

The implication of the increase in storm frequency and intensity to coastal housing markets

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Abstract

This paper analyzes the effects of storm frequency and intensity on housing values in Miami-Dade County over the last three decades. We found that higher storm exposure accelerates the housing price discount caused by augmented flood risk. The adverse effects of frequency and intensity have different impacts on perception of flood probabilities. Storm frequency affects housing prices in lower flood risk areas, whereas intensity influences the market in the higher risk zone, due to the different risk perceptions between the two factors. The results shed light on how increases in storm frequency and intensity impact the dynamics of flood risk perception in different floodplains on the coastal housing markets, suggesting future directions of flood prevention policies. Our findings highlight that one additional hurricane event is associated with a housing price discount of 1.3%. This adverse impact of frequency increases to 2.0% in the 500-year floodplain zones, while higher storm intensity reduces housing values in the 100-year floodplain zones by 1.5%.

KEYWORDS

disaster risk reduction, floodplain, policy appraisal, risk perception

1 | INTRODUCTION

According to the National Oceanic and Atmospheric Administration (NOAA)'s National Center for Environmental Information, tropical cyclones and severe storms caused 1.09 trillion dollars in damages with over 5,000 fatalities across the United States since 1980 (NOAA, 2018). Storms have become more frequent and destructive due to climate change (Murphy & Strobl, 2009). Rapid population growth in coastal cities has made these prime real estate markets more vulnerable to the increasing number of extreme weather events caused by climate change (Below, Beracha, & Skiba, 2017).

Meanwhile, coastal amenities such as view, proximity to beach, and recreational values, have been attractive

assets to real estate investors and developers. However, the geographical precondition of being in vicinity to coastlines can pose substantial risks and financial burdens to the oceanfront communities due to their high susceptibility to storm damages.

Many studies have explored the relations between coastal amenities and risks on housing values (Atreya & Czajkowski, 2019; Bin, Kruse, & Landry, 2008; Kellenberg & Mobarak, 2011). Moreover, several studies have attempted to model the intensity and frequency pattern of future extreme weather events associated with climate change and sea level rise (Knutson et al., 2010; Knutson, Tuleya, & Kurihara, 1998).

However, the direct impact of storm frequency and intensity on market dynamics, using household-level

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data, has not been explored due to storm unpredictability and limited availability of long-term historical sales data. Although storm frequency and intensity can largely impact housing market dynamics by the magnitude of damage immediately after the climate disasters, homeowners' perceived location-based risks can be another factor that influences price dynamics. In order to estimate the frequency and intensity impacts correctly, homeowners' risk perception of the storm characteristics and spatially different preexisting risk exposures such as floodplains should also be taken into consideration.

In this era of climate change, current floodplain policies such as the Flood Insurance Rate Map (FIRM) and local preparedness strategies need to be modified by considering this climatic transformation including these storm-caused intensity and frequency impacts, since many extreme cases have been realized. Evidently, Houston experienced three "500-year floods" in a 3 year period (Ingraham, 2017). To address the urgent challenges, this study analyzes big data to decipher the relationship between intensified storm frequency and current floodplain policies in a spatiotemporal and market perspective. Thereby, the study contributes to the existing housing literature by providing more accurate and objective measures of pricing effects on real estate and guides not only coastal home-seekers, but also flood policy-makers for future community resilience.

2 | LITERATURE REVIEW

There are a number of hedonic pricing studies showing that natural amenities such as ocean view, beach quality, and oceanfront proximity, among other coastal landscape features, impact the real estate market against adverse impacts of flood risks. Bin (2008) indicate that one degree increase of ocean view increases the mean willingness-to-pay by \$995, while flood risk (being located in a Special Flood Hazard Area) reduces housing prices by approximately 11%. Gopalakrishnan, Smith, Slott, and Murray (2011) suggest that wider beach and more frequent nourishments¹ against beach erosion positively influence property values. Hamilton and Morgan (2010) indicate that homeowners who live closer to water are willing to pay a premium due to the proximity to beach and views. Similarly, Bin, Poulter, Dumas, and Whitehead (2011) also found ocean frontage and estuarine water frontage commands a considerable price premium of 31–77%.

Several studies have examined the price discount effects of natural hazards, particularly flooding and storms in coastal properties. The majority of literature on flood risk suggests that there is a significant housing price discount in flood-prone areas compared with homes

located outside floodplains after a major flood event (Atreya, Ferreira, & Kriesel, 2013; Bin & Landry, 2013; Kousky, 2010). Bin, Kruse, and Landry (2008) found that flooding-induced price discounting is more pronounced in a 100-year floodplain than in a 500-year floodplain. Daniel, Florax, and Rietveld (2009) observed that a 1% increase in flood risk probability is associated with a 0.6% decrease in sales price from the meta-analysis of 19 case studies across the United States, and these discount effects can remain for up to 9 years after the flood event (Atreya et al., 2013).

