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

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Abstract

We study how professional investors capitalize flood risk in commercial real estate (CRE) markets after hurricane Sandy. We show that New York CRE exposed to flood risk trades at a large, persistent discount. CRE in Boston, which mostly escaped direct hurricane-related damage, also exhibits persistent price penalties. Those price effects are driven by asset-level capitalization rates, not building occupancy. Results from a placebo test using real estate prices in Chicago show that our inferences are not driven by coincidental, unrelated price trends for waterfront properties. Our results are consistent with professional investors responding to a persistent shift in the salience of flood risk post-Sandy, even in locations spared by the disaster.

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 effects of environmental risks on the prices of real assets (Carney, 2015, 2016). The flood risk exposure of coastal real estate is central to those concerns. However, the evidence on price discounts for real estate exposed to flood risk is mixed.[1] There are at least two possible explanations for those mixed results. First, most prior work is focused on the price of residential real estate held by uninformed households for the purpose of housing consumption. However, Bernstein et al. (2019) show that only the most sophisticated households buying residential real estate for investment purposes apply price discounts for flood risk exposure. Second, prior studies are often focused on flood risk emanating from sea-level rise, which is a slow and gradual process. Yet, Murfin and Spiegel (2020) and Giglio et al. (2020) argue that a shift in risk salience may be required to identify the negative effects of flood risk exposure on real estate prices. In this study, we assess the implications of flood risk exposure for real estate prices by studying real estate transactions completed by sophisticated investors around a sudden shift in flood risk salience.

Our study differs from related prior work in two key ways. First, we study commercial real estate (CRE), instead of residential properties. The U.S. CRE market is worth $32.8 trillion (Goetzmann et al., 2021). Yet, despite its economic value, the CRE market has largely been ignored in prior research on the effects of flood risk exposure on real estate prices.[2] Importantly, the assets in the CRE market are mostly held by public as well as private institutions and other professional investors. Figure 1 shows that approximately 95% of office transactions completed in the U.S. over the past two decades involved such professional investors. Thus, CRE investors are likely to be sophisticated agents with the skills and resources required to evaluate and price investment risks.

[Figure 1 about here.]

[1] Murfin and Spiegel (2020) show that coastal real estate prices are insensitive to flood risk. Bernstein et al. (2019) show that real estate exposed to flood risk trades at a significant discount. Baldauf et al. (2020) find that the price effects of flood risk exposure depend on buyers' beliefs about climate change.

[2] Some studies assess the consequences of natural disasters for local enterprise—but without considering the potential implications of local business closure and re-opening choices for the values of the properties housing those businesses (see, e.g., LeSage et al., 2011; Basker and Miranda, 2017; Indaco et al., 2020; Meltzer et al., 2021).

In further contrast to earlier works, we study hurricane-related flood risk, rather than flood risk emanating from sea-level rise. While hurricane-related flood risk has always been present along the southern parts of the U.S. east coast, a recent northward shift in hurricane patterns has put new locations at risk. As a case in point, Hurricane Sandy unexpectedly hit New York in 2012, but spared locations further north, such as Boston. Nonetheless, Sandy is viewed as an example of the type of event in store for that entire region, including Boston (Kossin et al., 2014; Reed et al., 2015). Thus, Sandy represents a discrete and unexpected event that increased the salience of flood risk in U.S. east coast locations previously considered immune to this type of disaster.

We study how the shift in flood risk salience induced by Sandy affects CRE prices using a sample of office transactions completed in New York, Boston, and Chicago between 2003 and 2017. Sandy's landfall in New York was widely considered unexpected and shocking in magnitude. Therefore, perceptions of hurricane-related flood risk in New York were almost certainly revised upward following the hurricane. However, Sandy inflicted direct physical and economic damages on real estate in New York. Any price effects we document in New York thus likely include the effects of such damages and of assets' exposures to future flood risk. To address this issue, we separately examine Boston. Real estate in Boston is now also considered exposed to hurricane-related flood risk but has not yet experienced major hurricane-related damages (Baldini et al., 2016). Any price effects we document in Boston thus represent discounts associated with assets' exposures to future flood risk only. Lastly, we analyze real estate prices in Chicago. Including those observations allows us to rule out that our inferences from transactions in New York and Boston are driven by concurrent but unrelated price dynamics in the markets for waterfront real estate.[3] With regards to hurricane-related flood risk exposure, the observations from Chicago, located on Lake Michigan, serve as a placebo test. Given this set of observations about the three markets we study, we expect to find post-Sandy price penalties associated with flood risk exposure 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 real estate transactions in Chicago.

[3]Such price dynamics may reflect the amenity values of waterfront locations; see, e.g., Albouy et al. (2016) and Chay and Greenstone (2005).

The ideal empirical experiment to evaluate the evidence for our hypotheses is a repeat sales model. To estimate such a model, we would want to observe the same real estate assets being sold before Sandy and after Sandy. We would then estimate the difference in observed prices as a function of the assets' flood risk exposures. However, we have insufficient observations to implement this approach in the three office markets we study. The scarcity of repeat sales observations is a key motivating factor behind the pseudo repeat sales approach developed in Guo et al. (2014). Following this approach, we match properties sold before and after Sandy within each of the three markets we study based on those assets' flood risk exposures (measured by their coastal proximity). Next, we filter pre-Sandy transactions prices through a standard hedonic pricing model to establish a set of plausible counterfactual prices for transactions that occur after Sandy. We then estimate the differences in the transactions prices of the properties in the matched pairs, adjusted for their respective hedonic characteristics, as a function of their flood risk exposures. A negative sign on the coefficient of coastal proximity in that estimation indicates slower price appreciation for real estate exposed to flood risk (i.e., a relative price discount).

