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

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**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 rationally respond to heightened flood risk by bidding down the prices of exposed assets. Using a detailed property-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 slower price appreciation after the storm than equivalent unexposed properties. We further show that: the price effect is not driven by physical damage incurred from Hurricane Sandy, nor by concurrent unrelated pricing trends for waterfront property; it persists through time, suggesting it does not reflect a temporary overreaction that is subsequently reversed; it is driven by higher risk premiums for exposed properties; and it is exacerbated by contagion from locally important occupiers.

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# 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 those concerns. However, empirical evidence on actual price discounts for real properties exposed to flood risk is mixed. Murfin and Spiegel (2018) document that coastal property prices are insensitive to flood risk. Bernstein et al. (2018) show that properties exposed to flood risk trade at a significant 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, prior studies focus on flood risk in residential properties owned by uninformed households for the purpose of housing consumption. We complement existing work by estimating the price effects of flood risk exposure of 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 deep penetration of the U.S. commercial real estate market by investment professionals, the marginal buyer is likely to be 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 flood risk is capitalized into real estate transaction 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 northward shift in hurricane patterns puts new locations at risk (Kossin et al., 2014; Reed et al., 2015). Hurricane Sandy unexpectedly 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, including Boston. Sandy 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 primarily a function of a property's proximity to the coast. However, this characteristic may also reflect the environmental amenity value of waterfront property (Albouy et al., 2016; Chay and Greenstone, 2005). Therefore, the empirical identification challenge is to separate any flood risk discount from this amenity premium. 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 (2001:Q1 to 2012:Q3). In those hedonic regressions we include a property's distance to the coast. The results suggest little environmental amenity value associated with that characteristic for the commercial properties in our sample. We then match estimated residual prices of properties sold after Sandy (2013:Q1 to 2017:Q4) with those sold before Sandy (2001:Q1 to 2012:Q3) based on their distance to the coast. Crucially, those residual prices are net of the impact of other observable value-relevant hedonics — including distance to the coast, which captures the amenity value associated with waterfront property prior to the shift in the salience of flood risk caused by Hurricane Sandy. We regress the residual price difference across matched properties sold in the pre- versus post-Sandy period on those properties' distance to the coast and a set of covariates. With this regression, we are able to conduct a clean test of the hypothesis that distance to the coast, as a proxy for flood risk exposure, affects price appreciation for otherwise equivalent properties between pre-Sandy and post-Sandy sales, after accounting for the potential amenity value of waterfront property.

Do investors capitalize information about flood risk into real estate values? If so, where? We study three locations; namely, New York, Boston, and Chicago. New York used to be considered immune to flood risk but experienced a severe storm when Hurricane Sandy hit in 2012:Q4. Boston is now also considered exposed to flood risk (Baldini et al., 2016), but has not yet experienced major damage. Chicago is located on the shore of Lake Michigan but occupies an inland location; Chicago is thus not exposed to hurricane-related flood risk and serves as a placebo test.

We estimate that a one-mile reduction in distance to the coast results in a slowdown in price appreciation for New York properties sold in the pre- versus post-Sandy period of 21%. Of course, real estate in New York suffered physical damage from Hurricane Sandy, and our results may reflect that. To mitigate the confounding effects of physical damage incurred, we replicate the analysis of commercial properties in New York for properties in Boston. Boston real estate has not experienced physical damage due to Sandy, but salience of hurricane-related flood risk in coastal locations long the eastern seaboard has increased since the hurricane struck New York. Our estimates suggest that a reduction in distance to the coast by one mile in Boston results in a slowdown in price appreciation across matched pre- versus post-Sandy transactions of 7%. Our results are consistent with Hurricane Sandy affecting the capitalization of flood risk exposure into real estate values in the area hit by the storm — but also further afield, in previously unaffected locations, through a shift in real estate investors' awareness of flood risk. Placebo tests in Chicago over the same period come out insignificant, confirming that our results are not driven by concurrent unrelated price trends for waterfront property. We are the first to document the price effects of hurricane-related flood risk exposure in commercial real estate markets across a range of location with varying degrees of past exposure to that type of disaster.

We then turn to the question over what timeframe flood risk affects property prices in New York and Boston after Hurricane Sandy struck in 2012:Q4. We document that the price effect of flood risk exposure persists over the subsequent five years until the end of our sample period in both locations. Our results suggest that the negative price effects of flood risk exposure represent a lasting level-shift in the pricing of fundamental property characteristics reflecting an asset's exposure to flood risk. We find no evidence that such value effects decay as time passes and the disaster becomes a more distant memory, or as an initial overreaction is reversed. This evidence is novel in that ours is the first study to assess the persistence of the initial price effects of flood risk exposure on commercial real estate values over a number of years after a disaster has struck.

Next, we analyze the channels through which flood risk affects property prices. A sub-sample analysis suggests that flood risk exposure affects property values through higher capitalization rates, which reflect higher risk premiums. 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 flood risk exposure. Our findings imply that agents in the property investment market respond to flood risk more than the actual users of space in buildings at risk of flood damage. The granular data we employ in our analysis is unique in that it enables us to disentangle the different channels through which flood risk exposure may affect commercial real estate prices.

We also document contagion from local occupiers to unrelated properties in their vicinity. Our results suggest that there is a temporary 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 own location being exposed to the storm. The evidence we present on short-term local contagion of hurricane exposure, to our knowledge, is novel to the literature.

Our inferences are robust to using several alternative testing approaches. The negative price effect of flood risk exposure holds when employing a broader measure of a given property's flood risk exposure based not only on distance to the coast, but also on combinations of distance and elevation above sea-level. We also verify that our results are robust to controlling for potential spikes in flood risk insurance premiums, which may apply to exposed properties after a disaster has struck, as discussed in Froot (2001), and which may have a mechanical negative effect on asset prices. Lastly, we confirm that the negative price effect of flood risk exposure we document is independent of the price effects of sea-level rise reported in Bernstein et al. (2018).

Our results relate to the broad literature on the drivers of investment demand and performance in real estate (see; e.g., Ghent (2018) and 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]

There are at least two possible explanations for those 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-related flood 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.