With respect to the market responses to storms and hurricanes, Ewing, Kruse, and Wang (2007) suggest that windstorms reduce housing value by 1.5–2% immediately after hurricanes or tornados. Beracha and Prati's (2008) short-term market impact study also suggests that home prices and transaction volumes drop temporarily during the first two quarters after major hurricanes, followed by a positive correction in the second two quarters. Murphy and Strobl (2009) argue that hurricane strikes increase house prices for several years and reach a maximum of 3–4% after 3 years of occurrence. This reverse result is caused by a temporary risk reduction resulting from enhanced risk preparedness for future storms, shortage of housing supply due to hurricane damages, or both (Below et al., 2017; Murphy & Strobl, 2009).

Other studies have also explored indirect factors related to housing price discounts experienced after a major hurricane. Hallstrom and Smith (2005) argue that risk information about new hurricanes decreases property values in Lee County, Florida by at least 19%. Epley (2017) suggests that higher insurance premiums, due to higher risk exposure, yield a lower sales price on residential properties. McKenzie and Levendis (2010) found that elevation has a positive relationship with selling prices, particularly in low-lying areas, and this elevation premium is pronounced after a high-powered storm. Fortifying building structures by implementing stricter building codes and reinforcing homes against major hurricanes yields a price premium (Dumm, Sirmans, & Smersh, 2012).

Regarding the effects of storm frequency on housing price, a similar logic was found in a study analysing four hurricanes between 1996 and 1999 (Graham, Hall, & Schuhmann, 2007). This study found an adverse pricing effect only in the last two hurricanes, while the price discount was tenuous in the earlier storms. The authors speculate that they found different results because homebuyers considered the first two storms to be random events. However, the relatively small storm samples within a short time period provide insufficient evidence of risk capitalization in the housing market. Although they suggest that increased susceptibility to hurricanes by recurrent storm experiences contributes to a housing

price discount, it is highly plausible that risk dynamics cannot be sufficiently explained by a singular causation. In this case, the four hurricanes do not generalize the continuity of frequency that relies upon individual intensity, occurrence interval, and other storm characteristics.

With respect to risk perception of hurricane, Zhang, Hwang, and Lindell (2010) indicate that perceived threats of floods and hurricanes affect property values. Otto, Mehta, and Liu (2018) suggests that a recent past storm experience influences the preparedness for future storms by overestimating risk information that is more easily recalled, called “availability heuristics.” Similarly, Meyer, Baker, Broad, Czajkowski, and Orlove (2014) argue that changes in risk perception between the before and after storm occurrence perceptions are biased by “hindsight” resulting in a failure to properly prepare for the actual threats imposed by hurricanes. Rapley and De Meyer (2014) indicate that risk perception can be also influenced by overestimating one’s preexisting hypothesis, called *myside bias* (or confirmation bias). However, risk perception caused by climatic events can be different based on prefabricated risks of risk probabilities and risk mitigation policies (e.g., floodplains and flood insurance). Furthermore, the weather-related individual risk perception tends to be locally clustered (Lo & Jim, 2015), because these can contagiously influence each other as social network theory of risk perception explains (Scherer & Cho, 2003). Similarly, inhabitants in flood-prone areas have very different risk perception from those who live in flood-risk free regions (Ludy & Kondolf, 2012). Thus, we assume that the effect of individual differences in risk perception on housing prices will be very small compared to the risk perception from extreme weather events. However, risk capitalization could be influenced by storm frequency and intensity that individual homeowners experienced because the market participants are already anticipating the risk in the area where consecutive hurricanes have recurred over a brief time-period (Graham Jr & Hall Jr, 2001).

Taken together, the existing literature typically focuses on a relatively small storm sample and covers a limited area. Since hurricanes and their affected sites are heterogeneous in nature, it is necessary to adopt a “big data” approach, covering historical sales data over longer time periods and including variables that can provide clues for interpreting the inherent risk perception, in order to better understand and more accurately generalize the impacts of storms on coastal housing prices.

3 | DATA

Data from several sources are utilized for this analysis. The principal data are historical sales transactions for

single family housing in Miami-Dade County from 1987 to 2017. The property data is obtained from the Miami-Dade County’s Open Data Hub and Florida Department of Revenue. The housing data include the number of bedrooms and bathrooms, number of stories, building square footage, lot area, built year, site coordinates, site and mailing addresses, three recent historical transaction dates and sales prices. A total of 322,385 single family houses was selected for the hedonic pricing model. Outliers were excluded, such as homes with more than 10 bedrooms, lot sizes greater than 5 acres, no bedroom unit, zero transaction price, and price less than \$10,000 or more than \$10 million. To avoid the omitted variable bias, we also have included the spatial (census tract level) and time (year) fixed effects in this model. A total of 409 census tracts and 31-year dummies are included in this study. Due to the recreational nature of the coastal communities, many vacation homes are assumed to be included in the sample. It is highly possible that owner-occupants may have different risk attitudes from vacation homeowners. To investigate whether a difference exists, we include the owner-occupancy dummy extracted from the site and mailing addresses.

