Climate Change and Commercial Real Estate: Evidence from Hurricane Sandy*

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Abstract

This study examines how sophisticated investors capitalize flood risk in commercial real estate markets. Using a detailed property-level transaction database, we document that New York commercial properties exposed to flood risk trade at a large persistent discount following Hurricane Sandy's landfall. Additionally, commercial properties in Boston, which largely escaped direct hurricane-related damage, exhibit persistent post-Sandy price penalties. In contrast, property prices in Chicago are unaffected by the storm. These results are consistent with a persistent shift in the salience of flood risk along the northeastern seaboard following Sandy's landfall, and reflect the northward migration of hurricanes induced by climate change.

Keywords: Climate change, flood risk, asset prices, investor sophistication, real estate
JEL Classification: G14, Q54, R33

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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 these concerns. However, empirical evidence on price discounts for real properties exposed to flood risk is mixed.[1] 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. For example, Bernstein et al. (2019) acknowledge that the price effects they document may be driven by the most sophisticated households in their sample. Second, prior studies focus on flood risk emanating from sea level rise, which is a slow and gradual process. In particular, Murfin and Spiegel (2020) and Giglio et al. (2020) point out that price effects may be stronger when the salience of environmental risk shifts. In this study, we focus on the U.S. commercial real estate market to examine how sophisticated investors capitalize flood risk exposure into property prices following a discrete shift in flood risk salience.

The U.S. commercial real estate market is a useful laboratory for testing the hypothesis that flood risk is capitalized into real estate transaction values. First, the market is large and important, with valuations totaling \$8.8 trillion and financing through a combination of equity (55%) and commercial real estate debt (45%) (Ling and Archer, 2018). In addition to its size, the sophistication of commercial real estate investors make it a potentially fruitful venue for the study of flood risk. In particular, 60% of the equity share of the market is held by public and private institutional investors, while the vast majority of 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 and price investment risk.[2]

To study how these professional investors capitalize flood risk into commercial real estate prices, we exploit the New York landfall of Hurricane Sandy. While hurricane-related flood risk has always been

[1] Murfin and Spiegel (2020) document that coastal property prices are insensitive to flood risk. In contrast, Bernstein et al. (2019) show that properties exposed to flood risk trade at a significant discount relative to equivalent unexposed properties. Baldauf et al. (2020) find that the price effect of flood risk exposure depends on buyer beliefs about climate change.

[2] We examine the composition of commercial property acquirers in Appendix A. We find that about 95% of U.S. office acquisitions between 2003 and 2017 were made by professional investors. See Figure A.1 for details.

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present along the southern parts of the U.S. East Coast, a recent northward shift in hurricane patterns has put new locations at risk (Kossin et al., 2014; Reed et al., 2015). Hurricane Sandy unexpectedly hit New York in the final week of October 2012, 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 northeastern coastal region, including Boston. As a consequence, Sandy represents a discrete and unexpected event that increased the salience of flood risk along U.S. East Coast locations previously considered immune to this type of disaster (Baldini et al., 2016).

We study the influence of Hurricane Sandy on how flood risk affects real estate prices using a proprietary set of commercial real estate transactions from Costar, a leading commercial real estate data provider. Based on the rich collection of transaction characteristics in the Costar data, including physical property attributes as well as details on transaction dates and prices, we fit a baseline hedonic pricing model using transactions from the pre-Sandy portion of our sample (2003:Q1–2012:Q3). The coefficients from this model capture the determinants of price dynamics prior to any shifts in hurricane-related perceptions of flood risk caused by Sandy. Importantly, we include coastal proximity as a key characteristic in the hedonic model to capture the amenity value associated with waterfront property prior to shifts in flood risk salience (Albouy et al., 2016; Chay and Greenstone, 2005).

Armed with pre-Sandy estimates of the value effects of observable property characteristics, we apply a within-city matching procedure. Specifically, we find nearest neighbors for each of our pre-Sandy transactions in the post-Sandy portion of our sample (2012:Q4–2017:Q4), based on coastal proximity and flood zone status. We then compute residual transaction prices, relative to those implied by the pre-Sandy hedonic model, for the entire sample of matched transactions. Finally, we examine whether differences in residual prices between the pre- and post-Sandy periods can be attributed to increased perceptions of flood risk.[3] In these tests, we adopt each post-Sandy transaction's coastal proximity as our measure of the degree to which perceptions of flood risk increased following the hurricane. Importantly, this is consistent with both the fact that storm surge is a principal driver of

[3]Our matched-pairs approach is essentially a specialized difference-in-differences estimate that accounts for potential sample composition effects. We adopt this approach because our sample lacks sufficient repeat sales to implement a more standard difference-in-differences framework featuring property fixed effects. Nevertheless, we also show that our main inferences are robust to adopting a difference-in-differences style estimator, as in Gupta et al. (2020).

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hurricane-related flood damage and our own analysis showing that coastal proximity is the dominant determinant of hurricane-related property damages, over and above property elevation. Furthermore, because our hedonic model controls for the price effect of proximity prior to Sandy, our residual difference approach accounts for the amenity value of waterfront property and provides a clean test of how flood risk exposure affects property prices following Sandy.

We implement our empirical approach in three large commercial real estate markets: New York, Boston, and Chicago. New York is a natural market to study for our purposes, in that Sandy's New York landfall was widely considered both unexpected and shocking in magnitude. As a result, perceptions of hurricane-related flood risk were almost certainly revised upward following the storm. However, because of the direct physical and economic damages inflicted by Sandy, any price effects we document in New York are likely to include both the effect of such damages and the potential impact of exposure to future flood risk. To address this issue, we separately examine Boston, where properties are now also considered exposed to hurricane-related flood risk, despite not yet experiencing major storm-related damages (Baldini et al., 2016).

To ensure that our analyses in New York and Boston do not capture the effects of concurrent, but unrelated, price dynamics in waterfront property markets, we also analyze property prices in Chicago. While Chicago sits on a major body of water, studying its transactions makes for an ideal placebo test, in that the city's inland location renders it immune to hurricane-related flood risk. Given this set of observations about the three markets we study, we expect to find post-Sandy price penalties associated with flood risk in both New York and Boston, albeit with smaller magnitude in the latter market. In contrast, we do not expect to find a post-Sandy pricing effect among properties in Chicago.

Our main tests in New York, Boston, and Chicago provide evidence consistent with our conjectures. In particular, our estimates in New York suggest that a one mile increase in proximity to the coast results in 21.6% slower price appreciation among properties sold in the post-Sandy period. Meanwhile, our Boston estimates indicate 9.5% slower price appreciation following Sandy. Both of these results are consistent with Hurricane Sandy affecting the capitalization of flood risk exposure into real estate values. The Boston result in particular highlights that this phenomenon is not limited to just areas

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hit by the storm, but also extends further afield, to as yet unaffected locations. Importantly, our placebo tests in Chicago over the same period yield economically and statistically insignificant results, confirming that our findings are not driven by concurrent unrelated price trends for waterfront property.

In addition to establishing average pricing effects across each of our markets of interest, we also study the time dynamics of how flood risk affects property prices following Hurricane Sandy. We document that the price effect of flood risk exposure persists over the subsequent five years (i.e., through the end of our sample period) in both locations. In New York, our results suggest that the negative price effects of flood risk exposure represent a lasting level-shift in how fundamental property characteristics reflecting an asset's flood risk exposure are priced. Meanwhile, in Boston, we find evidence of a slight decay in the negative value effects of flood risk exposure over time, as the disaster becomes a more distant memory.

Next, we ask through which channels flood risk affects property prices. The granular data we employ in our analysis is unique in that it enables us to disentangle the different mechanisms by which flood risk exposure may affect commercial real estate prices. In our first set of tests on this front, we exploit a subsample of transactions where we can observe capitalization and vacancy rates. We find that flood risk exposure affects property values primarily through higher capitalization rates, which may reflect higher risk premia. In contrast, we document no significant effects on vacancy rates, suggesting that current operating income, as driven by the occupancy of a property by rent-paying tenants, is unaffected by flood risk exposure. Taken together, these results imply that commercial property investors exhibit a stronger response to flood risk than the actual occupants of buildings at risk of damage.

In our second set of mechanism-focused tests, we document evidence of a contagion channel stemming from local occupiers that are negatively affected by Sandy. Our results indicate that there is a temporary decline in the prices of properties located in close proximity to the headquarters of public firms with abnormal negative returns following the hurricane. Importantly, we find evidence of this contagion channel even among Boston properties with no exposure to the storm.

In our final set of tests, we demonstrate that our inferences are robust to using several alternative testing approaches. First, we show that the negative price effect of flood risk exposure holds when accounting for elevation as an additional driver of property-level flood risk exposure. Moreover, the

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effect remains when we employ an expanded set of matching criteria for creating pairs of properties sold pre- and post-Sandy. Second, we demonstrate that the results from the matched pairs analysis employed in our main empirical tests also hold when we adopt a more standard difference-in-differences style estimator. Importantly, we confirm that the time dynamics of the effects we document do not appear to violate the estimator's parallel trends assumption. In other words, the post-Sandy price penalties we observe in New York and Boston are not driven by pre-existing trends unrelated to Hurricane Sandy. Finally, we show that the negative price effect of flood risk exposure we document is independent of the price effects of sea level rise featured in a recent strand of literature examining residential real estate markets (Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020).

Our results contribute to the literature that uses environmental catastrophes to examine the effects of flood risk on real estate values. A series of papers in this literature finds little evidence that natural disasters have sustained effects.[4] Most closely related to our work, Barr et al. (2017), Ortega and Taspinar (2016), and Gibson et al. (2017) examine the effect of Hurricane Sandy on New York housing values, and consistently find increased flood risk penalties following the event. However, while Ortega and Taspinar (2016) find that these effects are persistent, Barr et al. (2017) find that the penalties disappear after only one or two years.

