

# Learning the Hard Way?

## Hurricanes and Commercial Real Estate Values

PIET EICHHOLTZ

EVA STEINER

ERKAN YÖNDER

Maastricht University

Cornell University

Özyeğin University

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### **Abstract**

*We propose to study how investors learn to price the exposure of real assets to unfamiliar physical risks associated with climate change. We will focus on the pricing of hurricane risk in the \$8 trillion US commercial real estate market. Hurricanes, a primary physical risk factor related to climate change, have changed their geographical pattern over time, creating cross-sectional and time series variation in the level of prior experience with these disasters across different real estate markets. Real estate assets are fixed in location, allowing us to develop an asset-specific ex ante measure of hurricane risk. We will exploit exogenous variation in market-level experience and asset-level risk to analyze the extent to which investors learn to price unfamiliar risks from their own local experience, from experience with their own investments in other locations, or from observing hurricanes in unrelated locations. We will also explore whether investors forget lessons learned. Our results will be relevant for investors as well as for urban development and public policy.*

## 1 Introduction

Regulators and markets worry about the effect of climate change on asset values (Carney, 2016). Concerns include pricing the exposure of real assets to climate change-related physical risks, such as natural disasters. The pricing of climate change-related risks has potentially profound implications for insurers, financial stability and the economy (Carney, 2015). However, markets may underreact to these risks because they lack experience in assessing them (Hong, Li, and Xu, 2016). As a result, it is important to understand how markets learn to price unfamiliar risks. Our objective is to explore how markets learn from experience versus observation of natural disasters to price the associated risk to real assets.

Specifically, we will analyze the relationship between commercial property values and hurricane risk as a function of varying degrees of prior experience with hurricanes among market participants. We focus on hurricanes for the following reasons. First, extreme weather events such as hurricanes are among the primary concerns associated with climate change.<sup>1</sup> The frequency, duration and intensity of hurricanes have increased over recent decades, as have global temperatures (Mann and Emanuel, 2006). Average hurricane intensity and destructiveness are projected to increase further as the climate continues to warm (Emanuel, 2005). At the same time, the intensity of any given impending storm is forecast to become less predictable, making it harder to prepare and thus contributing to the potential damage caused (Emanuel, 2017). Overall, the evidence suggests that hurricanes are a pertinent physical risk factor associated with climate change.

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<sup>1</sup>Third National Climate Assessment Report 2014, <http://nca2014.globalchange.gov>

Second, the geographical pattern of hurricanes has changed. Hurricane risk used to be confined to tropical and subtropical regions. In the US, that includes locations such as Florida. Market participants there have ample experience with hurricanes. However, over recent decades the path of hurricanes has shifted north (Kossin, Emanuel, and Vecchi, 2014). Hurricane risk has thus expanded to a set of new locations, all along the US east coast, that were previously considered somewhat immune (Reed et al., 2015). Some of these new locations have already been hit. For instance, record-breaking Hurricane Sandy hit New York City in 2012. Market participants there now have first-hand experience with this previously unfamiliar event. Other locations along the east coast are now arguably also at risk but have thus far been spared major damage, such as Boston. Market participants there have no first-hand experience of the disaster but second-hand information about the experience of similar locations nearby. In our research design, we will exploit the exogenous variation across markets in their level of experience with hurricane risk.

We focus on the effect of hurricane risk on the value of real property because the economic damage to these assets caused by hurricanes is significant. The fallout from hurricanes in terms of injury and loss of life is tragic but the economic magnitude of damage to real property by far exceeds total death risk, especially in wealthy nations such as the US (Bunten and Kahn, 2014; Kahn, 2005).<sup>2</sup> The severe damage inflicted by hurricanes on real property creates a strong economic incentive to price exposure to hurricane risk correctly.

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<sup>2</sup>For example, Hurricane Sandy reportedly caused almost US\$ 69 billion of damage and a total of 159 deaths, see NOAA 2017, <https://www.ncdc.noaa.gov/billions/events/US/1980-2017>. In the same year, 419 people were classified as murder victims in New York City alone, see NYPD 2012, [http://www.nyc.gov/html/nypd/downloads/pdf/analysis\\_and\\_planning/murder\\_in\\_nyc\\_2012.pdf](http://www.nyc.gov/html/nypd/downloads/pdf/analysis_and_planning/murder_in_nyc_2012.pdf).

Much of the real property damaged by hurricanes, such as buildings and infrastructure, is fixed in location. Therefore, the exposure to hurricane risk is difficult to mitigate (Bunten and Kahn, 2014). Further, location-specific geographic and atmospheric characteristics allow us to develop an exogenous measure of *ex ante* hurricane risk. Boustan, Kahn, Rhode, and Yanguas (2017) explore the link between house prices and exposure to disasters *ex post*. We will develop an *ex ante* measure of hurricane risk as we are interested in the pricing by market participants in locations with varying levels of prior exposure to hurricanes, including locations that are theoretically at risk but have not yet actually been hit. For these locations, *ex post* disaster exposure data do not exist.