Historical hurricane tracks and detailed information about each storm are collected from NOAA (Figure 1). This study considered a total of 16 major storms having a peak wind speed greater than 20 miles per hour (Table 1). We use average maximum sustained wind speed from the World Meteorological Organization for each observation to identify the impacts of storm intensity, rather than using the Saffir-Simons Hurricane Scale which is essentially the reclassification of the wind speeds.

To increase the accuracy of identifying storm-impacted areas, for instance, when the left side of a hurricane track is smaller than its right side, we draw asymmetrical impact buffers from each hurricane track using the average maximum wind speed of each storm and the structural characteristics of the hurricane (Figure 2). Empirical results from recent major hurricane data analyses suggest that widespread damage is typically observed in areas within approximately three-fourths of the distance between the eye and outer edges of hurricane. In addition, the right side of the storm covers about 20% more area than the average impacted areas when adding the steering wind (a synoptic scale flow that dictates the movement of hurricanes) power, since hurricanes move counterclockwise in the northern hemisphere (Coch, 1995).

Other key environmental and site characteristics are captured from various geospatial data provided by the Florida Department of Environmental Protection and the Florida Geographic Data Library. To identify floor elevation of each house, we extracted elevation values from a 5 ft grid Digital Elevation Model (DEM) and overlaid



FIGURE 1 Site map. Illustration by author; mapping source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community; NOAA (2019)

TABLE 1 Major storms and hurricanes affecting Miami-Dade County (1987 Q1–2018 Q2)

Hurricane	Date	Wind (knots)	Rainfall (inch)	Category	Landfall	Declaration
Floyd	October 12, 1987	65	2.76	Hurricane 1	Yes	No
Ana	June 30, 1991	20	7.86	Misc. disturbances	No	No
Fabian	October 16, 1991	40	3.68	Tropical storm	No	No
Andrew	August 24, 1992	145	7.41	Hurricane 5	Yes	Disaster
Harvey	September 21, 1999	45	1.52	Tropical storm	No	No
Irene	October 15, 1999	70	10.99	Hurricane 1	Yes	Disaster, emergency
Charley	August 13, 2004	130	0.47	Hurricane 4	Yes	Disaster
Frances	September 4, 2004	95	3.49	Hurricane 2	Yes	Disaster
Ivan	September 21, 2004	25	1.11	Post-tropical	No	No
Jeanne	September 26, 2004	105	0.74	Hurricane 3	Yes	Disaster
Katrina	August 25, 2005	70	3.48	Hurricane 1	Yes	Disaster, emergency
Wilma	October 24, 2005	105	1.23	Hurricane 3	Yes	Disaster
Ernesto	August 30, 2006	40	1.53	Tropical storm	Yes	No
Bonnie	July 23, 2010	35	3.25	Tropical storm	Yes	No
Matthew	October 6, 2016	120	1.19	Hurricane 4	Yes	Emergency
Irma	September 10, 2017	115	6.33	Hurricane 4	Yes	Emergency

them onto each property. Using FIRM, we classified each home by three different flood hazard zones (100-year, 500-year, and non-floodplains). To control amenity and nuisance effects on housing value, we include nine types of amenity and locational variables, including road proximities, distances from green spaces, points of interests (i.e., cultural and commercial facilities), emergency shelters, beaches, and ocean, as well as homes located within floodplains, oceanfront, and soundfront (inland-side intra-coastal waterfront).

Since our model tracks property transactions over a long period of time, several housing cycles have also

occurred. To capture the cycle impacts, we include a house price index in the Miami region and a recession dummy from multiple US Censuses. All these market data are geocoded via site coordinates using ArcGIS. A list of variables and summary statistics is shown in Table 2.

4 | METHODOLOGY

This study uses a panel data hedonic pricing model and geospatial analysis to assess the impact of hurricane

