Valuing Adaptation: Real Estate Market Responses to Climate Change Adaptation Measures

Valuing adaptation:

Real estate market responses to climate change risk reduction measures

A dissertation presented

by

Seung Kyum Kim

to

Harvard University Graduate School of Design

in partial fulfillment of the requirements

for the degree of

Doctor of Design

Harvard University

Cambridge, Massachusetts

February 2019

Dissertation Advisor: Professor Richard B. Peiser Seung Kyum Kim

Valuing Adaptation:

Real Estate Market Responses to Climate Change Adaptation Measures

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.

This study highlights that natural green infrastructure as a climate adaptation measure is associated with a housing price appreciation of 9.6% in Miami-Dade County and 2.7% in New York City. Structural elevation achieved by raising foundations provides 6.6% and 13.8% in housing price increases in Miami-Dade County and New York City, respectively. Adaptation measures for storm surges provide the largest positive impact on housing prices at 15.4% 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. Together, this study helps to provide 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.

Table of Contents

Appendix

Acknowledgements

With a deep sense of gratitude, I wish to express my sincere thanks to all those who gave me the opportunity to complete this dissertation.

Especially, I would like to express my deepest gratitude to my advisor, Professor Richard Peiser. He has been an excecellent supervisor and a great mentor. He also guided my transformation from a landscape architect to a real estate and urban scholar. Professor Peiser's great experience and keen insight into the field of real estate and urban studies inspired me throughout my doctoral research.

I would also like to thank my committee members, Professor Peter Rowe and Professor James Hammitt, for their tireless support and invaluable comments.

I also thank the John R. Meyer Dissertation Fellowship at the Harvard Joint Center for Housing Studies and the Real Estate Research Grant Program at the GSD for their financial support and data consultation.

Finally, I feel a deep sense of gratitude toward my parents and all of my family members. They rendered me enormous support during my study. Without their dedication and encouragement, this accomplishment would not have been possible. I would like to thank all those whose direct and indirect support helped me complete my doctoral degree.

List of Common Acronyms

ACS	American Community Survey
BEF	Base Flood Elevation
CBRS	Coastal Barrier Resources System
ET	Extratropical Cyclone
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Rate Map
GIS	Geographic Information Systems
IHP	FEMA Individuals and Households Program
IPCC	Intergovernmental Panel on Climate Change
LOMR	Letter of Map Revision
MDC	Miami-Dade County
NFIP	National Flood Insurance Program
NHC	National Hurricane Center
NOAA	National oceanic and Atmospheric Administration
NWS	National Weather Service
NYC	New York City
SFHA	Special Flood Hazard Area
SLOSH	Sea, Lake, and Overland Surges from Hurricanes
TD	Tropical Depression
TS	Tropical Storm
USACE	The U.S. Army Corps of Engineers
USFWS	U.S. Fish and Wildlife Service
ZCTA	ZIP Code Tabulation Areas

List of Tables

List of Figures

All figures by the author unless otherwise noted.

1. Introduction

As climate change accelerates, extreme meteorological events such as coastal floods and storm surges have been occurring more frequently and with greater intensity (Rosenzweig et al., 2011). The ramifications of climate change cause 400,000 human deaths per year globally in coastal regions and decimates approximately 1.6% of global GDP annually (Fatemi & Fooladi, 2013). According to the National Oceanic and Atmospheric Administration (NOAA, 2018), Hurricane Harvey in 2017 alone caused a total damage amount of $125 billion within the United States. Hurricane Irma in the same year destroyed 25% of buildings in the Florida Keys. Moreover, the frequency of billion-dollar disaster events in the recent five years has doubled[1] from the average frequency between 1980 and 2016 (Smith, 2018).

In spite of the increase in disruptive climatic risks, coastal population density has grown, fueled by 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—spatial coexistence of urban growth and risk increase—causes exponential increase of vulnerability to climate risk, drawing our attention to climate adaptation.

To mitigate this lurking risk, managed retreat and relocation options have been widely discussed among planners and policy makers (Alexander, Ryan, & Measham, 2012; French, 2006; Reisinger et al., 2014). However, these coping strategies are highly unfavorable due to their

[1] An annual average frequency of billion-dollar (CPI-adjusted) disaster events from 1980 to 2016 is 5.8, while the average frequency over the last 5 years (2013-2017) is 11.6 (Smith, 2018).

financial burden, legal conflicts, and numerous socio-cultural issues (Hino, Field, & Mach, 2017). Consequently, coastal developers seek the most reliable adaptation strategies, generally in the categories of "protection"[2] and "accommodation"[3] to curb potential asset value degradation due to climate change (Bunten & Kahn, 2017; Mills-Knapp et al., 2011). Some home owners are purchasing expensive insurance or raising foundations to deal with potential flooding. Many coastal cities and municipalities are allocating a considerable amount of their budget toward climate change adaptation projects, including seawall and dike constructions, pump station installations, and shoreline erosion controls (Azevedo de Almeida & Mostafavi, 2016).

However, existing literature has paid insufficient attention to measuring the direct impacts of existing climate change adaptation measures in real estate markets in a comparative manner. This is primarily due to the unpredictability of the risks, their long-term[4] nature, and real estate market dynamics. Furthermore, due to its massive scale and complexity, climate change knowledge and information are mainly developed at a global level, rather than a regional level. Thus, the global level climate change model could be inadequately translated to the finer local level, resulting in over-reaction or underestimation of climate risks (Termeer et al., 2011).

Another caveat should be noted that climate risk perception is subjective, volatile, and "emotional and conceptual territory," which is deeply associated with individual sentiment, culturally influenced, and dependent upon individual memory and history (Boulton, 2016). On

[2] This adaptive classification includes not only hard structural measures such as dikes, seawalls, and levees, but also consists of green infrastructural measures including beach nourishment and the conservation of coastal ecosystems through soft technologies (Mimura, 2010).

[3] Accommodation includes adaptation policies (e.g., land use pattern changes and disaster insurance) and green infrastructural measures such as coastal ecosystem protection (Mimura, 2010).

[4] That is, a timescale that depends on uncertain climatic forecasting.

the other hand, climate change is also "massively distributed in time and space relative to humans" (Morton, 2013). Thus, threats of extreme weather may not be adequately responded at the human scale, due to their inability to completely experience this vast phenomenon at the equivalent level of the actual severity (Loewenstein & Schwartz, 2010; Morton, 2013). Although considering some other socio-economic theories, such as a network theory[5] of risk perception contagion, and applying sophisticated statistical techniques can address to some degree these shortcomings, current scientific data-driven measurements may not fully explain such vast phenomena as a whole (Morton, 2013; Scherer & Cho, 2003).

Despite this complexity, the impacts of these risk perception and climate adaptive measures can be alternatively measured through tangible assets such as housing transaction prices or analyzing real estate investment patterns in a comparative manner. For instance, if perceived risk is decreased due to adaptation measures, holding all other market factors constant, then more investment activities will be observed, or at least housing prices will increase.

Therefore, this study examines two major research questions to confirm the aforementioned hypothesis. First, how hurricanes impact housing market dynamics in two coastal built-up areas, both of which are highly vulnerable to extreme weather events, but in each a different risk perception of hurricanes might exist due to differences in hurricane frequency, intensity, and the amount of damages caused. Second, how the effects of adaptation measures, when interacting with hurricane characteristics and risk perception, can be changed and adjusted into individual housing transactions. In order to diagnose the efficiency of the multi-valued adaptation strategies

[5] This theory suggests that social networks influence individual perceptions by grouping "like-minded" individuals and create similar risk perceptions (Scherer & Cho, 2003).

on the housing markets, the adaptation projects are reclassified by five topics: adaptation types[6], adaptation techniques[7], project characteristics[8], hazard types[9], and project attributes[10]. Overall, the findings suggest the optimal strategies for sustainable real estate markets and improving resilience to future climate change.

---

[6] This category is classified based on the types of adaptation projects and includes eight subcategories: infrastructure, critical facility reinforcement, drainage system improvement, natural barriers, emergency preparedness, recovery operation, floodplain revision, and private building reinforcement.

[7] This refers to the techniques that have been used to implement the adaptation projects, and this category includes elevation, construction, reinforcement, equipment installation, demolition, and system improvement.

[8] All adaptation projects were classified by a total of 11 project characteristics. This category includes infrastructure reinforcement, new facility construction, existing building reinforcement, drainage improvement, green space restoration, equipment installation, structural elevation, land elevation, hurricane shelters, evacuation bus stops, and neighborhood resilience.

[9] Since the magnitude of damages could vary depending on the hazard types, it is important to consider what hazard types the adaptation projects aim to address. In this category, the most frequent hazard types are included (wind, flood, and storm surge) as they are described in the National Hurricane Center's storm reports. There is also included a multi-purpose type which combines other types, where meaningful.

[10] This category refers to instances of adaptation projects whether they are new, upgraded, repaired, existing, or removed projects.

2. Literature Review

A number of studies develop adaptation concepts and classifications (Hay & Mimura, 2006; McCarthy et al., 2001; Mendelsohn, 2000), identify risks and amenity effects on property values (Bin, Kruse, & Landry, 2008; Landry & Hindsley, 2011; Rambaldi, Ganegodage, & McAllister, 2017; Samarasinghe & Sharp, 2010), and assess economic evaluation methods and funding mechanisms for adaptation strategies (Banhalmi-Zakar et al., 2016; Brouwer & Van Ek, 2004; Chambwera et al., 2014; de Bruin et al., 2009). Several studies explore the relationship between hurricanes and housing market dynamics (Below, Beracha, & Skiba, 2017; Graham Jr & Hall Jr, 2001; Hallstrom & Smith, 2005; Murphy & Strobl, 2009). Other studies have also attempted to quantify the effects of hurricane characteristics and indirect factors associated with the risks and housing price interactions. This chapter reviews existing literature on each of the abovementioned topics.

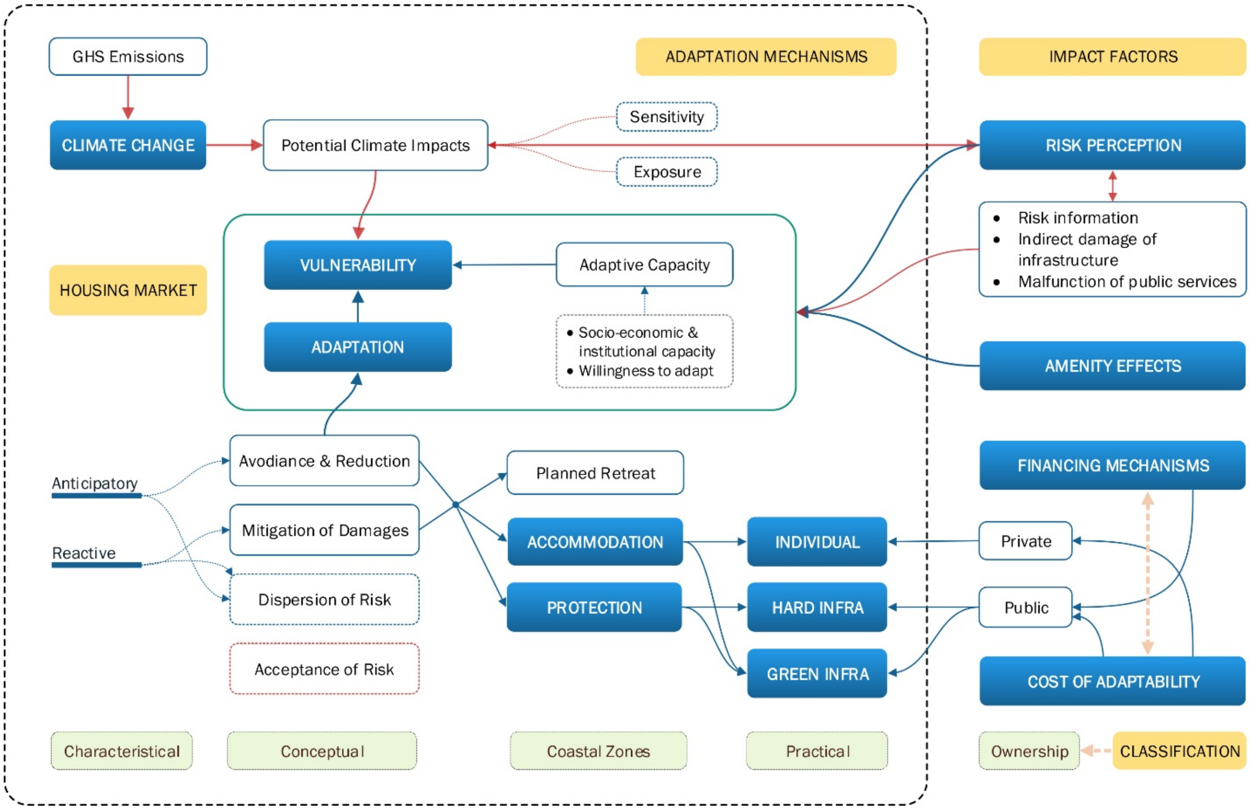


Figure 1. Conceptual diagram of climate change adaptation.

2.1 Climate Adaptation: Concepts and Classifications

The Intergovernmental Panel on Climate Change (IPCC, 1990) defines climate adaptation as "the process of adjustment to actual or expected climate and its effects." Similarly, recent literature defines climate adaptation as efforts to alleviate or prevent harm, caused by expected or unexpected climate change, from adversely affecting human and natural systems by human intervention (Field et al., 2014). This human intervention, to alleviate or prevent climate disasters, has been undertaken mainly through policies, infrastructural investments, and development of technology throughout the past century. In more recent decades, considerable attention has been devoted to the systematic characteristics of adaptation that influence a community's ability to adapt and their priority for adaptation measures. These characteristics have been called "determinants of adaptation," because these characteristics influence (promote, stimulate, dampen, or exaggerate) the nature of adaptations (IPCC, 2007). To differentiate the systematic characteristics, generic concepts (see Figure 2) such as vulnerability[11], sensitivity[12], adaptive capacity[13], resilience[14], and flexibility[15] have been widely used according to their need for adaptation (Adger & Kelly, 1999; Klein & Tol, 1997; Smithers & Smit, 1997). These

[11] Vulnerability is the predisposition of people, wealth, and landscape to be adversely affected (Pachauri et al., 2014). "Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (Smith et al., 2014). Reducing vulnerability can be achieved by enhancing the adaptive capacity and effectiveness of adaptation strategies (Isoard, Grothmann, & Zebisch, 2008).

[12] Sensitivity defines as the degree to which a system is affected, either adversely or beneficially, by climate variability (Gallopín, 2006).

[13] Adaptive capacity is "the ability of a system to adjust to climate change to moderate potential damages, to take advantage of opportunities, or to cope with the consequences" (IPCC, 2007).

[14] Resilience is often expressed as "the capacity of a system to be able to prevent, withstand, absorb, adapt to, or bounce-back from shock" (Jonker, Miller, & Brechwald, 2011).

[15] Flexibility refers to "the degree of maneuverability which exists within systems or activities" (Smithers & Smit, 1997).

concepts are reflected in socially constructed or endogenous risks (Blaikie et al., 2004; IPCC, 2007). Taken together, these dynamic characteristics of systems represent the adaptive capacity of such systems. Adaptive capacity involves human capital and other non-monetary factors such as technological, socio-economic, institutional, and educational capacities.

Socio-economic development and physical adaptation measures are both competitive and complementary to one another. For example, better protections may trigger additional investment in at-risk areas and increase adaptive capacity through complementary enhancements in human and other forms of capital. Simultaneously, this additional development can increase vulnerability to extreme events because of the greater concentration of people and assets in the area (Chambwera et al., 2014).

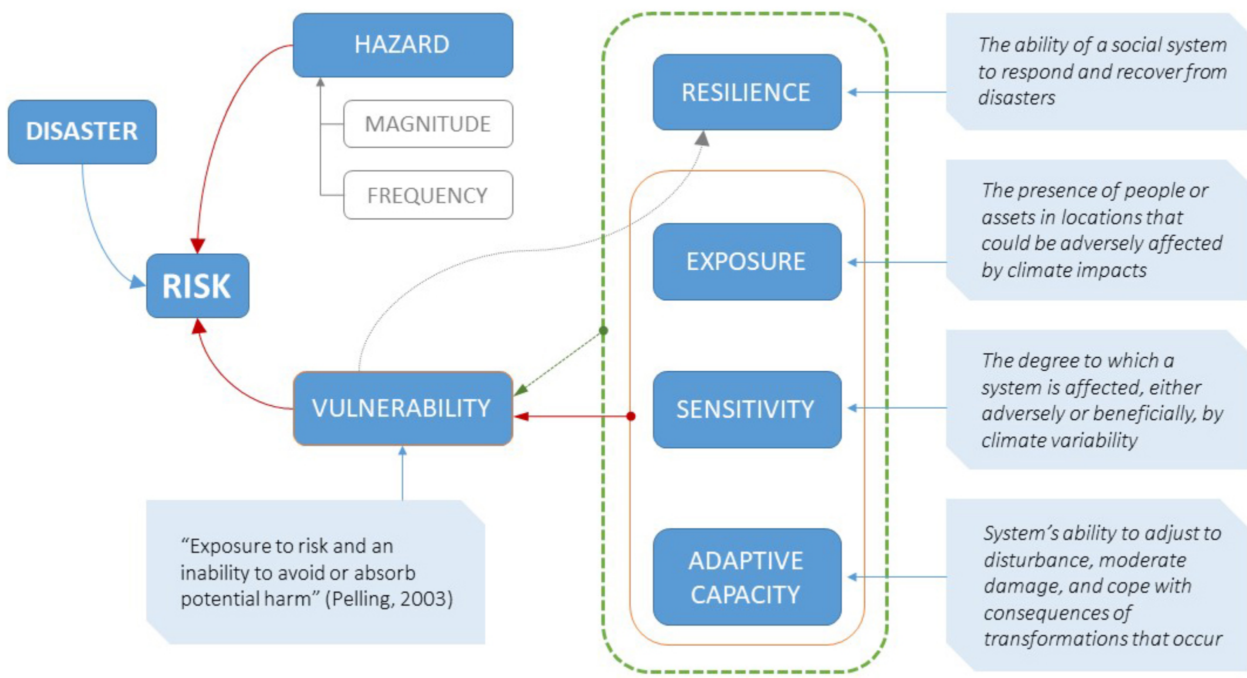


Figure 2. Conceptual frameworks of risk and vulnerability.
Sources: Gallopín, 2006; Pelling, 2003; & Vogel et.al, 2016.

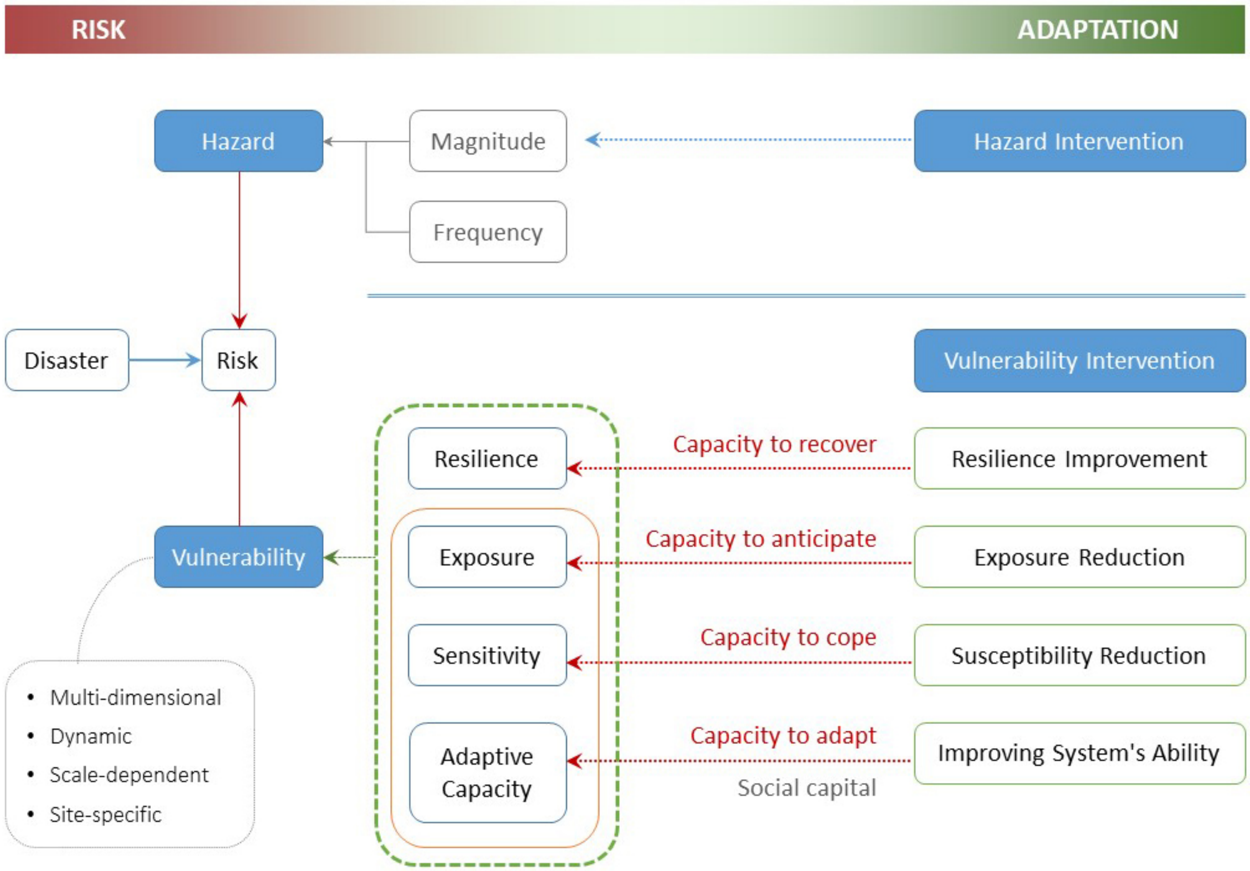


Figure 3. Conceptual frameworks of vulnerability and adaptation.

Taken together, Hay and Mimura (2006) grouped the basic concepts of adaptation into four categories. First, "avoidance and reduction": taking preventive measures against anticipated effects. Second, "mitigation of damages": relieving adverse consequences of a disaster and supporting recovery from those damages. This category is the reactive adaptation part of the model. Third, "dispersion of risk": lessening the costs of the damage by dispersing them over a larger population or for a longer period of time. The noteworthy example of this category is insurance. Last, "acceptance of risk and doing nothing": accepting the risk of harmful effects.

Focusing on the first category of the aforementioned adaptation concepts, Intergovernmental Panel on Climate Change (IPCC) specified adaptive measures for coastal zones in three categories: planned retreat, accommodation, and protection (IPCC, 1990; Mimura, 2010).

Another way to distinguish between adaptation types is based on the timing, goal, and motive of its implementation. Anticipatory adaptation (ex-ante strategies) refers to action that is taken in advance of impacts becoming observable, whereas reactive adaptation (ex-post strategies) is applied after observing initial impacts of climate change (Klein et al., 2008). The IPCC's adaptation categories can be both anticipatory and reactive. Retreat calls for managed withdrawal by zoning reformations or land use adjustment from unprotected coastal areas (Mills-Knapp et al., 2011). Accommodation strategies enable the maintenance of on-site operations while allowing some inundation to occur by protecting infrastructure and properties from damage. Natural stormwater management and green building techniques represent cases within this category, but some land use changes and regulation reinforcement are also involved to achieve this purpose (Mills-Knapp et al., 2011; Mimura, 2010). Protection encompasses a broad spectrum of design and policy interventions to curb damages, including various hard and green infrastructural measures for disaster-prevention, water resource management, and conservation of coastal ecosystems (Mills-Knapp et al., 2011).

Since adaptation strategies are undesirable when benefits from adaptation are less than the implementation costs, decision making for promoting adaptation calls for cost and benefit optimization (including economic and non-economic values). Timing of adaptation financing is also an essential factor in addition to the cost-benefit effectiveness, due to the uncertainties and variabilities of climate change—optimal adaptation strategies will vary over time relying on the magnitude of climate change and available technologies in the future (Chambwera et al., 2014).

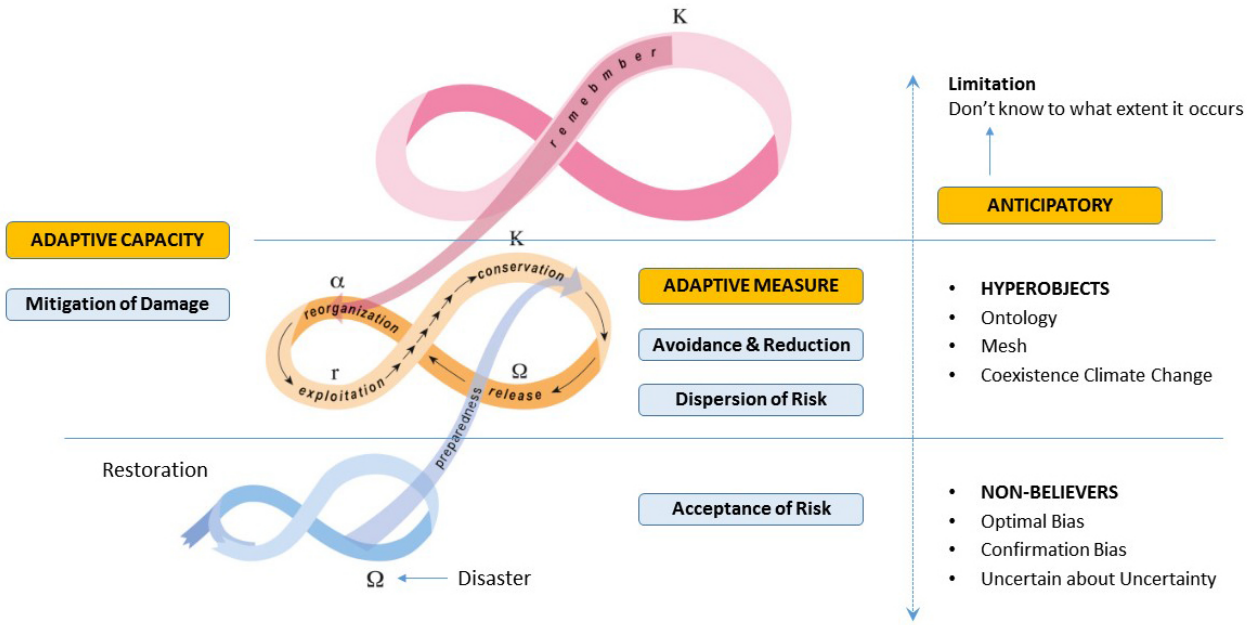


Figure 4. Panarchy adaptive cycle and adaptation categories.

Sources: Modified figure (Original source: Gunderson & Holling, 2002).

Notes: Modified Holling's illustration of Panarchy concept. Since adaptation has dynamic characteristics that emerge from the interactions between different scales, I borrow the structure of "Panarchy" and apply it to climate risk. Developed from the perspective of ecology, the adaptive cycle in Panarchy describes four phases of adaptive change. The *r* phase represents "exploitation, *α* phase of entrepreneurial growth." It is succeeded by the *K* phase of "conservation", characterized by the organizational consolidation growing stasis. The rapid *Ω* phase of "release" represents the collapse of the system. The causes of the collapse can be a natural disaster such as hurricane and flooding in this study context. The fourth α phase of "reorganization" stands for restructuring and symbolizes the beginning of a new cycle. This model of the adaptive cycle can be extended to a pattern of multiple phases of growth – one is a larger scale, called the "forward loop." The other is a smaller scale, called the "back loop." The two phases interact with each other and generate cross-scale effects; the "preparedness" (original term was "revolt" from Holling's Panarchy theory) from the back loop suggests a cascade effect where past events trigger a critical change in larger cycles, while the "remember" from the forward loop connection facilitates restructuring, drawing upon the experience and potential of maturity accumulated by a larger system (Gunderson & Holling, 2002). Conceptually, three ("avoidance and reduction", "mitigation of damage", and "dispersion of risk") of the four adaptation categories developed by Hay and Mimura (2006), plus adaptive capacity, take place in this interaction stage. The other one, "acceptance of risk" stays at the back loop because of the uncertain nature of risks and cognitive biases such as optimal bias (believing that they are at a lesser risk of experiencing a negative event compared to others) and confirmation bias (tendency to interpret information in a way that confirms one's preexisting beliefs or favors).

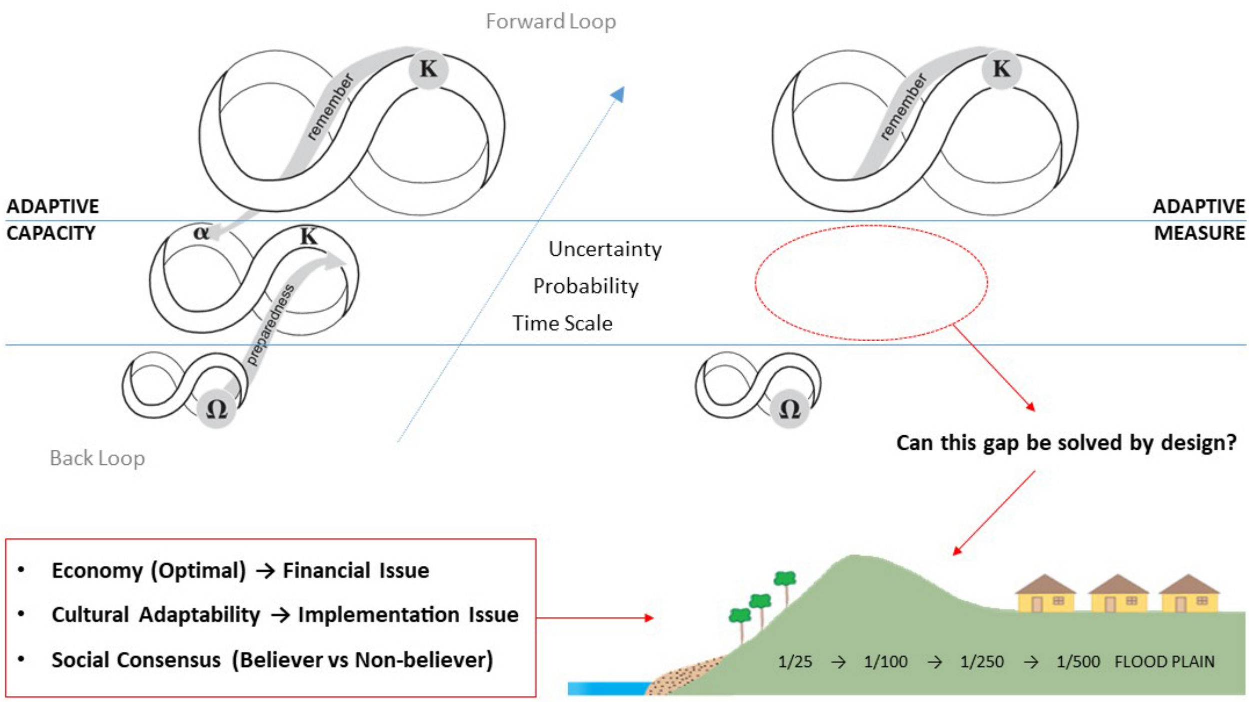


Figure 5. Limitations of Panarchy adaptive cycle in climate adaptation.

Sources: Modified figure (Original source: Gunderson & Holling, 2002).

Notes: Alternatively, adaptation can be distinguished by anticipatory adaptation (action that is taken in advance of impacts becoming observable) and reactive adaptation (action that is taken after observing initial impacts of climate change). However, the "anticipation" is also based on past experiences, and thus both anticipatory and reactive adaptations approaches are based on the cost-effectiveness criteria (Klein et al., 2008). Thus, it would be highly unfeasible to skip the following "forward loop." Evidently, the 2014 New York State Hazard Mitigation Plan projected a sea-level rise of 12 to 23 inches at Lower Hudson Valley and Long Island by the 2080s, or a range of 41 to 55 inches with a rapid ice-melt scenario (New York State, 2014). However, their adaptation plan does not consider a retreat option or building 55-inch height seawalls, since many other criteria, such as social consensus (believers vs. non-believers), cultural adaptability, available technologies, and financial issues, are involved in adaptation decision-making.

In this regard, Hochrainer and Mechler (2011) recommend a risk pooling[16] scheme for the cost effectiveness rather than risk reduction through engineering techniques, while Giordano (2012) suggests the use of modifiable infrastructure with a plausible climate scenario.

With respect to effectiveness of adaptation, Mendelsohn (2000) distinguished between private (individual) and public (joint) adaptation. Private adaptation is implemented by individuals for their own benefit, while public adaptation, which likely depends upon government action, is implemented for many beneficiaries to each action. The IPCC Third Assessment Report (IPCC, 2001) also indicated that a degree of adaptation will be autonomously executed by private parties. However, individuals alone will often not provide the desirable level of adaptation due to costs, disincentives, technical limits, and resource requirements (Chambwera et al., 2014). Thus, public intervention (joint adaptation) is required to maximize the net benefits from adaptation efforts and minimize market failures, such as externalities and distributional issues (impacts on equity). Since both private and public adaptations choose optimal levels and amounts of adaptation for maximizing their benefits, "most adaptation is likely to be reactive" (Mendelsohn, 2000).

Furthermore, Bunten and Kahn (2014), in their "event study style" hedonic real estate research, point out that real estate reflects the present discounted value of climate risks—climate risk capitalization in low-risk regions is underestimated, while the valuation of households in high-risk regions is overestimated. Thus, it is reasonable to assume that those who have already experienced significant losses from extreme climatic events are more actively investing in

[16] The risk pooling mechanism in this paper is "insuring public sector liabilities for infrastructure, liquidity support and relief to population" by forming a common pool at regional level against catastrophic risks such as floods or earthquakes (Hochrainer & Mechler, 2011).

adaptation measures, and the selection of homogeneous study areas to measure risk capitalization is logically reliable.

Among the aforementioned coastal adaptive classification, planned retreat and relocation options have been widely discussed among planners and policy makers, especially by western developed countries (Alexander, Ryan, & Measham, 2012; Mimura, 2010; Reisinger et al., 2014). However, these coping strategies are highly unfavorable due to their financial burden, legal conflicts, and numerous socio-cultural issues (Hino, Field, & Mach, 2017).

Consequently, coastal developers seek the most reliable adaptation strategies generally in the categories of “protection” and “accommodation” to curb potential asset value degradation due to climate change (Bunten & Kahn, 2017; Mills-Knapp et al., 2011). Some owners are purchasing expensive insurance and raising foundations to deal with the latent risks. Coastal cities and municipalities are allocating a significant amount of their budget toward climate change adaptation measures, including seawall and dike constructions, pump station installations, and shoreline erosion controls (Azevedo de Almeida & Mostafavi, 2016).

2.2 Risk Perception Factors and Amenity Effects

Several studies have found that there is a significant housing price discount in flood prone areas when compared with homes located outside the floodplains after a major flood event (Atreya, Ferreira, & Kriesel, 2013; Bin, Kruse, & Landry, 2008; Bin & Landry, 2013; Samarasinghe & Sharp, 2010). Daniel, Florax, and Rietveld (2009) researched the magnitude and determinants of the implicit price of the flood risk in a meta-analysis of 19 studies in the United States. An increase in the flood risk probability of 1% is associated with a 0.6% transaction price decrease. Bin, Kruse, and Landry (2008) study in Carteret County, North Carolina shows that an average sales price of residential properties located in a floodplain is 7.3% lower than properties outside of the floodplain and further illustrated the average discount price in a 100-year floodplain[17] is 25% lower than in a 500-year floodplain[18].

Similar to the flood risk impacts, many studies also have explored the relationship between hurricanes and housing market dynamics (Below, Beracha, & Skiba, 2017; Graham Jr & Hall Jr, 2001; Hallstrom & Smith, 2005; Murphy & Strobl, 2009). Murphy and Strobl (2009) found that typical hurricanes have an impact on housing price appreciation of up to 4% for a few years, due to the shortage of housing supply following a hurricane strike. Conversely, Beracha and Prati (2008) suggested that both housing sales volumes and transaction prices temporarily decrease within the first half year after a hurricane, then bounce back to prior levels. Although the majority of the literature suggests that the negative pricing effect of hurricanes is typically short-lived (Below, Beracha, & Skiba, 2017; Chivers & Flores, 2002; Ortega & Taspinar, 2017), the

[17] A 100-year floodplain is the area where there is a 1% or greater chance of a flood in any given year.

[18] A 500-year floodplain is the area with a 0.2% annual chance of flooding.

impacts of hurricanes can persist for several years depending on recovery speed and market idiosyncrasy (Atreya, Ferreira, & Kriesel, 2013; Bin & Landry, 2013). Timing of risk capitalization – risks are already capitalized into the housing price – could be another factor that can influence the sales price because it is plausible that housing market participants are already anticipating the risk in an area where consecutive hurricanes occurred over a brief period (Graham Jr & Hall Jr, 2001).

Other studies have also explored hurricane characteristics and other indirect factors related to housing price changes after a major hurricane. Ewing, Kruse, and Wang (2007) find that windstorms decrease housing value by 1.5 to 2% immediately after severe storms. Walls, Magliocca, and McConnell (2018) find that higher storm frequency lowers average land prices near the coast by 1.2 to 11.8% but does not deter coastal development since lower income households tend to locate there. Graham, Hall, and Schuhmann (2007) suggest that pricing effects differ based on the recurrence of hurricane landfalls by analyzing four consecutive hurricanes in North Carolina from 1996 to 1999. They found that only the last two hurricanes yielded adverse effects on housing prices because the first two storms were considered to be random events. Bin and Polasky (2004) find that flood risks lower market value, and the effect is significantly larger after a hurricane than before. Meyer et al. (2014), from their survey-based analysis, point out that hurricane wind force is overestimated while the threat imposed by flooding is underestimated due to the combined misconceptions which may be caused by the hurricane warning system (the Saffir-Simpson Scale is largely based on wind speed) and flood insurance policies. Hallstrom and Smith (2005) explored the effects of risk information about new hurricanes on the value of “near-miss” properties in Lee County, Florida, where no actual damage from Hurricane Andrew in 1992 was observed. Their findings indicate that risk information without any physical harms decreases housing prices by 19%, 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, Samarasinghe and Sharp (2010) confirmed that residential property values were lower where publicly available floodplain maps were available during sales activities. Kousky (2010) indicated that damaged infrastructure or stigma after a disaster as "risk-prone" can also influence property value outside of a floodplain. In addition, Nyce et al. (2015) found that there is approximately a 1% housing price decrease for every 10% average increase in insurance premiums. Similarly, Epley (2017) suggests that higher insurance rates are associated with lower housing values. 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.

With respect to the risk perception of hurricanes, Otto, Mehta, and Liu (2018) note that risk perceptions are influenced by the "availability heuristic." This finding suggests that a recent risk experience—which enables people to more easily recall, in this case, past storm events—influences their responses to future unrealized risks by altering their perception of the true risks. Meyer et al. (2014) argue that risk awareness between pre- and post-storm occurrences are biased by "hindsight" and thereby result in a failure to properly prepare for a storm by underestimating the actual threats imposed by tropical cyclones. Pryce, Chen, and Galster (2011) suggest that risk perceptions can be systemically underestimated by the effects of myopia[19] (underestimating future risks) and amnesia (forgetting past events). In human cognitive

[19] Myopic perception of risk can be caused by "discounting information from anticipated future events, with the discount rising progressively as the event becomes less imminent" (Pryce, Chen, & Galster, 2011).

perspective, since risk perception can be influenced by “myside bias” (propensity to interpret information as confirming their own preconceptions), perception of risk varies by individual's emotion and belief which are constructed by individual memories, learning, attention, and motivational priorities (Rapley & De Meyer, 2014; Tooby & Cosmides, 2008). These individually different perceptions can be also varied by cultural norms and social identities, because “individual perceptions are influenced by the perceptions of individuals in their social, or friendship, network” (Scherer & Cho, 2003).

In contrast to risks and vulnerability, property values are positively related by proximity to the coast because of the amenity effects, such as ocean views and accessibility to beaches (D’Acci, 2014; Jin et al., 2015), 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 in Seabrook Island, South Carolina. Similarly, Benson et al. (1998) confirmed that ocean view quality differentiates a sales price premium—10% for a partial ocean view, 32% for an unobstructed ocean view, and 147% for ocean frontage. Landry and Hindsley (2011) in Tybee Island on the Georgia coast shows the influence of beach quality on local property values is significantly positive within 1,000 feet. An additional meter of high- and low-tide beach width and dune field width is associated with housing price appreciation of $71, $74, and $52, respectively, and valued even more in closer proximity. This phenomenon suggests that the amenity effects with the absence of risk information are particularly strong in coastal cities in which preferably no major flood event has previously occurred.

Taken together, the two contrasting results signify that flood risks and coastal amenities are highly correlated—a closer proximity with lower elevations provides more amenities, yet simultaneously increases vulnerability to flood risks (Bin et al., 2008). Obfuscating amenity effects and risk exposure associated with proximity to water causes systematic bias in the implicit price of flood risk (Daniel, Florax, & Rietveld, 2009). Thus, on-site adaptation measures, including hard and green infrastructure, are gaining popularity among coastal property owners and real estate developers in coastal cities that have experienced a major flood event in recent years (Jin et al., 2015). Furthermore, the costs of adaptation are usually less than those of the damages imposed by the impacts, and therefore “adaptation is more cost-effective than reactive responses” (Mimura, 2010).

2.3 Economic Evaluation and Funding Mechanisms of Adaptation

Since adaptation is interacting with many factors including risks and vulnerability under inherent barriers, such as the uncertainties of climate change and the ancillary effects of adaptation, economic evaluation of public infrastructural adaptation often requires approximate approaches (Chambwera et al., 2014). The IPCC Fifth Assessment Report (2014) summarized popular economic decision-making tools, such as cost-benefit approach, multi-metrics approach, and non-probabilistic methodology.

A cost-benefit approach estimates the expected net present value of costs and benefits based on subjective probabilities for different climate futures. This analysis often requires the valuation of non-market costs and benefits, but valuation of non-monetary impact is difficult because values and preferences are heterogeneous (Chambwera et al., 2014). Multi-metric analysis encompasses cost-benefit and other non-market items by quantifying trade-offs (Martinez-Alier, Munda, & O'Neill, 1998). This analysis has been applied to adaptation issues including urban flood risk (Kubal et al., 2009; Viguié & Hallegatte, 2012) and choice of adaptation options in the Netherlands (Brouwer & Van Ek, 2004; de Bruin et al., 2009). However, consideration of the specific priorities and perspectives of the decision-makers will likely influence the criteria and the prioritization of the metrics for the analysis (Cowlin et al., 2014).

Unlike the cost-benefit and multi-metric methods, non-probabilistic approaches—such as the robust decision making[20], maxi-min[21] criterion, and mini-max[22] regret criterion—require no probability information. The maxi-min criterion is based on the best worst-case outcome, while mini-max regret criterion suggests choosing the decision with the smallest deviation from optimality. These methodologies are helpful in a context where such information is not available (Chambwera et al., 2014). A focus on best options is more appropriate when it is possible to predict particular future states. However, when the future is characterized by uncertainty, a focus on best options may carry significant risks (Smith, Taylor, & Takama, 2011). In this context, robustness criterion suggested robust options with flexibilities rather than best option in decision making strategies against multiple plausible climate futures. However, a narrow focus on quantifiable costs and benefits can bias decisions against the poor and against ecosystems and those in the future whose values can be understated or excluded. In order to avoid such maladaptation, sufficiently broad-based and comprehensive approaches are necessary (Chambwera et al., 2014).

Implementation of climate change adaptation plans creates new costs for local governments. These new costs result from, first, expenditure for direct adaptation initiatives, such as the construction of coastal protection structures and, second, increasing costs of maintaining and modifying existing service delivery to address climate change (Banhalmi-Zakar et al., 2016).

---

[20] Robust Decision Making (RDM) seeks “robust” strategies rather than “optimality” (to assess alternative policies) over a wider range of plausible future scenarios.

[21] Maxi-min approach (pessimistic criterion) is based on the worst possible result in each scenario, and selects the “best of the worst.”

[22] Mini-max approach chooses the minimum alternative of all “maximum regret” (best payoff – pay off received) across all scenarios.

Several options are available to local governments to cover the costs associated with implementation of climate change adaptation measures. The exact nature of the revenue sources varies by jurisdiction based on the relevant legislation. Many projects within climate adaptation function as public goods, thus spending taxation revenues is common (Banhalmi-Zakar et al., 2016). Taxes are collected from landowners on the basis of property value. Property taxes may consist of general rates and special levies, which may be targeted by a specific location identified as receiving certain benefits from public projects. Funding for climate change adaptation can also be through user charges—revenue derived from the direct provision of goods and services (Hensher, 2008). However, user charges are misaligned with project lifecycle costs—user charges require a service to be delivered but delivering adaptation services generally requires significant expenditure prior to the service being available. While revenue flows from user fees are misaligned with expenditure requirements for coastal protection works, user fees do provide an opportunity for governments to generate revenue to service debt. In this way they can form part of a package of mechanisms to fund coastal protection works (Banhalmi-Zakar et al., 2016). Another major option is intergovernmental fiscal transfers. This includes mechanisms such as the financial assistance grants scheme and the national disaster relief and recovery arrangements, and short-term programs such as the former coastal adaptation pathways program[23] (Teng & Gu, 2007). However, there are limits around the amount of control available to local governments regarding the sums available as well as the timing and purpose of the funding.

[23] Coastal Adaptation Pathways Program (CAP) was largely funded through the Australian government to explored flexible current and future adaptation options for the nine coastal regions (Bunbury, Busselton, Capel, Dardanup, Harvey, Mandurah, Murray, Rockingham and Waroona) of western Austrilia. The project was implemented between mid-2011 and late 2012 to address coastal inundation and erosion due to climate change (Rissik & Reis, 2013).

In addition to traditional mechanisms, infrastructure charges, value capture, strategic asset management, and public-private partnerships can be used as alternative funding mechanisms. “Infrastructure charges are fees levied on developers to compensate governments for providing facilities necessary for land development” (Henry, 2009). Value capture funding methods identify and collect an equitable portion of the value released through new zoning and other public improvements such that communities that create this value can also share in the wealth it generates (Ware, 2016). Strategic asset management involves taking inventory of public assets and making economic decisions as to how to extract maximum value from them, including land and developed property (Banhalmi-Zakar et al., 2016).

