Sea Level Rise and Commercial Office Markets in Southeast Florida

by
Katherine G. Salvatori
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Signature of Author

MIT Center for Real Estate
August 22, 2022

Certified by

Professor William Wheaton
Professor, MIT Center for Real Estate
Professor Emeritus, Department of Economics
Thesis Supervisor

Certified by

Anne Kinsella Thompson
Research Scientist and Visiting Lecturer
MIT Center for Real Estate
Thesis Co-Supervisor

Accepted by

Professor Siqi Zheng
Samuel Tak Lee Professor of Urban and RE Sustainability
Department of Urban Studies and Planning
Faculty Director, MIT Center for Real Estate

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Abstract

Sea level rise is an indisputably mounting predicament that has exacerbated consequences in Southeast Florida. In this thesis, we explore the impacts of sea level rise risk in commercial office markets in Miami-Dade County. We examine 560 commercial office properties with sale price records from 2000 to 2020, and 497 commercial office rental properties from 1988 quarter one through 2020 quarter four. For both sales and rental properties, we analyze each sample comprehensively, then we isolate the respective samples first by historic flood amount and then by flood risk metrics. We conclude by segregating properties in high-risk areas by historic flood amount to eradicate property location as a confounding variable.

Our results suggest that properties that have historic exposure to flooding from either or both major recent hurricanes, Katrina in 2005 and Irma in 2017, have lower sales prices and rental values when compared to properties that have not experienced historic hurricane flooding in comparable flood risk zones. Our results also indicate that generally, commercial office properties that are more concentrated near waterfront areas have experienced greater historic flooding and have larger predicted flood risk than properties farther inland.

Thesis Supervisor: Professor William Wheaton

Title: Professor, MIT Center for Real Estate and Professor Emeritus, Department of Economics

Thesis Co-Supervisor: Anne Kinsella Thompson

Title: Research Scientist and Visiting Lecturer. MIT Center for Real Estate

Acknowledgements

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1 Introduction

Is a rising sea influencing commercial real estate valuations in coastal Florida? In Miami, amidst a growing population and mounting corporate relocations, the evolving predicament of sea level rise, causing worsening flooding, storm surges, and radical weather events, bodes ominously. This contrast of commercial proliferation with an escalating climate crisis piqued the question of whether commercial office properties' sales prices and rent values account for this current and future heightened risk surrounding sea level rise.

In this paper, we examine the relationship between flood exposure and risk related to sea level rise and changes in commercial office properties' sales and rent data from 2000 to 2020. We focus on the Miami-Dade County market, where the Southeast Florida Regional Climate Change Compact predicts an increase in sea level (from the mean sea level [MSL] in 2000) of between 21 and 54 inches by 2070. Our analysis compares properties more affected by historic floods, including current and future flood risk correlated with an increasing sea level, with similar properties with less exposure. Leveraging data on historic flood levels from major 2005 and 2017 hurricanes, a predicted measure of flood risk, and historic repeat rent and sales information on commercial properties, we study how the intensifying prominence of sea level rise exposure over this time period may have impacted commercial real estate markets.

2 Background

In this section, we explore the causes and impacts of a rising sea level and consider how predicted sea levels until 2120 may alter the Miami-Dade County landscape. We also delve into the correlation between an increasing sea level and worsening storm impacts. We then consider the shifting landscape of increased commercial activity in Miami and note previous research on the relationship between sea level rise and residential real estate to underscore the need to assess if the commercial real estate market has begun to register the impact of flooding caused by sea level rise.

2.1 Sea Level Rise in Southeast Florida

Amid a changing climate, the sea level is rising rapidly due to the thermal expansion of the warming ocean, excess water from melting ice sheets, and the constant deceleration of the Gulf Stream[1]. Since 1950, the sea level surrounding Florida has increased eight inches[2]. Southeast Florida's geographical factors of porous limestone geology and low elevation exacerbate the impacts of sea level rise in the region[3].

The Southeast Florida Regional Climate Change Compact materialized across Broward, Miami-Dade, Monroe, and Palm Beach counties to generate regionally unified sea level rise projections. The Compact's most recent document, published in 2019, outlines anticipated sea level rise in Southeast Florida from 2000 to 2120 in terms of MSL and North America vertical datum as depicted in Figure 1[4]. The 2019 projections are centered upon estimates developed by the Intergovernmental Panel on Climate Change (IPCC) and the National Oceanic and Atmospheric Administration (NOAA). The report adjusts global projections to account for regional differences in Southeast Florida's rate of sea level rise by considering elements including ice melt, ocean dynamics, land movement, and thermal expansion from warming of the Florida Current.

[1] Lindsey, "Climate Change: Global Sea Level."
[2] NOAA, "Tides and Currents Virginia Key, Biscayne Bay, FL."
[3] SeaLevelRise.org, "Florida."
[4] Southeast Florida Climate Change Regional Compact, "2019 Compact Unified Sea Level Rise Projection."

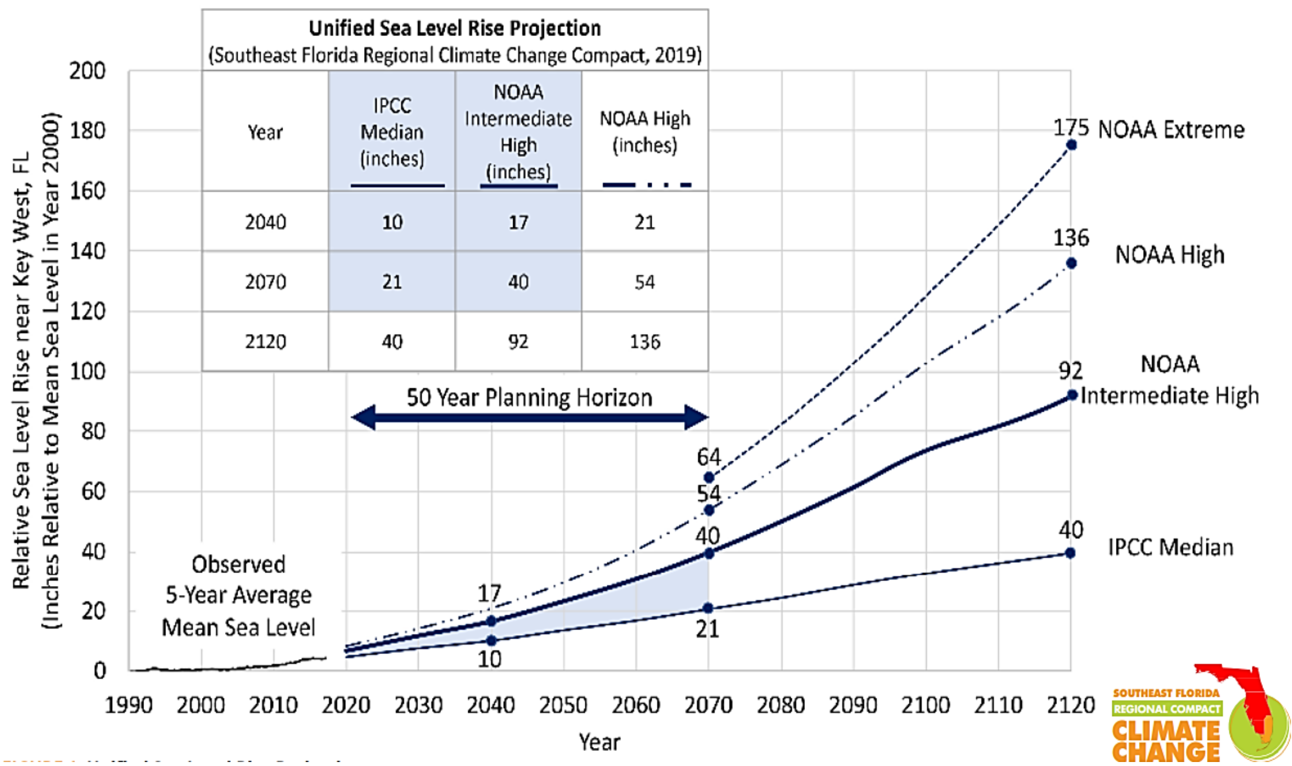
Figure 1: Sea Level Rise Projection, 2020 – 2120

DATUM: FEET 2000 MSL			
Year	**IPCC MED 50%**	**NOAA 2017 INT-HIGH**	**NOAA 2017 HIGH**
2000	0.00	0.00	0.00
2010	0.19	0.30	0.33
2020	0.39	0.56	0.69
2030	0.63	0.98	1.18
2040	0.84	1.38	1.74
2050	1.13	1.94	2.46
2060	1.40	2.56	3.38
2070	1.72	3.31	4.49
2080	2.03	4.17	5.74
2090	2.40	5.12	7.09
2100	2.72	6.14	8.56
2120	3.29	7.64	11.32

DATUM: FEET NAVD			
Year	**IPCC MED 50%**	**NOAA 2017 INT-HIGH**	**NOAA 2017 HIGH**
2000	-0.08	-0.78	-0.78
2010	-0.61	-0.49	-0.45
2020	-0.42	-0.22	-0.09
2030	-0.17	0.30	0.40
2040	0.04	0.60	0.96
2050	0.33	1.15	1.68
2060	0.60	1.78	2.60
2070	0.91	2.53	3.71
2080	1.23	3.38	4.96
2090	1.59	4.34	6.30
2100	1.92	5.35	7.78
2120	2.49	6.86	10.54

In Figure 2 below, the predictions are illustrated as curves adapted for regional relevance. The median of the IPCC curve represents the lowest boundary, the NOAA intermediate high curve is the upper boundary for short-term use until 2070, and the NOAA high curve is the upper boundary for medium and long-term use until 2120[5]. The NOAA extreme curve exemplifies the upper limit of sea level rise in response to an accelerated ice melt scenario[6]. The NOAA extreme scenario cautions that significantly greater sea level rise is possible without a substantial reduction in greenhouse gas emissions.

Figure 2: Sea Level Rise Relative to Mean Sea Level in 2000



[5] Southeast Florida Climate Change Regional Compact (n 4)
[6] NOAA, "2022 Sea level Rise Technical Report."

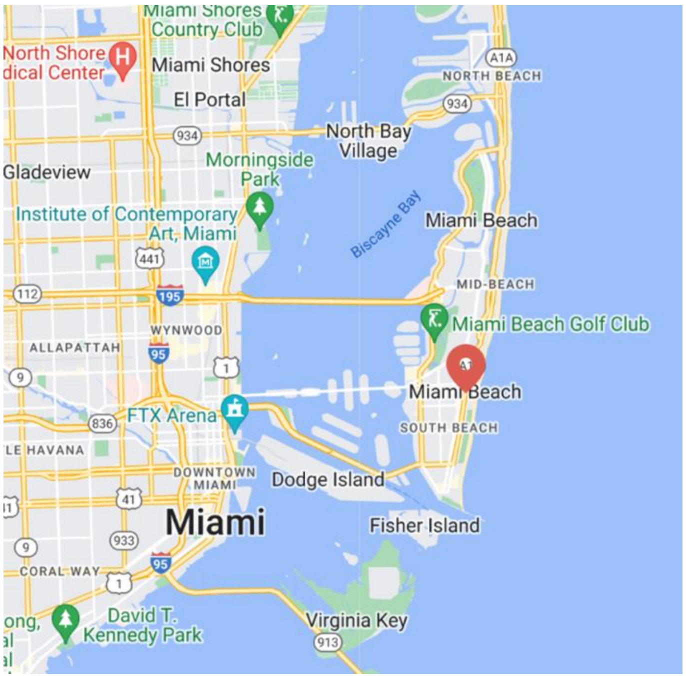
The sea level rose approximately 3.9 inches from 2000 to 2017, grounded on the five-year average of MSL at Key West. By 2040, the sea level is projected to rise 10 to 21 inches, and by 2070, the sea level is anticipated to rise 21 to 54 inches above the 2000 MSL in Key West, Florida. Long-term, sea level rise is forecasted to be between 40 and 136 inches by 2120. Notably, due to ambiguity surrounding future greenhouse gas emissions and reduction, projected sea level rise beyond 2070 has a significant range of uncertainty[7].