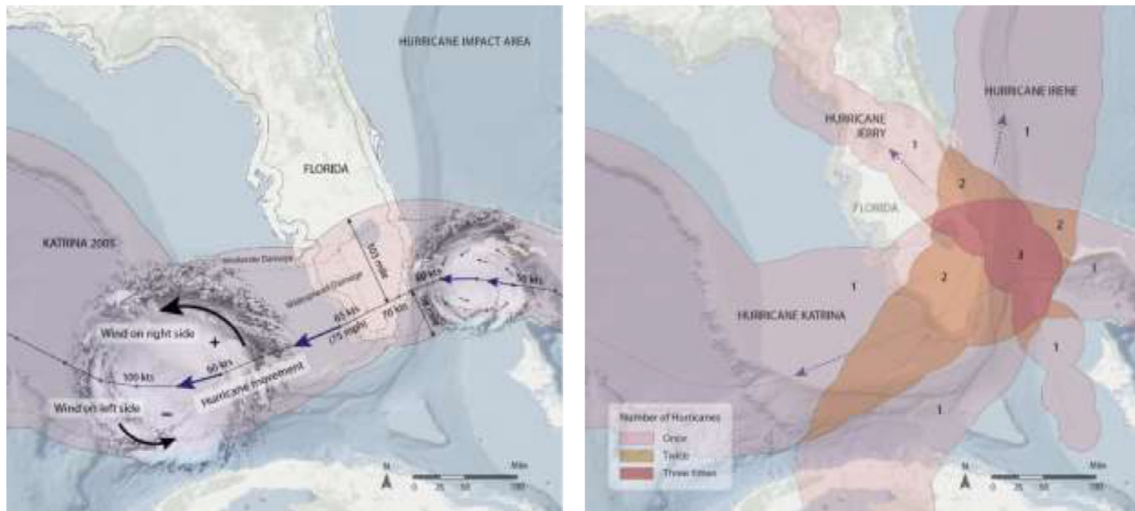


FIGURE 2 Hurricane influence (left) and frequency impact (right) areas illustrative map. Illustration by authors, source from NOAA (2018). Illustration by author; mapping source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community; NOAA (2019)

frequency and intensity on single family housing transaction prices. We explore the effect of hurricane risk and dynamics of the risk perception caused by a total of 16 major storms over the three decades in Miami-Dade County. To estimate the pricing effect of hurricane frequency and intensity on different risk exposures, we perform three sets of panel data regressions.

The first model, as a benchmark, examines the overall storm effects, including frequency and intensity, on housing prices. Below et al. (2017) used specific sales windows (e.g., within 60 days and 61–90 days after hurricane strikes) to estimate market dynamics. However, there were multiple housing cycles during the 30 years, and each storm has different impacts on prices depending on when the storm occurs relative to the market cycle.² In fact, storm impacts on housing values can be prolonged for several years (Murphy & Strobl, 2009). Thus, rather than constructing similar sales periods following the events, we calculated elapsed time of sales from each storm strike. Since the average interval of storm occurrences in Miami-Dade County over the last three decades is about 2 years, measuring elapsed time between storm strikes and home sales dates can capture market effects over time without causing selection bias.

In order to investigate whether major storms influence housing sales prices, we employ a *multi-way fixed effect* hedonic pricing model using the cluster-robust standard error. The model includes the structural variables and amenity characteristics, market factors, as well as major storm characteristics of each event (Table 2). Since subjective values, such as the value associated with the number of casualties, cannot be measured (e.g., human life value cannot be compared), the variables consist only

of objective factors which can be measured economically from the National Hurricane Center's tropical cyclone reports.

Furthermore, because of the large number of home sales, some homeowners might have fewer storm experiences. To address this, we added a repeated sales variable to distinguish the factor from storm frequency effects. Additionally, non-linear effects are anticipated with respect to elevation, proximity variables, and wind speed. Log or squared terms are applied to these variables. The first-set of regression equations is as follows:

$$\ln P_{ict} = \alpha_{ct} + \beta' H_i + \gamma' N_i + \eta' M_{ict} + \lambda' Storm_{ict} + \varepsilon_{ict} \quad (1)$$

where $\ln P_{ict}$ is the natural logarithm of the sales price (both inflation based on the Consumer Price Index and seasonally adjusted index) of single family property i in census tract c in year t ; α_{ct} are census tract–year effects, which allow for housing price variation over time at the census tract level; and, H_i and N_i are vectors of housing structure and amenity characteristics with coefficient β and γ , respectively. Our set of controls H_i consists of number of bedrooms, bathrooms, and stories, building square footage, lot size, housing age, presence of a swimming pool, owner occupancy status, and building floor elevation. Other popular variables in the previous research (e.g., centralized air condition, fireplace, garage, etc.) are not available. However, these unobserved variables are either influencing only small samples (e.g., only 1.3% of homes do not have an air-conditioning equipment in the Miami region) or are controlled by the two-way fixed effects. N_i , the amenity variables include five proximity (green spaces, points of

TABLE 2 Variables and summary statistics (single-family housing 1987 Q1–2018 Q2)