Dessaint and Matray (2017) report that the *temporary* salience of a disaster leads managers to put excessive weight on its probability in the short-term, even if their own firms were unaffected by a given disaster. The authors interpret that evidence as being consistent with behavioral salience theories of choice (Tversky and Kahneman, 1973, 1974). In contrast, Aretz et al. (2018) document that hurricanes have a *persistent* effect on the distress risk of hurricane-struck firms, reflecting a level-shift in the riskiness of those firms. That evidence is consistent with standard Bayesian theory of judgment under uncertainty. While Sandy itself did not change the objective probability of a hurricane strike on the eastern seaboard, its landfall unusually far north has

[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).

alerted investors to the risk to which locations along the East Coast are actually exposed. Our findings of a *persistent* effect of hurricane-related flood risk on property prices in such locations thus align more closely with the rational investor response documented in Aretz et al. (2018).

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 that experienced acute physical damage in the storm. 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. 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. We further expand on prior work by identifying possible economic channels (capitalization rates, vacancy, contagion from locally important occupiers) through which flood risk influences real property values.

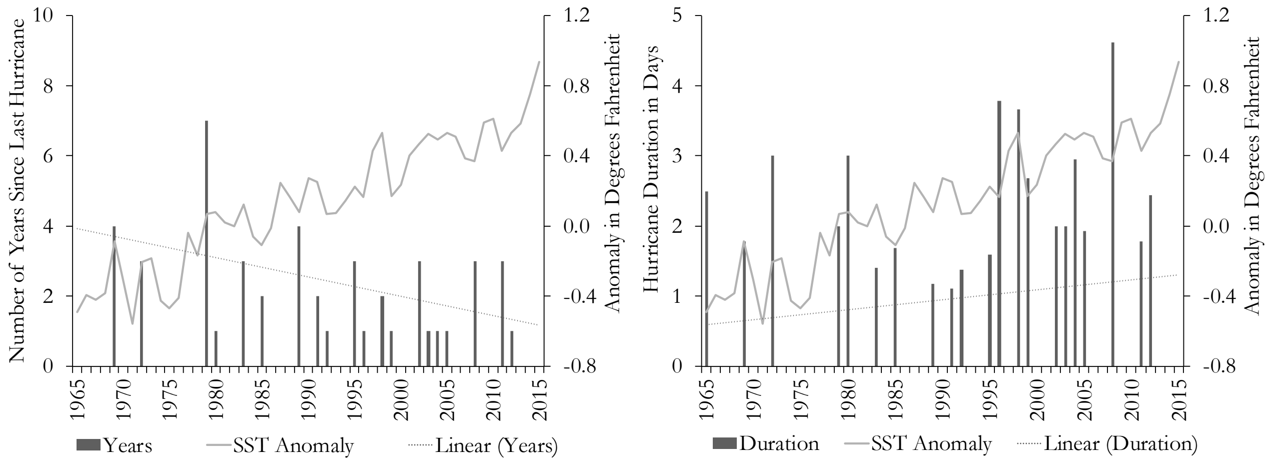
We proceed as follows. Section 2 describes stylized facts about hurricane patterns in the U.S. The data used in our study are presented in Section 3. Section 4 outlines our methodology. Section 5 discusses the empirical results. Section 6 presents robustness tests. Section 7 concludes.

## 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 those 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.

[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 U.S. https://www.epa.gov/climate-indicators.



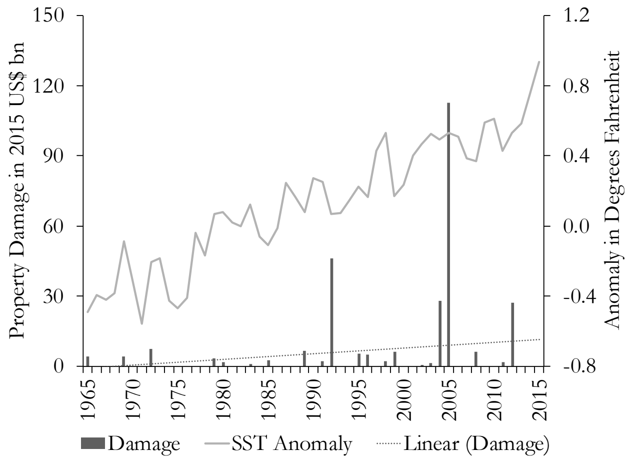

**(A)** Frequency of Hurricanes　　**(B)** Duration of Hurricanes

**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.

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.

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.




| 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 those 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.

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 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.

[3]USA Today, 11/29/17: Nightmarish, Destructive 2017 Hurricane Season Comes to an End.

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. Moreover, there is a lot of it, so increasing our sample size. 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 11,682 transactions.[4]

We compile property-specific data on flood 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 using topological modeling and GIS software. 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. To calculate elevation, we take the average of the elevation data for primary features in each county. We obtain property elevation with coordinates using Elevation API from Bing Maps REST Services.

We obtain data on hurricane damage to properties from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[5] SHELDUS is a county-level hazard data set for the U.S. and covers natural hazards such thunderstorms, hurricanes, floods, wildfires,

[4]Our results are robust to including properties built after Hurricane Sandy and lifting the 20-mile restriction.
[5]For details on the SHELDUS database, see; e.g., Cutter and Emrich (2005) or Arkema et al. (2013).

and tornadoes as well as perils such as flash floods, heavy rainfall, etc. The data set 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 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 completed before and after Hurricane Sandy by location. In New York, properties sold after Sandy have a mean price per sqft of $632, higher than the mean of $449 before Sandy. Those statistics are consistent with price trends observed in Boston and Chicago. They reflect that commercial real estate prices experienced a strong upward trend during the sample period. The average property sold post-Sandy in New York is located slightly closer to the coast than in the pre-Sandy period. Properties sold in New York post-Sandy are also slightly smaller, older (given the passage of time), and fewer of them are categorized as class A assets. The property characteristics are largely comparable across the assets sold in Boston and Chicago before versus after Hurricane Sandy, suggesting few significant changes in the composition of the traded real estate stock over the sample period. As we outline in the next section, our empirical approach accounts for the impact of observable value-relevant hedonics in the analysis of the price effect of flood risk in commercial property investments.