Our main tests in New York, Boston, and Chicago provide evidence consistent with our conjectures. We estimate that a one mile increase in coastal proximity in New York results in 21.6% slower price appreciation for real estate assets sold in the post-Sandy period relative to the pre-Sandy period. However, this effect likely also reflects the damages inflicted by Sandy on New York real estate. Our Boston estimates indicate 9.5% slower price appreciation following Sandy. Unlike the estimates for New York, this result is not contaminated by the effects of direct damages, as Sandy spared Boston. Our placebo tests in Chicago yield economically and statistically insignificant results. Those results indicate that our inferences from New York and Boston are not driven by concurrent unrelated price trends for coastal real estate. In sum, our results are consistent with Sandy affecting the capitalization of flood risk exposure into real estate prices. The Boston result in particular highlights that this phenomenon is not limited to areas hit by a hurricane, but also extends further afield, to as yet unaffected locations.

Next, we study the time dynamics of how flood risk exposure affects real estate prices following Sandy. We document that the price effects of flood risk exposure persist for five years post-Sandy (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 investors' asset-level risk assessments. Meanwhile, in Boston, we find evidence of a slight decay in the negative price effects of flood risk exposure over time, as the disaster becomes a more distant memory.

We dig deeper into our results and ask through which channels flood risk exposure affects real estate prices. We exploit a sub-sample of transactions where we can observe capitalization and vacancy rates. We find that flood risk exposure affects real estate prices 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 real estate asset by rent-paying tenants, is unaffected by flood risk exposure. Taken together, those results imply that CRE investors exhibit a stronger response to flood risk than the occupants of the buildings at risk of damage.

Lastly, we assess the robustness of our empirical results. We evaluate the sensitivity of our findings to key assumptions behind our main testing strategy, notably: (i) an asset's coastal proximity adequately captures its flood risk exposure, regardless of elevation; (ii) only the price impact of flood risk exposure changes after Sandy, not that of other hedonic characteristics; (iii) coastal proximity captures an asset's exposure to hurricane-related risk, regardless of sea-level rise. We show that our conclusions remain unchanged in modified testing procedures that capture variations on those key assumptions. Next, we evaluate our main results under alternative econometric specifications. Specifically, we employ an expanded set of matching criteria to form pairs of comparable assets sold before and after Sandy, including building location, quality, and flood zone status. Further, we test our main hypotheses using a matched difference-in-differences approach instead of the pseudo repeat sales model. Importantly, we use this framework to demonstrate parallel pre-trends in real estate prices—and the relative price divergence in the post-Sandy period—across the three markets included in our study.

Prior studies present mixed evidence that natural disasters have persistent price effects in real estate markets.[4]. Our focus on CRE in examining the effects of an environmental disaster on the pricing of flood risk is, to our knowledge, novel to the literature. Importantly, our CRE focus allows us to abstract from the fact that, in housing markets, coastal amenity prices are likely to offset—and potentially outweigh—the effect of flood risks (see, e.g., Atreya and Czajkowski, 2014). Accordingly, the magnitude of the price effects we document in New York compares favorably with that in prior studies on housing. Furthermore, our focus on CRE allows us to exploit granular data on capitalization rates, vacancy, and influential neighboring occupants to document the channels through which flood risks are priced.

Several existing works analyze the impact of floods and hurricanes among local real estate assets that avoided flooding (e.g., Atreya et al., 2013; Gibson et al., 2017). Our analyses in Boston, which largely escaped the damage induced by Sandy in New York, are novel to the literature. Further, our results inform the debate on the degree of persistence in flood risk penalties following major disasters. Previous papers find that price impacts in housing markets dissipate quickly. In contrast, our results in the CRE market suggest otherwise, demonstrating the importance of sophisticated investors in the pricing of environmental risks in real estate markets.

An emerging literature examines the effects of evolving flood risk on real estate prices. Several papers focus on sea-level rise and draw a link between investor sophistication and associated price penalties (see, e.g., Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020; Bernstein et al., 2021) We show that CRE markets, where sophisticated investors' perceptions of cash flows and risk drive asset prices, 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 on changes in flood risk salience through disclosures (Giglio et al., 2020). Critically, our findings highlight the importance of salience for risk recognition even among sophisticated professional investors.

[4] Harrison et al. (2001), Bin and Landry (2013), Atreya et al. (2013), and Atreya and Ferreira (2015) find that the price effects associated with floods are temporary. Barr et al. (2017), Ortega and Taspinar (2016), and Gibson et al. (2017) find increased flood risk penalties in New York house prices after Sandy. Ortega and Taspinar (2016) find that those effects are persistent. Barr et al. (2017) find that the penalties disappear quickly.

2 Data and Summary Statistics

Our empirical analyses require three types of data; namely, CRE transactions data, data on real estate-level flood risk exposure, and data on real estate damages from hurricane strikes. In this section, we outline each of our data sources and provide detail on variable measurement.