Within physical property, we focus on commercial real estate. Commercial real estate accounts for a substantial fraction of US wealth (Plazzi, Torous, and Valkanov, 2010). Savill's estimates its value in 2015 to be about \$8 trillion, or almost 30% of the US stock market. Moreover, there is a large market for commercial real estate investments in the US, allowing us to observe prices over time. For instance, Real Capital Analytics estimates the total investment volume for US commercial real estate in 2015 to be almost \$600 billion. Prior research has explored the effect of natural disasters on house prices (Boustan, Kahn, Rhode, and Yanguas, 2017). However, there is no research on the effect on commercial real estate.

Empirically, we will relate commercial property values before and after hurricane strikes in different locations to our *ex ante* measure of exposure to hurricane risk. In doing so, we plan to shed light on the way in which markets learn to price climate change-related physical risks to real assets: Do investors learn 'the hard way', that is, from (local) experience of disasters, or are they able to learn from observing the experience of similar locations?

Recent studies such as Daniel, Litterman, and Wagner (2016) and Giglio, Maggiori, Stroebel, and Weber (2015) show how efficient market pricing of climate change-related risks could inform policy. However, there is little evidence on whether markets price climate change-related risks, with notable exceptions. Bansal, Kiku, and Ochoa (2016) show that risks associated with rising temperatures are priced in the stock market. On the other hand, Hong, Li, and Xu (2016) show that the stock market underreacts to drought risk, due to a lack of experience with this risk. We will ask whether commercial real estate markets price hurricane risk, and how market participants overcome their potential lack of experience with this risk.

The literature on learning in financial markets, reviewed in Pastor and Veronesi (2009), covers issues related to, for instance, the volatility and predictability of asset returns, stock price bubbles, or portfolio choice. We will analyze the effect of learning from experience versus observation in pricing unfamiliar risks to real assets. Moreover, individuals and organizations often forget lessons learned from prior experiences (Agarwal, Driscoll, Gabaix, and Laibson, 2008; Castel et al., 2016; Haunschild, Jr., and Chandler, 2015). We plan to explore whether this holds for the pricing of climate-change related disaster risk to real assets as well.

Lastly, empirical evidence suggests that physical firm or asset location influences investment choice and performance (Becker, Cronqvist, and Fahlenbrach, 2011; Bernile, Kumar, and Sulaeman, 2015; Pirinsky and Wang, 2006). These effects are likely driven by information asymmetries that are more easily resolved through geographic proximity (Coval and Moskowitz, 2001; Fu and Gupta-Mukherjee, 2014; Hong, Kubik, and Stein, 2005). Our methodology will allow us to explore the effect of geographic proximity of investors and their assets to natural disasters on the way in which they learn to price the associated risks to real assets.

## 2 Methodologies and research design

Our research design is empirical and involves the following steps. First, although not the focus of our study, we will illustrate the relationship between rising temperatures and the incidence as well as severity of hurricanes. Next, we will create an asset-specific measure of *ex ante* hurricane risk. Lastly, we will incorporate our measure of hurricane risk into a hedonic model of commercial property prices. We will use this hedonic model to illustrate the ways in which investors learn to price hurricane risk.

### 2.1 *Rising temperatures and hurricanes*

We will show qualitatively that there is a positive relationship between rising sea surface temperatures, a primary indicator of climate change<sup>3</sup> identified by the EPA, and hurricane patterns in the US. The following figures present preliminary findings for the period 1965-2015.

[Figures 1 and 2 about here]

Panel (a) of Figure 1 plots the number of years since the most recent hurricane in the US, along with a linear trend line fitted to the data, against annual global sea surface temperatures. The data suggest a rising trend in sea surface temperatures. According to the EPA, sea surface temperatures have been consistently higher during the past three decades than at any other time since reliable observations began in the late 1800s. Along with rising temperatures, the incidence of hurricanes has increased, as illustrated by the declining trend in the number of years since the most recent hurricane in the US.

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<sup>3</sup>See: <https://www.epa.gov/climate-indicators>

Panel (b) of Figure 1 plots the average duration (in days) of hurricanes in the US, along with a linear trend line, against sea surface temperatures. The data suggest that increasing temperatures coincide with a positive trend in the average duration of hurricanes in the US.

Panel (a) of Figure 2 presents the time series evolution of total hurricane damage to property in the US, along with a linear trend line fitted to the data, against annual global sea surface temperatures. The positive trend in the severity of hurricanes is primarily driven by the period from 1992 onward. The most severe (category 5) hurricane strikes with the largest amount of property damage are Hurricane Andrew in 1992, Hurricane Ivan in 2004, and four hurricanes of category 5 in the 2005 season (Emily, Katrina, Rita and Wilma). The 2012 Atlantic hurricane season did not see any category 5 storms but two highly destructive category 3 storms, Michael and especially Sandy. Overall, the data suggest a positive correlation between sea surface temperatures and the severity of hurricanes.

