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The Economic Effects of Climate Change Adaptation Measures: Evidence from Miami-Dade County and New York City

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Abstract

This research examines the economic impact of climate change adaptation measures on the housing markets of two representative coastal cities in the United States located along the Atlantic Ocean. The results shed light on how adaptation measures and investments influence housing values and local economies with respect to their place-based and local forms of implementation. Numerous quantitative approaches, including multiple sets of geospatial modeling and panel-data hedonic regression analyses, are used to examine changes in property values associated with climate adaptation measures and the dynamics of risk perception. The results also signal how risk perception and hurricane characteristics are reflected in housing markets, thereby shedding light on the effects of anticipatory and reactive adaptation strategies in the reclassified categories of hard infrastructure, green infrastructure, adaptive capacity, and private adaptation on property values in these coastal communities. Collectively, the study suggests which adaptation strategies, characteristics, and attributes can contribute to maximizing both community resilience and economic benefits against the weather extremes caused by climate change.

Keywords:

Climate change adaptation; hurricane characteristics; risk perception; housing price; hedonic pricing; panel data

Research Highlights

- The study confirms that the hurricane characteristics and associated risk perception factors impact local housing market dynamics.
- Effective adaptation measures yield a rapid housing price appreciation within 5 months after hurricane strikes. Conversely, when adaptation measures are malfunctioning, housing sales prices depreciate faster during the first few months of hurricane occurrence.
- This study highlights that natural green infrastructure as a climate adaptation measure is associated with a housing price appreciation of 9.7% in Miami-Dade County and 2.7% in New York City.
- Structural elevation achieved by raising foundations provides 6.6% and 14.3% in housing price increases in Miami-Dade County and New York City, respectively.
- Adaptation measures for storm surges provides the largest positive impact on housing prices at 15.8% in Miami-Dade County.
- The study further suggests that implementation of climate adaptation should be based on local-specific information, rather than relying upon national or state-level data, due to local idiosyncrasies, location-specific storm characteristics, and the subjective nature of risk perception.
- The study provides a clearer understanding of how different types of climate adaptation measures interacting with storm characteristics and risk perception are contributing to reinforcing a coastal community resiliency.

1. Introduction

As climate change accelerates, extreme meteorological events such as coastal floods and storm surges have been occurring both more frequently, and with greater intensity (Rosenzweig et al., 2011). According to the National Oceanic and Atmospheric Administration (NOAA), in 2017 alone, Hurricane Harvey caused total damages in the amount of \$125 billion in the United States. In that same year, Hurricane Irma destroyed 25% of buildings in the Florida Keys. Moreover, the frequency of billion-dollar disaster events in the past five years has doubled from the average frequency between 1980 and 2016 (Smith, 2018).

Despite increases in disruptive climatic risks, coastal population density has grown, being fueled by the positive effects of coastal amenities (Bin et al., 2008) and flood insurances (Atreya & Czajkowski, 2014), and is now nearly three times that of the hinterlands over the past half-century (Barbier, 2014). This paradoxical phenomenon—the spatial coexistence of urban growth and risk increase—has led to an exponential increase of vulnerability to climate risk, demanding my attention with respect to climate adaptation.

To alleviate problems caused by this inconvenient coexistence, many coastal cities have been allocating a considerable amount of their budgets toward climate change adaptation projects, including planned retreat, nearshore armoring, and ways of enhancing adaptive capacity. Among the strategies that have been widely discussed over the last half century, though, retreat and relocation options have been seen as highly unfavorable on the basis of the financial burden, legal conflicts, and numerous other socio-cultural issues these strategies require (Hino, Field, & Mach, 2017). By contrast, on-site adaptation measures have been gaining more popularity, since these allow homeowners to keep coastal amenities whilst curbing potential asset value degradation due to climate change (Bunten & Kahn, 2017; Jin et al., 2015; Mills-Knapp et al., 2011).

However, the existing literature has paid insufficient attention to measuring the economic effects of these on-site climate adaptation measures. This is primarily due to factors such as the unpredictability of the risks in time and space; locally different disaster preparedness capacities; and the subjective nature of climate risk perception (Boulton, 2016). Furthermore, the reactive nature of adaptation projects—climate adaptation decision-making is mostly based on past climate events—prevents evaluating already implemented adaptation projects until the next climate event (Mendelsohn, 2000).

Such complexity aside, identifying the economic effects of adaptation measures on real estate markets is necessary, due to the significant share of the housing market in the urban economies, as well as the view of pragmatic economic dimensions concerning existing urban infrastructures. Therefore, I analyzed the effects of climate adaptation measures on housing prices in Miami-Dade County (MDC) and New York City (NYC), where various adaptation projects have taken place due to frequent hurricane damage. This study will contribute to improving the effectiveness of future adaptation policies and urban resilience strategies in coastal areas.

2. Literature Review

A number of studies identify the effects of coastal amenities on housing markets. The majority of the literature suggests that property values are positively related by proximity to the coast because of the amenity effects (such as ocean views and accessibility to beaches) and are particularly strong within 500 feet of the coastline (Conroy & Milosch, 2011). Pompe (1999) found that ocean views add approximately 45% to housing values on Seabrook Island in South Carolina. Similarly, Benson et al. (1998) confirmed that ocean view quality differentiates a sales price premium. Landry and Hindsley (2011) found that the influence of beach quality on local property values is significantly positive within 1,000 feet.

In contrast to the positive impacts of these coastal amenities, risks associated with major storms typically have adverse impacts on housing prices. Bin and Polasky (2004) indicated that flood risk decreases market values, and the effect is substantially larger post-storm occurrences than prior. Higher flood risk probability is associated with housing price decreases (Bin, Kruse, & Landry, 2008; Daniel, Florax, & Rietveld, 2009). Hallstrom and Smith (2005) confirmed that risk information without any physical harms decreases housing prices by 19%, which is similar to the effect in areas that have significant storm damages. This is not only because physical damages occurred, but also because of the perceived risk's negative effect on property value (Troy & Romm, 2004). Similarly, Kousky (2010) indicated that damaged infrastructure or the stigmatizing of an area as "risk-prone" after a disaster can also influence property values outside of a floodplain.

These adverse impacts of risk probability and information are influenced by human cognitive perspectives. Otto, Mehta, and Liu (2018) suggested that a newer risk experience affects individuals' response to future risks by modifying their true risk perception. Meyer et al. (2014) found that perceived risk between before and after a hurricane strikes can be altered by "hindsight." This cognitive tendency leads homeowners to underestimate the actual threats of hurricanes, resulting in a failure of adequate storm preparation. Pryce, Chen, and Galster (2011) indicated that risks can be influenced by discounting risk cognition of anticipated future events (myopic tendency about unrealized risk) while forgetting past events over time.

With respect to storm idiosyncrasies, individual characteristics of hurricane itself can play a significant role in housing market dynamics. Ewing, Kruse, and Wang (2007) discovered that windstorms adversely influence housing prices by 1.5 to 2% promptly after the storm events. On the contrary, Meyer et al. (2014) found that wind speed of hurricanes is overestimated while the flooding is underestimated because the current hurricane warning system (i.e., the Saffir-Simpson Hurricane Scale) largely relies on wind power.

Regardless of the individual storm characteristics, a major storm occurrence can directly affect local market dynamics. Murphy and Strobl (2009) indicated that major storms have a positive influence on housing values temporarily because of the shortfall of available housing supply immediately after a hurricane occurrence. Conversely, Beracha and Prati (2008) argued that both

home sales volumes and prices decline within several months post hurricane and rebound to the prices before the event. Although a large body of literature suggests that the adverse effect of hurricanes on housing prices is generally transitory (Below, Beracha, & Skiba, 2017; Chivers & Flores, 2002; Ortega & Taspinar, 2017), this negative impacts can be prolonged for years depending on local market economies (Atreya, Ferreira, & Kriesel, 2013; Bin & Landry, 2013).

Relatively few studies have been developed identifying the economic effects associated with on-site adaptation measures. Fell and Kousky (2015) found that levee-protected commercial properties sell for approximately 8% more than similar properties in 100-year floodplains without such protection. Jin et al. (2015) indicated that single-family homes located behind a seawall within 160 feet of waterbodies have a 10% price appreciation due to anticipated risk reduction against inundation.

Quantitative study of valuing green infrastructure and private adaptive measures on housing prices is mostly limited. Watson et al. (2016) roughly suggested that wetlands reduce flood damage by 54-78%. Green et al. (2016) argued that green infrastructure supports enhancing insurance value by reducing vulnerability and the costs of hard infrastructural adaptation to climate change. Natural green infrastructure can be more cost-effective than engineering approaches from a long-term perspective, since they generally have self-maintaining capacities and can host other ecosystem services (Bobbins & Culwick, 2016; Costanza et al., 2008). In terms of private adaptive measures, McKenzie and Levendis (2010) found that elevation has a positive relationship with sales 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).

Although coastal communities can reduce their risk exposure by investment in buildings and infrastructural resilience, it would be difficult to achieve long-term adaptive effects to climate change only with these approaches. Since limited budgets and resources prioritize certain climate adaptation projects in certain areas, poorer communities may be further marginalized by the risk exposure (de Coninck et al., 2018). Thus, “addressing the social structural causes of vulnerability is essential” by enhancing adaptive capacity, which is “often associated with access to technology, high education levels, economic equity, and strong institutions” (O'Brien & Selboe, 2015). To maximize climate adaptation efforts, then, cities and local governments would need to include both the infrastructural adaptation and adaptive capacity.