2.1 Commercial Real Estate Transactions Data

We collect commercial real estate transactions data from Costar, a leading CRE data provider. To our knowledge, this is the first study employing Costar data to assess the price effects of flood risk exposure on CRE prices. Costar comprehensively tracks CRE 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. CRE 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 asset characteristics, including real estate type, size, age, number of floors, building class, and exact address location.

Within the Costar database, we focus on offices. Relative to retail and industrial space, office space is fairly generic once location and building condition are taken into account. Further, office space is also highly redeployable, as it is not very specific to the current owner or user, thereby increasing the number of potential investors. Thus, our focus on offices reduces the potential influence of thin markets on observed price dynamics. In contrast, the prices of more specialized real estate types such as shopping malls and hotels are likely to be affected by smaller active investment markets (Demirci et al., 2020). We further restrict our analyses to coastal locations in each of the markets we study. Importantly, offices are the dominant CRE type in those locations. Therefore, our focus on coastal office real estate yields a sample with a large number of observations and a high degree of practical relevance.

We obtain data on office transactions from 2003 through 2017 in three major U.S. CRE markets: New York (NY), Boston (MA), and Chicago (IL). From the initial sample, we discard real estate assets built after Sandy, as such assets 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 real estate located within 20 miles of the coast, as flood risk becomes less relevant further inland.[5] The final sample contains 11,192 transactions, of which 6,631 (4,561) occurred before (after) Sandy.

2.2 Property-Level Flood Risk Data

We compile asset-level flood risk data for each of the CRE transactions in our sample. Specifically, we use the addresses provided in Costar to geo-code the location of each asset in our sample. We then measure the coastal proximity of each real estate asset 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 real estate asset's elevation, based on its coordinates, using the Elevation API from Bing Maps REST Services. Lastly, we obtain data on flood risk zones from FEMA, which allow us to identify whether a given real estate asset was located in a FEMA-designated flood risk zone at a given point in time.

2.3 Data on Property Damages from Hurricanes

We obtain data on hurricane damage to property from the Spatial Hazard Events and Losses Database for the U.S. (SHELDUS). As described in, e.g., Cutter and Emrich (2005) and Arkema et al. (2013), SHELDUS is a U.S. county-level data set that covers natural hazards, including hurricanes. The SHELDUS 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.

[5]Our results are robust to including real estate built after Sandy and to relaxing the sample selection criteria regarding coastal proximity.

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. We measure each county's coastal proximity as the mean coastal proximity of all Costar office properties located in the county. Similarly, we measure county-level elevation as the mean elevation of the Costar properties located in a given county. We use the county-level damage data to validate property-level measures of flood risk (coastal proximity, elevation). The results from those validation tests are shown in Appendix A.

2.4 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 proximity of 89 miles and average elevation of 53 feet. Those counties have an average population of 127,000 inhabitants.

[Table 1 about here.]

Panel B of Table 1 shows descriptive statistics for the CRE transactions in our sample. In New York, real estate assets sold after Sandy have a mean price per square foot of $622, higher than the mean of $455 before Sandy. CRE assets 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, real estate prices in Chicago were similar across the pre- and post-Sandy periods, with mean prices of $142 and $146 per square foot, respectively. Those statistics reflect that many CRE markets in the U.S. experienced an upward trend in transaction prices during the sample period.

Other than in terms of transactions prices, the statistics reported in Panel B of Table 1 show that the real estate characteristics are generally comparable across the assets sold in New York, Boston, and Chicago before versus after Sandy, suggesting few significant changes in the composition of the traded real estate stock over the sample period.

3 Methodology

3.1 Identification Strategy

To identify the effect of flood risk on real estate prices, we require variation in assets' flood risk exposure. Flood risk is a function of location characteristics, such as coastal proximity and elevation. However, those characteristics also capture the amenity value of coastal real estate (Albouy et al., 2016; Chay and Greenstone, 2005). Thus, cross-sectional regressions of real estate prices on coastal proximity and elevation alone are insufficient for identifying the price impact of flood risk.

We rely on variation in the salience of flood risk over time, and examine how the prices of exposed real estate assets are impacted by that variation. We obtain such variation from the unexpected strike of Sandy in New York in 2012:Q4 (October). Prior to Sandy, New York was considered immune to strong hurricanes because of its northern location. This belief was shattered when Sandy struck. Moreover, given the changing geographical patterns of hurricanes, 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 even further north than New York (Baldini et al., 2016).

Sandy caused significant physical and economic damage to real estate in New York. Thus, analyses of real estate prices before and after Sandy in New York alone would confound the effects of such damages and the potential price impact of exposure to future flood risk. To address this issue, we analyze not only real estate in New York, but also in Boston. Boston is located even further north than New York. However, the experience of Sandy in New York has raised the salience of flood risk along the entire U.S. east coast, including Boston (Baldini et al., 2016). Critically, unlike New York, Boston has thus far been spared major hurricane damage.

To ensure that our analyses capture the impact of flood risk, not other concurrent but unrelated price dynamics specific to coastal real estate, we also analyze CRE prices in Chicago. Chicago is situated on a major body of water (Lake Michigan). However, 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 analyses.