Our paper makes several important contributions to this literature. First, our focus on commercial properties in examining the effects of an environmental catastrophe on the pricing of flood risk is, to our knowledge, novel to the literature. Importantly, our commercial property focus allows us to abstract from the fact that, in housing markets, waterfront amenity values are likely to offset (and potentially even outweigh) the effect of flood risks (e.g., Atreya and Czajkowski, 2014).[5] Accordingly, the magnitude of the effect we document among New York properties compares favorably with that in studies on housing. Furthermore, our focus on commercial properties allows us to exploit granular data on capitalization rates, vacancies, and influential neighboring occupants to document the channels through which flood risks are priced.

[4]For example, Harrison et al. (2001), Bin and Landry (2013), Atreya et al. (2013), and Atreya and Ferreira (2015) all find that the price effects associated with floods are only temporary.

[5]Consistent with this idea, our baseline hedonic model estimates indicate the absence of a significant amenity value associated with waterfront properties in the commercial office space.

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A further innovation of our work is to show the extent to which environmental catastrophes affect not only properties in close proximity to the event, but also those further afield. While several papers examine the impact of floods and storms among local properties that avoided flooding (e.g., Atreya et al., 2013; Gibson et al., 2017), our analysis in Boston, which largely escaped the major Sandy-related damage experienced in New York, is novel to the literature. Finally, our analysis informs the debate on the degree of persistence in flood risk penalties following major catastrophic events. While previous papers find that price impacts in housing markets dissipate quickly, our results in the commercial property market suggest otherwise, demonstrating the importance of sophisticated investors in the pricing of catastrophic risks in real estate markets.

In this sense, our paper also contributes to recent work in the climate finance literature examining the effects of evolving flood risk on real estate values. In particular, several papers focus on sea level rise, and draw the link between investor sophistication and associated price penalties. For example, Bernstein et al. (2019) find that price penalties for homes exposed to sea level rise are driven by sophisticated non-occupying buyers. Using a different source of identifying variation, Murfin and Spiegel (2020) also find evidence consistent with the idea that sophisticated non-occupying investors price sea level rise in residential real estate. Baldauf et al. (2020) find that price penalties depend on neighborhood residents' climate change beliefs, but note that such beliefs are likely to be correlated with location-specific levels of buyer sophistication.[6]

Our evidence from the commercial real estate market complements and extends the results from these studies. Specifically, we show that commercial real estate markets, where sophisticated investors' perceptions of cash flows and risk are more likely to influence valuations than personal beliefs about climate change, exhibit strong flood risk penalties. Moreover, our findings of persistent post-Sandy flood risk discounts, based on a shock to the salience of hurricane-related flood risk, complement existing evidence that long run inundation threats are capitalized when sales listings make these risks salient through explicit disclosure of hurricane and flood zones (Giglio et al., 2020). Importantly, our findings highlight the importance of salience for risk recognition even among sophisticated professional investors.

[6] Bernstein et al. (2021) find evidence of such sorting on households' partisan beliefs. In particular, they document that registered Republicans (Democrats) are far more (less) likely than Independents to own homes in coastal communities exposed to sea level rise.

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2 Background and Data

2.1 Hurricane Patterns in the U.S.

We begin by describing the evolution of hurricane patterns in the U.S. between 1965 and 2015. In particular, Figures 1 and 2 show the relationship between the annual global sea surface temperature (SST) anomaly, a primary indicator of global climate conditions, and measures of U.S. hurricane incidence and severity.[7]

Panel A of Figure 1 depicts hurricane incidence in the U.S. against the annual global SST anomaly. 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 the bars. As illustrated by the declining trend in the number of years since the most recent storm, the incidence of hurricanes has increased with rising temperatures. Panel B of Figure 1 shows the average duration of hurricanes in the U.S., along with a linear trend line, against the SST anomaly. The data suggest that increasing sea surface temperatures coincide with a positive trend in the average duration of hurricanes in the U.S.

[Figure 1 about here.]

Panel A of Figure 2 presents time-series data on hurricane severity, measured as total property damages, along with a linear trend line. The data suggest a positive correlation between the SST anomaly 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 1986–1995 period, 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. The data are consistent with a northward migration of hurricanes along the U.S. East Coast, putting numerous densely populated centers of economic activity at risk.

[7] Sea surface temperature is the temperature of the upper millimeter of the ocean's surface. The temperature anomaly is the difference between the observed annual average temperature and the average temperature between 1971 and 2000. The United States Environmental Protection Agency provides details on this and other climate change indicators (`https://www.epa.gov/climate-indicators`).

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[Figure 2 about here.]

In all, the frequency, duration, and intensity of hurricanes have increased over recent decades (Mann and Emanuel, 2006). Moreover, this trend is projected to continue, with hurricanes expected to exhibit increased destructiveness in coming years (Emanuel, 2005). By way of reference, the economic toll of the 2017 hurricane season exceeded $200 billion, most of which was concentrated in real property.[8] In this study, we exploit the evolution of hurricane incidence and severity to examine how sophisticated investors respond to increased flood risk in commercial real estate markets.

2.2 Data and Summary Statistics

Our empirical analysis requires three types of data; namely, commercial property transactions data, data on property-level flood risk exposure, and data on property damages from hurricane strikes. In this section, we outline each of our data sources and provide detail on variable measurement.

2.2.1 Commercial Property Transaction Data

We collect property transactions 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 floors, building class, and exact address location.

While the Costar data cover transactions on all major types of commercial property, we choose to focus on offices for several reasons. First, relative to retail and industrial space, office space is fairly generic once location and condition are taken into account. Second, office space is also highly

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

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redeployable, as it is not very specific to the current owner or user, thus increasing the number of potential investors. As a result, our focus on offices reduces the potential influence of thin markets on observed price dynamics. In contrast, the prices of more specialized property types such as shopping malls and hotels are likely to be affected by smaller active investment markets (Demirci et al., 2020). In addition to focusing on offices, we further restrict our analysis to waterfront locations in each of the markets we study. Importantly, offices are the dominant commercial property type in these locations. As a result, our focus on waterfront office properties yields a sample with both a large number of observations and a high degree of practical relevance.[9]

We obtain data on office transactions from 2002 through 2017 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, as such properties may incorporate advanced building technology that is more resilient to hurricane strikes. Additionally, building codes may have evolved to require features that improve hurricane resiliency. We further restrict the sample to properties located within 20 miles of the coast, as flood risk becomes less relevant further inland. The final sample contains 11,242 transactions, of which 6,681 occurred before Sandy and 4,561 occurred afterward.[10]

2.2.2 Property-Level Flood Risk Data

We compile property-specific flood risk data for each of the Costar transactions in our sample. Specifically, we use the property addresses provided to geocode the location of each sample property, producing an exact latitude/longitude position. We then measure the distance of each property to the coast using topological modeling and GIS software. To do so, we obtain shape files for U.S. counties and the coastline from the Census Bureau and the U.S. Geological Survey. We also measure each property's

[9] Note that adding more property types to our analysis would not necessarily increase the statistical power of our tests. This is because different property types cannot reasonably be included in the same regression. Instead, we would need to run different hedonic regressions to control for value-relevant asset characteristics. Consider, for instance, the variable number of floors. For an office building, 10 floors or more are the norm, and a higher number of floors is positively correlated with property value. For a shopping center, more than two floors are rare, and a higher number of floors is likely to diminish property value, as the rent per square meter declines rapidly for higher floors (the rule of thumb in the appraisal industry is a 50% rent reduction per floor). For an industrial building, a single floor is the standard. Similar cross-property type differences apply to other hedonic characteristics. Moreover, simply including property type dummies in the model would not accurately address this problem, and we know of no study that puts different property types into a single hedonic regression model. As a result, we focus on the office sample.

[10] Our results are robust to including properties built after Hurricane Sandy and to lifting the sample selection criteria regarding distance to the coast.

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elevation, based on its coordinates, using the Elevation API from Bing Maps REST Services. Finally, we obtain data on flood risk zones from FEMA, which allow us to identify whether a given property was located inside a FEMA-designated flood risk zone at a given point in time.

2.2.3 Data on Property Damages from Hurricanes

We obtain data on hurricane damage to properties from the Spatial Hazard Events and Losses Database for the U.S. (SHELDUS).[11] SHELDUS is a U.S. county-level hazard data set that covers natural hazards, including hurricanes. The data contain information on the date of an event, the affected county and its population, as well as the direct losses caused by the event, including damage to physical property in U.S. dollars. The database covers the period from 1965 to 2015. The smallest geographical unit for which we observe damage is a U.S. county. We obtain damage data on a sample of 1,273 counties in U.S. East Coast states that were hit by a hurricane during the pre-Sandy period 1965–2012.

2.3 Descriptive Statistics

Table 1 presents descriptive statistics for the sample data. Panel A covers the county-level data from SHELDUS over the pre-Sandy period 1965–2012. County-level damages from the average hurricane amount to $56 million. Counties hit by hurricanes are naturally close to the coast and tend to be low-lying, with an average coastal distance of 89 miles and average elevation of 53 feet.[12] These counties have an average population of 127,000 inhabitants.

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 square foot of $622, higher than the mean of $455 before Sandy. Properties in Boston also experienced a positive price trend over time, with average prices per square foot of $235 after Sandy versus $191 beforehand. In contrast, property prices in Chicago were similar across the pre- and post-Sandy periods, with mean values of $142 and $146 per square foot, respectively. These statistics reflect that many

[11] For details on the SHELDUS database, see Cutter and Emrich (2005) or Arkema et al. (2013).

[12] We measure each county's distance to the coast as the mean distance to the coast of the sample properties located in the county. Similarly, county-level elevation is the mean elevation of the sample properties located in a given county.

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commercial real estate markets in the U.S. experienced an upward trend in transaction prices during the sample period.

The average property sold post-Sandy in New York is located slightly closer to the coast and has slightly higher elevation than in the pre-Sandy period. Properties sold in New York post-Sandy are also less likely to be located in a flood zone, and are marginally smaller, older (given the passage of time), and have a lower number of floors. 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. Importantly, as we outline in the next section, our empirical approach accounts for the impact of these and other observable value-relevant hedonics in analyzing the effect of flood risk on commercial property values.

[Table 1 about here.]