The Florida International University GIS Sea level Rise Toolbox provides an interactive sea level rise mapping tool that reflects LiDAR elevation data from Florida's Division of Emergency Management. Figure 3 (A–D) illustrates the impact of a two-foot, four-foot, and six-foot increase in sea level to the Miami and Miami Beach regions[8]. Markedly, in coordination with Southeast Florida Regional Climate Change Compact's predictions, Southeast Florida will face between a 1.75-foot and 4.5-foot rise in sea level by 2070.

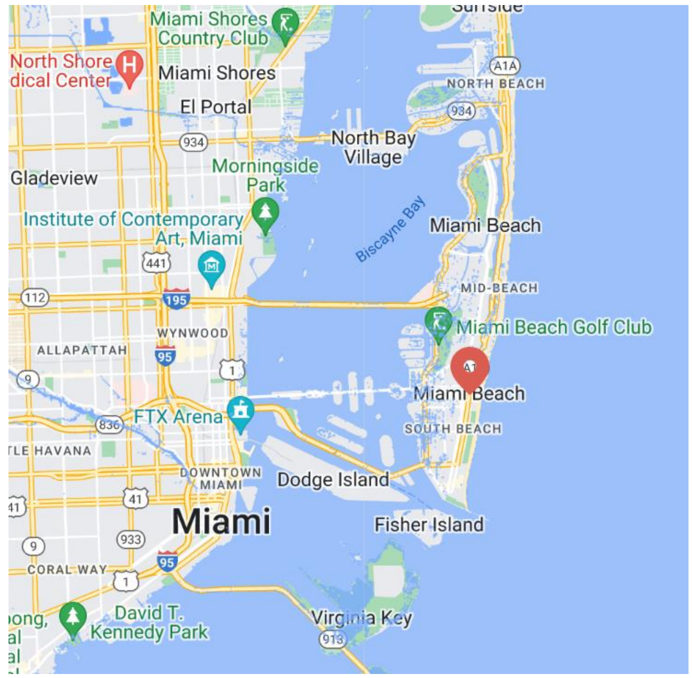
Sea level rise in Southeast Florida causes coastal inundation and erosion, reduced soil infiltration capacity, saltwater intrusion, and socio-economic impacts, including displacement and increased insurance costs. The state of Florida is dedicating $4 billion to mitigate the consequences of sea level rise, including sewage system protection, road elevation, stormwater system improvements, and seawall construction efforts[9]. Miami Beach has devoted $400 million to seawalls, pumps, and raising roads; the city of Fort Lauderdale has developed a $1 billion flood management plan; and Broward County has allocated $250 million toward sewage system protection[10],[11],[12].

[7] Southeast Florida Climate Change Regional Compact (n 4)
[8] Florida International University GIS Center, "Sea Level Rise Toolbox."
[9] SeaLevelRise.org (n 3)
[10] Flechas, Joey. "Miami Beach to Begin New $100 Million Flood Prevention."
[11] Southeast Florida Climate Change Regional Compact, "Regional Impacts of Climate Change and Issues for Stormwater Management."
[12] Gordon, "South Florida faces a variety of environmental issues and is working towards finding solutions for the future."

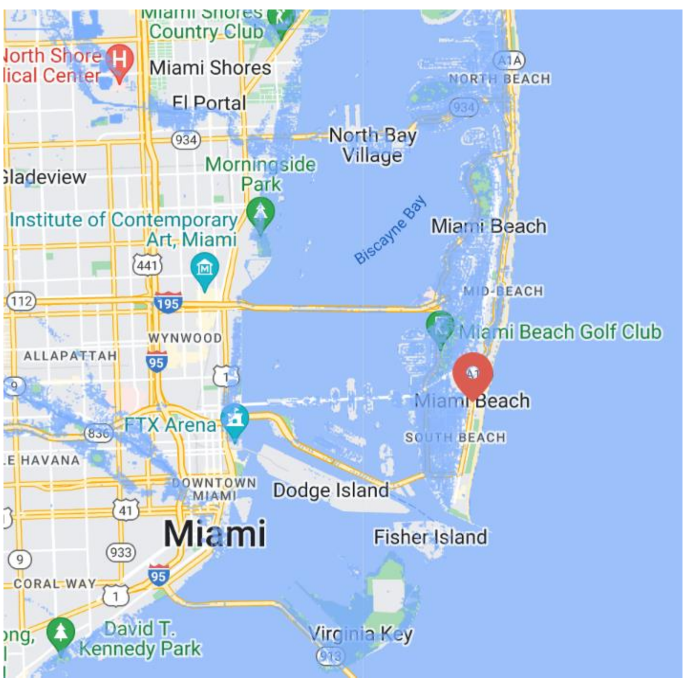
Figure 3: Geographic Impact of Sea level Rise, Miami FL



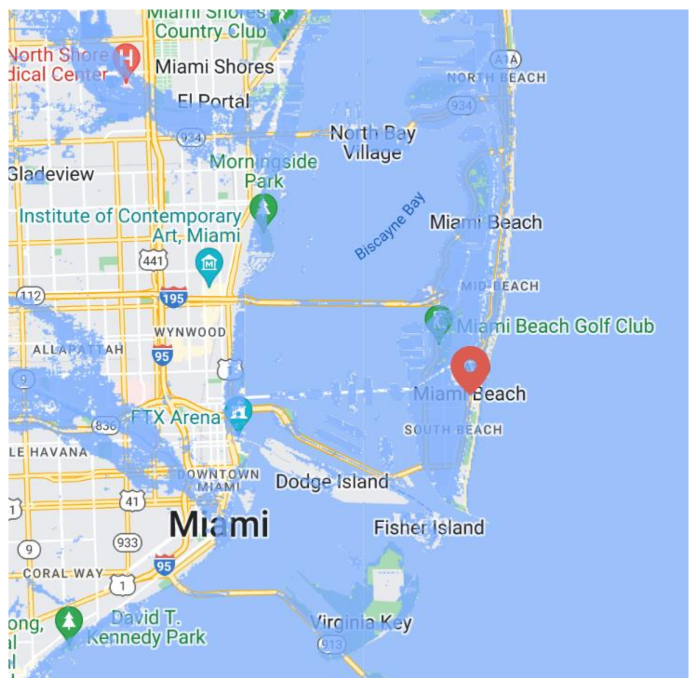
A. Current Map



B. Two-Foot Sea level Rise



C. Four-Foot Sea level Rise



D. Six-Foot Sea level Rise

2.2 Storm Impacts from Sea level Rise

Sea level rise contributes to more frequent flooding and more intense impacts of tropical storms and hurricanes. High-tide flooding, ascribable to high astronomical tides and typical and episodic storms, is occurring at accelerated rates as a result of sea level rise. The national average frequency of high-tide flooding has doubled in the past 30 years, and tidal flooding in Florida has increased by 352% since 2000[13].

Sea level rise amplifies the power of hurricanes by increasing the baseline elevations for waves and storm surges. Sea level rise has a non-linear positive impact on storm surges and increases in sea level result in a 23% relative increase in storm surges[14]. In 55 United States coastal regions, 100-year storm surges are predicted to become 10-year or even more frequent events by 2050[15]. In 2012, sea level rise extended Hurricane Sandy's reach 27 square miles and generated over $2 billion in storm damage in New Jersey and New York; in 2005, Hurricane Katrina would have flooded a 60% smaller area in New Orleans if the storm occurred at 1990 sea levels[16],[17]. In 2017, Hurricane Irma made landfall as a Category 4 hurricane in Monroe County in the Florida Keys and ultimately caused over $50 billion of extensive flooding and damage in Florida[18].

An analysis by the First Street Foundation examined the effects of Hurricane Irma at various sea levels to delineate the influence of sea level rise. Hurricane Irma's eight-foot storm surge impacted over 133,000 homes across Florida. If the storm had occurred at sea levels observed in 1970, 57,000 of those properties would not have been affected by the storm[19]. Conversely, if Hurricane Irma had impacted Florida at the sea level projected by the Army Corps of Engineers (USACE) for 2050 (15 inches above the current sea level), the storm surge would have affected an additional 200,000 homes, reflecting a 150% increase in damage.

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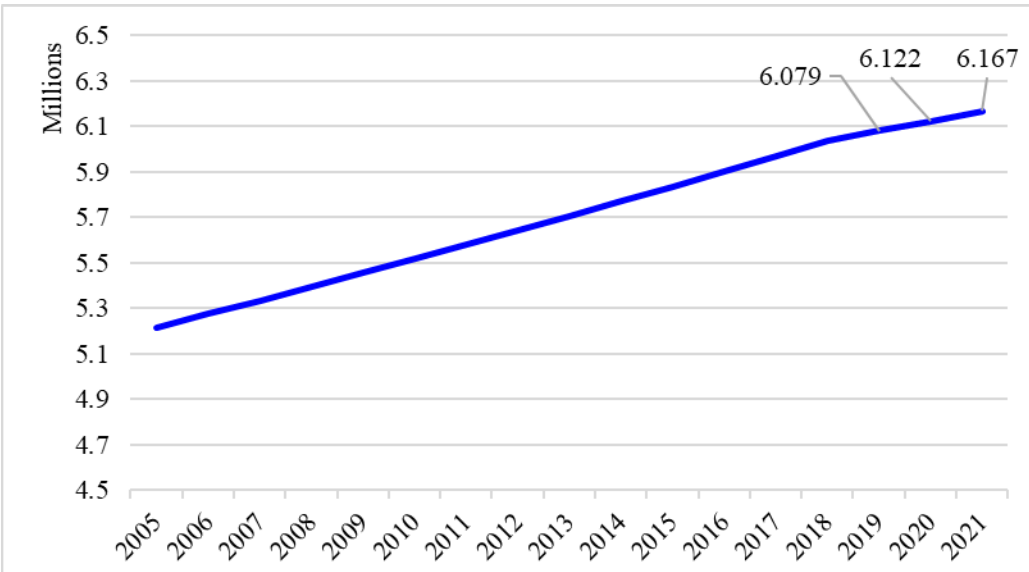
[13] NOAA, "2017 State of U.S. High Tide Flooding with a 2018 Outlook."
[14] Bilskie, et. al., "Dynamics of sea level rise and coastal flooding on a changing landscape."
[15] Tebaldi et. al., "Modelling sea level rise impacts on storm surges along US coasts."
[16] Miller et. al., "A geological perspective on sea level rise and its impacts along the U.S. mid-Atlantic."
[17] Irish et. al., "Simulations of Hurricane Katrina (2005) under sea level and climate conditions for 1900."
[18] NOAA, "September 2017 National Climate Report."
[19] Porter et. al., "Hurricane Irma: Sea Level Rise, Storm Surge and Damage."

2.3 Commercial Growth in Miami-Dade County

Despite palpable sea level rise considerations and flood risks, Miami-Dade County has seen swift commercial growth over the past four years. Throughout the pandemic, businesses relocated to Miami-Dade County from elsewhere at unprecedented rates. The U.S. Census Bureau reported that Miami-Dade County received 107,093 new business applications during 2020, over a 24% increase from those filed in 2019[20]. From 2015 to 2021, Miami experienced 5.67% growth in population, as exhibited in Figure 4[21].

Figure 4: Miami Metro Population, 2005 - 2021



Miami is an emerging technology hub and home to 10 startups valued at $1 billion or more[22]. On the financial side, companies that have relocated to Miami within the past year and a half represent about $2 trillion in assets under management[23]. Several large law firms, real estate companies, and startups have also relocated to the Miami area from the Northeast, Midwest, and West Coast in the past two years. These companies include Starwood Capital Group, Citadel, Blockchain.com, Millennium Management, and Sidley Austin.

[20] United States Census Bureau, "Business Formation Statistics."
[21] MacroTrends, "Miami Population."
[22] Kunthara, "Why Miami Is the Next Hot Tech Hub: 'This Is Not a Retirement Decision."
[23] Acosta, "Miami's Gold Rush: Finance Firms and Crypto Move In, Bringing Strains."