In sum, the main identifying assumption in our empirical approach is that the change in the hedonic price of coastal proximity from the pre-Sandy period to the post-Sandy period is due to a change in investors' beliefs about flood risk exposure—not due to changing preferences for coastal real estate for other reasons. Put differently, we assume that the price of a real estate asset's coastal proximity remains unchanged, except through an increase in investors' beliefs about the likelihood of flood exposure. Our placebo setting using transactions in Chicago serves as a direct test of this assumption.

3.2 Pseudo-Repeat Sales Model

The ideal empirical experiment to identify a negative effect of flood risk exposure on real estate prices after Sandy would be a repeat sales model. In that framework, we would observe the same real estate assets sold before and after Sandy. We would then estimate the differences in prices before and after Sandy as a function of the assets' coastal proximity, including property fixed effects to hold constant asset and micro-level location characteristics. A negative sign on the coefficient of coastal proximity would indicate a price discount for assets exposed to flood risk after Sandy. However, our sample does not contain enough repeat sales to implement this approach.

A feasible empirical experiment is the *pseudo* repeat sales approach developed in Guo et al. (2014). Instead of comparing the prices of the *same* properties sold before and after Sandy, as in the standard repeat sales approach, this approach compares the prices of *similar* properties. Specifically, we form pairs of similar properties by matching assets on their flood risk exposures (measured as coastal proximity). To account for differences in other property characteristics between the assets in our property pairs, we don't compare the *raw transactions prices* of the matched properties sold before and after Sandy. Rather, we compare their transaction prices after adjusting those prices for property characteristics. We obtain such *adjusted transactions prices* by filtering the pre-Sandy observations through a hedonic pricing model and applying the resulting coefficients to the post-Sandy raw transaction prices.

Specifically, we estimate the following hedonic pricing model:

$$Price_i = \beta_1 \mathbf{Hedonics_i} + \beta_2 \mathbf{Proximity_i} + \gamma_t + \delta_z + \epsilon_{i,t} \tag{1}$$

where $Price_i$ is the natural logarithm of the transaction price per square foot for asset i. $\mathbf{Hedonics_i}$ denotes the hedonic covariates; namely, asset size (natural logarithm of square footage), age, number of floors, building quality class, and a FEMA-designated flood zone indicator. 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. $\mathbf{Proximity_i}$ is an asset's coastal proximity, as described in Section 2.2. γ_t are year/quarter–fixed effects, and δ_z are zip code–fixed effects. We estimate Eq. (1) separately for each location; that is, for New York, Boston, and Chicago, to allow for variation in hedonic prices across those locations. The coefficients in Eq. (1) indicate the price of assets' hedonic characteristics prior to any shift in hurricane-related flood risk perception caused by Sandy.

Similar to Guo et al. (2014), we then consider the following within-pair first differences between the prices of properties i and j, sold before and after Sandy, respectively:

$$Price_i - Price_j = \beta_1(\mathbf{Hedonics_i} - \mathbf{Hedonics_j}) + (\beta_{2i} - \beta_{2j})\mathbf{Proximity_i} + \gamma_t + \delta_z + u_{i,t} \tag{2}$$

We assume that hedonic prices—except that of coastal proximity—remain the same after Sandy (see Section 3.1). Thus, β_1 is the same for assets i and j. However, we expect the coefficient of proximity to change following Sandy (β_{2i} vs. β_{2j}). As our matching procedure is based on proximity, $Proximity_i$ will equal $Proximity_j$. Rearranging Eq. (2) yields:

$$(Price_i - \beta_1 \mathbf{Hedonics_i}) - (Price_j - \beta_1 \mathbf{Hedonics_j}) = (\beta_{2i} - \beta_{2j})\mathbf{Proximity_i} + \gamma_t + \delta_z + u_{i,t} \tag{3}$$

where the left-hand side represents the difference in transactions prices, adjusted for hedonics, of the assets i and j in a matched pair.

We estimate Eq. (3) in two steps. First, we estimate Eq. (1) to obtain β_1 and calculate the adjusted price ($Price_i - \beta_1 \mathbf{Hedonics_i}$) for each asset. Then, we calculate the adjusted price difference for the assets in each matched pair and regress that variable on $\mathbf{Proximity}_i$:

$$\begin{aligned} \textit{Adjusted Price Difference}_p = \alpha_1 \mathbf{Proximity}_p + \alpha_2 \textit{Flood Zone}_p + \\ \alpha_3 \textit{Local Establishments}_{pt} + \gamma_t + \delta_z + u_p \end{aligned} \tag{4}$$

where $\textit{Adjusted Price Difference}_p$ is the difference in adjusted prices, obtained from Eq. (1), for each pair i of post-Sandy vs. pre-Sandy matched transactions.[6] $\mathbf{Proximity}_p$ is the value of our flood risk measure for the real estate asset in the matched pair that is transacted after Sandy.

In our final model, we also allow the coefficient of flood zone and local establishments to change following Sandy. $\textit{Flood Zone}_p$ indicates whether a matched asset pair is located in a FEMA-designated flood zone. We expect that the coefficient of flood zone captures the impact of flood insurance. $\textit{Local Establishments}_{pt}$ is the natural logarithm of the number of business establishments in the zip code of a post-Sandy real estate asset 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_p is the residual. Given the potentially non-standard distribution of residuals in Eq. 4, 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.[7]

We expect β_1 in Eq. (4) to be negative and significant in both New York and Boston—albeit with smaller magnitude in the latter market—reflecting lower price appreciation for assets located closer to the coast in New York and Boston after Sandy. 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.