3 Main Empirical Tests

3.1 Identification Strategy

To identify the effect of flood risk on observed property prices, we require variation in exposure to this risk. Flood risk is a function of location characteristics, such as distance to the coast and elevation. These characteristics are easy to measure for 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). As a result, cross-sectional regressions of property prices on these characteristics alone are insufficient for identifying the price impact of flood risk.

Instead, we rely on variation in the salience of flood risk over time, and examine how the prices of exposed properties are impacted. We obtain such 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 from strong hurricanes because of its location north of the (sub-) tropical regions where these storms typically occur. This belief was shattered when Hurricane Sandy struck. Moreover, given the changing

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geographical patterns of hurricanes, summarized in Section 2.1, Hurricane Sandy is an example of the kind of event now potentially in store for cities all along the U.S. East Coast, including coastal locations further north than New York itself (Baldini et al., 2016).

While Hurricane Sandy caused significant physical and economic damage to properties in New York, an analysis of property prices before and after the hurricane in New York alone would inadvertently confound the effect of such 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, properties 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 inland, it is unaffected by flood risk resulting from hurricanes. Chicago thus serves as a placebo test in our empirical analysis.

To be clear, the main identifying assumption in our empirical approach is that the change in the hedonic price of proximity to the coast from the pre-Sandy period to the post-Sandy period is due to a change in investor beliefs about flood risk exposure, and not due to changing preferences for coastal properties for other reasons (e.g., the amenity value of a coastal location). Put differently, we assume that the value of a property's proximity to the coast remains unchanged, except through an increase in investors' beliefs about the likelihood of flood exposure. Importantly, our placebo setting using transactions in Chicago serves as a direct test of this assumption.

3.2 Baseline Hedonic Pricing Model

We begin our empirical analysis by establishing a set of baseline hedonic pricing coefficients. In particular, we focus on the subsample of transactions that occurred *before* Hurricane Sandy in order to determine both the price dynamics of each market we study, and to establish a set of plausible

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counterfactual prices for transactions that occur *after* Sandy. Specifically, we filter observed transaction values through a hedonic pricing model that accounts for a set of variables known to determine property prices, including physical building characteristics, property location, and transaction date. We estimate the following OLS regression model for all sample transactions completed prior to Sandy (i.e., the period 2003:Q1 through 2012:Q3):

$$Price_{i,t} = \beta_1 \mathbf{Hedonics_{i,t}} + \gamma_t + \delta_z + u_{i,t} \tag{1}$$

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. $\mathbf{Hedonics_{i,t}}$ denotes the hedonic covariates; namely, property size (natural logarithm of square footage), age, number of floors, and building quality class. Building quality class is categorized by letters from A to C, with A (C) representing the highest (lowest) quality. Building class C is excluded from the estimation as reference category. The covariates also include each property's coastal proximity and a FEMA-designated flood zone indicator, both as described in Section 2.2.2. γ_t are year/quarter–fixed effects, and δ_z are zip code–fixed effects. $u_{i,t}$ is the residual.

The coefficients in this regression provide an indication of the price of characteristics prior to any shift in hurricane-related flood risk perception caused by Hurricane Sandy. We estimate the regression in Eq. (1) separately for each location; that is, for New York, Boston, and Chicago.

3.2.1 Estimation Results

Table 2 presents coefficients for the baseline hedonic pricing model estimated over the pre-Sandy period. Column (1) shows the estimation results for New York. Columns (2) and (3) show the results for Boston and Chicago, respectively. Across all columns, the estimated coefficients indicate that smaller, newer, and taller buildings of better quality commanded higher prices per square foot in New York, Boston, and Chicago prior to Hurricane Sandy. Potentially more interesting from our perspective, the estimates also suggest that properties across these three markets were relatively insensitive to variation in proximity to the coast before Hurricane Sandy. In other words, these results suggest little amenity

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value associated with a waterfront location for the commercial properties in our subsamples, after accounting for standard hedonic controls. Similarly, the estimates reported across the columns of Table 2 suggest that, conditional on being in a given zip code, being situated in a flood zone had no statistically significant association with transaction prices prior to Hurricane Sandy. This finding implies that, prior to Sandy, investors paid little attention to a property's flood risk exposure when assessing asset values.

[Table 2 about here.]

3.3 Effect of Flood Risk on Commercial Property Prices

In our main set of tests, we analyze the impact of Hurricane Sandy on commercial property values. In particular, we implement our identification strategy by examining how price dynamics changed in each of our sample locations following the hurricane strike in 2012:Q4 (October). Armed with pre-Sandy hedonic pricing model estimates for each location, we compute residual transaction prices for the entire sample of pre- and post-Sandy transactions. We then examine the extent to which differences in residual prices between the pre- and post-Sandy periods can be attributed to increased flood risk perceptions in each location.[13]

To account for potential differences in the composition of pre- and post-Sandy property transactions, we adopt a location-specific matched-pairs approach based on coastal proximity and flood zone status.[14] Specifically, for each property sold in a given location after Hurricane Sandy (i.e., from 2012:Q4 (after the strike) until 2017:Q4), we identify the "best match" in that market among the properties sold before the hurricane (i.e., properties sold between 2003:Q1 and 2012:Q3). We determine the best match based on each post-Sandy property's distance to the coast as well as its flood zone status. If the same property is sold before and after Hurricane Sandy, then its features are identical and it is selected as its own best match.

[13] Our baseline matched-pairs approach boils down to a specialized difference-in-differences estimate that accounts for potential sample composition effects. However, we also show that our main inferences are robust to adopting an unconditional difference-in-differences estimator. See Section 4.2 and Table 9 for details.

[14] As discussed in Section 2.2, Table 1 shows only minor differences in the composition of the traded real estate stock in the sample locations across the pre- and post-Sandy periods, reducing concerns around selection bias in terms of the properties traded before versus after Sandy.

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We calculate the difference in residual prices across the matched properties sold during the pre- versus post-Sandy sample periods.[15] Importantly, the residual prices are obtained from the location-specific hedonic pricing model outlined in Eq. (1), so the value effects of observable property characteristics, including the potential amenity value of waterfront property, are accounted for. We regress the residual price difference across matched properties on our flood risk measure:

$$\begin{aligned} \textit{Residual Price Difference}_i = \beta_1 \textit{Risk}_i + \beta_2 \textit{Flood Zone}_i + \\ \beta_3 \textit{Local Establishments}_{it} + \gamma_t + \delta_z + u_i \end{aligned} \tag{2}$$

where $\textit{Residual Price Difference}_i$ is the difference in residual prices, obtained from Eq. (1), for each pair i of post-Sandy vs. pre-Sandy matched transactions. $\textit{Risk}_i$ is the value of our flood risk measure for the property in the pair that is transacted after Hurricane Sandy. $\textit{Flood Zone}_i$ indicates whether a matched pair is in a flood zone. $\textit{Local Establishments}_{it}$ is the natural logarithm of the number of business establishments in the zip code of a post-Sandy property in year t, which we include in order to capture the effects of local economic activity on price dynamics. 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. Given the potentially non-standard distribution of errors in Eq. 2, we adopt a bootstrapping approach. In particular, we allow the empirical distribution of the sample itself to inform us about the properties of our estimator.[16]

We adopt coastal proximity ($Proximity$) as our measure of increased perceptions of flood risk after Hurricane Sandy. Recalling that our identification strategy relies on a shock to perceived flood risk after Sandy's landfall, we argue that coastal proximity is a natural measure for the strength of this shock. In particular, storm surge, the abnormal rise of coastal water generated by hurricane-force winds, is one of the principal drivers of property damage associated with hurricanes (in addition to wind and rain).[17] Properties located up and down the coast from the point of landfall may be damaged by the extreme surge-related flooding. Moreover, coastal properties may even be damaged by the surge generated by hurricanes that pass along the coast but do not make landfall. Accordingly, we argue

[15] If several pre-Sandy properties qualify as the best match, we compute the average of their residual prices and then compute the difference.

[16] See Chernick (2007) for a detailed discussion of our bootstrapping technique.

[17] See the National Hurricane Center's page on storm surge: `https://www.nhc.noaa.gov/surge/#facts`.

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that, holding location fixed, perceptions of a given property's hurricane-related flood risk are likely to be correlated with its coastal proximity.[18]

We expect β_1, our coefficient of interest in Eq. (2), to be negative and significant in both New York and Boston, albeit with smaller magnitude in the latter market. Such a result would indicate that New York and Boston properties with closer proximity to the coast (i.e., properties with greater exposure to flood risk) experienced lower price appreciation in the post-Sandy period than their counterparts in locations further away from the coast (i.e., properties that did not experience a shock in flood risk perceptions). In contrast, we expect β_1 to be indistinguishable from zero in Chicago, where post-Sandy perceptions of flood risk should remain unchanged relative to those before the hurricane.

3.3.1 Estimation Results

Panel A of Table 3 presents the results of the price impact analysis described in Eq. (2). Column (1) shows the price impact regression results for New York. The estimates suggest that, all else equal, a one-mile increase in proximity to the coast is associated with 21.6% slower price appreciation among New York transactions completed after Hurricane Sandy relative to those completed before the hurricane. In other words, properties located closer to the coast, which are at greater risk of flooding, experience significantly slower price appreciation after the hurricane than do equivalent properties further away from the coast. Importantly, since New York real estate experienced considerable physical damage during Hurricane Sandy, these results are likely to incorporate the economic costs of such damage. Thus, to disentangle the effects associated with increased flood risk versus those from direct physical damages, we also assess the extent to which proximity affects property price appreciation in Boston — a location ostensibly at risk of hurricane-related flooding, but that has not yet been exposed to a major hurricane strike.

We present the results for Boston in column (2). The estimates suggest that a one-mile increase in proximity to the coast is associated with 9.5% slower price appreciation after Hurricane Sandy. This result indicates that proximity to the coast significantly affects commercial property price appreciation

[18] In Appendix B, we validate this argument by demonstrating that coastal proximity is the dominant determinant of hurricane-related property damage. In particular, we run a horse race between proximity and elevation, and find that proximity drives out elevation in explaining county-level hurricane damages from SHELDUS. See Table B.1 for details. Furthermore, we verify that our main results on coastal proximity hold even when we include elevation and its interaction with proximity as additional flood risk measures. See Section 4.1 for details.