2.4 Sea Level Rise and Residential Real Estate

While much research has been done on the impact of sea level rise on residential real estate, the relationship between an increasing sea level and commercial real estate valuations remains uncharted. Collectively, this opacity of information with the recent influx of firms relocating to the Miami area drives us to examine the correlation between flood zones and historic flooding on both commercial office sales and rents in Miami-Dade County.

One study by the First Street Foundation explored the cost, in market value dollars, lost due to recurrent tidal flooding from sea level rise in Miami. The analysis concluded that residential properties projected to undergo tidal flooding by 2032 have lost $3.08 of value per square foot per year since 2005, and properties near roads that are projected to be inundated with tidal flooding by 2032 have lost $3.71 of value per square foot per year since 2005. Ultimately, the total lost market value from sea level rise impacts between 2005 and 2016 for homes in Miami-Dade County exceeds $465 million[24].

Benjamin Keys and Philip Mulder investigated changes in the capitalization of sea level rise risk in residential housing and mortgage markets in the paper “Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise.” They observed that while sales volumes in high sea level risk areas declined 16–20% compared to those in lower risk areas between 2013–2018, relative prices in at-risk markets only began to decline 5% from their apex between 2018–2020[25]. This “lead-lag” relationship between residential sales volumes and prices reflected mounting buyer apprehension regarding sea level rise that was not mirrored by seller concern. Further, the analysis found that mortgage lenders did not demonstrate sensitivity to sea level rise risk, as they did not enhance credit standards for high-risk areas, and all-cash and mortgage-financed purchases have contracted similarly.

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[24] McAlpine and Porter, “Estimating Recent Local Impacts of Sea Level Rise on Current Real-Estate Losses: A Housing Market Case Study in Miami-Dade, Florida.”

[25] Keys and Mulder, “Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise.”

3 Data

The analysis relies on three main data sources: office sales prices and characteristics from Real Capital Analytics (RCA), office rent data from CBRE, and data from the First Street Foundation on flood zone information and risk to measure sea level rise. This section describes how these data are used to construct the sample and variables used to conduct the commercial office sales and rent regressions.

3.1 Real Capital Analytics Data

RCA assembles data and analytics for commercial real estate investing and transactions; it has recorded over $40 trillion of commercial property transaction sales associated with over 200,000 investor and lender profiles[26]. The RCA data outline several geographical, transactional, and physical characteristics for each deal identification. Geographical information includes address, longitude and latitude, and submarket variables, while the physical building characteristics comprise square footage, year built, year renovated, total land area, walk and transit scores, tenancy type, number of floors, and number of parking spaces. The transaction variables consist of transaction type, property sale date, buyer objective and profile, total price and price per square foot, capitalization rate, quality score, and investment type (core/stabilized or value-add).

The RCA data contain 9,792 entries of commercial office sale records from 2000 through 2020 in Florida[27], of which 1,864 are sales within the area of focus for this research: Miami-Dade County. To further narrow the scope of records to 1,268 unique deals, we only consider conventional sales and disregard construction, debtor or trustee sales, publicization, privatization, public merger, and refinance transaction types. To achieve an accurate representation of commercial office buildings, we eliminate all remaining records of properties under 20,000 square feet for a remainder of 881 observations.

[26] MSCI, “Why Real Capital Analytics?”
[27] RCA Commercial Office Sales Data, 2000-2020

3.2 CBRE Data

CBRE provides capital market research, including historic rent data across real estate asset classes[28]. The CBRE data outlines identification information on observation identifier, latitude, and longitude. For each record, the data delineates market, time period (year and quarter), gross rent, and net rent. The CBRE data contains 295,423 records in Florida, tracking properties from the 1988 quarter one through 2020 quarter four[29]. As with the RCA data in Section 3.1, we only consider observations in Miami for this analysis, resulting in 89,364 potential rent observations associated with 677 tracked properties from 1988–2020. Because the rent for each property is tracked over time, the influence of building quality is not a factor in our analysis.

3.3 First Street Foundation Data

The First Street Foundation is a non-profit research and technology organization that quantifies climate risk. The First Street data outlines flood risk elements including flood factor, if the observed property underwent historic events one (Hurricane Katrina, 2005) and two (Hurricane Irma, 2017), and the maximum flood depth associated with each historic event. The data also includes the Federal Emergency Management Agency (FEMA) zone as a dummy variable with the input of one if the observation is within the 100-year flood zone and zero otherwise. The First Street data includes 340,677 observations in the Miami-Dade area[30].

The flood factor calculation provides a comprehensive assessment of a particular property's 30-year risk and incorporates historical flooding events to quantify risk. The model integrates all major flood types, including rainfall (pluvial), riverine flooding (fluvial), and coastal surge flooding, and interprets future environmental factors by integrating global climate model projections to forecast flood risk[31]. The predominant national standard for flood risk, FEMA Special Flood Hazard Areas (SFHA), calculates risk by understanding exposure to a 1-in-100 or 1-in-500-year flood event. Because the First Street Flood Factor quantifies property-specific flood risk and takes future anticipated risk into consideration, we elect to use the metric, rather

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[28] CBRE, "Insights & Research."
[29] CBRE Commercial Office Rent Data, 1988.1-2020.4
[30] First Street Foundation, Miami-Dade County Flood Factor and Historic Flood Data, 2022
[31] First Street Foundation, "Flood Methodology Addendum."

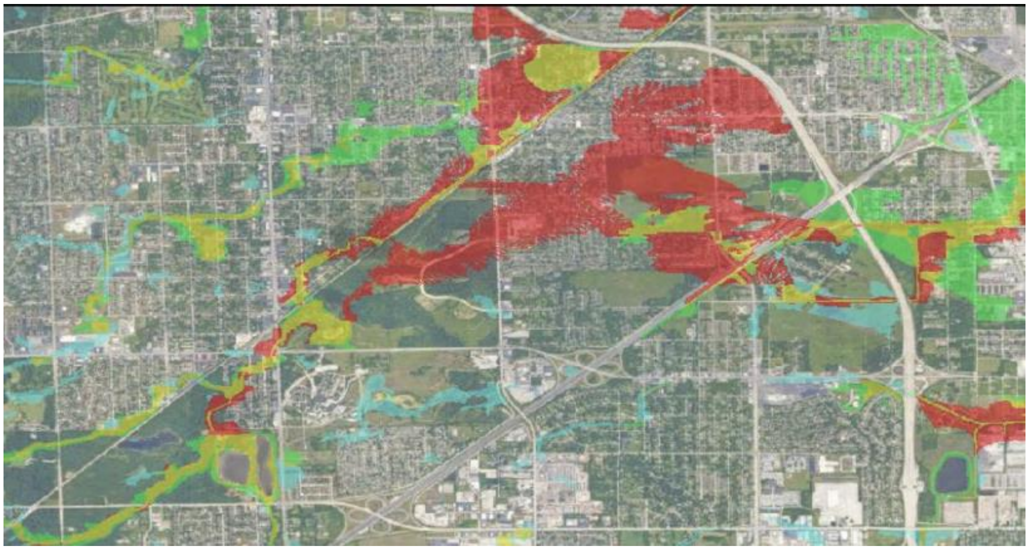
than FEMA zones, for this analysis to gain a more nuanced view of flood risk in Miami-Dade County. Compared to the same-probability FEMA SFHA zones, the First Street Flood Model 1-in-100 hazard layer captures about triple the flood risk[32]. Figure 5 exemplifies the extended prediction of flooding by the First Street Foundation Model when compared to the FEMA 100-year Flood Zone in a southwest Chicago suburb[33].

The First Street model forecasts costal flood risk by referencing NOAA's tide gauge to analyze storm surge, tidal variation, and long-term sea level rise. The model processes synthetic aperture radar (SAR) data from costal events to recreate historic storm flooding and constructs total water levels based on MSL over time surge frequencies[34]. Notably, hurricanes impact flood records disproportionately and produce acute effects on surge distributions. The model statistically quantifies anticipated flood risks and depths after the completion and validation of the hazard layers. The model inputs all historic flood depths available and utilizes a linear interpolation for unmodeled scenarios at various flood return periods in the current year and in 30 years to limit residual errors.

First Street then interprets these statistics to generate a streamlined flood risk score from 1–10, as illustrated in Figure 6, which reflects the probability and severity of predicted flooding for a particular property. This score is derived from the aggregation of annualized expectations of flooding from the current year to 30 years from now. The scores are then dispersed across the distribution of all properties nationally and clustered relative to values of the same risk metric[35].

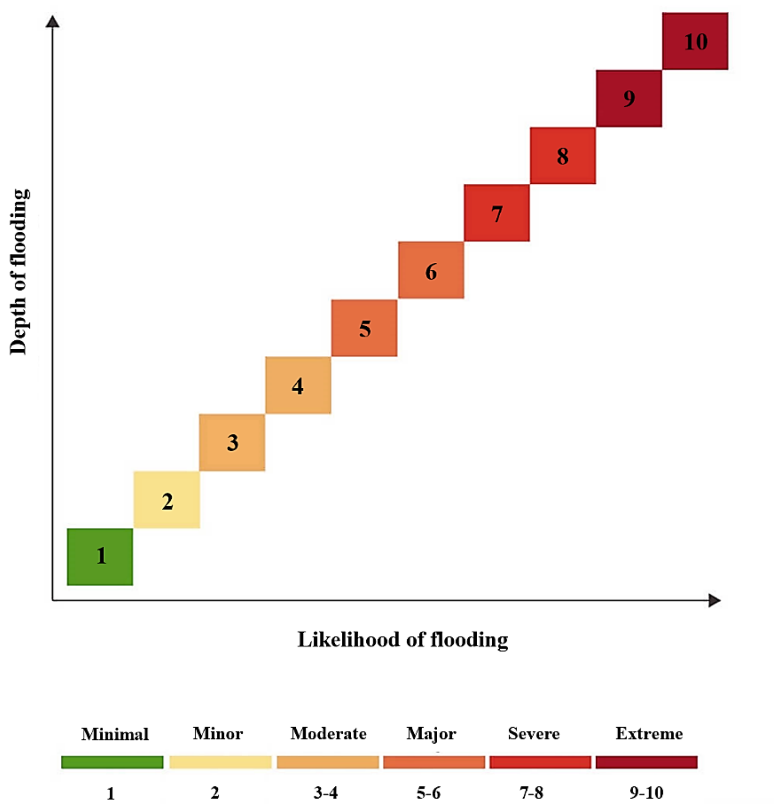
[32] First Street Foundation, "Why A Property's FEMA Zone Does NOT Impact It's Flood Factor."
[33] First Street Foundation, "First Street Foundation Flood Model (FSF-FM) Technical Documentation."
[34] Ibid.
[35] First Street Foundation (n 30)

Figure 5: First Street Foundation (FSF) and FEMA 100-year Flood



Red: Overprediction in FSF Model - Fluvial, Blue: Overprediction in FSF Model – Pluvial, Green: Underprediction in FSF Model, Yellow: Both Models Show Flooding

Figure 6: First Street Flood Factor Scale



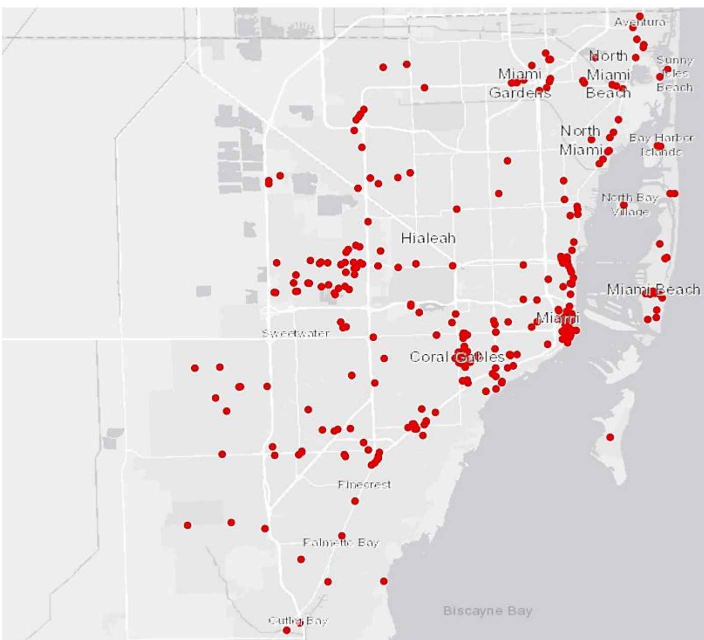
4 Methodology: Commercial Office Sales

To investigate the connection among sea level rise and commercial office sales, we analyze the relationship between flood zones and historic flooding impact with commercial office pricing over the past twenty years, taking into consideration two major flood events during this period.