Public-private partnerships can be understood as a spectrum of private sector involvement in public project delivery contracting. The various approaches along this spectrum are differentiated by the distribution of risk between the public and private sector (Mills, 2005). By accepting some of the risk, the private sector will expect a return. A public-private partnership generally involves both a financing and a funding mechanism (Banhalmi-Zakar et al., 2016). In determining between varying project delivery approaches, it is important to consider how the allocation of risk and control will support or conflict with project objectives and the objectives of the local government’s overall adaptation strategy.

Table 1. Summary of adaptation funding sources.

Type	Source	Advantage	Disadvantage
Borrowing	Bonds	• Can provide steady funding stream over the period of the bond • Can support construction-ready projects	• Possible interest charges • Require full repayment • Can have high transaction costs relative to requested amount
	Loans	• Some programs offer low- or possibly no-interest financing	• Require full repayment • One-time source of funds
Local Revenue	Fees	• Specific permit and inspection fees allows for more direct allocation of costs for services provided	• Developer impact fees may be an unreliable source when the market goes down
	Utility Charges	• Dedicated funding source • Sustainable and stable revenue	• Require significant administrative preparation (Approval by vote of the local legislative body)
	Taxes	• Consistent from year-to-year • Utilizes an existing funding system	• Competition for funds • Not equitable (Typically not all taxpayers can be a direct beneficiary)
Grants	State & Federal Grants	• Does not require repayment	• Competitive • Generally, project-specific or time-constrained funds
Private Sector	Private Sector	• Can reduce costs to government • Shared risk	• Perceived loss of public control • Contract negotiations could be difficult

Sources: Funding sources for green infrastructure (Frey et al., 2015).

2.4 Adaptation Measures (Hard, Green, Private, and Adaptive Capacity)

As a hard-infrastructural adaptation measure, construction of shoreline armors—sea walls, dikes, local protective barriers, groins, breakwaters or jetties, bulkheads, and piers—is widely applied to protect properties at risk (Landry & Hindsley, 2011). Although hard infrastructural adaptations require relatively significant up-front expenses, as well as operational and maintenance costs (Jones, Hole, & Zavaleta, 2012), this hard infrastructural adaptation maintains the waterfront proximity and amenity effects while reducing risks. The economic benefits associated with protective structures (e.g. seawalls and levees) have been identified among properties with such features. 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) found that single-family homes located behind a seawall have a 10% price appreciation due to anticipated risk reduction effects against inundation. However, the positive effect of seawall protection was limited to properties located within 164 feet (50 meters) of waterbodies (Jin et al., 2015).

Meanwhile, green infrastructure has emerged as a viable adaptation strategy to cope with environmental extremes, because it can curb some of the negative effects of climate-related hazards (Perini & Sabbion, 2016). "Green infrastructure involves the use of landscape features to store, infiltrate, and evaporate stormwater" (EPA, 2011). Popular green measures include coastal wetlands, sand dunes, beaches, and freshwater ponds, often hybridizing with existing hard infrastructure measures to reduce impacts from storm surges, extreme precipitation, and floods (Hill, 2015). According to Watson et al. (2016), wetlands reduce flood damage by 54 - 78%, and the economic value of wetland warrants consideration in land use decisions. Furthermore, green infrastructure supports enhancing insurance value by reducing vulnerability and the costs of hard infrastructural adaptation to climate change (Green et al., 2016). Additional benefits of coastal wetlands for storm protection is their self-maintaining function and hosting other ecosystem services, which vertical levees do not have (Costanza et al., 2008). However, integration of green infrastructure into urban planning could be difficult (de Coninck et al., 2018), since components of green infrastructure may require a longer time to provide full functions (e.g., trees take time to grow). Still, promoting green infrastructure can be more cost-effective than engineering approaches from a long-term perspective (Bobbins & Culwick, 2016).

Individually engineered solutions can also be achieved by raising structures and critical infrastructural system components to higher elevations (Rosenzweig et al., 2011). Since higher elevation of land and housing structure can help to alleviate flood risk (Landry & Hindsley, 2011), it is expected that the higher elevation will command a premium relative to homes at lower elevations. Fortifying building structures by implementing stricter building codes and reinforcing homes against major hurricanes yields a price premium (Dumm, Sirmans, & Smersh, 2012). Mendelsohn (2000) signifies that the amounts and degrees of individual adaptation (private adaptation in the author's classification) could be less if the joint (public) adaptations (hard and green infrastructural adaptations) are more, because those individuals are not willing to pay more than the actual risk exposures, which are already provided by the city, to maximize their economic benefits. However, the housing value would logically remain strong because the shared benefits (in risk reduction) from the joint (public) adaptations are already embedded in the market price.

As aforementioned, coastal communities can reduce their risk exposure by investment in buildings and infrastructure that are more resilient to past and future hurricanes. However, it would be difficult to achieve long-term adaptive effects to climate change only with these approaches. Limited budget and resources prioritize certain climate adaptation projects and so cannot address existing risk exposures in all areas. Consequently, poorer communities may be further marginalized (de Coninck et al., 2018). Thus, “addressing the social structural causes of vulnerability is essential” by enhancing adaptive capacity, “often associated with access to technology, high education levels, economic equity, and strong institutions” (O'Brien & Selboe, 2015). However, only relying on adaptive capacity may not always guarantee a successful adaptation, since implementation of any plan can be poor. For example, even a good evacuation plan that is not well-implemented can lack the intended effects. To maximize climate adaptation efforts, then, cities and local governments would need to include both the infrastructural adaptation and adaptive capacity, as well as recognize factors such as equality and inclusive participation (de Coninck et al., 2018; O'Brien & Selboe, 2015).

Table 2. Summary of adaptation measures.

Adaptation Measure	Conventional Projects	Advantage	Disadvantage
Hard Infrastructure	Sea walls, Dikes, Local protective barriers, Groins, Breakwaters, Jetties, Bulkheads, Piers	It maintains the waterfront proximity and amenity effects while reducing risks.	It requires relatively significant up-front expenses and maintenance costs.
Green Infrastructure	Wetland restoration, Riparian buffer zones, Sand dunes, Beach nourishment, Freshwater ponds	It requires lower maintaining costs and hosts other ecosystem services	It requires a longer time to provide full functions (e.g., trees take time to grow).
Adaptive Capacity	Local hurricane shelters, Evacuation plans and facilities, Emergency preparedness planning and education programs, Organization capacity building and training	It reinforces flexibility in decision-making and problem solving. It creates strong linkage between public and private.	Having capacity does not guarantee that adaptation actually takes place (a good evacuation plan may not be implemented)
Individual (Private) Adaptation	Raising foundation, LOMR (Letter of Map Revision), storm panels, hurricane shutter, private drainage improvement	It can directly address site-specific issues.	It could be less effective when climate change continues to acerbate (because individuals are typically not willing to pay more than the actual risk exposures).

3. Study Area and Climate Adaptation

Since the major site selection criteria are hurricane frequency and the area's adaptation efforts, this study selects Miami-Dade County and the five boroughs[24] of New York City to analyze the capitalized effects of climate adaptation measures on housing transaction prices. In addition to the current two study sites (Miami-Dade County and New York City), the sites I initially considered included New Orleans and Galveston to provide additional support for generalizing my study results. However, the housing market impacts and adaptation strategies of these two excluded sites turned out to be too different from Miami-Dade County and New York City. For example, the majority of damage in New Orleans from Hurricane Katrina were basically a result of the failure of the region's dike system, and planned retreat was massively promoted rather than utilizing other types of on-site adaptations. Hence, the reason I settled on Miami-Dade County and New York City is that the on-site adaptation strategies as well as other external factors which prevail in these two sites are reasonably comparable.

During the past half-century, the average annual storm frequencies[25] in Miami-Dade County and New York City are 0.44 and 0.23, respectively. In other words, a severe storm impacts Miami-Dade County every two years and New York City every five years. Due to the storm intensity and frequency, Miami-Dade County and New York City have spent more than $326 million and $1.6 billion dollars for climate adaptation projects including storm recoveries and preparations in

[24] New York City consists of five boroughs: Manhattan, Brooklyn, Queens, The Bronx, and Staten Island.

[25] From 1970 to 2017, Miami-Dade County has experienced 21 major storms including (Saffir–Simpson scale) category 1 to 5 hurricanes, tropical storms, tropical depression, and extratropical (See Appendix 3) within a 65 nautical mile radius from the center of the county. A total of 11 major storms impact New York City during the same period. Among these storms, 5 in Miami-Dade County and 2 in New York City were hurricanes stronger than Saffir–Simpson hurricane scale 1 (NOAA, 2018).

the past five years. Thus, the study areas, having high storm occurrences and high climate adaptation budgets, serve as clear subjects for analyzing the effects of adaptation measures.

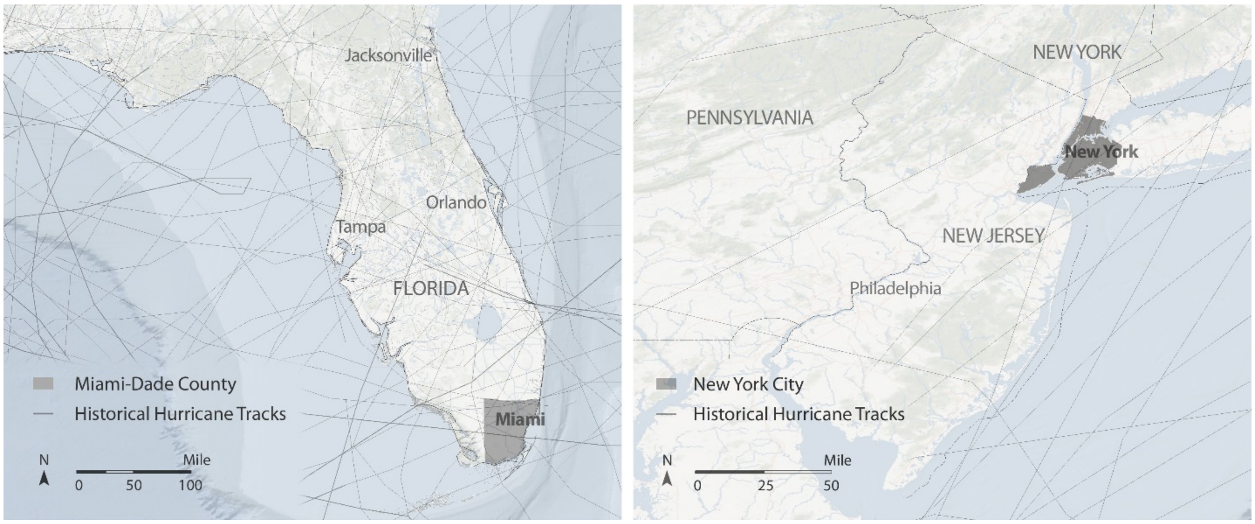


Figure 6. Site map with hurricane track: MDC (left) and NYC (right).

3.1 Site Characteristics

According to the Census data, Miami-Dade County has the largest population in Florida and the seventh largest population in the United States. The county is situated in the southeastern part of the Florida Peninsula. Because of its adjacency to the Gulf of Mexico to the southwest and Atlantic Ocean to the east, Miami-Dade is ranked[26] as one of the most hurricane-prone county in the nation. According to the county's geospatial database, approximately half of total residential parcels in the county are located in Special Flood Hazard Areas[27] identified by the Federal Emergency Management Agency (FEMA, 2018).

The average elevation in Miami-Dade County is 6 feet above mean sea level (NASA, 2006), while an average annual rainfall is about 52 inches. Thus, the county has invested a considerable amount of their budget to flood protection infrastructure, stormwater management, and drainage system improvements. More than 60% of the county is wetlands and part of Everglades National Park. From the American Community Survey (ACS) data, the county has a total of 2.75 million residents (ACS 2017, 5-year estimates) and experienced an approximate 22% increase in population over the past two decades (Census 2000).

---

[26] The rank is based on the number of hurricane direct hits on the mainland U.S. coastline and for individual states between 1851 and 2004. Florida appeared to be the most hurricane-prone state with a total of 110 hurricanes equal to or stronger than Saffir-Simpson hurricane category 1 within the survey period (Blake et al., 2005).

[27] Based on the Flood Insurance Rate Map (FIRM), areas lower than the base flood elevation (Zone V) or within a 100-year floodplain (Zone A) are considered to be special flood hazard areas. Any buildings within the zone A or V require purchasing flood insurance in communities that participate in the National Flood Insurance Program (see Figure 7). Both Florida and New York states have been participating in the program (FEMA, 2018).

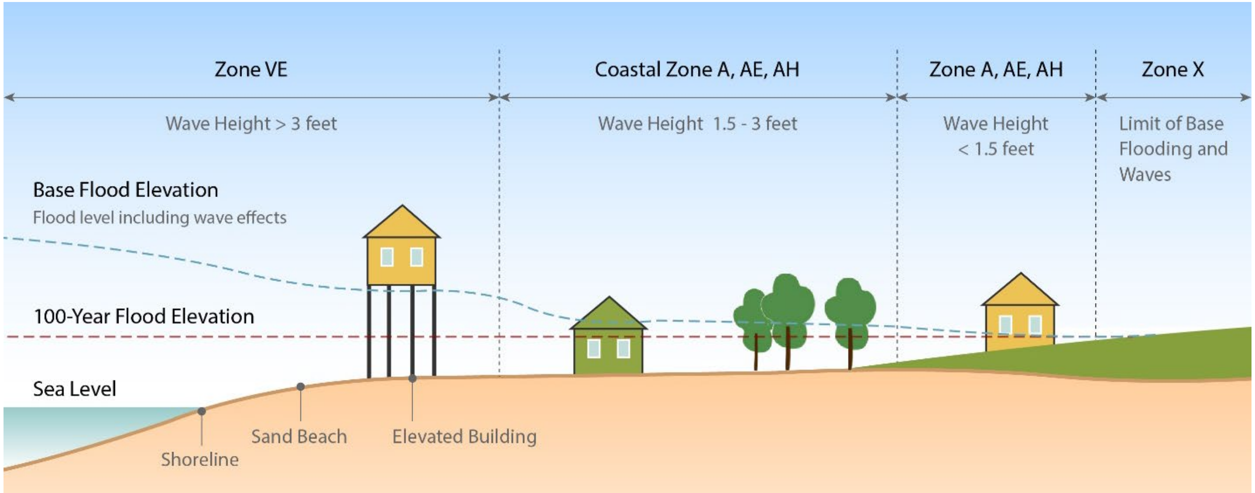


Figure 7. Flood hazard zones.

Notes: Modified FEMA illustration of special flood hazard areas (Original sources: FEMA, 2018).

Unlike Miami-Dade County with its vast natural wetlands, much of New York City is densely urbanized. The city is home for 8.62 million people and the population has increased by 7.6% on average since 2000. Even comparing with Miami-Dade's population density[28] within only the urban areas, New York City's population is almost five times denser, making the city the nation's most populous city. Geographically, the New York City is located at the mouth of the Hudson River, in the northeastern part of the United States. Similar to Miami-Dade, New York City borders Atlantic Ocean, making it the ninth[29] most vulnerable region to hurricanes in the

[28] The population density is 1,449 people per square mile. Excluding Everglades National Park and wetlands, the density within the urban area (424 square mile) increases to approximately 6,000 people per square mile (MDC, 2011).

[29] The rank is based on the number of hurricane direct hits on the mainland U.S. coastline and for individual states between 1851 and 2004. New York appeared to be the ninth most hurricane-prone state with a total of 12 hurricanes equal to or stronger than Saffir-Simpson hurricane category 1 within the survey periods (Blake et al., 2005).

nation. Although relatively minor[30] hurricanes have been predominant in New York since 1960, damage costs were as high as the top hurricane prone counties due to the dense population and at-risk infrastructure such as underground tunnels and transportation (Gerstacker, 2015). The mean elevation in the city is 33 feet above sea level, but more than 27,000 buildings are located in a 100-year floodplain or areas lower than the base flood elevation. According to the city's open data portal, approximately 14% of the land is green space.

Table 3. General statistics.

Areas	Miami-Dade County	New York City[1)]
Total population	2,751,796	8,622,698
Population density (per sq. mile)	1,449	28,603
Land area (sq. mile)	1,899	301
Median household income[2)]	$49,930	$64,624
Unemployment rates (10-year average)	7.4%	7.6%
Total housing units	1,024,289	3,497,344
Single family units (%)	49.5%	16.1%
Home ownership rates*	55.5%	39.6%
Occupied units	85.2%	90.3%
Owner-occupied	43.5%	29.5%
Renter-occupied	41.7%	60.8%
Median year structure built	1978	1939
Median home value	$288,100	$581,196

Notes: 1) New York City consists of five boroughs: Manhattan, Brooklyn, Queens, The Bronx, Staten and Island. 2) In 2017 inflation adjusted dollars. Sources: Social Explorer 2005-2018; ACS 2017 (5-year estimates); and FRED* Economic Data (2017).

[30] Hurricane intensities in New York City generally remain less than category 3 (NOAA, 2018). Because the sea surface temperature is relatively lower with a high altitude, a major hurricane (equal to or greater than category 3) has not occurred in the vicinity of New York City since 1960.

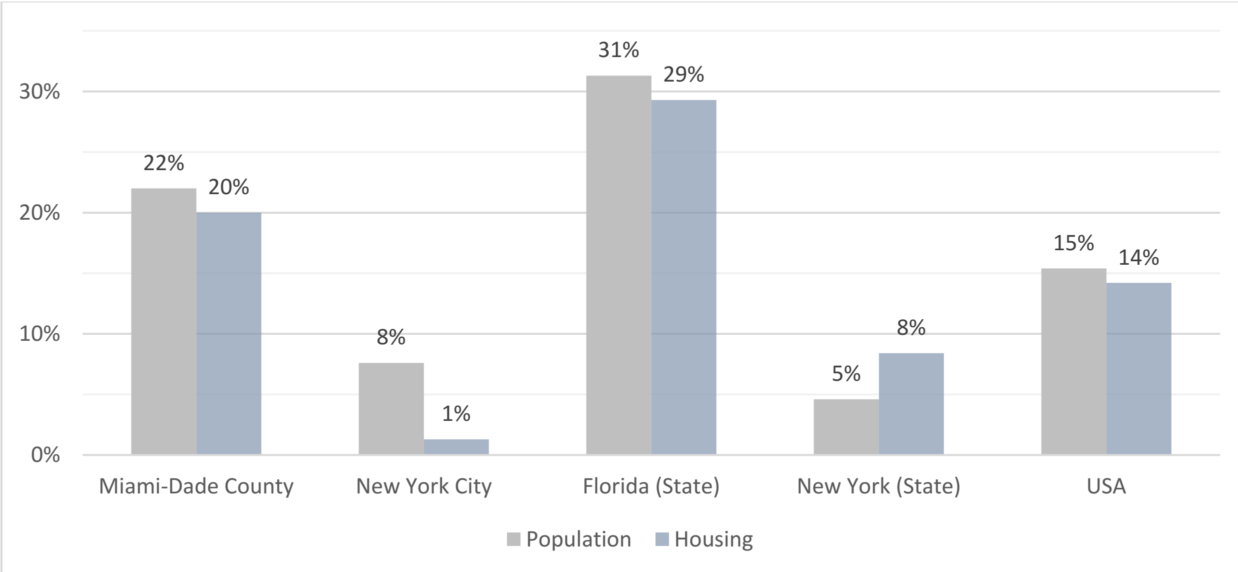


Figure 8. Population and number of housing units (percentage changes from 2000 to 2017).
Sources: ACS 2009-2017 (1-year estimates).

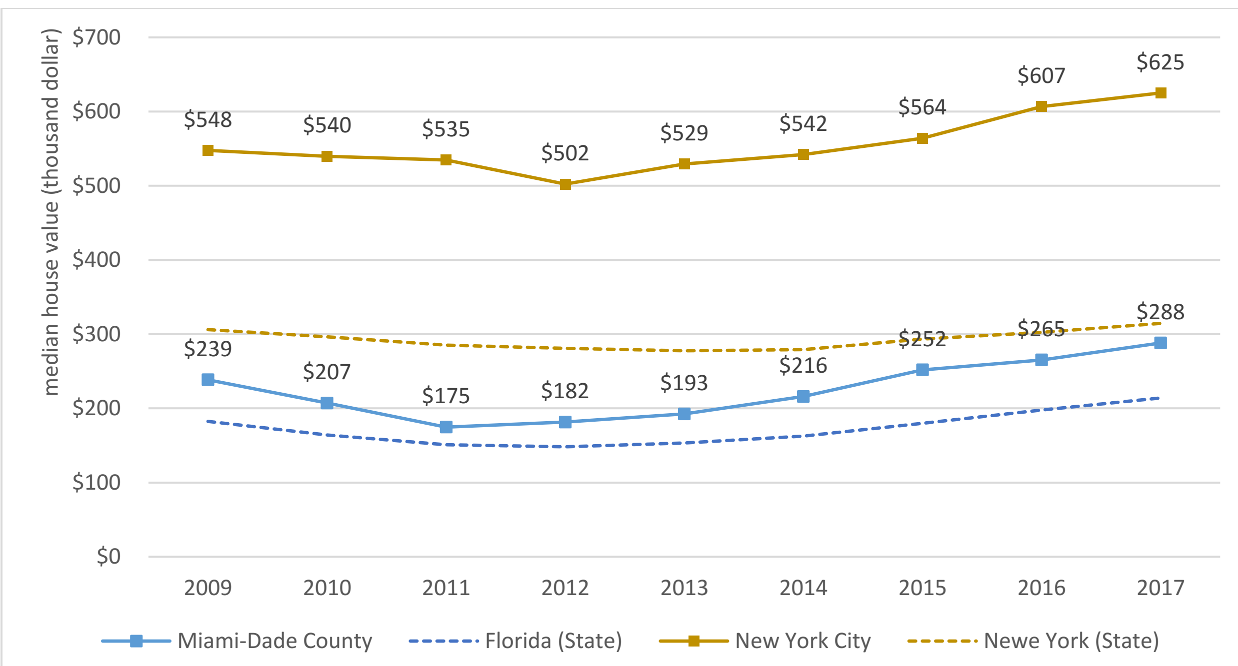


Figure 9. Median house value for all owner-occupied housing units.
Sources: ACS 2009-2017 (1-year estimates).

3.2 Socio-Economic Contexts

Miami-Dade County's median household income is $49,930[31] which is 5.3% less than that of Florida. A large income gap within the county is observed. Affluent communities such as Coral Gables, Key Biscayne, and Palmetto Bay have the highest median income, while relatively poorer communities such as Little Havana have the lowest income. A 10-year average median household income[32] gap between the highest and lowest is as much as $122,900. The county's 10-year[33] average unemployment rate is 7.4%, and the top three major industries are healthcare and social assistance (12.4%), retail trade (12.3%), and accommodation and food services (9.4%). Geographically, the lowest 10-year unemployment rate (3.9%) is observed in the oceanfront urban core areas, while agricultural suburbs such as Florida City have the highest unemployment rate of 16.7%[34].

The county has a total of 1,024,289 housing units (ACS 2017, 1-year estimates) which experienced a 20% increase over the last two decades. The median property value is $288,100, which is 1.35 times higher than the state's average of $214,000. After the subprime mortgage crisis, occurring between 2007 and 2010, the median housing price hit the bottom in 2011 and has increased continuously with an average appreciation of 8.7% until 2017. By contrast, the homeownership rate of Miami-Dade County has decreased continuously since 2009 and hit the

[31] According to the 2017 inflation-adjusted dollars, ACS 2017 (1-year estimates).

[32] Average value of annual median household incomes (in each year inflation-adjusted dollar) between 2009 and 2018, ACS (2013-2017) 5-year estimates.

[33] August 1, 2008 – August 1, 2018, FRED Economic Data, Federal Reserve Bank of St. Luis.

[34] The lowest unemployment rate of 3.9% (10-year average from 2009 to 2018) is observed at zip code 33149 (Key Biscayne and Virginia Key, located on a barrier island adjacent to the city of Miami), while zip code 33034 (Florida City, located in southwest Miami-Dade County) has the highest unemployment rate of 16.7%.

bottom at 50.6% in 2017. New private housing structures authorized by building permits dramatically increased (3.4 times) between 2016 (3,073) and 2017 (10,554). Vacancy rates are also geographically different. Relatively lower housing vacancy rates, less than 6%, were observed in the northern inland areas, where household income is relatively high, and unemployment is low. By contrast, higher average housing vacancy rates over 20% were observed at the oceanfront areas such as Miami Beach and Key Biscayne[35]. Especially, Sunny Isles Beach[36] (zip code 33160) has the highest 10-year average vacancy rate of as much as 51%.

Meanwhile, median household income[37] in New York City remains $64,624 which is 29.4% higher than that of Miami-Dade County. Among the boroughs, Manhattan is highest, followed by Richmond, and the Bronx has the lowest household income of $37,397. In the neighborhood level, Hunts Point and Mott Haven in Bronx has the lowest average median household income of $23,200, while Upper East Side in Manhattan has the highest. The gap between the highest and the lowest household income in the zip code level is about 20% lower ($97,735) than the income gap ($122,900) in Miami-Dade County. The economy of New York City employs 4 million people. A 10-year average unemployment rate in the city is 7.6%, and the largest industries in the city are administrative (12%), management (10.5%), and sales (9.9%). A higher unemployment rate is observed at the communities where the median income is low (especially

[35] Key Biscayne is a community located on a barrier island adjacent to the city of Miami.

[36] A city located on a barrier island in northeast Miami-Dade County.

[37] Average value of annual median household incomes (in each year inflation-adjusted dollar) between 2009 and 2018 in a total of 42 neighborhoods (162 Zip Code Tabulation Areas) in New York City, ACS (2013-2017) 5-year estimates.

in the Bronx). By contrast, a low unemployment rate is recorded at high-income boroughs[38] such as Manhattan and Staten Island. Upper East Side in Manhattan has the lowest unemployment rate of 4%, whereas the highest average unemployment rate of 16% was observed at Central Bronx neighborhood.

New York City accommodates a total of 3,159,674 housing units. Due to the limited amount of developable land, only 1.3% of the total residential units has added on since 2000. The median housing value has increased since 2012 by 4.5% on annual average. The homeownership rate of New York City is about 40%. Among the boroughs, Richmond has the highest homeownership rate at 73%, while Bronx and Manhattan are only at about 22%. An annual average number of building permits for the new private housing structures was about 1,300 over the last decade, but there was a surprising increase to 22,100 in 2017, which is about 17 times more than the annual average. Manhattan has the highest average vacancy rate of 12%, and the vacancies rates of the other boroughs are stable at 7-8% over the last decade. The highest vacancy rate of 18.4% was observed at Gramercy Park and Murray Hill neighborhoods in Manhattan, while Canarsie and Flatlands in Brooklyn had the lowest vacancy rate of 4.9%.

[38] The Bronx has the lowest median household income of $39,305 (10-year average), while unemployment rate in the Bronx is the highest (12.2%) among other boroughs in New York City. By contrast, Manhattan ($74,839) and Staten Island ($71,044) have high median incomes, while average unemployment rates are low (7% in Manhattan and 6.5% in Staten Island).

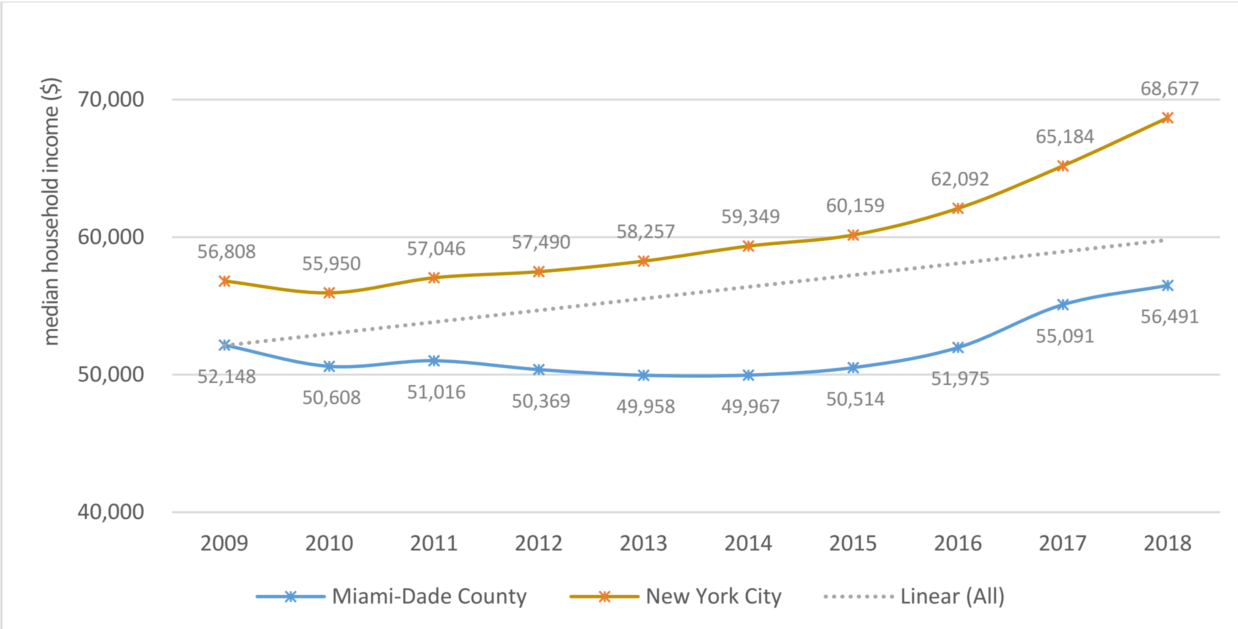


Figure 10. Median household income.

Sources: ZCTAs (Zip Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 median household income.

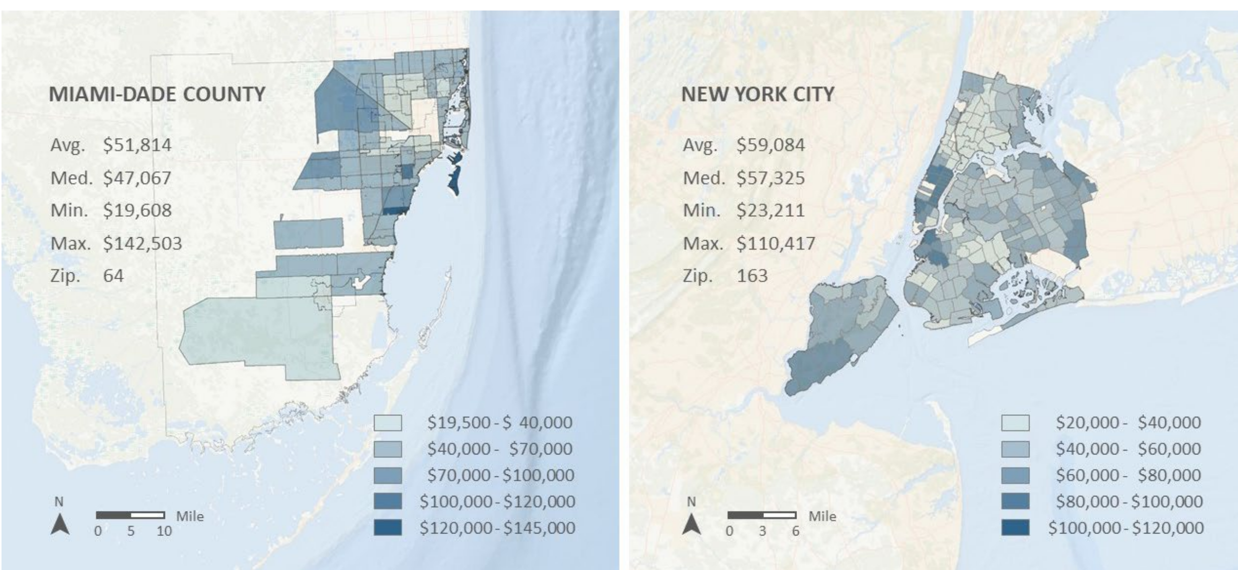


Figure 11. Median household incomes (10-year average) by zip code.

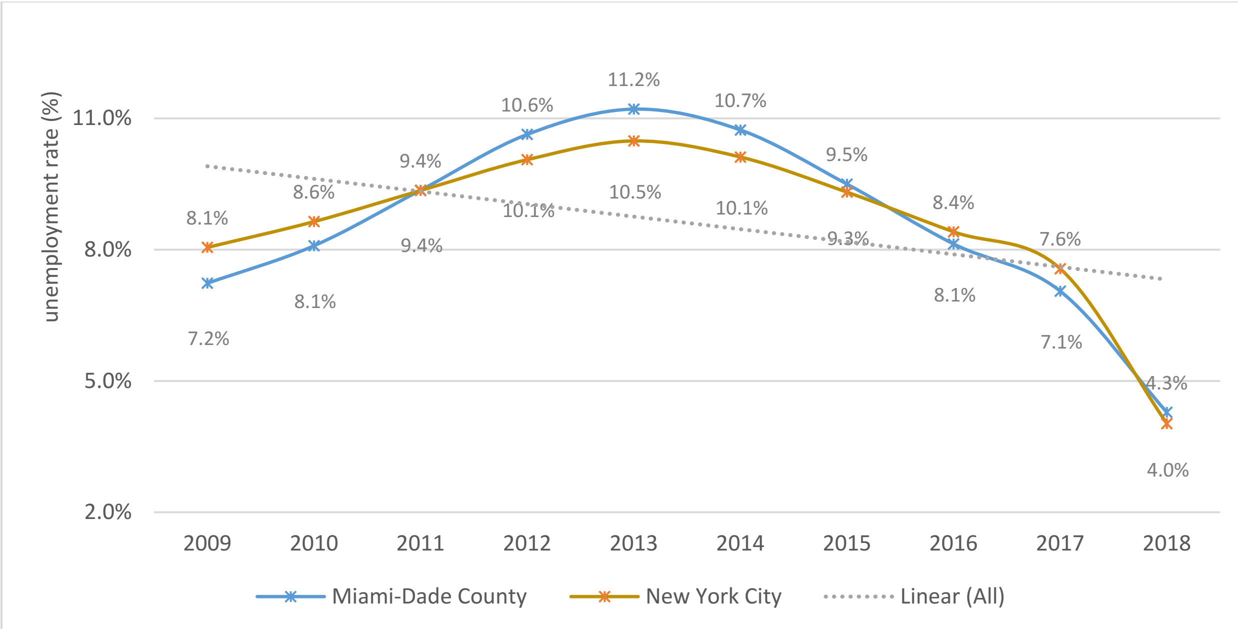


Figure 12. Unemployment rates.

Sources: ZCTAs data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Average unemployment rates (January - May 2018) from the Health Council of South Florida and New York State Department of Labor.

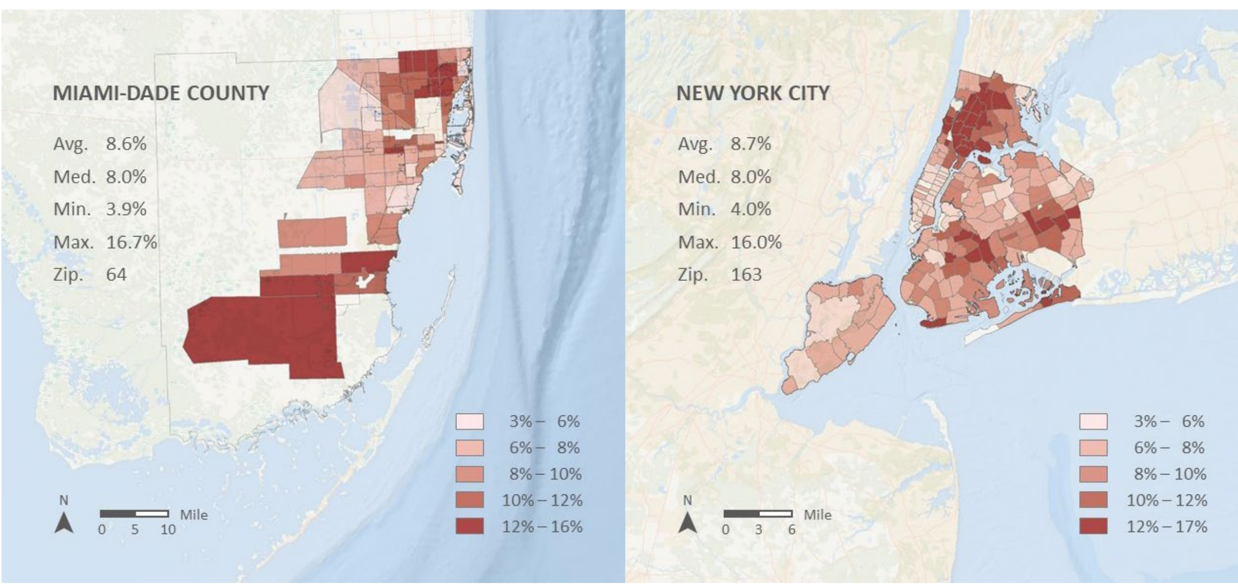


Figure 13. Unemployment rates (10-year average) by zip code.

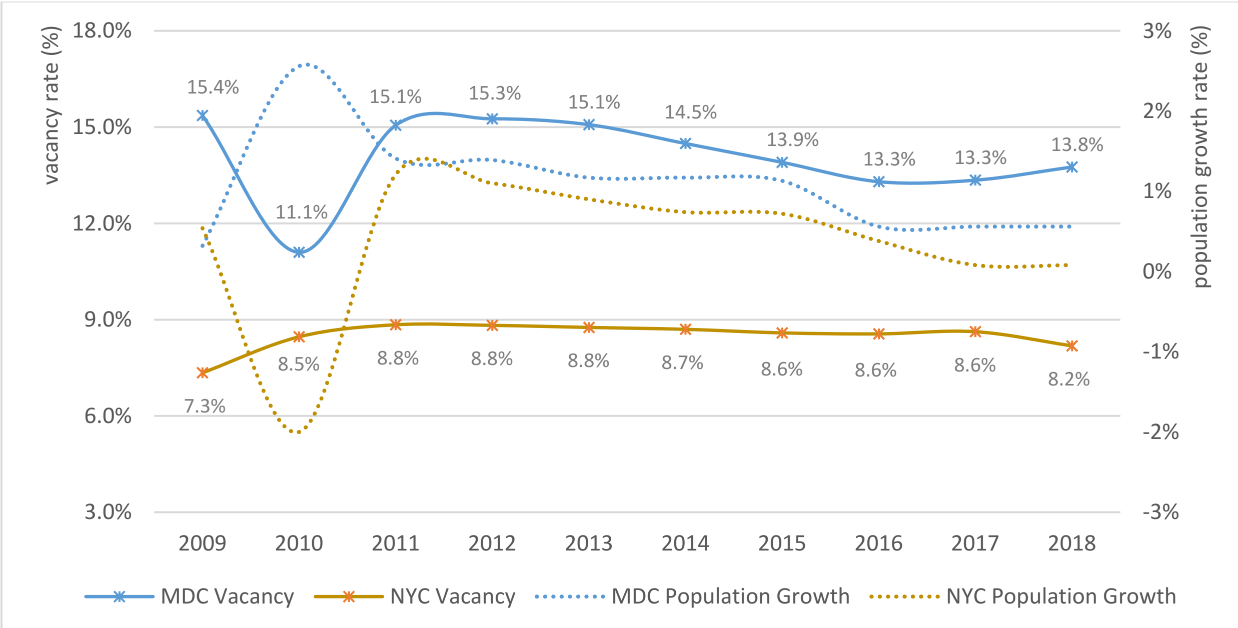


Figure 14. Vacancy rates.

Sources: ZCTAs data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 vacancy rate.

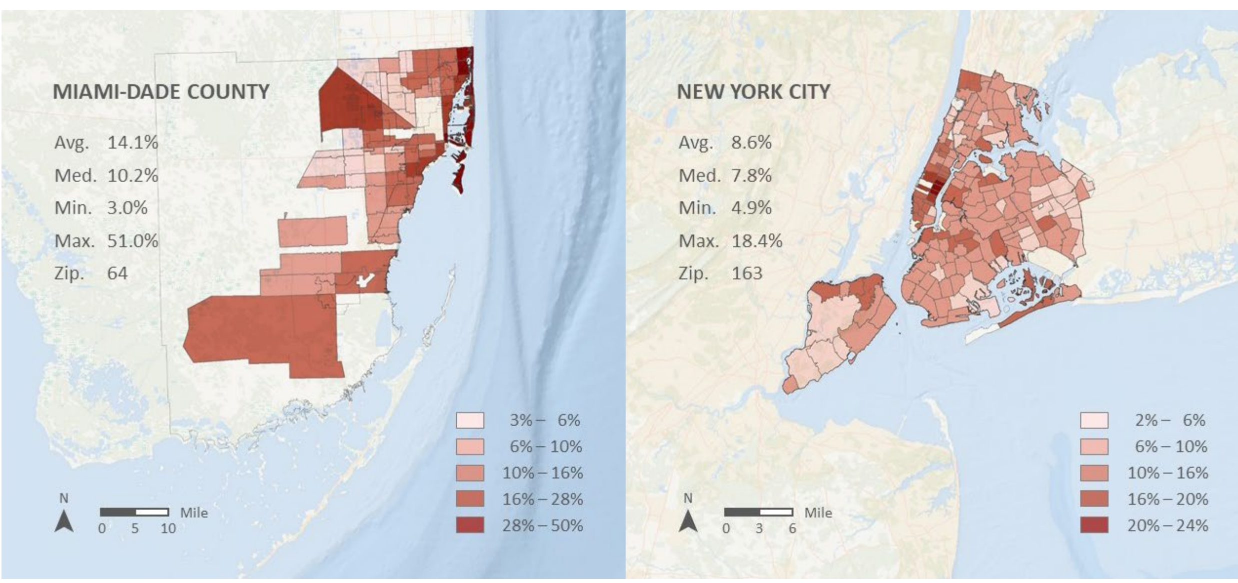


Figure 15. Vacancy rates (10-year average) by zip code.

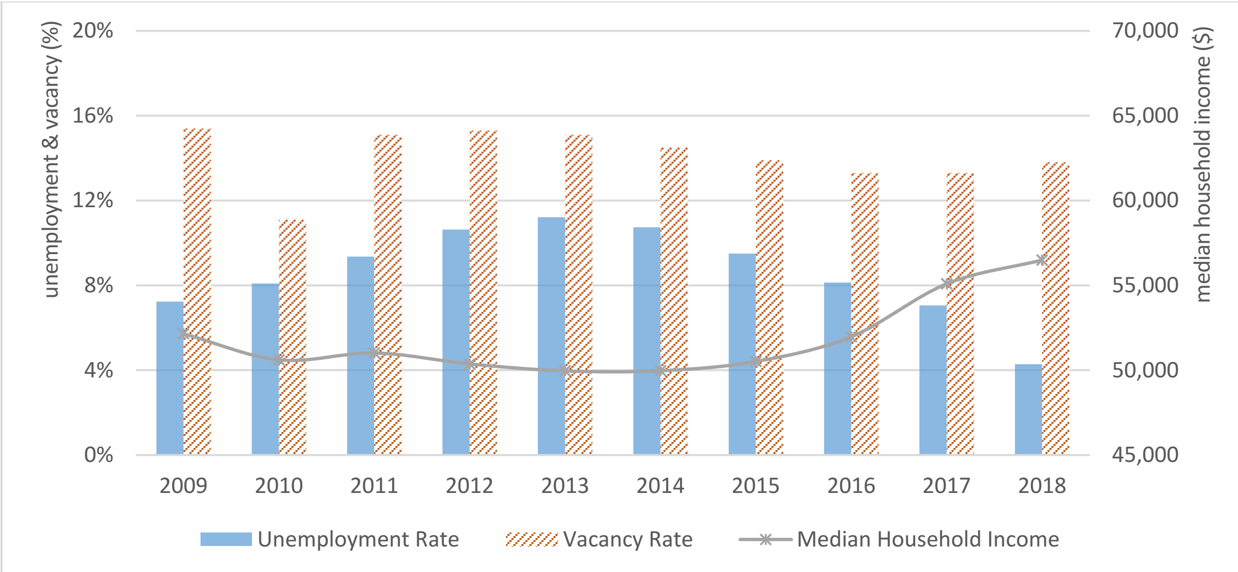


Figure 16. Miami-Dade County market trends.

Sources: ZCTAs data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 median household income.

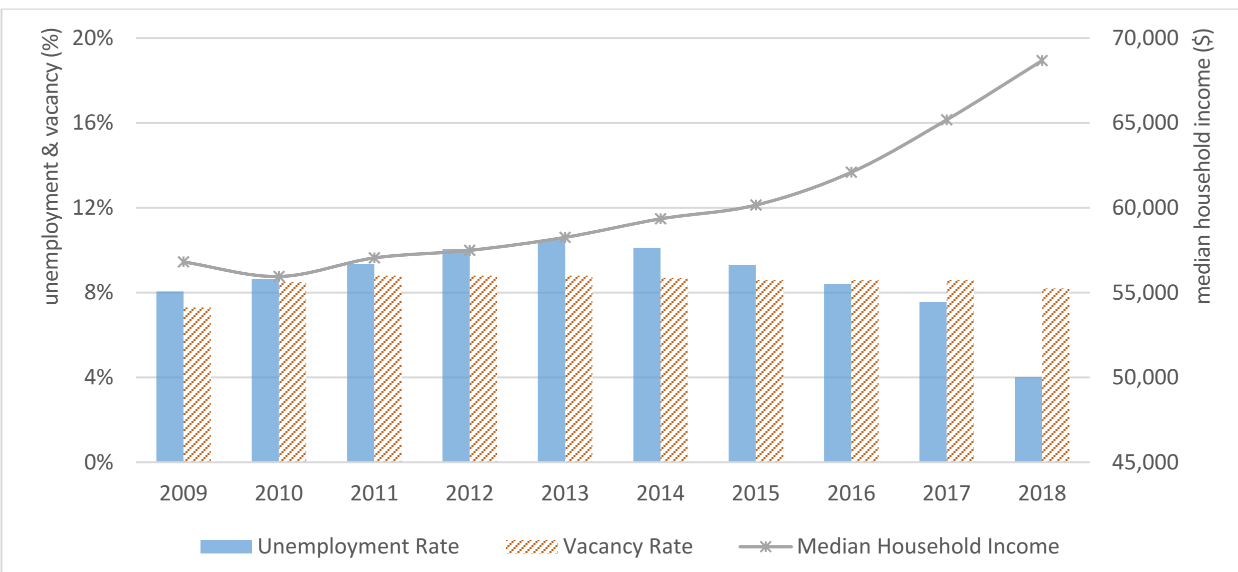


Figure 17. New York City market trends.