[6]In our actual estimation procedure, for each transaction after Sandy, we determine a set of best matches sold before Sandy if there are more than one match with the same proximity. We take the average of adjusted prices of those multiple matches sold before Sandy to smooth out unobservables if there are more than one match. We also deduct the time effect in the adjusted price for those real estate sold before Sandy.

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

4 Results

4.1 Hedonic Regression Results

Table 2 presents the results from estimating Eq. (1) 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. 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 Sandy. The estimates also indicate that real estate assets across those three markets were relatively insensitive to variation in coastal proximity before Sandy. Those results imply that coastal locations had little amenity value in CRE markets prior to Sandy, after accounting for standard hedonic controls. The estimates in Table 2 further suggest that, conditional on an asset being located in a given zip code, being situated in a flood zone had no statistically significant association with transactions prices prior to Sandy. Those findings imply that, prior to Sandy, investors paid little attention to flood risk exposure when pricing assets.

[Table 2 about here.]

4.2 Effect of Flood Risk on Commercial Property Prices

Table 3 presents output from Eq. (4). Column (1) shows the price impact regression results for New York. The estimates suggest that, all else equal, a one-mile increase in coastal proximity is associated with 21.6% slower price appreciation. We present the results for Boston in column (2). The estimates suggest that a one-mile increase in coastal proximity is associated with 9.5% slower price appreciation. The economic magnitude of this effect 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.

[Table 3 about here.]

Our placebo tests for Chicago, reported in column (3), show an 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 real estate near a body of water so far inland as Lake Michigan. It also provides reassurance that our New York and Boston results are not confounded by concurrent unrelated price trends in coastal real estate.

In all, our results columns (1) through (3) of Table 3 suggest that sophisticated investors in the CRE market capitalize flood risk into their real estate valuations. Moreover, this capitalization occurs in both markets experiencing disaster strikes, as well as those where the risk of such strikes becomes more salient. 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 hurricane 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.

4.3 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 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 analyses from Eq. (4) with interaction terms between coastal proximity and indicators for each year after Sandy's landfall.

Columns (4) through (6) of Table 3 present 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 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. Those results suggest that, rather than dissipating, the initial negative effect of flood risk exposure on real estate prices persists, and even increases in magnitude over time.

Column (5) presents the year-by-year analysis 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 coastal proximity 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. The placebo tests for Chicago, reported in column (6), suggest no significant decline in the pricing of coastal proximity in this location, where flood risk is not prevalent.

In sum, our results suggest that Sandy had more than a temporary effect on the pricing of CRE flood risk exposure. The estimates we present imply that Sandy's landfall generated a shift in the salience of flood risk for investors trading in CRE markets located along the U.S. northeastern seaboard. Our findings indicate that flood risk exposure has become a first-order determinant of real asset prices, 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.

4.4 Channels of Price Impact

CRE prices are a function of the cash flows the assets produce—driven by contractual rents and occupancy rates—and the yield applied to capitalize those cash flows, which incorporates a risk premium. While contractual rents are fixed for the term of the lease, vacancy and capitalization rates 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 main tests, we exploit a subset of transactions for which we observe those quantities.

Specifically, we replace the dependent variable in Eq. (4) with the differences in capitalization rates and, alternatively, the differences in vacancy rates, across matched transactions.[8] We focus these analyses on real estate in New York and Boston, where we document significant price effects of flood risk exposure. Since these analyses cover a smaller number of observations, we replace the main independent variable with an indicator that takes the value of one for properties located in the decile of transactions with the closest coastal proximity.

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 assets located closest to the coast grows by 87 basis points in New York and 157 basis points in Boston. The results in columns (3) and (4) show no significant association between flood risk exposure and vacancy rates.

[Table 4 about here.]

Those findings suggest that flood risk exposure is associated with higher capitalization rates. Capitalization rates increase if: (i) current income increases; (ii) the risk premium increases; or (iii) the expected growth rate of future income declines. As we control for net income in the first stage of the capitalization rate regressions, the increase in capitalization rates 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. Thus, we cannot provide direct evidence regarding the importance of those two factors in the increase in capitalization rates we document. However, 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 real estate assets 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.

[8] 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.

5 Robustness Tests

5.1 Modifying Key Assumptions

We assess the robustness of our results regarding three key assumptions in our analyses. First, we assume that coastal proximity is the most important determinant of flood risk. This is why choose coastal proximity as our main measure of an asset's flood risk exposure. However, coastal proximity may only be relevant for real estate in low-lying locations: a real estate asset at sea-level located a mile from the coast is directly exposed to flood risk, while a real estate asset right on the coast, but on top of a tall cliff, is not. We address this possibility by re-estimating Eq. (4), augmented with an interaction term between assets' coastal proximity and elevation. Columns (1) through (3) of Table 5 show the results. The estimates reported are consistent with our main findings. Notably, the elevation and interaction coefficients are statistically insignificant, while the proximity coefficients for New York and Boston remain significant and have similar magnitudes as in our baseline tests.

[Table 5 about here.]