Panel (b) of Figure 2 presents the states on the east coast of the US sorted from south to north and the total number of hurricanes experienced in these states by decade. The Figure shows that prior to 1986, no coastal state north of Florida experienced more than one or two hurricanes per 10-year period. Over the period 1986-1995, coastal states as far north as New York began experiencing a higher number of hurricanes, such as North Carolina (three hurricanes over 1986-1995), Maryland (four) or New York (three). Over the subsequent 10-year period 1996-2005, coastal states even north of New York, such as Massachusetts and New Hampshire, began experiencing higher numbers of hurricanes. Our data are consistent with climate-scientific studies suggesting a northward migration of hurricanes along the US east coast, putting new locations at risk.

## 2.2 Measuring hurricane risk

The National Hurricane Center concludes that storm surge poses the greatest hurricane-related threat to property along the coast. Further inland, flooding is the major threat to property as hurricanes often produce widespread heavy rain.<sup>4</sup> Damage to the physical structure of buildings from flooding as well as disruption to business operations can be insured. However, storm surge significantly alters the coastal environment far beyond immediate physical damage to buildings, as illustrated in Figure 3. Therefore, our *ex ante* measure of hurricane risk will be based on exposure to storm surge risk.

[Figures 3 and 4 about here]

Climate-scientific research suggests that the following geographic and atmospheric location-specific characteristics increase storm surge risk: elevation, distance to the tropical line, distance to the sea, sea surface temperature, average sea level, and wind speed on the nearest coastline.<sup>5</sup> Based on the final set of location characteristics to be identified, we will create an asset-specific *ex ante* hurricane risk score for the exact location of each property, observed as longitude and latitude. Our measure does not require data on actual damage incurred during past hurricane strikes. Given variations in atmospheric factors such as sea surface temperatures, we will allow our measure of hurricane risk to vary through time.

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<sup>4</sup>Storm surge is an abnormal rise of sea water generated by a storm's winds, which can reach heights well over 20 feet, span hundreds of miles of coastline, and travel several miles inland. Storm tide is the rise in sea water levels during a storm due to the combination of storm surge and the astronomical tide. Hurricanes may produce rains in excess of 6 inches, which may result in flash flooding, defined as a rapid rise in fresh water levels. Longer term flooding on rivers and streams can persist for several days after the storm. See <http://www.nhc.noaa.gov/prepare/hazards.php>.

<sup>5</sup>See: [https://www.nasa.gov/vision/earth/environment/HURRICANE\\_RECIPE.html](https://www.nasa.gov/vision/earth/environment/HURRICANE_RECIPE.html).

Geographic factors, such as proximity to the sea, may influence property prices for reasons other than hurricane risk. They may reflect a priced environmental amenity, such as an oceanfront location (Albouy, Graf, Kellogg, and Wolff, 2016; Chay and Greenstone, 2005). In developing our hurricane risk measure, we will systematically test for such relationships and, if required, focus on atmospheric factors, such as sea surface temperature and sea level. Atmospheric factors influence hurricane risk, but we do not expect them to affect property prices for other reasons. This allows us to achieve clean identification of hurricane risk.

### *2.3 Property prices and hurricane risk*

First, we will test whether experiencing a hurricane has a significant effect on property values overall. In this step, we will establish a baseline of estimates for whether property values respond to natural disasters *ex post*. Boustan, Kahn, Rhode, and Yanguas (2017) find evidence that county-level house price indexes are inversely related to an indicator measuring whether the county has experienced a super-severe disaster. With our results, we plan to extend the evidence to the commercial property market.

Next, we will explore how markets price exposure to hurricane risk *ex ante*. Here we will exploit the fact that the path of hurricanes has gradually shifted northwards, now putting a range of locations all along the US east coast at risk. However, not all locations on the east coast have been equally exposed to actual hurricane strikes yet. As a result, property investors in different locations have varying degrees of experience with hurricanes. If pricing of climate-change related risks is affected by the degree of market familiarity with these risks, as Hong, Li, and Xu (2016) suggest, then we expect that the sensitivity of property values to hurricane risk is a function of experience of the market with hurricane strikes.

At one end of the spectrum, there are locations in the south-east of the US, such as Florida, where hurricane strikes have always been relatively common. As a result, commercial real estate investors in those markets are experienced with this kind of disaster. We thus expect that investors in those markets are more alert to asset-specific hurricane risk and more readily incorporate it into their real estate valuations.