[Table 1 about here.]

# 4 Method

## *4.1 Identification Strategy*

To identify the effect of flood risk on observed property prices, we require variation in the exposure of properties to this risk. Flood risk is a function of location characteristics, such as distance to the coast and elevation. Those characteristics are easy to measure on the level of individual properties. However, proximity to the coast and low elevation may influence property prices for reasons other than flood risk, such as the amenity value of waterfront property (Albouy et al., 2016; Chay and Greenstone, 2005). Cross-sectional regressions of property prices on those metrics alone are thus insufficient to identify the price impact of flood risk. We additionally require variation in the salience of flood risk over time.

We obtain such time variation from the unexpected strike of Hurricane Sandy in New York in 2012:Q4 (October). Prior to Sandy, New York was believed to be immune to strong hurricanes because of its location north of the (sub-) tropical regions where these hurricanes typically occur. This belief was chattered when Hurricane Sandy struck. Moreover, given the changing geographical patterns of hurricanes, summarized in Section 2, Hurricane Sandy is an example of the kind of event now in store for cities all along the U.S. East Coast, including locations further north than New York itself (Baldini et al., 2016). However, hurricanes are a coastal phenomenon and do not much affect locations further inland.

Hurricane Sandy caused significant physical and economic 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 those damages and the potential price impact of exposure to future flood 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, as shown in Baldini et al. (2016), the experience of Hurricane Sandy in New York has raised the salience of flood risk along the entire U.S. East Coast, including Boston. Further, to ensure that our analysis captures the impact of flood risk alone, and not any other concurrent but unrelated price dynamics specific to waterfront property, we also analyze commercial property prices in Chicago. Chicago is situated on a major body of water (Lake Michigan), but due to its location far in-land it is insensitive to flood risk resulting from hurricanes. Chicago thus serves as a placebo test in our empirical analysis.

### *4.2 Measuring Flood Risk*

The National Hurricane Center reports that flooding from storm surge poses the greatest hurricane-related threat to coastal property.[6] Therefore, our measure of flood risk is based on exposure to storm surge risk. The most important location characteristics determining property exposure to storm surge risk are distance to the coast and elevation.[7] We use those two property-location variables as proxies to measure flood risk exposure on the property-level.

We assess the suitability of those two risk proxies by regressing actual flood damage on distance to the coast and elevation. If distance to the coast and elevation are related to actual damage, then those variables represent *ex ante* observable information about flood risk exposure that investors are able to incorporate into valuations. We estimate the following OLS regression:

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

where $Damage_{l,t}$ is the natural logarithm of hurricane damage to properties in county $l$ at time $t$, measured in 2015 \$ million. U.S. counties are the smallest geographic unit for which we observe damage data. $\beta_0$ is a constant. $Risk_{m,l}$ denotes the two flood risk measures; namely, $Distance_l$, which is distance to the coast of properties located in county $l$, and $Elevation_l$, which is elevation of properties located in county $l$. We aggregate the flood risk measures to the county level by calculating the average distance and elevation across the sample properties in a given county. $Population_{l,t}$ is the natural logarithm of population in county $l$ at time $t$. $\gamma_t$ are year–fixed effects. $\theta_t$ are month–fixed effects. $\delta_z$ are state–fixed effects. $u_{l,t}$ is the residual. We cluster standard errors by county.

[6] 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.

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

We expect negative coefficients $\beta_1$ on the flood risk measures in Eq. (1), indicating that closer proximity to the coast and lower elevation are associated with greater hurricane damage. However, we are *ex ante* agnostic about whether distance to the coast and elevation are equally important in determining flood damage, or whether one characteristic dominates the other. As a consequence, we use the results from the regression described in Eq. (1) to inform our choice of which of the two flood risk measures to use in the empirical analysis of flood risk and property prices. We describe the empirical procedure we employ for the analysis of commercial property prices in the next section.

### *4.3 Flood 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 those 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. $\beta_0$ 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. Building class A is excluded from the estimation as reference category. $\mathbf{Hedonics_{i,t}}$ also contains the properties' flood risk measures as described in Section 4.2. The resulting coefficient estimates provide an indication of the price of such characteristics prior to any shift in hurricane-related flood risk perception caused by Hurricane Sandy. The associated coefficient estimates thus capture the potential amenity value of waterfront property. $\gamma_t$ are year-quarter–fixed effects, and $\delta_z$ are zip code–fixed effects. $u_{i,t}$ is the residual. We estimate the regression in Eq. (2) separately for each location; that is, for New York, Boston, and Chicago.

We conduct the price impact analysis of Hurricane Sandy in each sample location using a matched-pairs approach. Hurricane Sandy hit New York in 2012:Q4 (October). For each property sold in a given location 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 period in 2001:Q1 and 2012:Q3. The "best match" is determined based on distance to the coast of the property transacted post-Sandy. As discussed in Section 3, Table 1 shows only minor differences in the composition of the traded real estate stock in the sample locations across pre- and post-Sandy periods, reducing concerns around selection bias in terms of the properties traded before versus after Sandy. We calculate the difference in residual prices across the matched properties sold during the pre- versus post-Sandy sample periods. Residual prices are obtained from the location-specific hedonic pricing model in Eq. (2), so the value effects of observable property characteristics, including the potential amenity value of waterfront property, 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 flood risk measure:

$$\textit{Residual Price Difference}_i = \beta_0 + \beta_1 \textit{Risk}_i + \gamma_t + \delta_z + u_i \tag{3}$$

where $\textit{Residual Price Difference}_i$ is the difference in residual prices, obtained from Eq. (2), for pair $i$ of post-Sandy versus pre-Sandy matched transactions. $\beta_0$ is a constant. $\textit{Risk}_i$ is the value of our flood risk measure for the property in the pair that is transacted after Hurricane Sandy. $\gamma_t$ are year–fixed effects for the year of the post-Sandy transaction, and $\delta_z$ are zip code–fixed effects. $u_i$ is the residual. We expect $\beta_1$ to be positive and significant. Such a result indicates that properties with greater distance to the coast or higher elevation, i.e. those properties less exposed to flood risk, experience stronger price appreciation from the pre-Sandy period to the post-Sandy period than those with greater flood risk exposure, i.e. properties located in closer proximity to the coast or with lower 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 (column (2)).[8] When including both measures in the same regression (column (3)), the effect of distance to the coast dominates that of elevation. In all, those results suggests that the location features we use to construct our flood risk measures contain relevant information about flood risk as reflected in property damage upon exposure to a storm. As the estimates reported under column (3) suggest that the effect of distance to the coast dominates that of elevation, we focus on distance to the coast as the main flood risk measure in the property-level analysis that follows.