Variable	Description	Mean	SD
PRICE	The actual single-family property sale price (thousand dollars)	308.257	523.808
Structural variables			
BEDROOM	Number of bedrooms	3.263	0.851
BATHROOM	Number of bathrooms	2.123	0.946
STORY	Number of stories	1.111	0.320
BLDGSF	Square footage of house (thousands)	2.278	1.171
LOTSIZE	Square footage of property (thousands)	10.541	12.531
AGE	Age of housing structure	47.342	20.777
POOL	Dummy variable, 1 if a property has a swimming pool; 0 otherwise	0.299	0.458
OWNEROCCUPY	Dummy variable, 1 if a property is owner-occupied; 0 otherwise	0.858	0.349
ELEVATION	Ground elevation above sea level (feet)	8.220	2.299
Amenity variables			
ROAD	Dummy variable, 1 if a home is located within 300 ft of highways, 150 ft of major roads, and 100 ft of minor roads; 0 otherwise	0.096	0.295
GREENPROX	Distance to green space (thousand feet)	1.654	1.188
POIPROX	Distance to points of interests (thousand feet)	8.805	5.673
SHELTERPROX	Distance to evacuation shelters (thousand feet)	20.111	13.683
BEACHPROX	Distance to beach (thousand feet)	28.795	15.017
OCEANPROX	Distance to ocean (thousand feet)	27.143	17.822
OCEANFRONT	Dummy variable, 1 if a property is an oceanfront home; 0 otherwise	0.006	0.077
SOUNDFRONT	Dummy variable, 1 if a property is a soundfront home; 0 otherwise	0.008	0.091
FLOODPL	Dummy variable, 1 if a home is within a 100-year or 500-year floodplains; 0 otherwise	0.424	0.494
FLP100	Dummy variable, 1 if a home is within a 100-year floodplains; 0 otherwise	0.359	0.480
FLP500	Dummy variable, 1 if a home is within a 500-year floodplains; 0 otherwise	0.064	0.244
Market variables			
RECESSION	Dummy variable, 1 if a home sold during the recessions; 0 otherwise	0.079	0.269
HP_INDEX	House price index for Miami-Miami Beach-Kendall, Florida, quarterly	74.420	343.0
REPEAT	Number of home sales	2.196	0.727
SALEOVER2YR	Dummy variable, 1 if a home sold after 2 years (average storm recurrence interval in the region) post-hurricanes; 0 otherwise	0.451	0.498
Storm variables			
ELAPSE	Elapsed period of time from storm to housing transactions	0.926	0.689
LOCALBUYER	Dummy variable, 1 if a home is purchased by a local buyer; 0 otherwise	0.840	0.367
RAINFALL	Total amount of rainfall (inch)	5.340	3.522
WIND	Maximum sustained wind speed (knots)	79.898	43.081
FREQ	Number of hurricanes between buying and selling home	2.553	1.767

interests, evacuation shelters, beaches, and ocean) and four dummy (road proximities, floodplains, oceanfront, and soundfront properties) variables. M_{ict} is a vector of market factors with coefficient η . The market factor variables include a house price index in the Miami region, recession dummy, number of repeated sales, and

elapsed period of time between storm strikes and home sales.

$Storm_{ict}$ represents measures of the storm characteristics with coefficient λ . This attribute group includes rainfall amount, wind speed, and storm frequency of property i in census tract c in year t . ε_{ict} is the error terms of each

TABLE 3 Robustness check result summary: spatial lag and spatial error models

	Spatial lag models				Spatial error models			
	Model 4		Model 5		Model 6		Model 7	
FREQ	−0.004**	(0.003)	−0.005**	(0.002)	−0.003**	(0.003)	−0.001*	(0.002)
FLP100	0.014	(0.013)	0.152***	(0.025)	0.051	(0.016)	0.172***	(0.026)
FLP500	−0.132***	(0.022)	0.073	(0.047)	−0.102***	(0.027)	0.059	(0.048)
SALEOVER2YR	−0.073*	(0.006)	−0.073*	(0.006)	−0.077*	(0.006)	−0.077*	(0.006)
FREQ × FLP100	−0.007	(0.004)			−0.004	(0.004)		
FREQ × FLP500	0.036***	(0.007)			0.032***	(0.008)		
sqrtWIND × FLP100			−0.018***	(0.003)			−0.015***	(0.003)
sqrtWIND × FLP500			−0.014	(0.005)			−0.010	(0.005)
Other variables	YES		YES		YES		YES	
Constant	5.319***	(0.006)	5.267***	(0.006)	12.472***	(0.193)	12.425***	(0.193)
Lambda					0.591***	(0.006)	0.590***	(0.006)
Lag coeff. (rho)	0.509		0.580		0.591		0.590	
Sigma-square	0.306		0.305		0.307		0.307	
R ²	0.580		0.580		0.578		0.578	

Note: Dependent variable: logPRICE (Inflation-adjusted price in 2018 dollars with seasonal index adjusted). $N = 32,241$ (the samples are randomly selected from the entire observations used in Models 1–4). The main entries in Models 4–7 report the coefficients estimated from the spatial lag and spatial error models by Spatial Weights Matrix using GeoDA with SE reported in brackets. Each model reports the result from one regression with controls for structural, amenity, market, and storm variables.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

observation in a respective time and zone. The storm frequency is calculated by counting only the number of storms that occurred within the period between buying and selling. We focus on this number because the previous owner's storm experience or future storms that occur after the date of sale do not affect the seller's perceptions of risk. Arguably, buyer's previous storm experiences may also affect housing prices, if a buyer is from the local area. Thus, a local buyer dummy variable is added in this model to capture a buyer's perception.