We also assume in the estimation of Eq. (4) that only the price impact of assets' coastal proximity changes post-Sandy, while the impacts of other hedonic characteristics on CRE prices remain constant. We show that our results are robust to relaxing this assumption by re-estimating Eq. (4), augmented with hedonic controls in the second stage. Importantly, we allow for the impact of *all* those hedonic characteristics to change post-Sandy. As shown in columns (4) through (6) of Table 5, the estimated coefficients for those hedonic characteristics are insignificant for the most part. Crucially, their inclusion does not affect the relationship between proximity and residual prices, thus validating our prior assumption.

Implicit in our analyses is the assumption that coastal proximity captures flood risk from hurricane exposure. However, assets in close coastal proximity may also be affected by flood risk from exposure to sea-level rise. Notably, Bernstein et al. (2019) document the impact of sea-level rise on house prices by focusing on a sample of real estate within a proximity of

0.25 miles to the coast. Based on data reported in their study, the critical level of real estate 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 prices of real estate assets that are less likely to be exposed to sea-level rise are still affected by flood risk emanating from hurricane exposure. Our findings remain significant, indicating that investors price increased perceptions of flood risk following Sandy separately from exposure to sea-level rise. The results from this robustness test are available on request.

5.2 Modifying the Matching Process

We perform a set of robustness tests adjusting our matching process. We first replicate our main analyses by expanding our matching criteria in forming pairs of comparable properties sold pre- versus post-Sandy. Specifically, we control more tightly for asset location and asset quality by matching properties based on county and building class in addition to coastal proximity and flood zone. Columns (1) through (3) of Table 6 present the results. The estimates reported confirm our central inferences.

[Table 6 about here.]

Our original matching criteria include a property's flood zone status. Alternatively, we drop all properties located in flood zones from our analyses. We then form pairs of comparable properties based on those assets' coastal proximity, before re-estimating Eq. (4). Columns (4) through (6) of Table 6 present the associated regression results. Our main findings remain unchanged.

5.3 Alternative Difference-in-Differences Approach

In our final set of robustness tests, we replace the pseudo repeat sales approach from our main analyses with a matched difference-in-differences strategy (see, e.g., Gupta et al., 2020). We implement this strategy by matching real estate assets sold before and after Sandy based on their coastal proximity and flood zone status, as in our main analyses. Then, we pool all observed transactions prices and regress them on the coastal proximity values of the matched pairs, an indicator that takes the value of one if a given real estate transaction occurs in the post-Sandy period, an interaction term between those two variables, and a set of covariates that account for observable real estate and transaction characteristics.

Columns (1) through (3) of Table 7 present the estimation results. The coefficients on the interaction terms between coastal proximity and the post-Sandy indicator are negative in both the New York and Boston samples (see columns (1) and (2)). The economic magnitudes of the impacts are also close to our original estimates. As in our baseline analyses, we find no evidence of price discounts for real estate closer to the lake shore in Chicago (see column (3) of Table 7). Further, the results are also robust to allowing the pricing of hedonics to change following Sandy as shown in columns (4) through (6) for New York, Boston, and Chicago, respectively. The evidence presented here is consistent with our main findings that flood risk exposure was associated with a discount to real estate prices in New York and Boston after Sandy struck.

[Table 7 about here.]

The advantage of the matched difference-in-differences approach is that we can directly evaluate the parallel pre-trends assumption. To assess the pre-trends in our sample, we interact proximity with year dummies before and after Sandy, treating 2012 as the base year (i.e., the year when Sandy struck). We illustrate the results of our pre-trend analyses in Figure 2. The figure shows that the proximity coefficients exhibit a relatively stable trend for both New York and Boston pre-Sandy. However, once Sandy hits, there is a sharp decline in the coefficients in 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 coastal proximity before and after Sandy, with no discernible effect associated with the disaster event itself. Overall, our graphical analyses is consistent with our main results and suggests that our findings are not driven by pre-existing trends unrelated to Sandy.

[Figure 2 about here.]

Instead of separately estimating the matched difference-in-differences models for New York, Boston, and Chicago, we alternatively combine the data from those three locations and estimate triple-interactions between coastal proximity, the post-Sandy indicators, and the assets' locations. Columns (1) through (3) of Table 8 present the results. The estimates reported are consistent with our central inferences from the pseudo repeat sales model in direction, statistical significance, and economic magnitude.

[Table 8 about here.]

In Columns (4) to (6) of Table 8, we replace the continuous proximity measure with a coastal real estate indicator denoting whether a real estate asset is located within one mile to the coastline. This alternative specification allows for a more natural interpretation of the triple interaction term. Again, the results confirm our main inferences.

6 Conclusion

Using the New York landfall of Sandy in late 2012 as a natural experiment, we examine how sophisticated investors in the CRE market capitalize flood risk exposure into their real estate 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 coastal real estate valuations, even in coastal cities along the northeastern seaboard that were spared by Sandy.

We test this conjecture using a large sample of CRE transactions data in Boston and New York. Combining a hedonic model that accounts for baseline determinants of real estate prices with a matched sample of transactions completed before and after Sandy, we find evidence of a downward price adjustment for coastal real estate in the CRE market. Further, we find that those 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 coastal CRE, we conduct a placebo test using transactions in Chicago. Consistent with the idea that Sandy's landfall had no impact on perceptions of flood risk for Chicago lakefront real estate, we find no post-Sandy price 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 CRE investors demand a premium for holding real estate subject to heightened flood risk, is the most likely source of our main findings.