[Table 2 about here.]

### 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 estimation results for New York. Columns (2) and (3) show the results for Boston and Chicago, respectively. The estimates in columns (1) indicate that in New York, property prices before Hurricane Sandy were insensitive to the effect of a given property's distance to the coast. The estimates reported in column (2) suggest that in Boston, property prices are weakly negatively related to variation in distance to the coast,

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

but that the effect is small in economic terms and only marginally significant. The estimates in column (3) suggest that property prices in Chicago are also insensitive to variation in distance to the coast. Our results suggest little amenity value associated with a waterfront location for the commercial properties in our sample locations.

[Table 3 about here.]

### *5.3 The Effect of Hurricane Risk on Property Prices*

Panel A of Table 4 presents the results of the price impact analysis described in Eq. (3). Columns (1) shows the price impact regression results for New York.

The estimates in column (1) suggest that a one-mile increase in distance to the coast is associated with 21% faster price appreciation between transactions completed in New York before versus after Hurricane Sandy. In other words, properties located in closer proximity to the coast, which are at greater risk of flooding, experience significantly slower price appreciation than equivalent but less exposed properties transacted across the pre- versus post-Sandy periods. However, New York real estate has experienced considerable physical damage during Hurricane Sandy, and the results presented here may partly reflect the economic cost of such damage. Thus, we also assess the extent to which flood risk exposure affects property price appreciation in Boston — a location that is at risk of hurricane-related flooding but has not yet been exposed to a major hurricane strike.

[Table 4 about here.]

The results for Boston are shown in column (2) of Table 4. The estimates reported there suggest that a one-mile increase in distance to the coast is associated with 7.3% faster price appreciation between matched transactions before and after Hurricane Sandy. This result indicates that distance to the coast significantly affects commercial property price appreciation in Boston even before that market has experienced a local hurricane strike. Importantly, in the regression specifications presented in Table 4, we control for zip code– and year–fixed effects to account for gentrification patterns that may occur in certain geographical sub-areas of the locations we analyze.

To wit, the economic magnitude of the effect of distance to the coast on property prices in Boston is equivalent to approximately one third of the effect we estimate in New York, suggesting that the remaining two thirds of the effect in New York represent the fallout from physical damage to properties incurred during Sandy.

The placebo tests over the same period for Chicago, shown in column (3) of Table 4, are insignificant, as could be expected given that hurricane-related flood risk is not present for property near an inland body of water. Those estimates indicate that our results are not confounded by concurrent unrelated price trends in waterfront property.

In all, our results suggest that the sophisticated investors in the commercial real estate market capitalize flood risk into their investment asset valuations in a forward-looking manner, after observing disaster strike elsewhere. While the landfall of Sandy in New York itself has not increased the objective probability of a hurricane striking Boston, our evidence suggests that the storm has alerted investors to the fact that the northward migration of hurricanes has put a broad range of locations all along the U.S. East Coast at risk (Baldini et al., 2016).

### *5.4 Dissecting the Price Effect of Hurricane Risk*

#### 5.4.1 Price Impact of Hurricane Risk Over Time

We dig deeper into our findings by investigating how the price effect of flood risk exposure evolves over time. Investors may initially react to Hurricane Sandy but the effect may decay over time as the event becomes an increasingly distant memory, or as an initial over-reaction is reversed. We assess the evidence for this hypothesis by augmenting the price impact analysis from Eq. (3) with interaction terms between distance to the coast and each year after Hurricane Sandy during which a transaction occurs.

Panel B of Table 4 presents the results. Column (4) reports the estimates for New York. In this specification, the main effect of *Distance* reflects the price effects of flood risk exposure in 2013, the first year after Hurricane Sandy. The results suggest that the initial effect of flood risk exposure persists over time, with no significant decay for further transactions completed in the subsequent years 2014–2017. Column (5) presents the main price effect and year-by-year effects of *Distance* in Boston. The results suggest that the price impact of flood risk exposure persists in Boston as well, with no evidence of a decay in the price effect of flood risk exposure as time passes. The placebo tests for Chicago, reported in column (6), suggest no systematic shifts in the pricing of distance to the waterfront in this location, where flood risk is not prevalent.

To summarize, our results suggest that Hurricane Sandy had more than a temporary effect on the pricing of a given property's flood risk exposure. The estimates we present imply that the storm has caused a level-shift in the salience of flood risk for coastal property. Our findings indicate that a property's flood risk exposure has become a become a persistent, first-order determinant of real asset values with significant implications for asset price appreciation over time, even in locations that have not experienced a major hurricane-related flood event yet.

#### 5.4.2 Channels of the Price Impact

In this section, we examine the mechanism through which flood risk influences real asset values. Fundamentally, commercial property values are a function of the cash flows they produce - which are driven by contract rents and vacancy rates - and the yield applied to capitalize the expected stream of future cash flows, which incorporates a risk premium for the property. Contract rents are fixed and do not react quickly to new market circumstances, but vacancy and the capitalization rate do. 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. Given that we want to investigate the mechanism behind the price effects, we focus on properties in New York and Boston, for this is where we observed these price effects. As this is a sub-sample analysis over a smaller number of observations, 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 order to maximize the number of high-quality matches over this smaller sub-sample, we match locations by county and building class for this stage of our analysis.

[Table 5 about here.]