4.1 Real Capital Analytics and First Street Foundation Data

To establish a complete set of observations to prepare for the regression analysis, we merge the RCA and First Street databases for Miami-Dade County. We first identify the First Street data which represent the centroid of an individual property's longitude and latitude and compute a polygon circle with 100-foot radius (diameter=200') buffer around each point. We then map the centroid of the RCA properties' longitude and latitude to determine if the property falls within the 100-foot buffer. Each record has a unique deal identification and can represent either single sale or repeat sales. Of the 881 RCA observations, 562 contained at least one First Street record and overall, 329 properties contained at least one First Street record. Figure 7 illustrates the amalgamation process utilizing ARCGIS PRO to extract the RCA property observations. To evaluate the relationship between price and other variables including flood risk we consider all unique deal identifications including properties with singular and repeat sales.

Figure 7: RCA and First Street Foundation Merged Data Map



4.2 Variable Analysis

Prior to running the regressions, we analyze the commercial office sales database to examine missing inputs, extreme outliers, and or impractical values.

As mentioned in Section 3.3, The First Street Foundation data includes variables surrounding flood risk, historic flood level, and flood zone for each property. To consolidate the First Street data, we calculate the Maximum Flood Depth (Max_Flood_Depth) occurring in either Historic Event one (Hist_1) or Historic Event two (Hist_2) as a singular variable. We also consider the variable Maximum Flood Factor (Max_Flood_Factor), or the indicator of a property's thirty-year risk of flooding ranging from 1 to 10. For this analysis, we disregard variables of Historic Event one and two (Hist_1, Hist_2), Number of Historic Events (Events_Total), and FEMA Zone (FEMA_Zone).

The RCA data includes variables surrounding individual property locations, physical characteristics, and transaction information. To distill the data for the regression analyses, we begin by eliminating two erroneous observations with total Square Feet (SF_Building) of zero for a remaining total of 560 commercial office sales observations. Next, we calculate the dependent variable of the natural logarithm of Price per Square Foot (Ln_Price_PSF) of each observation by dividing variables Price (Price_Amt) by Square Feet. We employ the natural logarithm to transform the data to be more normally distributed and to ensure a linear relationship between the independent and dependent variables. To calculate Age (Age_Building), we first replace six Year Built (Year_Built) observations formerly 'NA' with the average Year Built of 1978, and subsequently subtract the variable Year Built from the current year, 2022. Regarding variable Number of Floors (Floors_Building), we replace 74 unfeasible entries of either zero or one floors with the value of two floors. We utilize 21 dummy variables to consider the Year Sold (Year_Sold_Dummy) values of years 2000 through 2020, employing one if the variable matches the observation year sold and zero if not. We also consider RCA variables of Square Feet and Walk Score (Score_Walk) in the regression analysis, and disregard the remaining variables outlined in Section 3.1

Figure 8 identifies key variables we examine in this study, consisting of the natural logarithm of Sales Price per Square Foot, Building Age (Age_Building), Year Sold dummy variables 2000-2020 (Year_Sold_Dummy), Square Feet (SF_Building), Walk Score (Score_Walk), Number of Floors (Floors_Building), Maximum Flood Factor (Max_Flood_Factor), and Maximum Flood Depth (Max_Flood_Depth).

Figure 8: Index for Commercial Office Sales Regression Variables

Label	Description	Unit	Definition
Ln_Price_PSF	Natural Log of Sales Price per Square Foot	#	The natural logarithm of the sales price per square foot per unique deal identification
Age_Building	Building Age	#	The current building age, as of 2022
Floors_Building	Number of Floors	#	The number of floors per property
Year_Sold_Dummy	Year Sold Dummy (2000 - 2020)	1 = Year 0 = Not Year	Dummy variable indicating the year the conventional transaction sale occurred from years 2000 through 2020
SF_Building	Square Feet	SF	The total square footage of the building
Score_Walk	Walk Score	#	The metric rating level of convenience on a scale of 0-100
Max_Flood_Depth	Maximum Flood Depth	Centimeters	The maximum flood depth among the First Street observations
Max_Flood_Factor	Maximum Flood Factor	#	The maximum flood factor when more than one First Street observation is within the 100-foot RCA buffer on a scale of 1-10

4.3 Regression Approach

We perform seven hedonic regression analyses on the commercial office sales data containing 560 unique Deal Identifications[36]. In all regressions the natural logarithm of Sales Price per Square Foot (Ln_Price_PSF) is the dependent variable, and Building Age (Age_Building), Year Sold (variables 2000 – 2020), Square Feet (SF_Building), Walk Score (Score_Walk), Number of Floors (Floors_Building), Maximum Flood Factor (Max_Flood_Factor), and Maximum Flood

[36] Sopranzetti, "Hedonic Regression Models."

Depth (Max_Flood_Depth) are the independent variables. To perform the analyses, we exclude an exhaustive set of dummy variables: Year Sold 2020 to override a standard error message.

Commercial office sales Regression I considers all data for a total of 560 observations. This full sample model tests whether on average across 20 years if sales price levels are impacted by flood risk and history. To examine if trends within the sample are different, we segregate the total sales data by the First Street Foundation indicated Maximum Flood Depth (Max_Flood_Depth) and Maximum Flood Factor (Max_Flood_Factor).

Commercial office sales Regression II evaluates observations with a Maximum Flood Depth (Max_Flood_Depth) of zero centimeters, comprising 493 observations. Regression III contemplates only the unique office sales with the highest identified Maximum Flood Depth (Max_Flood_Depth) of over zero centimeters. Of these 67 observations, 63 properties experienced a major flood event in 2005, four in 2017, and three in both 2005 and 2017 that triggered structural flood impact of an average of 29.75 centimeters. Regression III omits Year Sold 2009 as no properties with a Maximum Flood Depth (Max_Flood_Depth) over zero centimeters were sold during this year.

We also analyze a pair of regressions split by the Maximum Flood Factor (Max_Flood_Factor) scale from 1 (lowest flood risk factor) to 10 (greatest flood risk factor). Regressions IV and V evaluate Maximum Flood Factors of 1-5 and 6-10 comprising 274 and 286 observations respectively. Neither regression pairs II and III nor IV and V include coefficients Maximum Flood Depth (Max_Flood_Depth) and Maximum Flood Factor (Max_Flood_Factor) in the regression results.

Lastly, Regressions VI and VII consider only high risk (Max_Flood_Factor 6-10) properties and partitions this sample of 286 observations by properties that have experienced historic flooding (Max_Flood_Depth greater than zero) comprising 67 properties, or not, totaling 219 properties. As in Regression III, we omit Year Sold 2009. This allows us to directly evaluate the impact of actual past flooding on properties in high-risk zones, and effectually analyze if either future risk or past exposure has an influence on pricing trends.

5 Commercial Office Sales Results

We first evaluate the hedonic regression results of the full sample in Regression I. Then, we compare Regressions II and III to regard the influence of historic flood amount, Regressions IV and V to analyze the impact of flood risk, and Regressions VI and VII to once again consider the impact of historic flood amount on pricing trends for high-risk properties only.

To calculate the graphs of predicted rents in Sections 5.2, 5.3, and 5.4, we take the product of the average of variables Age_Building (44.1), Floors_Building (6.49), Max_Flood_Depth (7.28), Max_Flood_Factor (4.85), Score_Walk (74.44), and SF_Building (95,624.19) by the coefficients for each variable per regression. For each year, we then sum this amount, which is consistent for all years, with the year variable (Time_Period_Dummy) coefficient, and constant per regression before exponentiating this output to produce an average predicted rent value per year.

Notably, all sales regression trends reveal a peak in prices in 2006 followed by a sharp decline due to the financial crisis. A second peak is perceptible in 2017, this time with Regressions II, IV, and VI stabilizing following the apex. However, price trends for Regressions III, V, and VII representing the high-risk, flood history properties ultimately wane. Thus, is plausible that increasing climate change awareness is altering valuations for high-risk properties.

5.1 Full Sample Regression Analysis

We evaluate the full commercial office sales sample in Regression I, which includes 560 properties in Miami-Dade County. The regression results, displayed in Figure 9, reveal that both Maximum Flood Depth (Max_Flood_Depth), coefficient 0.001593, and Maximum Flood Factor (Max_Flood_Factor), coefficient 0.01679, have a positive influence on sales price per square foot (Ln_Price_PSF). The walk score (Score_Walk) with coefficient 0.008 also has a positive influence on price while building age (Age_Building) with coefficient -0.005 has a negative influence. Collectively, these findings reveal that location is correlated to price, and properties in premium locations, often closer to bodies of water, along areas that are expected to be heavily impacted by sea level rise experience more flooding.

Figure 9: Commercial Office Sales Regression I: Full Sample

Regression I				
Dependent Variable:		Ln_Price_PSF		
Regression Statistics: Regression I for Ln_Price_PSF (26 variables, n=560)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.324	0.291	0.560	0.666
Coefficient Estimates: Ln_Price_PSF (26 variables, n=560)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	4.957	0.170	29.242	0.000
_2000	-1.032	0.221	-4.660	0.000
_2001	-0.995	0.199	-4.988	0.000
_2002	-0.748	0.199	-3.754	0.000
_2003	-0.837	0.188	-4.455	0.000
_2004	-0.643	0.179	-3.589	0.000
_2005	-0.402	0.175	-2.292	0.022
_2006	-0.171	0.178	-0.962	0.337
_2007	-0.134	0.184	-0.732	0.464
_2008	-0.203	0.210	-0.968	0.333
_2009	-0.555	0.213	-2.602	0.010
_2010	-0.629	0.210	-2.998	0.003
_2011	-0.582	0.204	-2.854	0.004
_2012	-0.674	0.184	-3.658	0.000
_2013	-0.482	0.182	-2.642	0.008
_2014	-0.223	0.174	-1.283	0.200
_2015	-0.150	0.172	-0.874	0.383
_2016	0.078	0.184	0.427	0.670
_2017	0.092	0.179	0.514	0.607
_2018	0.016	0.190	0.086	0.931
_2019	-0.054	0.181	-0.302	0.763
Age_Building	-0.005	0.001	-3.669	0.000
Floors_Building	-0.003240	0.005410	-0.599	0.549
Max_Flood_Deptl	0.001503	0.001095	1.373	0.170
Max_Flood_Factc	0.016794	0.008400	1.999	0.046
Score_Walk	0.008	0.001260	5.966	0.000
SF_Building	3.940E-07	3.313E-07	1.189	0.235
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	26.000	80.232	3.086	9.826
Residual	533.000	167.390	0.314	
Total	**559.000**	**247.622**		

5.2 Regression Analysis by Historic Flooding

We bifurcate commercial office sales Regressions II and III by historic flood amount. Regression II analyzes 493 properties that did not experience flooding during the 2005 and or 2017 hurricanes, and Regression III analyzes the 67 properties of the data that did experience flooding greater than zero centimeters during either or both events.

Figure 10 below outlines these regression results. Variability in the dependent variable is better explained by Regression III than Regression II, with R-Squared values of 0.598 and 0.298 respectively. In both regressions, building age (Age_Building) has a negative impact on price. Properties with historic flooding have a greater average price than those without flood exposure, evidenced in Figure 11. As revealed in Figure 12, the overall sample of properties in Regression III are clustered near the water, perhaps in areas which demand a price premium when compared to the Regression II sample. This premise is bolstered by the walk score (Score_Walk); Regression III and Regression II reveal coefficients of 0.018 and 0.006 respectively.