Sources: ZCTAs data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 median household income.

Figure 18. Population by age and sex.
Sources: 2013-2017 American Community Survey 5-Year Estimates.

Miami-Dade County has more middle adult population (ages between 40 and 50), while population of New York City has been characterized by having high concentration of young adults between 20 and 35 years of age (see Figure 18). However, populations of the both regions are comprised of a growing number of older adults. According to the latest U.S. Census data, this population group has been growing more rapidly (17.7% in MDC and 17.6% in NYC) than the regional population growth rates (8.3% in MDC and 4.7% in NYC) since 2010 (see Figure 19).

Meanwhile, approximately 6.5% of the overall population is under the age of 5 in both regions, and the children population have steadily increased (4.2% in MDC and 8.2% in NYC) over the last decade. Due to children's disproportionate dependency on others, such as child caretakers, they are more vulnerable to natural disasters (New York State, 2014).

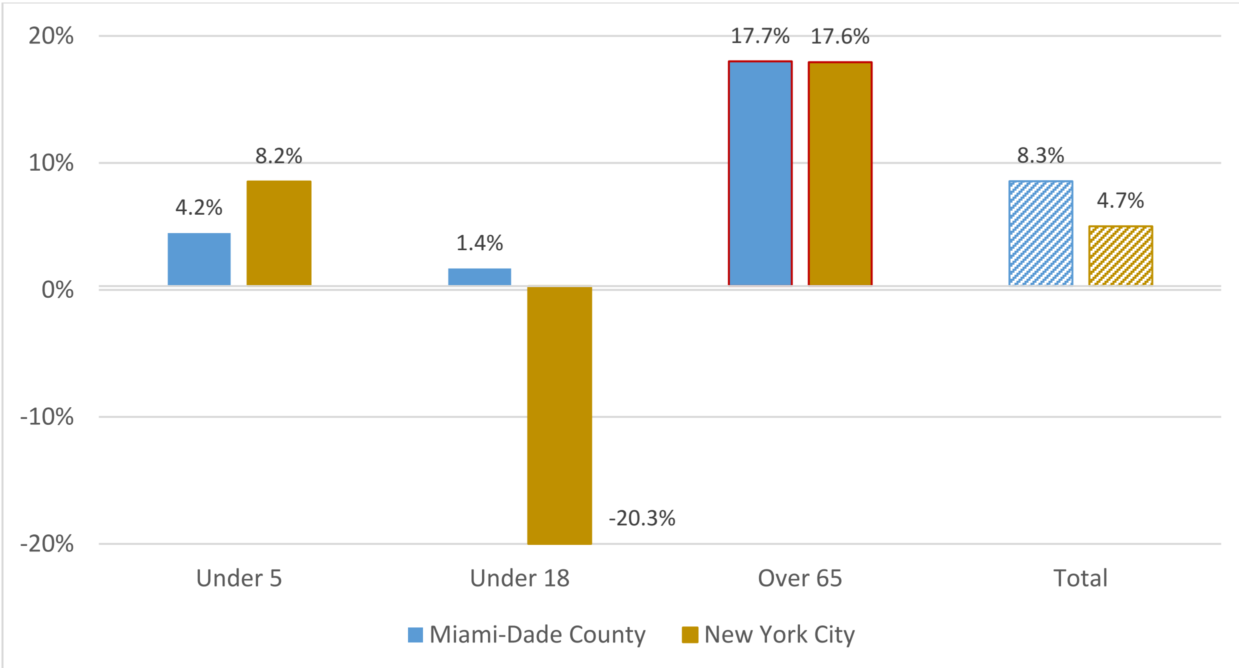


Figure 19. Population changes by age groups (2010 – 2017).

Sources: Census 2010 and 2017 Population Estimate (as of July 1, 2017), American Community Survey.

3.3 Storms and Hurricanes

A total of 64 major storms (see Appendix 1), that have wind speeds over 25 knots (28.8 miles per hour), occurred in Miami-Dade County over the past half century. About 70% of the storms were either a tropical storm[39] or tropical depression[40], but 16% were major hurricanes that classified as the Saffir–Simpson scale 3 or higher (See Appendix 3). Three-quarters of the storms occurred during the months between August and October.

The most devastating hurricanes in this county over the past three decades were Hurricane Andrew (1992) and Irma (2017). At the time of landfall on August 24, 1992, Hurricane Andrew was a Category 5 with the estimated wind speeds of 165 miles per hour. More than 25,000 homes were destroyed, and one-quarter million people were left temporarily homeless (NHC, 1993). Hurricane Irma in 2017 also caused significant damages to the county. Although the Category 4 hurricane did not directly strike[41] the county, a widespread flooding and extensive power outage caused significant property damages. According to the National Hurricane Center (NHC), more than 1,000 residential properties and about 50% of the agricultural industry sustained major damages with estimated losses near $250 million (NHC, 2018). Both hurricanes caused about 1.5 million residents to lose power across South Florida.

[39] Tropical storm is a tropical cyclone with maximum sustained wind between 39 and 73 miles per hour (mph).

[40] Tropical depression is one type of tropical cyclones that produce maximum sustained winds below 39 mph.

[41] Hurricane Irma made landfall in the Florida Keys and southwestern Florida (Marco Island).

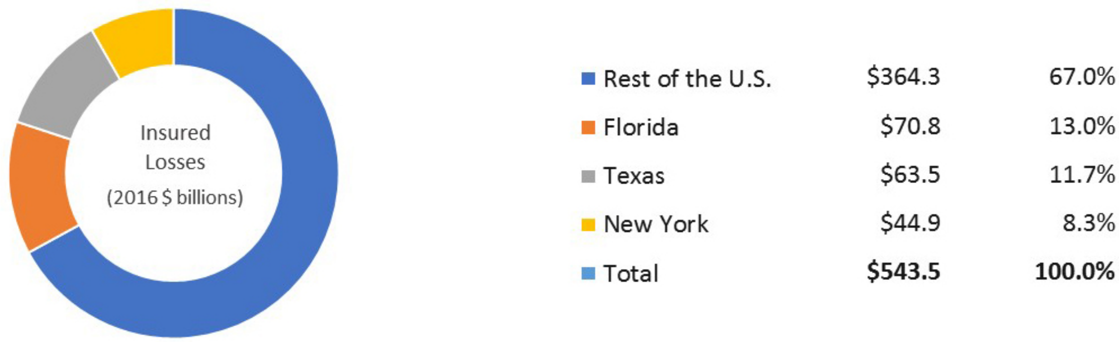


Figure 20. Top three states by inflation-adjusted insured catastrophe losses, 1987-2016.
Sources: Modified figure (Original source: Insurance Information Institute, 2018).

Table 4. Top 10 costliest (insured losses) hurricanes in the United States.

Rank	Year	Location (State)	Hurricane	Estimated insured losses ($ billion)
1	2005	AL, **FL**, GA, LA, MS, TN	Katrina	$50.7
2	2017	PR, UV	Maria	NA
3	2017	AL, **FL**, GA, NC, PR, SC, UV	Irma	NA
4	2012	CT, DC, DE, MA, MD, ME, NC, NH, NJ, **NY**, OH, PA, RI, VA, VT, WV	Sandy	20.2
5	2017	AL, LA, MS, NC, TN, TX	Harvey	NA
6	1992	**FL**, LA	Andrew	24.8
7	2008	AR, IL, IN, KY, LA, MO, OH, PA, TX	Ike	14.3
8	2005	**FL**	Wilma	12.7
9	2004	**FL**, NC, SC	Charley	9.5
10	2004	AL, DE, **FL**, GA, LA, MD, MS, NC, NJ, **NY**, OH, PA, TN, VA, WV	Ivan	9.1

Notes: Modified table (Original source: Insurance Information Institute, 2018). The estimated insured loss amounts are property coverage only. It does not include flood damage covered by the National Flood Insurance Program. The estimated losses are inflation-adjusted amount for 2017 dollars by the Insurance Information Institute using the GDP implicit price deflator. Loss estimates for hurricanes which occurred in 2017 (Maria, Irma, and Harvey) are not available from the Property Claim Services (PCS), but a relative ranking is provided.

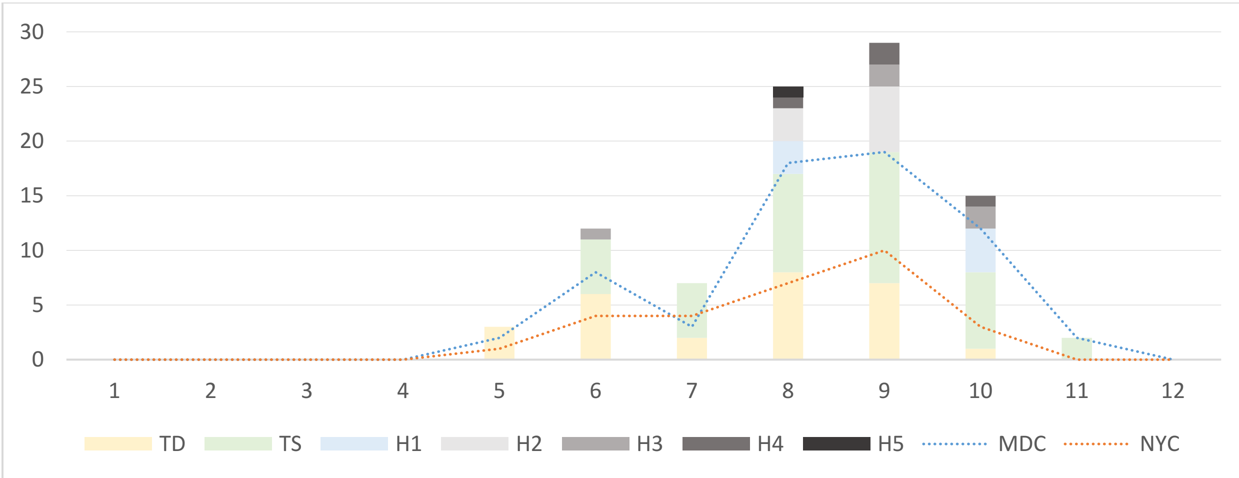


Figure 21. Storm frequency in month (1960 – 2017).

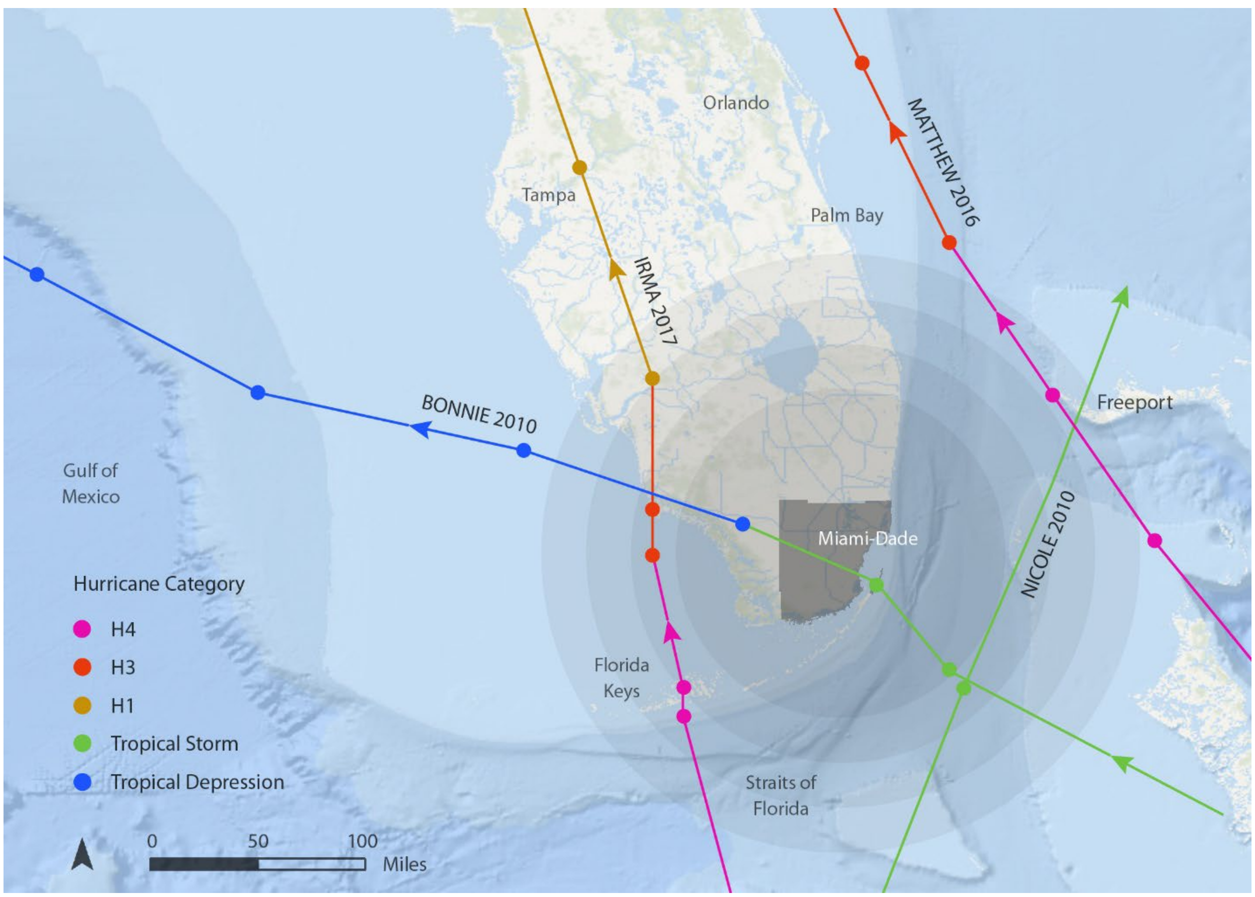


Figure 22. Miami-Dade County hurricane track map (2009 – May 2018).

Notes: H1 – H4 represents the Saffir-Simpson Hurricane Scale 1 – 4. This map is based on the NOAA's hurricane track data and NHC's tropical cyclone reports.

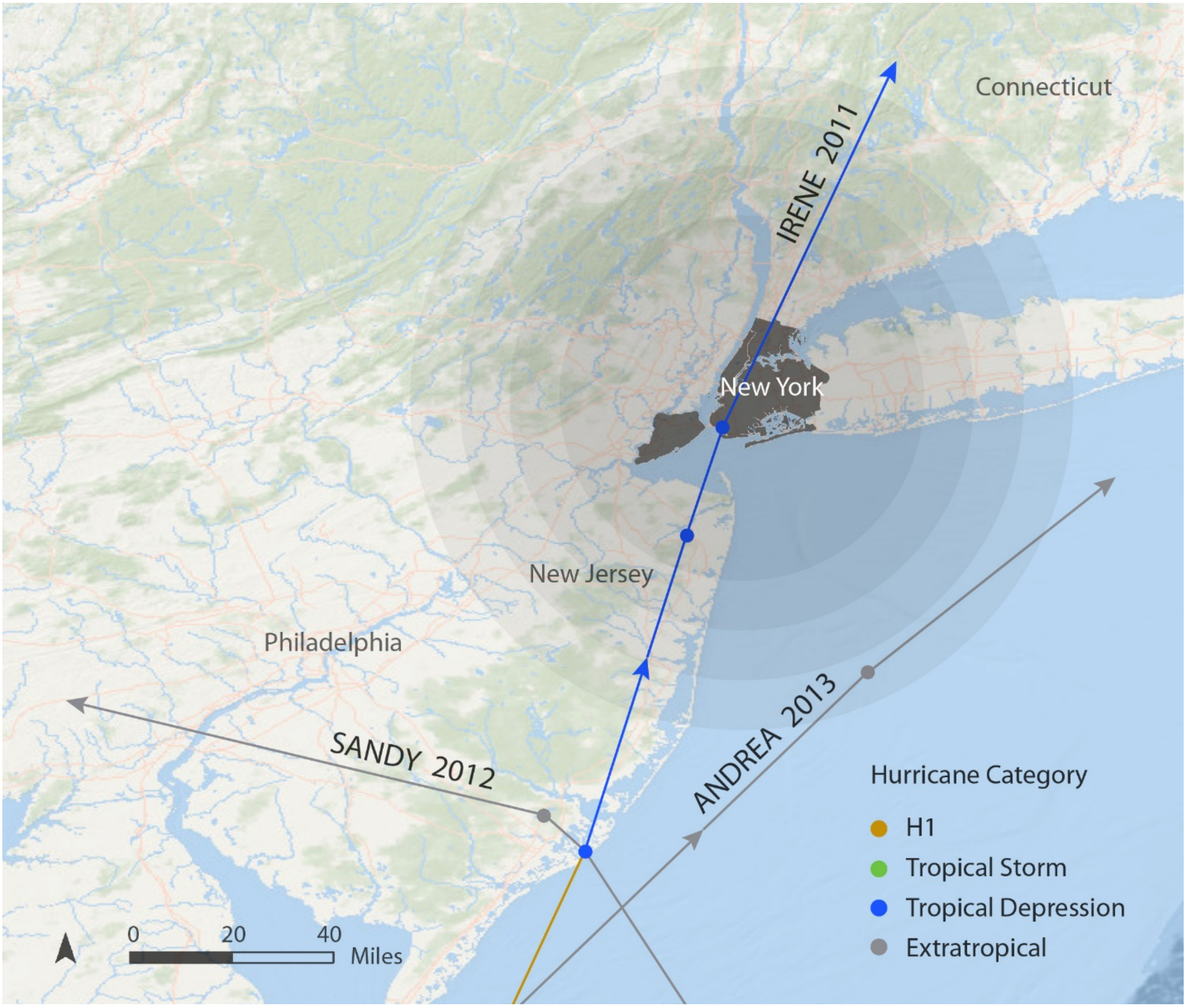


Figure 23. New York City hurricane track map (2009 – May 2018).

Notes: H1 represents the Saffir-Simpson Hurricane Scale 1. This map is based on the NOAA's hurricane track data and NHC's tropical cyclone reports.

Table 5. Hurricane summary (MDC, 2009 – May 2018).

Hurricane	Bonnie	Nicole	Matthew	Irma
Date	7/23/2010	10/30/2010	10/6/2016	9/10/2017
Category	TS	TS	H4	H4
Landfall	Elliot Key (SE)	No (East)	No	Cudjoe Key
Direction	SE → NW	S → NE	SE → N	S → N
Wind (kts)	35	40	115	115
Pressure (mb)	1007	994	937	931
Rain (inch total)	3.25	6.74	1.19	6.25
Gust (kts)	40	35	35	64
Storm Surge (feet)	0	0	0	3.7
Power loss (# of house)	15,870	0	150,000	815,650

Notes: Pressure and wind speed are average values of each storm in the study area. The hurricane category is categorized by the Saffir-Simpson scale, which is a 1 to 5 rating based on a storm's sustained wind speed. In the category, "TS" is an abbreviation of Tropical Storm, and "H" represents Hurricane. Source: NOAA (2018).

Table 6. Hurricane summary (NYC, 2009 – May 2018).

Hurricane	Irene	Sandy	Andrea
Date	8/28/2011	10/29/2012	6/8/2013
Category	TS	ET	ET
Direction	SE → NW	S → N	SW → NE
Wind (knot)	55	65	27
Pressure (mb)	963	943	997
Rain (inch total)	6.87	0.94	3.12
Gust (knots)	55	54	34
Storm Surge (feet)	0	12.65	0

Notes: Pressure and wind speed are average values of each storm in the study area. TS = Tropical Storm, ET = Extratropical. Source: NOAA (2018).

A total of 29 major storms (see Appendix 1), that have wind speeds over 25 knots (28.8 miles per hour), occurred in New York City since 1960. About 80% of the storms were either a tropical storm or tropical depression and there was no hurricane stronger than Category 3. More than 60% of the storms occurred either in August or September. The most devastating storm in recent years was Super Storm Sandy (2012). Although Sandy weakened when it made landfall near New Jersey, Sandy produced a catastrophic storm surge (e.g., 14.4 feet storm surge at Battery Park) by combining with high astronomical tides during a full moon at the New York Bight[42]. According to New York City's governor's office, about 305,000 homes were destroyed in the state by Sandy, and about 5 million residences lost electrical power across this region, which lasted for several weeks. The Office of Management and Budget estimated the damage amount to the city as high as $19 billion (Blake et al., 2013). Some other storms such as Irene (2011) and Andrea (2013) produced heavy rain and minor flooding.

[42] The New York Bight is a curve shaped indentation where the New York and New Jersey coastlines meet. This geographic characteristic increases the speed and intensity of storm surge funneling directly into the inland and harbor areas (New York State, 2014).

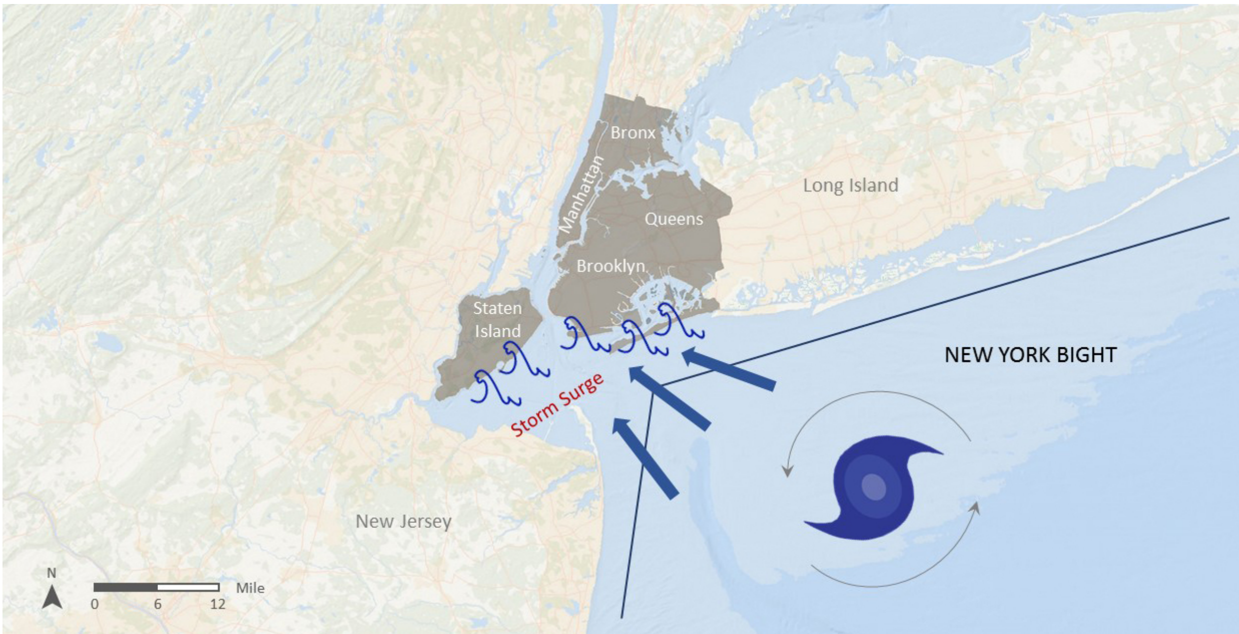


Figure 24. New York Bight.

Notes: Modified illustration of the New York Bight (Original sources: New York State, 2014)

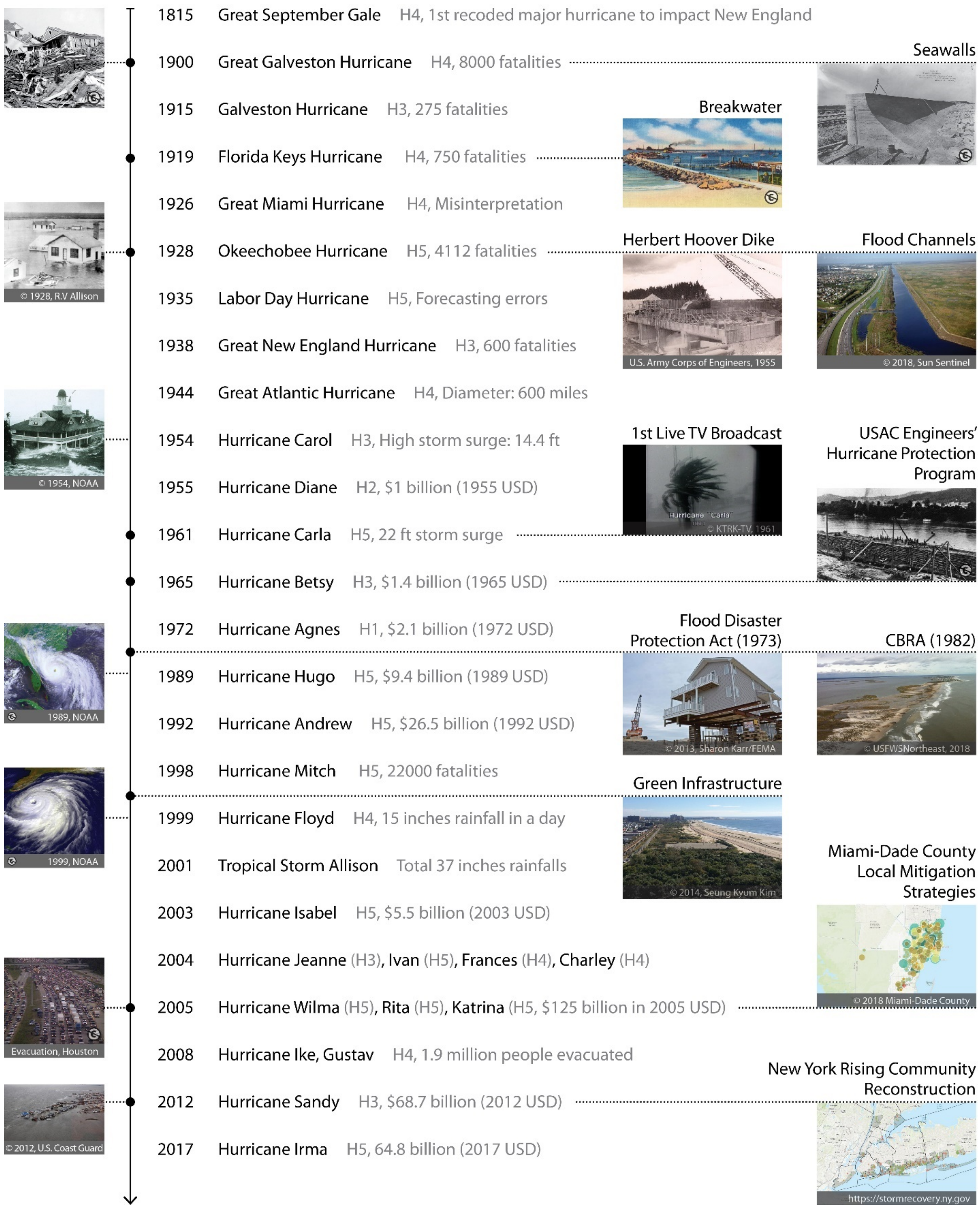


Figure 25. Featured hurricanes and adaptation history in the Atlantic and Gulf Coasts.

Data Sources: University of Rhode Island (2010-2015), NOAA / NWS.

Image Sources: Great Galveston Hurricane (Singley, 1900); Okeechobee Hurricane (Allison, 1928); Hurricane Carol (NOAA, 1954); Hurricane Hugo (NOAA, 1989); Hurricane Floyd (NOAA, 1999); Hurricane Rita (Houston Public Media, 2005); Hurricane Sandy (Tuckerton, 2012); Seawalls Construction after Great Galveston Hurricane (Public Domain), Retrieved from https://en.wikipedia.org/wiki/Galveston_Seawall#/media/File:No._3,_Sea_Wall,_From_West_of_Rapid_Fire_Battery,_Fort_Crockett_-_NARA_-_278143.jpg; Breakwater Walk (Postcards), Corpus Christi, Texas (Public Domain), Retrieved from https://www.digitalcommonwealth.org/search/commonwealth:zk51vn76c; Herbert Hoover Dike (U.S. Army Corps of Engineers, 1955); Flood Channels (Reid, 2018); 1st Live TV Broadcast (KTRK-TV, 1961); U.S. Army Corps Engineers' Hurricane Protection Program (U.S. Army Corps of Engineers, 1890); Flood Disaster Protection Act (Karr, 2013); Coastal Barrier Resources Act (USFWS Northeast, 2018); Green Infrastructure (Photograph by Seung Kyum Kim); Miami-Dade County Local Mitigation Strategies (Miami-Dade County, 2018); New York Rising Community Reconstruction (Governor's Office of Storm Recovery, 2018).

3.4 Climate Change Adaptation

Adaptation history in the modern era

Adaptations to protect against climate risks is not a new method to cope with increasingly adverse environmental conditions. According to recent literature, inhabitants in the low-lying coastal areas around the Rhine delta lived on dwelling mounds before the 9^{th} century (Lavell et al., 2012). Around a thousand years ago, dwellers living on the floodplain of the southern North Sea built the first dikes rings to protect people and domestic animals. This construction allowed for a significant population increase in these areas until the sea dikes were broken by a series of major storm surges through the 13th and 14th centuries (Borger & Ligtendag, 1998; Lavell et al., 2012). Through the errors and trials, major improvements and innovations in the technology of dike construction and drainage engineering were made, including development of windmills for pumping water, which by the 15th century rehabilitated and increased the population (Lavell et al., 2012).

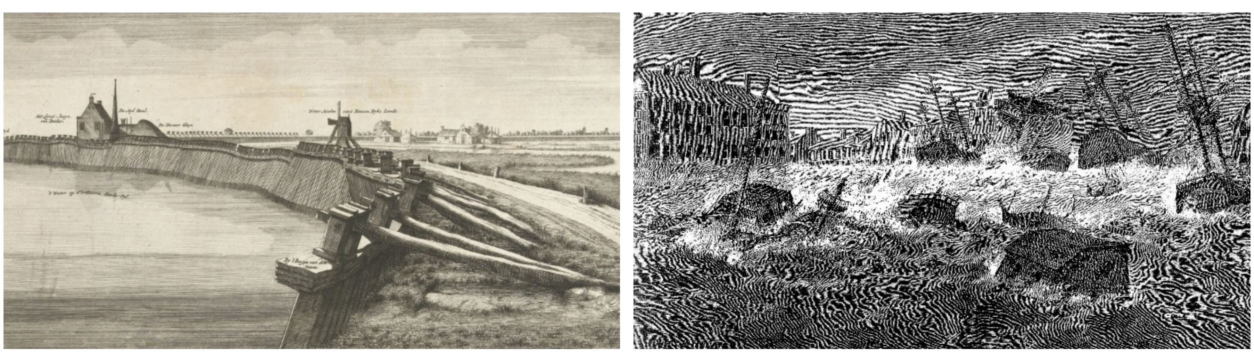


Figure 26. Sea dike in Diemen, Netherlands (left) and Great Storm of 1815 engraving.

Sources: De slechte toestand van de Zeedijk vanaf Diemen tot aan Jaap Hannes (eerste deel), 1705 (Public Domain), Retrieved from http://hdl.handle.net/10934/RM0001.COLLECT.472532; Great Storm of 1815 engraving (Public Domain), Retrieved from https://upload.wikimedia.org/wikipedia/commons/9/90/Great_Storm_of_1815_engraving.jpg.

The first recoded major hurricane in the modern era of the United States is the Great September Gale in 1815, which directly impacted the New England regions with an estimated strength equivalent to a Category 4 hurricane on the current Saffir-Simpson Wind Scale (Scowcroft et al., 2010). After a few more major hurricanes impacted regions of the Northern Atlantic Ocean and Gulf of Mexico, the notorious Great Galveston Hurricane in 1900 devastated the vicinity of Galveston, resulting in more than 8,000 human fatalities (Blake, Landsea, & Gibney, 2011). The ramifications of the hurricane resulted in construction of the first large-scaled land grading to raise elevation as well as a 17-foot high seawall construction, spanning around three miles (Roth, 2010). The effect of seawalls was proven when in 1915, the Galveston hurricane struck; only this time, 90% of the overall damages occurred outside of the seawalls (Scowcroft et al., 2010).

Although the US Weather Bureau was established in 1870, no sophisticated storm forecast technology existed in the early 19th century. Storm preparation mostly relied on ship reports and rumors. When the 1919 Florida Keys hurricane struck the Corpus Christi Bay, the rumors had spread that the hurricane made landfall in Louisiana and Mississippi, but the hurricane warnings were omitted in Corpus Christi, Texas (Roth, 2010). The result was that a significant amount of damage[43] was produced due to the forecasting error, and this led Corpus Christi to construct the first massive breakwater in 1925, and seawalls by 1940 (Roth, 2010; Scowcroft et al., 2010).

In the 1920s, two major hurricanes made landfall in the south of Florida within a two-year interval. The eye of the 1926 Great Miami hurricane directly passed over the city of Miami. Due to the eye's characteristics, which has light winds and clear skies, people underestimated the power of the Category 4 hurricane (Scowcroft et al., 2010). By the subsequent approaches of the

[43] Total estimated damages were $22 million (1919 USD) and more than 750 fatalities (Scowcroft et al., 2010).

eyewall[44], several city blocks in the city of Miami were inundated and this misinterpretation made the storm the most damaging single hurricane in US history, with $140-157 billion of estimated normalized damages (Pielke Jr et al., 2008). Two years later in 1928, the Category 5 Okeechobee hurricane caused more than 4,000 fatalities by widespread flooding (flooding an area 75-miles wide) along the south shore of Lake Okeechobee in Florida. As a result of these two disastrous events, construction of a hundred mile long series of dikes and numerous flood channels was begun, and completed in 1937 (Scowcroft et al., 2010).

In the second half of the 19th century, there was a considerable improvement in hurricane forecasting technologies (e.g., satellite), and key disaster prevention policies (e.g., national flood insurance policy) were established. As the first weather satellite was launched in 1960, hurricane Carla had the first live television broadcast in 1961 (Garber, 2012). After hurricane Betsy in 1965 (the first hurricane that caused damages over $1 billion), the U.S. Army Corps of Engineers' Hurricane Protection Program was launched to build new levees for New Orleans (Scowcroft et al., 2010). In 1968, the National Flood Insurance Act was legislated, making government flood insurance[45] available for the first time against flood damages. Five years later, the policy was amended by the Flood Disaster Protection Act of 1973 and made the purchase of flood insurance mandatory for homeowners of properties located within a 100-year floodplain (i.e. areas that have a 1% chance of flooding occurrence in any given year) or below (FEMA,

[44] Hurricane eyewall, surrounding regions of the eye, is the most dangerous part of the storm because it has the strongest winds.

[45] Although some of the standard homeowner's insurance policy included flood insurance before 1950, naturally occurred flood damages were not typically covered or insufficiently covered the damage amounts (Altmaier et al., 2017).

1997). Subsequently, a Letter of Map Change[46] (LOMC), revising or amending the Flood Insurance Rate Map (FIRM) by modifying topography, was encouraged, which has the advantage of saving the cost of purchasing mandatory flood insurance (FEMA, 2012). Around the late 1970s and early 1980s, the disaster protection paradigm shifted from focusing on engineering infrastructure to utilizing natural resources. Before 1980, the Federal Government had historically incentivized coastal development, resulting in a loss of human life, properties, and natural resources (USFWS, 2015). To minimize the loss and damages, the Coastal Barrier Resources Act was passed in 1982. The Coastal Barrier Resources System (CBRS) aimed to protect the mainland from storm surges and hurricane winds, as well as preserve natural resources by discouraging development in undeveloped coastal barriers.

Despite the technology improvements and policy developments, damages caused by major hurricanes have been even larger and more frequent because of climate change. Evidently, hurricane Andrew in 1992 moved across southern Florida, causing $26.5 billion (1992 USD) in damages. The Category 5 hurricane's exceptionally powerful winds also produced considerable environmental damages. Approximately 25% of the trees in Florida's Everglades were toppled, and almost all thriving Australian pine trees (an invasive species) which had occupied around 95% of Bill Baggs State Park in Florida were destroyed. This was followed by a large scale ecological restoration project to replace the invasive species with native trees (Scowcroft et al., 2010), and this nature-friendly strategy was expanded into the urban scale. The term "green infrastructure" was first introduced in a report to Florida's governor in 1994 as a land

[46] A LOMC consists of a Letter of Map Amendment (LOMA) and Letter of Map Revision Based on Fill (LOMR-F), and Letter of Map Revision (LOMR). LOMA is a letter to adjust the Flood Insurance Rate Map by proving a property is located in naturally higher ground than the base flood. A LOMR-F is a map modification based on raising structure or land elevation above FEMA's Base Flood Elevation by fill. And LOMR is a map revision by building drainage facilities altering the floodplain and floodway (FEMA, 2012).

conservation strategy (Firehock, 2010). Today, green infrastructures have been widely adopted as important climate change adaptation and disaster prevention strategies in many cities and local municipalities. In the late 1990s, along with the hard and green infrastructure developments, considerable attention had been paid to developing the systematic capability of communities to prepare for climate hazards in advance of, or after, storms—the so-called adaptive capacity (IPCC, 2007). The adaptive capacity can result in largely different consequences at different times and locations, due to societal transformations over time and having different coping abilities in each region (Rayner & Malone, 1998). For example, hurricane Mitch in 1998 had more than 20,000 fatalities due to the accompanying landslides and widespread flooding, but approximately 90% of the human causalities occurred in Honduras and Nicaragua (Scowcroft et al., 2010).

After experiencing four[47] major hurricanes in 2004 and three[48] consecutive Category 5 hurricanes in 2005, Miami-Dade County officially launched Local Mitigation Strategies (LMS) program to minimize the impact of the extreme weather. The program includes disaster preparedness, structural hardening, and infrastructure projects based on cost effectiveness and impact on overall communities. After Hurricane Sandy (also known as Super storm Sandy) in 2012, which caused more than $65 billion in damages in the United States, New York State also launched the New York Rising Community Reconstruction (NYRCR) program in April 2013. This program focused more on improving adaptive capacity by allotting more than $700 million

[47] Hurricane Charley (Category 4, August 9 – 15), Hurricane Frances (Category 4, August 24 – September 10), Hurricane Ivan (Category 5, September 2 – 25), and Hurricane Jeanne (Category 3, September 13 – 29).

[48] Hurricane Katrina (Category 5, August 23 – 31), Hurricane Rita (Category 5, September 18 – 26), and Hurricane Wilma (Category 5, October 16 – 27). Among the three Category 5 tropical cyclones, Hurricane Katrina earned the title of costliest hurricane in the US history with total estimate costs over $160 billion (Scowcroft et al., 2010).

in federal funds to improve essential infrastructure investments to critical public services and to help communities' post-storm recovery efforts (Bova-Hiatt, 2013). Nevertheless, the adaptation efforts, hurricane damages, and associated latent risks will never be completely eliminated. Evidently, Hurricane Irma in 2017 caused approximately $50 billion in damages in the United States. In 2018, Hurricane Florence caused 55 fatalities and Hurricane Michael led to damage costs over $6 billion, both in the U.S. Due to the limitations of adaptation budgets and resources, finding the most effective ways to enhance adaptive capacity, lessen the damages, and protect against loss of life by evaluating the current adaptation investments is an essential contribution to society.

Local adaptation programs and investments

Miami-Dade County's annual spending for climate adaptation projects averages $48 million, while the annual average mount for New York City is about $325 million.[49] Considering the population, Miami-Dade County invests $18 per capita per year, and New York City spends far more at $38 per capita per year on climate adaptation measures. However, the focus on certain adaptation types differs between the two regions. In Miami-Dade County, infrastructure hardening (e.g., levees, seawalls, elevating roadways, etc.) and public service building reinforcement are predominant, taking up about 80% of total spending (or $261 million).

[49] Original data from the New York Rising Community Reconstruction includes installation projects of new pre-fabricated modular building units. These projects account for 70% ($2.3 billion) of the total adaptation budget and were completed in the first quarter of 2015. Although the city allocated a significant amount of its budget to this category, it could be ambiguous whether these modular building projects qualify as climate adaptation measures. Thus, I excluded these projects from the cost calculation. When including these pre-fabricated modular building projects, the per capita spending for the adaptation in New York City is increased to $92 per capita per year.

Table 7. Climate adaptation projects and costs (2011– 2017).

Adaptation classification		Miami-Dade County[1] # of projects	Miami-Dade County[1] Amounts (US$)	Miami-Dade County[1] % of amounts	New York City[2] # of projects	New York City[2] Amounts (US$)	New York City[2] % of amounts
Hard	Infrastructure hardening	169	170,971,348	52.4%	27	108,270,000	6.7%
	Critical facility hardening	49	90,712,127	27.8%	219	832,520,000	51.2%
Green	Drainage improvement	15	7,124,833	2.2%	11	236,710,000	14.6%
Social	Emergency preparedness	19	17,958,152	5.5%	9	21,160,000	1.3%
	Recovery operation	53	39,653,416	12.1%	61	426,298,000	26.2%
Total		305	326,419,876	100%	327	1,624,958,000	100%

Notes: 1) Miami Dade County Emergency Management (Local Mitigation Strategies) from 2011 Q2 to 2017 Q4. 2) New York Rising Community Reconstruction (storyrecovery.ny.gov) from 2012 Q1 to 2016 Q4.

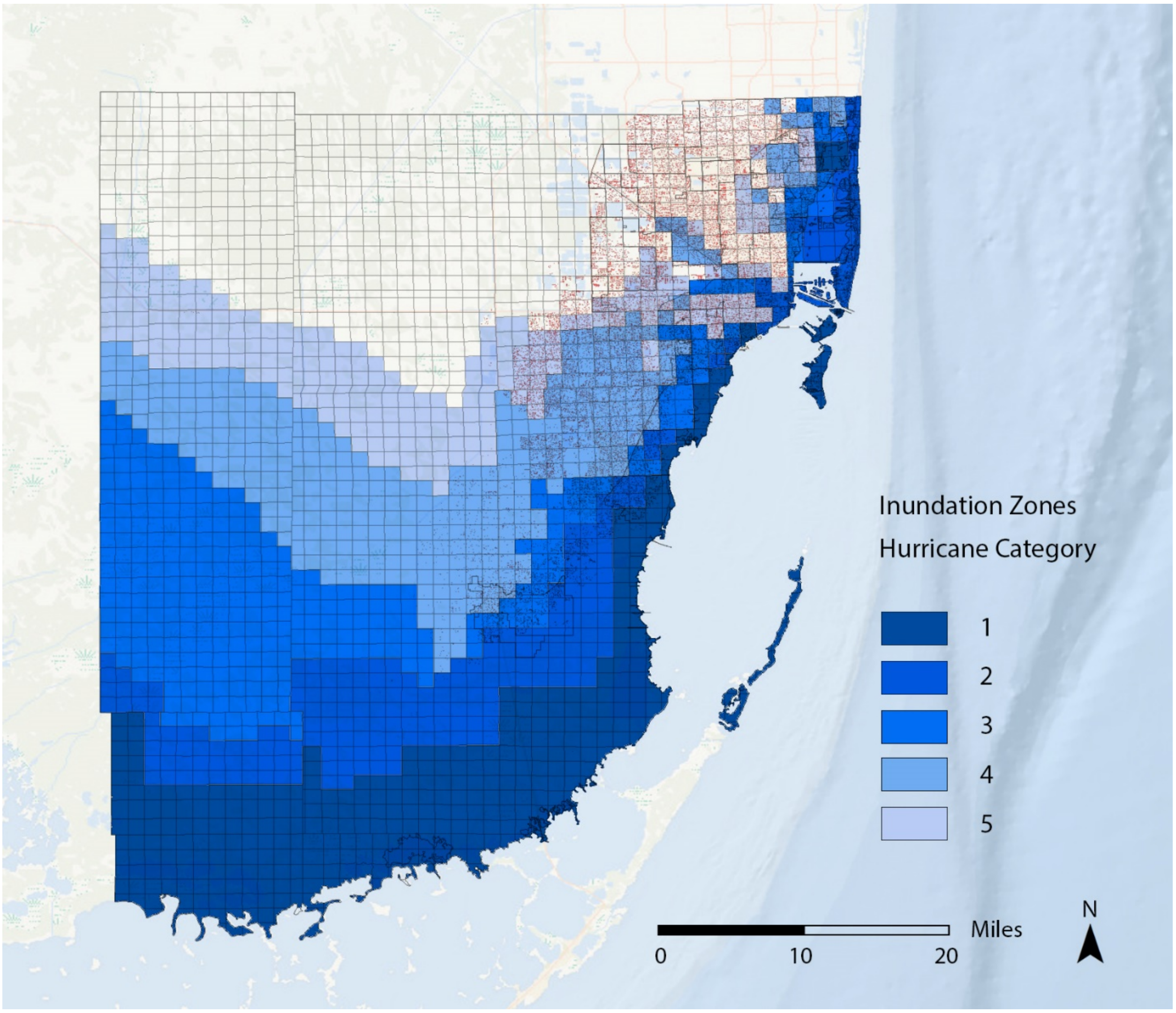


Figure 27. Miami-Dade County Hurricane Inundation Zones.

Notes: The hurricane category is categorized by the Saffir-Simpson scale, which is a 1 to 5 rating based on a storm's sustained wind speed (See Appendix 3).