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in Boston even before that market has experienced a local hurricane strike. The economic magnitude of the effect of coastal proximity on Boston property prices is equivalent to about 40% of the effect we estimate in New York. Given the absence of physical damages in Boston, We attribute this portion of the effect to increased salience and perception of flood risk, and the remaining 60% of the New York effect to the economic fallout from physical damages sustained during Sandy.

Importantly, both the New York and Boston regressions include annual controls for the number of local business establishments in each zip code. This allows us to capture the potential effects of variation in local economic activity on post-Sandy price dynamics. Additionally, the residual prices used to compute the dependent variable for our price impact regressions are obtained from the hedonic pricing model in Eq. (1), which includes control variables that account for standard determinants of commercial real estate prices, including coastal proximity. As a result, we argue that the price effects of coastal proximity that we document for New York and Boston are unlikely to be driven by contemporaneous variation in local economic activity, investor demand, or the supply of commercial properties. Instead, to the extent that our hedonic controls serve as effective price determinants in the post-Sandy period, we argue that the effects of coastal proximity on residual price differences are driven by increased exposure to flood risk.

Our placebo tests for Chicago, shown in column (3) of Table 3, confirm this interpretation. Specifically, the estimates reveal a statistically and economically insignificant relationship between commercial transaction prices and lake proximity. This non-result is consistent with our expectations, as hurricane-related flood risk is nonexistent for properties near a body of water so far inland as Lake Michigan. Perhaps more important, this non-result lends credibility to the idea that, absent increases in perceived flood risk, our baseline hedonic pricing model estimates from the pre-Sandy period are useful for explaining post-Sandy transactions. In turn, this provides reassurance that our New York and Boston results are not confounded by concurrent unrelated price trends in waterfront property.

[Table 3 about here.]

In all, our results in Table 3, Panel A suggest that sophisticated investors in the commercial real estate market capitalize flood risk into their property valuations. Moreover, this capitalization occurs in both markets experiencing disaster strikes, as well as those where the risk of such strikes becomes more salient.

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In particular, while the landfall of Sandy in New York itself has not increased the objective probability of a hurricane striking Boston, our evidence is consistent with the storm alerting investors to the fact that the northward migration of hurricanes has put a broader set of locations along the U.S. East Coast at risk.

3.4 Dissecting the Price Effect of Flood Risk

3.4.1 Price Impact of Flood Risk Over Time

We dig deeper into our findings by investigating how the price effect of flood risk exposure evolves over time. While investors may have initially reacted to Hurricane Sandy, the associated price effects may have also decayed over time as the event became an increasingly distant memory, or as initial over-reactions were reversed. We assess the evidence for this hypothesis by augmenting the price impact analysis from Eq. (2) with interaction terms between proximity to the coast and indicators for each year after Sandy's landfall.

Panel B of Table 3 presents the results. Column (4) reports the estimates for New York. In this specification, the main effect of *Proximity* reflects the price effects of flood risk exposure in late 2012 and 2013, the first year after Hurricane Sandy. The coefficients on the interaction terms between *Proximity* and the subsequent transaction years in the post-Sandy period are all negative. The coefficient on the interaction term for the year 2015 is also statistically significant. These results suggest that, rather than dissipating, the initial negative effect of flood risk exposure on property prices persists, and even increases in magnitude over time.

Column (5) presents the main price effect and year-by-year effects of *Proximity* in Boston. The estimates indicate that the initial price effect of *Proximity* decays over time, as the coefficients on the interaction terms between *Proximity* and the transaction years 2014 through 2017 are numerically positive. The positive coefficients reported for the interaction terms between *Proximity* and the transaction years 2015 and 2017 are also statistically significant, suggesting a significant reversal in the negative price effects of proximity to the coast as time passes. However, even the magnitude of the largest positive interaction coefficient for the Boston sample, that from 2017, amounts to less than 40% of the initial negative impact of coastal proximity on Boston office transactions in 2013. Meanwhile,

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the placebo tests for Chicago, reported in column (6), suggest no significant decline in the pricing of proximity 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 commercial properties' flood risk exposure. The estimates we present imply that the storm's New York landfall in late 2012 generated a shift in the salience of flood risk for investors transacting in commercial properties located along the U.S. northeastern seaboard. Our findings indicate that flood risk exposure has become a first-order determinant of real asset values, with significant implications for price appreciation over time, even in locations that have not yet experienced a major hurricane-related flood event. Our evidence also suggests that although market participants' initial reactions gradually dissipate over time, a majority of the initial valuation penalty associated with increased flood risk perceptions persists for at least five years after the event.

3.4.2 Channels of Price Impact

Fundamentally, commercial property values are a function of the cash flows they produce — which are the result of contractual rents and occupancy rates — and the yield applied to capitalize the expected stream of future cash flows, which incorporates a risk premium for the property. Contractual rents are fixed and respond slowly to new market circumstances. By contrast, vacancy and the capitalization rate typically respond more swiftly to changes in local market conditions. To assess the extent to which vacancy and capitalization rates drive the price effects documented in our baseline tests, we exploit a subset of Costar transactions where we can observe these quantities.

Specifically, we replace the dependent variable in Eq. (2) with the differences in capitalization rates and, alternatively, the differences in vacancy rates, across matched transactions.[19] We focus this analysis on properties in New York and Boston, where we document significant price effects of flood risk exposure. Since this is a subsample analysis over a relatively small number of observations, we replace the main independent variable with an indicator that takes the value of one when a post-Sandy transaction is located in the decile of transactions with greatest proximity (i.e., shortest distance) to the coast.

[19]Due to the limited number of observations, we compare post-Sandy capitalization rates with the mean of pre-Sandy residual capitalization rates by building class within a state.

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Table 4 presents the results. The estimates in columns (1) and (2) show that the difference in capitalization rates across post- versus pre-Sandy transactions for properties located closest to the coast grows by about 87 basis points in New York and 157 basis points in Boston. On the other hand, the estimates in columns (3) and (4) show no significant association between flood risk exposure and vacancy rates.

[Table 4 about here.]

These findings suggest that greater exposure to flood risk is associated with a significant increase in real estate capitalization rates. In principle, capitalization rates increase if: (i) current income increases; (ii) the risk premium increases; or (iii) the expected growth rate of future income declines. Our findings indicate no occupancy-driven decline in current operating income. Furthermore, because we additionally control for the logarithm of net income per square foot in the first stage of the capitalization rate regressions, the increase in capitalization rates we document is unlikely to be driven by an increase in current rental income (i.e., channel (i) listed above).

Distinguishing between the second and third channels is more difficult, since we are unable to observe independent variation in the risk premium and the expected future growth rate of income. Therefore, we cannot provide direct evidence regarding the importance of these two factors in the increase in capitalization rates we document. However, it is important to note that we control for the number of local business establishments in our regressions. Since this quantity is likely to at least partly reflect local income growth prospects, one might interpret the increase in capitalization rates among properties closest to the coast as capturing the effect of increased flood risk after accounting for local income growth prospects. Thus, an increase in the risk premium charged by investors for bearing flood risk seems to be the most plausible explanation for our findings.

3.4.3 Contagion Effects

In addition to property-level operating performance, as reflected in cash flows, vacancy rates, and risk premiums, real estate values may also be affected by the vibrancy of the neighborhood surrounding a given property. The vibrancy of an urban area depends on the composition of local real estate occupiers. Corporate space users may be affected to varying degrees by hurricane strikes, due to their

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respective lines 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.

To assess the importance of this contagion channel, we examine the degree to which Sandy-induced changes in stock market valuations among public companies headquartered in New York and Boston are associated with neighboring property price dynamics. Specifically, we identify the publicly listed firms headquartered within a 0.25-mile radius (and, alternatively, a 0.5-mile radius) of each of our sample properties in New York and Boston. Using daily returns on individual stocks and the value-weighted market portfolio from May 1, 2012 (Day –120) until October 19, 2012 (the last trading day before Sandy), we estimate capital asset pricing model (CAPM) betas for each of the neighboring public firms. We then compute cumulative abnormal returns (CAR) during the 5-day period from October 22, 2012 (Day 0, when Hurricane Sandy developed into a tropical storm in the Caribbean) to October 26, 2012 (Day 4, when New York declared a state of emergency). We construct *Negative CAR* as a variable that takes either the absolute value of the negative CAR or zero if a firm does not generate negative CAR during Sandy. We then re-estimate Eq. (2) for the residual price difference across matched properties, using *Negative CAR* of the firm headquartered closest to the property sold post-Sandy as the independent variable.

[Table 5 about here.]

Table 5 presents the results. The coefficient estimates on the variable *Negative CAR* in columns (1) and (2) consistently suggest that properties located in the vicinity of firms in New York that were adversely affected by Hurricane Sandy experience slower price appreciation, relative to their pre-Sandy matches, than otherwise equivalent properties not located in the vicinity of such firms. The results reported in columns (3) and (4) indicate that the same basic patterns also hold for properties in Boston. Importantly, the Boston results imply that natural disasters can negatively impact property values not only through physical damage or shifts in the salience of flood risk, but also by dampening neighborhood vibrancy.

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A comparison of the economic magnitude of the coefficient estimates on *Negative CAR* across columns (3) and (4) for Boston suggests that the contagion effects we document increase in the proximity of a given property to the headquarter location of a public firm negatively affected during Sandy. This pattern emphasizes the localized nature of such neighborhood contagion effects.

The estimates reported in Table 5 also indicate that the neighborhood contagion effects we document are short-lived. The coefficient estimates on *Negative CAR* we discuss above are based on transactions completed in 2013, the first year after Sandy. The interaction terms with 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 show that the economic toll of Hurricane Sandy was not limited to the immediate physical damage to properties and the ensuing revision of investors' evaluations 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.