3. Data

The study investigates the impacts of climate adaptation measures using single-family housing transaction data in MDC and NYC from July 1, 2009 to May 31, 2018. The study combines four large datasets from MDC, NYC, the Federal Emergency Management Agency (FEMA), and the National Oceanic and Atmospheric Administration (NOAA); datasets include: property transaction data, neighborhood and amenity characteristics, and historical hurricane tracks and storm reports. Local market statistics such as unemployment rates, housing vacancy rates, and median household incomes are provided by the U.S. Census Bureau.

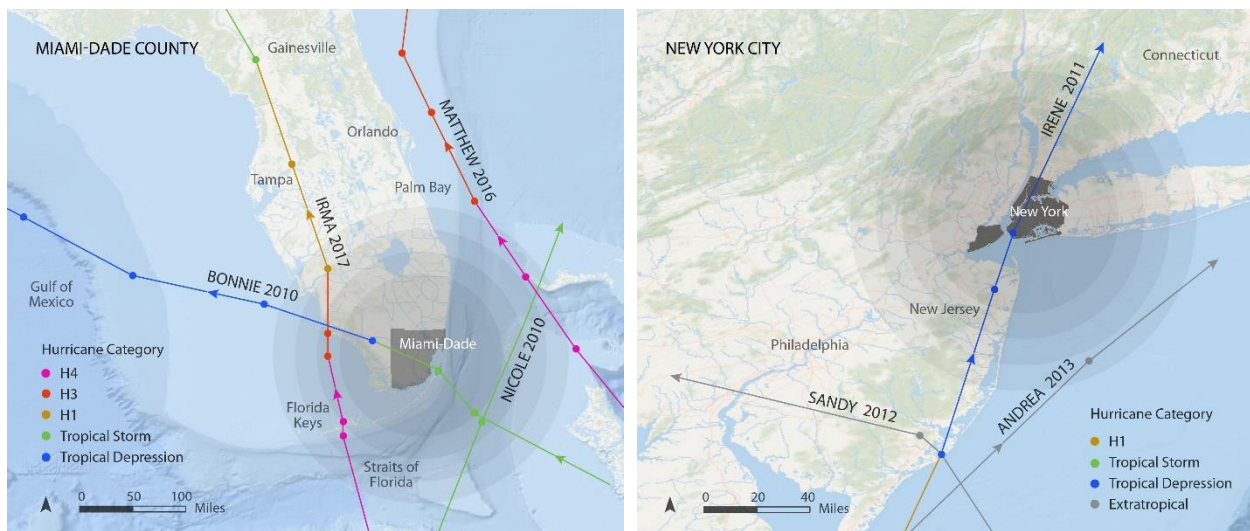


Figure 1. Site map with hurricane track between July 2009 and May 2018

Housing

The housing transaction data include typical structural information such as numbers of bedroom and bathrooms, square footage, building age, and transaction prices with sales dates. Since the spatial coordination of each property is excluded in NYC's dataset, the addresses of each property were manually batch-geocoded with ArcGIS. Outliers were excluded, such as homes with more than 8 bedrooms, lot sizes greater than 5 acres, zero transaction price, and inflation adjusted price less than \$60,000 or more than \$10 million. Consequently, a total of 79,184 and 90,811 single-family housing units in MDC and NYC, respectively, are analyzed in this study.

To capture location- and time-specific unobserved factors, the transaction data were clustered by 64 zip codes in MDC and 157 zip codes in NYC. Housing sales prices are adjusted to January 2018 prices using each region's monthly consumer price index for housing. The seasonality is also adjusted, and the average adjusted sales prices were \$459,000 in MDC and \$614,000 in NYC. About 70% of all transactions were within price ranges between \$150,000 and \$800,000 in

MDC; and between \$300,000 and \$800,000 in NYC. The average age of housing structures in NYC (around 74 years) is about 24 years older than that of MDC (around 50 years per structure). A typical lot size in MDC is 3-times larger than that of NYC, but the average number of stories in NYC is twice as high as MDC. Approximate 80% are owner-occupied properties for both regions. Only about 5% (in MDC) and 10% (in NYC) of homes are within a five-minute walking distance to the oceanfront. About 7% have an ocean view in MDC, but ocean-view properties in NYC are just 1%.

Major Storms

A total of 4 major storms directly influenced MDC, and 3 storms impacted NYC from July 2009 to May 2018. Although each storm was strong enough to homogeneously impact the entirety of each region, every storm has different characteristics. However, the storm characteristics do not sufficiently tell me about the causality. Of course, I can anticipate a higher probability of flooding from higher rainfalls, but it is not always the case due to interactions with other factors, such as rainfall durations and drainage conditions in an area, for example. Thus, in order to identify the effects of storm characteristics on housing prices more precisely, 3 types of the most common and economically measurable elements (i.e., wind, flood, and storm surge), which describe each individual hurricane in the National Hurricane Center’s tropical cyclone reports, are used in these analyses.

Table 1. Hurricane summary (July 2009 – May 2018)

Region	MDC				NYC		
Storm	Bonnie	Nicole	Matthew	Irma	Irene	Sandy	Andrea
Date	7/23/2010	10/30/2010	10/6/2016	9/10/2017	8/28/2011	10/29/2012	6/8/2013
Category	TS	TS	H4	H4	TS	ET	ET
Wind (knot)	35	40	115	115	55	65	27
Pressure (millibar)	1007	994	937	931	963	943	997
Rain (inch total)	3.25	6.74	1.19	6.25	6.87	0.94	3.12
Gust (knot)	40	35	35	64	55	54	34
Storm Surge (feet)	0	0	0	3.7	0	12.65	0

Notes: Pressure and wind speed are average values of each storm in the study area. Category is based on the Saffir-Simpson Hurricane Scale. “H” = Hurricane; “TS” = Tropical Storm; and “ET” = Extratropical.

Risk Perception Factors

Since human cognitive processes largely influence the risk perception (Lavell et al., 2012), I included the most common cognitive biases to estimate risk perception relating to natural hazards in this study. These factors were identified in existing literature from medical and psychology fields (Adams & Smith, 2001). Among the four typical mental biases—compression bias, availability heuristics, anchoring bias, and miscalibration—which are classified by Bogardus Jr, Holmboe, and Jekel (1999), anchoring bias (the tendency to rely heavily on one piece of information) and miscalibration (overconfidence about given facts) are less related to natural hazard risks due to the uncertain nature of climate disasters. Meanwhile, “availability heuristics” refers to the human tendency that relies more on immediate examples that quickly come to mind. This case suggests that a newer and more recent storm would have a greater influence on housing prices than one less recent. However, the availability heuristics category is insignificant for this study due to the relatively short study period with small storm samples. Contrarily, the myopia (discounting perceived risks from anticipated future disasters) and the concept of amnesia (forgetting past events over time; renamed as risk fadedness in this study), proposed by Pryce, Chen, and Galster (2011), are included in the risk perception framework due to the subjectivity of risk cognitions. For example, major factors that may influence risk perception would be storm frequency and time related variables.

In addition, insurance and government storm recovery grants could also have an influence on the individual risk cognition. Adaptation information can be another important factor in estimating effects of adaptation measures. Similar to the precedent studies that risk information without actual damage can also impact housing prices (Hallstrom & Smith, 2005; Troy & Romm, 2004), expected project information without actual completion or rumors even before announcing an adaptation project can influence adjacent property values.

Thus, the six factors of risk perception utilized for this study include: compression bias, risk fadedness, risk myopia, recovery grant effects, dispersion of risk, and expected project information (see Table 2). “Compression bias,” as discussed in psychology literature, refers to the human’s propensity to exaggerate rare risks and underestimate recurring risks. In this case, a less frequent storm experience would have a greater impact on housing prices. In order to identify the compression bias for this study, I constructed the storm frequency of each sold property within the period between buying and selling. Another factor to note here is “forgetfulness.” Risk awareness for a specific event typically decreases over time, unless it is traumatic. This human characteristic suggests that risk perception would be much stronger immediately after a hurricane strikes, then gradually fading out. To identify this risk fadedness effect, I created the elapsed periods between the previous storm strikes and home sales transaction dates after hurricanes within a specific effective period for each site. Since this effect would eventually vanish at some point, I set appropriate effective periods based on the storm frequencies and occurrence intervals of each study site—one-year for MDC and two-year post hurricane strikes for NYC—to measure the effect of risk fadedness.

By contrast, since the hurricane risk will never be eliminated, fear and anxiety about future risk could outweigh the positive effect of risk fadedness, and it could be even greater when homeowners experience a longer “peacetime.” However, it is also possible that homeowners can underestimate an anticipated future risk (Pryce, Chen, & Galster, 2011), because myopic tendency to unrealized future risks can offset the negative effects from the anxiety. To identify the effects of risk myopia (which is typically characterized by a tendency or an unwillingness to acknowledge the potential risks of future hurricane events), I constructed elapsed periods between sales transaction dates and the next hurricane strikes.

In order to measure the recovery grant and dispersion of risk effects, I also added recovery grant amounts approved by the Individual and Households Program (IHP) and a dummy variable that indicates flood insurance requirements for individual properties. To estimate the project information effect, I included another binary variable that specifies the sales transactions between initial announcement and actual completion dates of the adaptation projects.