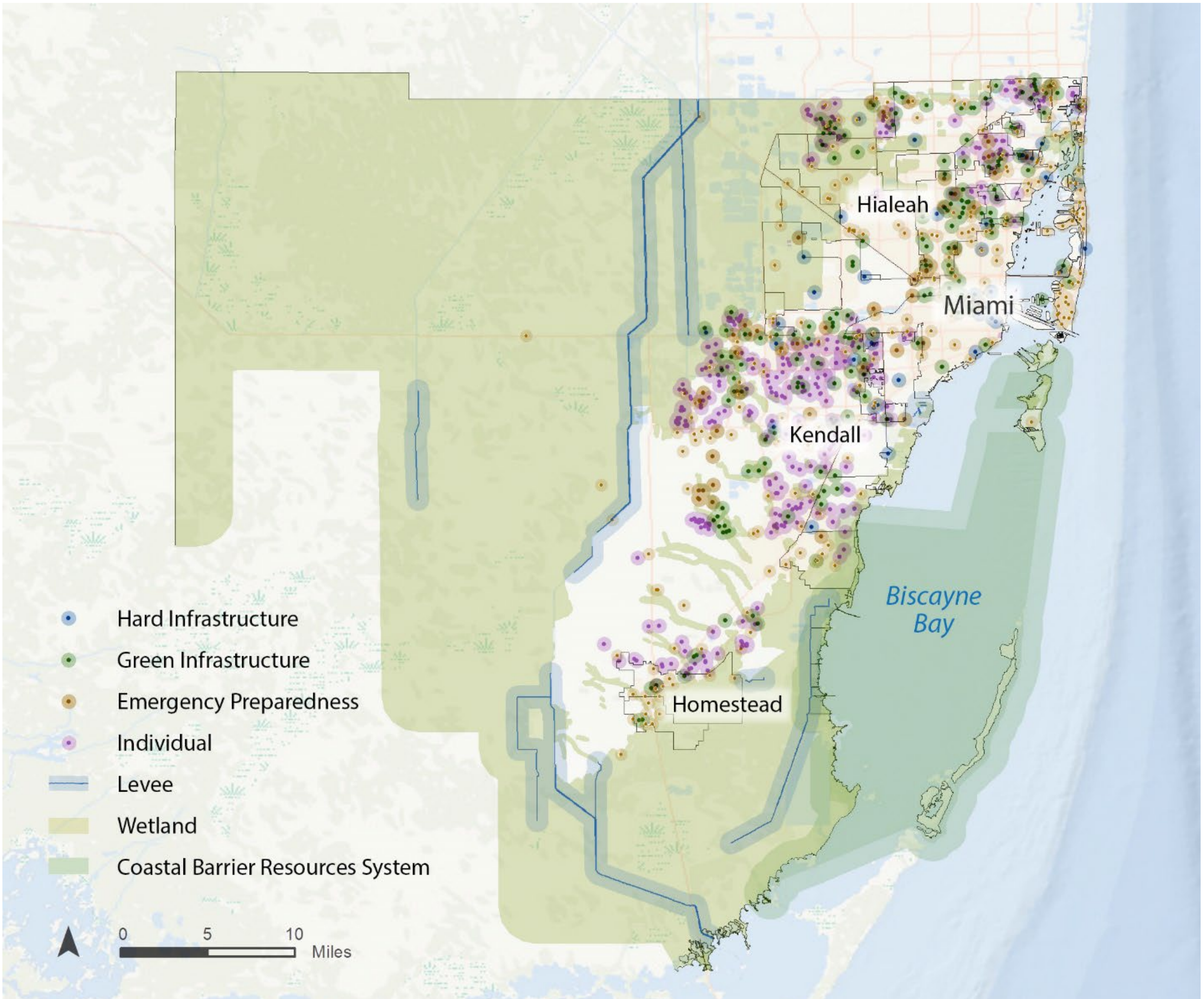


Figure 28. Map of site adaptation measures (MDC).

Similarly, New York City invested about 58% of their climate adaptation budget (or $940 million) on reinforcing public service buildings and hardening infrastructure. Adaptation projects in this category include hardening of shelters and existing protection measures. These projects aim to retrofit critical facilities and infrastructure to maintain continuous operation during hurricane events and other natural disasters. Of the total, about 26% of their adaptation project budget (or $426 million) was spent on disaster recovery, including replacement of damaged walkways, debris removal and public safety measures, and emergency restoration for public service operation. Finally, about 15% of the budget (or $237 million) was spent on drainage and stormwater system improvements. These projects are to expand the capacities of drainage infrastructures to manage heavy rainfall events. Green infrastructural shoreline protection projects such as beach nourishment and dune expansion are included in this category.

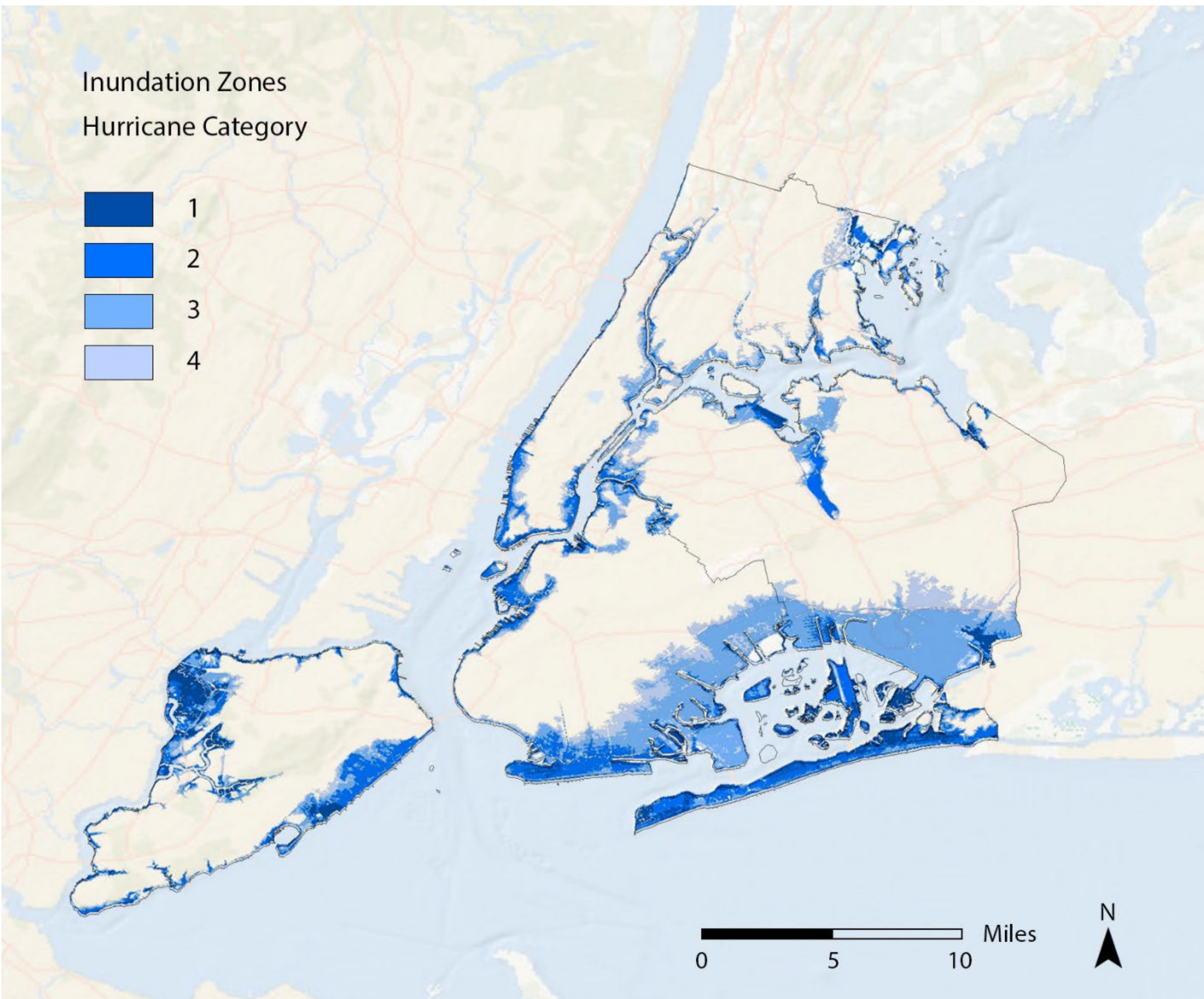


Figure 29. New York City Hurricane Inundation Zones.

Sources: SLOSH (Sea, Lake, and Overland Surge from Hurricanes) MOM (Maximum of Maximums) model, U.S. National Weather Service (NWS)

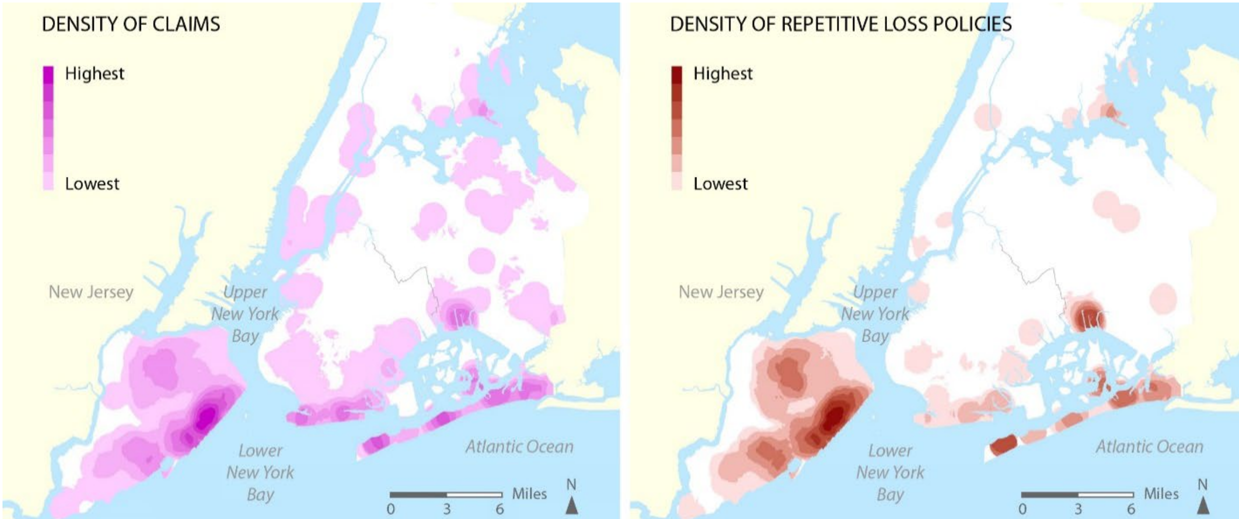


Figure 30. National flood insurance policy claims (left) and repetitive loss policies (right).

Notes: Modified the National Flood Insurance policy maps in NYC Hazard Mitigation Plan 2014 (p.180). Sources: New York State, 2014.

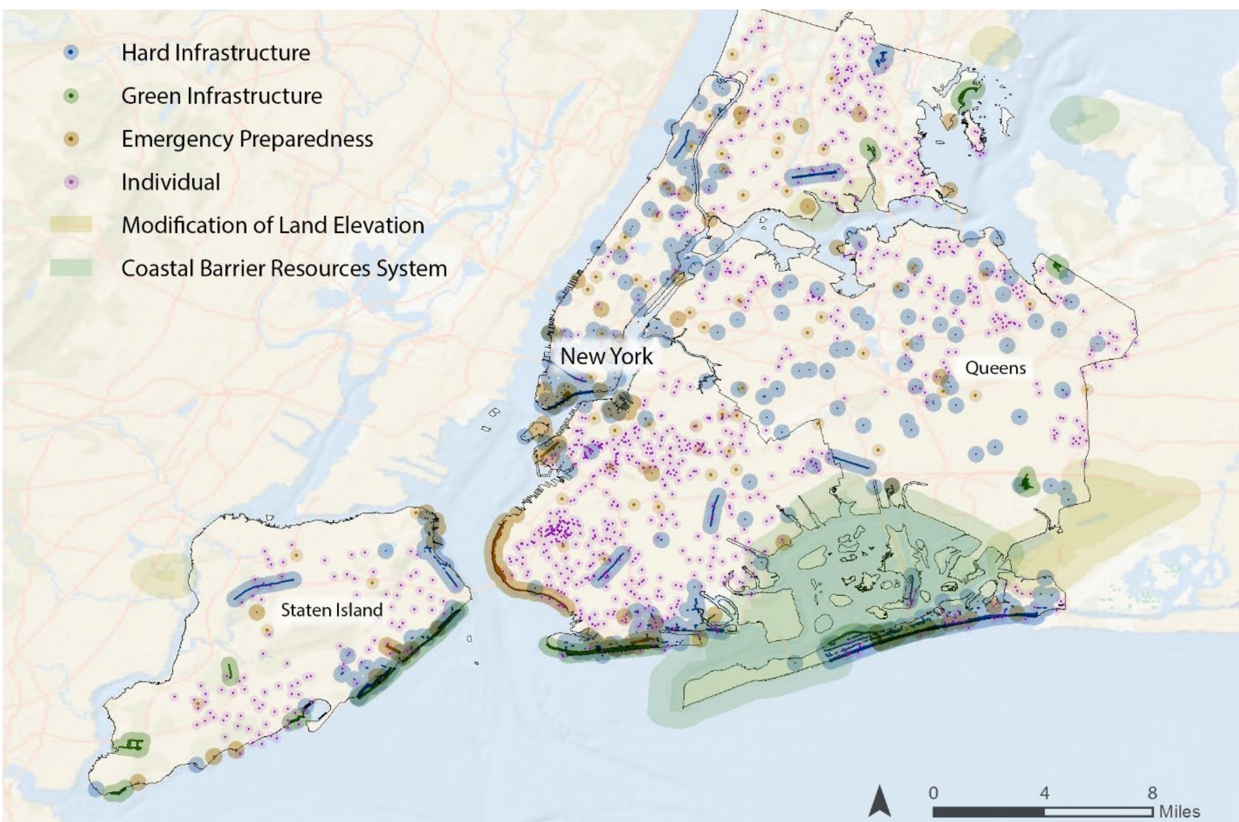


Figure 31. Map of site adaptation measures (NYC).

4. Analytical Framework

According to Chambwera et al. (2014), adaptation decisions are mainly based on realized climate change, because climate change scenarios may not be expected to vary substantially in the next few decades. However, past climate information and the preliminary assessment for an optimal adaptation decision-making do not represent the effects of post-adaption, because some adaptation measures could have already become obsolete over time by experiencing an extreme climate event that exceeds its adaptation capacity. It might also be possible that some other unexpected problems could arise from ancillary effects (co-benefits or co-costs), dynamics of adaptation (optimal adaptations which vary over time), and potential gaps between the level of public provision and social desirability of adaptation (Chambwera et al., 2014).

Despite this complexity, a well-functioning adaptation measure could provide a net positive effect in adjacent communities by reducing risk exposure to future climate events or provisioning positive co-benefits through improved adaptive capacity. In the decision-making stage, evaluating this "functionality" could dependent upon the economics of the adaptation measures, which fundamentally rely on the sizes and types of subjects (i.e., wind, flooding, storm surge, etc.) to be adapted. By contrast, estimating the effects of adaptation measures already built relies more on reduction of latent risks rather than cost-effectiveness. Thus, I hypothesize that a more effective adaptation measure decreases risk perception for future climate events. Although some characteristics, such as human lives and cultural heritage, are economically unmeasurable, the premise that the effects of adaptation economically influence directly or indirectly is prevalent in the existing literature.

Therefore, I also speculate that the risk reduction due to adaptation measures will have a positive impact on housing values. In this study, I limit the scope of measuring the value of adaptation to a tangible asset and analyze housing price dynamics spatially and temporally by estimating before and after the storms and the installation of adaptation measures. Furthermore, prevalent risk perception factors and storm characteristics are applied to the analysis model to find the potential interactions and ancillary effects among those attributes.

4.1 Data

The study investigates the impacts of climate adaptation measures using single-family housing transaction data in Miami-Dade County and New York City from July 2009 to May 2018. The study combines four large datasets from Miami-Dade County, New York City, 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. Other supplemental information demographics and statistics are collected from various websites, including Social Explorer and Federal Reserve Economic Data (FRED).

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. Unlike Miami-Dade County and any other cities, there is no information about the numbers of bedrooms and bathrooms publicly available in New York City. However, sufficient numbers of other structural and environmental variables supplement the drawback, omitting the bedroom and bathroom counts. Since the spatial coordination of each property is excluded in New York City's dataset, the addresses of each property were manually batch geocoded with ArcGIS.

FEMA data provides flood hazard information with site elevation and location of general flood mitigation structures such as levees and canals. NOAA database provides a comprehensive hurricane data and storm surge inundation information based on Sea, Lake, and Overland Surge from Hurricanes (SLOSH) Maximum of Maximums (MOM) model. Hurricane data contains details of each storm's characteristics, including hurricane tracks, dates of occurrence, damages, and storm intensity (i.e., wind speed and pressure).

Lists of adaptation measures from 2010 to 2017 with detailed information are provided by Miami Dade County Emergency Management Office and New York Rising Community Reconstruction. The information includes project types[50] and locations, initiation and completion dates, adaptation goals (i.e., which hazard to be addressed), construction stages, project costs, and detailed project descriptions.

This study uses a total of 79,184 and 90,811 single-family housing units that were sold between July 1, 2009 and May 31, 2018, in Miami-Dade County and New York City, respectively. 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. To avoid the omitted variable bias, the transaction data were clustered by 64 zip code in Miami-Dade County and 162[51] zip code in New York City. Housing sales prices are adjusted to January 2018 prices using each region's monthly consumer price index[52] for housing. The seasonality is also adjusted, and the average adjusted sales prices were $459,000 in Miami-Dade County and $614,000 in New York City. About 70% of all transactions were within price ranges between $150,000 and $800,000 in Miami-Dade County; and between 300,000 and 800,000 in New York

---

[50] Initial classification of their adaptation projects in the dataset is based on individual region's own adaptation strategies and funding sources.

[51] A total of 5 singleton groups (groups with only one observation) were dropped in the regressions. Singleton groups can lead to incorrect inference by overstating statistical significance of fixed effect models (Correia, 2015). Thus, the New York City data were eventually clustered by 157 zip codes.

[52] For Miami-Dade County, the home sales prices are adjusted based on the FRED Consumer Price Index for All Urban Consumers: Housing in Miami-Fort Lauderdale-West Palm Beach, FL. For New York City, the transaction prices are adjusted based on the FRED Consumer Price Index for All Urban Consumers: Housing in New York-Newark-Jersey City.

City. The average age of housing structures in New York City (around 74 years) is about 24 years older than that of Miami-Dade County (around 50 years per structure). A typical lot size in Miami-Dade County is 3-times larger than that of New York City, but the average number of stories in New York City is twice as high as Miami-Dade County. Approximate 80% are owner-occupied properties for both regions. Although New York City has rent regulations, such as rent control and rent stabilization, the requirements[53] to become rent regulated units do not include single-family housing. Miami-Dade County does not have such a restriction. Only about 5% (in the case of Miami-Dade County) and 10% (in New York City) of homes are within a five-minute walking distance to the oceanfront. About 7% have an ocean view in Miami-Dade, but ocean-view properties in New York City are just 1%.

Due to risk perception dynamics, I surmise that the effects of hurricanes in local housing markets change over time. 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 3 to 5 months, 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. About one-quarter of homes in the

[53] In New York City, the rent control program applies to an apartment in a one- or two-family unit constructed before February 1947. In order to be qualified for rent control, a tenant must have occupied a unit continuously since April 1, 1953. Meanwhile, the rent stabilization program applies to an apartment containing six or more units which were built before 1974 (NYC Rent Guidelines Board, 2018).

datasets are sold within the first and second sales windows. Transaction volumes in Miami-Dade County are relatively stable at 6% more in the hurricane season (from July to October) than the average, but average sales prices within the hurricane season are about 4% lower than that of the whole year. Likewise, transaction volumes in New York City are 8% higher than the hurricane season (from August to October), while the difference in average sales prices is miniscule (0.5%) between the hurricane season and the entire year.

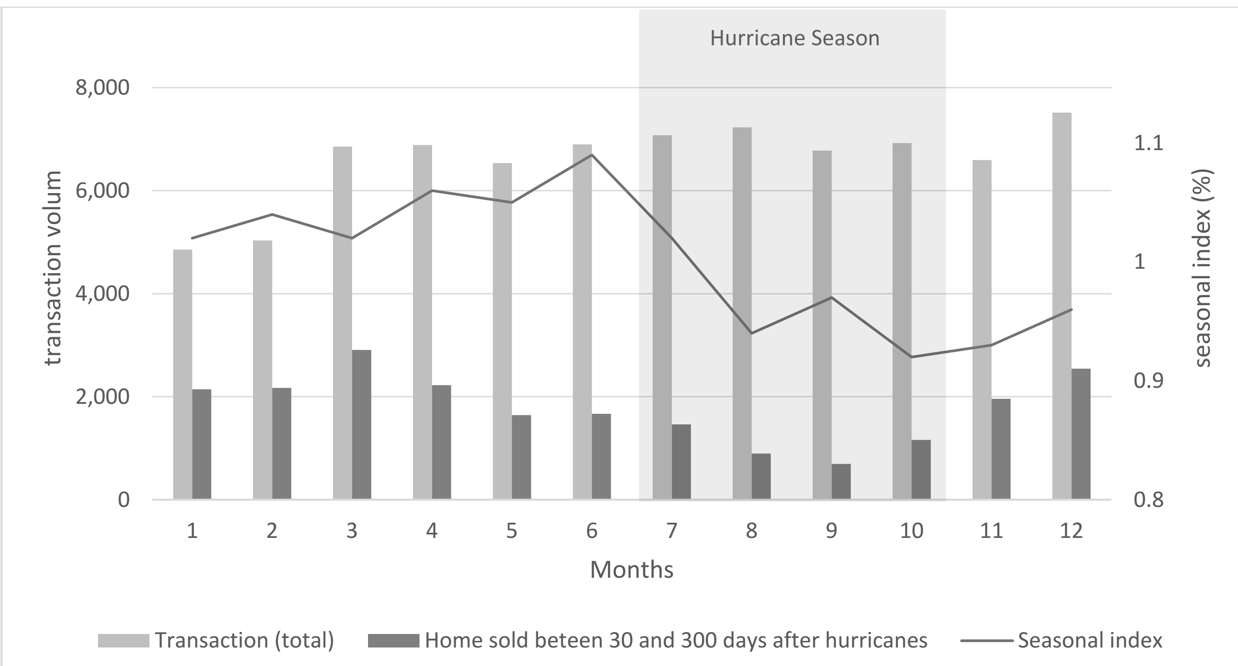


Figure 32. MDC monthly transaction volumes and seasonal index factor (2009 – 2018).

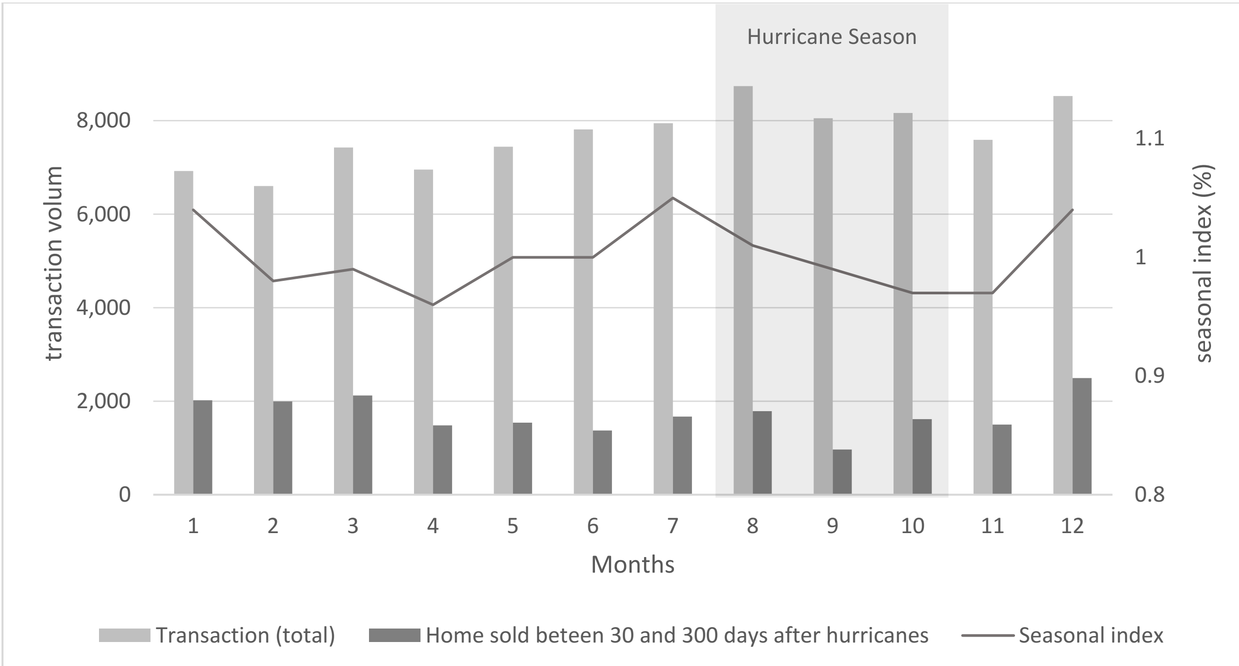


Figure 33. NYC monthly transaction volumes and seasonal index factor (2009 – 2018).

A total of 2 tropical storms and 2 hurricanes directly influence Miami-Dade County, and 3 major storms impacted properties in New York City from July 2009 to May 2018. Although each storm was strong enough to homogeneously impact entirely of each region, every storm has different characteristics (e.g., intensity, rainfall, wind speeds, etc.). However, the storm characteristics do not sufficiently tell us about the causality. Of course, we 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, 4 types[54] of the

[54] Wind speed, rainfall and flooding, storm surge, power outage, casualty, and damage statistics are generic elements that describe each individual hurricane in the National Hurricane Center's Tropical Cyclone Reports. Human casualty and damage amount are excluded in this study, as human casualty is economically unmeasurable, while the damage amount is too extensive, because it is generally aggregated at the state- and/or national-level.

most common storm damages (i.e., wind, flood, power outage, and storm surge) plus a landfall proximity are used in these analyses.

Table 8. Storm frequency and flood insurance requirement on housing sales.

Region		MDC		NYC	
		# of home	percentage	#of home	percentage
Storm Frequency	No storm	64,598	81.6%	60,663	65.8%
	1 storm experience	2,036	2.6%	9,562	10.4%
	2 storm experiences	3,393	4.3%	5,551	6.0%
	3 storm experiences	4,707	5.9%	16,402	17.8%
	4 storm experiences	4,450	5.6%		
Flood Insurance	No required	50,368	63.6%	88,386	95.9%
	Mandatory[1)]	28,816	36.4%	3,792	4.1%

Notes: 1) Houses located in the areas that classified as zone A (lower than the base flood elevation) and zone V (within a 100-year floodplain) require purchasing flood insurance.

Since the perception of risks is influenced by cognitive processes and corresponding mental models (Lavell et al., 2012), I established risk factors for natural hazards by reclassifying the most common errors in estimating risk. 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 (9 years) with small storm samples. By contrast, the concepts of myopia (discounting perceived risks from anticipated future disasters) and amnesia (forgetting past events over time; renamed as risk fadedness in this study), introduced by Pryce, Chen, and Galster (2011), are considered in this risk perception framework because of the dynamic nature of risks. 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.

Table 9. 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 effect	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
Expected project information	Rumors and information	Overestimating positive impacts of adaptation projects	Sales transaction prices between initial project announcement and actual completion dates
Availability bias	Previous experience	Overestimating risk information that is more easily recalled	Not used; due to the relatively short study period with small storm samples in this study
Anchoring bias	Available information	Overestimating risk by relying heavily on one piece of information	Not used; less related to natural hazard risks due to the uncertain nature of natural disasters
Miscalibration	Confidentiality of given facts	Overestimating or underestimating risks by overconfidence about given facts	Not used; less related to natural hazard risks due to the uncertain nature of natural disasters
Confirmation bias	Social identity, personal beliefs and emotions	Overestimating one's preexisting hypothesis or preconception on risks	Not used; generalized by other sophisticated statistical techniques and mitigated through adapting other social theories.

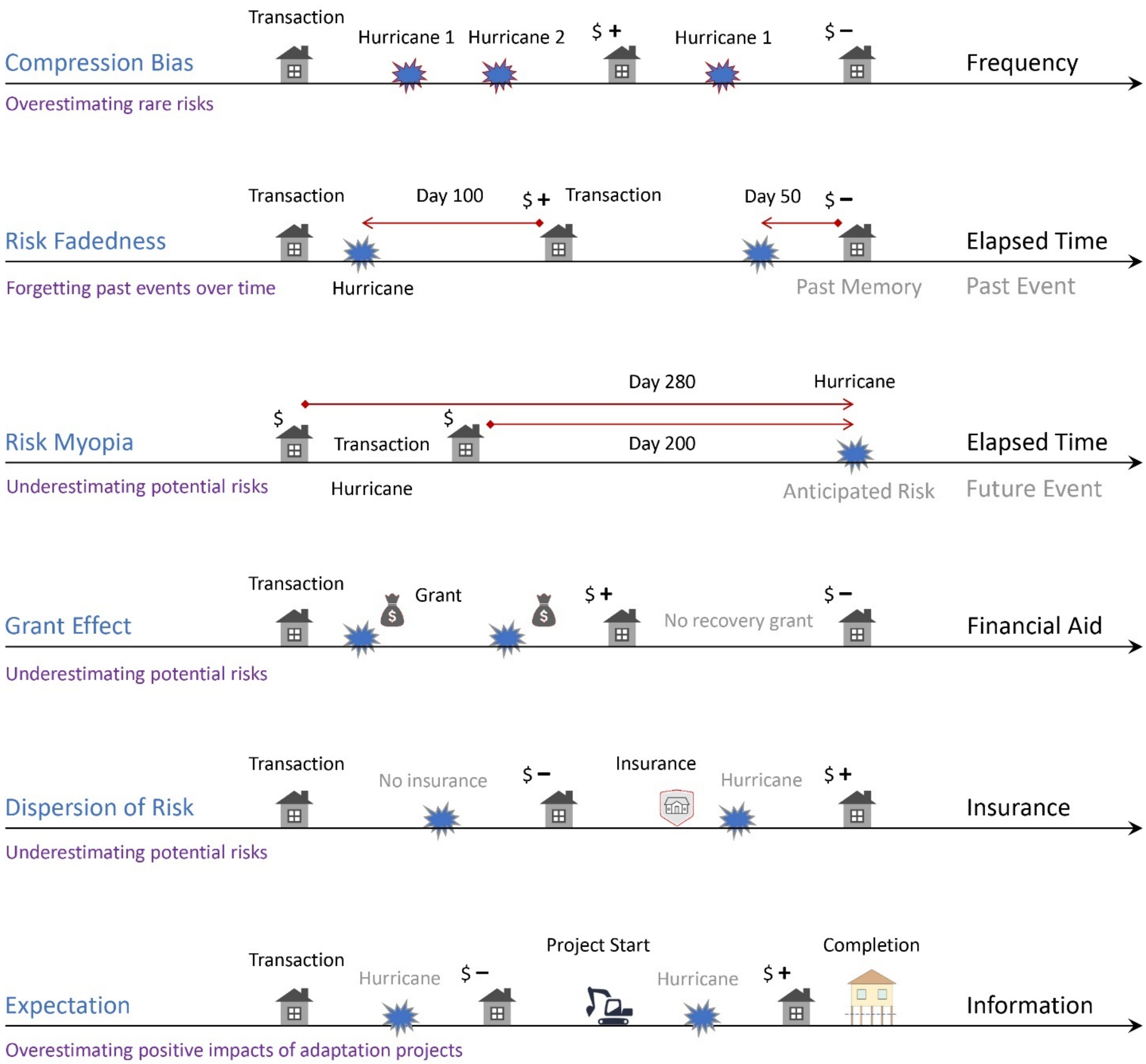


Figure 34. Risk perception factor diagram.

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 9 and Figure 34). "Compression bias," as discussed in psychology literature, refers to the human tendency to overestimate a rare risk and underestimate a chronic risk. 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 the transaction dates of housing sales after hurricane events within a specific, effective period of time for each site, respectively. Since this effect eventually vanishes at some point, I set the appropriate effective periods based on the frequencies of the storms and the intervals of occurrence for each study site (i.e., one-year for Miami-Dade County; and two-years post-hurricane strike for New York City) in order 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. Risk myopia is a technical term employed within the psychological literature (Pryce, Chen, & Galster, 2011; Rambaldi, Ganegodage, & McAllister, 2017) and it denotes a kind of cognitive “nearsightedness” (or “negligence”), which is typically characterized by a tendency or an unwillingness to acknowledge the potential risks of future hurricane events. To identify the effects of risk myopia, I constructed elapsed periods between sales transaction dates and the next hurricane strike. 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[55]) 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.

[55] The Individuals and Households Program (IHP) consists of Housing Assistance (HA) and Other Needs Assistance (ONA). HA includes financial support to reimburse for short-term accommodation and home repair. The current cap for the program is $33,300 and the approximate per-individual award amount is $8,500. ONA provides financial assistance for other disaster-related expenses (Lindsay & Reese, 2018).

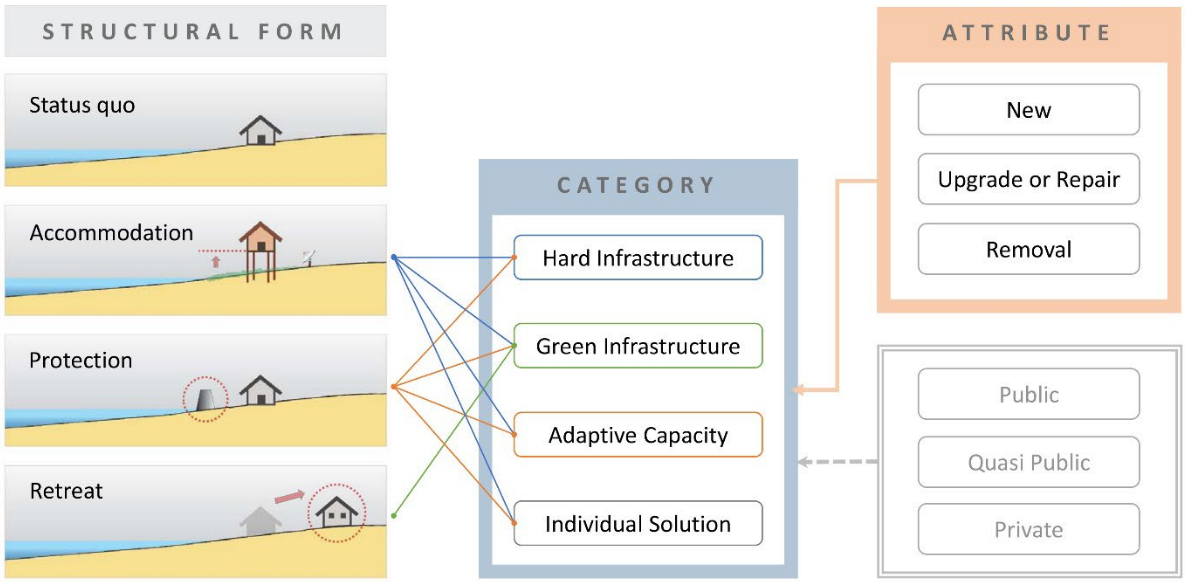


Figure 35. Structural forms of adaptation.

Table 10. Classification of adaptation projects by adaptation types.

Category	Type	Elements
Hard Infrastructure	Infrastructure hardening	Levee, Electric power utility, Flood protection berm, Breakwater, Elevating roadways
	Critical facility hardening	Public service building reinforcement
Green Infrastructure	Drainage improvement	Erosion control, Drainage and stormwater system, Beach nourishment, Dune improvement
	CBRS[1)] & wetland (inland)	Wetlands, Estuaries, Lagoons, Salt marshes
Adaptive Capacity	Emergency preparedness	Hurricane shelter, Hurricane bus stop, Back-up generators, At-risk building demolition
	Recovery operation	Emergency repair for public infrastructure and critical facilities
Individual Solutions	LOMR[2)]	Modification of base flood elevation
	Building hardening	Hurricane shutter, Storm panels, Structural elevation, Private drainage improvement

Notes: 1) Coastal Barrier Resources System, 2) Letter of Map Revision.

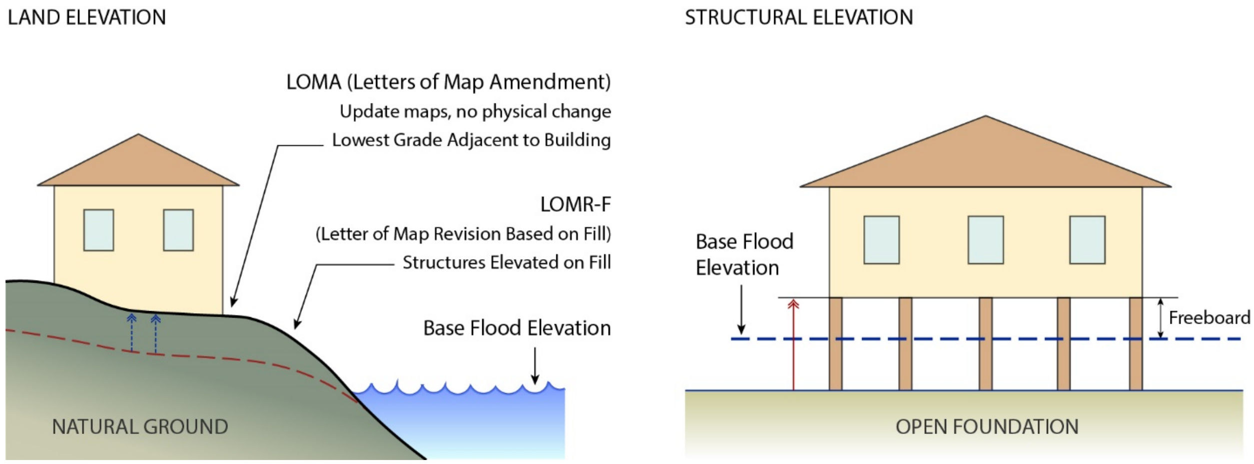


Figure 36. Land elevation vs. structural elevation.

Sources: Modified illustrations of Technical Fact Sheet No. 1.4: Lowest Floor Elevation (FEMA, 2013), LOMA and LOMR-F Factsheet (FEMA, 2017).

More than 300 individual adaptation projects have been implemented in each region since 2010. The adaptation projects include various types—ranging from critical facility hardening to green infrastructural approaches—and the completion dates vary by project. In order to analyze the effects of the implemented adaptation measures, I reclassify the individual projects into 8 subcategories (see Table 10). 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, such as seawalls, piers, and breakwaters, would already be reflected in housing prices, only newly added or renovated 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. Human-made green infrastructure projects, such as erosion control, drainage culvert installation, stormwater system improvement, and beach nourishment, fall into this subcategory. The fourth type, Coastal Barrier Resources System (CBRS) and wetlands, mostly deals with natural environments such as wetlands, lagoons, and salt marshes. The fifth type is “emergency preparedness” and includes hurricane ready shelters, bus stops for evacuation preparation, and installation of on-site power generators. The sixth adaptation type is “recovery operation projects.” These include emergency repairs for damaged public infrastructure as well as things like pump installations for draining flood water. The seventh type is “Letter of Map Revision”. This type is a modification of base flood elevation. The last type is “individual building hardening” such as installing hurricane shutters, storm panels, elevating housing structure, and individual, property-specific drainage improvements. Subcategories one to six 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.

However, classifying adaptation type into eight sub-categories does not fully represent the effect of individual adaptation characteristics, due to its multi-valued attribute, composite attribute, and anticipated interaction effects (see Figure 37). For example, on-site drainage can be improved by either infrastructure hardening, green infrastructural measure, or private implementation. Likewise, emergency preparedness can also be achieved by individual adaptation measures (e.g., private back-up generator) or critical facility hardening. Furthermore, the effects of private building reinforcement can also be influenced by public adaptation efforts. To eliminate a potential bias caused by the multi-valued attribute when classifying adaptation measures, I included four additional adaptation classifications by recalibrating the implemented projects and existing adaptation measures based on (1) adaptation technique, (2) project characteristics, (3) hazard types to address, and (4) project attribute (see Figure 38).

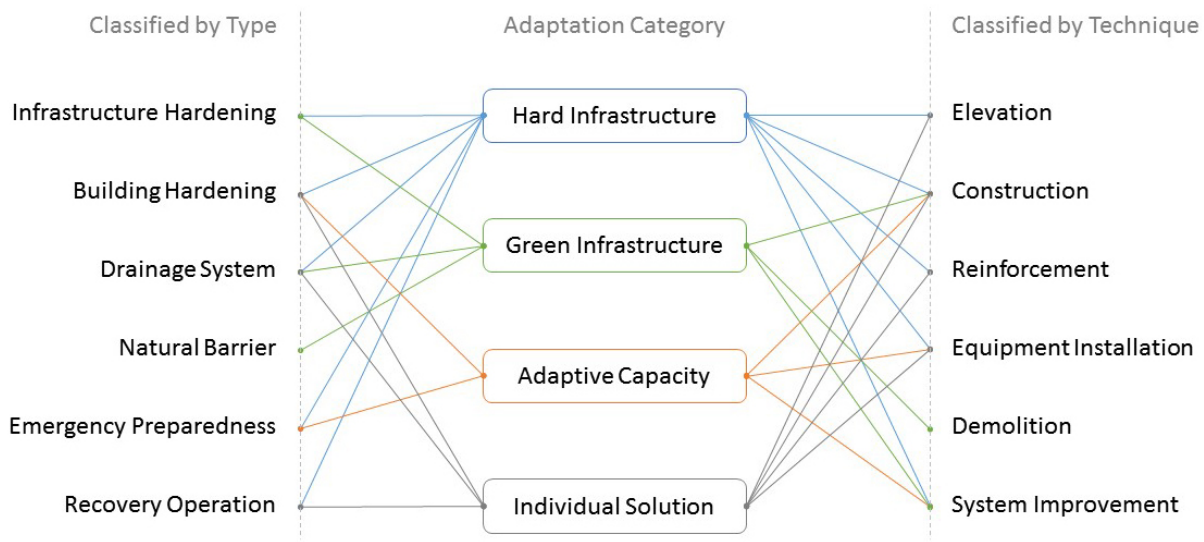


Figure 37. Adaptation classification.

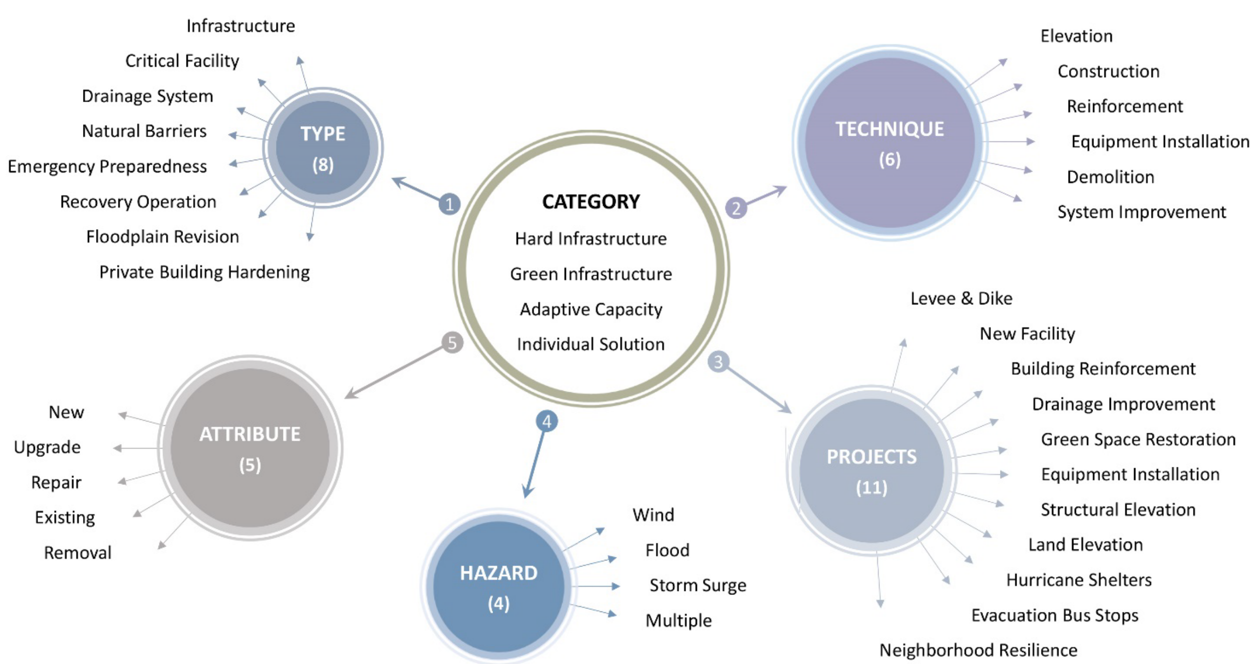


Figure 38. Analysis categories of adaptation measures.

The first additional model specification (categorized by adaptation "technique") includes six subcategories. The first is elevating the lowest floor elevation of a building by modifying either land or structural elevations (e.g., adding horizontal structural member). The second technique is "construction" and includes all new infrastructure (such as construction of levee and breakwater) and new critical facility for adaptation, regardless of adaptation category (i.e., hard, green, individual solutions). A third technique is "reinforcement" of existing building and infrastructure. Exterior hardening and retrofitting (or repair) of existing infrastructure fall into this subcategory. The fourth technique, "equipment", mainly deals with retrofitting or installation of new equipment such as synchronized generators and pumps. The fifth technique is "demolition" and includes structural demolition projects in order to mitigate flood risks or drainage improvement. The last technique is "system improvement," which includes all projects related to adaptive capacity (e.g., neighborhood improvement and recovery grant program, engineering study, disaster preparedness education, etc.), but may also include hard infrastructural projects.

The second addition of the model specification is reclassified by detailed project characteristics, and the elements include infrastructure reinforcement (levee, dike, pier, seawall, breakwater, etc.), new critical 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, evacuation bus stops, neighborhood resilience (mainly adaptive capacity programs).

Since each adaptation project deals with different types of risk, I further classified the initial adaptation category by hazard types as the third additional model specification. Four most common hazard types—wind, flood, storm surge, and multi-purpose—in the National Hurricane Center's tropical cyclone reports are included in this classification model.

In addition, the effects of adaptation on risk perception can vary depending on whether the project is completely new, upgraded and retrofitted, repaired, or an existing project. Thus, the last additional model has been constructed based on project attribute. The elements in this attribute category are reclassified based on whether the project was new, upgraded, repaired, existing, or removed.

Table 11. Variable definition.

