Quantifying the Impacts of Climate Shocks in Commercial Real Estate Market*

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Abstract
This study investigates the capitalization of climate shocks in commercial real estate owned and operated by sophisticated investors. We focus on Hurricanes Harvey and Sandy to quantify the price impacts of climate shocks on commercial buildings in the U.S. We find clear evidence of a decline in transaction prices in hurricane-damaged areas after the hurricane made landfall, compared to unaffected areas. We also observe that the *new news* about climate risks is significantly priced in both states – Assets in locations outside the FEMA floodplain (with less prior perception about climate risk) have experienced larger price discounts after the hurricanes. Investors could use realized flooding to learn about their flood risk. Moreover, the price discount is larger when the particular buyer has more climate awareness and has a more geographically diverse portfolio so it is easier for her to factor in this risk in the portfolio construction. Furthermore, we create an index using Google search to rank investors with respect to their environmental awareness and document that more pro-environment investors are likely to claim a larger price discount for properties in areas that face higher climate risk. Similarly, if a property is less replaceable in the investor's location choice set, the investors are willing to accept a smaller price discount because there are fewer alternatives. Our findings underline the importance of information provision and environmental awareness in order to accurately capitalize climate risk in commercial real estate as the cost of climate change becomes more salient.

Key words: Climate change, Asset prices, Commercial real estate, Flood risk
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1. Introduction

Climate risks are rapidly emerging as a factor relevant not just to policymakers, but also to the investment community and financial markets. Due to the immobility of assets, (commercial) real estate markets are especially vulnerable to climate risks. Climate shocks, including hurricanes, floods, storms, and wildfires, pose a significant risk to existing assets and the health of the local economy. With more frequent and severe climate events serving as a tangible reminder, investors are increasingly assessing the effects of climate risk on commercial real estate values. As climate shocks continue to damage commercial buildings and markets, the capitalization of such adverse conditions in commercial real estate prices becomes more salient.

Previous studies have documented the effect of sea-level rise and flooding events on the transaction price of exposed buildings. However, most of these studies focus on the capitalization of these risks in the *residential* market (Bin and Landry, 2013; Zhang, 2016; Ortega and Tapinar, 2018; Bernstein et al., 2019; Bauldalf et al., 2020), and little is known about the response of the commercial real estate market to climate shocks and the underlying mechanisms. Among the limited number of studies, Addoum et al. (2021) analyze commercial real estate transactions in New York, Boston, and Chicago after Hurricane Sandy, and document that investors respond rationally to heightened flood risk by bidding down the prices of exposed assets. Fisher and Rutledge (2021) examine the impact of 19 storms that occurred in the U.S. since 1988 on commercial real estate values and find that the effect of hurricanes peaks three years after landfall and dissipates over the subsequent two years. The authors also document that apartment and retail properties recovered faster than office, hotel, and industrial assets.

This study complements existing research by estimating the capitalization of climate shocks in commercial real estate owned and operated by sophisticated investors (relative to the common household owners of residential real estate). We focus on two of the most destructive billion-dollar climate events in the recent history of the U.S. – Hurricane Sandy and Hurricane Harvey. Specifically, we address the following two research questions: First, we are interested in quantifying the impact of hurricanes on the transaction prices of commercial real estate in the U.S.; Second, to identify the underlying mechanisms through which sophisticated commercial real estate investors respond to those climate shocks.

We find clear evidence of a decline in transaction prices in hurricane-damaged areas after the hurricane made landfall, compared to unaffected areas, and the effect lasts for about one year in New York, after which the transaction prices revert to pre-hurricane levels. In Texas, the effect lasts for a longer period and shows a sign or reversion to their previous levels four years after Hurricane Harvey.

We explore the mechanisms of these price effects from three perspectives by looking at the temporal variation in commercial real estate transaction prices, and investigating two sources of heterogeneity. First, we decompose the price effect into a risk premium channel (as reflected in the capitalization rate) and operating income channel (indirectly reflected in occupancy rates). While the capitalization rate in both New York and Texas shows no sign of significant changes, we document a decline in occupancy rates for properties in Texas, reflecting a lower current demand for assets prone to flood risk.

Second, while aggregate statewide results show evidence that damage from flood events is incorporated in the transaction price of commercial real estate assets, we find evidence of a larger flood discount in markets where these events can be considered as "*new news*". The "climate shock discount" in real estate prices depends on the ex-ante information of climate risk in a given location. We compare the market responses to hurricanes Harvey and Sandy between assets located inside FEMA flood zones and those located outside flood zones. We document that while a hurricane discount is weakly observed in areas located within flood zones, the majority of the market response to hurricanes is observed in damaged areas close to flood zones, where perceived flood risk was lower. Investors seem to update their perception of flood risk after the hurricane made landfall.

Third, we find stronger evidence of a flood discount for investors with a higher level of environmental awareness and a broader portfolio diversity. The capitalization of future climate risks in transaction prices depends on how investors price the risk in their decision making. Environmental awareness of investors would affect their climate change belief and their subsequent response to climate shocks. We construct a Google Green Index for real estate investors, following Zheng et al. (2012), to measure their environmental awareness. We document that those investors with a higher Google Green Index acquire properties from inundated areas with a larger price discount in the post-hurricane period. On the other hand, investors with larger portfolios, and therefore a broader choice set of where to buy and sell, would price climate risk differently as a particular property can be considered more easily replaceable. If a property is more replaceable in the investor's location choice set, given the same level of climate shock, the investor is asking for a larger price discount because they have sufficient alternatives to choose from. Following this logic, we do observe that assets owned by investors with a smaller geographic footprint experience smaller discounts after hurricanes, potentially due to the investors' limited choice sets.

This paper contributes to two strands of literature. First, we add to the existing body of research on the determinants of commercial real estate prices. By investigating the response of various commercial property types held by different types of investors to climate events, this paper documents, in a more comprehensive way, that how and through which mechanisms, climate shocks affect commercial real estate values.

Second, this paper adds to the literature on the consequences of climate change and environmental risk on commercial real estate. Previous studies primarily focus on the impact of climate change on the residential market (Atreya and Ferreira, 2015; Bin and Landry, 2013; Zhang, 2016; Ortega and Tapinar, 2018; Bernstein et al., 2019; Bauldalf et al., 2020), insurance and financial markets (Ouazad and Kahn, 2019; Giglio et al., 2021), migration (Deryugina et al., 2018; Boustan et al., 2020) and labor outcomes (Belasen and Polachek, 2008; Groen et al., 2020). While these studies tend to focus on market participants with limited access to complete information, there is little evidence on whether more sophisticated investors in the commercial real estate market are better equipped to evaluate and incorporate climate-related risk. Besides, the availability of income information of commercial properties provides us with a unique advantage over the residential sector to study the mechanisms at stake – if the price effect of climate shocks exists, we can distinguish between the income channel (current occupancy and rent changes) and the expectation channel (future risk perception changes). This study differs from Addoum et al. (2021) and Fisher and Rutledge (2021) in two aspects. First, we look at a broader set of commercial assets and different ownership attributes. Second, we explore the underlying mechanisms and heterogeneities for the observed climate shock discount in transaction values.

The paper is organized into five sections. Section two presents our data sources, stylized facts observed from the data, and model specifications. Empirical results are reported in the third section, followed by a discussion on possible channels in the fourth section. Section five provides a discussion and conclusion of our findings.

2. Data and Empirical Specifications

Data

Our analysis combines three datasets: information on commercial real estate transactions, information on the geographical areas affected by Hurricanes Harvey and Sandy, and local economic indicators. Table 1 report summary statistics for the data.