In addition, our data suggest that hurricanes become more frequent and severe over time. Therefore, we expect that investors who are experienced with hurricanes become more sensitive to this risk, generating an increase in the elasticity of property prices to hurricane risk. In this respect, our work will complement the evidence in Bansal, Kiku, and Ochoa (2016) that the elasticity of equity prices to rising temperatures increases over time.

Then, there are locations further north along the US east coast that were previously thought to be somewhat immune to hurricane damage because hurricanes rarely used to strike north of tropical or subtropical regions. Now even locations as far north as New York City have been exposed to destructive storms, such as Hurricane Sandy. As a result, investors in those locations used to be unfamiliar with hurricane strikes but now have first-hand experience. If investors learn how to price climate-change related risks from experience, then they may have learned to be alert to hurricane exposure risk and start to incorporate it into their valuations after experiencing the disaster first-hand. In this respect, our evidence will contribute to the literature on learning in financial markets, as reviewed in Pastor and Veronesi (2009).

Even further along the spectrum of locations, there are those which are now theoretically exposed to hurricane risk, due to changes in the path of these storms, but which have thus far

been spared. For instance, Boston has not yet experienced a severe storm such as Hurricane Sandy, but Sandy is viewed as an example of the type of event in store for that region of the US (Baldini et al., 2016). In other words, investors in Boston have no first-hand experience of severe hurricane strikes yet but they were able to observe Sandy in New York City and now have second-hand information about the impact of such a disaster on another location that was thought to be similarly immune in the past.

With the distinction between locations such as New York City and Boston, we ask whether investors only learn ‘the hard way’, meaning from first-hand experience in their own markets, or whether they also learn from observing hurricane damage in other, similar locations. To the extent that investors are forward-looking rather than adaptive, investors in locations such as Boston may learn to be alert to location-specific hurricane exposure risk and start to incorporate it into their valuations after observing a hurricane hitting a similar, possibly nearby, location such as New York City. With this part of our study, we plan to analyze the way in which investors learn in more detail. Furthermore, our analysis will allow us to explore the role of geographic proximity to disasters in shaping investor learning.

Lastly, we will explore the possibility that investors forget what they have learned. Specifically, we ask for how long markets reflect the occurrence of disasters in the pricing of hurricane risk. Research suggests that individuals over time develop a recency and positivity bias in their memories, creating stronger recall for recent positive events relative to negative experiences that lie further in the past (Castel et al., 2016). Similarly, households have been shown to learn how to make better financial decisions from experience, but that knowledge depreciates over time (Agarwal, Driscoll, Gabaix, and Laibson, 2008). Organizations are

prone to forgetting lessons learned from negative experiences as well (Haunschild, Jr., and Chandler, 2015). In this part of our project, we will establish a time line over which the effects of natural disasters are reflected in market prices for the properties at risk, again distinguishing between different levels of prior experience with hurricanes among investors in their respective locations. If investors forget what they have learned about pricing hurricane exposure risk, then we may expect that any measurable price effect decays over time.

### **3 Data, proposed tests and key predictions**

#### *3.1 Data sets*

Our analysis relies on three main data sets: property transaction data, hurricane risk data, and data on actual hurricane damage. In the following, we outline the main data sets we have secured thus far, including their sources and applications in our project.

First, we require property transaction data. We obtain sales transaction data from Real Capital Analytics (RCA). RCA has tracked commercial property sales in the US of \$2.5 million or greater since the year 2000. RCA relies on data sources including press releases, news reports, SEC filings, public records, and listing services. As of 2015, the RCA database includes a total of more than \$3 trillion US-based commercial real estate deals. Each record in the database contains both property- and transaction-specific information. RCA covers transactions on numerous types of commercial property, including office, retail, and industrial properties. Table 1 presents preliminary descriptive statistics for commercial property transactions in selected US states, over the period from 2000 to 2013.

[Table 1 about here.]

Next, we require asset location-specific data on hurricane risk. We will use the property addresses supplied in the transaction data to geocode the locations of the properties, producing an exact longitude/latitude position for each of them. For each property location, we will measure the geographic and atmospheric variables required for our hurricane risk measure using topological modeling and GIS software.

For the preliminary analysis shown in this proposal, we calculate distance to the tropical line, distance to the coastline or inland water, as well as elevation, for the counties in US east coast states. We obtain shape files for US counties, inland water, and coastline from the US Census Bureau and US Geological Survey. The US Board on Geographic Names provides primary feature attributes including elevation.<sup>6</sup> In order to calculate elevation, we take the average of the elevation data for primary features reported for each county.

The final data set we require is data on actual hurricane damage to properties to test the relevance of our *ex ante* risk measure. Here, we use data provided by the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS is a county-level hazard data set for the US and covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornadoes as well as perils such as flash floods, heavy rainfall, etc. The database contains information on the date of an event, affected location (county and state) and the direct losses caused by the event including damage to physical property in US\$. The database covers the period from January 1960 to December 2015. Data and maps are compiled and geo-referenced at the University of South Carolina.