Variable	Description
Price (logged)	Logged sales price[1)] (single-family housing)
Bedroom	Number of bedrooms
Bathroom	Number of bathrooms
Building SF	Building square footage
Lot SF	Lot square footage
Story	Number of stories
Building Age	Building age (year)
Occupancy	1 if a property is owner-occupied; 0 otherwise
Elevation	Ground elevation above sea level (feet)
Metro Station Proximity	1 if a home is within 400m of metro stations; 0 otherwise
Bus Stop Proximity	1 if a home is within 400m of bus stops; 0 otherwise
Cultural Proximity	1 if a home is within 400m of cultural facilities; 0 otherwise
Commercial Proximity	1 if a home is within 400m of major malls; 0 otherwise
School Proximity	1 if a home is within 400m of schools; 0 otherwise
Brownfield Sites	1 if a home is within brownfield sites; 0 otherwise
Green Space View	1 if a home has a green space view; 0 otherwise
Green Space Proximity	1 if a home is within 400m of green spaces; 0 otherwise
Ocean View	1 if a home has an ocean view; 0 otherwise
Ocean Proximity	1 if a home is within 400m of oceanfront; 0 otherwise
Sexual Crime Impact Zone	1 if a home is within 160m of sexual predators; 0 otherwise
Unemployment Rate	Annual unemployment rates by zip code
Vacancy Rate	Annual vacancy rates by zip code
Household Income	Annual median household income by zip code
Storm 30-150 days	1 if a home sold between 30 and 150 days post-hurricanes
Storm 150-300 days	1 if a home sold between 150 and 300 days post-hurricanes
Storm 300-450 days	1 if a home sold between 300 and 450 days post-hurricanes
Storm 450-600 days	1 if a home sold between 450 and 600 days post-hurricanes
Storm 600-750 days	1 if a home sold between 600 and 750 days post-hurricanes
Storm 750-900 days	1 if a home sold between 750 and 900 days post-hurricanes
Landfall	1 if a hurricane makes landfall; 0 otherwise
Flood Damage	1 if a hurricane causes a widespread flooding; 0 otherwise
Wind Damage	1 if a hurricane causes wind damages; 0 otherwise
Power Outage	1 if a hurricane causes power outage; 0 otherwise
Storm Surge	Storm surge heights of affected homes (feet)
Rainfall	Total amount of rainfall (inch)
Wind Speed	Sustained wind speed (knots)
Frequency	Number of hurricanes between buying and selling home
Fadedness	Elapsed period of time from hurricane to housing transactions, within one-year (MDC) and two-year (NYC) periods after a hurricane event, respectively
Myopia	Elapsed periods between the date of housing sales and the next hurricane
IHP Grants	1 if a home receives Individuals and Households Program (IHP) grant; 0 otherwise
Insurance	1 if an insurance purchase is required; 0 otherwise
Information	1 if a home sold between initial project announcement and actual completion dates

Table 11. (Continued).

Variable	Description
Infrastructure	1 if a home is located within 400m of infrastructure hardening; 0 otherwise
Critical Facility	1 if a home is located within 400m of critical facility hardening; 0 otherwise
Drainage System	1 if a home is located within 400m of drainage improvement; 0 otherwise
Natural Barriers	1 if a home is located within CBRS impact areas and wetland zones[2)]; 0 otherwise
Emergency Prep.	1 if a home is located within 400m of hurricane shelters or bus stops; 0 otherwise
Recovery Operation	1 if a home is located within 400m of storm recovery projects; 0 otherwise
Floodplain Revision	1 if a home modifies the base flood elevation; 0 otherwise
Private Building	1 if a home reinforces house structures for hurricanes; 0 otherwise
Elevation	1 if a home is located within 400m of elevation projects; 0 otherwise
Construction	1 if a home is located within 400m of infrastructure constructions; 0 otherwise
Reinforcement	1 if a home is located within 400m of structural hardening projects; 0 otherwise
Equipment Installation	1 if a home is located within 400m of equipment installation projects; 0 otherwise
Demolition	1 if a home is located within 400m of demolition projects; 0 otherwise
System Improvement	1 if a home is located within 400m of adaptive capacity projects; 0 otherwise
Infrastructure Reinforce	1 if a home is located within 400m of infrastructural reinforcements; 0 otherwise
New Facility	1 if a home is located within 400m of building new facilities; 0 otherwise
Building Reinforcement	1 if a home is located within 400m of building reinforcement projects; 0 otherwise
Drainage Improvement	1 if a home is located within 400m of drainage improvement projects; 0 otherwise
Green Space Restoration	1 if a home is located within 400m of green space restoration projects; 0 otherwise
Equipment Installation	1 if a home is located within 400m of equipment installation projects; 0 otherwise
Structural Elevation	1 if a home is located within 400m of structural elevation projects; 0 otherwise
Land Elevation	1 if a home is located within 400m of land elevation projects; 0 otherwise
Hurricane Shelters	1 if a home is located within 400m of hurricane shelters; 0 otherwise
Evacuation Bus Stops	1 if a home is located within 400m of hurricane evacuation bus stops, 0 otherwise
Neighborhood Resilience	1 if a home is located within 400m of adaptive capacity projects; 0 otherwise
Adapting Wind	1 if a home is located within 400m of wind adaptation projects; 0 otherwise
Adapting Flood	1 if a home is located within 400m of flood prevention projects; 0 otherwise
Adapting Storm Surge	1 if a home is located within 400m of storm surge prevention projects; 0 otherwise
Adapting Multi-purpose	1 if a home is located within 400m of multi-functional projects; 0 otherwise
New	1 if a home is located within 400m of new adaptation measures; 0 otherwise
Upgrade	1 if a home is located within 400m of adaptation measure upgrade; 0 otherwise
Repair	1 if a home is located within 400m of repairs for existing measures; 0 otherwise
Existing	1 if a home is located within 400m of existing adaptation measures; 0 otherwise
Remove	1 if a home is located within 400m of demolition projects; 0 otherwise

Notes: 1) Monthly inflation adjusted to 2018 dollars, seasonally adjusted (Source: U.S. Bureau of Labor Statistics, Federal Reserve Bank of St. Louis). 2) Wetland impact zones are defined by Miami-Dade County (2-mile buffer from basins, 500 feet buffer from depressional soils, and 500 feet buffer from hydric soils).

Table 12. Summary statistics (housing, neighborhood, market, storm, and risk variables).

Study region (Observation)	MDC (79,184)				NYC (90,811)			
Variables	Mean	S.D[1)]	Min	Max	Mean	S.D[1)]	Min	Max
Price[2)] ($100,000)	4.59	6.07	0.6	82.6	6.03	5.22	0.9	98.9
Price (logged)	12.64	0.80	11.1	15.9	13.14	0.54	11.4	16.1
Bedroom	3.29	0.86	1	8				
Bathroom	2.22	1.07	1	8				
Building SF (thousands)	2.33	1.19	0.6	19.5	1.63	0.67	0.6	7.0
Lot SF (thousands)	10.31	8.53	1.2	211.4	3.28	2.32	0.7	116.1
Story	1.12	0.33	1	4	2.47	0.63	1	4
Building Age (year)	50.21	20.57	1	117	74.32	26.97	1	218
Occupancy	0.81	0.39	0	1	0.80	0.40	0	1
Elevation (feet)	8.17	2.46	1	22	57.47	46.42	0	402
Metro Station Proximity	0.003	0.06	0	1	0.02	0.15	0	1
Bus Stop Proximity	0.66	0.47	0	1	0.23	0.42	0	1
Cultural Proximity	0.02	0.13	0	1	0.05	0.23	0	1
Commercial Proximity	0.003	0.05	0	1	0.80	0.40	0	1
School Proximity	0.39	0.49	0	1	0.30	0.46	0	1
Brownfield Sites	0.10	0.30	0	1	0.01	0.11	0	1
Green Space View	0.05	0.22	0	1	0.01	0.12	0	1
Green Space Proximity	0.46	0.50	0	1	0.44	0.50	0	1
Ocean View	0.07	0.26	0	1	0.01	0.10	0	1
Ocean Proximity	0.05	0.22	0	1	0.10	0.29	0	1
Sexual Crime Impact Zone	0.10	0.30	0	1				
Unemployment Rate	9.52	3.52	1.9	21.1	8.46	2.98	1.9	22.7
Vacancy Rate	11.37	8.37	0	58.6	6.91	2.39	0	25.3
Household Income (thousands)	51.59	19.33	19.0	159	65.14	15.45	19.3	137
Storm 30-150 days	0.13	0.33	0	1	0.10	0.30	0	1
Storm 150-300 days	0.14	0.35	0	1	0.12	0.33	0	1
Storm 300-450 days					0.13	0.34	0	1
Storm 450-600 days					0.13	0.33	0	1
Storm 600-750 days					0.14	0.35	0	1
Storm 750-900 days					0.15	0.36	0	1
Storm Surge (feet)	0.08	0.46	0	3.7	2.17	4.67	0	12.7
Rainfall (inch)	1.10	2.36	0	6.7	1.53	2.44	0	6.9
Wind Speed (knots)	12.27	30.05	0	115	18.43	26.95	0	65
Frequency	0.51	1.17	0	4	0.8	1.17	0	3
Fadedness	37	89	0	365	94	173	0	599
Myopia	729	654	0	2168	574	568	0	1816
IHP Grants ($100,000)	0.47	3.96	0	66.9	7.5	60.86	0	668.7
Insurance	0.36	0.48	0	1	0.04	0.20	0	1
Adaptation Information	0.01	0.11	0	1	0.01	0.11	0	1

Notes: 1) Standard Deviation. 2) The prices adjusted for seasonality and inflation in 2018 dollars.

Table 13. Summary statistics (adaptation variables).

Study region (Observation)		MDC	(79,184)	NYC	(90,811)
Category	Variables	Mean	S.D[1)]	Mean	S.D[1)]
Adaptation Type	Infrastructure	0.008	0.092	0.025	0.157
	Critical Facility	0.004	0.067	0.029	0.168
	Drainage System	0.024	0.152	0.008	0.089
	Natural Barriers	0.166	0.372	0.004	0.065
	Emergency Prep.	0.063	0.242	0.002	0.045
	Recovery Operation	0.001	0.037	0.005	0.071
	Floodplain Revision	0.005	0.069	0.003	0.166
	Private Building	0.004	0.060	0.010	0.098
Adaptation Technique	Elevation	0.006	0.080	0.002	0.039
	Construction	0.039	0.193	0.011	0.105
	Reinforcement	0.003	0.055	0.003	0.052
	Equipment Installation	0.002	0.042	0.002	0.047
	Demolition	0.002	0.123	0.001	0.027
	System Improvement	0.167	0.373	0.002	0.045
Project Characteristics	Infrastructure Reinforce	0.005	0.067	0.021	0.143
	New Facility	0.001	0.023	0.001	0.024
	Building Reinforcement	0.001	0.032	0.013	0.113
	Drainage Improvement	0.027	0.162	0.010	0.097
	Green Space Restoration	0.166	0.372	0.007	0.081
	Equipment Installation	0.001	0.037	0.001	0.035
	Structural Elevation	0.001	0.094	0.001	0.094
	Land Elevation	0.005	0.069	0.003	0.166
	Hurricane Shelters	0.025	0.158	0.004	0.199
	Evacuation Bus Stops	0.063	0.242		
	Neighborhood Resilience	0.001	0.025	0.024	0.153
Hazard Types	Adapting Wind	0.002	0.045	0.015	0.122
	Adapting Flood	0.182	0.386	0.002	0.039
	Adapting Storm Surge	0.020	0.139	0.007	0.081
	Adapting Multi-purpose	0.002	0.045	0.006	0.078
Project Attribute	New	0.005	0.071	0.005	0.073
	Upgrade	0.024	0.154	0.004	0.191
	Repair	0.005	0.070	0.005	0.073
	Existing	0.078	0.268	0.006	0.078
	Remove	0.002	0.151	0.002	0.048

Notes: 1) Standard Deviation. All of the adaptation variables are dummies. Minimum value of each variable is zero, and maximum value of each variable is 1.

4.2 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. Since the hedonic pricing model was introduced into housing studies by Rosen (1974), many studies have used this model to estimate how external price factors, such as environmental amenities, affect real estate property values (Xiao, 2017). I applied this pricing model to estimate the impacts of climate change adaptation measures on single-family housing transaction prices in Miami-Dade County and New York City 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 (See Appendix 2). Since hurricanes were mostly observed between June and October over the last 10 years, both seasonality and inflation have been adjusted to the sales transaction prices.

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. Hence, six sets of regressions are conducted.

The first set is to examine whether storms impact housing prices or not. The second to sixth sets are to identify the risk perception and adaptation effects on housing prices. If there is no pricing effect in the first set, finding the adaptation effects on housing prices are not logically meaningful. The main equation of the first set for estimating storm effects in different sales windows is specified as follows:

$$\text{(1.1)} \quad ln\, P_{ict} = \alpha_{ct} + \beta' X_i + \gamma' N_i + \eta' M_{ict} + \delta' Storm_{ict} + \varepsilon_{ict}$$

where $ln\, P_{ict}$ is the natural log of the sales price (both inflation and seasonality adjusted) 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 neighborhood amenity 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.

Our set of controls X_i includes 8 housing structural characteristics for Miami-Dade County and 6 characteristics for New York City. 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 New York City is not publicly available, these variables are included only in Miami-Dade County's model specifications. N_i, the neighborhood amenity characteristics, consists of 9 binary variables representing 5-minute walkability and views. Walkability variables include subway stations, bus stops, cultural facilities, major malls, schools, sexual offenders[56], brownfields, green spaces, and oceanfront. The two view variables are green space view and ocean view. M_{ict}, the market characteristics, includes unemployment rates, vacancy rates, and median household incomes.

The second to sixth 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.

As an extension of model (1.1), the main equation of the rest of the model specifications for testing these criteria is as follows:

$$\text{(1.2)} \quad ln\, P_{ict} = \alpha_{ct} + \beta' X_i + \gamma' N_i + \eta' M_{ict} + \delta' H_{it} + \varphi' R_i + \lambda' Adapt_{ict} + \varepsilon_{ict}$$

where H_{it} is a vector of hurricane characteristics to property i in time (year) t with coefficient δ and includes binary variables of landfall and four damage types (flood, wind, power outage, and storm surge) in the specification for Miami-Dade County. Unlike the storm characteristics in

[56] This variable is applied only in Miami-Dade County's model specifications, since the sexual crime data in New York City is not publicly available.

Miami-Dade County, all storms have impacted by two or more of the characteristics. For example, super storm Sandy in 2012 brought on devastating storm surges. Because of these surges, there was widespread flooding and power outages. Thus, instead of binary variables (such as damage types and hurricane landfall information), continuous variables (such as the total amount of rainfall, sustained wind speeds, and storm surge heights of affected homes) are used in the models for New York City. 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 number of days between storm strikes and home sales within a specific period (one year for Miami-Dade and two years for New York) after a hurricane strikes, for the effects of risk fadedness; the elapsed number of days 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 requirements; and a dummy variable to distinguish homes sold between adaptation project announcement and project completion dates for the effects of adaptation information. $Adapt_{ict}$ is a vector of completed adaptation measures to property i in zip code c in time (date) t with coefficient λ. To distinguish the effects of adaptation projects that have already been completed from those projects still under construction at the time of a sales transaction, $Adapt_{ict}$ only includes completed adaptation projects prior to a housing sale. This attribute group is eventually classified as hard infrastructure, green infrastructure, adaptive capacity, and private (individual) adaptations. To examine whether the adaptation measures are associated with housing prices, I extracted homes within an impact distance of 400m[57] from the individual adaptation project in each category.

[57] Where necessary, I indicate exceptions to the typical 400m distance in the footnotes below each table.

In order to estimate the multi-valued attributes of adaptation measures, five reclassified categories of adaptation measures (according to the attributes of: adaptation type, adaptation technique, project characteristics, hazard type to be adapted, and project attribute) will be substituted for the adaptation factors $Adapt_{icd}$ in the equation (1.2), as follows:

$$(2) \qquad \lambda' Adapt_{ict} = \sum_{j=1}^{8} \sigma_j \, Type_{j,ict}$$

where $Type_j$ is the eight variables of the adaptation project type and includes infrastructure, critical facility, drainage system, natural barriers, emergency preparedness, recovery operation, floodplain revision, and private building hardening.

$$(3) \qquad \lambda' Adapt_{ict} = \sum_{j=1}^{6} \sigma_j \, Technique_{j,ict}$$

where $Technique_j$ is the six adaptation variables, which are classified by project technique. This includes elevation, construction, reinforcement, equipment installation, demolition, and system improvement.

$$(4) \qquad \lambda' Adapt_{ict} = \sum_{j=1}^{11} \sigma_j \, Characteristics_{j,ict}$$

where $Characteristics_j$ is the eleven variables of the adaptation measures classified by project characteristics. This attribute group is subcategorized by infrastructure reinforcement, new facility, building reinforcement, drainage improvement, green space restoration, equipment installation, structural elevation, land elevation, hurricane shelters, evacuation bus stops, and neighborhood resilience.

$$\text{(5)} \qquad \lambda' Adapt_{ict} = \sum_{j=1}^{4} \sigma_j \, Hazard_{j,ict}$$

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

$$\text{(6)} \qquad \lambda' Adapt_{ict} = \sum_{j=1}^{5} \sigma_j \, Attribute_{j,ict}$$

where $Attribute_j$ is the five variables of the adaptation measures classified by project attribute. This includes new projects, upgraded, repaired, existing, and removal projects.

All other variables are the same as in model (1). Two-way fixed effects (for both year and zip code) are applied, and the standard errors are clustered by zip codes.

Table 14. Regression analysis of the storm effects.

	Price (logged)	MDC (1)		NYC (1)	
Housing Structure	Bedroom	0.021^{***}	(2.85)		
	Bathroom	0.069^{***}	(5.55)		
	Building SF	0.020^{***}	(13.43)	0.020^{***}	(25.76)
	Lot Size	0.001^{***}	(5.48)	0.004^{***}	(10.10)
	Story	0.107^{***}	(4.66)	0.036^{***}	(6.08)
	Building Age	-0.002^{**}	(-2.21)	-0.002^{***}	(-7.33)
	Occupancy	0.106^{***}	(8.85)	0.012^{***}	(3.12)
	Elevation	0.005	(0.93)	0.009^{***}	(4.09)
Neighborhood Amenity	Metro Station	-0.125^{***}	(-2.90)	-0.036^{*}	(-1.85)
	Bus Stop	-0.066^{***}	(-4.12)	-0.018^{**}	(-2.56)
	Cultural	0.045	(1.39)	0.025	(1.44)
	Commercial	-0.005	(-0.12)	-0.045^{***}	(-4.67)
	School	-0.038^{***}	(-3.14)	-0.016^{***}	(-2.96)
	Sexual Crime	-0.071^{***}	(-5.64)		
	Brownfield	-0.134^{**}	(-2.53)	-0.039^{***}	(-3.00)
	GS View	-0.006	(-0.42)	0.033^{*}	(1.95)
	GS Proximity	-0.010	(-0.70)	0.011	(1.23)
	Ocean View	0.141^{***}	(2.97)	0.037	(0.73)
	Ocean Proximity	0.213^{***}	(3.86)	-0.072	(-1.62)
Market	Unemployment Rate	-0.007	(-1.42)	-0.011^{***}	(-3.68)
	Vacancy Rate	-0.328	(-1.23)	-0.119	(-0.35)
	Household Income	-0.003	(-1.58)	0.004^{***}	(2.90)
Storm Impact	Storm 30-150 days	-0.024^{***}	(-3.31)	-0.019^{***}	(-3.24)
	Storm 150-300 days	0.023^{***}	(3.83)	-0.032^{***}	(-4.84)
	Storm 300-450 days			-0.016^{**}	(-2.47)
	Storm 450-600 days			-0.031^{***}	(-4.37)
	Storm 600-750 days			-0.006	(-1.23)
	Storm 750-900 days			0.010^{**}	(2.11)
	Constant	12.056^{***}	(75.66)	12.440^{***}	(91.78)
	Observations	79,184		90,811	
	Number of clusters (zip code)	64		157	
	Adjusted R^2	0.747		0.629	
	Spatial Fixed Effects (zip code)	YES		YES	
	Time Fixed Effects (year)	YES		YES	

Notes: t statistics in parentheses. Standard errors are clustered at the zip code level. Housing sales transaction data were between July 2009 and May 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15. Beta (standardized coefficients) regression results.

	Price (logged)	MDC (1)	MDC (2)	NYC (1)	NYC (2)
Housing Structure	Bedroom	0.023***	0.023***		
	Bathroom	0.092***	0.090***		
	Building size	0.290***	0.281***	0.251***	0.250***
	Lot size	0.088***	0.089***	0.191***	0.191***
	Story	0.044***	0.041***	0.042***	0.042***
	Building age	-0.047**	-0.040**	-0.083***	-0.083***
	Occupancy	0.052***	0.051***	0.009***	0.009***
	Elevation	0.016	0.038**	0.077***	0.076***
Neighborhood Amenity	Metro station proximity	-0.009***	-0.007**	-0.010*	-0.010*
	Bus stop proximity	-0.039***	-0.032***	-0.014**	-0.014**
	Cultural proximity	0.007	0.007	0.010	0.010
	Commercial proximity	-0.001	-0.001	-0.033***	-0.032***
	School proximity	-0.023***	-0.017**	-0.013***	-0.014***
	Sexual crime impact zone	-0.026***	-0.025***		
	Brownfield / Landfills	-0.050**	-0.050**	-0.008***	-0.008***
	Green space view	-0.002	-0.002	0.007*	0.007*
	Green space proximity	-0.006	-0.005	0.011	0.011
	Ocean view	0.046***	0.038***	0.007	0.010
	Ocean proximity	0.058***	0.053***	-0.040	-0.022
Market	Unemployment Rate	-0.030	-0.029	-0.060***	-0.059***
	Vacancy Rate	-0.034	-0.031	-0.005	-0.006
	Household Income	-0.082	-0.076	0.141***	0.142***
Storm Impact	Storm 30-150 days	-0.010***		-0.011***	
	Storm 150-300 days	0.010***		-0.020***	
	Storm 300-450 days			-0.010**	
	Storm 450-600 days			-0.019***	
	Storm 600-750 days			-0.004	
	Storm 750-900 days			0.007**	
Storm Characteristics	Wind damage / Wind		0.014**		0.028**
	Flood damage / Rainfall		-0.008**		-0.044***
	Storm surge		-0.010**		-0.051***
	Power outage		0.008		
	Landfall		-0.017***		
Risk Perception	Frequency		-0.009***		0.020*
	Fadedness		0.016***		0.021**
	Myopia		-0.027***		-0.007
	IHP grant		0.005*		0.029**
	Insurance		0.041***		-0.026**
	Information		0.007		-0.001
Adaptation (Hard)	Infrastructure		0.030***		-0.008
	Critical facility		0.010**		0.007
Adaptation (Green)	Drainage system		0.006		0.002
	Natural barrier		0.045***		0.003**
Adaptation (Social)	Emergency preparedness		-0.017**		0.006**
	Recovery operation		0.005		-0.018*
Adaptation (Private)	Floodplain revision		-0.003		0.002***
	Private building hardening		0.003		0.018***
	Observations	79,184	79,184	90,811	90,811
	Adjusted R^2	0.747	0.751	0.629	0.630

Notes: Standardized beta coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Results

The semi-log model was specified in the hedonic regression using Stata. The regression results indicate that the relationship between the dependent variable (the natural log of inflation and seasonality adjusted home sales prices) and the independent variables is strong (adjusted R^2 = 0.75 and 0.63 for MDC and NYC, respectively). 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.

As expected, all the structural characteristics are strongly related to the home sales prices. More rooms and stories, larger building square footage and lot sizes, newer homes, higher elevation, and owner-occupied homes are associated with a housing sales price increase. Among the structural variables, building square footage and lot size in both regions have a particularly strong relation to price increases (see Table 15, standardized beta[58] coefficients).

Proximity to subway stations and bus stops has a negative relation to housing price in both regions. When disadvantages exceed advantages to be closer in proximity to the public transport access points, these proximity variables would not function as a positive factor for housing prices. Noise, crime, and traffic congestion around the subway stations or bus stops could be a nuisance to adjacent residents. Furthermore, public transportation ridership as a means of transportation to work in MDC is only about 5%, but the ridership is over 50% in New York City. Neither too few nor too many beneficiaries may work as a positive factor for housing

[58] Unlike the regular regression coefficients, which cannot be compared since they use different scales, standardized coefficients all use the same scale so that they can be comparable.

prices. Five-minute walkability to cultural facilities such as museums and art centers has positive coefficients in both regions but are not statistically significant at 10% significance level. Proximity to major commercial facilities, such as a major mall or shopping center, has a negative influence on housing prices in New York City. Since this variable is not statistically significant in Miami-Dade County, the strength of nuisance or disamenity effects, from having commercial facilities nearby, may also differ based upon population densities. All specifications indicate that a closer proximity to schools has a negative influence on housing transaction prices. The "net nuisance" effect, caused by the school proximity penalty such as traffic congestion and noise, could overshadow the proximity benefits (Sah, Conroy, & Narwold, 2016). As expected, sexual offenders located within 160 meters[59] during the sales period has a negative influence on housing prices, but testing this variable is only available for Miami-Dade County due to a limitation[60] of database access in New York City. Brownfields and landfills are negatively associated with housing prices at the 5% and 1% significance levels in Miami-Dade County and New York City, respectively. Contrasting results of green space and ocean amenity variables were observed. As with the results[61] on the green space variables in New York City, 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

[59] This impact distance of 0.1 mile (160 meters) is identified by Linden and Rockoff (2008). Estimating the proximity costs to sexual crime risks in North Carolina, their study suggests that housing prices within the distance of a sex offender's location fall by about average 4%.

[60] By New York State's Sex Offender Registration Act, the offender's information and county level statistics are publicly available. However, access to the information is limited by searching last name and zip code.

[61] The coefficients of both green space view and proximity are positive, but only green space view variable is statistically significant at the 10% significance level in the table 14, NYC (1) model.

Miami-Dade County. 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 (see Figure 39).

Figure 39. Green spaces in Miami.

Notes: Jose Marti Park (left) and Bayfront Park (right) in downtown Miami. Photographs by Seung Kyum Kim.

A high outside temperature and the location of green spaces (about 50% of Miami-Dade's parks are located within a 5-minute walking distance of coastlines) would counteract the positive green space effects in Miami-Dade County. As expected, ocean view and oceanfront proximity are strong positive factors on housing prices in Miami-Dade, but surprisingly these coastal amenities are not statistically significant (at the 10% level) in New York City. From this result and the fact that Miami-Dade has many more accessible sandy beaches, I surmise that coastal recreation opportunities would boost positive effects of the coastal amenity on housing prices.

The regression results in both regions confirm that storms and hurricanes have a strong adverse impact on housing transaction prices. The coefficient of *Storm 30-150 days* variable implies that single-family properties sold between 30 and 150 days after a storm strike sell at a 2.4% and 1.9% discount on average compared with homes sold in the other period in Miami-Dade County and New York City, respectively (see Table 14). The negative impact of the storm becomes positive after five months following the storm occurrences in Miami-Dade, while the adverse effects live much longer in New York City, taking up about 1 year and half. The maximum discount effect of 3.2% on housing prices is observed in the period between the fifth months and a year after storm strikes in New York City. The results for Miami-Dade are well aligned with Beracha and Prati's (2008) findings that the transaction prices temporarily decrease during the first-half year after a hurricane, followed by an increase up to a prior level. The results for New York City are also supported by existing literature that the hurricane effects can stay up for a few years based on recovery speed and the local market conditions (Atreya, Ferreira, & Kriesel, 2013; Bin & Landry, 2013).

Storm Characteristics and Risk Perception Factors:

The majority of the storm characteristics and risk factors impact housing transaction prices. Storms that have made direct landfall and are accompanied by more rainfall that results in widespread flood damage have a negative impact on housing sales prices. 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. 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 (approximated by the Kraft rule[62]) on already fully saturated soils. The power outage variable is not statistically significant in Miami-Dade County and collinear with other variables for New York's models.

Storm frequency and flood insurance requirement factors produced contrasting results between the two regions, while risk fadedness variable has a positive impact on housing prices. Risk myopia variable has a negative effect in Miami-Dade County, but is not statistically significant in New York City. The adaptation project information variable has a positive sign in Miami-Dade County, but is not statistically significant in both regions. 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

[62] Maximum rainfall (inches) = 100 / forward motion speed in knots (Langousis & Veneziano, 2009).

homeowners to underestimate the actual risks, while a rare storm experience exaggerates the home seller's risk cognition. Based on this notion, I assume that the compression bias would not be present in homes sold without any storm experience. In fact, about 82% (or 64,598) single-family homes were transferred without having a storm experience in Miami-Dade, and 66% (or 59,759) of properties have been sold with no storms experienced by the home seller in New York City. By excluding the no-storm-experience-home from the regressions, the effects of storm frequency turned to be a strong positive at the 1% significance levels in both regions. The result confirms that the compression bias is associated with housing price appreciation (see Table 16).

With respect to the flood insurance requirement, about 36% (or 28,816) of Miami-Dade's single-family homes are required to purchase flood insurance (see Figure 40), while only 4% (or 3,792) of single-family residences in New York City are located within the mandatory flood insurance requirement zones (see Figure 41). Limited numbers of housing inventory that have no flood insurance requirement could make the insurance factor less significant in relation to housing sales prices in Miami-Dade County.

Table 16. Regression results with homes sold with at least one or more storm experiences.

	Price (logged)	MDC (2)		NYC (2)	
Housing Structure	Bedroom	0.025***	(2.90)		
	Bathroom	0.077***	(5.03)		
	Building size	0.018***	(10.98)	0.021***	(22.19)
	Lot size	0.001***	(5.41)	0.004***	(8.81)
	Story	0.094***	(3.39)	0.043***	(6.44)
	Building age	-0.002**	(-2.42)	-0.002***	(-6.73)
	Occupancy	0.107***	(7.72)	0.005	(0.99)
	Elevation	0.009	(1.57)	0.009***	(3.90)
Neighborhood Amenity	Metro station proximity	-0.064	(-1.25)	-0.047*	(-1.66)
	Bus stop proximity	-0.038***	(-2.81)	-0.019**	(-2.33)
	Cultural proximity	0.006	(0.18)	0.035	(1.64)
	Commercial proximity	-0.050	(-0.71)	-0.046***	(-4.08)
	School proximity	-0.032***	(-2.77)	-0.017***	(-2.68)
	Sexual crime impact zone	-0.069***	(-4.95)		
	Brownfield / Landfills	-0.129***	(-2.74)	-0.031	(-1.29)
	Green space view	-0.010	(-0.61)	0.040**	(2.11)
	Green space proximity	-0.003	(-0.02)	0.014	(1.42)
	Ocean view	0.127***	(3.16)	0.021	(0.44)
	Ocean proximity	0.199***	(3.27)	-0.034	(-0.67)
Market	Unemployment Rate	-0.006	(-0.87)	-0.013***	(-2.84)
	Vacancy Rate	0.046	(0.09)	-0.247	(-0.44)
	Household Income	-0.002	(-0.67)	0.003	(1.51)
Storm Characteristics	Wind damage / Wind	-0.002	(-0.06)	-0.014	(-1.21)
	Flood damage / Rainfall	-0.037*	(-1.99)	-0.175***	(-6.48)
	Storm surge	-0.016**	(-2.52)	-0.080***	(-4.53)
	Landfall	0.061	(1.04)		
Risk Perception	Frequency	0.094***	(2.94)	0.498***	(3.70)
	Fadedness	0.031	(1.51)	0.017***	(4.97)
	Myopia	-0.002	(-1.35)	-0.002**	(-2.07)
	IHP grant	-0.005	(-0.24)	0.001	(0.40)
	Insurance	0.056***	(2.73)	-0.075*	(-1.89)
	Information	-0.192***	(-6.47)	-0.031	(-0.79)
Adaptation (Hard)	Infrastructure	0.223**	(2.17)	0.030	(0.35)
	Critical facility	0.080	(1.33)	0.018	(0.25)
Adaptation (Green)	Drainage system	0.011	(0.54)	0.162*	(1.89)
	Natural barrier	0.060***	(2.75)	0.060***	(2.75)
Adaptation (Social)	Emergency preparedness	-0.048*	(-1.84)	0.051	(0.83)
	Recovery operation	0.218	(1.63)	-0.292*	(-1.80)
Adaptation (Private)	Floodplain revision	-0.037	(-0.79)	0.070	(1.13)
	Private building hardening	-0.052	(-1.15)	0.102***	(4.11)
	Constant	11.651***	(52.13)	12.568***	(64.50)
	Observations	14,585		31,055	
	Adjusted R^2	0.729		0.632	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

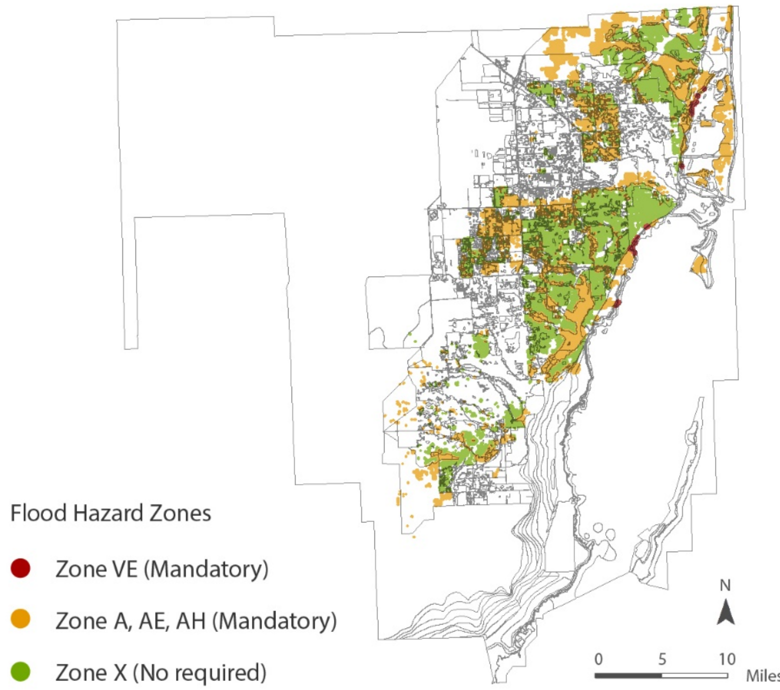


Figure 40. Special flood hazard areas in Miami-Dade County.

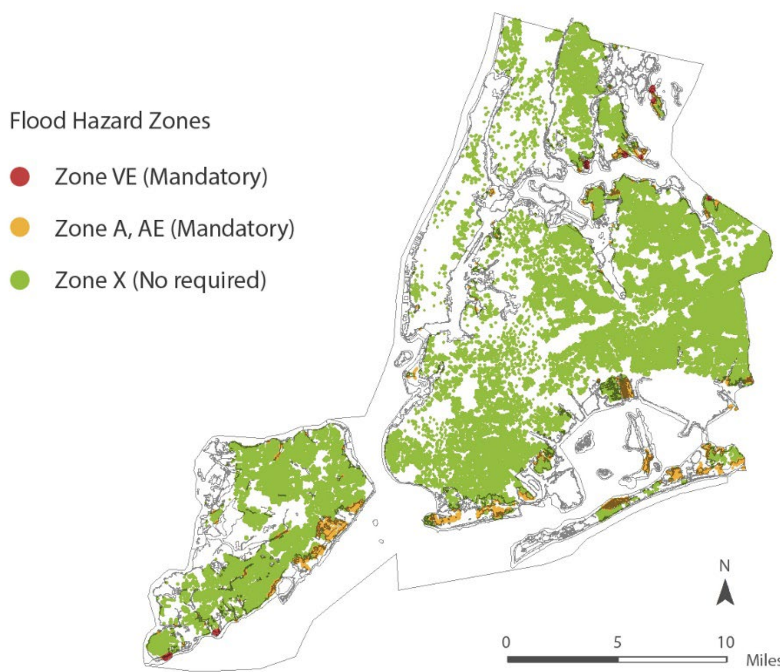


Figure 41. Special flood hazard areas in New York City.

Table 17. Regression analysis of the adaptation measures by type.

Price (logged)	MDC (2)		NYC (2)		All (2)	
Bedroom	0.021^{***}	(2.98)				
Bathroom	0.068^{***}	(5.81)				
Building SF	0.019^{***}	(13.39)	0.020^{***}	(25.91)	0.025^{***}	(22.42)
Lot Size	0.001^{***}	(5.25)	0.004^{***}	(10.14)	0.001^{***}	(5.44)
Story	0.101^{***}	(4.63)	0.036^{***}	(6.13)	0.053^{***}	(5.77)
Building Age	-0.002^{**}	(-2.03)	-0.002^{***}	(-7.40)	-0.002^{***}	(-5.52)
Occupancy	0.106^{***}	(9.06)	0.012^{***}	(3.01)	0.055^{***}	(6.95)
Elevation	0.012^{**}	(2.13)	0.009^{***}	(4.00)	0.001^{***}	(4.38)
Metro Station	-0.096^{**}	(-2.52)	-0.034^{*}	(-1.74)	-0.044^{**}	(-2.14)
Bus Stop	-0.055^{***}	(-4.11)	-0.018^{**}	(-2.56)	-0.040^{***}	(-4.52)
Cultural	0.047	(1.49)	0.024	(1.42)	0.025	(1.64)
Commercial	-0.008	(-0.23)	-0.043^{***}	(-4.59)	-0.049^{***}	(-4.45)
School	-0.028^{**}	(-2.60)	-0.016^{***}	(-3.06)	-0.025^{***}	(-4.10)
Sexual Crime	-0.067^{***}	(-5.55)				
Brownfield	-0.135^{**}	(-2.54)	-0.042^{***}	(-3.18)	-0.125^{***}	(-2.61)
GS View	-0.007	(-0.49)	0.031^{*}	(1.86)	0.003	(0.25)
GS Proximity	-0.009	(-0.62)	0.012	(1.31)	0.017	(0.19)
Ocean View	0.118^{***}	(2.70)	0.053	(1.20)	0.117^{***}	(2.98)
Ocean Proximity	0.196^{***}	(3.71)	-0.040	(-0.91)	0.015	(0.35)
Unemployment Rate	-0.007	(-1.42)	-0.011^{***}	(-3.65)	-0.006^{**}	(-2.23)
Vacancy Rate	-0.295	(-1.12)	-0.125	(-0.37)	-0.436	(-1.65)
Household Income	-0.003	(-1.47)	0.004^{***}	(2.92)	-0.001	(-1.20)
Landfall	-0.089^{***}	(-2.71)				
Wind	0.050^{**}	(2.31)	0.006^{**}	(2.35)	0.012^{***}	(7.74)
Rainfall	-0.031^{**}	(-2.55)	-0.097^{***}	(-5.02)	-0.017^{***}	(-8.95)
Storm Surge	-0.018^{**}	(-2.52)	-0.059^{***}	(-4.67)	-0.010^{***}	(-10.03)
Power Outage	0.024	(1.30)				
Frequency	-0.006^{***}	(-2.94)	0.090^{*}	(1.95)	0.002	(0.69)
Fadedness	0.016^{***}	(2.94)	0.006^{**}	(2.43)	0.016^{***}	(7.13)
Myopia	-0.003^{***}	(-3.32)	-0.001	(-1.38)	-0.004^{***}	(-9.35)
IHP Grant	0.024^{*}	(1.89)	0.003^{**}	(2.26)	0.003^{**}	(2.26)
Insurance	0.069^{***}	(2.72)	-0.070^{**}	(-2.23)	0.030	(1.37)
Information	0.054	(1.49)	-0.002	(-0.06)	0.037	(1.38)
Infrastructure	0.264^{***}	(2.70)	-0.028	(-1.54)	0.029	(0.45)
Critical Facility	0.119^{**}	(2.27)	0.024	(1.56)	0.037	(1.26)
Drainage System	0.033	(1.49)	0.010	(0.44)	0.021	(1.02)
Natural Barriers	0.096^{***}	(3.38)	0.027^{**}	(2.35)	0.120^{***}	(4.41)
Emergency Prep.	-0.055^{**}	(-2.13)	0.073^{**}	(2.03)	-0.058^{**}	(-2.18)
Recovery Operation	0.106	(1.07)	-0.135^{*}	(-1.72)	-0.131	(-1.59)
Floodplain Revision	-0.033	(-0.61)	0.080^{***}	(2.84)	-0.017	(-0.33)
Private Building	0.047	(0.50)	0.101^{***}	(4.18)	0.084^{***}	(2.72)
Constant	11.959^{***}	(73.63)	12.433^{***}	(91.83)	12.520^{***}	(133.67)
Observations	79,184		90,811		169,995	
Adjusted R^2	0.751		0.630		0.730	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Adaptation Type:

The four major categories of adaptation measures were examined by estimating each type of application within the categories of hard infrastructure, green infrastructure, adaptive capacity, and privately implemented adaptation, respectively. These types for each category are: infrastructure and critical facility hardening (in “hard infrastructure”); drainage improvement, and CBRS and wetland (in “green infrastructure”); emergency preparedness and recovery operation (in “adaptive capacity”); and, finally, LOMR and individual building hardening (in “private adaptation”).

Many of these adaptation measures in this classification are statistically significant, at the 5% level. Natural barriers (see Figure 42) such as Coastal Barrier Resources System (CBRS) and wetlands have a positive impact on housing transaction prices in both regions.

Figure 42. Natural barriers in Miami and New York.

Notes: Aerial view of Barrier Island in Miami (left) and Rockaway Beach in New York (right). Photographs by Seung Kyum Kim.

Hardening infrastructure and emergency preparedness such as hurricane shelters and evacuation bus stops, and private adaptation have a contradictory result (see Table 17)—infrastructure hardening projects have a positive impact while emergency preparedness and floodplain revision (private) projects have a negative impact on housing prices in Miami-Dade County. Opposite results on the same variables are observed in New York City. Since it is highly possible that the values of existing infrastructures, such as levees and seawalls, built before the study period are already capitalized into the property prices, only new infrastructure hardening projects that took place after 2010 are examined in this model specification. The detailed project profiles distinguish that Miami-Dade County has invested in active infrastructural projects including levee reinforcement and construction of flood protection berms. Meanwhile, the majority of New York's infrastructural projects were relatively 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. In other words, minor construction projects would not be enough to reduce the latent risks of future hurricanes.

With respect to emergency preparedness, hurricane shelters and bus stops in Miami-Dade County are mostly located in distressed areas, including mobile home sites. Although the zip code fixed effect is applied in the analysis model, the fixed effect does not capture this finer market characteristic. Recovery operation projects are associated with housing price decreases, but elevating building foundation and base flood elevation of private land has a strong positive impact in New York City. No impact on the same variables is observed in Miami-Dade County. General drainage improvement projects have a positive sign in both regions but not statistically significant at the 10% level in both regions.

Table 18. Regression analysis of the adaptation measures by technique.

Price (logged)	MDC (3)		NYC (3)		ALL (3)	
Bedroom	0.020***	(2.83)				
Bathroom	0.070***	(5.82)				
Building SF	0.019***	(13.79)	0.020***	(25.70)	0.025***	(22.32)
Lot Size	0.001***	(5.28)	0.004***	(10.12)	0.001***	(5.44)
Story	0.102***	(4.60)	0.036***	(6.00)	0.053***	(5.74)
Building Age	-0.002*	(-1.92)	-0.002***	(-7.38)	-0.002***	(-5.46)
Occupancy	0.106***	(9.08)	0.012***	(3.10)	0.055***	(6.99)
Elevation	0.013**	(2.35)	0.009***	(4.03)	0.001***	(4.41)
Metro Station	-0.117***	(-2.74)	-0.033*	(-1.73)	-0.045**	(-2.17)
Bus Stop	-0.057***	(-3.81)	-0.018**	(-2.55)	-0.041***	(-4.62)
Cultural	0.044	(1.37)	0.025	(1.45)	0.026*	(1.74)
Commercial	-0.018	(-0.46)	-0.043***	(-4.63)	-0.050***	(-4.62)
School	-0.035***	(-3.20)	-0.016***	(-3.01)	-0.028***	(-4.34)
Sexual Crime	-0.068***	(-5.56)				
Brownfield	-0.134**	(-2.56)	-0.043***	(-3.12)	-0.126***	(-2.65)
GS View	-0.007	(-0.50)	0.032*	(1.89)	0.003	(0.21)
GS Proximity	-0.009	(-0.62)	0.011	(1.26)	0.009	(0.11)
Ocean View	0.126***	(2.79)	0.047	(1.02)	0.116***	(2.92)
Ocean Proximity	0.205***	(3.82)	-0.044	(-0.90)	0.016	(0.36)
Unemployment Rate	-0.007	(-1.45)	-0.011***	(-3.70)	-0.006**	(-2.27)
Vacancy Rate	-0.299	(-1.13)	-0.125	(-0.37)	-0.434	(-1.65)
Household Income	-0.003	(-1.43)	0.004***	(2.86)	-0.001	(-1.19)
Landfall	-0.091***	(-2.78)				
Wind	0.052**	(2.44)	0.006**	(2.39)	0.011***	(7.59)
Rainfall	-0.030**	(-2.54)	-0.097***	(-5.06)	-0.017***	(-8.77)
Storm Surge	-0.019***	(-2.72)	-0.060***	(-4.72)	-0.010***	(-9.98)
Power Outage	0.024	(1.31)				
Frequency	-0.006***	(-2.91)	0.089*	(1.95)	0.001	(0.25)
Fadedness	0.015***	(2.88)	0.007**	(2.49)	0.015***	(7.09)
Myopia	-0.003***	(-3.24)	-0.001	(-1.37)	-0.004***	(-9.53)
IHP Grant	0.023*	(1.85)	0.002**	(2.39)	0.003**	(2.42)
Insurance	0.072***	(2.95)	-0.074**	(-2.38)	0.028	(1.30)
Information	0.060	(1.55)	0.002	(0.06)	0.041	(1.49)
Elevation	-0.043	(-0.82)	0.121**	(2.08)	-0.019	(-0.36)
Construction	0.071**	(2.35)	0.024	(0.64)	0.067**	(2.35)
Reinforcement	0.078***	(3.24)	-0.085*	(-1.82)	0.009	(0.24)
Equipment Installation	0.026	(0.63)	0.116	(1.18)	0.078	(0.99)
Demolition	-0.073	(-1.02)	-0.099	(-1.54)	-0.162*	(-1.88)
System Improvement	0.102***	(3.61)	0.059	(1.63)	0.125***	(4.61)
Constant	11.937***	(74.04)	12.442***	(92.26)	12.518***	(131.60)
Observations	79,184		90,811		169,995	
Adjusted R^2	0.750		0.629		0.730	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Adaptation Technique:

All the adaptation projects were reclassified by 6 adaptation techniques—elevation, construction, reinforcement, equipment installation, demolition, and system improvement. In Miami-Dade County, construction, reinforcement, and system improvement projects have a positive impact on housing transaction prices. In New York City, only the elevation variable is positively related to housing prices, while reinforcement and demolition projects are associated with housing price depreciation. Among these variables, system improvement in Miami-Dade and elevation in New York have a particularly strong positive impact on housing prices. The reinforcement factor produced contrasting results between the two regions—it is positive with a strong coefficient value in Miami-Dade County, but negative in New York City. Only the construction and system improvement variables satisfy the statistical significance of *p*-value less than 5% and have a positive impact on housing transaction prices in the combined model (see Table 18, ALL 3).