The second regression model is an extension of the first model to explore pricing effects on different floodplains, risk perceptions, and interaction between storm frequency and flood exposures. The third regression model is to identify the storm intensity (wind speed) effects on housing prices within the 100-year floodplain and 500-year floodplain zones. Since a nonlinearity effect in the storm intensity is expected, a squared term for intensity is used to estimate the interaction effects. All model specifications include year and census tract dummies to control for spatial- and time-specific fixed effects on the housing prices. The standard errors are clustered at the census tract level. To test the potential spatial dependence bias in the hedonic models, we conduct robustness checks with spatial lag (Models 4 and

5, Table 3) and spatial error models (Models 6 and 7, Table 3) using spatial weights matrix.

5 | RESULTS AND DISCUSSION

The semi-log model is specified in the hedonic regression using Stata. The regression results indicate that the relationship between the dependent variable (the natural log of inflation adjusted home sales prices) and independent variables are robust ($R^2 = 0.626$). The vast majority of the p values are also less than 5%, and the joint hypothesis F -statistics on each attribute group reject the null hypothesis at the 1% level. Thus, the hedonic regressions are statistically significant. The variance inflation factors (VIFs) for all estimated variables were tested. The mean VIF of 1.57 (ranged from 1.01 to 3.98), indicates that there was no multi-collinearity. From the spatial lag and spatial error models, all variables of interest have the same trends. The coefficients across the spatial regression models are broadly the same even though FLP500 and SALEOVER2YR exhibit a slight difference between the hedonic and spatial regressions. Thus, our results from the two-way fixed-effect hedonic models do not suffer from spatial interdependence errors (Table 3). The regression results are presented in Table 4.

TABLE 4 Regression result summary: hedonic model

	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
CONSTANT	13.076***	(0.441)	13.074***	(0.441)	13.004***	(0.440)
BEDROOM	0.045***	(0.004)	0.045***	(0.004)	0.045***	(0.004)
BATHROOM	0.041***	(0.005)	0.041***	(0.005)	0.041***	(0.005)
STORY	0.059***	(0.013)	0.059***	(0.013)	0.059***	(0.013)
BLDGSF	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
LOTSIZE	0.004***	(0.001)	0.004***	(0.001)	0.004***	(0.001)
AGE	-0.003***	(0.000)	-0.003***	(0.000)	-0.003***	(0.000)
POOL	0.041***	(0.005)	0.040***	(0.005)	0.041***	(0.005)
OWNEROCCUPY	0.086***	(0.005)	0.085***	(0.005)	0.085***	(0.005)
logELEVATION	0.038**	(0.019)	0.043**	(0.019)	0.043**	(0.019)
ROAD	-0.032***	(0.006)	-0.032***	(0.006)	-0.032***	(0.006)
logGREENPROX	0.003	(0.555)	0.003	(0.554)	0.020	(0.552)
logPOIPROX	-0.009	(0.017)	-0.009	(0.017)	-0.010	(0.017)
logSHELTERPROX	0.015	(0.014)	0.014	(0.014)	0.015	(0.014)
logBEACHPROX	-0.091***	(0.035)	-0.093***	(0.035)	-0.092***	(0.035)
logOCEANPROX	-0.119***	(0.017)	-0.119***	(0.017)	-0.119***	(0.017)
OCEANFRONT	0.123**	(0.056)	0.122**	(0.055)	0.123**	(0.055)
SOUNDFRONT	0.316***	(0.039)	0.314***	(0.039)	0.316***	(0.039)
FLOODPL	0.017	(0.011)	-		-	
RECESSION	-0.075**	(0.038)	-0.078**	(0.038)	-0.078**	(0.038)
HP_INDEX	0.005***	(0.000)	0.005***	(0.000)	0.005***	(0.000)
REPEAT	0.045***	(0.004)	0.045***	(0.004)	0.045***	(0.004)
ELAPSE	-0.027***	(0.009)	-		-	
LOCALBUYER	-0.015	(0.022)	-		-	
RAINFALL	-0.002	(0.003)	-0.002	(0.003)	-0.003	(0.003)
sqrtWIND	-0.014***	(0.005)	-0.014***	(0.005)	-0.008	(0.006)
FREQ	-0.013**	(0.006)	-0.013*	(0.007)	-0.011**	(0.005)
FLP100			0.028	(0.028)	0.159***	(0.048)
FLP500			-0.064***	(0.023)	0.025	(0.044)
SALEOVER2YR			-0.032*	(0.017)	-0.031*	(0.016)
FREQ × FLP100			-0.001	(0.009)		
FREQ × FLP500			0.020***	(0.008)		
sqrtWIND × FLP100					-0.015***	(0.005)
sqrtWIND × FLP500					-0.005	(0.005)
R ²	0.626		0.626		0.626	
Adjusted R ²	0.625		0.625		0.626	

Note: Dependent variable: logPRICE (inflation-adjusted price in 2018 dollars with seasonal index adjusted); $N = 322,385$. All models controlled for year and census tract fixed effects. SE in parentheses.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