Figure 10: Commercial Office Sales Regressions II and III: Historic Flood Amount

Regression II				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression II for Ln_Price_PSF (24 variables, n=493)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.298	0.262	0.555	0.647
Coefficient Estimates: Ln_Price_PSF (24 variables, n=493)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	5.042	0.182	27.709	0.000
_2000	-1.077	0.244	-4.405	0.000
_2001	-0.942	0.216	-4.354	0.000
_2002	-0.806	0.219	-3.672	0.000
_2003	-0.823	0.205	-4.016	0.000
_2004	-0.632	0.198	-3.188	0.002
_2005	-0.425	0.194	-2.194	0.029
_2006	-0.155	0.196	-0.792	0.429
_2007	-0.143	0.205	-0.700	0.485
_2008	-0.188	0.225	-0.837	0.403
_2009	-0.563	0.226	-2.492	0.013
_2010	-0.534	0.225	-2.375	0.018
_2011	-0.611	0.219	-2.790	0.005
_2012	-0.625	0.204	-3.061	0.002
_2013	-0.599	0.202	-2.969	0.003
_2014	-0.201	0.192	-1.045	0.297
_2015	-0.163	0.189	-0.865	0.387
_2016	0.002	0.203	0.010	0.992
_2017	0.093	0.198	0.469	0.639
_2018	0.005	0.207	0.022	0.983
_2019	-0.004	0.199	-0.023	0.982
Age_Building	-0.005	0.001	-3.401	0.001
Floors_Building	0.004481	0.006721	0.667	0.505
Score_Walk	0.006996	0.001311	5.336	0.000
SF_Building	0.000000	0.000000	0.195	0.845
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	24.000	61.364	2.557	8.287
Residual	468.000	144.392	0.309	
Total	**492.000**	**205.756**		

Regression III				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression III for Ln_Price_PSF (23 variables, n=67)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.598	0.383	0.570	0.726
Coefficient Estimates: Ln_Price_PSF (23 variables, n=67)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	4.244	0.795	5.335	0.000
_2000	-0.572	0.608	-0.941	0.352
_2001	-1.102	0.584	-1.887	0.066
_2002	0.077	0.566	0.135	0.893
_2003	-0.281	0.673	-0.418	0.678
_2004	-0.354	0.482	-0.735	0.466
_2005	0.022	0.470	0.048	0.962
_2006	0.085	0.482	0.177	0.860
_2007	0.238	0.457	0.520	0.606
_2008	0.031	0.665	0.047	0.963
_2009	0.000	0.000	0.000	0.000
_2010	-1.942	0.694	-2.799	0.008
_2011	0.238	0.694	0.343	0.733
_2012	-0.542	0.541	-1.002	0.322
_2013	0.519	0.475	1.091	0.281
_2014	-0.107	0.436	-0.246	0.807
_2015	0.538	0.613	0.878	0.385
_2016	0.724	0.498	1.453	0.154
_2017	0.315	0.449	0.702	0.486
_2018	0.807	0.603	1.339	0.188
_2019	-0.022	0.477	-0.046	0.963
Age_Building	-0.007	0.006	-1.128	0.266
Floors_Building	-0.024115	0.012346	-1.953	0.057
Score_Walk	0.018351	0.007644	2.401	0.021
SF_Building	0.000001	0.000001	0.922	0.362
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	23.000	20.786	0.904	2.780
Residual	43.000	13.976	0.325	
Total	**66.000**	**34.762**		

Figure 11: Commercial Office Sales Regressions II and III Comparison

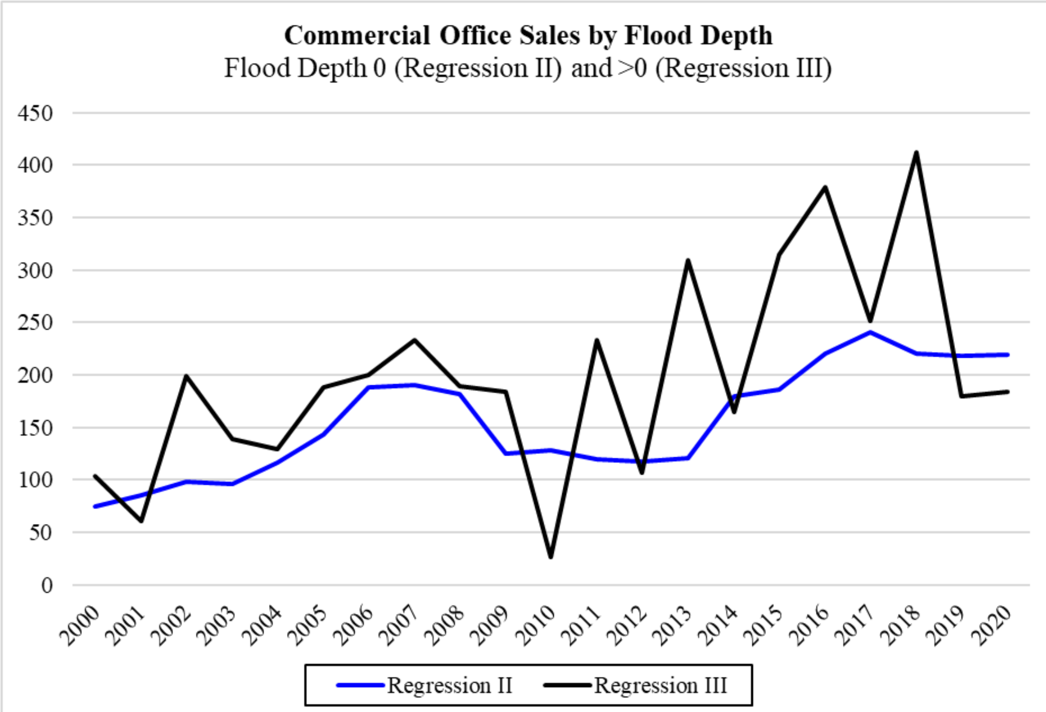
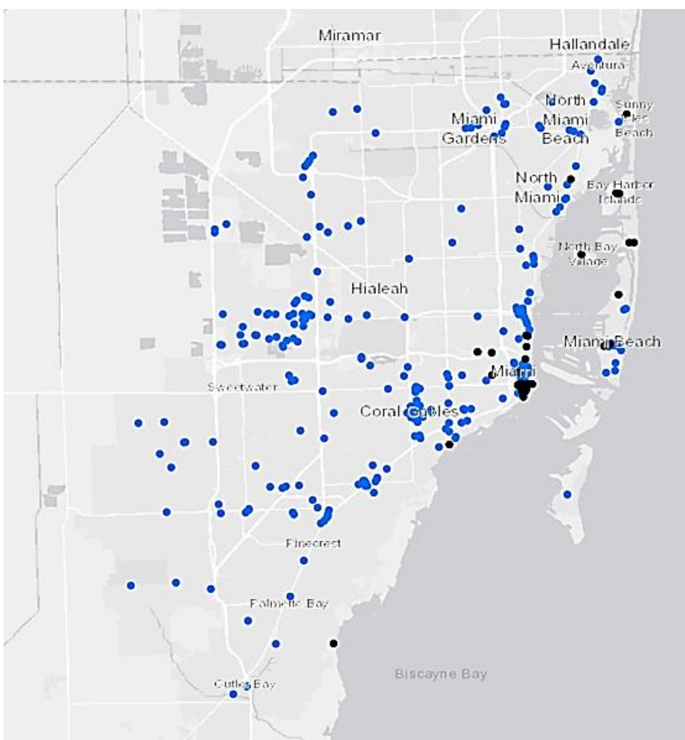


Figure 12: Commercial Office Sales Regressions II and III Map



5.3 Regression Analysis by Flood Risk

In Regressions IV and V, we consider future flood risk and divide the full sample by observations with Flood Factors between 1-5, totaling 274 properties, and Flood Factors between 610, comprising 286 properties.

Figure 13 displays the regression results, and Figure 14 graphically compares the results of these regressions. Overall, the results reveal similar findings to the regressions in Section 5.2. Using the calculation method outlined in Section 5, the sample with the lower flood risk, Regression IV, has a lower average predicted sales price per square foot of 142.03 than Regression V with an average price per square foot of 172.39. The R-Squared values for both regressions are very similar; Regression V has a R-Squared value of 0.355 and Regression IV has a R-Squared value of 0.344. As in Section 5.2, the properties in Regression V have a higher walk score (Score_Walk) than those in Regression IV, with walk scores of 0.010 and 0.005 respectively, and the samples are segregated in Figure 15, alluding that premium locations demand higher prices.

Figure 13: Commercial Office Sales Regressions IV and V: Flood Risk

Regression IV				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression IV for Ln_Price_PSF (24 variables, n=274)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.334	0.270	0.508	0.595
Coefficient Estimates: Ln_Price_PSF (24 variables, n=274)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	5.071	0.212	23.971	0.000
_2000	-1.124	0.275	-4.090	0.000
_2001	-0.827	0.244	-3.394	0.001
_2002	-0.666	0.255	-2.608	0.010
_2003	-0.687	0.249	-2.760	0.006
_2004	-0.579	0.236	-2.460	0.015
_2005	-0.257	0.223	-1.152	0.251
_2006	-0.084	0.237	-0.356	0.723
_2007	-0.078	0.238	-0.326	0.744
_2008	-0.454	0.367	-1.235	0.218
_2009	-0.417	0.268	-1.554	0.122
_2010	-0.292	0.274	-1.067	0.287
_2011	-0.626	0.274	-2.281	0.023
_2012	-0.333	0.241	-1.377	0.170
_2013	-0.593	0.237	-2.500	0.013
_2014	0.051	0.224	0.226	0.821
_2015	-0.010	0.221	-0.045	0.964
_2016	0.049	0.235	0.209	0.835
_2017	0.122	0.231	0.530	0.597
_2018	0.124	0.243	0.511	0.610
_2019	-0.007	0.231	-0.028	0.977
Age_Building	-0.005	0.002	-2.949	0.003
Floors_Building	-0.012856	0.010961	-1.173	0.242
Score_Walk	0.005614	0.001624	3.456	0.001
SF_Building	0.000000	0.000000	1.015	0.311
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	24.000	32.245	1.344	5.202
Residual	249.000	64.310	0.258	
Total	**273.000**	**96.555**		

Regression V				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression V for Ln_Price_PSF (24 variables, n=286)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.355	0.296	0.599	0.714
Coefficient Estimates: Ln_Price_PSF (24 variables, n=286)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	4.940	0.265	18.635	0.000
_2000	-0.807	0.356	-2.265	0.024
_2001	-1.202	0.325	-3.698	0.000
_2002	-0.778	0.308	-2.527	0.012
_2003	-0.945	0.280	-3.376	0.001
_2004	-0.719	0.267	-2.691	0.008
_2005	-0.483	0.272	-1.778	0.077
_2006	-0.274	0.262	-1.044	0.297
_2007	-0.134	0.278	-0.482	0.630
_2008	-0.185	0.286	-0.647	0.518
_2009	-0.674	0.335	-2.011	0.045
_2010	-0.935	0.315	-2.971	0.003
_2011	-0.560	0.298	-1.881	0.061
_2012	-0.953	0.277	-3.441	0.001
_2013	-0.378	0.275	-1.375	0.170
_2014	-0.471	0.264	-1.788	0.075
_2015	-0.286	0.262	-1.091	0.276
_2016	0.149	0.282	0.528	0.598
_2017	0.085	0.270	0.316	0.752
_2018	-0.035	0.292	-0.120	0.905
_2019	-0.126	0.274	-0.459	0.646
Age_Building	-0.004	0.002	-2.174	0.031
Floors_Building	-0.002791	0.007154	-0.390	0.697
Score_Walk	0.010337	0.002045	5.055	0.000
SF_Building	0.000000	0.000000	1.020	0.309
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	24.000	51.625	2.151	5.995
Residual	261.000	93.652	0.359	
Total	**285.000**	**145.277**		