First, we obtain commercial property transaction data from Real Capital Analytics (RCA). RCA tracks property sales of over $2.5 million in the U.S. as of 2000. As Hurricane Sandy mainly affected the New York Metropolitan Area and Hurricane Harvey caused most damage in South Texas, we obtain information on commercial real estate transactions five years before and after each hurricane, that is, from 2007 to 2017 in New York and from 2012 to 2021 in Texas.[2]

Each transaction record in the database contains detailed information on the transaction date, price, property attributes, location at the Census block group level, and buyer and seller characteristics. Our sample is composed of apartment (36.09% in Texas and 55.35% in New York), industrial (18.16% in Texas and 6.93% in New York), office (18.03% in Texas and 13.92% in New York), and retail (27.71% in Texas and 23.8% in New York) assets. These two markets are quite different. The median transaction value in our sample is some $148.67 per square foot in Texas and $450.31 per square foot in New York prior to the hurricanes making landfall. About 20.69% (in Texas) and 24.36% (in New York) of the buildings in the sample are part of a portfolio transaction. In terms of buyer groups, about 74.95% (in Texas) and 82.16% (in New York) of the buyers are private buyers, respectively. The percentages for private sellers are 69.96% (in Texas) and 80.01% (in New York), respectively. Figure 1 depicts the overall yearly transaction price trend of commercial properties in Texas and New York. As illustrated by the figures, the commercial real market is trending upwards in both states despite severe hurricanes and floods.

[Insert Figure 1 here]

Second, information on hurricanes is collected from the Federal Emergency Management Agency (FEMA). We obtain information on the extent of flooding from the FEMA Modeling Task Force, which uses high-water marks and surge sensor data to capture inundation. The maps report hurricane surge heights on a raster of three-by-three meters, based on which we calculate block group-level averages. Hurricane Sandy hit the East Coast of the U.S. in October 2012 and caused severe flooding in the New York Metropolitan Area, with $77.4 billion in

[2] To construct a more comparable treatment and control group, we focus on transactions in New York-Newark CBSA (mostly damaged by Hurricane Sandy) and Texas State.

estimated damages. Hurricane Harvey made landfall on Texas and Louisiana in August 2017, causing catastrophic flooding, and inflicting $98.1 billion in damage.[3] Figure 2 display the average surge levels by Census block group in Texas (with a focus on Houston) and New York (with a focus on New York City).

[Insert Figure 2 here]

In addition to the inundation information, we also obtain flood zone information from FEMA's 100-year floodplain maps to measure the ex-ante perceived flood risk of a given area. FEMA's floodplain maps are the primary source of information to determine if a land parcel is within or outside the 100-year floodplain (a 1% chance of flooding per year)[4], which is often used as the basis for local land use regulations (Hino and Burke, 2011). Buildings within FEMA's flood zone are potentially more severely affected by future hurricanes and floods. As shown in Tables 1, the average hurricane surge level in each Census block group is about 1.12 feet in Texas and 0.47 feet in New York; about 8.64% in Texas and 9.16% in New York of transacted assets are located in a FEMA flood zone.

[Insert Table 1 here]

Economic models: model development and causal inference

We begin our empirical analysis by employing the quasi-experimental econometric method of Difference-in-Differences (DID) to explore causal inferences regarding the capitalization of climate shocks into commercial property prices:

$$Price_{it} = \alpha_0 + \alpha_1 \times Surge_i + \alpha_2 \times Surge_i \times Post + \beta \times Hedonics_{it} + T_t + \sigma_c + \mu_{ict} \quad (1)$$

where $Price_{it}$ is the natural logarithm of the transaction price per square foot for property i transacted at quarter t; *post* takes the value of 1 if the transaction happened after the specific hurricane (post-Aug 2017 for properties in Texas relative to Hurricane Harvey and post-Oct 2012 for properties in New York relative to Hurricane Sandy); $Surge_i$ is the hurricane damage measure. We employ three types of measures here: a dummy variable taking the value of 1 if the property is located in a block group with a positive surge level; a continuous variable of surge height at the block group level to measure the inundation severity; and two categorical

[3] Billion-Dollar Weather and Climate Disasters: Table of Events (Report). National Oceanic and Atmospheric Administration. January 8, 2018. Archived from the original on January 21, 2018. Retrieved January 8, 2018.
[4] FEMA maps is one way to measure flood risk in the US context, and is mainly used to determine whether flood insurance is mandatory for residential buildings. In this paper, we take the maps as provided as we do not aim to evaluate how accurately the maps can capture the real flood risk.

measures of the surge level. Specifically, we follow Meltzer et al. (2020) and define *Highsurge* as the indicator for severely damaged block groups (more than 3 feet of surge) and *Lowsurge* as the indicator for moderately damaged block groups (a surge less than 3 feet).

Apparently, properties located in inundated areas may be systematically different from those outside inundated areas regarding distance to the coast, elevation, age, size, and other property characteristics.[5] Therefore, we include a rich set of hedonic attributes and granular-level fixed effects (Census tract fixed effects) to control for the observed and unobserved differences between the treatment and control groups. $Hedonics_{it}$ incorporates the covariates of building attributes, such as property type (apartment, industrial, office, retail), building age, size, number of stories, buyers and sellers' characteristics, and building quality.[6] Year-quarter fixed effects T_t account for time-varying factors common to all transactions, while Census tract fixed effects σ_c adjust for all time-invariant locational attributes.

3. Baseline Results

3.1 The Hedonic Pricing Model

Table 2 documents differences in transaction prices before and after each hurricane with different surge levels. Columns (1) to (3) report the estimates for Hurricane Harvey, while columns (4) to (6) report estimates for Hurricane Sandy. The treatment group includes assets transacted after the hurricanes. The coefficients on the interaction term in Table 2 suggest that transaction prices are significantly and negatively impacted in the period following both hurricanes. A one standard deviation increases in the surge level of the block group where the building is located is associated with a price discount of some 3.5% for assets transacted in the post-Harvey period, which corresponds to about \$4.41/sq. ft, and \$311,500 for the average building in our sample. This magnitude is about 1.5% for buildings transacted in New York in the post-Sandy period, which corresponds, on average, to about \$5.49/sq. ft, and \$100,335 per building. In addition, we explore an alternative measure of the severity of a hurricane's damage. Rather than assuming that the impact of hurricane damage on commercial property values is linear, we construct two categorical variables indicating the severity of the flooding. Columns

[5] In Table A2 we include the comparison between properties located in inundated areas and those outside the inundated areas.

[6] We use the national Q Score developed by RCA for each property as the building quality measure. The Q Score is an objective, analytical measurement tool that captures and ranks the spectrum of value attributes of real estate properties. It is essentially the transaction value at which the property falls in the distribution of the whole RCA database.

(3) and (6) indicate that the coefficients of the interaction between the surge severity indicators and post-hurricane indicators are negative and significantly different from zero, indicating a decrease in transaction prices for buildings located in flooded areas after the hurricanes – The discount is also increasing with the severity of damage caused by the hurricanes: the average transaction price for properties located in high-surge areas was 8.8% lower after Hurricane Harvey.

[Insert Table 2 here]

Next, we investigate how the hurricane discount in commercial real estate transaction prices evolves over time. The identification of causality of results in Table 2 requires that, conditional on the factors included in Eq. (1), any remaining variation in hurricane damage is random. That is to say, without the hurricanes, the price trend of the treatment and control group – those surged and those non-surged – should follow the same pattern. We construct interaction terms between the surge level indicator in Eq. (1) and indicators for each 6-month period surrounding the two hurricanes. Figures 3 and 4 model the impact of Hurricanes Harvey and Sandy, split evenly between a pre- and post-period. First, while there is little evidence that exposure to hurricane damage affects transaction prices during the pre-hurricane period, a gap between surged and non-surged area start to emerge after each hurricane. After Hurricane Harvey, damaged areas experienced a moderate decline in transaction prices. The effect is most severe two years after the event, after which the transaction prices remain depressed and show a sign of reversion to their previous levels four years after the hurricane. For New York, we find that buildings in Sandy-affected areas experience a discount in transaction price right after the event, and the discount lasts for only about one year before dissipating.