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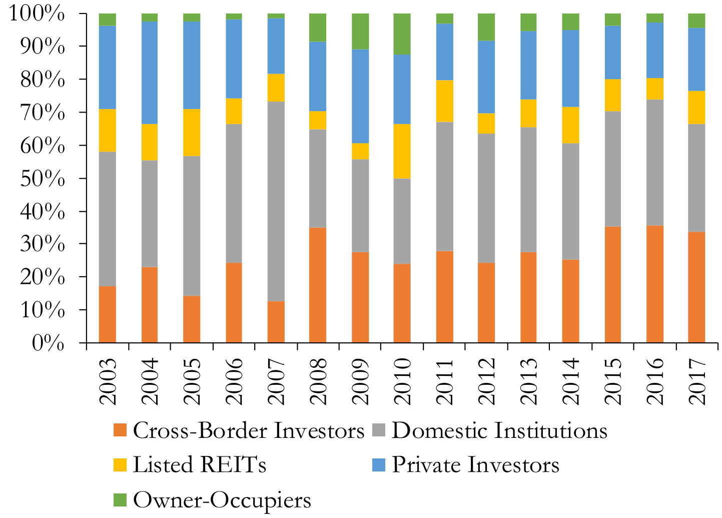

Figure 1. Composition of Annual U.S. Office Acquisition Volumes by Investor Types. The figure depicts the breakdown of total annual acquisition volumes of U.S. office properties by investor types over the 2003–2017 period. Data are from Real Capital Analytics.

Figure 2. 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 **??**. 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.

Table 1. Descriptive Statistics

This table shows descriptive statistics for the main variables used in our empirical analyses. Panel A presents the descriptive statistics for the county-level variables. 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 distance to the coast of the sample properties located in a given county, measured in miles, multiplied by -1. *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 descriptive statistics for the transaction-level data from New York, Boston, and Chicago, by sub-period. The pre-Sandy sub-period runs from the start of our sample in 2003: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 period in 2017:Q4. *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 one 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.

(A) County-Level Data

	Mean	SD	Min	Max	N
Damage	55.74	501.35	0.00	12,129.93	4,888
Proximity	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

(B) Transaction-Level Data

	Before Sandy					After Sandy					Difference
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	
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: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2. Hedonic Pricing Model

This table reports output from Eq. (1). The regression is estimated over the pre-Sandy period (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) (Column (3)) presents results for Boston (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.

	New York (1)	Boston (2)	Chicago (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.

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

This table reports output from Eq. (4). The dependent variable is the difference in adjusted prices across matched transactions from the pre- and post-Sandy 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. Adjusted 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 coastal proximity 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 a property's zip code for each year. Fixed effects are included as indicated. Bootstrapped z-statistics are reported in parentheses.

	Main Effect			By Transaction Year		
	New York	Boston	Chicago	New York	Boston	Chicago
	(1)	(2)	(3)	(4)	(5)	(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: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 4. Price Impact of Hurricane Risk by Performance Metric

This table reports output from Eq. (4). 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.

	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: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5. Price Impact Analyses with Alternative Assumptions

This table reports output from Eq. (4). 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) (and (4) to (6)) 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. The first three columns allow for elevation interactions. The last three columns allow the price of hedonics to change following 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.

	Elevation Interaction Effects			Post-Sandy Hedonics		
	New York (1)	Boston (2)	Chicago (3)	New York (4)	Boston (5)	Chicago (6)
Proximity	-0.232***	-0.078***	-0.006	-0.222***	-0.088***	0.001
	(-2.705)	(-2.627)	(-0.095)	(-2.645)	(-3.104)	(0.030)
× 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**	-0.431***	0.157	-0.686**
	(-2.783)	(1.880)	(-2.405)	(-2.579)	(1.485)	(-2.464)
Zip Code-Level Establishments	-0.133	1.785	0.790	-0.006	1.665	0.786
	(-0.127)	(1.395)	(0.769)	(-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	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	0.201	0.284	0.195	0.206	0.290

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

Table 6. Price Impact Analyses with Alternative Specifications

This table reports output from Eq. (4). 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). Columns (1) to (3) (and (4) to (6)) 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. In the first three columns, 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. The last three columns is based on matching by proximity and flood zone as in the main specification but exclude properties located in flood zones. *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.

	Additional Matching Criteria			Flood-Zone Properties Excluded		
	New York	Boston	Chicago	New York	Boston	Chicago
	(1)	(2)	(3)	(4)	(5)	(6)
Proximity	-0.178***	-0.075**	0.016	-0.224***	-0.098***	-0.001
	(-2.611)	(-2.525)	(0.348)	(-2.749)	(-3.291)	(-0.015)
Flood Zone	-0.446**	0.105	-0.852**			
	(-2.473)	(1.198)	(-2.482)			
Zip Code-Level Establishments	-0.964	1.451	0.377	0.357	2.021	0.834
	(-0.981)	(1.139)	(0.335)	(0.320)	(1.469)	(0.799)
Year–Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code–Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,199	1,378	945	2,181	1,292	942
Adj. R-squared	0.131	0.193	0.277	0.183	0.199	0.283

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

Table 7. Price Impact Using Matched Difference-in-Differences Analyses

This table reports output from the matched difference-in-differences analyses outlined in Section 5.2. Columns (1) through (3) present results for the basic matched difference-in-differences analyses. Columns (4) through (6) present results for the matched difference-in-differences analyses where the prices of property hedonics other than coastal proximity can also vary after Sandy. *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 (FE) are included as indicated. Heteroskedasticity-robust t-statistics are reported in parentheses.