Table 5 presents the results. The estimates in columns (1) and (2) show that the difference in capitalization rates across pre- versus post-Sandy transactions for properties located closest to the coast increases by 75 basis points in New York and 97 basis points in Boston. The estimates in columns (3) and (4) suggest that there is no discernible effect of flood risk exposure on vacancy in New York or Boston.

Our results imply that the value effects of flood 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 occupancy-driven decline in operating income from properties with greater exposure to flood risk due to tenant departures or delays to re-letting. By contrast, our results suggest that greater exposure to flood risk is associated with an increase in capitalization rates. Given our evidence that property occupancy is unaffected by flood risk exposure, this increase in capitalization rates is more likely to be due to an increase in risk premiums charged by investors for bearing heightened exposure to flood risk.

#### 5.4.3 Contagion Effects

In addition to property-level operating performance, as reflected in cash flows, vacancy rates, and risk premiums, real estate values are also affected by the vibrancy of the neighborhood surrounding a given property. The vibrancy of an urban area is a function of the composition of the set of local real estate 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 also 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 0.25-mile, 0.5-mile, or 1-mile radius of each of our sample properties in New York and Boston. 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 replicate 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. As in the previous Section 5.4.2, the contagion analysis reported here relies on a smaller sub-sample of properties. In order to optimize the matching of pre- and post-Sandy transactions, we again match on property county and building class.

[Table 6 about here.]

Table 6 presents the results. The coefficient estimates on the variable *Negative CAR* in columns (1) through (3) consistently suggest that properties located in the vicinity of firms in New York that were adversely affected by Hurricane Sandy experience slower price appreciation against their pre-Sandy matches than otherwise equivalent properties not located in the vicinity of such firms. The results reported in columns (4) through (6) indicate that the same basic patterns also hold for properties in Boston. Those results imply that natural disasters can negatively impact property values not only through physical damage to a building's structure or through a shift in the salience of flood risk, causing a revision in investors' required risk premia, but also by dampening neighborhood vibrancy.

A comparison of the economic magnitude of the coefficient estimates on *Negative CAR* across column (1) through (3) for New York, and (4) through (6) for Boston, also suggests that the contagion effects we document monotonically increase in the proximity of a given property to the headquarter location of a firm whose performance was negatively affected during Sandy. Those results emphasize the localized nature of such neighborhood contagion effects.

The estimates reported in Table 6 also indicate that the neighborhood contagion effects we document are short-lived. The coefficient estimates on *Negative CAR* discussed above refer to observations where a transaction was completed in 2013, the first year after Sandy. The interaction terms with the subsequent years in the post-Sandy sample indicate that the initial negative price effects reversed swiftly, suggesting that neighborhood 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 ensuing persistent revision of investors' evaluation of real asset flood risk exposure. Rather, our findings suggest that there are — at least in the short-term — further-reaching, economically important effects stemming from the adverse impact of Hurricane Sandy on individual occupiers in a given area. The findings reported here indicate that there is also a decline in the value of real assets due to diminished local economic activity.

# 6 Robustness Tests

In this section, we report results from several robustness tests. First, we replicate the estimation of our main price impact analysis from Eq. (3) with a more broadly defined flood risk measure that relies on a combination of distance to the coast and elevation of a given property. In subsequent tests, we verify that the negative price effect of flood risk that we document is not the mechanical results of an increase in flood insurance risk premiums applied to exposed properties following Hurricane Sandy. Lastly, we test whether the hurricane-related flood risk exposure affects properties separately from the exposure to sea-level rise, which has been explored in prior literature; see, e.g., Bernstein et al. (2018).

### *6.1 Accounting for Elevation in Measuring Flood Risk Exposure*

In our main analysis, we focus on flood risk exposure as proxied by a given property's distance to the coast. That choice was informed by the empirical results presented in Section 5.1, which indicate that distance to the cost dominates elevation as a predictor of actual damage incurred from flooding. In this robustness test, we replicate our main price impact analysis for an alternative measure of flood risk that takes into account distance to the coast as well as elevation of a given property.

We construct a *Flood Risk Score* based on each property's distance to the coast and elevation. We first create categories of distance to the coast and, separately, elevation, for the sample properties in each location. We then assign flood risk scores ranging from one to five, with a higher number indicating greater risk exposure. We assign scores as follows. The distribution of properties' distance to the coast in each location is divided into four quartiles. The distribution of sample properties' elevation in each location is divided along the median.[9] Properties in the first quartile; i.e., those closest to the coast, which are also in the lower elevation category (lower 50% of the distribution), receive the highest risk score with a value of five. Properties in the closest distance category but higher elevation category, as well as properties in the second-closest distance quartile but the lower elevation category, receive a score of four. Properties in the second-closest distance quartile but in the higher elevation category, as well as properties in the third-closest distance quartile but lower elevation category, receive a score of three. Properties located furthest from the coast (fourth quartile) and in either elevation category receive the lowest risk score with a value of one.

Table 7 presents the results. Panel (A) of Table 7 shows that for each unit increase in *Flood Risk Score*, property price appreciation is 13.3% slower across pre- and post-Sandy transactions in New York (column (1)). The corresponding coefficient estimates show 8.3% slower price appreciation in Boston (column (2)), and no significant effect in Chicago (column (3)). Our findings again indicate that exposure to hurricane-related flood risk, as proxied by a property's

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

distance to the coast as well as elevation, is priced into asset values by the sophisticated investors in the commercial property market. The estimates presented reflect our earlier finding that the price effects we document are not simply a result of physical damages to properties affected by Sandy. We draw this inference based on the evidence we show of a significant deceleration in price appreciation for properties in Boston, a location which has not experienced a major hurricane-related flood event yet.

[Table 7 about here.]

Panel (B) of Table 7 presents the results for indicator variables representing the individual values that *Flood Risk Score* can take, with the lowest risk category (score of one) being excluded as the reference category. The estimates reported indicate that in New York and Boston, the negative price impact of flood risk exposure increases monotonically in the degree of exposure of a given property to flood risk, as reflected in higher risk scores (column (4) and (5)). Specifically, the results suggest that in New York, properties with the two highest risk score values of four and five drive the price impact (column (4)). By contrast, in Boston, properties with risk score values of three, four, and five drive the price impact results we document (column (5)). Column (6) again shows no significant results for the placebo tests in the Chicago commercial real estate market.