As expected, the majority of structural and amenity variables have a strong relation to home sales price. More bedrooms and bathrooms, higher number of stories, larger building square footage, newer homes, swimming pools, owner-occupied homes, and having a higher floor elevation are positively associated with the price increase. Although lower elevation of property can provide easy access to coastal amenities, the positive pricing effect in higher elevations also can be explained by the fact that risks to storm surge and flooding are higher at lower elevations. Adjacency to principal roads has a negative influence on housing values, because of disamenity factors such as noise, dust, and light exposure at night. By contrast, the amenity factors such as closer distance to beaches and ocean are strongly associated with home value increases. Both variables of $\log\text{BEACHPROX}$ ($\beta = -0.091$; $p < .01$) and $\log\text{OCEANPROX}$ ($\beta = -0.119$; $p < .01$) indicate that increasing distance from the shoreline has a strong adverse pricing effect. Similarly, both oceanfront and soundfront homes are positively related to price appreciation. The positive coastal amenity impacts were consistent with previous empirical findings (Bin, Crawford, et al., 2008; Hamilton & Morgan, 2010). While distances to major cultural and commercial facilities ($\log\text{POIPROX}$) as well as emergency shelters could have either negative or positive signs due to a “net nuisance” effect (Sah, Conroy, & Narwold, 2016), it was interesting to note that distance to green spaces ($\log\text{GREENPROX}$) was statistically insignificant in all models. The insignificance of $\log\text{GREENPROX}$ was likely associated with a high outside temperature and location of green spaces. In fact, approximately 50% of Miami-Dade’s parks are located within a 5-min walking distance of coastlines. The value of ocean proximity would counteract the positive green space effects, resulting in this factor being statistically insignificant. It was surprising to note that being located in a floodplain (FLOODPL) was statistically insignificant with a positive sign (Model 1, Table 4). The insignificance of FLOODPL was likely associated with the non-linear gradient of flood risk probability. Thus, new dummy variables, FLP100 (homes located in the 100-year floodplain) and FLP500 (home located in the 500-year floodplain), were specified and adopted in Models 2 and 3.

Among the market variables, the negative effects of recession (RECESSION , Table 4) explicitly implied that a market crash could cause adverse pricing effects. Positive pricing effects were observed in house price index and repeatedly sold homes. One additional repeat sale increases housing prices by 4.5%, holding all other variables constant (Models 1–3, Table 4). This result signifies that fewer storm experiences by homeowners are associated with housing price increases likely due to perception

of lower risk. Although LOCALBUYER (Model 1, Table 4) is not statistically significant, its negative sign supports the interpretation that local buyers’ greater hurricane experience makes them less likely to pay a higher price for their homes.

With respect to storm characteristics, it was clear that rainfall and wind intensities have an adverse impact on housing prices, due to more property damage potential and subsequent risk increase. In contrast to empirical findings that storms adversely impact the housing market in the short term (Beracha & Prati, 2008; Ewing et al., 2007), the coefficient of ELAPSE was negative and statistically significant ($\beta = -0.027$; $p < .01$). One reason for this contrasting result could be an inward shift in the supply for housing from storm damage. Although storms can affect the demand for housing, housing demand could be relatively inelastic since temporal displacement would occur within the region. Another reason may be that chronic storm risks are already capitalized into housing prices, especially in areas where consecutive hurricanes occurred over a short period (Graham Jr & Hall Jr, 2001). The contrasting result also can be supported by confirmation bias (overestimating one’s preexisting hypothesis). Although climatic events are unpredictable, residents have a general sense about storm frequency and intensity in the area, amplifying anxiety about the future storm when the “peace time” is longer (Lazrus, Morrow, Morss, & Lazo, 2012). To check the assumption of this cognitive effect, ELAPSE was replaced by a dummy variable (SALEOVER2YR) in Models 2 and 3. Since the average storm occurrence interval in the study area is approximately 2 years, it is reasonable to assume that perception can be altered by the preexisting hypothesis that storms occur every 2 years. The significance of SALEOVER2YR ($\beta = -0.032$, $p < .1$) suggests that risk perception with respect to storm frequency could affect prices.

The maximum number of storms a new homeowner experiences before sale is 5, while the average is 2.6. The coefficient of FREQ reveals that a higher frequency of hurricanes has a negative effect on housing price at the 5% significance level (Model 1, Table 4). The result indicates that the number of storm events during the time period when households possessed their homes is associated with a housing price decrease of 1.3%. In Model 2, homes located in the 500-year floodplain zones are associated with a price decrease of 6.4%, and the significance of $\text{FREQ} \times \text{FLP500}$ ($\beta = 0.020$, $p < .01$) indicated that the frequency would accelerate the discount in the 500-year floodplains. Although the interaction between storm frequency and the 100-year floodplain is marginal and statistically insignificant, the negative sign of $\text{FREQ} \times \text{FLP100}$ ($\beta = -0.001$, $p > .10$) also supports the adverse impacts of the storm frequency.