Figure 43. Storm surge barrier construction.

Notes: Precast concrete walls to prepare for storm surge in Rockaway, New York. Photograph by Seung Kyum Kim.

Table 19. Regression analysis of the adaptation measures by project characteristics.

Price (logged)	MDC (4)		NYC (4)		ALL (4)	
Bedroom	0.021***	(2.96)				
Bathroom	0.069***	(5.79)				
Building SF	0.019***	(13.70)	0.020***	(25.77)	0.025***	(22.27)
Lot Size	0.001***	(5.24)	0.004***	(10.11)	0.001***	(5.45)
Story	0.101***	(4.61)	0.036***	(6.06)	0.054***	(5.74)
Building Age	-0.002**	(-2.01)	-0.002***	(-7.38)	-0.002***	(-5.49)
Occupancy	0.106***	(9.09)	0.012***	(3.06)	0.055***	(6.96)
Elevation	0.013**	(2.33)	0.009***	(3.99)	0.001***	(4.37)
Metro Station	-0.112***	(-2.69)	-0.033*	(-1.74)	-0.044**	(-2.10)
Bus Stop	-0.055***	(-3.87)	-0.019***	(-2.63)	-0.041***	(-4.53)
Cultural	0.042	(1.32)	0.025	(1.48)	0.025*	(1.68)
Commercial	-0.011	(-0.28)	-0.044***	(-4.67)	-0.050***	(-4.57)
School	-0.031***	(-2.80)	-0.016***	(-3.06)	-0.027***	(-4.20)
Sexual Crime	-0.067***	(-5.56)				
Brownfield	-0.134**	(-2.54)	-0.044***	(-3.32)	-0.125***	(-2.63)
GS View	-0.006	(-0.42)	0.031*	(1.86)	0.003	(0.22)
GS Proximity	-0.007	(-0.50)	0.011	(1.16)	0.012	(0.14)
Ocean View	0.120***	(2.71)	0.050	(1.09)	0.117***	(2.94)
Ocean Proximity	0.199***	(3.69)	-0.042	(-0.90)	0.015	(0.33)
Unemployment Rate	-0.007	(-1.42)	-0.011***	(-3.63)	-0.006**	(-2.26)
Vacancy Rate	-0.277	(-1.05)	-0.152	(-0.45)	-0.446*	(-1.70)
Household Income	-0.003	(-1.48)	0.004***	(2.82)	-0.001	(-1.23)
Landfall	-0.090***	(-2.75)				
Wind	0.051**	(2.40)	0.006**	(2.40)	0.012***	(7.72)
Rainfall	-0.030**	(-2.53)	-0.097***	(-5.03)	-0.017***	(-8.93)
Storm Surge	-0.018**	(-2.64)	-0.059***	(-4.68)	-0.010***	(-9.96)
Power Outage	0.023	(1.26)				
Frequency	-0.006***	(-2.98)	0.088*	(1.90)	0.001	(0.49)
Fadedness	0.016***	(2.94)	0.006**	(2.43)	0.016***	(7.12)
Myopia	-0.003***	(-3.21)	-0.001	(-1.39)	-0.004***	(-9.48)
IHP Grant	0.023*	(1.87)	0.003**	(2.20)	0.003**	(2.34)
Insurance	0.071***	(2.83)	-0.077**	(-2.61)	0.030	(1.36)
Information	0.061	(1.59)	0.007	(0.00)	0.037	(1.36)
Infrastructure Reinforce	0.338***	(4.18)	-0.037*	(-1.70)	-0.732	(-0.13)
New Facility	0.346***	(5.91)	0.014	(0.43)	0.133	(0.85)
Building Reinforcement	0.082***	(2.81)	0.071***	(3.87)	0.063***	(3.33)
Drainage Improvement	0.041*	(1.90)	0.021	(1.08)	0.028	(1.50)
Green Space Restoration	0.097***	(3.41)	0.059***	(3.67)	0.121***	(4.54)
Equipment Installation	0.038	(0.68)	0.102	(1.55)	0.062	(1.32)
Structural Elevation	0.066***	(2.78)	0.138***	(4.14)	0.026	(1.31)
Land Elevation	-0.034	(-0.69)	0.080***	(2.79)	-0.016	(-0.30)
Hurricane Shelters	0.029	(0.75)	0.149**	(1.98)	-0.034	(-1.45)
Evacuation Bus Stops	-0.067*	(-1.71)				
Neighborhood Resilience	0.040	(0.27)	0.026*	(1.96)	0.001	(0.07)
Constant	11.951***	(73.42)	12.446***	(92.22)	12.521***	(133.38)
Observations	79,184		90,811		169,995	
Adjusted R^2	0.750		0.630		0.729	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Project Characteristics:

A total of 11 variables of adaptation characteristics were examined in this attribute group. The majority of tested variables are statistically significant at the 5% level. Building reinforcement, green space restoration, and structural elevation have a positive impact on housing transaction prices in both regions (see Table 19). In addition, infrastructure reinforcement, new facility construction, and drainage improvement projects are associated with housing price appreciation in Miami-Dade County, while land elevation, hurricane shelter, and neighborhood resilience projects have a positive impact in New York City. Infrastructure reinforcement yields contrasting results between the two regions (positive in Miami-Dade County, but negative in New York City). Infrastructure reinforcement and new facility variables in Miami-Dade County have particularly strong coefficients, while structural elevation projects and hurricane shelters produce relatively higher coefficients in New York City.

Figure 44. Building reinforcement by installing hurricane shutters and storm panels.

Sources: Hurricane shutters (left) installation (Flavelle, 2018). Aluminum storm panels (right) installed home in Miami (Photograph by Seung Kyum Kim).

Table 20. Regression analysis of the adaptation measures by hazard type.

Price (logged)	MDC (5)		NYC (5)		All (5)	
Bedroom	0.020***	(2.79)				
Bathroom	0.071***	(5.77)				
Building SF	0.019***	(14.06)	0.020***	(25.71)	0.025***	(22.46)
Lot Size	0.001***	(5.35)	0.004***	(10.11)	0.001***	(5.48)
Story	0.105***	(4.76)	0.036***	(6.02)	0.054***	(5.77)
Building Age	-0.002*	(-1.95)	-0.002***	(-7.37)	-0.002***	(-5.48)
Occupancy	0.105***	(8.98)	0.012***	(3.07)	0.055***	(6.95)
Elevation	0.013**	(2.29)	0.009***	(4.05)	0.001***	(4.42)
Metro Station	-0.123***	(-2.77)	-0.034*	(-1.76)	-0.044**	(-2.08)
Bus Stop	-0.054***	(-3.47)	-0.019***	(-2.64)	-0.040***	(-4.42)
Cultural	0.040	(1.28)	0.025	(1.46)	0.025*	(1.68)
Commercial	-0.031	(-0.80)	-0.044***	(-4.66)	-0.050***	(-4.58)
School	-0.035***	(-3.13)	-0.016***	(-2.97)	-0.028***	(-4.24)
Sexual Crime	-0.068***	(-5.53)				
Brownfield	-0.133**	(-2.53)	-0.041***	(-3.16)	-0.124***	(-2.62)
GS View	-0.007	(-0.54)	0.032*	(1.88)	0.002	(0.15)
GS Proximity	-0.011	(-0.74)	0.011	(1.25)	0.001	(0.01)
Ocean View	0.125***	(2.73)	0.048	(1.02)	0.117***	(2.90)
Ocean Proximity	0.204***	(3.76)	-0.043	(-0.89)	0.015	(0.34)
Unemployment Rate	-0.007	(-1.42)	-0.011***	(-3.66)	-0.006**	(-2.20)
Vacancy Rate	-0.308	(-1.16)	-0.151	(-0.44)	-0.447*	(-1.69)
Household Income	-0.003	(-1.58)	0.004***	(2.85)	-0.001	(-1.24)
Landfall	-0.090***	(-2.67)				
Wind	0.051**	(2.33)	0.006**	(2.39)	0.011***	(7.66)
Rainfall	-0.029**	(-2.39)	-0.097***	(-5.06)	-0.017***	(-8.88)
Storm Surge	-0.019***	(-2.73)	-0.059***	(-4.68)	-0.010***	(-9.91)
Power Outage	0.023	(1.28)				
Frequency	-0.006***	(-2.84)	0.088*	(1.91)	0.001	(0.30)
Fadedness	0.016***	(2.97)	0.006**	(2.46)	0.015***	(7.11)
Myopia	-0.003***	(-3.24)	-0.001	(-1.34)	-0.004***	(-9.53)
IHP Grant	0.023*	(1.88)	0.003**	(2.26)	0.003**	(2.37)
Insurance	0.076***	(3.08)	-0.076**	(-2.43)	0.033	(1.49)
Information	0.062	(1.61)	0.001	(0.03)	0.039	(1.44)
Adapting Wind	0.021	(0.74)	0.042*	(1.94)	0.025	(0.98)
Adapting Flood	0.053**	(2.35)	0.077	(1.58)	0.076***	(3.15)
Adapting Storm Surge	0.154**	(2.34)	0.043**	(2.58)	0.130**	(2.15)
Adapting Multi-purpose	0.162***	(2.92)	0.033	(1.06)	0.031	(0.77)
Constant	11.957***	(75.63)	12.443***	(92.23)	12.524***	(132.14)
Observations	79,184		90,811		169,995	
Adjusted R^2	0.749		0.629		0.729	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hazard Types:

Adaptation projects that address flood, storm surge, or multiple hazards (more than one hazard) are positively associated with housing prices in Miami-Dade County. In New York City, only the adaptation projects for storm surge protection have a positive impact on housing transaction prices with the statistical significance of *p*-value less than 5%. Particularly strong coefficient values were observed for the storm surge and multi-purpose project variables for Miami-Dade (see Table 20).

Figure 45. Sand dune construction to prepare for storm surge.

Notes: Sand dune construction in Rockaway Beach, New York. Photograph by Seung Kyum Kim.

Table 21. Regression analysis of the adaptation measures by project attribute.

Price (logged)	MDC (6)		NYC (6)		ALL (6)	
Bedroom	0.020***	(2.84)				
Bathroom	0.070***	(5.72)				
Building SF	0.019***	(13.57)	0.020***	(25.64)	0.025***	(22.21)
Lot Size	0.001***	(5.33)	0.004***	(10.09)	0.001***	(5.46)
Story	0.103***	(4.55)	0.036***	(6.01)	0.054***	(5.72)
Building Age	-0.002**	(-2.15)	-0.002***	(-7.35)	-0.002***	(-5.50)
Occupancy	0.105***	(8.94)	0.012***	(3.09)	0.055***	(6.93)
Elevation	0.013**	(2.30)	0.009***	(4.04)	0.001***	(4.41)
Metro Station	-0.113**	(-2.61)	-0.034*	(-1.76)	-0.044**	(-2.14)
Bus Stop	-0.059***	(-3.83)	-0.019**	(-2.59)	-0.044***	(-4.63)
Cultural	0.044	(1.40)	0.025	(1.46)	0.026*	(1.70)
Commercial	-0.003	(-0.08)	-0.043***	(-4.63)	-0.049***	(-4.41)
School	-0.034***	(-2.88)	-0.016***	(-2.92)	-0.027***	(-3.93)
Sexual Crime	-0.069***	(-5.73)				
Brownfield	-0.136**	(-2.58)	-0.043***	(-3.40)	-0.127***	(-2.63)
GS View	-0.007	(-0.50)	0.031*	(1.86)	0.003	(0.23)
GS Proximity	-0.008	(-0.58)	0.012	(1.26)	0.014	(0.16)
Ocean View	0.134***	(2.81)	0.047	(1.01)	0.123***	(2.96)
Ocean Proximity	0.202***	(3.62)	-0.040	(-0.83)	0.015	(0.32)
Unemployment Rate	-0.006	(-1.36)	-0.011***	(-3.68)	-0.006**	(-2.13)
Vacancy Rate	-0.312	(-1.19)	-0.145	(-0.42)	-0.450*	(-1.69)
Household Income	-0.003	(-1.47)	0.004***	(2.81)	-0.001	(-1.21)
Landfall	-0.092***	(-2.82)				
Wind	0.052**	(2.44)	0.006**	(2.40)	0.012***	(7.81)
Rainfall	-0.030**	(-2.52)	-0.097***	(-5.01)	-0.017***	(-8.92)
Storm Surge	-0.019***	(-2.76)	-0.059***	(-4.69)	-0.010***	(-10.12)
Power Outage	0.024	(1.30)				
Frequency	-0.006***	(-2.85)	0.085*	(1.85)	0.001	(0.42)
Fadedness	0.015***	(2.89)	0.006**	(2.46)	0.015***	(7.22)
Myopia	-0.003***	(-3.19)	-0.001	(-1.30)	-0.004***	(-9.43)
IHP Grant	0.023*	(1.89)	0.002**	(2.20)	0.003**	(2.35)
Insurance	0.081***	(3.35)	-0.074**	(-2.34)	0.038*	(1.79)
Information	0.060	(1.52)	-0.006	(-0.00)	0.036	(1.30)
New	0.113	(1.21)	-0.052*	(-1.81)	-0.031	(-0.54)
Upgrade	0.032*	(1.85)	0.091***	(3.38)	0.054***	(3.33)
Repair	-0.029	(-1.02)	0.027	(0.92)	-0.017	(-0.77)
Existing	-0.021	(-0.76)	0.033*	(1.96)	-0.024	(-0.86)
Remove	-0.100*	(-1.80)	0.077***	(3.31)	0.089***	(3.04)
Constant	11.966***	(74.74)	12.446***	(91.68)	12.530***	(132.42)
Observations	79,184		90,811		169,995	
Adjusted R^2	0.748		0.629		0.729	

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Project Attribute:

In this model specification, I decomposed and restructured the adaptation measures into five subcategories of the project attribute: new project, upgraded, repaired, already constructed before the study timeline, and removal projects. In Miami-Dade, upgrade is associated with housing price increase, while removal projects have a negative impact on housing transaction prices among the five subcategories. In New York City, upgrade, existing, and removal projects have a positive impact, while new projects are negatively associated with housing prices. Only upgrade projects have a positive impact in both regions (see Table 21).

Taken together, the results from the analyses of the aforementioned five classifications epitomize as follows:

The following three attributes: the green infrastructural measures (such 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 (see Table 22).

By region, the positive effects of publicly operated hard and green infrastructure measures are pronounced in Miami-Dade County; while the positive impacts of private (individual) adaptation measures, such as private building reinforcement and raising house foundation, are particularly strong in New York City.

Lastly, combining all data between Miami-Dade and New York, a total of 169,995 single family houses were analyzed to compare the effects of adaptation measures between each of the two specific locations themselves, as well as for both coastal regions combined. A similar result from the analyses for each region was found. Adaptive capacity (system improvement variable) and green infrastructure (natural barriers and green space restoration variables) measures provide homeowners with a particularly strong positive pricing effect in this dataset. The results also indicate that projects for flood mitigation, upgrade projects, and at-risk structure removal projects are positive factors with a strong coefficient value.

Table 22. Result summary of adaptation categories.

Classification	Variables	MDC	NYC	ALL
Type	Infrastructure	0.264^{***}	-0.028	0.029
	Critical Facility	0.119^{**}	0.024	0.037
	Drainage System	0.033	0.010	0.021
	Natural Barriers	0.096^{***}	0.027^{**}	0.120^{***}
	Emergency Prep.	-0.055^{**}	0.073^{**}	-0.058^{**}
	Recovery Operation	0.106	-0.135^{*}	-0.131
	Floodplain Revision	-0.033	0.080^{***}	-0.017
	Private Building	0.047	0.101^{***}	0.084^{***}
Technique	Elevation	-0.043	0.121^{**}	-0.019
	Construction	0.071^{**}	0.024	0.067^{**}
	Reinforcement	0.078^{***}	-0.085^{*}	0.009
	Equipment Installation	0.026	0.116	0.078
	Demolition	-0.073	-0.099	-0.162^{*}
	System Improvement	0.102^{***}	0.059	0.125^{***}
Project Characteristics	Infrastructure Reinforce	0.338^{***}	-0.037^{*}	-0.732
	New Facility	0.346^{***}	0.014	0.133
	Building Reinforcement	0.082^{***}	0.071^{***}	0.063^{***}
	Drainage Improvement	0.041^{*}	0.021	0.028
	Green Space Restoration	0.097^{***}	0.059^{***}	0.121^{***}
	Equipment Installation	0.038	0.102	0.062
	Structural Elevation	0.066^{***}	0.138^{***}	0.026
	Land Elevation	-0.034	0.080^{***}	-0.016
	Hurricane Shelters	0.029	0.149^{**}	-0.034
	Neighborhood Resilience	0.040	0.026^{*}	0.001
Hazard Type	Adapting Wind	0.021	0.042^{*}	0.025
	Adapting Flood	0.053^{**}	0.077	0.076^{***}
	Adapting Storm Surge	0.154^{**}	0.043^{**}	0.130^{**}
	Adapting Multi-purpose	0.162^{***}	0.033	0.031
Attribute	New	0.113	-0.052^{*}	-0.031
	Upgrade	0.032^{*}	0.091^{***}	0.054^{***}
	Repair	-0.029	0.027	-0.017
	Existing	-0.021	0.033^{*}	-0.024
	Remove	-0.100^{*}	0.077^{***}	0.089^{***}
	N	79,184	90,811	169,995

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness Checks:

Since results differ from each region, I further examine whether these results are sensitive to other externalities. Perhaps storm experience (no storm occurs between buying and selling versus at least one storm occurs) could be a significant factor for housing prices, rather than the effects of storm frequency (the total number of storms the homeowners experienced prior to sell). Or, perhaps the adaptation effects can be weighted more on lower priced houses. To test whether they are clearly different, I estimated alternative models with the three different samples that 1) have at least one storm occurrence between buying and selling dates, 2) include properties valued above the average, and 3) consist of housing priced below the average.

The results present that the *frequency* (i.e., total number of storms) variable becomes a positive factor with the homeowners who have at least one storm or more within their residence period in Miami-Dade County (see Table 23, MDC 1). In this specification, only storm surge among the storm characteristics negatively influence property values at the 5% significance level. Project information has negative impact on housing prices, possibly due to net nuisance effects from the construction activities including noise, dust, and traffic congestion. Adaptation effects are dominantly observed in the properties with below average prices (see Table 23, MDC 3). All of the effects from storm characteristics and risk perception factors, except the insurance effect, do not exist in the homes priced above the average, while the positive effects of critical facility and infrastructure reinforcements are pronounced only in the higher priced homes in Miami-Dade County (see Table 23, MDC 2). The results imply that higher valued homes already equipped with some degrees of hurricane resilience by adapting more fastidious building code and regulation, and thus only a few critical infrastructural measures that can directly influence property protection from hurricanes, may positively capitalize into property values.

By contrast, the compression bias (underestimating common risks) effect is more pronounced among homeowners who experienced at least one or more hurricanes during their residency in New York City (see Table 23, NYC 1). In this specification, reinforcing existing hard infrastructure and equipment installation variables become statistically significant (at the 1% level). In New York City, the positive effects of adaptation measures are more pronounced in properties valued above the average (see Table 23, NYC 2). Surprisingly, the explanatory power of the specification (see Table 23, NYC 3), consisting of homes priced below the average, significantly drops from 63% to 24%. These results signify there may be an issue of spatial distribution of public adaptation projects (adaptation priority set on wealthier communities), while a less strict building regulation for storm resistance in this region may not sufficiently address the actual storm risks.

In addition, the results still do not sufficiently manifest what elements in each adaptation category affect the housing prices, due to the adaptation's multi-valued attribute and interaction effects. To identify the causal inference between adaptation measures and housing prices, I excluded the samples that can be influenced by two or more adaptation measures from each adaptation category of hard infrastructure, green infrastructure, adaptive capacity, and privately implemented adaptation projects.

Table 23. Results of storm experience and housing price controls by region.

Price (logged)	MDC (1)	MDC (2)	MDC (3)	NYC (1)	NYC (2)	NYC (3)
Sample Criteria	Only storm experienced	Price above average	Price below average	Only storm experienced	Price above average	Price below average
Wind damage / Wind	-0.002	0.001	0.041*	-0.014	0.005	0.012***
Flood damage / Rainfall	-0.037*	-0.013	0.002	-0.175***	-0.006	-0.093***
Storm surge	-0.016**	0.001	-0.027***	-0.080***	-0.030*	-0.053***
Landfall	0.061	0.078	-0.080***			
Frequency	0.094***	-0.005	-0.004**	0.498***	-0.034	-0.008
Fadedness	0.031	0.003	0.014***	0.017***	0.004	0.005**
Myopia	-0.002	-0.003	-0.002***	-0.017**	0.004	-0.005
IHP grant	-0.005	0.004	0.011	0.001	0.002***	0.003
Insurance	0.056***	0.063***	0.046***	-0.075*	0.001	-0.076***
Information	-0.192***	-0.037	0.021	-0.031	0.010	-0.014
Infrastructure	0.223**	0.149*	-0.094	0.030	-0.008	-0.003
Critical facility	0.080	0.162**	0.022	0.018	0.006	-0.002
Drainage system	0.011	-0.047*	0.006	0.162*	0.022	0.004
Natural barrier	0.060***	0.079	0.054***	0.060***	0.010	0.037***
Emergency preparedness	-0.048*	-0.071*	-0.002	0.051	0.090***	-0.017
Recovery operation	0.218	0.121	0.105***	-0.292*	-0.091*	-0.041
Floodplain revision	-0.037	-0.052	0.023	0.070	0.027	0.002
Private building hardening	-0.052	0.173	-0.023	0.102***	0.091***	0.032*
Elevation	-0.036	-0.046	0.009	0.044	0.113***	-0.009
Construction	0.043**	0.057	0.021	0.072	0.035	0.003
Reinforcement	0.049	-0.026	0.083***	-0.096	-0.124***	0.021
Equipment Installation	0.121	-0.096	0.064**	0.209***	0.153***	0.007
Demolition	-0.078		-0.084	-0.002	-0.076*	-0.099**
System Improvement	0.065***	0.082	0.056***	0.022	0.069***	-0.021
Infrastructure Reinforce	0.287***	0.259**	0.072	-0.183***	-0.011	-0.021
New Facility	0.370***	-0.023	0.165***	-0.009	-0.089	-0.026**
Building Reinforcement	0.115**	-0.022	0.181***	0.097***	0.061***	0.038**
Drainage Improvement	0.016	-0.058**	0.011	0.073	0.025	0.013
Green Space Restoration	0.059***	0.078	0.054***	0.057***	0.038	0.039*
Equipment Installation	0.143	-0.015	0.062***	0.223*	0.032	-0.001
Structural Elevation	0.127***	-0.013	0.083***	0.160***	-0.047	0.055***
Land Elevation	-0.043	-0.056	0.023	0.071	0.025	0.003
Hurricane Shelters	0.036	0.056	-0.022	0.379***	0.188***	-0.023
Neighborhood Resilience	-0.073	0.014		-0.079	-0.001	0.006
Observations	14,585	20,893	58,286	31,055	30,545	60,261
Adjusted R^2	0.73	0.65	0.50	0.63	0.66	0.24

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results present that reinforcing existing hard infrastructure and critical facilities provides positive effects on housing prices in Miami-Dade County (see Table 24, MDC 1). These positive project elements include construction of new critical facilities, elevating roads, and fortifying existing protective structures such as levees and seawalls. By contrast, hard infrastructural adaptation measures are less effective compared to other adaptation categories in New York City. Only drainage improvement projects have a positive effect in this region (see Table 24, NYC 1).

Improving overall flood and storm surge protection measures through green infrastructural elements is positively associated with housing price increase in both regions (see Table 24, MDC 2 and NYC 2). Exemplary projects in this category includes wetlands, detention ponds, restoring large scale natural barriers such as CBRS (Costal Barrier Resources System), sand dune, beach nourishment, and riparian buffer restoration. In Miami-Dade County, the positive effects are more pronounced on projects that enhance its functionality of green infrastructure such as expanding existing riparian buffers and permeable surfaces. On the other hand, creating new green infrastructure such as restoring green spaces and sand dunes has a stronger impact on housing prices in New York City. Regardless of this difference, green infrastructure preserves accessibility to natural amenities and provides a similar function of the retreat through creating buffer spaces that can mitigate direct impacts of hurricanes.

The positive effects of adaptive capacity projects on housing price in both regions are mostly presented on the projects that establish new facilities, organizations, education programs, and preparing portable equipment to address storm damage and preparedness (see Table 24, MDC 3 and NYC 3). Meanwhile, structural elevation (such as raising foundation) and building reinforcement projects provide strong positive impacts on housing price in the private adaptation category for both regions (see Table 24, MDC 4 and NYC 4).

Table 24. Results of adaptation category controls by region.

Price (logged)	MDC (1)	MDC (2)	MDC (3)	MDC (4)	NYC (1)	NYC (2)	NYC (3)	NYC (4)
Sample Criteria	Hard	Green	Capacity	Private	Hard	Green	Capacity	Private
Elevation	-0.084*	-0.092*		-0.047	0.103			0.078
Construction	0.102*	0.032	0.043		0.014	0.019	0.057**	0.136***
Reinforcement	0.071***	-0.020	0.029	0.104***	-0.068	-0.003		-0.020
Equipment Installation	-0.076	-0.350	0.126	-0.087	0.156*			
Demolition			-0.067		-0.075	0.086***	0.041	
System Improvement	0.257***	0.099***	0.292***			0.047**	0.029	
Infrastructure Reinforce	0.277***	0.112***	0.045		-0.044	-0.046**	-0.027	
New Facility	0.316***		0.322***		0.016		0.024	
Building Reinforcement	0.050**		0.070**	0.074**	-0.018		0.040	0.080***
Drainage Improvement	0.014	0.030	0.074*		0.034**	-0.001	0.023	
Green Space Restoration		0.099***	-0.070			0.052***	0.090***	
Equipment Installation	-0.016		0.052**	0.023	0.110		0.030***	
Structural Elevation	0.071**			0.086***				0.136***
Land Elevation				-0.035				0.084***
Hurricane Shelters			0.031				0.141*	
Neighborhood Resilience	0.240*	0.019	0.248***		0.024*	-0.053***	0.024	
Adapting Wind	0.019		0.047	0.096***	-0.062**	-0.164	0.023	0.077***
Adapting Flood	-0.006	0.056**	0.042**	-0.046	0.052			0.068*
Adapting Storm Surge	-0.205***	0.161**	-0.517			0.025**	0.083*	
Adapting Multi-purpose	0.134**	-0.348	0.193***	0.015	0.101*	0.052**	0.017	0.125***
Observations	59,745	72,629	63,201	58,813	88,095	84,868	86,479	84,528
Adjusted R^2	0.76	0.75	0.76	0.76	0.625	0.623	0.626	0.627

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Due to the multi-valued attribute in each adaptation variable and local-specific nature of adaptation measures, the five subcategorized models of adaptation measures do not sufficiently present the relationship between adaptation effects and risk perception. Perhaps, a positive adaptation effect could be generated because it drops some of the effects of risk perception factors or interacts with market factors. To test the adaptation effects on risk perception and market trends, I integrated the five sub-classified models into the original adaptive category of hard infrastructure, green infrastructure, adaptive capacity, and privately implemented adaptation.

Like the results from the previous regression models (see Table 22), hard- and green-infrastructural measures in Miami-Dade County and green- and privately implemented adaptation in New York City have positive pricing effects (see Table 25, Specification 2 and 3).

From the results of each specification, representing (1) without adaptation, (2) all adaptation without categorization, and (3) with categorized adaptation measures, I found that the adaptation effects are related to risk perception or market trends factors by region.

Although most of the coefficients are stable across the specifications, the coefficients of ocean view, vacancy rate, and insurance variables have changed as the hard- and green- infrastructural measures are statistically significant in Miami-Dade County, while the coefficients of vacancy rate and risk frequency variables marginally increased by the effects of adaption measures in New York City (see Table 25, Specification 1 and 2). Thus, I confirmed that the risk perception and market factors interact with the adaptation effects. In Miami-Dade County, hard infrastructures and natural barriers have reduced the positive values of ocean view and proximity, while the hard and green adaptive measures have reduced the positive impact of flood insurance by decreasing potential hurricane risks. On the other hand, the effects of adaptation measures could be related to market resilience, since the negative effects of vacancy increase are offset by the positive effects of adaptation measures in New York City.

Table 25. Results of adaptation effects by categories.

Price (logged)	MDC (1) *B*	MDC (2) *B*	MDC (3) β	NYC (1) *B*	NYC (2) *B*	NYC (3) β
Bedroom	0.011*	0.012**	0.012**			
Bathroom	0.056***	0.054***	0.072***			
Building SF	0.014***	0.014***	0.201***	0.014***	0.014***	0.171***
Lot Size	0.001***	0.001***	0.055***	0.003***	0.003***	0.120***
Story	0.083***	0.082***	0.033***	0.029***	0.029***	0.033***
Building Age	-0.001*	-0.001*	-0.031*	-0.001***	-0.001***	-0.065***
Occupancy	0.085***	0.086***	0.042***	0.008**	0.008**	0.006**
Elevation	0.006*	0.006	0.018	0.005***	0.005***	0.043***
Metro Station	-0.077**	-0.060*	-0.004*	-0.025	-0.025	-0.007
Bus Stop	-0.040***	-0.038***	-0.022***	-0.011**	-0.011**	-0.009**
Cultural	0.025	0.027	0.004	0.025*	0.025*	0.011*
Commercial	0.027	0.028	0.002	-0.026***	-0.026***	-0.019***
School	-0.025***	-0.020**	-0.012**	-0.007*	-0.007*	-0.006*
Brownfield	-0.101***	-0.102***	-0.038***	-0.005	-0.007	-0.001
GS View	-0.011	-0.012	-0.003	0.031**	0.032**	0.007**
GS Proximity	-0.008	-0.010	-0.006	0.003	0.003	0.002
Ocean View	0.073**	0.062**	0.020**	0.028	0.030	0.006
Ocean Proximity	0.165***	0.159***	0.043***	-0.023	-0.023	-0.013
Unemployment Rate	-0.004	-0.004	-0.020	-0.007**	-0.007**	-0.040**
Vacancy Rate	-0.363	-0.350	-0.036	-0.847**	-0.845**	-0.038**
Household Income	-0.009***	-0.009***	-0.209***	0.002	0.002	0.073
Wind	0.015	0.014	0.004	0.047***	0.048***	0.217***
Rainfall	0.008	0.007	0.002	-0.039**	-0.039**	-0.018**
Storm Surge	-0.025***	-0.024***	-0.014***	-0.075***	-0.075***	-0.065***
Frequency	0.010	0.009	0.013	0.367***	0.374***	0.081***
Fadedness	0.015***	0.015***	0.016***	-0.002	-0.002	-0.007
Myopia	-0.002***	-0.002***	-0.020***	-0.002***	-0.002***	-0.021***
IHP Grant	0.010	0.011	0.002	0.003**	0.003**	0.029**
Insurance	0.047***	0.040**	0.024**	-0.052**	-0.053***	-0.019***
Information	0.030	0.030	0.004	-0.003	-0.003	-0.001
Storm Experience (1 to 3)	-0.044	-0.042	-0.020	-0.265***	-0.268***	-0.237***
Lower Price (below avg.)	-0.673***	-0.670***	-0.368***	-0.478***	-0.477***	-0.420***
Hard Infrastructure		0.283**	0.033**		-0.006	-0.002
Green Infrastructure		0.053**	0.025**		0.032**	0.010**
Adaptive Capacity		-0.033	-0.006		-0.033	-0.004
Private Adaptation		0.030	0.003		0.051**	0.009**
Constant	13.011***	13.011***		13.112***	13.111***	
Observations	79,184	79,184	79,184	90,811	90,811	90,811
Adjusted R^2	0.806	0.807	0.807	0.714	0.714	0.714

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. B, unstandardized coefficients; β, standardized coefficients.

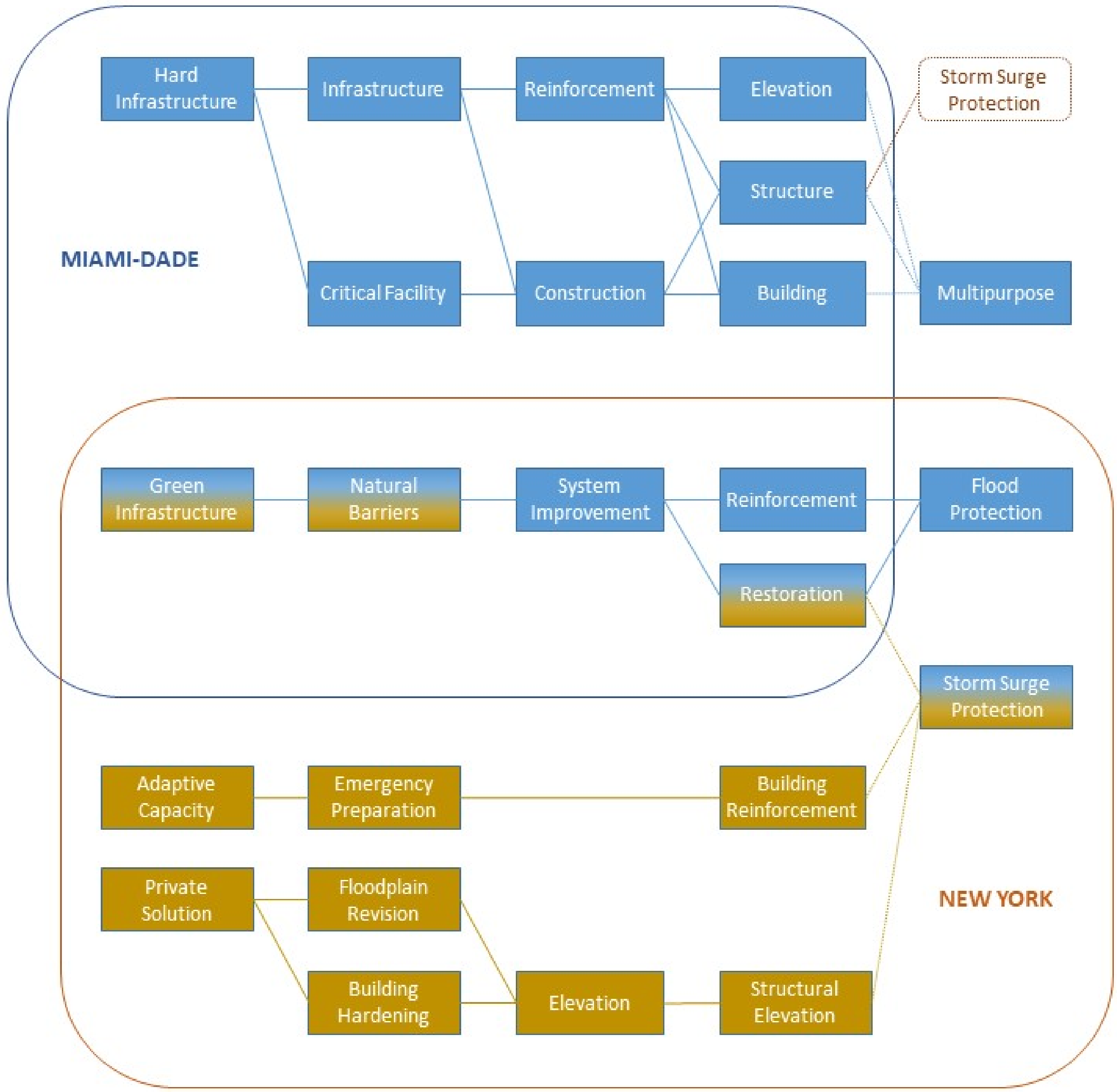


Figure 46. Result Summary Diagram.

6. Discussion

The regression results show that hurricanes have a strong adverse impact on housing transaction prices. The negative impact of the storm becomes positive after five months following storm occurrences in Miami-Dade, while the adverse effects live much longer in New York City, 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 *Storm 30-150 days* (homes sold between 30 - 150 days after hurricanes) 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.

Among the risk perception factors, risk fadedness has a positive impact on housing prices in both regions. Surprisingly, having a mandatory flood insurance requirement is associated with housing price increases in Miami-Dade County. A possible reason would be a limited supply of available housing inventory which is free from the flood insurance requirement. From this study, using the frequency variable to test the compression bias yields a negative impact on housing prices. The contrasting result indicates that the compression bias would not be present in homes sold without any storm experience. In fact, about 82% (or 64,598) single-family homes were transferred without having a storm experience in Miami-Dade County, and 66% (or 59,759) of properties have been sold with no storms experienced by the home seller in New York City. By excluding the no-storm-experience-home in the regression, the effects of storm frequency turned to be a strong positive at the 1% significance levels in both regions (see Table 23, Specification 1 of each region). Surprisingly, project information has a negative impact on housing prices in the regression model that consists of properties sold with at least one or more storm experience in Miami-Dade County (see Table 23, MDC 1). The result implies that negative nuisance effects from the construction activities including noise, dust, and traffic congestion can surpass the potential positive effects of risk reduction upon the project completion for those who have experienced a storm event.

With respect to the adaptation measures, the overall result concluded that green infrastructural projects, adaptation projects characterized by building reinforcement and structural elevation, and projects for storm surge protection are consistently and particularly strong in both regions. The green infrastructural projects in Miami-Dade County are characterized by enhancing its functionality through expanding and retrofitting the existing features, while New York City 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.

However, different impacts of the adaptation measures in each region were also observed. From the inconsistent results between the two 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, storm surge and flood vulnerabilities in New York City could be greater than Miami-Dade, because New York has a much higher population density than Miami-Dade as well as a particular geographic characteristic called "bight" (see Figure 24). In fact, when Super Storm Sandy made landfall in New York City 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 New York City.

Furthermore, the adaptation effects are dominantly observed in homes sold below the average transaction price in Miami-Dade County, whereas the positive effects of adaptation measures are more pronounced in homes valued above the average sales price in New York City (see Table 23, MDC 3 and NYC 2). This contrasting result signifies that pre-existing adaptation policies such as building code and regulation, as well as local adaptation priorities in decision-making, may largely influence the effects of adaptation measures. Storm frequency in Miami-Dade County is about 2.5 times greater than New York City, and its intensity is also stronger in general, resulting in Miami-Dade County's more fastidious building code and regulation. Thus, a certain degree of in-house adaptation attributes may already have been capitalized in housing prices in Miami-Dade County. The study findings of Dumm, Sirmans, and Smersh (2012) that fortifying building structures by implementing stricter building codes against hurricanes yields a price premium, also support this interpretation. By contrast, more public adaptation measures have been built adjacent to shorelines and barrier islands in New York City, where the wealthier homes are more highly concentrated. This issue of the uneven spatial distribution of public adaptation projects may result in higher priced homes garnering more positive benefits from adaptation measures.

With respect to the causal inferences between adaptation effects and risk perception, the coefficients of insurance, ocean view, and vacancy rate variables have been influenced by the hard- and green- infrastructural measures in Miami-Dade County, while the coefficients of vacancy rate and risk frequency variables marginally affected by the overall adaption measures in New York City. All other coefficients in risk perception and market factors are fairly stable across the specifications. The results imply that the positive effects of adaptation measures in Miami-Dade County may occur through reducing perceived risks of flooding and storm surges, whereas the effects of adaptation measures in New York City can be realized by offsetting potential adverse impacts of market economy (such as housing vacancy increase), rather than being influenced by homeowner's perceptions.

In addition, scales and amounts of local investments on adaptation measures would also be a significant impact factor. For example, Miami-Dade County 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 New York City. As a result, a particularly strong impact has been observed on public infrastructure adaptation measures in Miami-Dade County and private building reinforcement projects in New York City.

Another considerable factor could be the cost-effectiveness of adaptation. Due to climate uncertainty, limited adaptation budgets, and technological availability, the past optimal adaptation measures may not be the best option today. If the past infrastructural adaptation is not properly managed due to a lack of maintenance budget, the adaptation effects of the infrastructure could also not be maintained, as a structural deterioration is expected over time. For such a reason, green infrastructure, especially utilizing natural resources, has a strong positive impact on housing prices, because green infrastructure provides a net positive effect through preserving natural amenities as well as requiring less maintenance costs.

Plausible reasons that private adaptation measures are strong in New York City could result from issues surrounding of the uneven spatial distribution of adaptation measures as well as gaps between the level and quality of public provision and the social desirability of such adaptations (Chambwera et al., 2014). In order words, residents far from the coastline could have the same magnitude of risk that the coastal residents have because the intensity of hurricanes can be strong enough to impact the entire city. However, public adaptation projects were mainly focused on the coastline communities, and thus, the benefits of public infrastructure are not equally distributed. Even if the distribution issue of adaptation provisions is considered to be minor, public adaptation cannot satisfy everybody due to its cost-effectiveness characteristics. Therefore, the greater the gaps between the level of public provision and individual desirability of adaptation, the greater the anticipated effect of private adaptation (i.e., elevating or reinforcing their properties).

A few possible reasons supporting the result that the adaptation measures for wind damages have less impact on property prices could include overestimation of wind factor in the hurricane information, prevailing construction materials, and local landscape plant species. Hurricane wind damages typically occurred by flying debris and failures of existing infrastructure. Evidently, hurricane Andrew in 1992 pulled out approximately 25% of the trees in Florida's Everglades, and of these, almost all were Australian pine trees, which are an invasive species (Scowcroft et al., 2010). Meanwhile, current hurricane intensity (i.e. the Saffir-Simpson Scale) is largely based on sustained wind speeds, excluding other significant factors such as rainfall and storm surge. However, there is much historical evidence (such as Super Storm Sandy) to show us that other storm characteristics should also be considered as well.

Surprisingly, hard-infrastructural projects for storm surge protection generate negative impacts on property values in Miami-Dade County (see Table 24, MDC 1). Two persuasive reasons can be inferred to support this result. First, hard-infrastructural projects such as storm surge barriers may not effectively reduce a homeowner's perceived risk of storm surge, due to financial and aesthetic reasons. For example, Hurricane Andrew in 1992 caused a storm tide that reached about 16 feet in Miami-Dade County. However, constructing 16 feet height storm surge barriers has not been considered, since many other criteria, such as social consensus coupled with climate uncertainty, cultural adaptability, and budgeting issues for implementation are involved in adaptation decision-making. Second, taller barriers can deprive the value of ocean view and other amenity benefits.

Finally, the discrepancy of the analysis results between both regions, separately and combined, support the premise that implementation of climate adaptation should be based on local circumstance and hurricane characteristics. Generalized climate information without considering local and time specific heterogeneities may exaggerate or underestimate the actual risks, and thereby could produce malfunctions of adaptation in extreme cases. Hurricane Katrina in New Orleans is an exemplary case supporting this claim. The U.S. Army Corps Engineer constructed new levees in this area, specifically designed to resist a fast-moving major hurricane, after Hurricane Betsy in 1965. When the slow-moving Category 5 hurricane Katrina made a landfall in 2005, the levees collapsed resulting enormous damages (Scowcroft et al., 2010).

In addition, since locally specific factors (i.e., market factors, adaptive capacity level to major storms, and financial mechanism of adaptation projects) influence adaptation effects, generalizing study findings may result in the suggestion and/or implementation of inadequate adaptation strategies for a specific site. For example, Miami-Dade County has more available lands to expand housing development than New York City, resulting higher vacancy rates. Many aging underground infrastructure systems with peculiar geographic features (New York Bight) make New York City more vulnerable to storm surge effects. By contrast, Miami-Dade County has a stronger capacity for dealing with major storms due to much greater experience (i.e., the overall frequency and number of storm evets dealt with). Costs of adaptation could also be localized, thereby offsetting the direct benefits of adaptation. Since the 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 on new construction and maintenance (Jin et al., 2015). Potential economic benefits of risk reduction by such protective measures could be offset by a special tax imposition.

Furthermore, risk perceptions are influenced by the effects of adaptation measures. Since climate risk perception exists in emotional and conceptual territory, human perception is deeply influenced by cultural norms and individual beliefs on climate change, personal memories of storm events, and attitudes toward disaster preparedness. Although, individually distinct risk perceptions can contagiously influence each other within like-minded groups and one's belonging to certain communities, as the social network theory of risk perception explains

(Scherer & Cho, 2003), adapting general remedies to address such vast phenomena as climate change, which are “massively distributed in time and space” throughout human history (Morton, 2013), may not be the correct countermeasure to the locally specialized problems. Therefore, although results from the overall merged dataset provide a broader picture of which adaptation measures generally work better for coastal housing market resilience, the effects of adaptation measures should rely more on locally analyzed results.

7. Conclusions and Recommendations

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 decades, 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.

Estimate models two through six illustrate which adaptation types and techniques, project characteristics, and hazard types that adaptation projects address, as well as the impact of project attributes on housing transaction prices. Among the adaptation types, natural green infrastructural measures (such as coastal barrier resource systems and wetlands) have a particularly strong positive impact on housing sales prices throughout the regions. Because it is a matter of preserving not only the positive values of natural amenities and other ecological services, but also reducing adverse risk perception of hurricanes by providing a similar function of planned retreat. In the adaptation techniques, system improvement has a positive effect on housing prices in both regions. This outcome sheds light on how a long-term adaptive capacity enhancement can be a significant factor for housing market resilience through alleviating conceived risks. In the sub-classification of project characteristics, building reinforcement, green space restoration, and structural elevation are strongly associated with housing price increases. Adaptation measures for storm surge and flooding protections in the hazard type sub-category, and retrofitting projects in the attribute classification, have a positive impact in the housing market throughout the study area.

However, the effects of adaptation measures vary in each region. This is because neighborhood and storm idiosyncrasies, as well as different risk perceptions, can be deeply influenced by local cultures and social identities. Public adaptation including infrastructure construction and critical facility reinforcement also has a strong positive impact in Miami-Dade County. By contrast, private adaptation solutions, such as installing storm panels and hurricane shutters, as well as raising foundations structurally or revising land elevation, has a positive impact on housing prices in New York City. These discrepancies in the analysis results between the two regions implies that adapting generalized information for use in a particular region in order to implement adaptation measures could be risky, even possibly causing malfunctions in adaptation. Although I included variables for hurricane characteristics, neighborhood idiosyncrasies, and factors of risk perception in this study, it is almost impossible to capture all local specific heterogeneities and individually different risk perceptions. Thus, locally analyzed results may provide more robust suggestions for implementation of cost-effective adaptation measures to the local stakeholders.