Table 2. Description of common risk perception factors and measurement criteria

Factors	Determinants	Potential effects	Measurement criteria
Compression bias	More experience	Overestimating rare risks and underestimating common ones	Storm frequency of each sold property within the period between buying and selling
Risk fadedness	Length of time elapsed since previous event	Forgetting past events over time	Elapsed period of time between previous storm occurrence and home sales
Risk myopia	Intensity of anxiety with respect future risk event	Underestimating the anticipated risk of the occurrence future events	Elapsed period of time between the date of housing sales and the occurrence of next hurricane event
Recovery grant	Financial supports	Underestimating actually realized and/or potential risks	Recovery grant amounts approved by the Individual and Households Program
Dispersion of risk	Insurance coverage	Underestimating potential risks	Flood insurance requirements for individual properties
Project information	Rumors and information	Overestimating positive impacts of adaptation projects	Sales transaction prices between initial project announcement and actual completion dates

Climate Change Adaptation

More than 300 individual adaptation projects have been implemented in each region from 2010 to 2017. Lists of adaptation measures with detailed information are provided by Miami Dade County Emergency Management Office and New York Rising Community Reconstruction. The information includes project types and locations, initiation and completion dates, adaptation goals (i.e., which hazard to be addressed), construction stages, project costs, and detailed project descriptions. In order to analyze the effects of the implemented adaptation measures, I reclassify the individual projects into 8 categories.

Table 3. Major public climate adaptation projects and costs (2011– 2017)

Classification	Elements	Amounts (Million US\$)			
		MDC ¹		NYC ²	
Infrastructure hardening	Levee, Dike, Seawall, Flood protection berm, Breakwater, Elevating roadways, etc.	171	52.5%	108	6.7%
Critical facility hardening	Public service building reinforcement (excluding raising foundation)	91	27.9%	833	51.2%
Drainage improvement	Erosion control, Drainage and stormwater system, Beach nourishment, etc.	7	2.1%	237	14.6%
Emergency preparedness	Hurricane shelter, Back-up generators, Pump installation, At-risk building demolition, etc.	18	5.5%	21	1.3%
Recovery operation	Emergency repair for public infrastructure and critical facilities, etc.	39	12.0%	426	26.2%
Total		326	100%	1,625	100%

Notes: 1. Miami Dade County’s Local Mitigation Strategies from 2011 Q2 to 2017 Q4. 2. New York Rising Community Reconstruction from 2012 Q1 to 2016 Q4.

The first is “infrastructure hardening.” This project type includes levee construction or reinforcements, electric power utility projects, flood protection infrastructure, and elevating roadways. Since the effects of existing infrastructure would already be reflected in housing prices, only newly added or retrofitted projects since 2010 are considered. The second adaptation type is “critical facility hardening” and includes all projects related to public service building reinforcements. A third type is “drainage improvement.” Man-made green infrastructural projects, such as erosion control, stormwater system improvement, and beach nourishment, fall into this subcategory. The fourth type, “Coastal Barrier Resources System (CBRS)” such as wetlands, lagoons, and salt marshes. The fifth type is “emergency preparedness” and includes hurricane ready shelters, on-site power generators, and installation of pump stations. The sixth adaptation type is “recovery operation projects.” These include emergency repairs for damaged public infrastructure and facilities. The seventh type is “floodplain revision.” This type is a modification of base flood elevation by elevating either housing structure or land. The last type is

“individual building hardening” such as installing hurricane shutters, storm panels, and individual property-specific drainage improvements. The first six categories are public projects, each of which tend to be implemented by a local government. The last two types are private projects solely based on an individual homeowner’s decision.

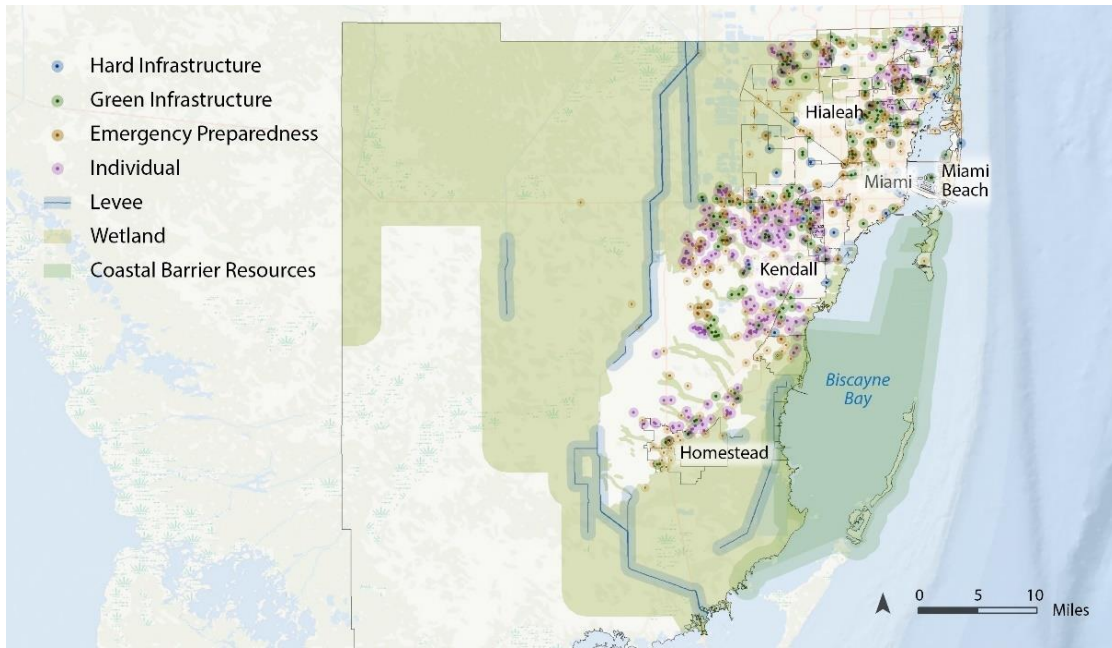


Figure 2. Map of site adaptation measures in MDC

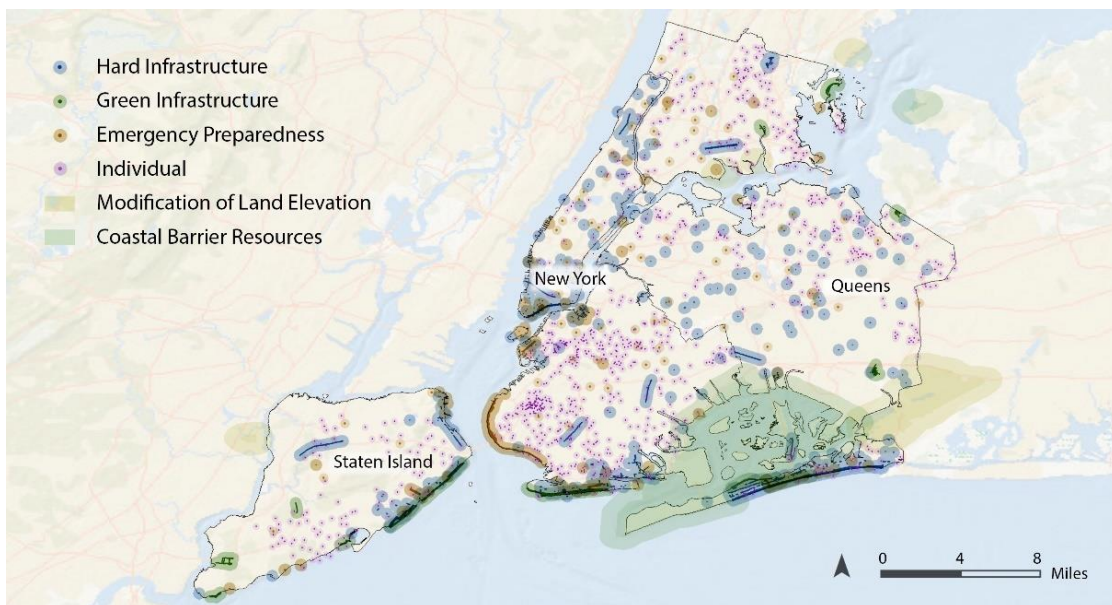


Figure 3. Map of site adaptation measures in NYC

4. Method

This study uses a panel data hedonic pricing model in combination with geospatial analysis. Hedonic pricing is an economic technique that decomposes a property's sale price into a set of non-market characteristics, thereby quantifying the effects of the inherent attributes associated with the property on housing sales price. I applied this pricing model to estimate the impacts of climate change adaptation measures on single-family housing transaction prices in MDC and NYC over the last decade. Due to the foreseeable effects of risk dynamics, this study also includes risk perception factors and individual storm characteristics. A semi-log model is widely adopted in the hedonic literature (Panduro & Veie, 2013). In addition, due to expected nonlinear effects and the overall site characteristics in this analysis (Freeman III, Herriges, & Kling, 2014), the multiple semi-log regression model is most suitable for examining the effects of climate change adaptation measures on property values.