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<sup>6</sup>See: [https://geonames.usgs.gov/domestic/download\\_data.htm](https://geonames.usgs.gov/domestic/download_data.htm). On this basis, we have currently obtained elevation data for 85% of our sample. We plan to use Bing Maps Elevation API Service to calculate elevation data for missing locations.

### 3.2 Proposed tests and key predictions

#### Testing the *ex ante* measure of hurricane risk

We will run an OLS regression of hurricane damage on the *ex ante* measure of hurricane risk. If our *ex ante* asset-specific risk measure is a meaningful predictor for actual hurricane damage, then it represents relevant information that investors are able to incorporate into their valuations. The hurricane risk measure will be constructed on the property level, but the smallest geographical unit for which SHELDUS supplies damage data is the county level. We will aggregate the risk measure to the county level by calculating the average exposure of the sample properties in a county, or, alternatively, by measuring the exposure of properties nearest the physical center of a county. We plan to estimate the following regression:

$$\ln Damage_{i,t} = \beta_0 + \beta_1 Risk_i + \beta_2 CTRL_{i,t} + u_{i,t} \quad (1)$$

where  $\ln Damage$  is the natural logarithm of county (i) and disaster (t) level damage data (in 2015 US\$) and  $Exposure$  is the county (i) level *ex ante* measure of hurricane risk.  $CTRL$  contains a set of county and time specific control variables, including storm severity, county-level population density, and other relevant variables to be determined. We will also control for relevant fixed effects and cluster standard errors by county.

*Prediction 1:* We expect that the *ex ante* measure of hurricane risk is a significant predictor of actual damage, therefore we expect a positive and significant coefficient  $\beta_1$  in Equation (1).

[Table 2 about here.]

Table 2 presents regression results for county-level hurricane damage, as a function of some of the geographic variables that will potentially feature in our hurricane risk measure. We find that if a county is 100 km further away from the coastline, hurricane damage is reduced by around 45%. If elevation of a county increases by around 100 meters, damage decreases by 19%. Proximity to the tropical line and inland water also increase hurricane damage. We also document nonlinearity in the effect of distance to coastline and elevation. Additionally, the interaction term between the two variables is also highly significant. Our preliminary findings confirm the suitability of these geographic variables as proxies for hurricane risk.

#### Testing the elasticity of property prices to hurricane risk

We will begin by estimating whether property values respond to hurricanes *ex post*. We will regress location-level, e.g. MSA, commercial real estate prices on location-level exposure to hurricanes in the past, in the spirit of Boustan, Kahn, Rhode, and Yanguas (2017):

$$\ln MV_{i,t} = \beta_0 + \beta_1 Hurr_{i,t} + \beta_2 Hurr5_{i,t} + \beta_3 HCt_{i,t} + \beta_4 HCt1_{i,t} + \beta_5 CTRL_{i,t} + u_{i,t} \quad (2)$$

where  $\ln MV$  is the natural logarithm of median location (i) commercial property values per square foot at the end of the decade (t),  $Hurr$  is an indicator for whether the location has experienced any hurricane during the decade,  $Hurr5$  is an indicator for whether it has experienced a category 5 hurricane,  $HCt$  is the number of hurricanes experienced, and  $HCt1$  is an indicator for whether the location has experienced more than one hurricane. We also will consider including actual damage experienced. The control variables  $CTRL$  will include relevant economic fundamentals. We will cluster standard errors by county.

*Prediction 2:* Based on Boustan, Kahn, Rhode, and Yanguas (2017), we expect that the actual exposure to hurricanes is at least to some extent reflected in property values, implying a negative and significant value on one or more of the coefficients  $\beta_1$  to  $\beta_4$  in Equation (2).

In order to test whether commercial real estate markets overall price *ex ante* property-level hurricane risk, we will estimate the following hedonic model:

$$\ln P_{i,t} = \beta_0 + \beta_1 Risk_i + \beta_2 CTRL_{i,t} + u_{i,t} \quad (3)$$

where  $\ln P$  is the natural logarithm of property (i) level transaction prices per square foot at time (t) as properties may sell multiple times, *Risk* is the property (i) level *ex ante* measure of hurricane risk, and *CTRL* contains property- and transaction-specific characteristics.

*Prediction 3:* Based on efficient market pricing, we expect a negative and significant value on the coefficient  $\beta_1$  in Equation (3).

Next, we will outline the remainder of our proposed tests and associated key predictions, which are all variants of the model described in Equation (3). In order to test whether the pricing of hurricane exposure risk is a function of market-level experience with hurricanes, in the spirit of Hong, Li, and Xu (2016), we will adjust Equation (3) by including an interaction term between the risk measure and a measure of market-level exposure to hurricanes, proxied by the disaster variables discussed in the context of Equation (2).