These site-specific results could be supported by two postulations: scale and distribution of adaptation measures as well as vagueness in existing adaptation classification. Due to the massive scale of hurricane impacts, a collection of reactive and small-scale adaptation projects would not fully address the widespread damages, and thus any decrease of risk perception would be meager. The effect of the investments in adaptive capacity, which mainly dealt with emergency preparedness for future climate, is negative in site-specific (-5.5% in MDC), as well as overall sites (-5.8% in the merged dataset); but the positive impacts of the adaptive capacity variables in the other classification subcategories (such as system improvement and neighborhood resilience) are arguably strong. More balanced and comprehensive investment would improve storm resilience primarily due to both hidden interactions and ancillary effects, but would also help to address the issue of the uneven distribution of adaptation provisions.

In addition, existing adaptation projects for climate change tend to be based on the government's budget spending categories, rather than actual functions of climate resilience. For example, spending for common building maintenance such as boiler repairs, office interior repairs, and pavement surfacing would not be directly related to climate adaptation. Nevertheless, New York City includes these typical maintenance projects on their original classification of critical facility hardening for climate adaptation. Thus, more comprehensive and longer-term approaches using local climate change information are suggested for maximizing the positive effects of future investments on climate change adaptation measures.

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 9.6% in Miami-Dade County and 2.7% in New York City (holding all other variables constant). Structural elevation provides a 6.6% housing price appreciation in Miami-Dade County and 13.8% in New York City, respectively. Adapting for storm surges provides the largest positive impact on housing prices by 15.4% in Miami-Dade County 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. Adaptation effects can vary according to existing local building policies on hurricane resilience as well as by the spatial distribution of public adaptation provisions, which can influence both adaptation capacities and housing markets.

Together, adaptation effects and market resilience can be improved by the following recommendations for each region. For Miami-Dade County, 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% of their overall adaptation budget spending), especially in lower income communities. 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 in lower income communities. The study also found that the effects of public adaptation interact with insurance effects by reducing associated risk perception. To increase the positive effects, promoting quality of private adaptation through providing insurance incentives would be supportive.

For New York City, 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. An issue concerning the spatial distribution of public adaptation provisions is observed in New York City—infrastructural adaptation projects are more prevalent along coastal areas where more expensive homes are located, while recovery operation projects are more frequent in lower income neighborhoods. Although a special levy for nearshore protective projects could be imposed only on homeowners near or along coastlines, but the main sources of adaptation projects on these sites are general taxes from federal and state funds under the New York Rising Community Reconstruction Program. Thus, with respect to the sites treated here, the importance of issues surrounding the spatial distribution of public adaptation provisions surpasses the potential negative effects of local spatial assessments on nearshore properties.

Furthermore, recovery operation does not improve adaptive capacity, while investment for emergency preparation projects is very low, as much as 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. Although New York adapted stronger building regulations for promoting hurricane resistance in 2003, the building code does not affect old homes. Expanding tax incentives on private building reinforcement for hurricane resistance might be an alternative solution for housing structures constructed before 2003. These complementary policy suggestions may lead to a convergence between public and private adaptations. Since a relatively short history of active investments on mitigating climate risks resulted in an imbalance of climate strategies (due to its local dependency character), local governments may invest more in the projects they have focused on less thus far. Consequently, future adaptation measures would (hopefully) become more balanced and mixed, ultimately moving toward 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. Over the next hundred years, retreat, as an effective adaptation measure, could be the eventual option because of the ongoing sea level rise and acceleration, as well as shrinking coastlines. However, inherent conflicting factors such as uncertainty of climate, cost-effectiveness of adaptation, legal conflicts, and other socio-economic issues, make a large-scale retreat the hardest measure to implement over the next few decades, especially where much development has already taken place, as in New York and Miami-Dade. Thus, 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 at least for this century.

References

Adams, A., & Smith, A. (2001). Risk perception and communication: recent developments and implications for anaesthesia. *Anaesthesia, 56*(8), 745-755.

Adger, W. N., & Kelly, P. M. (1999). Social vulnerability to climate change and the architecture of entitlements. *Mitigation and adaptation strategies for global change, 4*(3-4), 253-266.

Alexander, K. S., Ryan, A., & Measham, T. G. (2012). Managed retreat of coastal communities: understanding responses to projected sea level rise. *Journal of Environmental Planning and Management, 55*(4), 409-433.

Allison, R. V. (1928). Houses under water - 1928 hurricane (Photograph). from University of Florida http://weatherplus.blog.palmbeachpost.com/2011/01/21/new-study-tweaks-1926-and-1928-hurricanes-strength

Altmaier, D., Case, A., Chaney, M., Dolese, N., Donelon, J. J., Farmer, R. G., . . . Travis, T. (2017). *Flood Risk and Insurance*. In CIPR Study Series 2017-1. Retrieved from https://www.naic.org/documents/cipr_study_1704_flood_risk.pdf

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.

Azevedo de Almeida, B., & Mostafavi, A. (2016). Resilience of infrastructure systems to sea-level rise in coastal areas: Impacts, adaptation measures, and implementation challenges. *Sustainability, 8*(11), 1115.

Banhalmi-Zakar, Z., Ware, D., Edwards, I., Kelly, K., & Becken, S. (2016). Mechanisms to finance climate change adaptation. In: National Climate Change Adaptation Research Facility.

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.

Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (2004). *At risk: natural hazards, people's vulnerability and disasters*: Routledge.

Blake, E., Kimberlain, T., Berg, R., Cangialosi, J., & Beven, J. (2013). *Hurricane Sandy, 22 - 29 October, 2012* (AL182012). Retrieved from https://www.nhc.noaa.gov/data/tcr/AL182012_Sandy.pdf

Blake, E., Rappaport, E., Jarrell, J., & Landsea, C. (2005). *The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2004 (and other frequently requested hurricane facts)*. Retrieved from https://www.nhc.noaa.gov/pdf/NWS-TPC-4.pdf

Blake, E. S., Landsea, C. W., & Gibney, E. J. (2011). *The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2010 (and Other Frequently Requested Hurricane Facts)*. (NOAA Technical Memorandum NWS NHC-6). National Hurricane Center Retrieved from https://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf.

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.

Borger, G. J., & Ligtendag, W. A. (1998). The role of water in the development of the Netherlands—a historical perspective. *Journal of Coastal Conservation, 4*(2), 109-114.

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.

Bova-Hiatt, L. (2013). *NY Rising Community Reconstruction Program*. New York State Retrieved from https://stormrecovery.ny.gov/sites/default/files/crp/community/documents/Final%20FAQs_12211.pdf.

Brouwer, R., & Van Ek, R. (2004). Integrated ecological, economic and social impact assessment of alternative flood control policies in the Netherlands. *Ecological Economics, 50*(1-2), 1-21.

Bunten, D., & Kahn, M. E. (2014). *The impact of emerging climate risks on urban real estate price dynamics*. Retrieved from

Bunten, D., & Kahn, M. E. (2017). Optimal real estate capital durability and localized climate change disaster risk. *Journal of Housing Economics, 36*, 1-7.

Chambwera, M. a., Heal, G., Dubeux, C., Hallegatte, S., Leclerc, L., Markandya, A., . . . Neumann, J. (2014). Economics of adaptation.

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.

Correia, S. (2015). Singletons, cluster-robust standard errors and fixed effects: A bad mix. *Technical Note, Duke University*.

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.

Cowlin, S. C., Heimiller, D., Macknick, J., Mann, M., Pless, J., & Munoz, D. (2014). *Multi-Metric Sustainability Analysis*: National Renewable Energy Laboratory.

D'Acci, L. (2014). Monetary, subjective and quantitative approaches to assess urban quality of life and pleasantness in cities (hedonic price, willingness-to-pay, positional value, life satisfaction, isobenefit lines). *Social Indicators Research, 115*(2), 531-559.

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 Bruin, K., Dellink, R., Ruijs, A., Bolwidt, L., van Buuren, A., Graveland, J., . . . Roetter, R. (2009). Adapting to climate change in The Netherlands: an inventory of climate adaptation options and ranking of alternatives. *Climatic Change, 95*(1-2), 23-45.

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.

EPA. (2011). *Land Revitalization Fact Sheet: Green Infrastructure*. Retrieved from https://www.epa.gov/sites/production/files/2015-08/documents/fs_green_infrastructure.pdf

Epley, D. (2017). Residential Property Insurance Risk by Location. *Journal of Real Estate Literature, 25*(1), 189-205.

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.

Fatemi, A. M., & Fooladi, I. J. (2013). Sustainable finance: A new paradigm. *Global Finance Journal, 24*(2), 101-113.

Fell, H., & Kousky, C. (2015). The value of levee protection to commercial properties. *Ecological Economics, 119*, 181-188.

FEMA. (1997). *The National Flood Insurance Act of 1968, as amended, and the Flood Disaster Protection Act of 1973, as amended*. (42 U.S.C. 4001 et seq.). Federal Emergency Management Agency Retrieved from https://www.fema.gov/media-library-data/20130726-1545-20490-9247/frm_acts.pdf.

FEMA. (2012). *Understanding FEMA's Summary of Map Actions and Revalidation Letter*. Federal Emergency Management Agency Retrieved from https://www.fema.gov/media-library-data/1508774636852-7ae4bd0c74316ac37ef5ca80a4441fd8/Understanding_FEMA_SummaryOfMapActionsAndRevalidationLetter.pdf.

FEMA. (2018, September 14, 2018). Special Flood Hazard Area. Retrieved from https://www.fema.gov/special-flood-hazard-area

Field, C. B., Barros, V. R., Mastrandrea, M. D., Mach, K. J., Abdrabo, M.-K., Adger, N., . . . Barnett, J. (2014). Summary for policymakers. In *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1-32): Cambridge University Press.

Firehock, K. (2010). *A Short History of the Term Green Infrastructure and Selected Literature*. Retrieved from http://www.gicinc.org/PDFs/GI%20History.pdf

Flavelle, C. (2018). Hurricane shutter Installation (Photograph). from Insurance Journal https://www.insurancejournal.com/news/national/2018/06/20/492784.htm

Freeman III, A. M., Herriges, J. A., & Kling, C. L. (2014). *The measurement of environmental and resource values: theory and methods*: Routledge.

French, P. W. (2006). Managed realignment–the developing story of a comparatively new approach to soft engineering. *Estuarine, Coastal and Shelf Science, 67*(3), 409-423.

Frey, M., Kosco, J., Williams, C., & LaDuca, A. (2015). *Green Infrastructure Opportunities that Arise During Municipal Operations* (EPA 842-R-15-002). Retrieved from https://www.epa.gov/sites/production/files/2015-09/documents/green_infrastructure_roadshow.pdf

Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global environmental change, 16*(3), 293-303.

Garber, M. (2012, October 29). Dan Rather Showed the First Radar Image of a Hurricane on TV. *The Atlantic*.

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

Giordano, T. (2012). Adaptive planning for climate resilient long-lived infrastructures. *Utilities Policy, 23*, 80-89.

Governor's Office of Storm Recovery. (2018). New York Rising Community Reconstruction Projects (Interactive Map). from New York State http://nystormrecovery.maps.arcgis.com/apps/webappviewer/index.html?id=15a0e751746647818f1ab2b0b1c7673a

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.

Graham Jr, J. E., & Hall Jr, W. W. (2001). Hurricanes, housing market activity, and coastal real estate values. *The Appraisal Journal, 69*(4), 379.

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.

Gunderson, L. H., & Holling, C. S. (2002). Panarchy: understanding transformations in systems of humans and nature. In: Island Press, Washington, DC.

Hallstrom, D. G., & Smith, V. K. (2005). Market responses to hurricanes. *Journal of Environmental Economics and Management, 50*(3), 541-561.

Hay, J., & Mimura, N. (2006). Supporting climate change vulnerability and adaptation assessments in the Asia-Pacific region: an example of sustainability science. *Sustainability Science, 1*(1), 23-35.

Henry, K. (2009). *Australia' s future tax system: Report to the Treasurer*. Retrieved from http://taxreview.treasury.gov.au/content/downloads/final_report_part_2/afts_final_report_part_2_vol_1_consolidated.pdf

Hensher, D. A. (2008). Climate change, enhanced greenhouse gas emissions and passenger transport–What can we do to make a difference? *Transportation Research Part D: Transport and Environment, 13*(2), 95-111.

Hill, K. (2015). Coastal infrastructure: a typology for the next century of adaptation to sea-level rise. *Frontiers in Ecology and the Environment, 13*(9), 468-476.

Hino, M., Field, C. B., & Mach, K. J. (2017). Managed retreat as a response to natural hazard risk. *Nature Climate Change, 7*(5), 364.

Hochrainer, S., & Mechler, R. (2011). Natural disaster risk in Asian megacities: A case for risk pooling? *Cities, 28*(1), 53-61.

Houston Public Media. (2005). Thousands of individuals evacuate Houston as Hurricane Rita approaches (Photograph). from University of Rhode Island http://hurricanescience.org/history/storms/2000s/rita

Insurance Information Institute. (2018). Top Coastal Counties Most Frequently Hit By Hurricanes: 1960-2008. *Facts and Statistics: Hurricanes.* Retrieved from https://www.iii.org/fact-statistic/facts-statistics-hurricanes

IPCC. (1990). Climate Change - The IPCC Impacts Assessment. In: Australian Government Publishing Service.

IPCC. (2001). *Climate Change 2001: IPCC Third Assessment Report*: Intergovernmental Panel on Climate Change.

IPCC. (2007). Working Group II: Impacts, adaptation, and vulnerability. In: Glossary.

Isoard, S., Grothmann, T., & Zebisch, M. (2008). *Climate change impacts, vulnerability and adaptation: Theory and concepts.* Paper presented at the Workshop'Climate change impacts and adaptation in the European Alps: Focus water', UBA, Vienne (Autriche).

Jin, D., Hoagland, P., Au, D. K., & Qiu, J. (2015). Shoreline change, seawalls, and coastal property values. *Ocean & Coastal Management, 114*, 185-193.

Jones, H. P., Hole, D. G., & Zavaleta, E. S. (2012). Harnessing nature to help people adapt to climate change. *Nature Climate Change, 2*(7), 504.

Jonker, L., Miller, A., & Brechwald, D. (2011). *EnviRenew Resilience Report, Part 1: Creating Resilient Communities*. Retrieved from http://resilience.abag.ca.gov/wp-content/documents/resilience/toolkit/Envirenew%20Resilience%20Part%201%20Report_Creating%20Resilient%20Communities.pdf

Karr, S. (2013). More examples of mitigation and elevation of homes is evident in Ortley Beach (Photograph). from Federal Emergency Management Agency http://floodlist.com/protection/elevation-buildings-flood-prone-locations

Klein, R. J., Kartha, S., Persson, Å., Watkiss, P., Ackerman, F., Downing, T. E., . . . Schipper, L. (2008). Adaptation: Needs, financing and institutions. *Stockholm Environment Institute*.

Klein, R. J., & Tol, R. S. (1997). Adaptation to climate change: Options and technologies. *Institute for Environmental Sciences, Vrije Universiteit, Amsterdam*.

Kousky, C. (2010). Learning from extreme events: Risk perceptions after the flood. *Land economics, 86*(3), 395-422.

KTRK-TV. (1961). KTRK-TV coverage of Hurricane Carla (Photograph). from ABC Inc. https://abc13.com/57-years-ago-hurricane-carla-slammed-into-the-texas-coast/1503768

Kubal, C., Haase, D., Meyer, V., & Scheuer, S. (2009). Integrated urban flood risk assessment–adapting a multicriteria approach to a city. *Natural hazards and earth system sciences, 9*(6), 1881-1895.

Landry, C. E., & Hindsley, P. (2011). Valuing beach quality with hedonic property models. *Land economics, 87*(1), 92-108.

Langousis, A., & Veneziano, D. (2009). Theoretical model of rainfall in tropical cyclones for the assessment of long-term risk. *Journal of Geophysical Research: Atmospheres, 114*(D2).

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.

Linden, L., & Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from Megan's laws. *American Economic Review, 98*(3), 1103-1127.

Lindsay, B., & Reese, S. (2018). *FEMA and SBA Disaster Assistance for Individuals and Households: Application Process, Determinations, and Appeals*. Retrieved from https://fas.org/sgp/crs/homesec/R45238.pdf

Loewenstein, G., & Schwartz, D. (2010). Nothing to fear but a lack of fear: climate change and the fear deficit. *G8 Magazine*, 60-62.

Martinez-Alier, J., Munda, G., & O'Neill, J. (1998). Weak comparability of values as a foundation for ecological economics. *Ecological Economics, 26*(3), 277-286.

McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., & White, K. S. (2001). *Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change* (Vol. 2): Cambridge University Press.

McKenzie, R., & Levendis, 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.

MDC. (2011). *2012-13 Business Plan, Adopted Budget, and Five-Year Financial Outlook*. Miami-Dade County Retrieved from http://www.miamidade.gov/budget/library/FY2012-13/adopted/volume1/FY2012-13-volume1.pdf.

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.

Miami-Dade County. (2018). Miami-Dade County Local Mitigation Strategies (Interactive Map). from Miami-Dade County https://mdc.maps.arcgis.com/apps/webappviewer/index.html?id=662b7c50e5714041962e695b616937ad

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.

Mills, E. (2005). Insurance in a climate of change. *Science, 309*(5737), 1040-1044.

Mimura, N. (2010). Scope and roles of adaptation to climate change. In *Adaptation and Mitigation Strategies for Climate Change* (pp. 131-140): Springer.

Morton, T. (2013). *Hyperobjects: Philosophy and Ecology after the End of the World*: U of Minnesota Press.

Murphy, A., & Strobl, E. (2009). The impact of hurricanes on housing prices: evidence from US coastal cities.

NASA. (2006). Miami, Florida metropolitan area as seen from STS-62. Retrieved October 28, 2018, from The National Aeronautics and Space Administration https://web.archive.org/web/20071201191110/http://images.jsc.nasa.gov/luceneweb/caption_direct.jsp?photoId=STS062-85-026

New York State. (2014). *2014 New York Hazard Mitigation Plan*. Retrieved from http://www.dhses.ny.gov/recovery/mitigation/plan.cfm.

NHC. (1993). *Hurricane Andrew, 16 - 28 August, 1992*. Retrieved from https://www.nhc.noaa.gov/1992andrew.html

NHC. (2012). *Minor Modification to Saffir-Simpson Hurricane Wind Scale*. Retrieved from https://www.nhc.noaa.gov/pdf/sshws_2012rev.pdf

NHC. (2018). *Hurricane Irma, 30 August - 12 September 2017* (AL112017). Retrieved from National Hurricane Center: https://www.nhc.noaa.gov/data/tcr/AL112017_Irma.pdf

NOAA. (1954). Hurricane Carol lashes the Edgewood Yacht Club (Photograph). from U.S. National Oceanic and Atmospheric Administration Photo Library https://en.wikipedia.org/wiki/Hurricane_Carol#/media/File:Carol_in_Rhode_Island.jpg

NOAA. (1989). Hurricane Hugo at peak intensity east of the Windward Islands (Satellite Image). from U.S. National Oceanic and Atmospheric Administration https://en.wikipedia.org/wiki/Hurricane_Hugo#/media/File:Hurricane_Hugo_1989_sept_21_1844Z.jpg

NOAA. (1999). Hurricane Floyd (Satellite Image). from U.S. National Oceanic and Atmospheric Administration http://hurricanescience.org/history/storms/1990s/floyd

NOAA. (2018). Historical Hurricane Tracks. from National Oceanic and Atmospheric Administration https://coast.noaa.gov/hurricanes/

NOAA. (2018). U.S. Billion-Dollar Weather and Climate Disasters. Severe Storm and Tropical Cyclone Billion-Dollar Disasters to affect the U.S. from 1980-2018 (CPI-Adjusted) Retrieved 3 Sept 2018, from National Centers for Environmental Information https://www.ncdc.noaa.gov/billions/

NYC Rent Guidelines Board. (2018). Rent Stabilization. Retrieved from https://www1.nyc.gov/site/rentguidelinesboard/resources/rent-stabilization.page

Nyce, C., Dumm, R. E., Sirmans, G. S., & Smersh, G. (2015). The capitalization of insurance premiums in house prices. *Journal of Risk and Insurance, 82*(4), 891-919.

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.

Perini, K., & Sabbion, P. (2016). *Urban sustainability and river restoration: green and blue infrastructure*: John Wiley & Sons.

Pielke Jr, R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., & Musulin, R. (2008). Normalized hurricane damage in the United States: 1900–2005. *Natural Hazards Review, 9*(1), 29-42.

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.

Rambaldi, A. N., Ganegodage, K. R., & McAllister, R. R. (2017). *Myopia and Amnesia in Property Prices. Evidence from Two Floods.* Paper presented at the Society for Economic Measurement Annual Conference.

Rapley, C., & De Meyer, K. (2014). Climate science reconsidered. *Nature Climate Change, 4*(9), 745.

Rayner, S., & Malone, E. L. (1998). *Human choice and climate change: an international assessment*: Citeseer.

Reid, A. (2018). South Florida taxpayers face mounting maintenance costs for both flood control structures and Everglades restoration projects (Photograph). from South Florida Sun Sentinel https://www.sun-sentinel.com/local/palm-beach/fl-flood-control-fixes-20150101-story.html

Reisinger, A., Lawrence, J., Hart, G., & Chapman, R. (2014). From coping to resilience: The role of managed retreat in highly developed coastal regions of New Zealand. *Climate change and the coast: Building resilient communities. London: CRC Press.*

Rissik, D., & Reis, N. (2013). Developing Flexible Adaptation Pathways for the Peron Naturaliste Coastal Region of Western Australia 2011 – 2012. In *National Climate Change Adaptation Research Facility*: Australian Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy, 82*(1), 34-55.

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.

Roth, D. (2010). Texas hurricane history. *National Weather Service, Camp Springs, MD, 17*.

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.

Samarasinghe, O., & Sharp, B. (2010). Flood prone risk and amenity values: a spatial hedonic analysis. *Australian Journal of Agricultural and Resource Economics, 54*(4), 457-475.

Scherer, C. W., & Cho, H. (2003). A social network contagion theory of risk perception. *Risk Analysis: An International Journal, 23*(2), 261-267.

Scowcroft, G., Ginis, I., Knowlton, C., Yablonsky, R., Morin, H., & McIntire, D. (2010, 2015). Hurricanes: Science and Society. *Featured Storms.* Retrieved from http://hurricanescience.org/history/storms

Singley, B. L. (1900). Seeking valuables in the wreckage, Galveston, Texas (Stereograph). from Library of Congress https://no.wikipedia.org/wiki/Fil:Seeking_valuables_in_the_wreckage,_Galveston,_Texas.jpg

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

Smith, B., Taylor, R., & Takama, T. (2011, June 15, 2018). Robust Decision Making (RDM). Retrieved from https://www.weadapt.org/knowledge-base/adaptation-decision-making/robust-decision-making

Smith, K., Woodward, A., Campbell-Lendrum, D., Chadee, D., Honda, Y., Liu, Q., . . . Sauerborn, R. (2014). Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the fifth assessment report of the Intergovernmental Panel on Climate Change. In: Cambridge: Cambridge University Press) Human health: impacts, adaptation, and co-benefits.

Smithers, J., & Smit, B. (1997). Human adaptation to climatic variability and change. *Global environmental change, 7*(2), 129-146.

Teng, F., & Gu, A. (2007). Climate change: national and local policy opportunities in China. *Environmental Sciences, 4*(3), 183-194.

Termeer, C., Dewulf, A., Van Rijswick, H., Van Buuren, A., Huitema, D., Meijerink, S., . . . Wiering, M. (2011). The regional governance of climate adaptation: a framework for developing legitimate, effective, and resilient governance arrangements. *Climate law, 2*(2), 159-179.

Tooby, J., & Cosmides, L. (2008). The evolutionary psychology of the emotions and their relationship to internal regulatory variables.

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.

Tuckerton, N. J. (2012). Inundated on Oct. 30 by the storm surge from Superstorm Sandy (Photograph). from U.S. Coast Guard https://blogs.ei.columbia.edu/2012/10/29/science-behind-sandy

U.S. Army Corps of Engineers. (1890). Mississippi_River_Improvement 1890 (Photograph). http://www.hq.usace.army.mil/history/Brief/05-growing-nation/River-improvement-lg.jpg

U.S. Army Corps of Engineers. (1955). Herbert Hoover Dike construction around Lake Okeechobee in 1955 (Photograph). http://weatherplus.blog.palmbeachpost.com/2017/04/28/ten-things-to-know-about-the-herbert-hoover-dike-and-why-trump-is-weighing-in

USFWS. (2015, November 1, 2017). Coastal Barrier Resources System. Retrieved from https://www.fws.gov/cbra/Act.html

USFWS Northeast. (2018). Costal Barrier Resources System (Photograph). from U.S. Fish and Wildlife Service https://twitter.com/USFWSNortheast/status/973284039904890881

Viguié, V., & Hallegatte, S. (2012). Trade-offs and synergies in urban climate policies. *Nature Climate Change, 2*(5), 334.

Walls, M., Magliocca, N., & McConnell, V. (2018). Modeling coastal land and housing markets: Understanding the competing influences of amenities and storm risks. *Ocean & Coastal Management, 157*, 95-110.

Ware, D. (2016, May 2, 2017). Financial and funding mechanisms for adaptation to climate change. Retrieved from https://coastadapt.com.au/resources-adaptation-including-innovative-financing-mechanisms

Watson, K. B., Ricketts, T., Galford, G., Polasky, S., & O'Niel-Dunne, J. (2016). Quantifying flood mitigation services: The economic value of Otter Creek wetlands and floodplains to Middlebury, VT. *Ecological Economics, 130*, 16-24.

Xiao, Y. (2017). Hedonic Housing Price Theory Review. In *Urban Morphology and Housing Market* (pp. 11-40): Springer.

Appendix 1. Major Storms from 1960 to 2017

MIAMI-DADE COUNTY			
Name	year	month	category
Donna	1960	9	H4
Florence	1960	9	TS
Alma	1962	8	TD
Cleo	1964	8	H2
Isbell	1964	10	H3
Betsy	1965	9	H3
Alma	1966	6	H3
Inez	1966	10	H1
Abby	1968	6	TS
Brenda	1968	6	TD
Dolly	1968	8	TD
Gerda	1969	9	TD
Jenny	1969	10	TS
Unnamed	1969	6, 8	TD
Felice	1970	9	TD
Greta	1970	9	TS
Unnamed	1971	8	TD
Dawn	1972	9	TD
Unnamed	1974	10	TS
Dottie	1976	8	TS
David	1979	9	H2
Unnamed	1979	6	TD
Dennis	1981	8	TS
Unnamed	1981	7	TD
Alberto	1982	6	TD
Isidore	1984	9	TS
Unnamed	1984	10	TD
Bob	1985	7	TS
Floyd	1987	10	H1
Unnamed	1987	5	TD
Chris	1988	8	TD
Unnamed	1988	6	TD
Marco	1990	10	TS
Fabian	1991	10	TS
Andrew	1992	8	H5
Unnamed	1993	6	TD
Gordon	1994	11	TS
Erin	1995	8	H1
Jerry	1995	8	TS
Georges	1998	9	H2
Mitch	1998	11	TS
Harvey	1999	9	TS
Irene	1999	10	H1
Charley	2004	8	H4
Frances	2004	9	H2
Ivan	2004	9	TD
Jeanne	2004	9	H3
Katrina	2005	8	H2

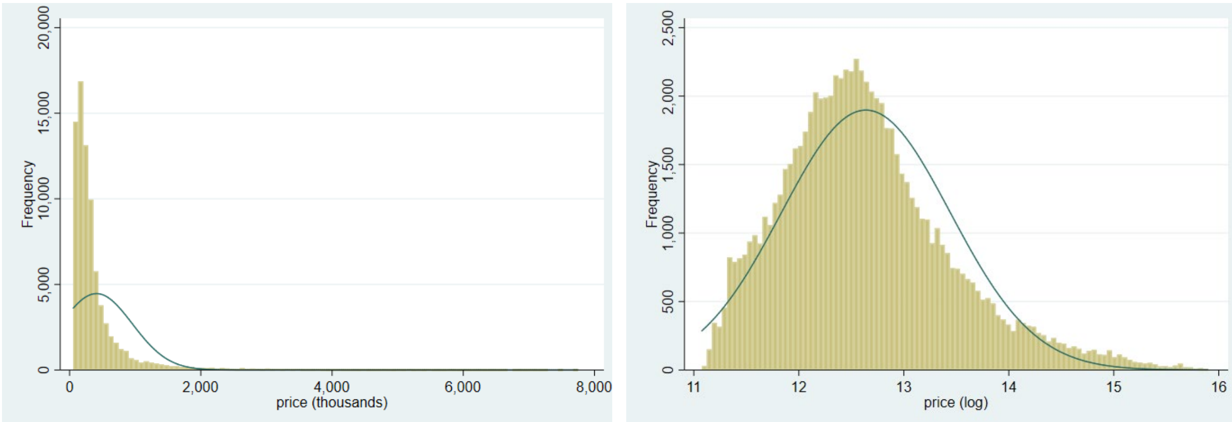
MIAMI-DADE COUNTY (continued)			
Name	year	month	category
Ophelia	2005	9	TD
Rita	2005	9	H2
Tammy	2005	10	TS
Wilma	2005	10	H3
Ernesto	2006	8	TS
Fay	2008	8	TS
Bonnie	2010	7	TS
Nicole	2010	9	TS
Isaac	2012	8	TS
Dorian	2013	8	TD
Ana	2015	5	TD
Hermine	2016	8	TD
Julia	2016	9	TD
Matthew	2016	10	H4
Irma	2017	9	H4

NEW YORK CITY			
Name	year	month	category
Brenda	1960	7	TS
Donna	1960	9	H2
Unnamed	1961	9	TS
Doria	1971	8	TS
Agnes	1972	6	TS
Belle	1976	8	H1
David	1979	9	TS
Gloria	1985	9	H2
Henri	1985	9	TS
Bob	1991	8	H2
Danielle	1992	9	TS
Bertha	1996	7	TS
Josephine	1996	10	TS
Floyd	1999	9	TS
Gordon	2000	9	TD
Allison	2001	6	TS
Bonnie	2004	8	TD
Charley	2004	8	TS
Gaston	2004	8	TS
Cindy	2005	7	TD
Twenty-two	2005	10	TS
Beryl	2006	7	TS
Barry	2007	6	TS
Hanna	2008	9	TS
Irene	2011	8	H1
Sandy	2012	10	H1
Andrea	2013	6	TS
Ana	2015	5	TD
Hermine	2016	9	TS

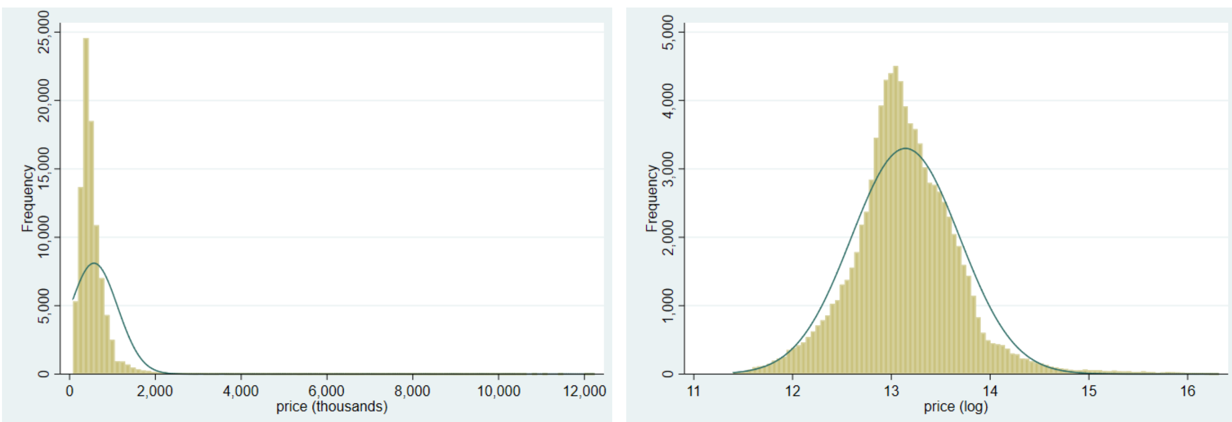
Notes: H1-H5: Saffir–Simpson scale 1 to 5; TS: Tropical Storm; TD: Tropical Depression.

Appendix 2. Histograms (housing price vs. logged price)

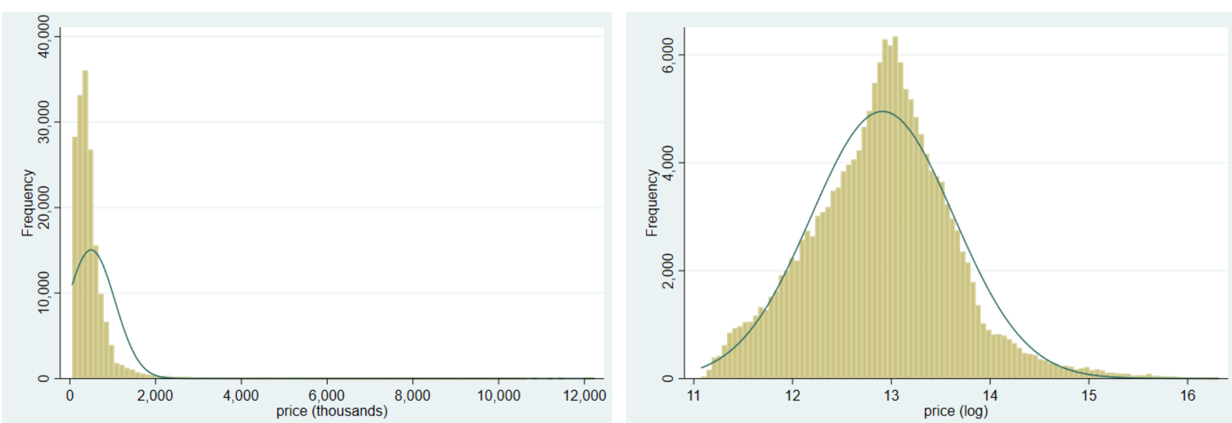
Miami-Dade County (n: 79,184, July 2009 – May 2018)



New York City (n: 92,159, July 2009 – May 2018)



Miami-Dade County + New York City (n: 171,337, July 2009 – May 2018)



Appendix 3. Classification of Major Storms and Saffir-Simpson Hurricane Scale

Classification of Major Storms	
Major Storms	Description
Extratropical *(Nor'easter)*	An intense storm that can cause heavy rain and snow, strong winds, and coastal flooding. Nor'easters have cold, low barometric cores
Tropical Depression	A tropical cyclone with sustained winds of 38 mph or less
Tropical Storm	An organized system of strong thunderstorms with a defined surface circulation and maximum sustained winds of 39-73mph
Hurricane	Tropical cyclones, formed in the atmosphere over warm ocean areas, in which wind speeds reach 74mph or more and blow in a large spiral around a relatively calm center or "eye". Circulation is counterclockwise in the Northern Hemisphere

Saffir-Simpson Hurricane Scale				
Category	Storm Surge (ft.)	Winds	Damage	Damage Description
1	6.1 – 10.5	74-95 mph 64-82 kt 119-153 km/h	Moderate	Damage primarily to trees and unanchored homes. Some damage to poorly constructed signs. Coastal road flooding.
2	13.0- 16.6	96-110 mph 83-95 kt 154-177 km/h	Moderate-Severe	Some roofing material, door, and window damage to buildings. Considerable damage to shrubbery and trees. Flooding of low-lying areas.
3	14.8-25	111-129 mph 96-112 kt 178-208 km/h	Extensive	Some structural damage to residences and utility buildings. Foliage blown off trees and large trees blown down. Structures close to the coast will have structural damage by floating debris.
4	24.6-31.3	130-156 mph 113-136 kt 209-251 km/h	Extreme	Curtainwall failures with utilities and roof structures on residential buildings. Shrubs, trees, and signs all blown down. Extensive damage to doors and windows. Major damage to lower floors of structures near the shore.
5	Not predicted	≥ 157 mph ≥ 137 kt ≥ 252 km/h	Catastrophic	Complete roof failure on many residences and industrial buildings. Some complete building and utility failures. Severe, extensive window and door damage. Major damage to lower floors of all structures close to shore.

Sources: 2014 New York Hazard Mitigation Plan (3.12-2, 3.12-5: Table 3-12a), Minor Modification to Saffir-Simpson Hurricane Wind Scale (New York State, 2014; NHC, 2012)

Appendix 4. Miami-Dade County Unemployment Rates by Zip Code

Zip Code	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
33010	9.8%	10.9%	12.3%	15.0%	15.3%	15.2%	13.4%	11.1%	7.6%	5.8%
33012	6.8%	7.6%	8.7%	9.4%	10.5%	9.9%	9.0%	8.1%	7.3%	4.0%
33013	9.1%	10.1%	13.1%	15.0%	16.1%	13.0%	11.4%	8.7%	6.1%	5.4%
33014	8.5%	9.5%	11.7%	12.5%	14.4%	13.8%	12.4%	7.7%	6.1%	5.1%
33015	5.2%	5.8%	7.0%	7.8%	7.6%	7.1%	6.1%	6.5%	5.8%	3.1%
33016	8.5%	9.5%	11.3%	12.5%	13.3%	13.8%	11.9%	8.7%	6.8%	5.0%
33018	6.2%	6.9%	9.0%	9.2%	10.6%	10.4%	7.8%	5.4%	4.8%	3.7%
33030	10.6%	11.8%	13.8%	14.8%	17.1%	16.3%	14.7%	11.5%	9.2%	6.3%
33031	6.9%	7.7%	6.7%	9.4%	11.9%	11.4%	9.4%	8.5%	5.9%	4.1%
33032	10.4%	11.6%	12.3%	12.6%	15.6%	16.1%	14.8%	12.7%	11.5%	6.1%
33033	9.3%	10.5%	9.9%	11.5%	13.0%	12.5%	14.2%	13.0%	12.0%	5.5%
33034	14.0%	15.6%	15.0%	15.9%	19.6%	20.7%	21.1%	18.8%	17.6%	8.3%
33054	9.9%	11.0%	13.5%	13.9%	14.2%	14.5%	12.0%	10.9%	11.8%	5.8%
33055	9.9%	11.1%	13.6%	14.8%	15.1%	14.9%	14.0%	10.5%	8.7%	5.9%
33056	12.6%	14.1%	14.6%	18.1%	17.9%	17.8%	17.7%	16.3%	13.7%	7.5%
33125	5.8%	6.5%	8.5%	9.8%	9.4%	8.2%	6.6%	6.1%	5.2%	3.5%
33126	8.7%	9.8%	11.5%	13.5%	13.5%	12.6%	11.8%	9.5%	8.0%	5.2%
33128	10.6%	11.8%	9.7%	13.0%	13.2%	15.9%	16.1%	15.2%	14.2%	6.3%
33129	4.3%	4.8%	5.1%	6.0%	6.1%	6.9%	6.5%	4.5%	4.6%	2.6%
33130	3.9%	4.4%	5.9%	6.2%	5.8%	6.3%	4.4%	3.8%	3.7%	2.3%
33132	4.5%	5.1%	5.8%	6.8%	8.2%	6.8%	5.3%	4.3%	4.5%	2.7%
33133	7.3%	8.2%	9.0%	10.7%	11.1%	11.8%	9.3%	8.2%	7.1%	4.3%
33134	6.1%	6.9%	9.4%	10.7%	10.6%	9.4%	7.2%	4.8%	4.4%	3.6%
33135	9.8%	10.9%	10.4%	13.9%	16.0%	14.6%	14.0%	11.9%	9.1%	5.8%
33137	8.0%	9.0%	12.2%	12.9%	12.4%	12.0%	10.4%	7.6%	6.5%	4.8%
33138	9.2%	10.3%	13.2%	13.3%	14.2%	13.2%	11.3%	9.3%	10.1%	5.4%
33139	3.6%	4.0%	4.8%	6.0%	4.8%	4.9%	4.2%	4.0%	4.2%	2.1%
33140	3.8%	4.2%	4.9%	5.3%	5.1%	5.2%	5.6%	4.8%	4.0%	2.2%
33141	4.7%	5.2%	5.4%	7.2%	7.4%	6.5%	5.8%	5.9%	5.0%	2.8%
33143	5.8%	6.5%	8.5%	8.3%	8.8%	7.8%	6.5%	7.1%	6.5%	3.4%
33144	10.6%	11.9%	16.1%	17.4%	16.0%	16.7%	14.0%	10.0%	7.8%	6.3%
33145	6.4%	7.1%	6.9%	8.9%	10.1%	9.8%	8.8%	7.6%	6.4%	3.8%
33146	4.5%	5.0%	6.9%	6.7%	7.6%	6.7%	4.5%	4.8%	4.3%	2.7%
33149	3.3%	3.7%	3.0%	3.4%	5.4%	4.7%	4.8%	4.7%	4.3%	1.9%
33154	4.8%	5.3%	6.2%	6.6%	7.8%	6.5%	5.5%	5.5%	5.8%	2.8%
33155	5.7%	6.3%	6.9%	8.6%	9.4%	9.5%	7.6%	5.9%	4.3%	3.4%
33156	4.8%	5.4%	5.4%	6.6%	7.0%	7.6%	7.0%	5.7%	4.8%	2.8%
33157	7.4%	8.3%	10.0%	10.7%	10.9%	10.9%	9.5%	8.7%	7.5%	4.4%
33158	4.8%	5.4%	4.3%	5.3%	9.0%	8.2%	6.3%	5.7%	5.4%	2.8%
33160	4.3%	4.8%	6.1%	6.5%	6.7%	5.8%	5.4%	4.4%	4.9%	2.6%
33161	10.2%	11.4%	12.8%	14.0%	15.9%	14.9%	13.4%	12.1%	10.7%	6.0%
33162	11.1%	12.4%	13.3%	17.5%	17.8%	16.7%	14.5%	12.5%	10.2%	6.6%
33165	5.0%	5.6%	7.0%	7.5%	8.1%	7.8%	6.6%	5.1%	4.0%	3.0%
33166	7.8%	8.7%	10.6%	13.2%	12.8%	12.5%	10.0%	7.4%	5.5%	4.6%
33167	10.1%	11.3%	14.8%	15.2%	14.3%	13.5%	13.8%	11.5%	10.2%	6.0%
33168	11.1%	12.4%	14.2%	15.6%	16.3%	17.1%	14.1%	12.3%	12.3%	6.6%
33169	10.5%	11.8%	12.4%	15.4%	16.0%	15.3%	14.3%	13.5%	10.2%	6.2%
33172	6.6%	7.4%	9.8%	10.8%	11.2%	9.6%	8.4%	6.3%	4.8%	3.9%
33173	6.3%	7.1%	8.1%	10.8%	11.6%	9.1%	6.8%	6.9%	5.1%	3.8%
33174	6.6%	7.4%	8.7%	10.2%	10.5%	10.6%	8.2%	6.6%	6.3%	3.9%
33175	6.5%	7.2%	10.8%	10.9%	10.4%	9.2%	7.2%	5.7%	5.5%	3.8%
33176	6.6%	7.4%	9.3%	10.8%	10.7%	9.2%	8.2%	7.3%	5.6%	3.9%
33178	3.5%	3.9%	4.3%	4.6%	5.1%	4.5%	4.6%	4.6%	4.6%	2.1%
33179	7.2%	8.0%	8.7%	9.2%	10.0%	10.1%	9.9%	10.0%	8.1%	4.2%
33180	6.3%	7.1%	9.1%	10.9%	10.1%	9.5%	7.7%	6.2%	4.9%	3.8%
33181	7.8%	8.7%	11.3%	11.1%	12.0%	10.9%	8.3%	8.4%	9.7%	4.6%
33182	5.7%	6.4%	7.5%	10.1%	9.4%	8.1%	7.6%	6.7%	2.9%	3.4%
33183	6.9%	7.7%	8.2%	9.9%	11.4%	11.0%	9.2%	7.4%	6.4%	4.1%
33184	5.5%	6.2%	5.3%	6.3%	8.5%	8.9%	8.3%	7.2%	6.2%	3.3%
33185	5.1%	5.7%	6.2%	7.2%	7.8%	7.9%	6.8%	6.2%	5.1%	3.0%
33187	7.0%	7.8%	10.7%	12.3%	10.4%	8.4%	9.0%	7.1%	6.5%	4.1%
33189	7.1%	8.0%	10.4%	10.7%	10.6%	9.9%	9.5%	7.1%	7.5%	4.2%
33193	6.2%	7.0%	8.6%	9.9%	9.9%	8.8%	7.4%	6.8%	6.0%	3.7%
33194	5.6%	6.3%	8.2%	9.7%	8.0%	7.6%	5.7%	7.0%	5.5%	3.3%

Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). The Health Council of South Florida (Average unemployment rates from January to May 2018).