Since individual adaptation projects have multi-valued attributes, constructing multiple classifications of adaptation measures is necessary to avoid a potential bias caused by categorizing the adaptation projects that can fall into more than one category. For example, on-site drainage can be improved by either infrastructure hardening, green infrastructural measure, or private implementation. Likewise, emergency preparedness can be achieved not only by public adaptation, but also by individually (e.g., private back-up electricity generator). To eliminate a potential bias caused by the multi-valued attribute, I included two additional adaptation classifications by recalibrating the adaptation projects based on (1) project characteristics and (2) hazard types which to be addressed (see Figure 4). Hence, a total of four sets of regressions are conducted.

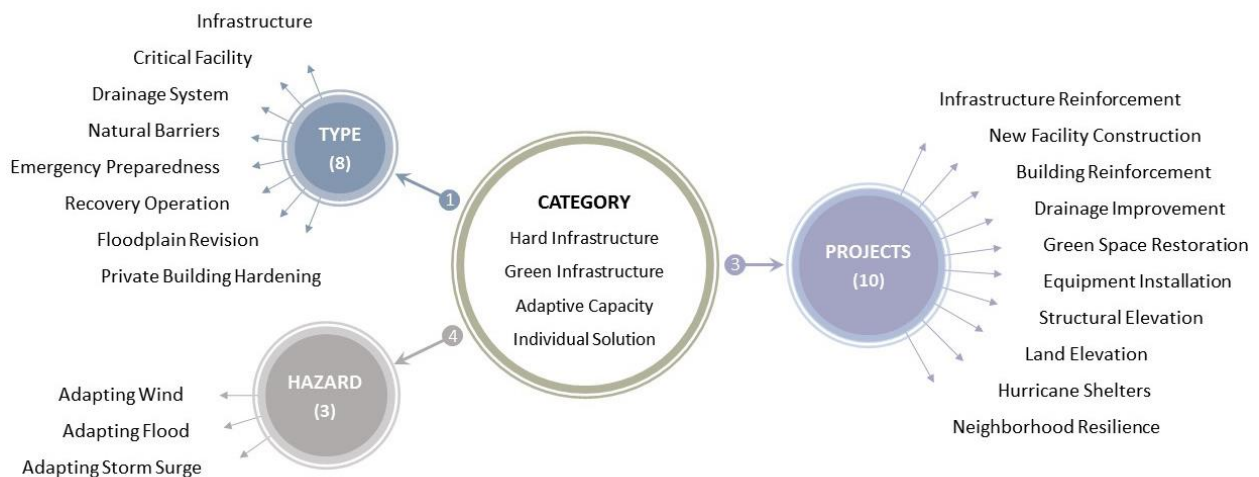


Figure 4. Analysis categories of adaptation measures

Table 4. Definition and summary statistics of variables

Region			MDC		NYC	
Category	Variables		Mean	S.D.	Mean	S.D.
	PRICE	Sales price of single-family home (\$100,000)	4.59	6.07	6.03	5.22
Housing	BEDROOM	Number of bedrooms	3.29	0.86		
Structure	BATHROOM	Number of bathrooms	2.22	1.07		
	BLDG_SF	Building square footage (thousands)	2.33	1.19	1.63	0.67
	AREA	Lot square footage (thousands)	10.31	8.53	3.28	2.32
	STORY	Number of stories	1.12	0.33	2.47	0.63
	BLDG_AGE	Building age (year)	50.21	20.57	74.32	26.97
	OCCUPANCY	1 if a property is owner-occupied; 0 otherwise	0.81	0.39	0.80	0.40
	G-ELEV	Ground elevation above sea level (feet)	8.17	2.46	57.47	46.42
Location	METRO	1 if a home is within 400m of metro stations; 0 otherwise	0.003	0.06	0.02	0.15
	BUS	1 if a home is within 400m of bus stops; 0 otherwise	0.66	0.47	0.23	0.42
	COMMERCIAL	1 if a home is within 400m of major malls; 0 otherwise	0.003	0.05	0.80	0.40
	SCHOOL	1 if a home is within 400m of schools; 0 otherwise	0.39	0.49	0.30	0.46
	BROWNFIELD	1 if a home is within brownfield sites; 0 otherwise	0.10	0.30	0.01	0.11
	GREEN_VIEW	1 if a home has a green space view; 0 otherwise	0.05	0.22	0.01	0.12
	GREEN_PROX	1 if a home is within 400m of green spaces; 0 otherwise	0.46	0.50	0.44	0.50
	OCEAN_VIEW	1 if a home has an ocean view; 0 otherwise	0.07	0.26	0.01	0.10
	OCEAN_PROX	1 if a home is within 400m of oceanfront; 0 otherwise	0.05	0.22	0.10	0.29
Market	UNEMPLOY	Annual unemployment rates by zip code	9.52	3.52	8.46	2.98
Factor	VACANCY	Annual vacancy rates by zip code	11.37	8.37	6.91	2.39
	INCOME	Annual median household income (thousand dollar) by zip code	51.59	19.33	65.14	15.45
Storm	H30-150	1 if a home sold between 30 and 150 days post-hurricanes	0.13	0.33	0.10	0.30
Impact	H150-300	1 if a home sold between 150 and 300 days post-hurricanes	0.14	0.35	0.12	0.33
	H300-450	1 if a home sold between 300 and 450 days post-hurricanes			0.13	0.34
	H450-600	1 if a home sold between 450 and 600 days post-hurricanes			0.13	0.33
	H600-750	1 if a home sold between 600 and 750 days post-hurricanes			0.14	0.35
	H750-900	1 if a home sold between 750 and 900 days post-hurricanes			0.15	0.36
Storm	WIND	Sustained wind speed (knots)	12.27	30.05	18.43	26.95
Feature	RAINFALL	Total amount of rainfall (inch)	1.10	2.36	1.53	2.44
	SURGE	Storm surge heights of affected homes (feet)	0.08	0.46	2.17	4.67
Risk	FREQUENCY	Number of hurricanes between buying and selling home	0.51	1.17	0.8	1.17
Perception	FADEDNESS	Elapsed period of time from hurricane to housing transactions	37	89	94	173
	MYOPIA	Elapsed periods between the date of housing sales and the next hurricane	729	654	574	568
	GRANT	1 if a home receives IHP grant (\$100,000); 0 otherwise	0.47	3.96	7.5	60.86
	INSURANCE	1 if an insurance purchase is required; 0 otherwise	0.36	0.48	0.04	0.20
	INFORMATION	1 if a home sold between project announcement and completion dates	0.01	0.11	0.01	0.11
Adaptation	T-INFRA	1 if a home is located within 400m of infra hardening; 0 otherwise	0.008	0.092	0.025	0.157
Type	T-FACILITY	1 if a home is located within 400m of facility hardening; 0 otherwise	0.004	0.067	0.029	0.168
	T-DRAINAGE	1 if a home is located within 400m of drainage projects; 0 otherwise	0.024	0.152	0.008	0.089
	CBRS	1 if a home is located within CBRS and wetland zones; 0 otherwise	0.166	0.372	0.004	0.065
	EMERGENCY	1 if a home is located within 400m of hurricane shelters; 0 otherwise	0.063	0.242	0.002	0.045
	RECOVERY	1 if a home is located within 400m of storm recovery; 0 otherwise	0.001	0.037	0.005	0.071
	LOMR	1 if a home modifies the base flood elevation; 0 otherwise	0.005	0.069	0.003	0.166
	PRIVATE	1 if a home reinforces house structures for hurricanes; 0 otherwise	0.004	0.060	0.010	0.098
Adaptation	P-INFRA	1 if a home is located within 400m of infra reinforcements; 0 otherwise	0.005	0.067	0.021	0.143
Project	P-FACILITY	1 if a home is located within 400m of new facilities; 0 otherwise	0.001	0.023	0.001	0.024
	BLDG_REINF	1 if a home is located within 400m of building hardening; 0 otherwise	0.001	0.032	0.013	0.113
	P-DRAINAGE	1 if a home is located within 400m of drainage projects; 0 otherwise	0.027	0.162	0.010	0.097
	RESTORATION	1 if a home is located within 400m of green restoration; 0 otherwise	0.166	0.372	0.007	0.081
	EQUIPMENT	1 if a home is located within 400m of equipment projects; 0 otherwise	0.001	0.037	0.001	0.035
	ELEV_STR	1 if a home is located within 400m of structural elevation; 0 otherwise	0.001	0.094	0.001	0.094
	ELEV_LAND	1 if a home is located within 400m of land elevation; 0 otherwise	0.005	0.069	0.003	0.166
	SHELTER	1 if a home is located within 400m of hurricane shelters; 0 otherwise	0.025	0.158	0.004	0.199
	CAPACITY	1 if a home is located within 400m of adaptive capacity; 0 otherwise	0.001	0.025	0.024	0.153
Adaptation	ADP-WIND	1 if a home is located within 400m of wind adaptation; 0 otherwise	0.002	0.045	0.015	0.122
Purpose	ADP_FLOOD	1 if a home is located within 400m of flood prevention; 0 otherwise	0.182	0.386	0.002	0.039
	ADP_SURGE	1 if a home is located within 400m of storm surge projects; 0 otherwise	0.020	0.139	0.007	0.081

Storm impacts on housing market:

The first set is to examine whether storms impact housing prices or not, because if there is no pricing effect in the first set, further finding the adaptation effects on housing prices are not logically meaningful. The second to fifth sets are to identify the risk perception and adaptation effects on housing prices. In order to estimate the storm impacts on housing transaction prices, I constructed specific sales time windows after each storm. As a rule of thumb, damage recovery generally takes about 5 months in the study areas, and the housing market remains relatively slow-moving. I set the market impact intervals for every 150 days. For example, the first sales time window includes all transactions between 30 and 150 days after each storm. The second window includes the transactions occurring between 150 and 300 days after an event. Since a given housing sales transaction typically takes around one month on average, the transaction decisions immediately after storm strikes would not be related to the storm experiences. Thus, the transactions within 30 days after storms were excluded from the first sales window. The equation of the first set for estimating storm effects in different sales windows is specified as follows:

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

where $\ln P_{ict}$ is the natural log of the inflation and seasonality adjusted sales price of single family property i in zip code c in time (date) t , α_{ct} are zip code–time effects, which allow for housing price variation over time at the zip code level, X_i and N_i are vectors of house and location characteristics with coefficient β and γ , respectively. M_{ict} is a vector of market factors to property i in zip code c in time (year) t with coefficient η . $Storm_{ict}$ is housing transaction dummies representing the sales windows post-hurricanes with 150 days interval (e.g. 30-150 days, 150-300 days, and 300-450 days) with coefficient δ , and ε_{ict} is an error-term of property i in zip code c in time (year) t . All specifications also include year and zip code dummies to control for time-specific and spatial fixed effects in the housing market. In all models, the standard errors are clustered at the zip code level.