*Prediction 4:* Based on Hong, Li, and Xu (2016), we expect the coefficient on the interaction term between hurricane risk and market experience to be negative and significant.

In order to test whether markets experienced with hurricanes become increasingly sensitive to this risk over time, consistent with Bansal, Kiku, and Ochoa (2016) who document increasing sensitivity of equity prices to the long-run risks of rising temperatures, we will adjust the model in Equation (3) by including an interaction term between the hurricane risk measure and a measure of time passing. Here, we focus on locations with ample hurricane experience.

*Prediction 5:* Based on Bansal, Kiku, and Ochoa (2016), we expect the coefficient on the interaction term between hurricane risk and time passing to be negative and significant.

Next, we will test whether investors learn to price hurricane risk ‘the hard way’, that is, from first-hand experience of the disaster, in locations previously unfamiliar with this risk. The leading example for this type of location is New York City with its unusual experience of Hurricane Sandy. Here, we will employ a diff-in-diff model. The treatment group is the group of properties in New York City that are highly exposed to hurricane risk, the control group contains similar local properties that are less exposed. The treatment is Hurricane Sandy.

*Prediction 6:* Consistent with learning from experience, we expect to observe no difference in prices for the two groups of properties in New York City prior to Sandy, reflecting that hurricane risk was considered negligible, and lower prices for high-risk properties compared to low-risk properties following the storm.

We then plan to test whether investors also learn from observation. We will set up another diff-in-diff model for locations that were previously unaffected by hurricanes, are now exposed to this risk, but have not yet actually experienced a severe storm. Here, the leading example is Boston. The treatment group is the group of properties in Boston that are highly exposed to

hurricane risk, the control group are similar properties that are less exposed. The treatment is Hurricane Sandy, which hit New York in 2012 but did not affect properties in Boston.

*Prediction 7:* Consistent with learning from observation, we expect to observe no difference in prices for the two groups of properties in Boston prior to Sandy, and lower prices for high-risk properties relative to low-risk properties following the storm.

We plan to investigate the extent to which investors forget lessons learned about pricing by tracing the evolution of the price effect of *ex ante* hurricane risk over time. If investors learn and then forget, the gap between the price effect of hurricane risk on differentially exposed properties widens shortly after the storm but then narrows with the passage of time. We will modify the diff-in-diff set-up to measure the price impact of hurricane risk at different points in time following the disaster. Here, we will focus on locations with newly acquired experience with hurricanes or knowledge of hurricanes striking in similar locations.

*Prediction 8:* Consistent with forgetting lessons learned, we expect the price differential between high- and low-risk properties in locations with newly acquired experience of the disaster (either first-hand or by observation) to narrow as time passes following the disaster.

Table 3 summarizes how our planned tests and key predictions will map to the sets of results we plan to tabulate as the project progresses. In addition to ensuring exogeneity of our hurricane risk measure with respect to property prices in the first place, the diff-in-diff models of property prices in different locations before and after exogenous hurricane strikes, as described above, should help us achieve clean identification of the hypothesized relationships.

[Table 3 about here.]

## Additional implications

We plan to refine our main analysis described above in a number of different directions, to be explored in more detail as the project progresses. First, we plan to add to the analysis on learning from observation by accounting for spatial factors such as the geographical distance between the location where we measure pricing and the location of the disaster that local market participants were able to observe.

Second, we intend to explore further implications relating to the role of investor-level rather than market-level prior experience with disasters in pricing *ex ante* exposure risk to hurricanes, using the information on investor identity provided by RCA, which allows us to trace investor holdings through time and across locations.

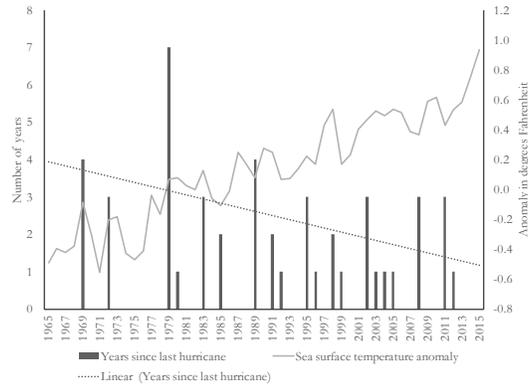
We further plan to supplement the hedonic property price regressions with additional estimations of related metrics, such as the likelihood that a building will sell as a function of *ex ante* hurricane risk, the rent a building will fetch, the occupancy rate of the building, the transaction yield, or the return on the investment, which we can measure for the properties sold multiple times during our sample period. The extent to which we can implement these additional tests depends on data availability.

