. Is that also why we don't differentiate between markets anymore? How can we have negative adj. R-squared? Is that a little weird? How are s.e. treated? Clustered?

This table reports output from Eq. (3). The dependent variable is the difference in operating performance metrics across matched transactions from the pre- and post-Sandy sub-periods. The pre-Sandy sub-period runs from the start of our sample in 2001:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2013:Q1 to the end of our sample in 2017:Q4. Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on zip code and building quality class. Odd columns present the results for differences in the capitalization rate across matched transactions pre- and post-Sandy. Even columns present the results for differences in vacancy rate across matched transactions pre- and post-Sandy. Columns (1) and (2) present results for an indicator that takes the value of one when a given property is in the lowest decile of the sample distribution for distance to the coast. Columns (3) and (4) present results for an indicator that takes the value of one when a given property has a *Hurricane Risk Score* of four (highest risk). *Hurricane Risk Score* is the hurricane risk measure constructed from property-level distance to the coast and elevation. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Difference in Performance Metrics			
	(1) Capitalization Rate	(2) Vacancy	(3) Capitalization Rate	(4) Vacancy
Lowest-Decile Distance	0.678**	0.667		
	(2.450)	(0.196)		
Hurricane Risk Score=4			0.663***	-1.702
			(2.726)	(-0.615)
Constant	-2.687***	4.129***	-2.686***	4.233***
	(-8.241)	(2.904)	(-8.265)	(2.952)
Year Fixed Effects	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	No	No	No	No
Observations	298	1,069	298	1,069
Adj. R-squared	0.182	-0.003	0.182	-0.003

Statistical significance is indicated as follows: * p <0.1; ** p <0.05; *** p <0.01.

Table 7. Price Impact Analysis of Contagion Effects

How are s.e. treated? Clustered? Which markets are these results for, I assume NY and Boston? Or only NY?

This table reports output from Eq. (3). The dependent variable is the difference in residual prices across matched transactions from the pre- and post-Sandy sub-periods. The pre-Sandy sub-period runs from the start of our sample in 2001:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2013:Q1 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (2), estimated for all transactions in the pre-Sandy period (see Table 3, column (1), for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on zip code and building quality class. Panel (A) presents results for post-Sandy transactions in 2013. Panel (B) presents results for post-Sandy transactions completed between 2014 and 2017. In each panel, columns (1) and (2) present results for *Negative CAR* calculated on publicly listed firm headquarters located within one mile of the sample properties, whilst columns (3) and (4) present results for *Negative CAR* calculated on publicly listed firm headquarters located within 0.5 miles of the sample properties. *Negative CAR* takes the absolute values of negative CAR experienced during Sandy by listed firms headquartered in the vicinity of the sample properties, and zero if such a firm does not generate negative CAR during Sandy. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Residual Price Difference			
	Panel (A) First Year After Hurricane Sandy (2013)			
	(1) Within 1 mile	(2) Within 1 mile	(3) Within 0.5 miles	(4) Within 0.5 miles
Negative CAR	-3.599***	-2.489**	-3.149***	-3.082**
	(-4.014)	(-2.266)	(-3.082)	(-2.460)
Constant	0.632***	0.617***	0.642***	0.641***
	(20.334)	(19.809)	(19.009)	(18.601)
Year Fixed Effects	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	No	Yes	No	Yes
Observations	471	471	389	389
Adj. R-squared	0.022	0.107	0.014	0.058
	Panel (B) Later Years After Hurricane Sandy (2014–2017)			
	(1) Within 1 mile	(2) Within 1 mile	(3) Within 0.5 miles	(4) Within 0.5 miles
Negative CAR	0.122	0.271	0.246	0.083
	(0.225)	(0.398)	(0.417)	(0.116)
Constant	0.983***	1.010***	1.001***	1.051***
	(21.607)	(23.837)	(20.836)	(22.026)
Year Fixed Effects	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	No	Yes	No	Yes
Observations	1,407	1,407	1,131	1,131
Adj. R-squared	0.013	0.185	0.011	0.186

Statistical significance is indicated as follows: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8. Price Impact Analysis Controlling for Flood Risk Classification

Why distance to the coast, not the hurricane risk score? How are s.e. treated? Clustered?

This table shows output from Eq. (2) and Eq. (3) for properties in New York. Column (1) replicates the results from estimating Eq. (2) during the pre-Sandy period. The dependent variable is the natural logarithm of property transaction price per sqft. In addition to the covariates included per the description of Eq. (2), this regression also includes *Flood Zone (2007)*, an indicator that takes the value of one when a property is located in a flood risk zone under the 2007 FEMA maps. Columns (2) and (3) replicate the results from estimating Eq. (3) for the properties in New York. The dependent variable is the difference in residual prices across matched transactions from the pre- and post-Sandy sub-periods. In addition to the covariates included per the description of Eq. (3), this regression also includes *Flood Zone (2015)*, an indicator that takes the value of one when a property is located in a flood risk zone under the updated FEMA maps from 2015. *Distance* is a given property's distance to the coast, measured in miles. Column (3) breaks the main effect of *Distance* down by the year after Sandy in which a transaction occurred. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Property Transaction Price	Residual Price Difference	
	(1)	(2)	(3)
Distance		0.202***	0.200***
		(2.713)	(2.594)
× *Year=2014*			0.021
			(1.081)
× *Year=2015*			0.032
			(1.586)
× *Year=2016*			0.009
			(0.426)
× *Year=2017*			0.025
			(1.219)
Flood Zone (2007)	-0.116		
	(-1.294)		
Flood Zone (2015)		-0.112	-0.141
		(-1.096)	(-1.363)
Constant	7.133***	-1.633***	-0.752
	(36.777)	(-2.741)	(-1.216)
Property Characteristics	Yes	No	No
Year-Quarter Fixed Effects	Yes	No	No
Year Fixed Effects	No	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes
Observations	3,329	2,110	2,110
Adj. R-squared	0.514	0.222	0.168

Statistical significance is indicated as follows: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.