[Insert Figure 3 and Figure 4 here]

The results suggest that commercial real estate investors incorporate climate events into commercial real estate transaction prices. Properties located in damaged areas are often closer to the coast, thus also face a greater risk of flooding in the future. The hurricane discount we observe is likely the result from both current physical damages and the perceived rising future flood risks. In the subsequent sections, we investigate the mechanisms through which hurricanes affect commercial property values.

4. Mechanism exploration

The baseline analysis quantified the climate shock discount in commercial real estate prices for hurricanes Harvey and Sandy. This section evaluates the possible mechanisms underlying the observed hurricanes' price impact, including two sources of heterogeneity that may affect the hurricane discount for asset values. We start our analysis with some of the main drivers of commercial real estate values: capitalization and occupancy rates.

The market value of commercial real estate is a function of current cash flow (net operating income) and the capitalization rate. Current cash flow depends on both contract rent and occupancy rate (which does not necessarily respond quickly to market conditions, particularly with long-term leases), while the capitalization rate reflects the risk premium for the asset, which contains investors' expectation of future risk.[7] To explore the underlying mechanism, we start by examining the capitalization rate and occupancy rate of the observed buildings. Using information on the capitalization rate and occupancy rate at the time of transaction from RCA, we are able to investigate which of these performance indicators is affected, and to what extent, by hurricanes and subsequently leads to a change in the transaction price by replacing the dependent variable in Equation (1) with the capitalization rate and occupancy rate. Information on occupancy rates and capitalization rates is not populated for every transaction in our dataset. Using a reduced sample might be informative to explore this particular mechanism:

$$CapRate_{it} = \alpha_0 + \alpha_1 \times Surge_i + \alpha_2 \times Surge_i \times Post + \beta \times Hedonics_{it} + T_t + \sigma_c + \mu_{ict} \quad (2)$$

$$Occupancy_{it} = \alpha_0 + \alpha_1 \times Surge_i + \alpha_2 \times Surge_i \times Post + \beta \times Hedonics_{it} + T_t + \sigma_c + \mu_{ict} \quad (3)$$

Table 3 presents the estimations of Eq. (2) and (3). The results indicate that buildings located in hurricane inundated areas experience no significant changes in capitalization rates. Interestingly, we document a decline in occupancy rates in the Texas commercial real estate market. One standard deviation increase in surge levels is associated with about a 0.4 percentage point decrease in occupancy rates. This suggests an occupancy-driven decline in operating income for commercial real estate markets in Texas.

[Insert Table 3 here]

The previous results provide weak evidence that hurricane Harvey led to a decrease in occupancy rate, we subsequently investigate heterogeneity in the price discount based on the

[7] Under the assumption that operating expenses are constant.

extent to which investors respond to the climate shocks. Investors might update their beliefs regarding the likelihood of climate shocks in a certain location, which would lead to a change in transaction values. Information provided by FEMA 100-year floodplain maps serves as the major information source of pre-existing flood risk for investors. However, while some of the inundated areas are located within flood zones, a large proportion of the damaged areas are located outside flood zones, indicating a discrepancy between ex-ante information on flood risk and ex-post real damages. Table 4 provides the information on the inconsistency between perceived flood risk (designated flood zones) and real damages (inundation due to flooding). In New York, 13.72% of the properties located outside a flood zone are inundated, the fraction is 27.93% in Texas.

[Insert Table 4 here]

We construct a measure of ex-ante perceived flood risk from FEMA 100-year floodplain maps. We test whether the ex-ante perception difference in such flood risk is associated with a difference in the market response to major hurricanes. We calculate the distance of the center of the block group where the building is located to the nearest flood zone boundary, and we conduct four sub-sample regressions of Eq. (1) based on different distance cut-off values: within the flood zone; outside the flood zone, outside the flood zone and within 500 meters; outside the flood zone and within 1,000 meters.

Table 5 presents the sub-group estimation results of Eq. (1). Columns (1) and (5) show that being located within the flood zone is not significantly associated with price changes after the hurricanes, both in Texas and New York. One possible explanation is that investors have already capitalized flood risks into their asset value based on the flood zone designation, so this hurricane is no longer *new news*. In addition, the flood zone designation is also associated with mandatory insurance requirements under certain circumstances and asset owners could use insurance as protection against climate shocks. To compare, columns (2) and (6) indicate that being located outside a flood zone is associated with a much larger and more significant discount in transaction values after Hurricanes Harvey and Sandy, which suggests that when investors receive the *new* news for those locations outside the flood zone but really get inundated, they quickly update their belief of flood risks at that location and price such risks in the asset value. Columns (2) to (4) documents that the hurricane discount we observe from Table 2 is mainly observed in locations outside the flood zone, and the effect is robust when we narrow the distance buffer to 1,000 meters. Columns (5) to (8) show that in New York, even though the average climate shock discount for inundated properties is only marginally significant (as shown in Table 2), the effect is more statistically significant for properties outside of but closer to flood zones. Importantly, the hurricane discount we observe in Table 5 captures the impact of new information embedded in inundation caused by flooding. As such, the hurricanes serve as an important belief update to investors about future flood risk.

[Insert Table 5 here]

Next, we explore how hurricanes' impact on transaction values vary among different groups of investors. Environmental awareness of investors would affect their climate change beliefs and how they respond to climate shocks. Investors with different portfolio sizes could price climate risks differently in their investment. On the other hand, given the same level of climate shock, if a property (and the associated location) is less replaceable in the investor's location choice set, prospective buyers may be willing to accept a smaller price discount because of the lack of sufficient alternatives.

Along the environmental awareness dimension, previous literature provides various potential explanations of why investors' beliefs about climate risks may affect equilibrium prices after climate disasters occur. Bakkensen and Barrage (2017) study the effect of different climate risk beliefs on residents' selection choice between coastal and inland homes, and they find that coastal flood zone residents have both lower flood risk perceptions and higher waterfront amenity valuations than the inland residents. Bernstein et al. (2019) look at the association between beliefs about climate change and owner-occupied coastal property prices, and document that the SLR exposure discount is significantly larger among sophisticated buyers, compared to their counterparts with less concern about climate change. Baldauf et al. (2020) find that residential real estate prices are affected by differences in beliefs about the occurrence and effects of climate change, and the existence of equilibria in which agents sort into geographically different neighborhoods by belief.

To understand the effect of heterogeneous environmental literacy of investors on commercial real estate prices, we follow Zheng et al. (2012) to propose a Google Green Index to measure investors' "greenness". First, we use Google to search for each investor's name and record the total number of entries, which serves as the denominator in the Index. Next, we search for the investor's name plus ten greenness-related keywords that are frequently used by the media.[8] We calculate the ratio of the count of joint searches to the total number of Google entries per

[8] Table A3 presents the ten key words we use in the Google Green Index construction.

investor, which yields our Google Green Index (the index varies between 0 and 1), as is shown in Eq. (4). The index captures to what extent investors pay attention to greenness-related business practices which we use as an outcome to measure the investors' environmental awareness. Investors with a higher value of this index are more pro-environment. We expect transactions conducted by investors with a higher Green Index to exhibit larger price discounts with respect to hurricane damage.

$$\textit{Google Green Index} = \frac{\#\,\textit{Queries of "investor name + green key word"}}{\#\,\textit{Queries of "investor name"}} \tag{4}$$

Figure 5 shows the distribution and descriptive statistics of the Google Green Index for commercial real estate investors in Texas and New York. Generally, investors in New York show greater environmental literacy than investors in Texas, as their average and median value of Green Index are much higher. About 13.4% of Texas buyers and 7.0% of New York buyers have a Green Index of zero, indicating that they are not marketing green-related attributes of the company. The maximum Green Index for investors in these two areas are 9.5% and 19.6%, respectively, meaning that among all media pieces of the "greenest" investor in Texas (New York), about 9.5% (19.6%) of them are environmentally related.