Figure 14: Commercial Office Sales Regressions IV and V Comparison

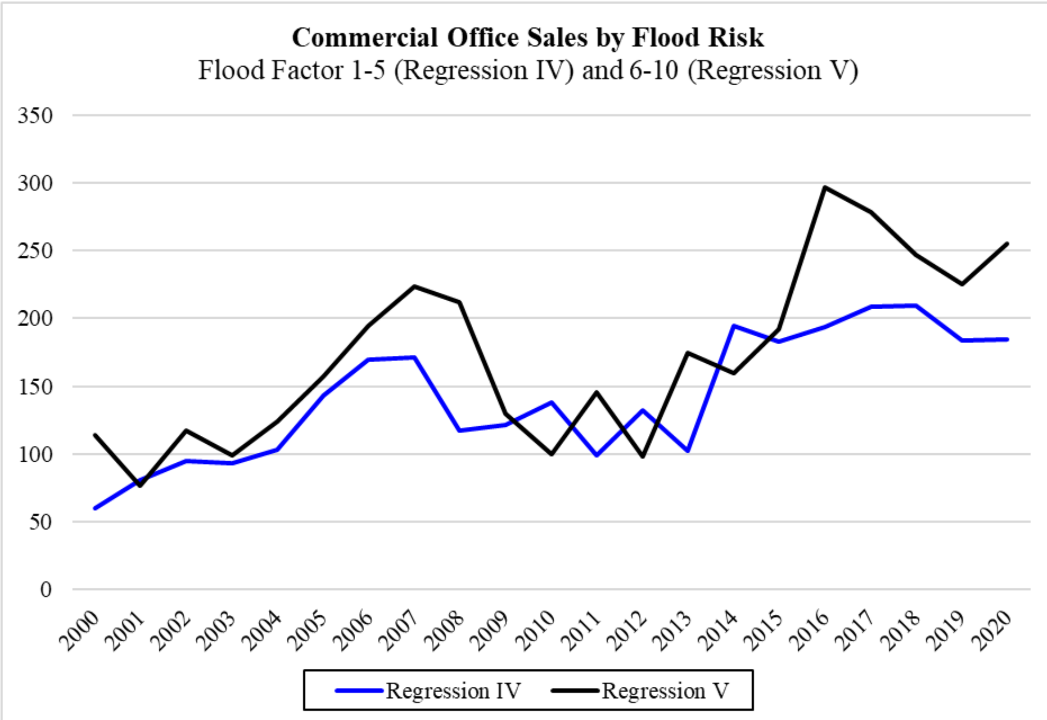
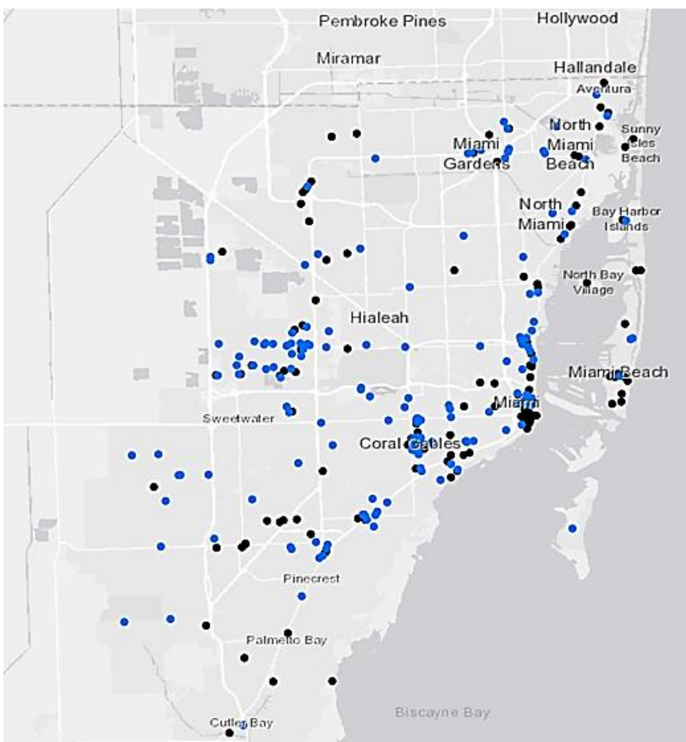


Figure 15: Commercial Office Sales Regressions IV and V Map



5.4 Regression Analysis by Historic Flooding, High-Risk

In Regressions VI and VII, we evaluate only the high-risk properties within the sample. We split the properties with Flood Factors of 6-10 into subgroups that have not and that have experienced flooding comprising 219 and 67 properties respectively.

As revealed by the regression results in Figure 16 and comparison graph in Figure 17, partitioning by historic flood amount within high-risk areas displays a contrasting result to the regressions in Section 5.2. Here, the predicted sales prices for properties that have experienced greater than zero centimeters of flooding in either or both 2005 and 2017 events are lower than those that have not experienced flooding. The average price we calculated for Figure 17 is 188.155 for Regression VI, but only 138.03 for Regression VII. The walk scores for both samples are similar with coefficients of 0.009 for Regression VI and 0.018 for Regression VII. This indicates that within more comparable micro-locations as shown in Figure 18, flood history has a significant impact on commercial office sales prices throughout the past 20 years.

Figure 16: Commercial Office Sales Regressions VI and VII: Historic Flood Amount, High-Risk

Regression VI				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression VI for Ln_Price_PSF (24 variables, n=219)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.331	0.248	0.607	0.700
Coefficient Estimates: Ln_Price_PSF (24 variables, n=219)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	5.070	0.327	15.521	0.000
_2000	-0.778	0.466	-1.668	0.097
_2001	-1.089	0.411	-2.651	0.009
_2002	-0.894	0.397	-2.253	0.025
_2003	-0.981	0.352	-2.790	0.006
_2004	-0.729	0.348	-2.097	0.037
_2005	-0.587	0.353	-1.665	0.097
_2006	-0.306	0.339	-0.903	0.368
_2007	-0.176	0.367	-0.480	0.631
_2008	-0.207	0.357	-0.581	0.562
_2009	-0.718	0.393	-1.828	0.069
_2010	-0.788	0.383	-2.060	0.041
_2011	-0.647	0.366	-1.767	0.079
_2012	-0.972	0.357	-2.720	0.007
_2013	-0.610	0.357	-1.709	0.089
_2014	-0.543	0.342	-1.586	0.114
_2015	-0.362	0.334	-1.082	0.281
_2016	0.019	0.364	0.052	0.959
_2017	0.061	0.351	0.172	0.863
_2018	-0.083	0.367	-0.226	0.821
_2019	-0.080	0.357	-0.225	0.822
Age_Building	-0.005	0.002	-1.978	0.049
Floors_Building	0.012432	0.012055	1.031	0.304
Score_Walk	0.008988	0.002305	3.900	0.000
SF_Building	-0.000001	0.000001	-0.684	0.495
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	24.000	35.316	1.472	3.993
Residual	194.000	71.486	0.368	
Total	**218.000**	**106.802**		

Regression VII				
Dependent Variable:	Ln_Price_PSF			
Regression Statistics: Regression VII for Ln_Price_PSF (23 variables, n=67)				
	R-Squared	**Adj.R-Sqr.**	**Std.Err.Reg.**	**Std.Dep.Var.**
	0.598	0.383	0.570	0.726
Coefficient Estimates: Ln_Price_PSF (23 variables, n=67)				
Variable	**Coefficient**	**Std.Err.**	**t-Statistic**	**P-value**
Constant	4.244	0.795	5.335	0.000
_2000	-0.572	0.608	-0.941	0.352
_2001	-1.102	0.584	-1.887	0.066
_2002	0.077	0.566	0.135	0.893
_2003	-0.281	0.673	-0.418	0.678
_2004	-0.354	0.482	-0.735	0.466
_2005	0.022	0.470	0.048	0.962
_2006	0.085	0.482	0.177	0.860
_2007	0.238	0.457	0.520	0.606
_2008	0.031	0.665	0.047	0.963
_2009	0.000	0.000	0.000	0.000
_2010	-1.942	0.694	-2.799	0.008
_2011	0.238	0.694	0.343	0.733
_2012	-0.542	0.541	-1.002	0.322
_2013	0.519	0.475	1.091	0.281
_2014	-0.107	0.436	-0.246	0.807
_2015	0.538	0.613	0.878	0.385
_2016	0.724	0.498	1.453	0.154
_2017	0.315	0.449	0.702	0.486
_2018	0.807	0.603	1.339	0.188
_2019	-0.022	0.477	-0.046	0.963
Age_Building	-0.007	0.006	-1.128	0.266
Floors_Building	-0.024115	0.012346	-1.953	0.057
Score_Walk	0.018351	0.007644	2.401	0.021
SF_Building	0.000001	0.000001	0.922	0.362
Source	Deg. Freedom	Sum Squares	Mean Square	F-Statistic
Regression	23.000	20.786	0.904	2.780
Residual	43.000	13.976	0.325	
Total	**66.000**	**34.762**		

Figure 17: Commercial Office Sales Regressions VI and VII Comparison

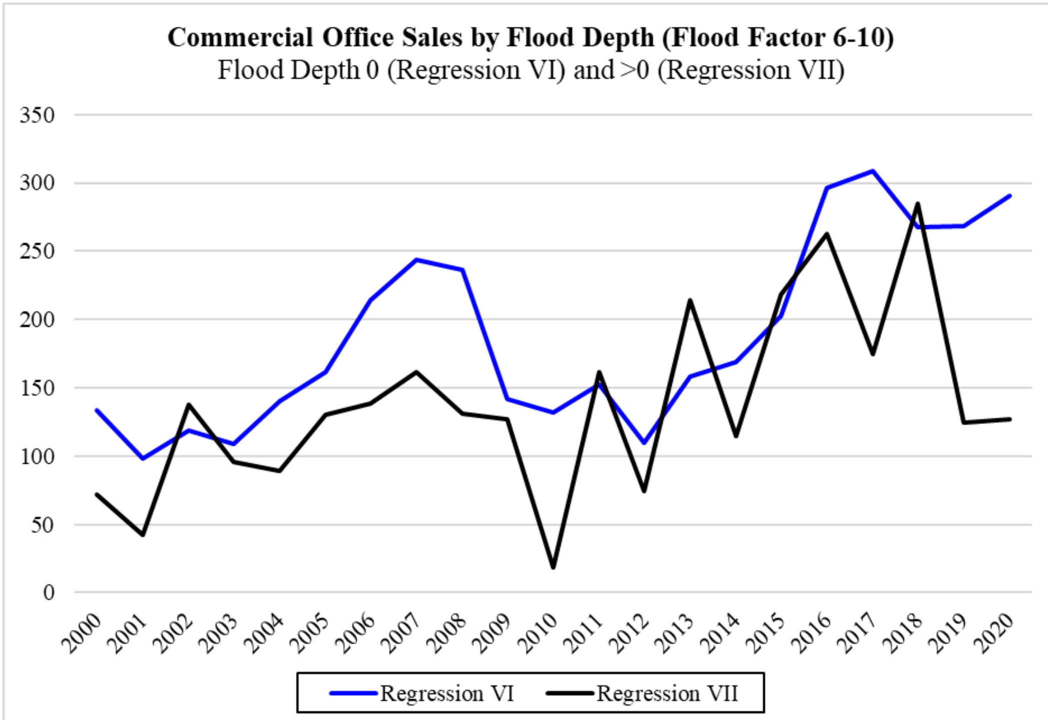
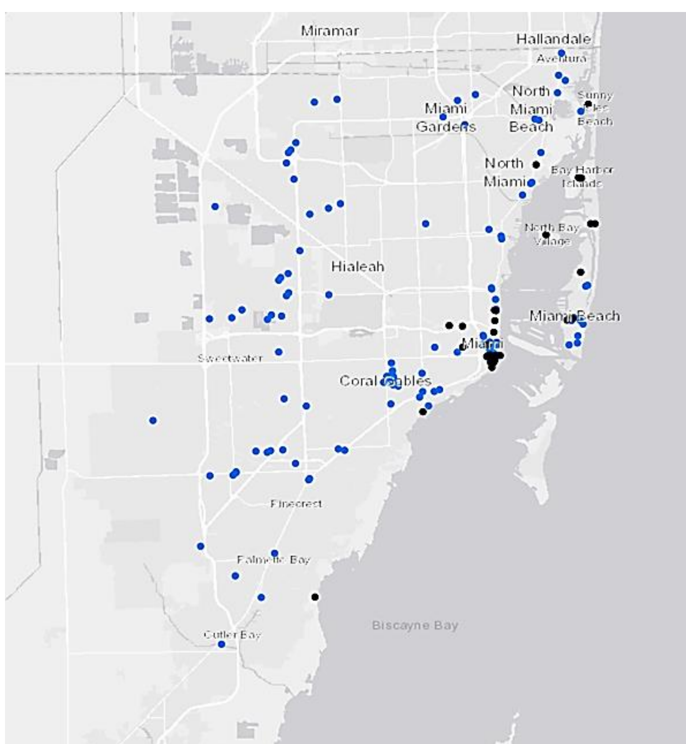