In Model 3, the interaction between storm intensity and floodplains was defined. The negative impacts of storm intensity have been clearly revealed by reference to the significance of the interaction between sqrtWIND and FLP100 ($\beta = -0.015$, $p < .01$) and the negative sign of $\text{sqrtWIND} \times \text{FLP500}$ ($\beta = -0.005$, $p > .10$). However, it was interesting to find that homes located in the 100-year floodplains have a premium rather than a discount. One possible explanation is that other positive amenity externalities of being located in closer proximity to the ocean would counter-balance the effects of flood risk capitalization. Another postulation is that the pricing effect of flood risks in the 100-year floodplain might have been altered by public flood adaptation measures (e.g., seawalls, levees, and storm barriers) or flood insurances. Due to the higher flood probability caused by the low Base Flood Elevations (BFEs) in the 100-year floodplain, it is highly possible that the local government has implemented stronger flood adaptation measures in those areas. Consequently, the real flood risks, inherently associated with the spatial characteristics, might have been altered by the flood adaptation measures which influence homeowner's risk perception (Kim, 2020). Furthermore, property owners in the 100-year floodplain of the study area are required to purchase flood insurance, and this mandatory insurance policy can also affect homeowners' risk perception.

The results suggest that the storm risk can be perceived differently with respect to storm frequency and intensity in zones having 100 year versus 500 year flood risk exposure, since actual risks can be offset by public and private flood reduction measures, as well as other externalities. These policies and investments, which most likely were designed to protect against the 100-year flood probability, may effectively reduce risks from storm recurrence. However, when the flood risks are larger than the 100-year flood, such as when a 500-year flood occurs in the 100-year floodplains, a residual flood risk still exists (Carter, 2005), and thus the adverse impacts from higher storm intensity could be increased in higher flood risk areas. Conversely, levees and storm barriers in the 500-year floodplains are designed to endure the 500-year flood, and thus the vulnerability to intense storms up to the same level of intensity can be decreased. However, it is not surprising that homeowners underestimate flood risk in a lower flood risk area where flood insurance is not mandatory (Ludy & Kondolf, 2012). More flood experiences by higher storm frequency, regardless of storm intensity, could negatively influence their subjective risk perception, resulting in price depreciation in the 500-year floodplains. Together, the results suggest that storm intensity is an important factor to be taken into account for improving flood prevention

policies in the 100-year floodplain zones ($\text{sqrtWIND} \times \text{FLP100}$, Model 3, Table 1), while storm frequency is more relevant for improving housing market resilience in the 500-year floodplains ($\text{FREQ} \times \text{FLP500}$, Model 2, Table 1). With respect to risk perception, the confirmation bias may cause greater price depreciation in both floodplains by amplifying anxiety about future storms and flood risks where recent storm experiences exceed residents' preexisting perceptions about storm frequency and intensity.

6 | CONCLUSION

This paper contributes to the literature about the effects of climate change on the coastal housing market and flood policy. Using a big dataset of housing transactions and major storms over three decades, we examine how hurricanes, particularly the storm frequency and intensity, influence housing prices in zones having different flood risks.

Our results shed light on how storm frequency and intensity effects can vary according to the degree of risk exposure. From the analytical models, we confirm that the effect of stronger hurricane frequency and intensity is negatively capitalized into home sales price. Different effects were observed when the storm characteristics interact with the different floodplain zones in those housing transactions where homeowners lived in a home longer than the average storm recurrence. The research highlights that one additional hurricane event is associated with housing price depreciation of 1.3% (equivalent to US\$4,006, holding all other factors constant) in Miami-Dade County, and the adverse impact can be amplified in the 500-year floodplain. However, the adverse storm intensity effect is only significant in the higher flood risk zone. These results suggest that lower flood risk does not necessarily mean that housing prices are insulated from storm exposure in this era of more rapid climate change.

Our findings also support recent evidence that raises questions about the validity of existing flood policy. Some locations experienced 500-year floods almost annually over the last decade, leading to active discussion about modifying flood insurance maps based on climate change and sea level rise. Although it is of great interest to further develop policy suggestions, the findings suggest that the flood map modification should be weighted based upon, not just base floor elevation, but also consideration of key environmental externalities such as hurricane intensity and frequency factors. Our results also indicate that certain areas which currently are defined as having lower flood risk are no longer safe, suggesting that these areas should be prioritized for future flood mitigation and climate resiliency.

Since climate risk cannot be eliminated in coastal areas, where much development has already occurred, an accurate understanding of the impact of storm characteristics and interactive effects with risk exposures on housing markets and relevant mitigation policies will greatly help to improve coastal market resiliency. Further studies on the effect of climate adaptation measures and developing more comprehensive flood policy recommendations to keep abreast with current and future climate change may reinforce our study results.

CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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ENDNOTES

- ¹ Beach nourishment is a policy to patch eroding beaches with dredged sand from other locations (Gopalakrishnan et al., 2011).
- ² For example, storms occurring during the housing down-cycle would be expected to show greater price depreciation because of the soft housing market.

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