4 Robustness Tests

In this section, we report results from several robustness tests. First, we replicate the estimation of our main price impact analysis using an expanded matching algorithm. We also account for low elevation as an additional determinant of flood risk exposure. In subsequent tests, we verify that the negative price impact of flood risk we document in our main results is robust to using an alternative difference-in-differences style empirical approach. Lastly, we test whether hurricane-related flood risk exposure affects properties separately from the exposure to sea level rise, which has been explored in prior studies on residential real estate (e.g., Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020).

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4.1 Accounting for Elevation and Expanded Matching Criteria

County-level damage regression results presented in Table B.1 indicate that, when considering proximity to the coast and elevation in the same regression, the latter is rendered insignificant as a predictor of local property damages from hurricane strikes. This is likely a result of the high correlation between proximity and elevation (nearly 65% in the sample used for the damage regressions). Thus, as we outline in Appendix B, we focus on coastal proximity as our primary flood risk measure in the property-level analysis. However, one can argue that proximity to the coast is only relevant for low-lying locations: a property at sea level located a mile from the coast is directly exposed to flood risk, while a property right at the coast, but on top of a 150-foot cliff is not.

To address this potential concern, we re-estimate our main price impact specification interacting proximity with elevation. The results from these robustness tests are presented in Table 6. The estimates reported are consistent with both our main findings and our hurricane damage analysis. Notably, both the elevation and interaction coefficients are statistically insignificant, while the proximity coefficients for both New York and Boston remain significant and have similar magnitudes as in our baseline tests.

[Table 6 about here.]

We also rerun our main analysis by extending our matching criteria. We match properties based on county and building class in addition to proximity to the coast and flood zone. While our residual price model already removes the quality component of prices, matching based on property quality provides an additional layer of control for property quality. On the other hand, this approach limits the number of matches for each property. Table 7 presents the results. The estimates reported suggest very similar inferences to those from our main specification.

[Table 7 about here.]

4.2 Alternative Difference-in-Differences Style Analysis

Our residual difference model mainly assumes that, other than through coastal proximity, the impact of property characteristics on commercial property prices does not change following Hurricane Sandy.

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We show that our results are robust to relaxing this assumption by rerunning our model with hedonic controls in the second stage, allowing for the impact of all property characteristics to change post-Sandy. As shown in Table 8, the property characteristic coefficients are insignificant for the most part. More importantly, their inclusion does not affect the relationship between proximity and residual prices, validating our main assumption.

[Table 8 about here.]

We further employ a difference-in-differences (DD) style approach to test our hypothesis. In an ideal DD setting, we would observe a sample of properties which differ in their proximity to the coast (and other observable characteristics). Further, we would observe a transaction for each of those properties before and after Sandy. We would then specify a regression model which contains each property's proximity to the coast, an indicator that takes the value of one if a given property transaction occurs in the post-Sandy period, an interaction term between these two variables, and a set of covariates. A negative sign on the coefficient of the interaction term between proximity to the coast and the post-Sandy indicator would indicate that coastal proximity is negatively associated with property value in the post-Sandy period, relative to the pre-Sandy period. Such a finding would imply that flood risk exposure (i.e., a given property's proximity to the coast) negatively impacts real estate prices.

To implement this ideal DD approach we would require a sample of repeat sales. However, given the long average holding periods in commercial real estate, we do not have a sufficiently large sample of repeat sale observations to implement the ideal approach. Instead, for robustness, we conduct a DD-style analysis that approximates the general DD approach. We again match properties sold before and after Sandy based on their proximity to the coast and flood zone, as in our main analysis. Then, we pool all observed property prices and regress them on the proximity to the coast of the matched pairs, an indicator that takes the value of one if a given property transaction occurs in the post-Sandy period, an interaction term between these two variables, and a set of covariates that account for observable property and transaction characteristics. This approach is similar to that adopted by Gupta et al. (2020).

Table 9 presents the results of this analysis. The estimates reported indicate that the coefficients on the interaction terms between proximity to the coast and the post-Sandy indicator are negative

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in both the New York and Boston samples. Importantly, the economic impacts are very similar to those in our main specification (i.e., 22% vs. 23% for New York and 9.5% vs. 8.1% for Boston, in the respective main and DD model specifications). This finding implies that properties in New York and Boston which are located closer to the coast experienced a price discount in the post-Sandy period, relative to equivalent properties sold in the pre-Sandy period. We find no evidence of price discounts for properties closer to the lake shore in Chicago. These results are fully consistent with our main findings that flood risk exposure has a negative impact on property prices in New York and Boston post-Sandy.

[Table 9 about here.]

Since the dependent variable of the DD-style model employed in this robustness test is the transaction price per square foot, the results presented in Table 9 provide insight into the price discount for waterfront properties in terms of price levels. This complements our main analysis of residual price differences, which speaks to the effect of flood risk exposure, proxied by proximity to the coast, on price appreciation from the pre- to the post-Sandy period. The evidence presented here is consistent with our main findings that flood risk exposure was associated with a discount to property prices in New York and Boston after Hurricane Sandy struck.

Next, we evaluate the parallel trend assumption of our DD-style model. Specifically, we interact proximity with year dummies before and after Sandy, treating 2012 as the base year (i.e., the year Hurricane Sandy struck). Table 10 presents the regression results.

[Table 10 about here.]

For New York and Boston, the year interactions following Hurricane Sandy are all significantly negative. In contrast, the post-Sandy interactions are all insignificant for the Chicago sample. Importantly, the year interactions before Sandy exhibit insignificant coefficients for all three locations back to at least 2009, supporting the parallel trend assumption of the DD estimator.

We also show a graphical representation of the coastal proximity coefficients over time in Figure 3. Before Hurricane Sandy, the proximity coefficients exhibit a relatively stable trend for both New York and Boston. However, once Hurricane Sandy hits, there is a sharp decline in the coefficients in

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both locations beginning in 2013. Importantly, the negative impacts persist for both New York and Boston, with a larger magnitude for New York corresponding to the direct hurricane strike. In contrast, Chicago reflects a mild increase in the impact of proximity to the coast before and after Hurricane Sandy, with no discernible effect associated with the disaster event itself. Overall, our graphical analysis is consistent with our main results and suggests that our findings are not driven by pre-existing trends unrelated to Hurricane Sandy.

[Figure 3 about here.]

4.3 Accounting for Exposure to Sea Level Rise

In our final set of tests, we investigate whether the flood risk we document is priced separately from the risk emanating from sea level rise examined in a strand of the climate finance literature (e.g., Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020). In particular, Bernstein et al. (2019) 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. Based on information reported in their study, the critical level of property elevation for exposure to sea level rise is around six feet. Thus, 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 increased perceptions of flood risk following Hurricane Sandy separately from exposure to sea level rise. The results from this robustness test are available on request.

5 Conclusion

Using the New York landfall of Hurricane Sandy in late 2012 as a natural experiment, we examine how sophisticated investors in the commercial real estate market capitalize flood risk exposure into their property valuations. Exploiting the relation between physical location and hurricane-related flood damages, we motivate coastal proximity as a measure of the potential shock to investors' perceptions of flood risk following Sandy. In turn, we argue that an increase in investors' perceptions of flood risk is likely to have a negative impact on waterfront property valuations, even in coastal cities along the northeastern seaboard.

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We test this conjecture using a large sample of commercial property transaction data in Boston and New York. Combining a hedonic model that accounts for baseline determinants of property prices with a matched sample of transactions completed before and after Hurricane Sandy, we find evidence of a downward price adjustment for coastal properties in the commercial real estate market. Further, we find that these price effects persist over time, and that, despite the absence of Sandy-related physical damages, the impact of heightened risk perceptions in Boston is associated with large post-Sandy valuation penalties amounting to about 60% of those in New York. Importantly, to allay the concern that our results in Boston and New York reflect general trends in the pricing of waterfront commercial property, we conduct a placebo test using transactions in Chicago. Consistent with the idea that Hurricane Sandy's landfall had no impact on perceptions of flood risk for Chicago lakefront property, we find no post-Sandy pricing effects in this placebo sample.

We also perform tests aimed at understanding the economic channels driving the effects we document. We find no evidence supporting a cash-flow channel driven by a drop in rental rates or a spike in vacancies. Instead, we find that a risk-based channel, whereby commercial property investors demand a premium for holding properties subject to heightened flood risk, is the most likely source of our main findings.

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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, Greg Guannel, Gregory Verutes, Spencer Wood, Anne Guerry, Mary Ruckelshaus, Peter Kareiva, Martin Lacayo, and Jessica 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, 2020, Does Climate Change Affect Real Estate Prices? Only If You Believe in It, *Review of Financial Studies* 33, 1256–1295.

Baldini, Lisa, James Baldini, Jim McElwaine, Amy Benoit Frappier, Yemane Asmerom, Kam-Biu Liu, Keith Prufer, Harriet Ridley, Victor Polyak, Douglas Kennett, Colin Macpherson, Valorie Aquino, Jaime Awe, and Sebastian 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, Working paper, Department of Economics, Rutgers University, Newark.

Bernstein, Asaf, Stephen B. Billings, Matthew Gustafson, and Ryan Lewis, 2021, Voting with their sandals: Partisan residential sorting on climate change risk, Working Paper 27989, National Bureau of Economic Research.

Bernstein, Asaf, Matthew Gustafson, and Ryan Lewis, 2019, Disaster on the Horizon: The Price Effect of Sea Level Rise, *Journal of Financial Economics* 134, 253–272.

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

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.

Chernick, Michael, 2007, *Bootstrap Methods: A Guide for Practitioners and Researchers*, Second edition (Wiley Series in Probability and Statistics).

Electronic copy available at: https://ssrn.com/abstract=3206257

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

Demirci, Irem, Umit G. Gurun, and Erkan Yönder, 2020, Shuffling through the bargain bin: Real estate holdings of public firms, *Review of Finance* 24, 647–675.

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

Gibson, Matthew, Jamie 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, 2020, Climate Change and Long-Run Discount Rates: Evidence from Real Estate, *Review of Financial Studies* Forthcoming.

Gupta, Arpit, Stijn Van Nieuwerburgh, and Constantine Kontokosta, 2020, Take the Q Train: Value Capture of Public Infrastructure Projects, Working Paper 26789, National Bureau of Economic Research.