[Insert Figure 5 here]

To test the effect of environmental literacy on the hurricane discount of properties, we use the following model:

$$\begin{aligned} Price_{it} = \alpha_0 + \alpha_1 \times Surge_i + \alpha_2 \times Surge_i \times Post + \alpha_3 \times Post \times Green + \alpha_4 \times Surge_i \times Post \times Green + \\ \beta \times Hedonics_{it} + T_t + \sigma_c + \mu_{ict} \end{aligned} \tag{5}$$

where we include interaction terms between the hurricane damage, post-period indicator, and *Green,* which is a binary variable based on the median value of the Google Green Index that we construct. If the index of an investors is higher than the median value, *Green* takes the value of 1; otherwise, *Green* takes the value of 0.

The estimation results of Eq. (5) are reported in Table 6. Based on sub-sample regressions for the two sets of investors, while controlling for other factors, we document that the hurricane discount is only significant for investors that are considered "greener." On average, "green" investors claim a price discount of about 7.5% in New York and 5.6% percent in Texas for assets in hurricane-affected areas compared to areas outside the inundated areas. Only "green" investors extract a price discount, as the coefficient of interest in columns (2) and (4) are not statistically significant[9]. This result corroborates the findings in Baldauf et al. (2020) that house prices reflect heterogeneity in beliefs about climate risks. Houses projected to be underwater in believer neighborhoods sell at a discount compared to houses in denier neighborhoods. We conclude that heterogeneity in investors' priority of climate risks, which is reflected by their environmental literacy, significantly affects asset prices after climate related damages occur.

[Insert Table 6 here]

Another way to examine the priority of climate risks in investors' decision making is to examine heterogeneity in investors' portfolio size. For instance, buyers with a larger geographic investment footprint are likely to manage a more diversified portfolio than other investors. Hence, they have a comparative advantage to buy and sell assets in a larger portfolio with a broader choice set. Therefore, a specific asset and the associated location is more "replaceable" in those investors' portfolios, and they might claim a larger discount on assets affected by climate shocks.

To further explore the effect of climate shocks on investors with different geographic scope of their portfolios, we calculate the geographic scope of previous transactions of the investors in our sample. Specifically, we record the number of different locations (county-level) that the investors have operated in and use it as a footprint diversity measure. While the constructed footprint diversity measure may not accurately reflect the diversity of the overall portfolio of the investors, as we observe transactions in designated areas, we view the footprint measure here as a proxy for investors' previous transaction experience in the surrounding area. For investors with a more geographically diverse footprint, it is easier to relocate their investment activity to more climate-resilient locations and put higher priority on climate considerations in their portfolio management.

To assess the effect of investors' footprint diversity on the hurricane discount of properties, we use the following model:

$$Price_{it} = \alpha_0 + \alpha_1 \times Surge_i + \alpha_2 \times Surge_i \times Post + \alpha_3 \times Post \times Diverse + \alpha_4 \times Surge_i \times Post \times Diverse + \beta \times Hedonics_{it} + T_t + \sigma_c + \mu_{ict} \quad (6)$$

[9] We conduct Fisher's permutation tests for difference in coefficients between the two groups (green vs. non-green), and the observed difference is significant (p-value = 0.000 for the comparison in both Texas and New York).

where we include interaction terms between the hurricane damage, post-period indicator, and *Diverse,* which is a binary variable based on the median value of the number of unique counties where the buyer has previous transaction experience. If the number of counties is higher than the median value, *Diverse* takes the value of 1; otherwise, *Diverse* takes the value of 0.

Table 7 shows the estimation results for Eq. (6). Specifically, we interact our hurricane damage measure with a "*diverse*" binary variable. The interaction term between the post-hurricane indicator, hurricane damage, and footprint diversity is significantly negative, confirming that relative to investors who operate in a limited geographic area, those with broader transaction experience responds to climate shocks with a larger price discount. The effects are consistent across both states. As documented in Column (3), a one-standard-deviation increase in surge level is associated with a 2.2% decrease in the transaction price for properties damaged by flooding in Texas. The magnitude of the discount is higher for buyers with diverse portfolios by about 0.2%. In New York, the same pattern holds, and the climate shock discount for diverse buyers is as high as 1.1%.

[Insert Table 7 here]

The results in Tables 6 and 7 show that the priority of climate risk in investment decisions affects the response to climate events. A combination of climate risk awareness and more diverse investment experience shapes the observed climate shock discount. Our findings are in line with Hino and Burke (2021), who document that well-informed, sophisticated buyers would price climate risk more than a typical buyer. Providing reliable information on future climate risk in a certain location in addition to FEMA flood plain maps could aid the market in accurately pricing climate risk in commercial real estate transactions.

Conclusion

This paper explores how climate shocks, such as hurricanes, affect commercial real estate markets. Specifically, we examine how transaction prices of commercial real estate in New York and Texas respond to severe damages caused by Hurricanes Sandy and Harvey, respectively. We find evidence of a decline in transaction prices in hurricane-damaged areas after the hurricane made landfall, compared to unaffected areas. Properties transacted in affected areas in New York yield a price 1.5% lower than their counterparts in unaffected areas, and the effect lasts for about one year, after which the transaction prices revert to pre-hurricane levels. In Texas, the effect is about 3.5% for property values, and lasts for a longer period before shows a sign of recovery after four years.

In addition, we briefly explore the potential channels and heterogeneity of the hurricane discount. In Texas, we find that a decline in occupancy rates, reflecting a decrease in demand for assets prone to flood risk, is the primary channel. We also document that the "climate shock discount" depends on whether this shock is the new news for investors at that location, and also the relative "priority" level of climate shocks, among other factors, that investors consider when they make their acquisition decision. Being located within a FEMA flood zone is not significantly associated with price changes after the hurricanes because such risk has been already absorbed by investors, while inundated properties located outside of but close to the flood zones have experienced a significant decline in transaction prices in the post-hurricane period when they update their belief about the future risk at that specific location. This *new news* effect is true in both states, suggesting that many properties outside the FEMA floodplain with "hidden risks" might be overvalued, and later climate events, such as Hurricanes Harvey and Sandy, may help correct the risk pricing.

Using the Google Green Index, we document that those pro-environment investors are proactively pricing climate risks into their asset valuations and acquisition decisions. Our results indicate that market efficiency could be improved by improving awareness of climate risk, which may lead to higher insurance take-up and more active adaptation strategies towards future climate risk. In addition, under the same level of climate shock, if a current asset (and associated location) is less replaceable in the investor's location choice set, it suffers from a smaller price discount as the investor does not have enough alternatives. We find that investors with more geographically diverse portfolios are able to put climate risks at a relatively higher priority and thus they are more asking for a larger price discount for those locations prone to such risks.

Our study has three limitations that are worth noting. First, the location of the asset is observed at the Census block group level. Hence the hurricane damage measure is aggregated at the same unit of observation. Inundation levels caused by hurricanes Harvey and Sandy may vary within Census block groups. The potential mismeasurement of inundation at the exact location of the asset may lead the analysis to under- or overestimate the actual observed inundation at the property. Second, the analysis does not incorporate the impact of insurance or post-disaster mitigation policies on property values. Gallagher (2014) suggest that the insurance take-up rate in the residential sector spikes one year after a flood before reverting to the mean. Therefore, insurance take-up in inundated and neighboring areas may also increase in the commercial real estate market, at least in the short term. The observed price reversion of assets in inundated areas point to the possibility that financial aid from the government might affect the recovery of the market. Third, the measurement of investors' environmental awareness serves as a proxy. Previous studies use Google search frequency as a measure of attention (Da et al., 2011; Afkhami et al., 2017). Search results using environment-related keywords are likely to include results that are either positive or negative. We posit that media exposure of behavior harming or helping the environment is not systematically different among investors. Whereas our measure of environmental awareness arguably contains noise, it is not believed to skew the results in a particular direction.