### *6.2 Controlling for Rising Insurance Premiums*

In our second robustness test, we replicate our main price impact analysis controlling for flood risk classification. Flood risk may be covered by flood insurance, and premiums may spike after disaster strikes (Froot, 2001). A rise in flood insurance premiums for properties exposed to flood risk would reduce asset values for exposed properties, irrespective of past damages incurred. 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. To do so, we obtain shape files for the 2007 and 2013 versions of the New York flood maps from the New York Department of Environmental Protection. 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 those 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, as a proxy for those properties that would have experienced an increase in flood risk insurance premiums, 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 proximity to the coast remains significant after controlling for rising insurance premiums for properties newly classified as being located in a flood risk zone. Those results imply that our findings are robust to the influence of rising flood insurance premiums.

[Table 8 about here.]

### *6.3 Accounting for Exposure to Sea-Level Rise*

In our final analysis, we investigate whether flood risk is priced separately from the risk relating to sea-level rise. 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 six feet. We discard observations that are located less than one mile from the coast and with elevation of up to six feet to test whether the values of properties that are less likely to be exposed to sea-level rise are still affected by flood risk. Our findings remain significant, indicating that investors price flood risk separately from an asset's exposure to sea-level rise. The results from this robustness test are available on request.

## 7 Conclusion

We examine whether sophisticated investors in the commercial real estate market 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 have little environmental amenity value before Hurricane Sandy. After Hurricane Sandy, properties in closer proximity to the coast experience significantly slower price appreciation over their otherwise equivalent pre-Sandy counterparts. 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 flood risk on commercial property in Boston indicates that investors price flood risk exposure already after observing the effects of such disasters elsewhere. Further, we show that the impact of flood risk on price appreciation persists through time, and does not dissipate as the event becomes an increasingly distant memory, or as an initial overreaction is reversed. Placebo tests in Chicago, also situated on a major body of water but immune to hurricane-related flood risk given its inland location, confirm our results.

We dig deeper into our findings to identify the channel through which flood risk affects real estate values. We show that flood 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. We confirm that our findings are robust to alternative measures of properties' flood risk exposure, to accounting for an increase in flood insurance risk premiums for properties exposed to flood risk, and that the price effects of hurricane-related flood risk are not confounded by the potential asset value impact of properties' exposure to sea-level rise. In sum, in contrast to prior literature finding insignificant effects of flood risk exposure on the value of residential real estate held by uninformed households for the purpose of housing consumption rather than investment, our findings show that sophisticated investors in commercial real estate markets rationally respond to flood risk by adjusting their valuation of exposed properties downward.

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**Table 1.** Descriptive Statistics

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). Descriptive statistics are shown separately by location; i.e., for New York, Boston, and Chicago. *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 floors in a given property. *Class* indicates building quality and ranges from A (highest quality) to C (lowest quality). Difference indicates the difference in mean statistics between properties sold post-Sandy and pre-Sandy.

| | 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) Transaction-Level Property Data | | | | | | | | | | |
| | Before Sandy | | | | | After Sandy | | | | | Difference |
| | New York | | | | | | | | | | |
| *Price* | 448.62 | 344.79 | 9.27 | 1,546.15 | 3,323 | 631.87 | 428.77 | 9.27 | 1,546.00 | 2,109 | 183.25*** |
| *Distance* | 8.23 | 2.95 | 0.18 | 20.00 | 3,323 | 7.93 | 3.19 | 0.15 | 20.00 | 2,109 | -0.30*** |
| *Elevation* | 5.17 | 4.77 | 0.00 | 43.96 | 3,323 | 5.38 | 5.08 | 0.00 | 42.00 | 2,109 | 0.21 |
| *Size* | 135.00 | 235.00 | 1.10 | 1,070.00 | 3,323 | 121.00 | 226.00 | 1.10 | 1,070.00 | 2,109 | -14.00** |
| *Age* | 67.68 | 32.68 | 0.00 | 203.00 | 3,323 | 73.12 | 33.28 | 2.00 | 216.00 | 2,109 | 5.43*** |
| *Stories* | 9.49 | 9.99 | 1.00 | 102.00 | 3,323 | 9.12 | 9.74 | 1.00 | 60.00 | 2,109 | 0.37 |
| *Class A* | 0.14 | 0.35 | 0.00 | 1.00 | 3,323 | 0.12 | 0.33 | 0.00 | 1.00 | 2,109 | -0.02** |
| *Class B* | 0.41 | 0.49 | 0.00 | 1.00 | 3,323 | 0.42 | 0.49 | 0.00 | 1.00 | 2,109 | 0.02 |
| *Class C* | 0.45 | 0.50 | 0.00 | 1.00 | 3,323 | 0.45 | 0.50 | 0.00 | 1.00 | 2,109 | 0.00 |
| | Boston | | | | | | | | | | |
| *Price* | 188.88 | 153.26 | 9.27 | 1,546.15 | 2,212 | 236.87 | 219.02 | 9.27 | 1,546.15 | 1,358 | 48.00*** |
| *Distance* | 8.45 | 4.91 | 0.02 | 20.00 | 2,212 | 8.50 | 4.97 | 0.02 | 19.96 | 1,358 | 0.05 |
| *Elevation* | 7.46 | 6.39 | 0.00 | 32.81 | 2,212 | 7.77 | 6.67 | 0.00 | 32.81 | 1,358 | 0.31 |
| *Size* | 51.49 | 108.00 | 1.10 | 1,070.00 | 2,212 | 47.45 | 95.85 | 1.10 | 1,070.00 | 1,358 | -4.05 |
| *Age* | 60.75 | 44.82 | 0.00 | 259.00 | 2,212 | 69.64 | 45.21 | 2.00 | 274.00 | 1,358 | 8.89*** |
| *Stories* | 3.77 | 4.24 | 1.00 | 62.00 | 2,212 | 3.69 | 3.81 | 1.00 | 46.00 | 1,358 | -0.08 |
| *Class A* | 0.10 | 0.30 | 0.00 | 1.00 | 2,212 | 0.08 | 0.28 | 0.00 | 1.00 | 1,358 | 0.01 |
| *Class B* | 0.44 | 0.50 | 0.00 | 1.00 | 2,212 | 0.44 | 0.50 | 0.00 | 1.00 | 1,358 | 0.00 |
| *Class C* | 0.46 | 0.50 | 0.00 | 1.00 | 2,212 | 0.47 | 0.50 | 0.00 | 1.00 | 1,358 | 0.00 |
| | Chicago | | | | | | | | | | |
| *Price* | 140.36 | 110.05 | 9.27 | 1,439.69 | 1,752 | 145.95 | 141.26 | 9.27 | 1,546.15 | 928 | 5.59 |
| *Distance* | 4.98 | 4.27 | 0.50 | 19.20 | 1,752 | 5.05 | 4.41 | 0.57 | 19.19 | 928 | 0.07 |
| *Elevation* | 4.98 | 3.74 | 0.66 | 15.75 | 1,752 | 4.82 | 3.69 | 0.66 | 14.76 | 928 | -0.16 |
| *Size* | 117.00 | 219.00 | 1.10 | 1,070.00 | 1,752 | 115.00 | 225.00 | 1.10 | 1,070.00 | 928 | -2.00 |
| *Age* | 48.34 | 33.72 | 0.00 | 156.00 | 1,752 | 58.68 | 34.54 | 3.00 | 144.00 | 928 | 10.34*** |
| *Stories* | 7.37 | 11.48 | 1.00 | 110.00 | 1,752 | 7.11 | 11.34 | 1.00 | 110.00 | 928 | -0.26 |
| *Class A* | 0.11 | 0.31 | 0.00 | 1.00 | 1,752 | 0.10 | 0.30 | 0.00 | 1.00 | 928 | 0.01 |
| *Class B* | 0.42 | 0.49 | 0.00 | 1.00 | 1,752 | 0.48 | 0.50 | 0.00 | 1.00 | 928 | 0.06*** |
| *Class C* | 0.47 | 0.50 | 0.00 | 1.00 | 1,752 | 0.42 | 0.49 | 0.00 | 1.00 | 928 | -0.05** |