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

Kossin, James, Kerry Emanuel, and Gabriel 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, and Kerry Emanuel, 2006, Atlantic Hurricane Trends Linked to Climate Change, *Eos, Transactions American Geophysical Union* 87, 233–241.

Murfin, Justin, and Matthew Spiegel, 2020, Is the Risk of Sea Level Capitalized in Residential Real Estate?, *Review of Financial Studies* 33, 1217–1255.

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, Michael Mann, Kerry Emanuel, Ning Lin, Benjamin Horton, Andrew Kemp, and Jeffrey 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.

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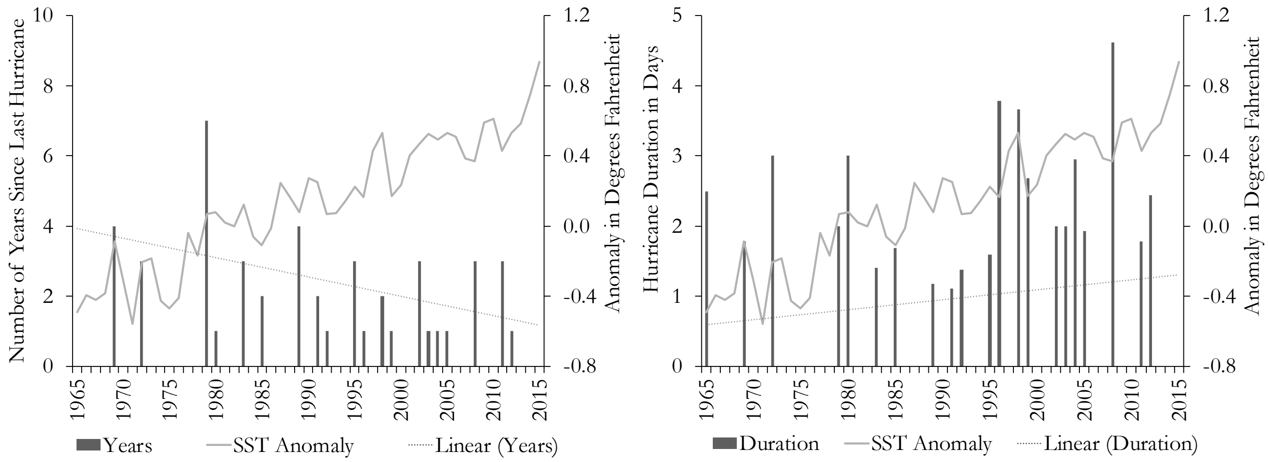

(A) Frequency of Hurricanes

(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.

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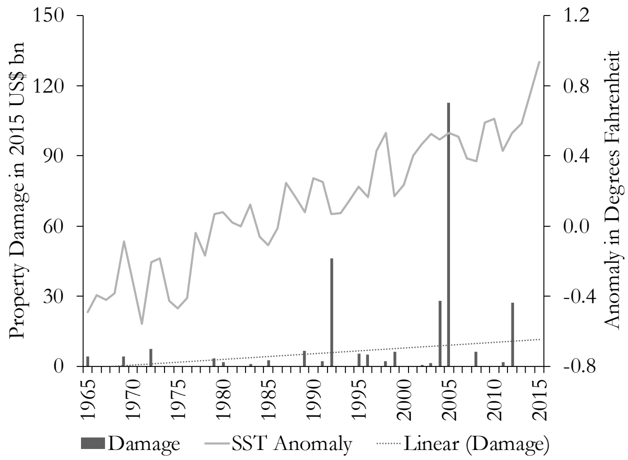

(A) Severity of Hurricanes

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

(B) Northward Migration of Hurricanes

Figure 2. Hurricane Patterns in the U.S., 1965–2015. 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. 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.

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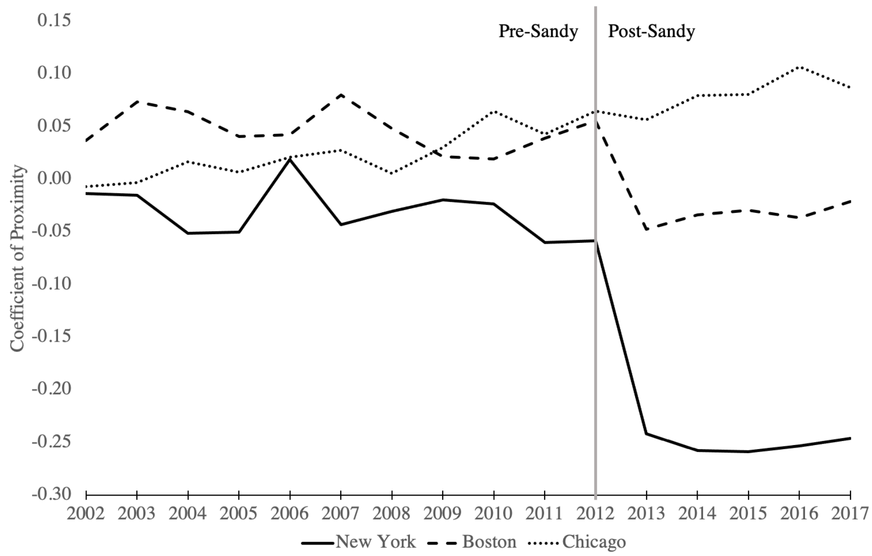

Figure 3. Estimated Coefficient of Proximity to the Coast on Property Prices. The figure depicts the time series evolution of the coefficient estimates on proximity to the coast derived from the regressions reported in Table 10. In the figure, 2012 covers the impact of proximity for the transactions occurred in 2012 until Hurricane Sandy hit and 2013 covers for the transactions occurred in late 2012 after Sandy hit and in 2013.

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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 located on the U.S. East Coast that were hit by a hurricane during the 1965–2012 period. *Damage* is county-level hurricane damage, measured in 2015 $ million. *Proximity* is the mean negative distance to the coast of the sample properties located in a given county, measured in miles. *Elevation* is the mean elevation of the sample properties in a given county, measured in 10 feet. *Population* is county-level population, measured in '000 inhabitants. Panel B presents the sample of property transactions obtained from Costar by sub-period: The pre-Sandy sub-period runs from the start of our sample in 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Descriptive statistics are shown separately by location; i.e., for New York, Boston, and Chicago. *Price* is property transaction price per square foot. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Elevation* is a given property's elevation, measured in 10 feet. *Flood Zone* is an indicator that takes the value of 1 if a given property is located in a FEMA flood risk zone. *Size* is property size, measured in '000 square feet. *Age* is property age, measured in years. *Floors* 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 before Sandy versus after Sandy.

Panel A County-Level Damage Data					
	Mean	SD	Min	Max	N
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

Table continued overleaf.

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	Panel B Transaction-Level Property Data										
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	
	Before Sandy					After Sandy					Difference
						New York					
Price	455.44	347.17	9.44	1,565.73	3,114	621.85	432.77	9.44	1,565.73	2,216	166.41***
Distance	8.20	2.97	0.18	20.00	3,114	7.95	3.28	0.15	20.00	2,216	-0.25***
Elevation	5.23	4.84	0.00	43.96	3,114	5.67	5.72	0.00	46.26	2,216	0.44***
Flood Zone	0.03	0.16	0.00	1.00	3,114	0.02	0.12	0.00	1.00	2,216	-0.01
Size	137.00	239.00	1.16	1,100.00	3,114	120.00	228.00	1.16	1,100.00	2,216	-17.00***
Age	68.49	32.10	1.00	203.00	3,114	72.09	33.96	1.00	216.00	2,216	3.60***
Stories	9.43	9.95	1.00	102.00	3,114	8.95	9.71	1.00	60.00	2,216	-0.48*
Class A	0.14	0.35	0.00	1.00	3,114	0.13	0.33	0.00	1.00	2,216	-0.01
Class B	0.41	0.49	0.00	1.00	3,114	0.42	0.49	0.00	1.00	2,216	0.01
Class C	0.45	0.50	0.00	1.00	3,114	0.45	0.50	0.00	1.00	2,216	0.00
						Boston					
Price	190.75	155.36	9.44	1,565.73	2,017	235.30	215.58	9.44	1,565.73	1,394	44.55***
Distance	8.41	4.88	0.02	20.00	2,017	8.54	5.02	0.02	19.96	1,394	0.13
Elevation	7.36	6.35	0.00	32.81	2,017	7.79	6.64	0.00	32.81	1,394	0.43*
Flood Zone	0.07	0.26	0.00	1.00	2,017	0.07	0.26	0.00	1.00	1,394	0.00
Size	52.03	108.00	1.16	1,100.00	2,017	0.48	0.96	1.16	1,100.00	1,394	-0.05
Age	61.61	44.66	1.00	259.00	2,017	69.23	45.29	1.00	274.00	1,394	7.62***
Stories	3.79	4.25	1.00	62.00	2,017	3.65	3.78	1.00	46.00	1,394	-0.14
Class A	0.09	0.29	0.00	1.00	2,017	0.09	0.29	0.00	1.00	1,394	0.00
Class B	0.44	0.50	0.00	1.00	2,017	0.44	0.50	0.00	1.00	1,394	0.00
Class C	0.47	0.50	0.00	1.00	2,017	0.47	0.50	0.00	1.00	1,394	0.00
						Chicago					
Price	142.47	112.33	9.44	1,439.69	1,500	145.81	141.59	9.44	1,565.73	951	3.34
Distance	4.89	4.29	0.50	19.20	1,500	5.03	4.39	0.57	19.19	951	0.14
Elevation	4.92	3.72	0.66	15.75	1,500	4.81	3.67	0.66	14.76	951	-0.11
Flood Zone	0.01	0.10	0.00	1.00	1,500	0.01	0.10	0.00	1.00	951	0.00
Size	122.00	224.00	1.16	1,100.00	1,500	113.00	226.00	1.16	1,100.00	951	-9.00
Age	50.67	33.33	1.00	156.00	1,500	58.48	34.64	3.00	144.00	951	7.81***
Stories	7.68	11.81	1.00	110.00	1,500	6.99	11.23	1.00	110.00	951	-0.69
Class A	0.11	0.31	0.00	1.00	1,500	0.10	0.30	0.00	1.00	951	-0.01
Class B	0.42	0.49	0.00	1.00	1,500	0.48	0.50	0.00	1.00	951	0.06***
Class C	0.47	0.50	0.00	1.00	1,500	0.42	0.49	0.00	1.00	951	-0.05**