Our study has some implications. First, the presence of climate risk does impact commercial real estate markets in a comprehensive way. Real estate investors are starting to incorporate various strategies to price and manage climate risks, yet clearly there is still a big information gap and more sophisticated climate risk evaluations are needed. Second, since investors do update their risk perception when being exposed to climate events, it is important for policy makers and government agencies to provide more accurate information on climate risk to aid the decision-making process of all stakeholders and improve market efficiency. Our findings highlight the importance of efficient climate risk pricing to mitigate real estate value losses from future climate events.

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Figures and Tables

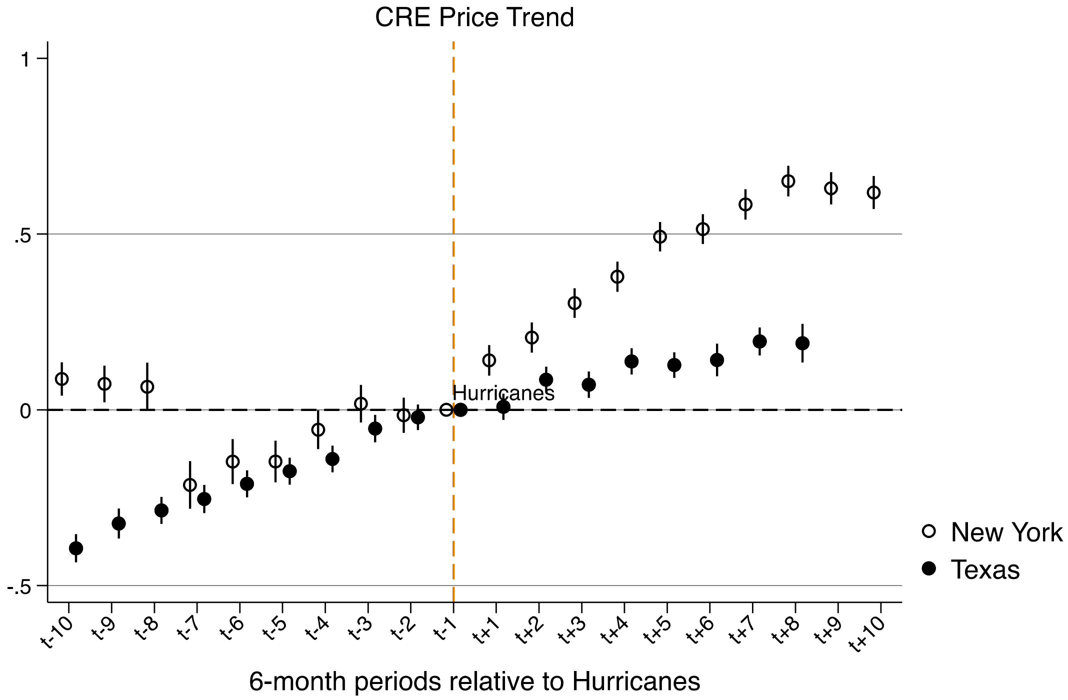
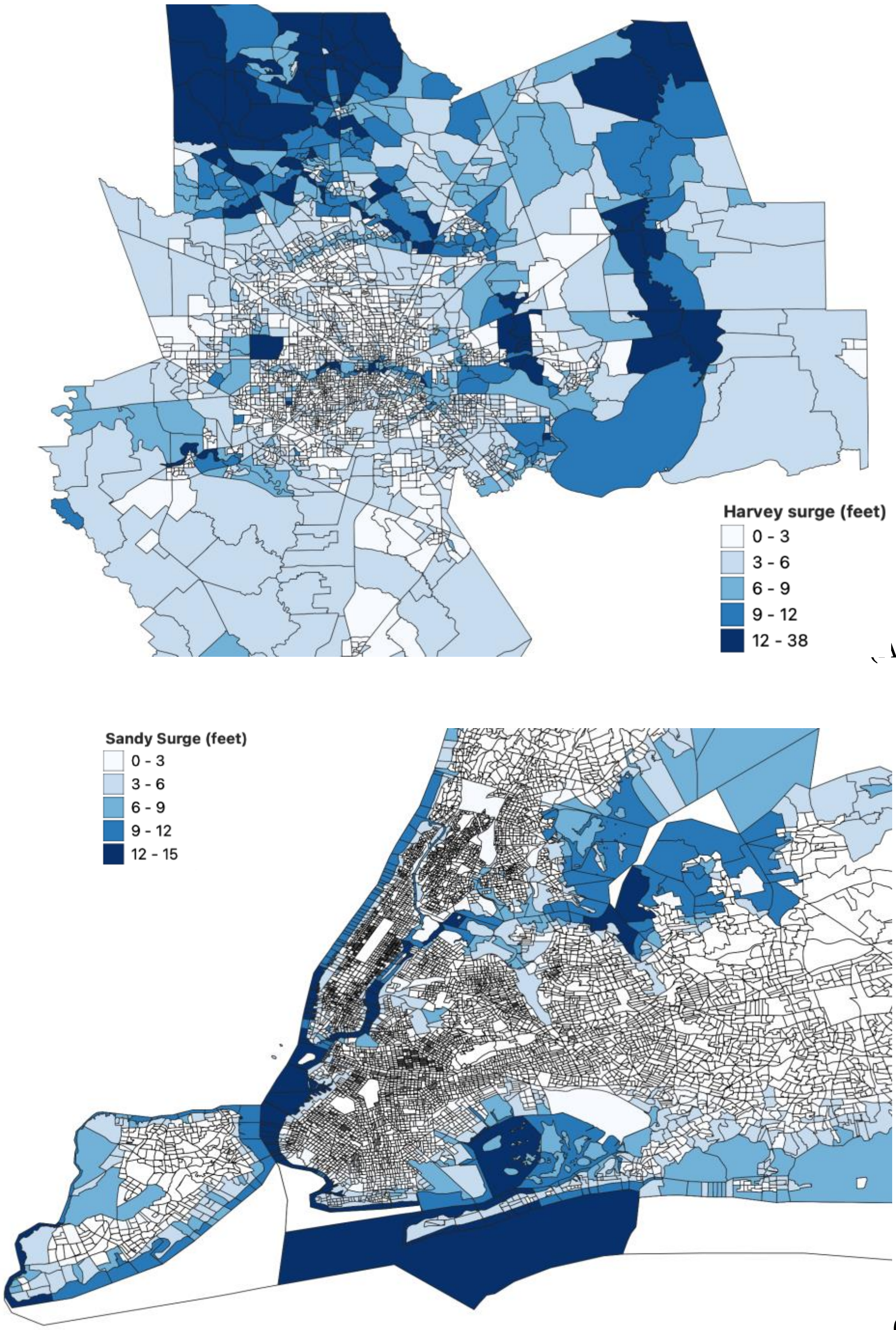


Figure 1. 6-month period transaction price trend of commercial properties

Notes: The figure depicts the yearly trend of commercial properties in Texas and New York. We use the year fixed effect model to regress the hedonic price model, and plot the coefficient of year fixed effects.



(B)

Figure 2. I**nundation zone of Hurricane Harvey and Sandy**

Notes: Panel A shows the surge level of inundation area by Census block group in Texas, with a focus on Houston. Panel B shows the surge level of inundation area by Census block group in New York, with a focus on New York City. The blue shades indicate surge level (feet).