Figure 18: Commercial Office Sales Regressions VI and VII Map



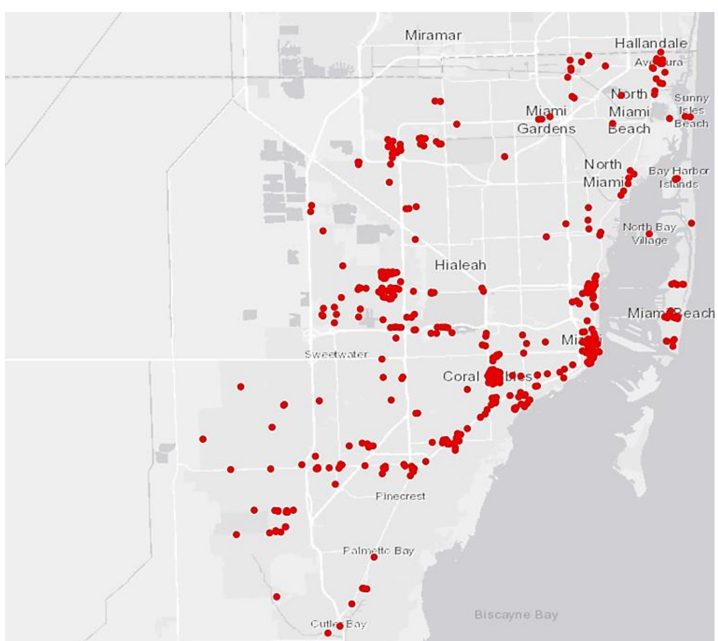
6 Methodology: Commercial Office Rents

We modify the commercial office sales analysis process in Section 4 to investigate the relationship between flood zones and historic flooding impact with quarterly commercial office rent from 1988 through 2020.

6.1 CBRE and First Street Foundation Data

We repeat the merging process as outlined in Section 4.1, this time merging the CBRE repeat rent data with the First Street data utilizing ARCGIS PRO. To capture a sufficient number of CBRE properties, we apply a polygon circle with a 200-foot radius (diameter=400') buffer around each First Street observation's longitude and latitude, rather than the 100-foot radius used when merging the RCA and First Street data. We then map the centroid of the CBRE properties' longitude and latitude to determine if the property falls within the 200-foot buffer. As illustrated below in Figure 19, of the 677 CBRE properties, 497 contained at least one First Street record. These 497 properties contain 65,604 potential rent observations. Of the potential rent observations, 25,545 records have positive gross rents when space was available and quoted.

Figure 19: CBRE and First Street Foundation Merged Data Map



6.2 Variable Analysis

We employ the same First Street data consolidation as outlined in Section 4.2. We consider variables Maximum Flood Depth (Max_Flood_Depth), Maximum Flood Factor (Max_Flood_Factor) in the commercial office rent regression analysis.

The CBRE data includes time period and rent value variables. To prepare the data for regression analysis, we consider only the positive gross rent observations. Of the 65,604 merged CBRE and First Street observations, 25,545 had positive rents when space was both vacant and quoted. These data comprise the rent observations (Ln_GrossRent_PSF) sufficient for an unbalanced panel model; for the purposes of this analysis each building need not have the same number of years in which there is data. We utilize 132 dummy variables to consider the Time Period (Time_Period_Dummy) values of periods from 1988 quarter one through 2020 quarter four, employing one if the variable matches the observation period and zero otherwise. On average, the data contained rents for only 28 of the 132 year-quarters for each property.

Figure 20 identifies key variables we examine in this study, consisting of the natural logarithm of Rent per Square Foot (Ln_GrossRent_PSF), the Time Period dummy variables 1998.1 – 2020.4 (Time_Period_Dummy), Maximum Flood Factor (Max_Flood_Factor), and Maximum Flood Depth (Max_Flood_Depth).

Figure 20: Index for Commercial Office Sales Regression Variables

Label	Description	Unit	Definition
Ln_GrossRent_PSF	Rent per Square Foot	#	The rent per square foot per unique deal identification
Time_Period_Dummy	Time Period Dummy Variable (1988.1 – 2020.4)	1 = Period 0 = Not Period	Time period dummy variable associated with each rent observation from 1988 quarter one through 2020 quarter four
Max_Flood_Depth	Maximum Flood Depth	Centimeters	The maximum flood depth among the First Street observations
Max_Flood_Factor	Maximum Flood Factor	#	The maximum flood factor when more than one First Street observation is within the 200-foot RCA buffer on a scale of 1-10

6.3 Regression Approach

For the commercial office rent regressions, we perform a fixed effects regression to control for time-invariant unobserved individual characteristics that can be correlated with the observed independent variables in panel data[37]. The panel model produces a fixed effect for each property and each period. The Log panel model assumes that each rent observation (property-period) comes from the product of the property fixed effect and the period fixed effect.

We perform seven fixed effect regression analyses on the merged rent data containing 25,545 positive rent observations. In all regressions the natural logarithm of Gross Rent per Square Foot (Ln_GrossRent_PSF) is the dependent variable. Rent for i at period j is assumed to be the product of a unique base year rent for each building (v_i) by a common rent inflation factor (y_j). We then take the natural logarithm of Gross Rent (Ln_GrossRent_PSF), value v_i, and time period y_j. The gross rent for all buildings moves parallel and the difference between the buildings remains a constant ratio. Thus, while each buildings rent value is unique, over time rents move with a common trend for all buildings. When we bifurcate the sample by either Maximum Flood Depth (Max_Flood_Depth) or Maximum Flood Factor (Max_Flood_Factor), we assume the overarching trend is distinct for each subsample.

In Regression I we consider all 497 properties or 25,545 observations. Rather than employing fixed effects, this model inputs the Maximum Flood Depth (Max_Flood_Depth) and Maximum Flood Factor (Max_Flood_Factor) per property. Regressions II and III evaluate observations split by a Maximum Flood Depth (Max_Flood_Depth) of zero centimeters, comprising 436 properties, and a Maximum Flood Depth (Max_Flood_Depth) of over zero centimeters, comprising 61 properties, running separate panel models for each. As in Section 4.3, we also analyze the sample by flood risk. Regressions IV and V evaluate Maximum Flood Factors (Max_Flood_Factor) of 1-6 and 7-10 comprising 325 and 172 properties respectively. Lastly, we consider only high risk (Max_Flood_Factor 7-10) properties and split the sample of 172 by properties that have not experienced historic flooding (Max_Flood_Depth of zero) comprising 117 properties for Regression VI, and those that have experienced historic flooding (Max_Flood_Depth greater than zero), totaling 55 properties for Regression VII.

[37] Allison, "Fixed Effects Regression Models: Quantitative Applications in the Social Sciences."

7 Commercial Office Rent Results

Commercial office rent Regression I produces coefficient results while the fixed effect model for Regressions II through VII outputs an average rent value per time period. We compare Regressions II and III to determine the influence of historic flood amount on gross rent, Regressions IV and V to analyze the impact of flood risk, and Regressions VI and VII to revisit the weight of flood history on a narrower scope of high-risk properties. To generate the outcome graphs in Sections 7.2, 7.3, and 7.4, we input the average predicted gross rent (Ln_GrossRent_PSF) across 132 periods (Time_Period_Dummy) produced in the fixed panel model per regression, benchmarked to 100 in 1988 quarter one.

7.1 Full Sample Regression Analysis

Commercial office rent Regression I evaluates the full sample comprising 25,545 observations and 497 properties. Figure 21 below shows that as both Maximum Flood Depth (Max_Flood_Depth), coefficient 0.00150917, and Maximum Flood Factor (Max_Flood_Factor), coefficient 0.01100252, increase, the single time path shifts upwards. This output demonstrates that the average Gross Rent (Ln_GrossRent_PSF) level for all years is positively related to flood risk in terms of both historical flood depth and future flood risk. One plausible explanation for this is that buildings that demand premium rents are located in higher-risk areas near the water.

Figure 21: Commercial Office Rent Regression I: Full Sample

Regression I: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	25545
Degrees of Freedom	24866
Skipped/Missing (from 608755)	583210
Centered R^2	0.0550081
R-Bar^2	0.0292418
Uncentered R^2	0.9862255
Mean of Dependent Variable	3.0710458607
Std Error of Dependent Variable	0.3735135890
Standard Error of Estimate	0.3680119574
Sum of Squared Residuals	3367.6720249
Regression F(678,24866)	2.1349
Significance Level of F	0.0000
Log Liklihood	-10366.8913

Variable	Coefficient	Std Error	T-Statistic
Max_Flood_Depth	0.00150917	6.011E-05	25.10691
Max_Flood_Factor	0.01100252	0.0008849	12.4337

7.2 Regression Analysis by Historic Flooding

Regressions II and III split the sample by historic flood amounts. Regression II evaluates 21,802 observations or 436 properties with historic flood depth of zero centimeters, while Regression III analyzes 3743 observations or 61 properties with historic flood depth greater than zero centimeters. Figure 22 outlines the results of these regressions and Figure 23 graphically illustrates the period fixed effects from both models.

Bifurcating the sample by flood history reveals shows both rents running even from 1988 – 2008, but the properties with flood history demonstrate a decline and without recovery after 2008. This volatility, evidenced in the Regression III curve in Figure 23 may be explained by the smaller relative sample size of properties with flood history. The consistent decline over the last seven years from an apex of 139.85 in 2015 quarter three to 93.59 in 2020 quarter four of gross rent index for historically flooded properties compared to non-flooded properties is significant. Properties that have experienced historic flood in Regression III explain more variation of the dependent variable than no flood history in Regression II, with Centered R-Squared values of 0.572 and 0.405 respectively. Figure 24 reveals that properties that have experienced flooding are clustered closer to waterfront areas.