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

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Table 2. Hedonic Pricing Model

This table reports output from Eq. (1). The regression is estimated over the sub-sample period prior to Hurricane Sandy; that is, 2002:Q1 through 2012:Q3. The dependent variable is the natural logarithm of property transaction price per square foot. Column (1) presents results for New York. Column (2) presents results for Boston. Column (3) presents results for Chicago. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Size* is property size, measured in '000 square feet. *Age* is property age, measured in years. *Floors* 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 C is the excluded category. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Transaction Price Per Square Foot		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity	-0.034	0.036*	0.022
	(-0.678)	(1.843)	(0.930)
Flood Zone	-0.097	0.002	-0.201*
	(-1.059)	(0.035)	(-1.815)
Size	-0.167***	-0.205***	-0.207***
	(-11.523)	(-13.145)	(-10.574)
Age	-0.070***	-0.101***	-0.176***
	(-3.934)	(-5.225)	(-8.328)
Stories	0.006**	0.023***	0.012***
	(1.971)	(5.675)	(4.736)
Class A	0.300***	0.444***	0.396***
	(4.238)	(6.818)	(4.833)
Class B	0.183***	0.145***	0.088**
	(5.793)	(4.501)	(2.088)
Year-Quarter–Fixed Effects	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes
Observations	3,114	2,017	1,550
Adj. R-squared	0.518	0.450	0.354

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

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Table 3. Price Impact of Hurricane Risk by Property Location and Transaction Year

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated by location for all transactions in the pre-Sandy period (see Table 2, column 1 for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on distance to the coast and flood zone. Columns (1) and (4) present results for New York. Columns (2) and (5) (respectively, (3) and (6)) present results for Boston (Chicago). Columns (1) through (3) report results for the main effect of *Proximity*. Columns (4) through (6) present results for the main effect of *Proximity* and interaction terms between this variable and indicators for the year of the post-Sandy transaction. In those columns, the main effect of *Proximity* reflects the price impact of hurricane-related flood risk exposure in late 2012 and 2013, the first year after Hurricane Sandy. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Local Establishments* is the number of business establishments within the zip code that a property is located for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Residual Prices					
	Panel A: Main Effect			Panel B: By Transaction Year		
	New York (1)	Boston (2)	Chicago (3)	New York (4)	Boston (5)	Chicago (6)
Proximity	-0.216***	-0.095***	-0.004	-0.193**	-0.114***	-0.020
	(-2.579)	(-3.346)	(-0.082)	(-2.250)	(-3.974)	(-0.432)
× *Year=2014*				-0.020	0.026*	0.017
				(-1.039)	(1.857)	(0.971)
× *Year=2015*				-0.043**	0.039***	0.036**
				(-2.223)	(2.681)	(1.979)
× *Year=2016*				-0.024	0.017	0.052***
				(-1.164)	(1.076)	(2.667)
× *Year=2017*				-0.020	0.045**	0.011
				(-0.884)	(2.428)	(0.547)
Flood Zone	-0.434***	0.175*	-0.687**	-0.473***	0.171*	-0.705***
	(-2.697)	(1.730)	(-2.448)	(-2.953)	(1.674)	(-2.615)
Local Establishments	-0.157	1.739	0.781	0.069	1.285	0.677
	(-0.149)	(1.362)	(0.762)	(0.061)	(1.008)	(0.661)
Year–Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,216	1,394	951	2,216	1,394	951
Adj. R-squared	0.190	0.200	0.286	0.190	0.205	0.291

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

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Table 4. Price Impact of Hurricane Risk by Performance Metric

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated by location for all transactions in the pre-Sandy period (see Table 2, column 1 for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on building class and flood zone. 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) and (4) present the results for differences in vacancy rates 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). *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Local Establishments* is the number of business establishments within the zip code that a property is located for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Performance Metrics			
	Capitalization Rate		Vacancy	
	New York (1)	Boston (2)	New York (3)	Boston (4)
Lowest-Decile Distance	0.867***	1.572**	4.940	-5.473
	(2.639)	(2.030)	(1.040)	(-1.081)
Flood Zone	1.216**	-1.262***	-6.850	-4.339
	(2.280)	(-3.000)	(-1.043)	(-1.150)
Local Establishments	-0.819***	-0.737**	-4.272***	-0.082
	(-6.030)	(-2.338)	(-3.959)	(-0.034)
Year–Fixed Effects	Yes	Yes	Yes	Yes
Observations	192	113	714	364
Adj. R-squared	0.302	0.124	0.026	-0.005

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

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Table 5. Price Impact Analysis of Contagion Effects

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated for all transactions in the pre-Sandy period (see Table 2, 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, building class, and flood zone. Columns (1) and (2) ((3) and (4)) present results for properties in New York (Boston). Odd (even) columns present results for *Negative CAR* calculated on publicly listed firm headquarters located within a 0.5 mile (0.25 miles) radius of the sample properties. *Negative CAR* takes the absolute values of negative CAR experienced during Sandy by the listed firm headquartered closest to each of the sample properties, and zero if that firm does not generate negative CAR during Sandy. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Local Establishments* is the number of business establishments within the zip code that a property is located for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Residual Prices			
	New York		Boston	
	0.5 mile (1)	0.25 miles (2)	0.5 mile (3)	0.25 miles (4)
Negative CAR	-0.271	-0.757**	-0.624**	-0.688*
	(-0.915)	(-2.156)	(-1.986)	(-1.750)
× *Year=2014*	3.553	2.806	6.087*	6.095
	(1.634)	(1.131)	(1.861)	(1.331)
× *Year=2015*	-0.098	1.604	1.099	1.792
	(-0.089)	(1.356)	(0.345)	(0.392)
× *Year=2016*	3.136*	3.251	2.951	3.120
	(1.740)	(1.598)	(0.911)	(0.606)
× *Year=2017*	2.405	2.141	-4.300	-4.478
	(1.032)	(0.601)	(-0.720)	(-0.298)
Flood Zone	-0.126	-0.130	0.005	0.112
	(-0.789)	(-0.809)	(0.038)	(0.691)
Local Establishments	2.349	2.234	2.970	2.976
	(1.443)	(1.091)	(1.628)	(1.080)
Year–Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,128	831	383	248
Adj. R-squared	0.198	0.172	0.238	0.145

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

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Table 6. Price Impact Analysis With Interaction Effects of Elevation

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated by location for all transactions in the pre-Sandy period (see Table 2 for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on distance to the coast and flood zone. Columns (1) to (3) present results for New York, Boston, and Chicago, respectively. In those columns, the main effect of *Proximity* reflects the price impact of hurricane-related flood risk exposure in late 2012 and 2013, the first year after Hurricane Sandy. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Elevation* is elevation of a subject property, measured in 10 feet. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Local Establishments* is the number of business establishments within the zip code that a property is located for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Residual Prices		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity	-0.232***	-0.078***	-0.006
	(-2.705)	(-2.627)	(-0.095)
× *Elevation*	-0.001	0.001	-0.001
	(-0.734)	(0.969)	(-0.215)
Elevation	-0.003	-0.003	0.024
	(-0.171)	(-0.186)	(0.489)
Flood Zone	-0.452***	0.193*	-0.676**
	(-2.783)	(1.880)	(-2.405)
Local Establishments	-0.133	1.785	0.790
	(-0.127)	(1.395)	(0.769)
Year–Fixed Effects	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes
Observations	2,216	1,394	951
Adj. R-squared	0.190	0.201	0.284

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

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Table 7. Price Impact Analysis using Additional Matching Criteria

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated by location for all transactions in the pre-Sandy period (see Table 2 for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on distance to the coast, flood zone, county, and building class. Columns (1) to (3) present results for New York, Boston, and Chicago, respectively. In those columns, the main effect of *Proximity* reflects the price impact of hurricane-related flood risk exposure in late 2012 and 2013, the first year after Hurricane Sandy. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Local Establishments* is the number of business establishments within the zip code that a property is located for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Residual Prices		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity	-0.178***	-0.075**	0.016
	(-2.611)	(-2.525)	(0.348)
Flood Zone	-0.446**	0.105	-0.852**
	(-2.473)	(1.198)	(-2.482)
Local Establishments	-0.964	1.451	0.377
	(-0.981)	(1.139)	(0.335)
Year–Fixed Effects	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes
Observations	2,199	1,378	945
Adj. R-squared	0.131	0.193	0.277

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

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Table 8. Price Impact Analysis using Post-Sandy Hedonics

This table reports output from Eq. (2). 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 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Residual prices are obtained from the hedonic pricing regression in Eq. (1), estimated by location for all transactions in the pre-Sandy period (see Table 2 for coefficient estimates). Each property sold in the post-Sandy sub-period is matched to a property sold pre-Sandy, based on distance to the coast and flood zone. Columns (1) to (3) present results for New York, Boston, and Chicago, respectively. In those columns, the main effect of *Proximity* reflects the price impact of hurricane-related flood risk exposure in late 2012 and 2013, the first year after Hurricane Sandy. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. The models also include property characteristics. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Difference in Residual Prices		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity	-0.222***	-0.088***	0.001
	(-2.645)	(-3.104)	(0.030)
Flood Zone	-0.431***	0.157	-0.686**
	(-2.579)	(1.485)	(-2.464)
Local Establishments	-0.006	1.665	0.786
	(-0.006)	(1.288)	(0.768)
Size	-0.007	0.006	0.046
	(-0.253)	(0.216)	(1.642)
Age	-0.044	-0.068	-0.054
	(-1.236)	(-1.610)	(-1.081)
Stories	-0.006	-0.015**	-0.002
	(-1.203)	(-2.062)	(-0.630)
Class A	0.135	0.023	0.042
	(1.103)	(0.220)	(0.313)
Class B	-0.132***	-0.143**	0.057
	(-2.658)	(-2.328)	(0.888)
Year–Fixed Effects	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes
Observations	2,216	1,394	951
Adj. R-squared	0.195	0.206	0.290