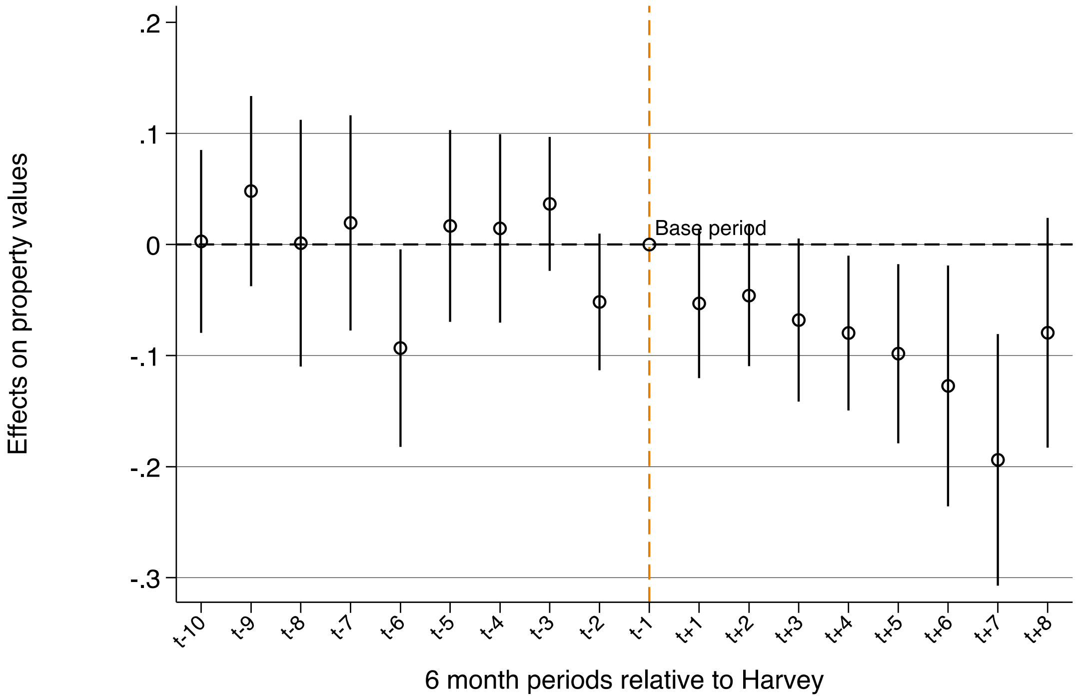


Figure 3. Transaction price increment over time - Hurricane Harvey

Notes: This Figure presents how the transaction price of all property types in Texas is affected pre- and post-Hurricane Harvey. These point estimates are based on regression estimates. Each dot represents the point estimate; the whiskers represent a 95% confidence interval.

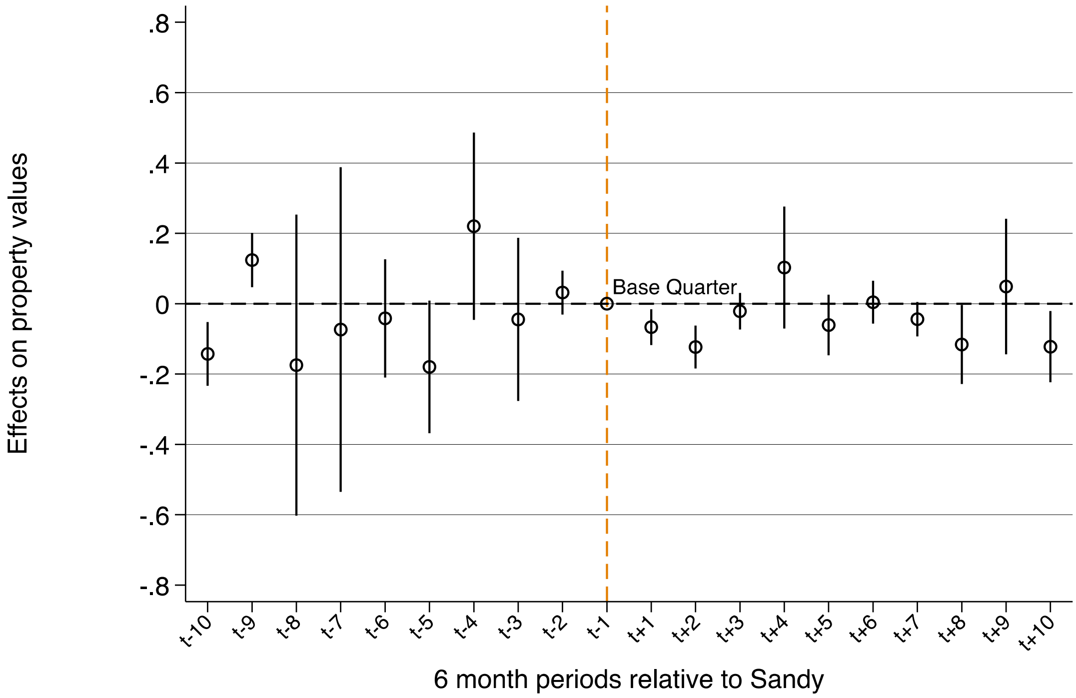
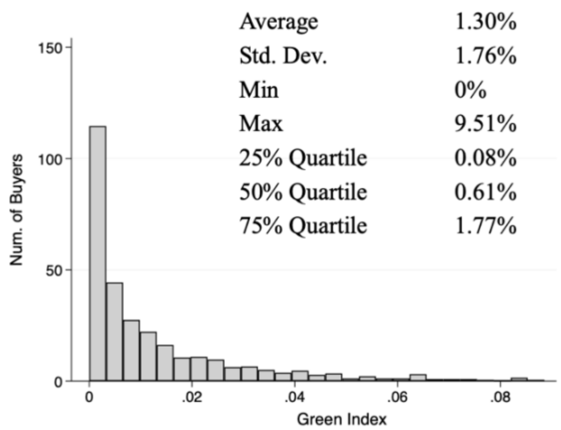
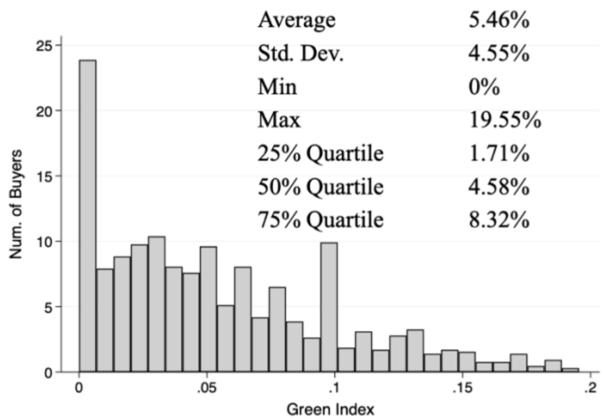


Figure 4. Transaction price increment over time - Hurricane Sandy

Notes: This Figure presents how the transaction price of all property types in New York is affected pre- and post-Hurricane Sandy. These point estimates are based on regression estimates. Each dot represents the point estimate; the whiskers represent a 95% confidence interval.



(A)



(B)

Figure 5. The distribution and descriptive statistics of the Google Green Index

Notes: The figure depicts the distribution and descriptive statistics of the Google Green Index that we construct for commercial real estate buyers for properties in Texas (Panel A) and New York (Panel B).