Appendix 5. Miami-Dade County Housing Vacancy Rates by Zip Code

Zip Code	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
33010	4.9%	3.5%	4.7%	4.6%	3.6%	3.1%	3.7%	3.1%	3.9%	3.7%
33012	5.8%	4.2%	7.6%	7.4%	6.3%	6.4%	5.3%	4.4%	4.1%	5.7%
33013	4.9%	3.5%	4.5%	4.4%	4.0%	3.0%	3.7%	4.0%	3.4%	3.7%
33014	5.9%	4.2%	6.5%	5.5%	4.1%	5.7%	6.6%	5.6%	5.8%	5.5%
33015	10.0%	7.3%	10.4%	9.0%	8.4%	7.1%	6.6%	5.9%	6.1%	7.3%
33016	6.1%	4.4%	4.6%	4.8%	4.0%	4.4%	4.5%	4.3%	3.7%	4.2%
33018	4.0%	2.9%	3.6%	3.7%	3.6%	3.4%	3.1%	3.0%	2.9%	3.2%
33030	14.3%	10.3%	9.3%	9.6%	7.9%	6.7%	6.9%	6.1%	6.5%	7.3%
33031	13.4%	9.7%	9.8%	11.1%	9.6%	4.1%	6.3%	4.3%	7.1%	7.1%
33032	16.9%	12.2%	16.1%	15.8%	14.0%	13.0%	9.3%	8.4%	8.6%	11.6%
33033	22.1%	16.0%	15.7%	15.0%	12.4%	10.7%	10.3%	10.4%	7.8%	11.3%
33034	19.1%	13.8%	18.0%	18.6%	17.7%	17.2%	13.0%	11.9%	12.9%	14.9%
33054	16.3%	11.8%	14.4%	15.9%	15.9%	15.1%	15.6%	16.6%	12.8%	14.6%
33055	6.4%	4.6%	7.0%	7.7%	6.2%	6.2%	5.5%	5.1%	5.2%	5.9%
33056	7.6%	5.5%	12.1%	14.0%	13.5%	13.2%	13.3%	10.4%	8.8%	11.7%
33125	12.9%	9.3%	11.3%	10.3%	11.0%	10.0%	9.7%	7.8%	8.6%	9.4%
33126	10.4%	7.5%	11.8%	11.7%	11.9%	11.9%	9.6%	8.9%	8.5%	10.2%
33128	10.7%	7.7%	18.5%	19.0%	16.9%	13.3%	13.0%	11.9%	9.3%	13.9%
33129	23.9%	17.2%	28.3%	29.8%	30.6%	29.0%	31.5%	30.1%	30.3%	28.7%
33130	21.1%	15.2%	20.9%	23.2%	21.3%	22.5%	23.1%	21.1%	22.0%	21.1%
33132	33.8%	24.4%	37.6%	45.6%	49.4%	49.0%	48.4%	48.8%	43.4%	44.2%
33133	18.8%	13.6%	19.6%	18.6%	19.3%	20.3%	19.1%	18.6%	18.9%	18.4%
33134	14.6%	10.5%	12.3%	11.1%	10.2%	9.9%	10.9%	10.3%	12.4%	10.6%
33135	9.2%	6.6%	10.4%	9.8%	10.0%	9.1%	8.3%	6.7%	6.9%	8.4%
33137	26.8%	19.3%	26.6%	27.0%	26.6%	25.0%	20.5%	18.3%	17.9%	22.2%
33138	17.4%	12.6%	19.4%	20.0%	18.2%	17.1%	15.7%	13.6%	12.5%	15.9%
33139	37.5%	27.1%	35.5%	35.4%	37.8%	38.4%	38.4%	38.0%	38.1%	35.9%
33140	58.6%	42.3%	40.5%	41.4%	40.7%	40.0%	40.7%	45.5%	46.8%	40.5%
33141	32.1%	23.2%	31.4%	30.1%	28.9%	27.6%	26.9%	24.7%	24.6%	26.6%
33143	14.4%	10.4%	15.3%	15.4%	15.3%	14.8%	13.7%	11.7%	11.9%	13.4%
33144	6.0%	4.3%	5.1%	5.1%	3.8%	3.2%	3.3%	3.1%	3.1%	3.7%
33145	12.2%	8.8%	15.3%	16.2%	15.3%	15.7%	13.0%	11.9%	11.3%	13.5%
33146	12.2%	8.8%	20.3%	19.6%	22.0%	23.9%	22.1%	18.4%	20.8%	20.2%
33149	46.3%	33.5%	33.6%	37.5%	42.2%	41.1%	40.7%	40.5%	41.5%	38.0%
33154	46.8%	33.8%	41.4%	39.2%	37.3%	37.2%	39.4%	39.8%	42.4%	37.9%
33155	6.6%	4.7%	7.0%	7.0%	6.2%	5.3%	6.2%	6.2%	6.1%	6.0%
33156	14.1%	10.2%	13.5%	13.2%	13.2%	12.5%	12.3%	13.3%	14.5%	12.7%
33157	10.2%	7.4%	9.4%	8.1%	8.3%	8.2%	7.5%	6.7%	7.0%	7.6%
33158	5.8%	4.2%	11.3%	8.4%	10.5%	7.3%	8.5%	5.9%	8.8%	8.3%
33160	52.1%	37.6%	51.2%	51.8%	53.1%	53.8%	54.6%	52.6%	52.6%	50.7%
33161	14.3%	10.4%	13.9%	13.2%	12.2%	13.1%	11.6%	10.8%	10.2%	11.6%
33162	15.9%	11.5%	16.4%	16.1%	15.5%	13.7%	12.7%	12.0%	12.2%	13.5%
33165	3.9%	2.8%	5.7%	5.6%	5.3%	5.3%	4.8%	4.0%	4.3%	4.8%
33166	11.2%	8.1%	10.7%	9.6%	8.6%	8.1%	8.8%	11.4%	15.4%	10.0%
33167	12.0%	8.7%	10.9%	11.1%	10.9%	7.0%	5.5%	6.6%	4.3%	7.7%
33168	8.5%	6.2%	7.0%	8.2%	9.1%	10.7%	7.7%	7.4%	6.8%	7.8%
33169	9.6%	6.9%	12.8%	13.1%	13.5%	14.3%	12.4%	11.0%	11.3%	12.1%
33172	10.5%	7.6%	8.7%	10.4%	9.9%	10.7%	10.7%	11.8%	11.5%	10.1%
33173	7.5%	5.4%	8.2%	7.4%	6.0%	6.2%	6.7%	6.4%	8.2%	6.7%
33174	4.1%	3.0%	8.2%	7.7%	8.0%	6.5%	6.4%	6.6%	4.8%	6.6%
33175	4.2%	3.1%	4.3%	5.2%	5.6%	4.7%	4.7%	4.2%	4.7%	4.6%
33176	10.4%	7.5%	10.6%	10.7%	10.8%	11.1%	10.8%	9.1%	7.5%	9.7%
33178	19.8%	14.3%	18.0%	17.3%	19.8%	20.9%	20.4%	21.9%	27.2%	20.0%
33179	14.6%	10.6%	14.2%	15.0%	16.0%	16.1%	14.2%	12.6%	12.9%	13.8%
33180	41.7%	30.1%	41.3%	43.5%	45.3%	46.7%	46.4%	44.0%	44.0%	42.7%
33181	26.9%	19.5%	23.6%	25.4%	25.9%	21.8%	19.9%	19.5%	16.8%	20.9%
33182	3.4%	2.5%	2.0%	2.1%	4.1%	3.5%	3.1%	3.1%	3.6%	3.0%
33183	7.3%	5.3%	7.8%	7.6%	6.2%	6.3%	4.8%	4.4%	4.5%	5.7%
33184	3.8%	2.8%	3.1%	3.8%	6.3%	5.4%	4.5%	4.3%	4.7%	4.4%
33185	5.1%	3.7%	3.1%	3.1%	3.6%	3.8%	3.5%	3.2%	3.5%	3.3%
33187	9.0%	6.5%	10.8%	12.4%	8.8%	9.6%	5.9%	5.2%	4.4%	7.8%
33189	11.1%	8.0%	8.2%	8.1%	9.6%	8.0%	6.6%	8.6%	8.1%	7.8%
33193	8.6%	6.2%	11.1%	11.8%	9.8%	8.5%	6.8%	5.0%	3.9%	7.7%
33194	7.5%	5.4%	11.1%	6.6%	3.0%	0.0%	0.0%	0.0%	0.0%	2.8%

Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 vacancy rate.

Appendix 6. Miami-Dade County Median Household Income by Zip Code

Zip Code	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
33010	$24,447	$23,724	$23,916	$22,564	$22,523	$22,530	$22,423	$23,876	$25,539	$26,188
33012	$33,846	$32,846	$33,111	$33,654	$32,273	$32,670	$30,742	$30,901	$31,010	$31,798
33013	$31,763	$30,825	$31,074	$29,836	$29,269	$30,272	$28,948	$28,886	$31,145	$31,936
33014	$39,863	$38,686	$38,998	$38,979	$38,332	$37,098	$36,788	$37,142	$36,257	$37,178
33015	$54,949	$53,326	$53,756	$52,161	$51,076	$50,914	$48,897	$48,170	$48,450	$49,681
33016	$39,559	$38,390	$38,700	$40,448	$39,085	$40,843	$39,729	$40,299	$43,579	$44,686
33018	$51,779	$50,249	$50,655	$51,672	$49,769	$51,701	$52,106	$52,752	$54,232	$55,610
33030	$32,360	$31,404	$31,658	$30,164	$29,994	$27,553	$30,695	$31,888	$36,069	$36,985
33031	$73,214	$71,051	$71,625	$68,385	$62,609	$54,446	$58,161	$54,500	$71,404	$73,218
33032	$47,349	$45,950	$46,321	$42,500	$41,469	$43,296	$42,667	$42,710	$44,415	$45,543
33033	$43,153	$41,878	$42,216	$44,095	$44,817	$43,689	$42,584	$41,415	$43,369	$44,471
33034	$28,419	$27,579	$27,802	$27,418	$27,996	$29,063	$28,800	$32,096	$36,572	$37,501
33054	$26,866	$26,073	$26,283	$25,660	$24,966	$25,083	$23,563	$22,840	$21,977	$22,535
33055	$44,678	$43,358	$43,708	$44,469	$42,841	$39,429	$39,007	$40,930	$42,950	$44,041
33056	$44,640	$43,321	$43,671	$42,207	$41,291	$41,748	$39,386	$37,776	$38,330	$39,304
33125	$26,596	$25,811	$26,019	$24,106	$24,296	$23,887	$22,820	$23,754	$25,815	$26,471
33126	$35,294	$34,252	$34,528	$32,384	$32,221	$32,665	$31,906	$32,561	$34,088	$34,954
33128	$19,677	$19,096	$19,250	$19,447	$21,003	$18,975	$19,693	$20,180	$19,138	$19,624
33129	$56,255	$54,593	$55,034	$59,135	$54,127	$59,192	$59,787	$73,306	$74,755	$76,654
33130	$21,355	$20,724	$20,891	$21,479	$22,813	$23,440	$23,717	$25,166	$27,033	$27,720
33132	$52,933	$51,369	$51,784	$53,182	$57,843	$55,560	$62,242	$70,012	$69,973	$71,750
33133	$56,454	$54,787	$55,229	$53,125	$55,134	$59,226	$59,457	$61,210	$63,428	$65,039
33134	$53,580	$51,997	$52,417	$50,115	$52,316	$53,841	$57,911	$58,733	$65,197	$66,853
33135	$20,397	$19,794	$19,954	$20,199	$21,576	$22,329	$23,049	$23,994	$25,707	$26,360
33137	$44,054	$42,753	$43,098	$47,111	$48,959	$48,887	$51,992	$55,522	$57,690	$59,155
33138	$41,717	$40,484	$40,811	$41,021	$39,949	$40,167	$40,920	$42,566	$43,607	$44,715
33139	$45,833	$44,479	$44,838	$45,725	$46,612	$43,972	$46,354	$47,982	$50,565	$51,849
33140	$58,801	$57,064	$57,525	$58,431	$53,699	$57,500	$60,066	$68,916	$75,257	$77,169
33141	$37,586	$36,476	$36,770	$36,820	$37,317	$36,560	$37,807	$42,145	$43,439	$44,542
33143	$65,489	$63,554	$64,067	$67,549	$63,268	$65,489	$65,076	$64,220	$65,581	$67,247
33144	$38,389	$37,255	$37,556	$34,509	$35,968	$33,783	$35,058	$36,885	$42,306	$43,381
33145	$41,102	$39,888	$40,210	$38,921	$37,167	$36,959	$39,674	$41,712	$46,856	$48,046
33146	$107,887	$104,700	$105,545	$105,514	$111,838	$113,835	$112,571	$113,380	$116,536	$119,496
33149	$116,785	$113,335	$114,250	$120,502	$121,624	$121,023	$121,434	$124,504	$128,563	$131,829
33154	$65,368	$63,437	$63,949	$61,072	$60,347	$60,833	$64,219	$64,463	$70,848	$72,648
33155	$54,311	$52,707	$53,132	$54,609	$54,725	$55,827	$57,021	$60,442	$60,853	$62,399
33156	$96,494	$93,643	$94,399	$92,150	$91,353	$96,299	$95,945	$100,531	$107,244	$109,968
33157	$64,239	$62,342	$62,845	$61,572	$59,768	$60,760	$57,385	$58,890	$60,325	$61,857
33158	$137,754	$133,685	$134,764	$142,620	$135,833	$138,257	$147,014	$141,434	$154,868	$158,802
33160	$45,920	$44,563	$44,923	$46,817	$45,627	$47,451	$47,959	$48,455	$50,070	$51,342
33161	$34,409	$33,392	$33,662	$33,857	$33,056	$32,623	$31,439	$32,898	$36,051	$36,967
33162	$42,677	$41,417	$41,751	$38,750	$39,191	$38,090	$38,332	$38,756	$40,932	$41,972
33165	$45,670	$44,321	$44,679	$44,189	$43,344	$43,248	$43,184	$43,227	$46,844	$48,034
33166	$52,540	$50,988	$51,400	$49,426	$50,180	$46,667	$47,866	$49,223	$51,738	$53,052
33167	$37,916	$36,796	$37,093	$36,434	$36,942	$36,131	$35,265	$36,471	$39,931	$40,945
33168	$47,160	$45,767	$46,136	$43,555	$42,605	$42,794	$42,861	$41,886	$43,036	$44,129
33169	$47,350	$45,951	$46,322	$43,270	$42,860	$38,907	$38,031	$38,965	$41,999	$43,066
33172	$42,668	$41,408	$41,742	$41,351	$41,410	$42,126	$42,151	$42,111	$44,368	$45,495
33173	$61,081	$59,276	$59,755	$54,900	$54,300	$55,426	$59,618	$62,054	$65,482	$67,145
33174	$37,407	$36,302	$36,595	$36,777	$35,776	$37,027	$39,432	$42,908	$46,390	$47,568
33175	$53,721	$52,134	$52,555	$52,320	$49,729	$49,212	$48,097	$51,250	$51,582	$52,892
33176	$61,843	$60,017	$60,501	$59,384	$60,472	$60,722	$60,146	$63,848	$67,866	$69,590
33178	$75,683	$73,447	$74,040	$73,816	$72,704	$75,139	$75,928	$76,276	$78,690	$80,689
33179	$47,044	$45,654	$46,023	$47,280	$44,325	$43,971	$42,198	$43,253	$44,241	$45,365
33180	$70,258	$68,183	$68,733	$64,630	$68,317	$64,882	$66,299	$63,479	$65,374	$67,035
33181	$41,433	$40,209	$40,534	$40,702	$37,718	$38,097	$40,851	$43,098	$44,305	$45,430
33182	$75,094	$72,876	$73,464	$64,897	$66,422	$65,119	$63,180	$67,042	$70,500	$72,291
33183	$55,504	$53,864	$54,299	$52,886	$52,571	$50,429	$48,899	$51,505	$53,546	$54,906
33184	$54,046	$52,450	$52,873	$52,656	$50,268	$49,944	$46,628	$47,442	$50,493	$51,776
33185	$85,330	$82,810	$83,478	$74,959	$76,293	$75,832	$76,229	$74,547	$80,429	$82,472
33187	$66,531	$64,566	$65,087	$65,725	$68,571	$66,513	$65,000	$69,976	$74,902	$76,805
33189	$52,824	$51,263	$51,677	$46,380	$47,695	$46,389	$45,639	$49,036	$53,438	$54,795
33193	$50,566	$49,072	$49,468	$48,032	$50,329	$49,945	$50,838	$50,396	$54,132	$55,507
33194	$77,565	$75,273	$75,881	$75,139	$68,521	$71,620	$79,229	$79,587	$94,535	$96,936

Notes: Inflation-adjusted dollar in each year. Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 median household income.

Appendix 7. Regression Results (MDC, n: 79,184)

Dependent Var.	Price (logged)	(1) STORM	(2) TYPE	(3) TECH.	(4) PROJECT	(5) HAZARD	(6) ATTRI.
Housing Structure	Bedroom	0.021^{***}	0.021^{***}	0.020^{***}	0.021^{***}	0.020^{***}	0.020^{***}
	Bathroom	0.069^{***}	0.068^{***}	0.070^{***}	0.069^{***}	0.071^{***}	0.070^{***}
	Building SF	0.020^{***}	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}
	Lot Size	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	Story	0.107^{***}	0.101^{***}	0.102^{***}	0.101^{***}	0.105^{***}	0.103^{***}
	Building Age	-0.002^{**}	-0.002^{**}	-0.002^{*}	-0.002^{**}	-0.002^{*}	-0.002^{**}
	Occupancy	0.106^{***}	0.106^{***}	0.106^{***}	0.106^{***}	0.105^{***}	0.105^{***}
	Elevation	0.005	0.012^{**}	0.013^{**}	0.013^{**}	0.013^{**}	0.013^{**}
Neighborhood Amenity	Metro Station	-0.125^{***}	-0.096^{**}	-0.117^{***}	-0.112^{***}	-0.123^{***}	-0.113^{**}
	Bus Stop	-0.066^{***}	-0.055^{***}	-0.057^{***}	-0.055^{***}	-0.054^{***}	-0.059^{***}
	Cultural	0.045	0.047	0.044	0.042	0.040	0.044
	Commercial	-0.005	-0.008	-0.018	-0.011	-0.031	-0.003
	School	-0.038^{***}	-0.028^{**}	-0.035^{***}	-0.031^{***}	-0.035^{***}	-0.034^{***}
	Sexual Crime	-0.071^{***}	-0.067^{***}	-0.068^{***}	-0.067^{***}	-0.068^{***}	-0.069^{***}
	Brownfield	-0.134^{**}	-0.135^{**}	-0.134^{**}	-0.134^{**}	-0.133^{**}	-0.136^{**}
	GS View	-0.006	-0.007	-0.007	-0.006	-0.007	-0.007
	GS Proximity	-0.010	-0.009	-0.009	-0.007	-0.011	-0.008
	Ocean View	0.141^{***}	0.118^{***}	0.126^{***}	0.120^{***}	0.125^{***}	0.134^{***}
	Ocean Proximity	0.213^{***}	0.196^{***}	0.205^{***}	0.199^{***}	0.204^{***}	0.202^{***}
Market	Unemployment Rate	-0.007	-0.007	-0.007	-0.007	-0.007	-0.006
	Vacancy Rate	-0.328	-0.295	-0.299	-0.277	-0.308	-0.312
	Median Household Income	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
Storm Impact	Storm 30-150 days	-0.024^{***}					
	Storm 150-300 days	0.023^{***}					
Storm Characteristics	Landfall		-0.089^{***}	-0.091^{***}	-0.090^{***}	-0.090^{***}	-0.092^{***}
	Wind Damage		0.050^{**}	0.052^{**}	0.051^{**}	0.051^{**}	0.052^{**}
	Flood Damage		-0.031^{**}	-0.030^{**}	-0.030^{**}	-0.029^{**}	-0.030^{**}
	Storm Surge		-0.018^{**}	-0.019^{***}	-0.018^{**}	-0.019^{***}	-0.019^{***}
	Power Outage		0.024	0.024	0.023	0.023	0.024
Risk Perception	Frequency		-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	Fadedness		0.016^{***}	0.015^{***}	0.016^{***}	0.016^{***}	0.015^{***}
	Myopia		-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	IHP Grant		0.024^{*}	0.023^{*}	0.023^{*}	0.023^{*}	0.023^{*}
	Insurance		0.069^{***}	0.072^{***}	0.071^{***}	0.076^{***}	0.081^{***}
	Adaptation Information		0.054	0.060	0.061	0.062	0.060
Adaptation Type	Infrastructure		0.264^{***}				
	Critical Facility		0.119^{**}				
	Drainage System		0.033				
	Natural Barriers		0.096^{***}				
	Emergency Prep.		-0.055^{**}				
	Recovery Operation		0.106				
	Floodplain Revision		-0.033				
	Private Building		0.047				
Adaptation Technique	Elevation			-0.043			
	Construction			0.071^{**}			
	Reinforcement			0.078^{***}			
	Equipment Installation			0.026			
	Demolition			-0.073			
	System Improvement			0.102^{***}			
Project Characteristics	Infrastructure Reinforce				0.338^{***}		
	New Facility				0.346^{***}		
	Building Reinforcement				0.082^{***}		
	Drainage Improvement				0.041^{*}		
	Green Space Restoration				0.097^{***}		
	Equipment Installation				0.038		
	Structural Elevation				0.066^{***}		
	Land Elevation				-0.034		
	Hurricane Shelters				0.029		
	Evacuation Bus Stops				-0.067^{*}		
	Neighborhood Resilience				0.040		
Hazard Types	Adapting Wind					0.021	
	Adapting Flood					0.053^{**}	
	Adapting Storm Surge					0.154^{**}	
	Adapting Multi-purpose					0.162^{***}	
Project Attribute	New						0.113
	Upgrade						0.032^{*}
	Repair						-0.029
	Existing						-0.021
	Remove						-0.100^{*}
	_cons	12.056^{***}	11.959^{***}	11.937^{***}	11.951^{***}	11.957^{***}	11.966^{***}
	adj. R^2	0.747	0.751	0.750	0.750	0.749	0.748

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the zip code level. All specifications include year and zip code dummies to control for spatial- and time-specific fixed effects.

Appendix 8. New York City Unemployment Rates by Neighborhoods

Borough	Neighborhood	2009	2010	2011	2012	2013	2014	2015	2016	2017
Bronx	Central Bronx	15.0%	16.1%	16.6%	18.4%	19.2%	19.4%	17.7%	16.0%	14.5%
	Bronx Park and Fordham	13.0%	13.9%	13.6%	15.0%	16.4%	16.5%	15.7%	14.6%	13.4%
	High Bridge and Morrisania	13.0%	14.0%	15.2%	16.7%	17.6%	16.5%	15.2%	12.8%	11.5%
	Hunts Point and Mott Haven	12.3%	13.2%	15.8%	16.3%	16.6%	15.4%	13.3%	11.5%	11.0%
	Kingsbridge and Riverdale	7.7%	8.3%	8.3%	8.8%	9.3%	9.9%	10.0%	8.2%	8.1%
	Northeast Bronx	10.3%	11.1%	11.5%	12.9%	13.6%	13.4%	12.4%	10.7%	9.0%
	Southeast Bronx	8.8%	9.4%	8.0%	9.5%	10.7%	10.9%	10.9%	11.1%	10.0%
Brooklyn	Central Brooklyn	9.6%	10.3%	11.2%	11.8%	12.0%	11.8%	11.6%	9.9%	9.5%
	Southwest Brooklyn	7.2%	7.7%	7.8%	8.8%	9.5%	9.2%	8.6%	7.8%	6.9%
	Borough Park	6.8%	7.3%	7.8%	8.3%	8.8%	8.2%	7.8%	7.3%	6.9%
	Canarsie and Flatlands	9.0%	9.6%	9.3%	11.0%	11.3%	12.1%	11.5%	9.4%	8.1%
	Southern Brooklyn	8.9%	9.5%	9.2%	10.8%	11.4%	11.2%	10.6%	10.1%	8.8%
	Northwest Brooklyn	6.9%	7.4%	8.1%	8.5%	8.8%	8.5%	8.2%	7.3%	6.7%
	Flatbush	9.9%	10.6%	12.3%	12.7%	13.3%	12.8%	11.2%	9.6%	8.4%
	East New York and New Lots	10.2%	11.0%	11.6%	12.8%	13.6%	12.9%	11.7%	10.8%	9.8%
	Greenpoint	5.3%	5.7%	6.1%	6.2%	6.6%	6.7%	6.2%	5.6%	5.5%
	Sunset Park	8.4%	9.0%	10.1%	10.8%	11.4%	10.7%	9.2%	8.5%	7.5%
	Bushwick and Williamsburg	11.3%	12.2%	10.8%	12.8%	14.5%	14.9%	14.6%	13.3%	11.0%
Manhattan	Central Harlem	9.4%	10.1%	11.6%	11.4%	10.7%	11.4%	11.1%	10.5%	9.8%
	Chelsea and Clinton	6.3%	6.7%	8.4%	8.9%	8.6%	7.4%	6.6%	5.9%	5.1%
	East Harlem	10.4%	11.1%	13.9%	12.8%	13.0%	11.9%	11.3%	10.5%	10.8%
	Gramercy Park and Murray Hill	4.2%	4.5%	5.7%	6.0%	6.1%	5.3%	4.7%	3.6%	3.2%
	Greenwich Village and Soho	4.6%	4.9%	6.0%	6.1%	6.1%	5.3%	5.1%	4.6%	4.1%
	Lower Manhattan	4.9%	5.2%	5.2%	6.0%	5.4%	5.5%	6.1%	5.9%	5.5%
	Lower East Side	6.5%	7.0%	8.3%	8.4%	8.5%	7.9%	6.9%	6.6%	6.1%
	Upper East Side	3.8%	4.0%	4.7%	5.2%	5.4%	4.7%	3.9%	3.7%	3.0%
	Upper West Side	5.1%	5.4%	6.1%	6.3%	6.8%	6.4%	5.6%	5.3%	4.7%
	Inwood and Washington Heights	10.9%	11.7%	13.6%	14.0%	14.3%	13.1%	12.2%	11.3%	9.8%
Queens	Northeast Queens	5.9%	6.3%	7.0%	7.6%	8.2%	7.7%	6.7%	5.7%	5.1%
	North Queens	6.8%	7.3%	9.2%	9.5%	9.7%	8.5%	7.4%	6.0%	4.9%
	Central Queens	8.1%	8.7%	9.7%	10.7%	10.7%	9.6%	8.4%	8.4%	8.1%
	Jamaica	11.1%	11.9%	12.5%	13.1%	14.3%	14.2%	13.1%	12.0%	10.6%
	Northwest Queens	7.4%	7.9%	9.1%	9.3%	9.6%	9.6%	8.1%	7.3%	6.8%
	West Central Queens	6.1%	6.6%	7.4%	7.6%	8.1%	7.7%	7.1%	6.2%	5.6%
	Rockaways	9.1%	9.7%	10.2%	11.7%	12.0%	11.0%	10.6%	9.3%	8.8%
	Southeast Queens	7.2%	7.7%	7.9%	8.8%	9.1%	9.0%	8.5%	7.9%	7.3%
	Southwest Queens	8.3%	8.9%	9.9%	10.6%	10.8%	10.5%	9.5%	8.7%	7.7%
	West Queens	6.6%	7.1%	7.8%	8.8%	9.0%	8.4%	7.4%	6.6%	5.6%
Staten Island	Port Richmond	7.3%	7.8%	8.7%	9.1%	10.4%	9.8%	8.3%	6.9%	6.0%
	South Shore	5.5%	5.9%	5.8%	6.5%	6.8%	7.2%	6.6%	6.2%	5.3%
	Stapleton and St. George	6.5%	7.0%	7.6%	8.0%	8.4%	8.1%	7.6%	6.7%	6.1%
	Mid-Island	5.1%	5.5%	5.9%	6.2%	6.6%	6.3%	5.5%	5.6%	5.1%

Notes: Zip code-level data is used to regressions. A total of 157 unemployment rates in each zip code area are averaged into the 42 neighborhoods in New York City. Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). New York State Department of Labor (Average unemployment rates from January to May 2018).

Appendix 9. New York City Housing Vacancy Rates by Neighborhoods

Borough	Neighborhood	2009	2010	2011	2012	2013	2014	2015	2016	2017
Bronx	Central Bronx	6.7%	7.7%	8.1%	8.3%	7.7%	7.1%	6.5%	6.0%	5.0%
	Bronx Park and Fordham	6.5%	7.5%	7.8%	7.6%	7.8%	7.4%	6.3%	5.2%	5.2%
	High Bridge and Morrisania	5.4%	6.2%	6.4%	6.5%	6.4%	6.0%	6.0%	5.2%	4.6%
	Hunts Point and Mott Haven	7.7%	8.9%	9.3%	8.6%	8.4%	8.8%	8.6%	9.0%	8.5%
	Kingsbridge and Riverdale	7.9%	9.2%	9.6%	10.1%	10.2%	10.1%	9.6%	8.5%	7.9%
	Northeast Bronx	5.6%	6.4%	6.7%	7.0%	7.2%	7.5%	6.8%	5.9%	5.5%
	Southeast Bronx	6.4%	7.4%	7.7%	7.5%	7.6%	7.4%	7.6%	7.6%	6.4%
Brooklyn	Central Brooklyn	9.5%	11.0%	11.5%	11.4%	10.9%	11.0%	10.7%	10.0%	9.7%
	Southwest Brooklyn	5.8%	6.7%	7.0%	6.9%	6.9%	7.0%	7.0%	7.4%	8.1%
	Borough Park	5.1%	5.9%	6.1%	6.4%	6.2%	6.2%	6.2%	6.1%	6.4%
	Canarsie and Flatlands	3.9%	4.5%	4.7%	4.8%	4.7%	4.9%	5.3%	5.1%	5.5%
	Southern Brooklyn	5.9%	6.7%	7.0%	7.4%	7.8%	8.4%	8.4%	8.1%	7.9%
	Northwest Brooklyn	8.9%	10.3%	10.8%	10.4%	9.9%	9.4%	8.5%	8.1%	8.1%
	Flatbush	5.9%	6.8%	7.1%	7.2%	7.9%	7.7%	7.8%	8.1%	8.1%
	East New York and New Lots	9.4%	10.9%	11.4%	12.0%	12.5%	13.1%	13.1%	12.7%	12.1%
	Greenpoint	8.2%	9.4%	9.8%	9.7%	9.1%	8.6%	7.3%	6.3%	6.2%
	Sunset Park	5.6%	6.4%	6.7%	6.7%	7.0%	7.6%	7.0%	5.9%	5.9%
	Bushwick and Williamsburg	9.4%	10.8%	11.3%	11.0%	10.2%	9.2%	9.0%	8.1%	7.9%
Manhattan	Central Harlem	10.4%	12.0%	12.6%	12.0%	11.8%	10.2%	9.8%	9.8%	9.3%
	Chelsea and Clinton	10.8%	12.4%	12.9%	13.6%	14.2%	13.6%	13.7%	14.8%	15.0%
	East Harlem	7.4%	8.5%	8.9%	9.3%	10.0%	9.2%	8.8%	7.8%	6.8%
	Gramercy Park and Murray Hill	15.8%	18.2%	19.0%	18.7%	19.2%	19.2%	18.5%	18.9%	18.9%
	Greenwich Village and Soho	12.0%	13.8%	14.4%	15.0%	14.0%	13.3%	14.4%	14.3%	14.0%
	Lower Manhattan	8.4%	9.7%	10.2%	9.6%	11.1%	10.5%	11.0%	10.6%	11.9%
	Lower East Side	7.3%	8.4%	8.7%	8.3%	8.4%	8.1%	8.4%	8.2%	8.5%
	Upper East Side	14.4%	16.6%	17.4%	16.6%	17.3%	17.0%	15.9%	15.2%	15.5%
	Upper West Side	10.9%	12.5%	13.1%	13.2%	13.6%	14.6%	15.0%	15.6%	16.1%
	Inwood and Washington Heights	5.8%	6.6%	6.9%	6.4%	6.5%	6.3%	6.0%	6.3%	6.3%
Queens	Northeast Queens	4.3%	5.0%	5.2%	4.8%	5.2%	5.4%	5.1%	5.3%	5.3%
	North Queens	5.5%	6.4%	6.6%	6.5%	6.5%	7.3%	7.8%	8.7%	9.2%
	Central Queens	5.2%	6.0%	6.2%	6.9%	6.4%	6.4%	6.8%	6.5%	6.6%
	Jamaica	6.9%	7.9%	8.3%	8.4%	7.8%	7.5%	7.2%	6.8%	6.8%
	Northwest Queens	6.6%	7.7%	8.0%	7.7%	7.8%	8.0%	8.3%	9.5%	11.7%
	West Central Queens	5.1%	5.9%	6.2%	6.6%	6.9%	7.1%	7.3%	7.5%	7.9%
	Rockaways	10.4%	12.0%	12.5%	12.7%	12.8%	12.1%	12.0%	10.7%	10.4%
	Southeast Queens	4.7%	5.4%	5.6%	5.6%	4.9%	4.9%	5.3%	5.4%	5.2%
	Southwest Queens	6.2%	7.1%	7.5%	7.3%	6.8%	7.5%	7.6%	7.8%	7.7%
	West Queens	6.4%	7.4%	7.7%	7.8%	7.6%	7.8%	8.2%	9.4%	10.9%
Staten Island	Port Richmond	8.6%	10.0%	10.4%	10.9%	11.3%	11.0%	10.2%	10.4%	10.1%
	South Shore	4.3%	5.0%	5.2%	5.5%	5.4%	4.7%	4.5%	5.0%	5.2%
	Stapleton and St. George	8.3%	9.6%	10.0%	10.1%	9.5%	10.2%	9.7%	9.4%	9.6%
	Mid-Island	4.2%	4.8%	5.0%	5.6%	4.9%	5.1%	5.3%	5.1%	5.5%

Notes: Zip code-level data is used to regressions. A total of 157 unemployment rates in each zip code area are averaged into the 42 neighborhoods in New York City. Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 vacancy rate.

Appendix 10. New York City Median Household Income by Neighborhoods

Borough	Neighborhood	2009	2010	2011	2012	2013	2014	2015	2016	2017
Bronx	Central Bronx	$25,034	$24,656	$25,139	$24,397	$24,242	$24,304	$23,685	$24,322	$25,802
	Bronx Park and Fordham	$30,585	$30,123	$30,713	$30,940	$31,481	$31,422	$32,604	$33,430	$34,303
	High Bridge and Morrisania	$24,774	$24,400	$24,878	$25,260	$25,395	$25,041	$24,931	$26,019	$26,970
	Hunts Point and Mott Haven	$22,040	$21,708	$22,133	$21,465	$23,245	$23,098	$23,452	$24,305	$24,672
	Kingsbridge and Riverdale	$62,207	$61,268	$62,468	$62,284	$63,028	$64,519	$68,352	$69,081	$69,907
	Northeast Bronx	$50,380	$49,620	$50,592	$50,320	$51,004	$51,121	$50,579	$51,664	$54,097
	Southeast Bronx	$49,773	$49,022	$49,982	$48,326	$49,982	$51,544	$52,064	$53,375	$56,210
Brooklyn	Central Brooklyn	$39,451	$38,855	$39,616	$41,107	$41,389	$42,488	$42,927	$45,947	$47,466
	Southwest Brooklyn	$51,958	$51,174	$52,176	$53,391	$54,517	$56,198	$58,946	$60,314	$62,142
	Borough Park	$43,120	$42,468	$43,300	$43,880	$43,601	$44,234	$44,931	$46,968	$48,793
	Canarsie and Flatlands	$50,957	$50,187	$51,170	$51,192	$51,922	$51,911	$52,002	$53,619	$56,397
	Southern Brooklyn	$40,735	$40,120	$40,906	$41,076	$40,543	$40,532	$41,503	$44,196	$46,720
	Northwest Brooklyn	$73,569	$72,458	$73,877	$75,980	$79,149	$82,689	$84,568	$88,856	$95,515
	Flatbush	$45,178	$44,495	$45,367	$46,073	$46,871	$47,102	$47,953	$50,030	$52,691
	East New York and New Lots	$34,139	$33,623	$34,282	$34,154	$34,012	$34,172	$34,975	$36,745	$37,699
	Greenpoint	$51,395	$50,618	$51,610	$53,404	$55,294	$58,777	$63,408	$66,291	$72,200
	Sunset Park	$37,929	$37,356	$38,088	$39,416	$40,588	$41,318	$41,684	$44,181	$48,234
	Bushwick and Williamsburg	$33,971	$33,458	$34,113	$34,609	$36,036	$37,656	$38,788	$40,420	$44,187
Manhattan	Central Harlem	$35,968	$35,425	$36,119	$37,081	$37,561	$39,223	$39,183	$42,005	$43,996
	Chelsea and Clinton	$76,510	$75,355	$76,831	$80,555	$84,169	$85,681	$90,862	$94,371	$100,712
	East Harlem	$28,987	$28,549	$29,108	$28,734	$28,211	$29,105	$29,387	$29,697	$30,974
	Gramercy Park and Murray Hill	$102,729	$101,177	$103,159	$103,168	$103,238	$105,623	$109,836	$110,833	$119,003
	Greenwich Village and Soho	$81,201	$79,975	$81,542	$83,929	$92,934	$100,787	$103,833	$108,336	$112,863
	Lower Manhattan	$65,200	$64,215	$65,473	$65,934	$66,074	$73,988	$76,379	$82,910	$85,032
	Lower East Side	$58,529	$57,645	$58,775	$61,022	$61,896	$63,881	$63,656	$65,724	$66,804
	Upper East Side	$104,588	$103,009	$105,026	$104,270	$105,460	$108,056	$110,955	$112,718	$121,780
	Upper West Side	$93,420	$92,009	$93,811	$94,622	$94,002	$97,638	$99,794	$104,566	$110,803
	Inwood and Washington Heights	$37,128	$36,568	$37,284	$38,582	$39,125	$41,464	$42,047	$43,516	$46,541
Queens	Northeast Queens	$79,891	$78,684	$80,226	$80,920	$80,344	$81,083	$81,903	$81,381	$82,916
	North Queens	$62,719	$61,772	$62,982	$61,858	$60,133	$61,042	$60,058	$60,562	$62,343
	Central Queens	$61,512	$60,583	$61,769	$61,353	$61,150	$61,633	$62,854	$66,014	$63,165
	Jamaica	$55,309	$54,474	$55,541	$56,988	$57,041	$56,852	$57,581	$59,389	$61,861
	Northwest Queens	$49,905	$49,151	$50,114	$51,573	$52,417	$54,271	$54,905	$57,975	$62,571
	West Central Queens	$60,012	$59,106	$60,264	$61,545	$61,294	$61,800	$62,857	$66,095	$69,346
	Rockaways	$49,525	$48,777	$49,732	$50,587	$52,569	$51,754	$53,131	$54,124	$55,810
	Southeast Queens	$77,048	$75,884	$77,371	$76,517	$77,366	$76,761	$76,543	$78,474	$82,422
	Southwest Queens	$57,712	$56,840	$57,954	$59,071	$60,913	$61,351	$61,623	$63,967	$67,234
	West Queens	$51,577	$50,798	$51,793	$50,704	$50,827	$50,679	$50,911	$51,845	$55,386
Staten Island	Port Richmond	$58,184	$57,305	$58,427	$56,492	$56,768	$57,233	$58,268	$60,088	$63,568
	South Shore	$84,157	$82,886	$84,510	$85,622	$84,392	$85,427	$83,162	$85,066	$88,895
	Stapleton and St. George	$56,826	$55,967	$57,064	$57,707	$60,258	$61,601	$60,498	$61,202	$62,143
	Mid-Island	$78,474	$77,289	$78,803	$79,820	$77,242	$78,962	$77,331	$77,761	$80,956

Notes: Zip code-level data is used to regressions. A total of 157 unemployment rates in each zip code area are averaged into the 42 neighborhoods in New York City. Inflation-adjusted dollar in each year. Sources: ZCTAs (ZIP Code Tabulation Areas) data from the U.S. Census Bureau, 2013-2017 American Community Survey 5-Year Estimates (2009 – 2017). Social Explorer ACS 2017 (5-Year Estimates) for estimating 2018 median household income.

Appendix 11. Regression Results (NYC, n: 90,811)

Dependent Var.	Price (logged)	(1) STORM	(2) TYPE	(3) TECH.	(4) PROJECT	(5) HAZARD	(6) ATTRI.
Housing Structure	Building SF	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	Lot Size	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	Story	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***
	Building Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	Occupancy	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	Elevation	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
Neighborhood Amenity	Metro Station	-0.036*	-0.034*	-0.033*	-0.033*	-0.034*	-0.034*
	Bus Stop	-0.018**	-0.018**	-0.018**	-0.019***	-0.019***	-0.019**
	Cultural	0.025	0.024	0.025	0.025	0.025	0.025
	Commercial	-0.045***	-0.043***	-0.043***	-0.044***	-0.044***	-0.043***
	School	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	Landfills	-0.039***	-0.042***	-0.043***	-0.044***	-0.041***	-0.043***
	GS View	0.033*	0.031*	0.032*	0.031*	0.032*	0.031*
	GS Proximity	0.011	0.012	0.011	0.011	0.011	0.012
	Ocean View	0.037	0.053	0.047	0.050	0.048	0.047
	Ocean Proximity	-0.072	-0.040	-0.044	-0.042	-0.043	-0.040
Market	Unemployment Rate	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	Vacancy Rate	-0.119	-0.125	-0.125	-0.152	-0.151	-0.145
	Median Household Income	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
Storm Impact	Storm 30-150 days	-0.019***					
	Storm 150-300 days	-0.032***					
	Storm 300-450 days	-0.016**					
	Storm 450-600 days	-0.031***					
	Storm 600-750 days	-0.006					
	Storm 750-900 days	0.010**					
Storm	Wind		0.006**	0.006**	0.006**	0.006**	0.006**
	Rainfall		-0.097***	-0.097***	-0.097***	-0.097***	-0.097***
	Storm Surge		-0.059***	-0.060***	-0.059***	-0.059***	-0.059***
Risk Perception	Frequency		0.090*	0.089*	0.088*	0.088*	0.085*
	Fadedness		0.006**	0.007**	0.006**	0.006**	0.006**
	Myopia		-0.001	-0.001	-0.001	-0.001	-0.001
	IHP Grant		0.003**	0.002**	0.003**	0.003**	0.002**
	Insurance		-0.070**	-0.074**	-0.077**	-0.076**	-0.074**
	Adaptation Information		-0.192	0.200	0.007	0.106	-0.006
Adaptation Type	Infrastructure		-0.028				
	Critical Facility		0.024				
	Drainage System		0.010				
	Natural Barriers		0.027**				
	Emergency Prep.		0.073**				
	Recovery Operation		-0.135*				
	Floodplain Revision		0.080***				
	Private Building		0.101***				
Adaptation Technique	Elevation			0.121**			
	Construction			0.024			
	Reinforcement			-0.085*			
	Equipment Installation			0.116			
	Demolition			-0.099			
	System Improvement			0.059			
Project Characteristics	Infrastructure Reinforce				-0.037*		
	New Facility				0.014		
	Building Reinforcement				0.071***		
	Drainage Improvement				0.021		
	Green Space Restoration				0.059***		
	Equipment Installation				0.102		
	Structural Elevation				0.138***		
	Land Elevation				0.080***		
	Hurricane Shelters				0.149**		
	Neighborhood Resilience				0.026*		
Hazard Types	Adapting Wind					0.042*	
	Adapting Flood					0.077	
	Adapting Storm Surge					0.043**	
	Adapting Multi-purpose					0.033	
Project Attribute	New						-0.052*
	Upgrade						0.091***
	Repair						0.027
	Existing						0.033*
	Remove						0.077***
	_cons	12.440***	12.433***	12.442***	12.446***	12.443***	12.446***
	adj. R^2	0.629	0.630	0.629	0.630	0.629	0.629

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the zip code level. All specifications include year and zip code dummies to control for spatial- and time-specific fixed effects.

Appendix 12. Regression Results (All, n: 169,995)

Dependent Var.	Price (logged)	(2) TYPE	(3) TECH.	(4) PROJECT	(5) HAZARD	(6) ATTRI.
Housing Structure	Building SF	0.025***	0.025***	0.025***	0.025***	0.025***
	Lot Size	0.001***	0.001***	0.001***	0.001***	0.001***
	Story	0.053***	0.053***	0.054***	0.054***	0.054***
	Building Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	Occupancy	0.055***	0.055***	0.055***	0.055***	0.055***
	Elevation	0.001***	0.001***	0.001***	0.001***	0.001***
Neighborhood Amenity	Metro Station	-0.044**	-0.045**	-0.044**	-0.044**	-0.044**
	Bus Stop	-0.040***	-0.041***	-0.041***	-0.040***	-0.044***
	Cultural	0.025	0.026*	0.025*	0.025*	0.026*
	Commercial	-0.049***	-0.050***	-0.050***	-0.050***	-0.049***
	School	-0.025***	-0.028***	-0.027***	-0.028***	-0.027***
	Landfills	-0.125***	-0.126***	-0.125***	-0.124***	-0.127***
	GS View	0.003	0.003	0.003	0.002	0.003
	GS Proximity	0.017	0.009	0.012	0.001	0.014
	Ocean View	0.117***	0.116***	0.117***	0.117***	0.123***
	Ocean Proximity	0.015	0.016	0.015	0.015	0.015
Market	Unemployment Rate	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**
	Vacancy Rate	-0.436	-0.434	-0.446*	-0.447*	-0.450*
	Median Household Income	-0.001	-0.001	-0.001	-0.001	-0.001
Storm	Wind	0.012***	0.011***	0.012***	0.011***	0.012***
	Rainfall	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	Storm Surge	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
Risk Perception	Frequency	0.002	0.001	0.001	0.001	0.001
	Fadedness	0.016***	0.015***	0.016***	0.015***	0.015***
	Myopia	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	IHP Grant	0.003**	0.003**	0.003**	0.003**	0.003**
	Insurance	0.030	0.028	0.030	0.033	0.038*
	Adaptation Information	0.037	0.041	0.037	0.039	0.036
Adaptation Type	Infrastructure	0.029				
	Critical Facility	0.037				
	Drainage System	0.021				
	Natural Barriers	0.120***				
	Emergency Prep.	-0.058**				
	Recovery Operation	-0.131				
	Floodplain Revision	-0.017				
	Private Building	0.084***				
Adaptation Technique	Elevation		-0.019			
	Construction		0.067**			
	Reinforcement		0.009			
	Equipment Installation		0.078			
	Demolition		-0.162*			
	System Improvement		0.125***			
Project Characteristics	Infrastructure Reinforce			-0.732		
	New Facility			0.133		
	Building Reinforcement			0.063***		
	Drainage Improvement			0.028		
	Green Space Restoration			0.121***		
	Equipment Installation			0.062		
	Structural Elevation			0.026		
	Land Elevation			-0.016		
	Hurricane Shelters			-0.034		
	Neighborhood Resilience			0.001		
Hazard Types	Adapting Wind				0.025	
	Adapting Flood				0.076***	
	Adapting Storm Surge				0.130**	
	Adapting Multi-purpose				0.031	
Project Attribute	New					-0.031
	Upgrade					0.054***
	Repair					-0.017
	Existing					-0.024
	Remove					0.089***
	_cons	12.520***	12.518***	12.521***	12.524***	12.530***
	adj. R^2	0.730	0.730	0.729	0.729	0.729

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the zip code level. All specifications include year and zip code dummies to control for spatial- and time-specific fixed effects.