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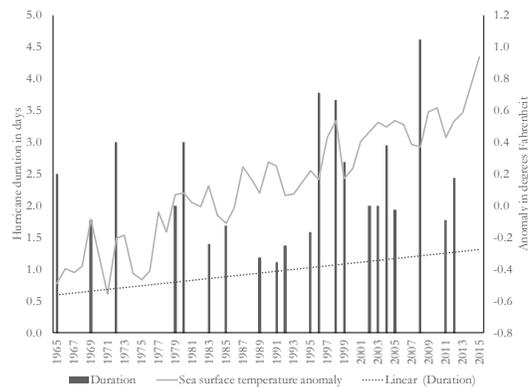
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## 4 Figures and Tables

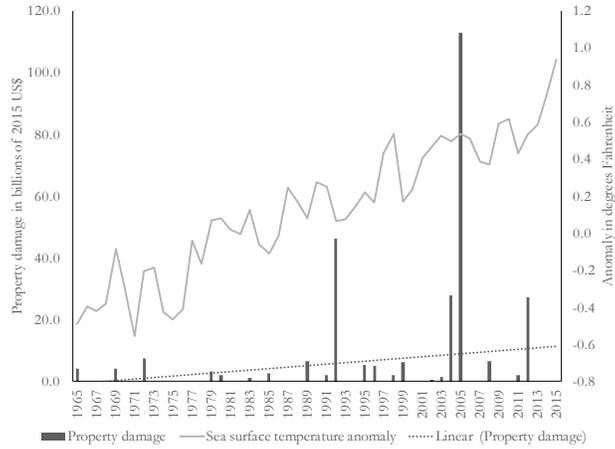


(a) *Sea surface temperatures and frequency of hurricanes*



(b) *Sea surface temperatures and duration of hurricanes*

**Figure 1:** *Sea surface temperatures and hurricanes in the US, 1965-2015. Panel (a) shows the time series evolution of the number of years since the most recent hurricane in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. Panel (b) shows the average duration (in days) of hurricanes in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. This graph uses the 1971-2000 global temperature average as a baseline for depicting temperature anomalies. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.*



(a) Sea surface temperatures and severity of hurricanes

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

(b) Northward migration of hurricanes

**Figure 2:** Hurricane patterns in the US, 1965-2015. Panel (a) shows the time series evolution of total hurricane damage to property in the US, along with a linear trend line fitted to the data, against annual global sea surface temperature anomalies in degrees Fahrenheit. This graph uses the 1971-2000 global temperature average as a baseline for depicting temperature anomalies. Panel (b) shows the states on the east coast of the US sorted from south to north and the total number of hurricanes experienced in these states by decade. To illustrate geographical and time series patterns in hurricane exposure, the shading of the cells becomes darker as the number of hurricanes increases. Hurricane data are obtained from SHELDUS. Sea surface temperature data are obtained from NOAA.



**Figure 3:** *Ocean front before and after Hurricane Ike on the Bolivar Peninsula, Texas, September 2008. Photo published by the United States Geological Survey, obtained from NOAA.*



(a) Beach front road and boardwalk damaged by Hurricane Jeanne (2004)



(b) Damaged boats in a marina

**Figure 4:** Storm surge damage. Panel (a) shows how currents created by tides combine with the waves to severely erode beaches and coastal highways. Buildings that survive hurricane winds can be damaged if their foundations are undermined and weakened by erosion. Photo published by FEMA, obtained from NOAA. Panel (b) shows how, in confined harbors, the combination of storm tides, waves, and currents can also severely damage marinas and boats. In estuaries and bayous, salt water intrusion endangers public health, kills vegetation, and can send animals, such as snakes and alligators, fleeing from flooded areas. Photo published by the United States Coast Guard Digital, obtained from NOAA.

VARIABLES	Obs.	Mean	Std. Dev.
Price per sqft (\$)	11,243	186.371	382.877
Property Size (sqft)	11,243	212,442	279,568
Property Age	11,243	23.557	20.668
CBD Dummy	11,243	0.117	0.321
Renovated Indicator	11,243	0.188	0.391
Portfolio Sale Indicator	11,243	0.372	0.483
Office Indicator	11,243	0.265	0.441
Retail Indicator	11,243	0.349	0.477
Industrial Indicator	11,243	0.230	0.421
Apartment Indicator	11,243	0.157	0.363