Table 1 Descriptive statistics

	Texas		New York	
	Pre-	Post-	Pre-	Post-
Transaction Price	148.67	193.95	450.31	698.07
($/sq. ft)	(124.95)	(247.32)	(655.33)	(1148.41)
Surge dummy	0.29	0.27	0.15	0.16
(0/1)	(0.45)	(0.44)	(0.36)	(0.37)
Surge Level	1.12	1.13	0.49	0.47
(feet)	(2.43)	(2.68)	(1.41)	(1.28)
High surge (>3 feet)	0.14	0.14	0.08	0.07
	(0.35)	(0.35)	(0.27)	(0.25)
Low surge (<=3 feet)	0.14	0.13	0.08	0.09
	(0.35)	(0.33)	(0.27)	(0.29)
100-year Floodplain (%)	9.56	8.64	3.25	2.62
	(29.41)	(28.10)	(17.72)	(15.97)
RCA Quality Score	0.43	0.42	0.75	0.76
	(0.25)	(0.25)	(0.23)	(0.23)
Capitalization Rate	0.07	0.06	0.06	0.05
Occupancy Rate	87.18	95.45	63.64	69.37
Building size	150.77	135.16	73.38	63.75
Portfolio Sale (%)	20.74	19.2	22.17	24.91
CBD (%)	2.3	2.37	90.78	91.36
Tenancy Type (%)				
Multi Tenant	75.17	73.69	76.07	77.95
Single Tenant	18.09	22.56	10.40	9.56
Vacant	6.74	3.74	13.53	12.49
Construction Vintage (%)				
1960-1969	9.88	10.60	85.96	84.65
1970-1979	15.97	14.33	2.79	2.88
1980-1989	24.83	22.55	3.85	3.46
1990-1999	13.38	12.39	2.03	2.04
2000-2009	25.94	21.28	4.64	4.59
2010 or after	10.00	18.85	0.73	2.38
Number of Stories (%)				
Less than 5 stories	93.13	93.96	37.82	44.38
5-10 stories	3.95	4.20	52.35	46.04
More than 10 stories	2.92	1.83	9.83	9.59
Buyer Incentive (%)				
Condo Conversion	0.02	0.02	0.79	0.28
Investment	90.29	90.95	83.38	82.69
Occupancy	3.97	2.21	4.40	3.67
Redevelopment	1.55	0.77	7.13	7.39
Renovation	4.17	6.05	4.31	5.97
Buyer Type (%)				
Institutional	16.63	13.41	9.68	10.20
Private	71.67	79.10	80.56	82.83
Public	6.62	3.79	2.70	2.67
User/Other	5.08	3.70	7.07	4.29
Seller Type (%)				
Institutional	20.41	14.44	11.43	11.32
Private	66.23	74.69	78.62	80.60
Public	6.55	4.39	1.64	2.06
User/Other	6.80	6.48	8.31	6.02
Observations	8,010	6,329	3,297	7,824

Notes: Standard deviations in parentheses.

Table 2 Price effect of hurricanes on CRE market

	Dependent Variable: Log (Price/sq. ft.)					
	Texas			New York		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.028	-0.040	-0.029	0.595***	0.594***	0.595***
	(0.049)	(0.048)	(0.048)	(0.033)	(0.033)	(0.033)
Surge Dummy	-0.093**			0.043*		
	(0.040)			(0.025)		
Post × Surge Dummy	-0.033*			-0.009		
	(0.017)			(0.021)		
Mean Surge		0.026**			0.004	
		(0.010)			(0.010)	
Post × Mean Surge		-0.035***			-0.015*	
		(0.008)			(0.008)	
High Surge			-0.052			0.010
			(0.042)			(0.033)
Low Surge			-0.143***			0.057*
			(0.043)			(0.031)
Post × High Surge			-0.088***			-0.033
			(0.022)			(0.029)
Post × Low Surge			0.028			0.013
			(0.023)			(0.028)
Hedonic attributes (including property type dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.629***	6.591***	6.632***	5.615***	5.621***	5.614***
	(0.070)	(0.069)	(0.070)	(0.364)	(0.364)	(0.364)
Observations	15,312	15,312	15,312	10,359	10,359	10,359
R^2	0.703	0.703	0.703	0.912	0.912	0.912

Notes: This table reports estimates from Eq. (1). The dependent variable is the log transaction price per square foot at the property level. The post-hurricane period runs from 2012 Q4 to 2017 Q4 for New York and 2017 Q3 to 2021 Q2 for Texas. *Surge Dummy* is an indicator that takes the value of one when a given property is in the inundated area. *Mean Surge* is an indicator of the average surge level in feet of the given block group. *High Surge* (*Low Surge*) is an indicator that takes the value of 1 if the given property is in a block group with a surge level higher (less) than 3 feet. Census tract fixed effects and Year-quarter fixed effects are included. Standard errors are reported in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and ***.

Table 3 Effect of hurricanes on CRE's operating performance

	Texas		New York	
	Cap Rate	Occupancy	Cap Rate	Occupancy
	(1)	(2)	(3)	(4)
Post	0.327	-1.138	-0.972***	2.424
	(0.228)	(1.263)	(0.367)	(1.978)
Mean Surge	0.107	0.347*	-0.076	0.226
	(0.086)	(0.202)	(0.101)	(0.454)
Post × Mean Surge	0.042	-0.396**	-0.005	-0.157
	(0.068)	(0.164)	(0.084)	(0.343)
Hedonic attributes (including property type dummies)	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	2,539	8,563	1,573	3,615
R^2	0.779	0.879	0.789	0.970

Notes: This table reports estimates from Eq. (2) and (3). The dependent variable is the capitalization rate and occupancy rate at the property level. The post-hurricane period runs from 2012 Q4 to 2017 Q4 for New York and 2017 Q3 to 2021 Q2 for Texas. *Mean Surge* is an indicator of the average surge level in feet of the given block group. Census tract fixed effects and Year-quarter fixed effects are included. Standard errors are reported in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and ***.

Table 4 Inconsistency between FEMA 100-year floodplain map and hurricane damage

	Inundation area		No inundation area	
Panel A				
	FEMA 100-year floodplain	Outside-floodplain	FEMA 100-year floodplain	Outside-floodplain
Texas	8.89%	91.11%	9.26%	90.74%
New York	15.79%	84.21%	0.36	99.64%
Panel B				
	FEMA 100-year floodplain		Off-floodplain	
	Inundation	No inundation	Inundation	No inundation
Texas	27.04%	72.96%	27.93%	72.07%
New York	89.1%	10.9%	13.72%	86.28%

Table 5 Price effect of hurricanes on CRE market: the price of information

	Dependent Variable: Log (Price/sq. ft.)							
	Texas				New York			
	Inside-zone	Outside-zone	<500m	<1000m	Inside-zone	Outside-zone	<500m	<1000m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.064	-0.020	-0.058	-0.062	0.853***	0.608***	0.698***	0.628***
	(0.202)	(0.054)	(0.080)	(0.062)	(0.228)	(0.033)	(0.054)	(0.040)
Mean Surge	0.290**	0.033*	0.040*	0.039**	-0.127	0.010	0.018	0.013
	(0.117)	(0.018)	(0.024)	(0.020)	(0.083)	(0.010)	(0.012)	(0.010)
Post × *Mean Surge*	-0.019	-0.042***	-0.041***	-0.039***	-0.020	-0.011	-0.023**	-0.018**
	(0.029)	(0.010)	(0.013)	(0.011)	(0.044)	(0.008)	(0.010)	(0.009)
Hedonic attributes (including property type dummies)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,313	6,582	10,184	11,575	312	10,809	3,448	6,518
R^2	0.811	0.741	0.731	0.724	0.937	0.915	0.905	0.910

Notes: This table reports sub-group regressions from Eq. (1). The dependent variable is the log transaction price per square foot at the property level. The post-hurricane period runs from 2012 Q4 to 2017 Q4 for New York and 2017 Q3 to 2021 Q2 for Texas. *Mean Surge* is an indicator of the average surge level in feet of the given block group. *Floodplain* is an indicator that takes the value of 1 if the given property is located within a FEMA 100-year flood zone. Census tract fixed effects and Year-quarter fixed effects are included. Columns (1) and (5) present the sub-sample results for properties located within the flood zone, while columns (2) and (6) reports the sub-sample results for properties located outside the flood zone. Columns (3) and (7) report the sub-sample results for properties located within a 500-meter buffer from the flood zone. Columns (4) and (8) report the sub-sample results for properties located within a 1000-meter buffer from the flood zone. Standard errors are reported in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and ***.