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

**Table 2.** County-Level Hurricane Damage

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 | Yes | Yes | Yes |
| 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

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 for New York. Column (2) presents results for Boston. Column (3) presents results for Chicago. *Distance* is a given property's distance to the coast, measured in miles. *Size* is property size, measured in '000 sqft. *Age* is property age, measured in years. *Age Squared* is the square of property age. *Stories* is the number of floors in a given property. *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 | | |
|---|---|---|---|
| | New York (1) | Boston (2) | Chicago (3) |
| *Distance* | 0.042 | -0.032* | -0.028 |
| | (0.856) | (-1.794) | (-1.211) |
| *Size* | -0.174*** | -0.207*** | -0.204*** |
| | (-12.422) | (-14.044) | (-10.649) |
| *Age* | -0.007*** | -0.007*** | -0.009*** |
| | (-4.586) | (-6.660) | (-4.258) |
| *Age Squared* | 0.000*** | 0.000*** | 0.000*** |
| | (4.172) | (5.626) | (3.065) |
| *Stories* | 0.007** | 0.024*** | 0.014*** |
| | (2.490) | (6.014) | (5.569) |
| *Class B* | -0.123** | -0.297*** | -0.335*** |
| | (-2.125) | (-5.579) | (-5.278) |
| *Class C* | -0.307*** | -0.434*** | -0.410*** |
| | (-4.497) | (-7.196) | (-5.336) |
| Constant | Yes | Yes | Yes |
| Year-Quarter–Fixed Effects | Yes | Yes | Yes |
| Zip Code–Fixed Effects | Yes | Yes | Yes |
| Observations | 3,323 | 2,212 | 1,752 |
| Adj. R-squared | 0.514 | 0.454 | 0.339 |

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

**Table 4.** Price Impact of Hurricane Risk by Property Location and Transaction Year

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 by location for all transactions in the pre-Sandy period (see Table 3 for coefficient estimates). Each property sold in a given location during the post-Sandy sub-period is matched to a property sold in that location pre-Sandy, based on distance to the coast. 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 *Distance*. Even columns present results for *Distance* and interaction terms between this variable and indicators for the year of the post-Sandy transaction. The main effect of *Distance* in the even columns reflects the price impact of hurricane-related flood risk exposure in 2013, the first year after Hurricane Sandy. *Distance* is a given property's distance to the coast, measured in miles. Fixed effects are included as indicated. Heteroskedasticity-robust $t$-statistics are reported in parentheses.

| | Residual Price Difference | | | | | |
|---|---|---|---|---|---|---|
| | Panel (A) Property Location | | | Panel (B) Transaction Year | | |
| | New York (1) | Boston (2) | Chicago (3) | New York (4) | Boston (5) | Chicago (6) |
| *Distance* | 0.214*** | 0.073** | -0.019 | 0.197** | 0.084*** | -0.004 |
| | (2.825) | (2.307) | (-0.406) | (2.561) | (2.592) | (-0.084) |
| × *Year 2014* | | | | 0.022 | -0.024 | -0.018 |
| | | | | (1.110) | (-1.424) | (-0.903) |
| × *Year 2015* | | | | 0.032 | -0.013 | -0.024 |
| | | | | (1.594) | (-0.779) | (-1.197) |
| × *Year 2016* | | | | 0.010 | -0.001 | -0.051** |
| | | | | (0.488) | (-0.029) | (-2.535) |
| × *Year 2017* | | | | 0.025 | -0.025 | -0.006 |
| | | | | (1.201) | (-1.174) | (-0.287) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Year–Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip Code–Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,109 | 1,358 | 928 | 2,109 | 1,358 | 928 |
| Adj. R-squared | 0.167 | 0.179 | 0.251 | 0.166 | 0.179 | 0.254 |