**Table 1:** *Descriptive statistics (2000-2013). The Table presents the descriptive statistics for a sample of RCA transactions for selected states. Our data set includes New York, Florida, Massachusetts, Maine, New Hampshire, Vermont, Rhode Island, Connecticut, New Jersey, Pennsylvania, Maryland, Delaware, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Texas, Louisiana, Mississippi, and Alabama. The CBD indicator denotes properties located in central business district areas. The portfolio sale indicator denotes whether a property is sold within a portfolio.*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Property Damage (in logs)						
Distance to Coastline (100 km)	-0.440*** [0.039]	-0.772*** [0.065]	-0.357*** [0.037]	-0.604*** [0.062]	-0.458*** [0.054]	-0.575*** [0.056]	-0.615*** [0.072]
Squared Distance to Coastline (100 km)		0.060*** [0.008]		0.044*** [0.008]			0.039*** [0.009]
Elevation (km)					-0.037 [0.270]	-1.936*** [0.390]	-1.837*** [0.523]
Squared Elevation (km)							1.582*** [0.406]
Distance to Coastline $\times$ Elevation						0.507*** [0.064]	
Distance to Tropical Line (100 km)	-0.177*** [0.036]	-0.182*** [0.036]	-0.130*** [0.035]	-0.135*** [0.035]	-0.056 [0.044]	-0.033 [0.045]	-0.054 [0.044]
Distance to Inland Water (100 km)	-1.259*** [0.555]	-1.294** [0.546]	-0.931* [0.477]	-0.975** [0.468]	-0.748 [0.546]	-0.631 [0.496]	-0.629 [0.499]
Duration of Hurricane (in logs, days)			2.069*** [0.087]	2.052*** [0.087]	2.089*** [0.096]	2.068*** [0.095]	2.071*** [0.095]
Population (in logs)			0.152*** [0.030]	0.144*** [0.029]	0.178*** [0.033]	0.169*** [0.032]	0.168*** [0.032]
Constant	9.840*** [0.514]	10.079*** [0.514]	6.945*** [0.620]	7.245*** [0.624]	6.822*** [0.677]	6.966*** [0.673]	7.158*** [0.680]
Year Fixed Effects	Yes						
Month Fixed Effects	Yes						
State Fixed Effects	Yes						
Observations	5,791	5,791	5,788	5,788	4,888	4,888	4,888
Adjusted R-squared	0.380	0.383	0.445	0.447	0.369	0.373	0.372

**Table 2:** Preliminary regression results for hurricane damage (1965-2012): The Table presents the regression results of county-level property damage, conditional on a county being hit by a hurricane, as a function of some of the geographic variables that we will examine as potential components of our ex ante measure of hurricane risk. The sample includes 1,862 counties in US east coast states that were hit by a hurricane during the period 1965 to 2012. Heteroskedasticity robust standard errors are in brackets and clustered by county. \* indicates significance at the 10% level. \*\* indicates significance at the 5% level. \*\*\* indicates significance at the 1% level.

Planned results table	Test	Prediction	Implication
(1) Hurricane damage and <i>ex ante</i> hurricane risk	OLS of location-level damage on county-level risk measure	Positive and significant coefficient on risk measure	Risk measure is a relevant predictor of hurricane exposure
(2) Property prices and exposure to hurricanes	OLS of location-level prices on measures of location-level exposure to hurricanes	Negative and significant coefficient on one or more exposure variables	Average property prices respond to hurricane strikes <i>ex post</i>
(3) Property prices and <i>ex ante</i> hurricane risk	OLS of property-level prices on property-level <i>ex ante</i> risk measure	Negative and significant coefficient on risk measure	Property markets price <i>ex ante</i> risk of hurricanes
(4) Elasticity of prices to hurricane risk as a function of experience	OLS of property-level prices on property-level <i>ex ante</i> risk measure, interacted with location-level experience with hurricanes	Negative and significant coefficient on interaction between risk measure and measures of experience	Pricing of hurricane risk is a function of market-level experience with hurricane risk
(5) Elasticity of prices to hurricane risk over time, experienced markets	OLS of property-level prices on property-level <i>ex ante</i> risk measure, interacted with time variable	Negative and significant coefficient on interaction between risk measure and measure of time	Price elasticity to hurricane risk increases over time (as hurricanes become more frequent/severe)
(6) Diff-in-diff evidence for ‘learning the hard way’	Diff-in-diff of prices for properties with higher versus lower risk in NYC before and after Hurricane Sandy	Larger effect of risk on prices following the local disaster (negative and significant coefficient)	Property markets learn from firsthand experience of previously unfamiliar risks
(7) Diff-in-diff evidence for learning from observation	Diff-in-diff of prices for properties with higher versus lower risk in Boston before and after Hurricane Sandy	Larger effect of risk on prices following the disaster in a similar location (negative and significant coefficient)	Property markets learn from second-hand information, that is, observation of previously unfamiliar risks
(8) Decay in price effect of hurricane risk over time	Modified diff-in-diff of prices for properties with higher versus lower risk in NYC and, separately, Boston, before and after Hurricane Sandy	Coefficient on risk variable after the treatment, interacted with the time passed since the treatment, is positive and significant	Property markets forget what they have learned about pricing hurricane risk, price gap between exposed/non-exposed properties declines over time

**Table 3:** *Planned results tables with tests, key predictions and implications for the proposed study.*