Table 6 Price effect of hurricanes on CRE market: the impact of investor's environmental awareness

	Dependent Variable: Log (Price/sq. ft.)					
	Texas			New York		
	Green	Less green	All	Green	Less green	All
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.263*	-0.117	-0.012	0.702***	0.796***	0.735***
	(0.149)	(0.138)	(0.087)	(0.127)	(0.077)	(0.054)
Mean surge	0.025	0.038	0.031*	0.006	0.021	0.011
	(0.032)	(0.025)	(0.019)	(0.017)	(0.042)	(0.012)
Post × Mean Surge	-0.058**	-0.012	-0.022	-0.043**	0.031	0.005
	(0.026)	(0.025)	(0.017)	(0.016)	(0.032)	(0.015)
Post × Mean Surge × Green			-0.316**			-0.012*
			(0.153)			(0.005)
Hedonic attributes (including property type dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,091	2,619	5,710	2,247	2,266	4,513
R^2	0.796	0.849	0.753	0.938	0.943	0.925

Notes: This table reports estimates from Eq. (5). The dependent variable is the log transaction price per square foot at the property level. The post-hurricane period runs from 2012 Q4 to 2017 Q4 for New York and 2017 Q3 to 2021 Q2 for Texas. *Mean Surge* is an indicator of the average surge level in feet of the given block group. *Green* is an indicator that takes the value of 1 if the Google Green Index of the buyer of a given property is above the median value of all buyers in our sample. Census tract fixed effects and Year-quarter fixed effects are included. Columns (1) and (3) present the sub-sample results for buyers with a higher Google Green Index, while columns (2) and (4) reports the sub-sample results for buyers with a lower Google Green Index. Standard errors are reported in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and ***.

Table 7 Price effect of hurricanes on CRE market: investor's geographic footprint

	Dependent Variable: Log (Price/sq. ft.)					
	Texas			New York		
	Not diversified	Diversified	All	Not diversified	Diversified	All
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.094	0.047	-0.019	0.527***	0.751***	0.551***
	(0.083)	(0.076)	(0.052)	(0.047)	(0.110)	(0.041)
Mean Surge	0.032	0.057***	0.032**	-0.012	0.071**	-0.011
	(0.025)	(0.022)	(0.015)	(0.013)	(0.032)	(0.012)
Post × Mean Surge	-0.020	-0.045***	-0.030***	0.003	-0.069***	0.000
	(0.015)	(0.012)	(0.011)	(0.011)	(0.025)	(0.008)
Post × Mean Surge × Diverse			0.003			-0.010
			(0.002)			(0.014)
Hedonic attributes (including property type dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE			(0.002)	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5533	6970	12503	7488	2383	10290
R^2	0.815	0.746	0.735	0.838	0.882	0.836

Notes: This table reports estimates from Eq. (6). The dependent variable is the log transaction price per square foot at the property level. The post-hurricane period runs from 2012 Q4 to 2017 Q4 for New York and 2017 Q3 to 2021 Q2 for Texas. *Mean surge* is an indicator of the average surge level in feet of the given block group. *Diverse buyer* is an indicator that takes the value of 1 if the buyer's investment footprint is geographically more diverse than the median value of all buyers in our sample. Census tract fixed effects and Year-quarter fixed effects are included. Columns (1) and (4) present the sub-sample results for buyers with a more diverse footprint, while columns (2) and (5) reports the sub-sample results for buyers with a less diverse footprint. Standard errors are reported in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and ***.

Appendix

Table A1 Summary statistics: All properties

	Texas (1)	New York (2)
Transaction Price ($/sq. ft)	168.66	624.62
Surge dummy (0/1)	0.28	0.16
Surge Level (feet)	1.12	0.47
RCA Quality Score	0.47	0.81
High surge (>3 feet)	0.14	0.07
Low surge (<=3 feet)	0.14	0.09
100-year Floodplain (%)	2.81	9.16
Capitalization Rate	0.06	0.05
Occupancy Rate	94.50	92.21
Building size (Thousands sq. ft)	143.88	66.61
Portfolio Sale (%)	0.20	0.24
CBD (%)	0.03	0.91
Tenancy Type (%)		
Multi-Tenant	74.52	77.39
Single Tenant	20.06	9.81
Vacant	5.42	12.80
Construction Vintage (%)		
1960-1969	10.20	85.04
1970-1979	15.25	2.85
1980-1989	23.82	3.58
1990-1999	12.94	2.04
2000-2009	23.89	4.60
2010 or after	13.91	1.89
Number of Stories (%)		
Less than 5 stories	93.50	42.43
5-10 stories	4.06	47.91
More than 10 stories	2.44	9.66
Buyer Incentive (%)		
Condo Conversion	0.00	0.43
Investment	90.58	82.90
Occupancy	3.19	3.88
Redevelopment	1.21	7.31
Renovation	5.00	5.48
Buyer Type (%)		
Institutional	15.21	10.04
Private	74.95	82.16
Public	5.37	2.68
User/Other	4.47	5.12
Seller Type (%)		
Institutional	17.78	11.36
Private	69.96	80.01
Public	5.60	1.93
User/Other	6.66	6.70
Observations	14,339	11,121

Notes: Standard deviations in parentheses.

Table A2 Summary statistics: Properties within/outside inundated block groups

	Texas		New York	
	Inundated	Other	Inundated	Other
Transaction Price ($/sq. ft)	159.99	172.00	659.22	622.91
100-year Floodplain (%)	8.90	9.26	32.31	1.35
Capitalization Rate	0.06	0.06	0.05	0.05
Occupancy Rate	89.66	90.21	65.39	67.68
Building size (Thousands sq. ft)	145.32	143.33	154.92	62.25
Portfolio Sale (%)	18.51	20.66	11.85	24.70
CBD (%)	4.18	2.16	87.00	91.39
Tenancy Type (%)				
Multi-Tenant	75.58	74.11	60.42	78.23
Single Tenant	19.11	20.43	16.06	9.50
Vacant	5.31	5.46	23.52	12.27
Construction Vintage (%)				
1960-1969	9.17	10.59	75.72	85.50
1970-1979	19.58	13.57	6.31	2.68
1980-1989	21.54	24.71	6.31	3.44
1990-1999	11.42	13.53	2.29	2.03
2000-2009	25.34	23.32	6.31	4.52
2010 or after	12.95	14.28	3.06	1.83
Number of Stories (%)				
Less than 5 stories	92.41	93.92	49.52	42.08
5-10 stories	4.98	3.70	30.21	48.78
More than 10 stories	2.60	2.38	20.27	9.13
Buyer Incentive (%)				
Condo Conversion	0.03	0.02	0.38	0.43
Investment	90.08	90.77	70.17	83.53
Occupancy	3.03	3.26	7.07	3.73
Redevelopment	1.40	1.13	14.53	6.95
Renovation	5.46	4.82	7.84	5.36
Buyer Type (%)				
Institutional	11.97	16.46	15.49	9.78
Private	79.04	73.37	71.13	82.70
Public	4.76	5.61	4.21	2.60
User/Other	4.23	4.56	9.18	4.92
Seller Type (%)				
Institutional	17.23	17.99	13.19	11.27
Private	70.20	69.87	76.10	80.20
Public	6.11	5.40	2.68	1.90
User/Other	6.46	6.74	8.03	6.63
Observations	3,993	10,346	523	10,598

Notes: Standard deviations in parentheses.

Table A3 Google Green Index construction - key words

1	climate change
2	extreme weather
3	global warming
4	green building
5	renewable energy
6	sea level
7	carbon emission
8	environment
9	ESG
10	sustainable