The set of controls X_i includes 8 housing structural characteristics for MDC and 6 characteristics for NYC. The common variables are building square footage, lot size, stories, housing age, occupancy status, and land elevation. Since the information of bedroom and bathroom counts in NYC is not publicly available, these variables are included only in MDC's model specifications. N_i , the location characteristics, consists of 9 binary variables representing 5-minute walkability and views. The variables include subway stations, bus stops, major malls, schools, brownfields, green spaces, oceanfront, green space view, and ocean view. M_{ict} , the market characteristics, includes unemployment rates, vacancy rates, and median household incomes.

Valuing climate change adaptation measures:

The second to fourth sets estimate the pricing effects of adaptation measures on housing transactions. The model specifications include storm characteristics, as well as the factors that could influence risk perception in order to identify how storm heterogeneity and risk perception factors interact with the effects of adaptation measures.

To estimate the multi-valued attributes of adaptation measures, the equations for testing three reclassified categories of adaptation measures (by the attributes of adaptation type, project characteristics, and hazard type to be adapted) are as follows:

$$(2) \quad \ln P_{ict} = \alpha_{ct} + \beta' X_i + \gamma' N_i + \eta' M_{ict} \\ + \delta' H_{it} + \varphi' R_i + \sum_{j=1}^8 \sigma_j Type_{j,ict} + \varepsilon_{ict}$$

where H_{it} is a vector of hurricane characteristics to property i in time (year) t with coefficient δ and includes three damage types (flood, wind, and storm surge) in the specification. R_i is a vector of the risk perception factors to property i with coefficient φ . This attribute group includes storm frequencies to test compression bias; the elapsed date counts between storm strikes and home sales within a specific period (one year for MDC and two years for NYC) after a hurricane strikes for the effects of risk fadedness; the elapsed dates from a housing transaction to a next hurricane for the effects of risk myopia; the amounts of public grants; a binary variable for flood insurance requirement; and a dummy variable to distinguish home sold between adaptation project announcement and project completion dates for the effects of adaptation information. $Type_j$ is the eight variables of the adaptation project type and includes infrastructure, critical facility, drainage system, natural barriers (CBRS and wetlands), emergency preparedness, recovery operation, floodplain revision (raising land and structural foundation), and private building hardening that impact housing price within the distances of 400m from the individual adaptation project. To distinguish the effects of adaptation projects that have already been completed from the projects under construction at the point of sales transaction, I only include completed adaptation projects prior to a housing sale.

$$(3) \quad \ln P_{ict} = \alpha_{ct} + \beta' X_i + \gamma' N_i + \eta' M_{ict} \\ + \delta' H_{it} + \varphi' R_i + \sum_{j=1}^{10} \sigma_j Characteristics_{j,ict}$$

where $Characteristics_j$ is the eleven variables of the adaptation measures classified by project characteristics. This attribute group is recategorized by infrastructure reinforcement (levee, dike,

seawall, breakwater, etc.), new facility construction, public (existing critical facilities) and private (single-family houses) building reinforcement, drainage improvement, green space restoration, equipment installation, structural elevation, land elevation, hurricane shelters, and neighborhood system improvement projects (mainly adaptive capacity programs).

$$(4) \quad \ln P_{ict} = \alpha_{ct} + \beta'X_i + \gamma'N_i + \eta'M_{ict} \\ + \delta'H_{it} + \varphi'R_i + \sum_{j=1}^4 \sigma_j Hazard_{j,ict}$$

where $Hazard_j$ is the three variables which are classified by hazard types to be addressed by the adaptation measures and includes: wind, flood, and storm surge.

All other variables are the same as in model (1). Both time (year) and spatial (zip code) fixed effects are applied in all specifications, and the standard errors are clustered at the zip code level in each region.

5. Results and discussion

The regression results indicate that the relationship between the dependent variable and the independent variables is strong (adjusted $R^2 = 0.75$ and 0.63 for MDC and NYC, respectively). The majority of the variables' p -values are smaller than 0.05 , and the joint hypothesis f -statistics on each attribute group rejects the null hypothesis at the 1% level. Therefore, the panel data hedonic regressions are statistically significant.

Table 5. Results of hedonic regression (Model 1)

Category	Price (logged)	Model 1			
		MDC B	MDC β	NYC B	NYC β
Housing Structure	BEDROOM	0.021**	0.023**		
	BATHROOM	0.069**	0.092**		
	BLDG_SF	0.020**	0.291**	0.020**	0.251**
	AREA	0.001**	0.089**	0.004**	0.191**
	STORY	0.106**	0.044**	0.036**	0.042**
	BLDG_AGE	-0.002*	-0.047*	-0.002**	-0.083**
	OCCUPANCY	0.107**	0.052**	0.012**	0.009**
	G-ELEV	0.006	0.017	0.009**	0.078**
Location	METRO	-0.118**	-0.008**	-0.036	-0.010
	BUS	-0.065**	-0.039**	-0.018*	-0.014*
	COMMERCIAL	-0.005	-0.000	-0.044**	-0.033**
	SCHOOL	-0.036**	-0.022**	-0.016**	-0.013**
	BROWNFIELD	-0.135*	-0.050*	-0.039**	-0.008**
	GREEN_VIEW	-0.004	-0.001	0.033	0.007
	GREEN_PROX	-0.009	-0.006	0.011	0.010
	OCEAN_VIEW	0.140**	0.046**	0.036	0.007
	OCEAN_PROX	0.213**	0.058**	-0.073	-0.040
Market Factor	UNEMPLOY	-0.007	-0.030	-0.011**	-0.060**
	VACANCY	-0.327	-0.034	-0.117	-0.005
	INCOME	-0.003	-0.081	0.004**	0.142**
Storm Impact	H30-150	-0.024**	-0.010**	-0.020**	-0.011**
	H150-300	0.023**	0.010**	-0.032**	-0.020**
	H300-450			-0.016*	-0.010*
	H450-600			-0.031**	-0.019**
	H600-750			-0.006	-0.004
	H750-900			0.010*	0.007*
	Constant	12.042**		12.439**	
	Observations	79,184		90,811	
	Number of clusters (zip code)	64		157	
	Adjusted R^2	0.746		0.629	
	Spatial Fixed Effects (zip code)	YES		YES	
	Time Fixed Effects (year)	YES		YES	

Notes: * $p < 0.05$, ** $p < 0.01$. B, unstandardized coefficients; β , standardized coefficients.

As anticipated, all the housing structural variables have a positive relationship with transaction prices. More rooms and stories, larger building size and lot square footage, recently-built homes, and owner-occupied homes are associated with a housing sales price increase. Among the housing structural variables, the coefficients of building square footage and lot size variables in both regions are particularly strong (see Table 5, standardized beta coefficients).

Proximity to subway stations, bus stops, and schools has a negative relation to housing price in both regions. The “net nuisance” effect, caused by the public transportation and school proximity penalty such as traffic congestion and noise, could overshadow the proximity benefits (Sah, Conroy, & Narwold, 2016). Five-minute walkability to major commercial facilities, such as a major mall or shopping center, has a negative influence on housing prices in NYC. Since this variable is not statistically significant in MDC, the strength of nuisance or disamenity effects from having commercial facilities nearby, may also differ based upon population densities. Brownfields are negatively associated with housing prices at the 5% and 1% significance levels in MDC and NYC, respectively. Contrasting results of green space and ocean amenity variables were observed. As with the results on the green space variables in NYC, green space proximity and view often have a positive relation to housing prices in hedonic literature. However, these green space amenity variables have a negative sign, as well as not being statistically significant in MDC. A high outside temperature and the location of green spaces (about 50% of MDC’s parks are located within a 5-minute walking distance of coastlines) would counteract the positive green space effects in MDC. Based on my observation from a site visit, just a few dog sitters and homeless people used the parks and green spaces during the daytime. As expected, ocean view and oceanfront proximity are strong positive factors on housing prices in MDC, but surprisingly these coastal amenities are not statistically significant (at the 10% level) in NYC. From this result and the fact that MDC has many more accessible sandy beaches, I surmise that coastal recreation opportunities would boost positive effects of the coastal amenity on housing prices.