	Matched Difference-in-Differences			With Post×Hedonic Interactions		
	New York (1)	Boston (2)	Chicago (3)	New York (4)	Boston (5)	Chicago (6)
Proximity	-0.034	0.048	0.028	-0.046	0.046	0.024
	(-0.395)	(1.405)	(0.716)	(-0.536)	(1.336)	(0.596)
× Post-Sandy	-0.221**	-0.081**	0.046	-0.200**	-0.079*	0.053
	(-2.215)	(-1.996)	(0.924)	(-1.999)	(-1.935)	(1.059)
Flood Zone	-0.036	0.036	-0.544***	0.281*	-0.061	0.005
	(-0.367)	(0.584)	(-3.266)	(1.663)	(-0.574)	(0.016)
× Post-Sandy				-0.470**	0.145	-0.845**
				(-2.274)	(1.109)	(-2.397)
Size	-0.184***	-0.166***	-0.147***	-0.230***	-0.182***	-0.157***
	(-14.185)	(-10.862)	(-9.064)	(-9.576)	(-6.893)	(-5.528)
× Post-Sandy				0.065**	0.024	0.013
				(2.275)	(0.740)	(0.366)
Age	-0.064***	-0.113***	-0.221***	-0.067**	-0.108***	-0.217***
	(-3.738)	(-5.407)	(-9.073)	(-2.348)	(-3.429)	(-5.981)
× Post-Sandy				0.007	-0.007	-0.013
				(0.199)	(-0.156)	(-0.266)
Stories	0.005*	0.015***	0.007***	0.008*	0.021***	0.007*
	(1.821)	(2.933)	(3.149)	(1.947)	(2.831)	(1.776)
× Post-Sandy				-0.005	-0.010	0.002
				(-1.032)	(-1.048)	(0.331)
Class A	0.331***	0.410***	0.360***	0.323***	0.398***	0.328***
	(5.557)	(6.322)	(4.834)	(2.982)	(3.747)	(2.688)
× Post-Sandy				0.018	0.031	0.054
				(0.138)	(0.234)	(0.352)
Class B	0.115***	0.086**	0.061*	0.142***	0.187***	0.022
	(4.108)	(2.431)	(1.708)	(2.702)	(3.007)	(0.352)
× Post-Sandy				-0.037	-0.149**	0.061
				(-0.595)	(-1.969)	(0.790)
Year-Quarter–FE	Yes	Yes	Yes	Yes	Yes	Yes
Post×Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,157	2,107	1,457	3,157	2,107	1,457
Adj. R-squared	0.54	0.505	0.491	0.541	0.505	0.492

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

Table 8. Matched Difference-in-Differences Analyses with Triple Interactions

This table reports output from the difference-in-differences analyses outlined in Section 5.2 by combining observations across different locations and introducing triple interaction terms. *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. *New York (Boston) Coastal* is a binary indicator whether a property is located within one mile to coastline. *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.

	(1)	(2)	(3)	(4)	(5)	(6)
Proximity	0.008	0.004	0.019			
	(0.196)	(0.095)	(0.484)			
× New York	-0.044	-0.045				
	(-0.485)	(-0.483)				
× Boston	0.044		0.030			
	(0.825)		(0.587)			
× Post-Sandy	0.061	0.066	0.053			
	(1.141)	(1.203)	(1.021)			
× Post-Sandy × New York	-0.282***	-0.272**				
	(-2.596)	(-2.465)				
× Post-Sandy × Boston	-0.149**		-0.131**			
	(-2.212)		(-2.017)			
New York Coastal				0.252*	0.241	
				(1.756)	(1.619)	
× Post-Sandy				-0.455***	-0.429***	
				(-3.561)	(-3.230)	
Boston Coastal				0.182		0.229
				(0.835)		(1.143)
× Post-Sandy				-0.365*		-0.363**
				(-1.826)		(-1.979)
Flood Zone	0.001	0.201	-0.061	-0.041	0.126	-0.099
	(0.017)	(1.387)	(-0.641)	(-0.477)	(0.828)	(-1.064)
× Post-Sandy	-0.074	-0.523***	0.045	-0.012	-0.411**	0.054
	(-0.708)	(-2.945)	(0.378)	(-0.124)	(-2.282)	(0.501)
Samples Included						
New York Properties	Yes	Yes	-	Yes	Yes	-
Boston Properties	Yes	-	Yes	Yes	-	Yes
Chicago Properties	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Post-Sandy × Zip Code FE	Yes	Yes	Yes	-	-	-
Zip Code FE	-	-	-	Yes	Yes	Yes
Post-Sandy × Metro Area FE	-	-	-	Yes	Yes	Yes
Observations	6,721	4,614	3,564	4,934	3,523	2,661
Adj. R-squared	0.660	0.677	0.519	0.592	0.608	0.524

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

Appendix A 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:

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

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 (A.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 (A.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.

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

Table A.1 presents the regression results for county-level hurricane damage from Equation (A.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]

The regression results in Table A.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.

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

Table A.1. County-Level Hurricane Damage

This table reports output from Eq. (A.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.

	(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:
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.