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

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Table 9. Price Impact Analysis using Difference-in-Difference Style Approach

This table reports output from the difference-in-differences analysis outlined in Section 4.2. The dependent variable is the transaction price per square foot. In Panel A (B) transactions from the pre- and post-Sandy sub-periods are matched based on distance to the coast (distance to the coast, county, and building quality class). The pre-Sandy sub-period runs from the start of our sample in 2002:Q1 to 2012:Q3. Sandy struck in 2012:Q4 (October). The post-Sandy sub-period runs from 2012:Q4 to the end of our sample in 2017:Q4. Columns (1) to (3) present results for New York, Boston, and Chicago, respectively. *Proximity* is a given property's distance to the coast, measured in miles, multiplied by -1. *Post-Sandy* is an indicator that takes the value of one if a transaction occurred in the post-Sandy period. *Flood Zone* is an indicator that takes the value of 1 if property i was located in a FEMA-designated flood zone at time t. *Size* is property size, measured in '000 square feet. *Age* is property age, measured in years. *Floors* 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 C is the excluded category. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Transaction Price per Square Foot		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity	-0.034	0.048	0.028
	(-0.395)	(1.405)	(0.716)
× Post-Sandy	-0.221**	-0.081**	0.046
	(-2.215)	(-1.996)	(0.924)
Flood Zone	-0.036	0.036	-0.544***
	(-0.367)	(0.584)	(-3.266)
Size	-0.184***	-0.166***	-0.147***
	(-14.185)	(-10.862)	(-9.064)
Age	-0.064***	-0.113***	-0.221***
	(-3.738)	(-5.407)	(-9.073)
Stories	0.005*	0.015***	0.007***
	(1.821)	(2.933)	(3.149)
Class A	0.331***	0.410***	0.360***
	(5.557)	(6.322)	(4.834)
Class B	0.115***	0.086**	0.061*
	(4.108)	(2.431)	(1.708)
Year-Quarter–Fixed Effects	Yes	Yes	Yes
Post-Sandy × Zip Code Fixed Effects	Yes	Yes	Yes
Observations	3,157	2,107	1,457
Adj. R-squared	0.540	0.505	0.491

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

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Table 10. Parallel Trend Analysis using Difference-in-Difference Style Approach

This table reports output from the difference-in-differences analysis outlined in Section 4.2. The variable descriptions are similar to Table 9. Fixed effects are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Transaction Price per Square Foot		
	New York	Boston	Chicago
	(1)	(2)	(3)
Proximity (Base Year=2012)	-0.058	0.055	0.065
	(-0.665)	(1.458)	(1.558)
× *Year=2002*	0.045	-0.019	-0.072**
	(1.174)	(-0.722)	(-2.504)
× *Year=2003*	0.043	0.018	-0.068**
	(1.188)	(0.685)	(-2.370)
× *Year=2004*	0.007	0.009	-0.048
	(0.216)	(0.393)	(-1.583)
× *Year=2005*	0.008	-0.015	-0.058**
	(0.255)	(-0.603)	(-2.018)
× *Year=2006*	0.077**	-0.013	-0.043
	(2.567)	(-0.592)	(-1.570)
× *Year=2007*	0.015	0.025	-0.037
	(0.539)	(1.105)	(-1.409)
× *Year=2008*	0.028	-0.007	-0.059**
	(1.147)	(-0.288)	(-2.167)
× *Year=2009*	0.038	-0.034	-0.035
	(1.204)	(-1.435)	(-1.204)
× *Year=2010*	0.035	-0.036	0.000
	(1.203)	(-1.382)	(0.000)
× *Year=2011*	-0.002	-0.016	-0.022
	(-0.066)	(-0.728)	(-0.796)
× *Year=2013*	-0.183*	-0.103**	-0.008
	(-1.818)	(-2.308)	(-0.150)
× *Year=2014*	-0.199**	-0.089**	0.015
	(-1.972)	(-1.995)	(0.291)
× *Year=2015*	-0.200**	-0.085*	0.016
	(-1.985)	(-1.903)	(0.306)
× *Year=2016*	-0.195*	-0.092**	0.043
	(-1.933)	(-2.037)	(0.814)
× *Year=2017*	-0.188*	-0.077*	0.023
	(-1.856)	(-1.703)	(0.431)
Property Characteristics	Yes	Yes	Yes
Year-Quarter–Fixed Effects	Yes	Yes	Yes
Post-Sandy × Zip Code Fixed Effects	Yes	Yes	Yes
Observations	3,157	2,107	1,457
Adj. R-squared	0.539	0.503	0.491

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

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Appendix A U.S. Office Acquisition by Investor Types

We argue that the buyers of commercial real estate are more likely to be professional investors than the average home buyer. As a consequence, commercial real estate buyers are more likely to have the skills and resources required to adequately assess an investment property's risk profile, including its flood risk exposure. To back up our argument, we analyze the composition of investor categories that acquire the types of assets included in our sample.

Figure A.1 depicts the breakdown of annual U.S. office acquisition volumes by investor type over the 2003–2017 period. The underlying data on office acquisition volumes by investors type are obtained from Real Capital Analytics. The figure shows that domestic institutional investors on average account for 37% of annual office acquisitions, followed by cross-border investors (26%), private-market investors (22%), and listed real estate investment trusts (REITs, 10%). By contrast, owner-occupiers — the non-professional investors in our sample — account for only 5% of the average annual office acquisition volume over the 2003–2017 period. In sum, consistent with our argument, the marginal buyer in the U.S. office markets is likely to be an institution: a professional investor with the expertise and the resources required to assess real estate investment risk.

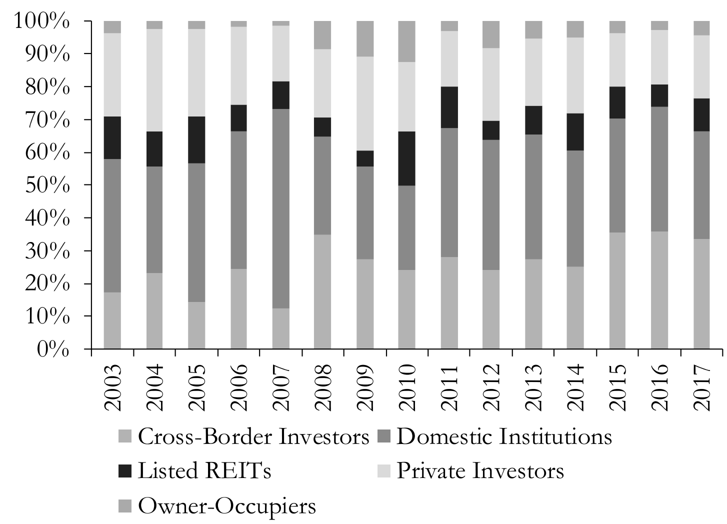

Figure A.1. Composition of Annual U.S. Office Acquisition Volumes by Investor Types. The figure depicts the breakdown of total annual acquisition volumes of U.S. office properties by investor types over the 2003–2017 period. Data are from Real Capital Analytics.

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Appendix B Validating Flood Risk Measures

The most important property location characteristics determining flood risk exposure are proximity to the coast and elevation.[1] We use these two property location characteristics as proxies for property-level flood risk exposure. We assess the suitability of our chosen proxies by regressing actual flood damage on distance to the coast and elevation. If proximity to the coast and elevation are related to actual damage, then these variables represent *ex ante* observable information about flood risk exposure that investors are able to incorporate into valuations. We estimate the following OLS regression:

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

where $Damage_{l,t}$ is the natural logarithm of hurricane damage to properties in county l at time t, measured in 2015 \$ million. $Risk_{m,l}$, where $m \in \{Proximity_l, Elevation_l\}$, denotes the two flood risk measures; namely, $Proximity_l$ and $Elevation_l$. We compute $Proximity_l$ ($Elevation_l$) for county l as the mean negative distance to the coast (elevation) of the sample properties located in county l. $Population_{l,t}$ is the natural logarithm of population in county l at time t. γ_t are year–fixed effects. θ_t are month–fixed effects. δ_z are state–fixed effects. $u_{l,t}$ is the residual. We cluster standard errors by county.

We expect a positive (negative) coefficient β_1 for proximity (elevation) on the flood risk measures in Equation (B.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 proximity 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 Equation (B.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.

Table B.1 presents the regression results for county-level hurricane damage from Equation (B.1). The estimates in column (1) suggest that a one-standard deviation increase in proximity to the coast increases property damage by \$1.1 million, on average. For elevation, column (2) indicates that the estimated average effect is \$1.7 million.[2]

[1] See, for example, NASA's website on the Recipe for a Hurricane (`https://www.nasa.gov/vision/earth/environment/hurricane_recipe.html`).

[2] For *Proximity*, coefficient 0.009 × standard deviation of *Distance* 97.18 = 0.09; the exponential of this value is approximately \$1.1 million. For *Elevation*, coefficient –0.075 × standard deviation of *Elevation* 6.97 = –0.52; the exponential of this value is approximately \$1.7 million.

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The regression results in Table B.1 suggest that the location features we use to construct our flood risk measures each contain relevant information about flood risk, as reflected in property damages upon exposure to a storm. However, the estimates reported in column (3), where we include both proximity and distance, imply that the effect of proximity to the coast dominates that of elevation. As a result, we adopt proximity to the coast as our main flood risk measure in the property-level analysis and subsequently replicate the analysis by interacting with elevation.

Table B.1. County-Level Hurricane Damage

This table reports output from Eq. (B.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. *Proximity* and *Elevation* are county-level hurricane risk factors, aggregated across the sample properties in a given county. *Proximity* is mean distance to the coast of the sample properties located in a given county, measured in miles, multiplied by -1. *Elevation* is mean elevation of the sample properties in a given county, measured in 10 feet. *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)
Proximity	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)
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:
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

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