Storm impact on housing market

The regression results show that hurricanes have a strong adverse impact on housing transaction prices. The coefficient of *H30-150* variable implies that single-family properties sold between 30 and 150 days after a storm strike sell at a 2.4% and 2% discount on average compared with homes sold in the other period in MDC and NYC, respectively (see Table 5). The negative impact of the storm becomes positive after five months following storm occurrences in MDC, while the adverse effects persist much longer in NYC, lasting around a year and a half. This contradictory impact over time signifies that risk perception and job market factors may be stronger than the power of housing market dynamics. If hurricanes affect the local housing supply and demand, the coefficient of *H30-150* should be positive, due to the supply decrease caused by storm-induced property damages, but the negative result was observed in this study. This result indicates either the majority of hurricane damaged properties are still available in the market, or the local housing market dynamics are not much influenced by hurricanes. However,

two plausible factors (job market and risk perception) may explain that there are negative impacts on housing prices during the first five months, followed by positive turns. Since hurricanes cause demand shocks in the job markets (Belasen & Polachek, 2008), these unemployment shocks can trigger increases in mortgage delinquency and foreclosure rates, resulting in housing vacancy escalation. The economic decline caused by hurricanes deters the inflow of job seekers, and subsequently higher unemployment rates can negatively impact the housing transaction prices. Another reason would be that a stronger risk awareness makes people hesitate to buy-in. Consequently, housing demand decreases and, thus, housing prices drop for a few months.

Storm characteristics and risk perception factors:

The majority of the storm characteristics and risk factors impact housing transaction prices. Storms that are accompanied by more rainfall have a negative impact on housing prices in NYC. A stronger storm surge is also associated with housing sales price depreciation in both regions. Surprisingly, the results indicate that storms accompanying a higher wind speed have a positive influence on housing prices in NYC. A plausible explanation is that the wind factor often influences a storm's movement speed. It is not always the case, but generally the forwarding wind speed is one of the factors that determining the movement speed. If the movement speed is slow, greater flood damage would be anticipated due to increased rainfall on already fully saturated soils. Another possible reason supporting the result could include overestimation of wind factor in the hurricane information. Current hurricane intensity (i.e. the Saffir-Simpson Scale) is largely based on sustained wind speeds, excluding other significant factors. However, there is much historical evidence (such as Super Storm Sandy) to show that other storm characteristics should also be considered as well.

Among the risk perception variables, risk frequency factor has a negative effect on housing prices in MDC but is not statistically significant in NYC. The storm frequency is calculated by counting the number of storm experiences that a homeowner has before the home transaction to a new homebuyer, and the homeowner's risk perception to the storms is affected by the frequency because the compression bias is applied—more storm experiences would lead homeowners to underestimate the actual risks, while a rare storm experience exaggerates the home seller's risk cognition. Based on this notion, the counterintuitive result indicates that the compression bias would not be present in homes sold without any storm experience. In fact, about 82% of single-family homes (or 64,598) were transferred without having a storm experience in MDC, and 66% of properties (or 59,759) have been sold with no storms experienced by the home seller in NYC.

FEDEDNESS has a positive impact on housing prices in both regions, while *MYOPIA* and *GRANT* are associated with home prices increase in NYC but are not statistically significant in MDC. The results confirm that homeowners have tendencies to forget past events over time (risk fadedness effect) and to underestimate anticipated future disasters (risk myopia effect).

Table 6. Results of hedonic regression (Model 2-4)

Variables	Model 2		Model 3		Model 4	
	MDC	NYC	MDC	NYC	MDC	NYC
BEDROOM	0.021**		0.021**		0.020**	
BATHROOM	0.068**		0.069**		0.071**	
BLDG_SF	0.019**	0.020**	0.019**	0.020**	0.019**	0.020**
AREA	0.001**	0.004**	0.001**	0.004**	0.001**	0.004**
STORY	0.101**	0.036**	0.101**	0.036**	0.105**	0.036**
BLDG_AGE	-0.002*	-0.002**	-0.002	-0.002**	-0.002	-0.002**
OCCUPANCY	0.106**	0.012**	0.106**	0.012**	0.106**	0.012**
G-ELEV	0.013*	0.009**	0.014*	0.009**	0.013*	0.009**
METRO	-0.090*	-0.034	-0.106*	-0.033	-0.110**	-0.034
BUS	-0.055**	-0.018*	-0.056**	-0.019**	-0.053**	-0.019*
COMMERCIAL	-0.010	-0.042**	-0.021	-0.043**	-0.028	-0.043**
SCHOOL	-0.025*	-0.016**	-0.030**	-0.016**	-0.033**	-0.016**
BROWNFIELD	-0.136*	-0.042**	-0.135*	-0.044**	-0.134*	-0.041**
GREEN_VIEW	-0.005	0.031	-0.005	0.030*	-0.006	0.032
GREEN_PROX	-0.008	0.012	-0.007	0.011	-0.010	0.011
OCEAN_VIEW	0.117*	0.053	0.118*	0.050	0.124*	0.049
OCEAN_PROX	0.196**	-0.040	0.202**	-0.043	0.204**	-0.044
UNEMPLOY	-0.007	-0.011**	-0.007	-0.011**	-0.007	-0.011**
VACANCY	-0.293	-0.120	-0.280	-0.147	-0.307	-0.135
INCOME	-0.003	0.004**	-0.003	0.004**	-0.003	0.004**
WIND	0.003	0.008**	0.002	0.008**	0.002	0.008**
RAINFALL	-0.017	-0.098**	-0.016	-0.098**	-0.016	-0.099**
SURGE	-0.015*	-0.041**	-0.016*	-0.041**	-0.017*	-0.041**
FREQUENCY	-0.006**	0.030	-0.006**	0.029	-0.006**	0.030
FADEDNESS	0.013**	0.006*	0.013**	0.006*	0.013**	0.006*
MYOPIA	-0.002	0.007**	-0.003	0.007**	-0.003	0.007**
GRANT	0.032	0.003*	0.030	0.003*	0.030	0.003*
INSURANCE	0.069**	-0.070*	0.071**	-0.077*	0.077**	-0.075*
INFORMATION	0.056	-0.003	0.062	-0.001	0.062	-0.001
T-INFRA	0.265**	-0.028				
T-FACILITY	0.121*	0.023				
T-DRAINAGE	0.032	0.010				
CBRS	0.097**	0.027*				
EMERGENCY	-0.056*	0.071*				
RECOVERY	0.109	-0.136				
LOMR	-0.033	0.077**				
PRIVATE	0.049	0.101**				
P-INFRA			0.342**	-0.037		
P-FACILITY			0.357**	0.014		
BLDG_REINF			0.091**	0.071**		
P-DRAINAGE			0.038	0.020		
RESTORATION			0.099**	0.057**		
EQUIPMENT			0.046	0.102		
ELEV_STR			0.066**	0.143**		
ELEV_LAND			-0.035	0.077**		
SHELTER			-0.035	0.146		
CAPACITY			0.033	0.026		
ADP-WIND					0.023	0.042
ADP_FLOOD					0.053*	0.077
ADP_SURGE					0.158*	0.055**
Constant	11.927**	12.417**	11.919**	12.430**	11.921**	12.425**
Observations	79,184	90,811	79,184	90,811	79,184	90,811
Adjusted R ²	0.750	0.630	0.749	0.630	0.748	0.629

Notes: * $p < 0.05$, ** $p < 0.01$.

Surprisingly, having a mandatory flood insurance requirement is associated with housing price increases in MDC. A possible reason would be a limited supply of available housing inventory which is free from the flood insurance requirement. In fact, about 36% of MDC's single-family homes (or 28,816) are required to purchase flood insurance, while only 4% of single-family residences (or 3,792) in NYC are located within the mandatory flood insurance requirement zones. Thus, limited numbers of housing inventory that have no flood insurance requirement could make the insurance factor less significant than other location factors in relation to housing sales prices in MDC. The project information has no effect on housing prices in both regions. Although homeowners would have a positive expectation about future adaptive projects, the nuisance effects from the construction activities including noise, dust, and traffic congestion, would offset the positive effects.

Effects of adaptation measures:

The eight categories of adaptation measures were examined by estimating each type of application. Many of these adaptation measures in this classification are statistically significant, at the 5% level. CBRS and wetlands have a positive impact on housing transaction prices in both regions (See Table 6, Model 2). The green infrastructural projects in MDC are characterized by enhancing its functionality through expanding and retrofitting the existing features, while NYC projects have focused more on restoring natural elements such as green spaces and sand dunes. Regardless of this distinction, overall green infrastructural projects in both regions preserve accessibility to natural amenities and recreational opportunities as well as provide a similar function of planned retreat strategy by creating room to mitigate adverse impacts of hurricanes.

Infrastructure hardening and critical facility reinforcement projects are associated with housing price increases, while modifying floodplain has a strong positive impact in NYC. The detailed project profiles distinguish that MDC has invested in active infrastructural projects including levee reinforcement and construction of flood protection berms. Meanwhile, the majority of NYC's infrastructural projects were relatively small and passive infrastructural projects, such as roadway elevation, pavement resurfacing, and breakwater installation for erosion controls. These passive infrastructural projects would not have an influence as strong as the impact of active infrastructural projects on an individual homeowner's risk cognition.