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

**Table 5.** Price Impact of Hurricane Risk by Performance Metric

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. Columns (1) and (2) present the results for differences in the capitalization rate across matched transactions pre- and post-Sandy in New York and Boston, respectively. Columns (3) ad (4) present the results for differences in vacancy rate across matched transactions pre- and post-Sandy in New York and Boston, respectively. *Lowest-Decile Distance* is 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 in its respective location (New York or Boston). Fixed effects are included as indicated. Heteroskedasticity-robust $t$-statistics are reported in parentheses.

| | Difference in Performance Maetrics | | | |
|---|---|---|---|---|
| | Capitalization Rate | | Vacancy | |
| | New York (1) | Boston (2) | New York (3) | Boston (4) |
| *Lowest-Decile Distance* | 0.750** | 0.974** | 4.736 | -5.543 |
| | (2.093) | (2.222) | (1.021) | (-1.209) |
| Constant | Yes | Yes | Yes | Yes |
| Year–Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 190 | 113 | 704 | 371 |
| Adj. R-squared | 0.233 | 0.025 | -0.002 | -0.002 |

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

**Table 6.** Price Impact Analysis of Contagion Effects

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. Results are presented separately for properties in New York and Boston. Under each location, each column presents results for *Negative CAR* calculated on publicly listed firm headquarters located within a 1 mile radius of the sample properties, a 0.5 mile radius, and a 0.25 mile radius, respectively. *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 | | | | | |
|---|---|---|---|---|---|---|
| | New York | | | Boston | | |
| | 1 mile (1) | 0.5 mile (2) | 0.25 mile (3) | 1 mile (4) | 0.5 mile (5) | 0.25 mile (6) |
| *Negative CAR* | -5.601*** | -5.632*** | -6.449*** | -7.318*** | -9.522*** | -11.372*** |
| | (-4.433) | (-4.110) | (-4.214) | (-3.918) | (-5.579) | (-5.866) |
| × *Year 2014* | 9.921*** | 9.738*** | 9.357*** | 6.885*** | 7.794*** | 9.006*** |
| | (5.414) | (4.560) | (3.905) | (3.045) | (3.131) | (2.890) |
| × *Year 2015* | 7.533*** | 7.606*** | 8.329*** | 6.821*** | 5.245*** | 6.477*** |
| | (5.350) | (5.152) | (5.080) | (2.662) | (2.683) | (2.843) |
| × *Year 2016* | 10.159*** | 10.510*** | 10.755*** | 6.174** | 7.845*** | 8.362*** |
| | (7.578) | (7.340) | (6.028) | (2.424) | (2.815) | (2.757) |
| × *Year 2017* | 11.230*** | 10.807*** | 10.614*** | 2.685 | 4.715 | 4.863 |
| | (6.629) | (5.672) | (3.739) | (0.676) | (0.929) | (0.929) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Year–Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip Code–Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,307 | 1,131 | 833 | 571 | 389 | 253 |
| Adj. R-squared | 0.109 | 0.089 | 0.074 | 0.183 | 0.149 | 0.096 |

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

**Table 7.** Price Impact Analysis Controlling for Distance to the Coast and Elevation

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 by location for all transactions in the pre-Sandy period (see Table 3 for coefficient estimates). Each property sold in a given location during the post-Sandy sub-period is matched to a property sold in that location pre-Sandy, based on hurricane risk score, county, and building quality class. Columns (1) through (3) present results for New York, Boston, and Chicago, for the range of values of *Flood Risk Score*; i.e., one for lowest risk, to five for highest risk. Columns (4) through (6) present the results for New York, Boston, and Chicago, for indicators representing the different values that *Hurricane Risk Score* can take, with the lowest risk category (score of one) being excluded as reference category. Fixed effects are included as indicated. Heteroskedasticity-robust $t$-statistics are reported in parentheses.

| | Residual Price Difference | | | | | |
|---|---|---|---|---|---|---|
| | Panel (A) Risk Score | | | Panel (B) Risk Indicators | | |
| | New York (1) | Boston (2) | Chicago (3) | New York (4) | Boston (5) | Chicago (6) |
| *Flood Risk Score* | -0.133*** | -0.083** | -0.012 | | | |
| | (-3.144) | (-2.171) | (-0.247) | | | |
| *Flood Risk Score of 2* | | | | 0.069 | -0.160 | 0.020 |
| | | | | (0.803) | (-1.582) | (0.163) |
| *Flood Risk Score of 3* | | | | -0.100 | -0.326** | 0.240 |
| | | | | (-1.042) | (-2.364) | (1.449) |
| *Flood Risk Score of 4* | | | | -0.565*** | -0.373** | 0.112 |
| | | | | (-3.410) | (-2.424) | (0.585) |
| *Flood Risk Score of 5* | | | | -0.643*** | -0.394** | 0.016 |
| | | | | (-3.345) | (-2.440) | (0.081) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Year–Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip Code– Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,109 | 1,358 | 928 | 2,109 | 1,358 | 928 |
| Adj. R-squared | 0.181 | 0.302 | 0.382 | 0.187 | 0.301 | 0.383 |

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

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* | 0.039 | 0.191*** | 0.195** |
| | (0.798) | (2.585) | (2.538) |
| × *Year 2014* | | | 0.022 |
| | | | (1.119) |
| × *Year 2015* | | | 0.024 |
| | | | (1.174) |
| × *Year 2016* | | | 0.001 |
| | | | (0.026) |
| × *Year 2017* | | | 0.018 |
| | | | (0.882) |
| *Flood Zone (2007)* | -0.114 | | |
| | (-1.260) | | |
| *Flood Zone (2015)* | | -0.418*** | -0.433*** |
| | | (-3.227) | (-3.242) |
| Constant | Yes | Yes | Yes |
| Property Characteristics | Yes | No | No |
| Year/Quarter FE | Yes | No | No |
| Year FE | No | Yes | Yes |
| Zip Code FE | Yes | Yes | Yes |
| Observations | 3,323 | 2,109 | 2,109 |
| Adj. R-squared | 0.514 | 0.227 | 0.173 |

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