EMERGENCY variable has a contradictory result—emergency preparedness projects including hurricane shelters have a negative impact on housing prices in MDC. In contrast, a positive impact on the same variable is observed in NYC. Hurricane shelters in MDC are mostly located in distressed areas, whereas the shelters in NYC are distributed more evenly. Although the zip code fixed effect is applied in the analysis model, the fixed effect does not capture this finer market characteristic. No impact on drainage improvement and recovery operation variables is observed at the 10% significance level in both regions.

To specify the effects of multi-valued assets, all the adaptation projects were reclassified by 10 adaptation project characteristics. The majority of tested variables are statistically significant at the 1% level. Building reinforcement, green space restoration, and structural elevation have a positive impact on housing transaction prices in both regions (see Table 6, Model 3). In addition, infrastructure reinforcement and new facility construction are associated with housing price appreciation in MDC, while raising base flood land elevation has a positive impact in NYC. Infrastructure reinforcement and new facility variables in MDC have particularly strong coefficients, while structural elevation projects produce relatively higher coefficients in NYC.

With respect to another set of reclassifications by adaptation projects for each of three hazard types, the projects that address flood and storm surge are positively associated with housing prices in MDC. In NYC, only the adaptation projects for storm surge protection have a positive impact on housing transaction prices. Particularly strong coefficient values were observed for the storm surge adaptation projects for MDC (see Table 6, Model 4).

Taken together, the following three attributes: the natural green infrastructural measures (such as coastal barrier resources and wetlands), building reinforcement (especially by structural elevation), and projects to prepare for storm surge are revealed to have positive pricing factors with the statistical significance of p -value less than 5% in both regions. By region, the positive effects of publicly operated hard and green infrastructure measures are pronounced in MDC; while the positive impacts of private (individual) adaptation measures, such as private building reinforcement, raising house foundation, modifying land elevation, are particularly strong in NYC.

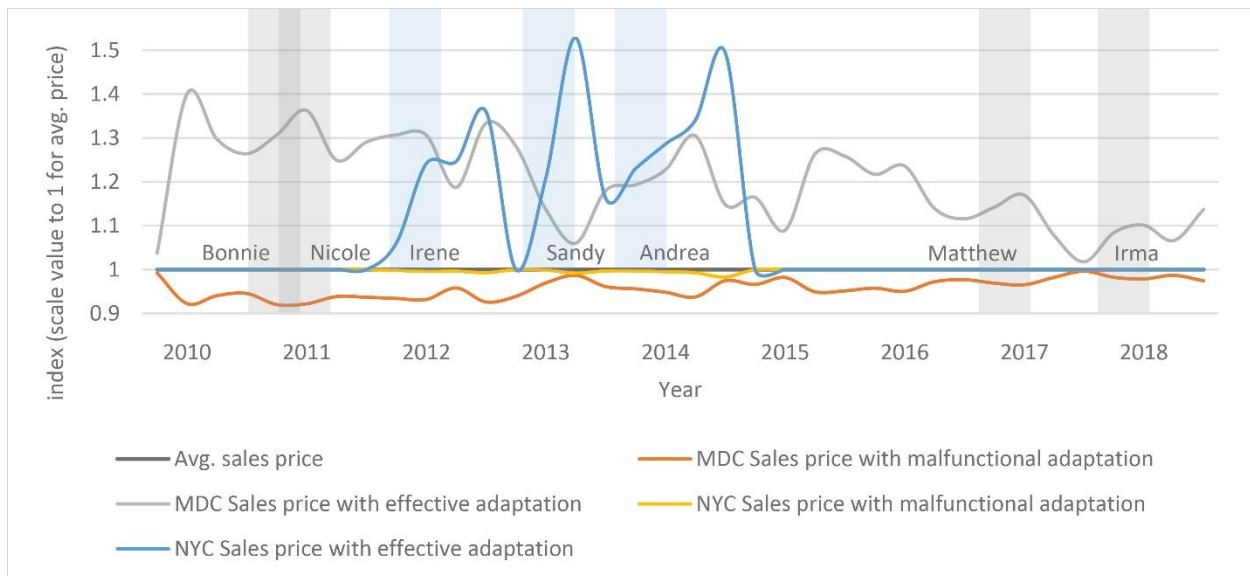


Figure 5. Home sales price changes based on the effectiveness of adaptation measures (scale value to 1 for avg. price)

To identify the market effects of adaptation efficacy, I normalized housing sales prices that affected by well-functioning and malfunctioning adaptation measures respectively to the average transaction prices of the homes sold within the first sales window. The indexed values indicate that effective adaptation measures (homes affected by the adaptation measures that have a positive impact on housing prices in each site) generally appreciate sales prices faster within 5 months of hurricane occurrences in both regions. Similarly, when adaptation is malfunctioning (homes influenced by the adaptation measures that have no impact or negative values), a rapid depreciation is also observed in MDC within the same period (see Figure 5).

With respect to the discrepancy of the analysis results between both regions, I assume that the effects of local adaptation measures interact with regional idiosyncrasies such as socio-environmental characteristics, urban structures, and economic conditions. For instance, MDC has a stronger capacity to deal with major storms due to more frequent experiences. Storm surge and flood vulnerabilities in NYC could be greater than MDC, because NYC has a much higher population density than MDC, as well as a particular geographic characteristic called “New York Bight” (a curve shaped indentation where the New York and New Jersey coastlines meet). In fact, when Super Storm Sandy made landfall in NYC in 2012, it had been downgraded to an “Extratropical Storm” with less than 1 inch of rainfall. However, the damages from the accompanying storm surges were disastrous, due to the dense population and at-risk infrastructure, such as underground tunnels and transportation (Gerstacker, 2015). Thus, it is not surprising that the impacts of land and structural elevation projects on housing prices are pronounced in NYC.

In addition, scales and amounts of local investments on adaptation measures would also be a significant impact factor. For example, MDC has invested more on infrastructure and critical facility hardening projects, whereas a considerable numbers of building reinforcement projects have been implemented by individual homeowners in NYC. As a result, a particularly strong impact has been observed on public infrastructure adaptation measures in MDC and private solutions in NYC. Costs of adaptation could also be localized and thereby offsetting direct benefits of adaptation—since main beneficiaries of nearshore structural protections are most likely homeowners in proximity to the shoreline, local governments could charge these homeowners a levy to cover expenses of bond issuance of new construction and maintenance (Jin et al., 2015). Potential economic benefits of risk reduction by such protective measures could be offset by the special tax imposition. Therefore, the effects of adaptation measures should rely more on locally analyzed results.

6. Conclusion

This study contributes to the literature on the effects of climate change adaptation measures on risk perception as well as real estate market. Using single-family housing transactions, major storm data, and implemented adaptation measures over the last decade, I have examined how the adaptation measures, in interacting with risk perception and storm specific characteristics, influence housing markets in these coastal communities. The results shed light on implemented climate adaptation effects on housing market dynamics. From the first set of analysis models, I confirmed that the impacts of major storms on coastal housing prices are closely related to a temporary change in housing prices.

The study highlights the fact that risk perceptions are influenced by the effects of adaptation measures is confirmed. Having natural green infrastructural adaptation projects within a 400-meter proximity is associated with a housing price appreciation by 9.7% in MDC and 2.7% in NYC (holding all other variables constant). Structural elevation provides a 6.6% housing price appreciation in MDC and 14.3% in NYC, respectively. Adapting for storm surges provides the largest positive impact on housing prices by 15.8% in MDC among the variables that have a consistent result throughout the regions. Unlike other large-scale development projects or urban infrastructure provisions, adaptation project information does not effectively influence reducing adverse storm risks due to “net negative nuisance” effects.

Together, adaptation effects and market resilience can be improved by the following recommendations for each region. For MDC, current parks and green spaces are not functionally effective because of the low utilization and potential backyard effects—i.e. private backyards have more value than public open spaces (Peiser & Schwann, 1993). Improving the design of parks and green spaces by adding adaptive functions can enhance community resilience. Although hard and green infrastructural adaptive measures provide a strong positive impact on housing prices, investment on drainage improvement is far behind (2.1% of their overall adaptation budget spending). Utilizing these positive attributes of hard and green infrastructure for drainage improvement, such as expanding canal and riparian buffers, could effectively decrease potential flood risk.

For NYC, the study suggests that hard infrastructural projects have a negative influence on housing prices due to scale and distribution issues. In this case, protecting key urban infrastructure, such as subway systems and underground tunnels, could be more effective for housing market resilience because such measures can enhance adaptive capacity in this high density setting. Furthermore, recovery operation does not improve adaptive capacity (because it does not exceed the level of past capacity), while investment for emergency preparation projects is very low, as much as 1.3% of their total spending on adaptation. In this respect, establishing emergency preparation funding and grant programs would be a potential solution to enhance market resilience.

These complementary policy suggestions may possibly lead a convergence between public and private adaptations. Since a relatively short history of active investments on mitigating climate risks resulted in imbalance of climate strategies due to its local dependency character, the local governments may invest more in the projects that they have neglected so far. Consequently, future adaptation measures would be more balanced, mixed, and moved toward to convergence.

Since climate risk is unavoidable in coastal areas, an accurate understanding of the effects of adaptation measures on housing prices will greatly help those who engage in real estate investment and development in coastal areas. Furthermore, this study helps to provide a clearer understanding of how climate adaptation efforts and their interaction with storm characteristics and risk perception can also be directly or indirectly related to improving a coastal community resiliency.

References

- Adams, A., & Smith, A. (2001). Risk perception and communication: recent developments and implications for anaesthesia. *Anaesthesia*, 56(8), 745-755.
- Atreya, A., & Czajkowski, J. (2014). Is flood risk universally sufficient to offset the strong desire to live near the water. *Risk Management and Decision Processes Center, The Wharton School of the University of Pennsylvania*.
- Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the flood? An analysis of the flood risk discount over time. *Land Economics*, 89(4), 577-596.
- Barbier, E. B. (2014). A global strategy for protecting vulnerable coastal populations. *Science*, 345(6202), 1250-1251.
- Belasen, A. R., & Polachek, S. W. (2008). How hurricanes affect wages and employment in local labor markets. *American Economic Review*, 98(2), 49-53.
- Below, S., Beracha, E., & Skiba, H. (2017). The Impact of Hurricanes on the Selling Price of Coastal Residential Real Estate. *Journal of Housing Research*, 26(2), 157-178.
- Benson, E. D., Hansen, J. L., Schwartz, A. L., & Smersh, G. T. (1998). Pricing residential amenities: the value of a view. *The Journal of Real Estate Finance and Economics*, 16(1), 55-73.
- Beracha, E., & Prati, R. S. (2008). How major hurricanes impact housing prices and transaction volume. *Real Estate Issues - American Society of Real Estate Counselors*, 33(1), 45.
- Bin, O., Crawford, T. W., Kruse, J. B., & Landry, C. E. (2008). Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics*, 84(3), 434-448.
- Bin, O., Kruse, J. B., & Landry, C. E. (2008). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *Journal of Risk and Insurance*, 75(1), 63-82.
- Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, 65(3), 361-376.
- Bin, O., & Polasky, S. (2004). Effects of flood hazards on property values: evidence before and after Hurricane Floyd. *Land Economics*, 80(4), 490-500.
- Bobbins, K., & Culwick, C. (2016). A framework for a green infrastructure planning approach in the Gauteng City-Region.
- Bogardus Jr, S. T., Holmboe, E., & Jekel, J. F. (1999). Perils, pitfalls, and possibilities in talking about medical risk. *JAMA*, 281(11), 1037-1041.
- Boulton, E. (2016). Climate change as a 'hyperobject': a critical review of Timothy Morton's reframing narrative. *Wiley Interdisciplinary Reviews: Climate Change*, 7(5), 772-785.
- Bunten, D., & Kahn, M. E. (2017). Optimal real estate capital durability and localized climate change disaster risk. *Journal of Housing Economics*, 36, 1-7.
- Chivers, J., & Flores, N. E. (2002). Market failure in information: the national flood insurance program. *Land Economics*, 78(4), 515-521.

- Conroy, S. J., & Milosch, J. L. (2011). An estimation of the coastal premium for residential housing prices in San Diego County. *The Journal of Real Estate Finance and Economics*, 42(2), 211-228.
- Costanza, R., Pérez-Maqueo, O., Martinez, M. L., Sutton, P., Anderson, S. J., & Mulder, K. (2008). The value of coastal wetlands for hurricane protection. *AMBIO: A Journal of the Human Environment*, 37(4), 241-248.
- Daniel, V. E., Florax, R. J., & Rietveld, P. (2009). Flooding risk and housing values: An economic assessment of environmental hazard. *Ecological Economics*, 69(2), 355-365.
- de Coninck, H., Revi, A., Babiker, M., Bertoldi, P., Buckeridge, M., Cartwright, A., . . . Hourcade, J.-C. (2018). Strengthening and implementing the global response.
- Dumm, R., Sirmans, G. S., & Smersh, G. (2012). Building code, wind contours, and house prices. *Journal of Real Estate Research*, 34(1), 73-98.
- Ewing, B. T., Kruse, J. B., & Wang, Y. (2007). Local housing price index analysis in wind-disaster-prone areas. *Natural Hazards*, 40(2), 463-483.
- Fell, H., & Kousky, C. (2015). The value of levee protection to commercial properties. *Ecological Economics*, 119, 181-188.
- Freeman III, A. M., Herriges, J. A., & Kling, C. L. (2014). *The measurement of environmental and resource values: theory and methods*: Routledge.
- Gerstacker, D. (2015, September 21, 2015). The Most Hurricane-Prone U.S. States. Retrieved from <https://www.theactivetimes.com/adventure/survival/most-hurricane-prone-us-states>.
- Graham, E., Hall, W., & Schuhmann, P. (2007). Hurricanes, catastrophic risk, and real estate market recovery. *Journal of Real Estate Portfolio Management*, 13(3), 179-190.
- Green, T. L., Kronenberg, J., Andersson, E., Elmqvist, T., & Gomez-Baggethun, E. (2016). Insurance value of green infrastructure in and around cities. *Ecosystems*, 19(6), 1051-1063.
- Hallstrom, D. G., & Smith, V. K. (2005). Market responses to hurricanes. *Journal of Environmental Economics and Management*, 50(3), 541-561.
- Hino, M., Field, C. B., & Mach, K. J. (2017). Managed retreat as a response to natural hazard risk. *Nature Climate Change*, 7(5), 364.
- Jin, D., Hoagland, P., Au, D. K., & Qiu, J. (2015). Shoreline change, seawalls, and coastal property values. *Ocean & Coastal Management*, 114, 185-193.
- Kousky, C. (2010). Learning from extreme events: Risk perceptions after the flood. *Land Economics*, 86(3), 395-422.
- Landry, C. E., & Hindsley, P. (2011). Valuing beach quality with hedonic property models. *Land Economics*, 87(1), 92-108.
- Lavell, A., Oppenheimer, M., Diop, C., Hess, J., Lempert, R., Li, J., . . . Myeong, S. (2012). Climate change: new dimensions in disaster risk, exposure, vulnerability, and resilience.
- McKenzie, R., & Leventis, J. (2010). Flood hazards and urban housing markets: The effects of Katrina on New Orleans. *The Journal of Real Estate Finance and Economics*, 40(1), 62-76.

- Mendelsohn, R. (2000). Efficient adaptation to climate change. *Climatic Change*, 45(3-4), 583-600.
- Meyer, R. J., Baker, J., Broad, K., Czajkowski, J., & Orlove, B. (2014). The dynamics of hurricane risk perception: Real-time evidence from the 2012 Atlantic hurricane season. *Bulletin of the American Meteorological Society*, 95(9), 1389-1404.
- Mills-Knapp, S., Bourdeau, E., Falco, G., Resler, C., Tovar, H., & Zoegall, S. (2011). Climate change adaptation and sustainable design at the port authority of New York and New Jersey. In: May.
- Murphy, A., & Strobl, E. (2009). The impact of hurricanes on housing prices: evidence from US coastal cities.
- O'Brien, K., & Selboe, E. (2015). *The adaptive challenge of climate change*: Cambridge University Press.
- Ortega, F., & Taspinar, S. (2017). Rising Sea Levels and Sinking Property Values: The Effects of Hurricane Sandy on New York's Housing Market.
- Otto, P., Mehta, A., & Liu, B. (2018). Mind the gap: Towards and beyond impact to enhance tropical cyclone risk communication. *Tropical Cyclone Research and Review*, 7(2), 140-151.
- Panduro, T. E., & Veie, K. L. (2013). Classification and valuation of urban green spaces—A hedonic house price valuation. *Landscape and Urban planning*, 120, 119-128.
- Peiser, R. B., & Schwann, G. M. (1993). The private value of public open space within subdivisions. *Journal of Architectural and Planning Research*, 91-104.
- Pompe, J. J. (1999). Establishing fees for beach protection: paying for a public good. *Coastal Management*, 27(1), 57-67.
- Pryce, G., Chen, Y., & Galster, G. (2011). The impact of floods on house prices: an imperfect information approach with myopia and amnesia. *Housing Studies*, 26(02), 259-279.
- Rosenzweig, C., Solecki, W. D., Blake, R., Bowman, M., Faris, C., Gornitz, V., . . . Leichenko, R. (2011). Developing coastal adaptation to climate change in the New York City infrastructure-shed: process, approach, tools, and strategies. *Climatic Change*, 106(1), 93-127.
- Sah, V., Conroy, S. J., & Narwold, A. (2016). Estimating school proximity effects on housing prices: The importance of robust spatial controls in hedonic estimations. *The Journal of Real Estate Finance and Economics*, 53(1), 50-76.
- Smith, A. (2018). 2017 U.S. billion-dollar weather and climate disasters: a historic year in context. Retrieved from <https://www.climate.gov/news-features/blogs/beyond-data/2017-us-billion-dollar-weather-and-climate-disasters-historic-year>.
- Troy, A., & Romm, J. (2004). Assessing the price effects of flood hazard disclosure under the California natural hazard disclosure law (AB 1195). *Journal of Environmental Planning and Management*, 47(1), 137-162.
- Watson, K. B., Ricketts, T., Galford, G., Polasky, S., & O'Neil-Dunne, J. (2016). Quantifying flood mitigation services: The economic value of Otter Creek wetlands and floodplains to Middlebury, VT. *Ecological Economics*, 130, 16-24.