Figure 22: Commercial Office Rent Regressions II and III: Historic Flood Amount

Regression II: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	21802
Degrees of Freedom	20996
Skipped/Missing (from 608755)	586953
Centered R^2	0.4048203
R-Bar^2	0.3820008
Uncentered R^2	0.9918632
Mean of Dependent Variable	3.0399528358
Std Error of Dependent Variable	0.3579051986
Standard Error of Estimate	0.2813597506
Sum of Squared Residuals	1662.1128416
Regression F(805,20996)	17.7401
Significance Level of F	0.0000
Log Liklihood	-2877.4819

Regression III: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	3743
Degrees of Freedom	3031
Skipped/Missing (from 608755)	605012
Centered R^2	0.5724856
R-Bar^2	0.472201
Uncentered R^2	0.9933321
Mean of Dependent Variable	3.2521546315
Std Error of Dependent Variable	0.4094133917
Standard Error of Estimate	0.2974379110
Sum of Squared Residuals	268.15048127
Regression F(711,3031)	5.7086
Significance Level of F	0.0000
Log Liklihood	-377.6363

Figure 23: Commercial Office Rent Regressions II and III Comparison

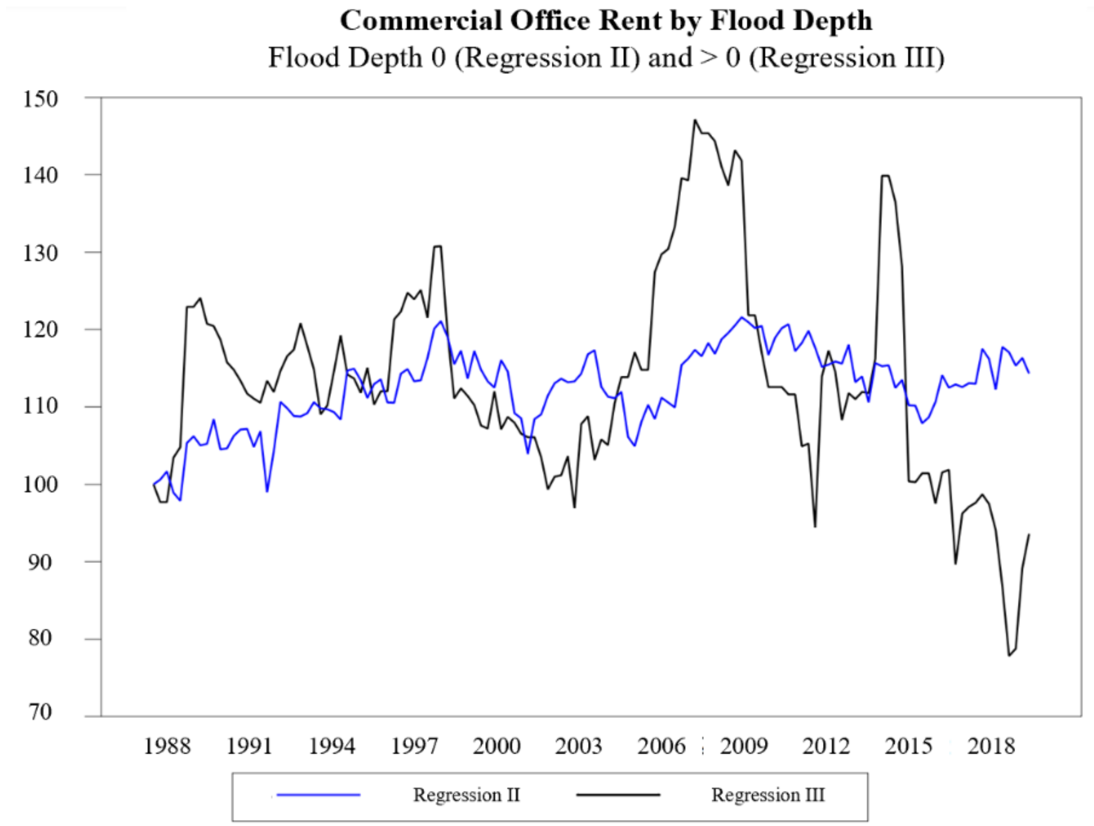
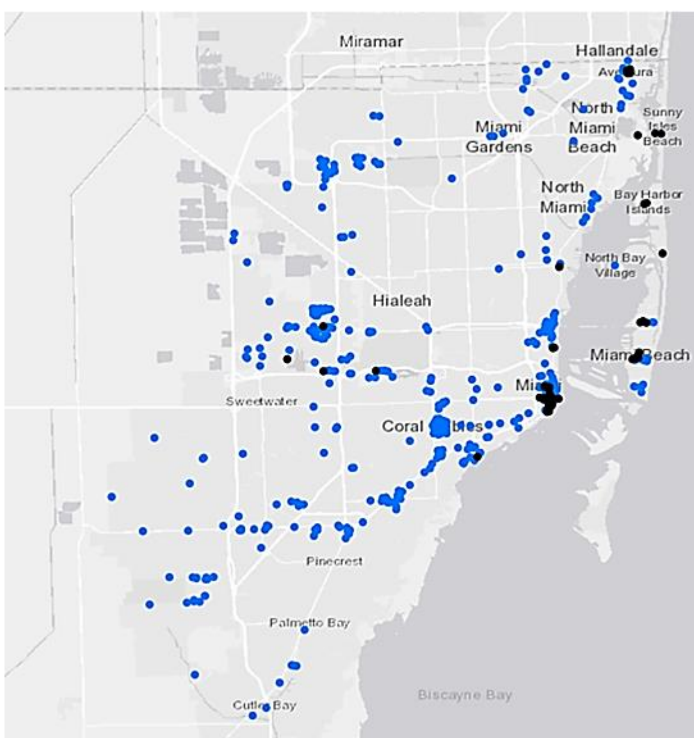


Figure 24: Commercial Office Rent Regressions II and III Map



7.3 Regression Analysis by Flood Risk

Regressions IV and V partition the sample by flood risk. Regression IV evaluates 15,685 observations or 325 properties with Flood Factors of 1-6, while Regression V analyzes 9,860 observations or 172 properties with Flood Factors of 7-10, indicating higher risk. Figure 25 displays risk regression results and Figure 26 exhibits the period fixed effects from the models.

A greater number of the observed variation in Regression V can be explained by the model's inputs than in Regression IV, with Centered R-Squared values of 0.513 and 0.453 respectively. Segmentation by risk reveals a significant increase in rents for risky properties in the late 1980s. Beginning in 1992, the low-risk group in Regression IV demonstrates a gradual upward trend while the high-risk group in Regression V remains relatively flat. The difference in mean rent is stark in this regression comparison; high-risk properties with Flood Factors between 7-10 that are more concentrated in locations more susceptible to sea level rise, as evidenced by the map in Figure 27, have consistently higher rents than the lower risk properties. Further, the lower risk properties with flood factors between 1-6 show steady recovery since 2016 while rents for high-risk properties have declined since that time.

Figure 25: Commercial Office Rent Regressions IV and V: Flood Risk

Regression IV: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	15685
Degrees of Freedom	14892
Skipped/Missing (from 608755)	593070
Centered R^2	0.4529644
R-Bar^2	0.4238715
Uncentered R^2	0.9927089
Mean of Dependent Variable	3.0385273878
Std Error of Dependent Variable	0.3531670490
Standard Error of Estimate	0.2680648428
Sum of Squared Residuals	1070.1206535
Regression F(792,14892)	15.5696
Significance Level of F	0.000
Log Liklihood	-1199.460

Regression V: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	9860
Degrees of Freedom	9096
Skipped/Missing (from 608755)	598895
Centered R^2	0.5134976
R-Bar^2	0.4726883
Uncentered R^2	0.9922107
Mean of Dependent Variable	3.1227752976
Std Error of Dependent Variable	0.3983580546
Standard Error of Estimate	0.2892726165
Sum of Squared Residuals	761.14096992
Regression F(763,9096)	12.5829
Significance Level of F	0.0000
Log Liklihood	-1362.9192

Figure 26: Commercial Office Rent Regressions IV and V Comparison

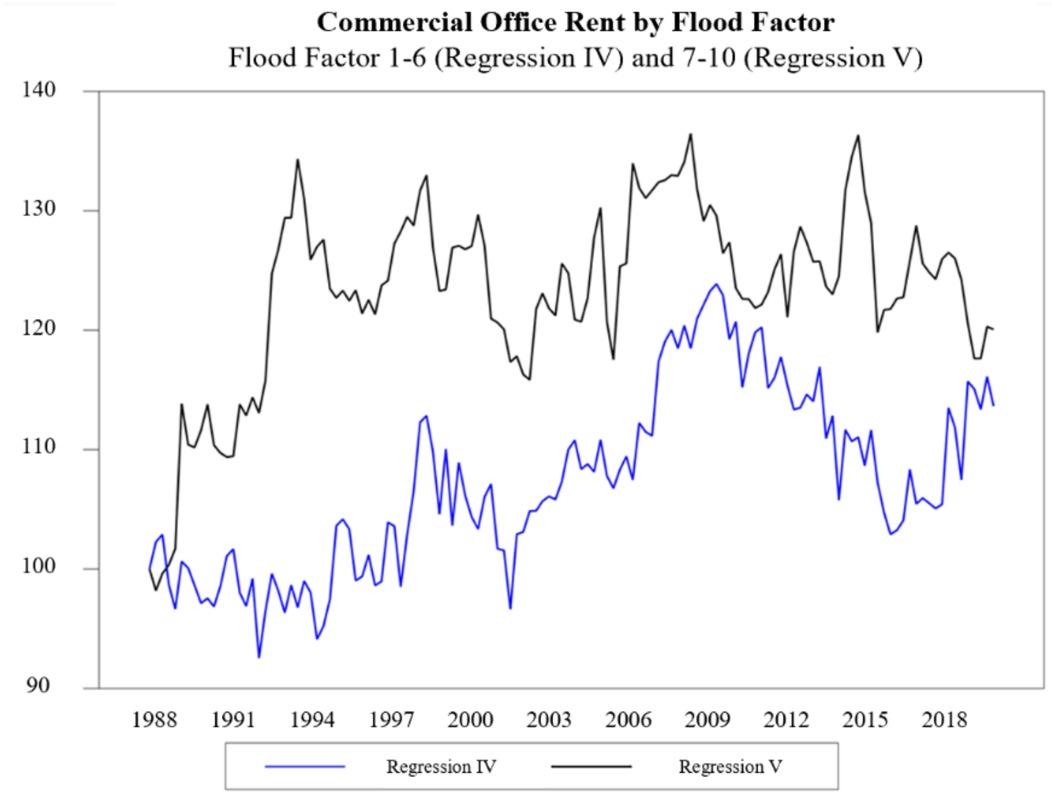
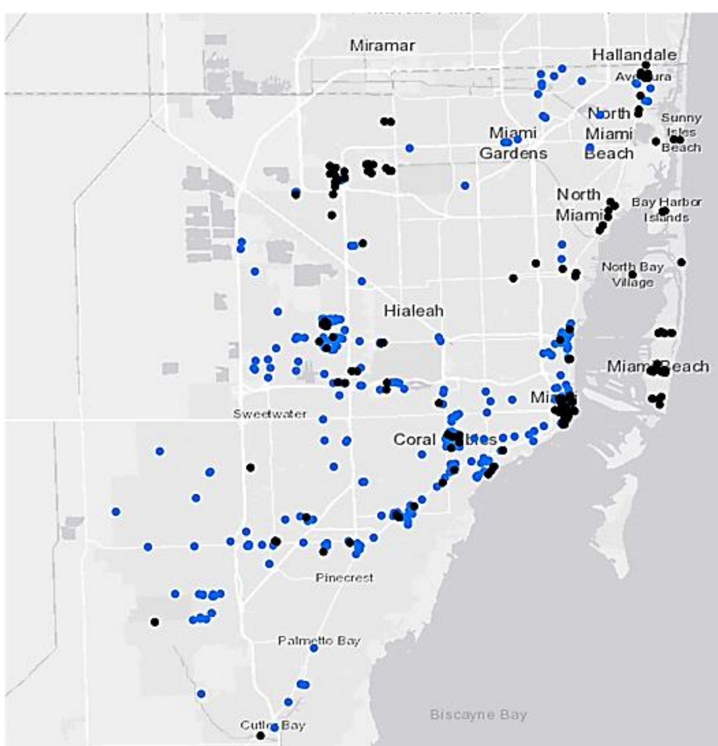


Figure 27: Commercial Office Rent Regressions IV and V Map



7.4 Regression Analysis by Historic Flooding, High Risk

We find that high-risk is a sufficient but not necessary condition for flooding. Of the 61 observations that have experienced historic flooding, all are high-risk, but not all high-risk observations have experienced historic flooding. In Regressions VI and VII, we only consider high-risk (Flood Factor 7-10) properties and partition this sample by 117 properties that have not experienced historic flooding and 55 properties that have experienced flooding.

The results for Regressions VI and VII, shown in Figure 28 and graph of period fixed effects for these regressions, in Figure 29, are similar to results in Regressions II and III as all historically flooded properties are considered to be high-risk. Considering flooded properties, Centered R-Squared value in Regression VII, 0.575445, only differs slightly from the Centered R-Squared value in Regression III, 0.5724856; as in Section 7.2 more variation of the dependent variable can be explained by the independent variables for the sample with properties that have experienced historic flood than the one with properties without flood history. Figure 30 illustrates that the samples in Regressions VI and VII are clustered in more comparable locations, revealing impact of historic flooding on rent values, particularly over the past seven years.

Figure 28: Commercial Office Rent Regressions VI and VII: Historic Flood Amount, High Risk

Regression VI: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	14792
Degrees of Freedom	13994
Skipped/Missing (from 608755)	593963
Centered R^2	0.4792021
R-Bar^2	0.4495411
Uncentered R^2	0.9926662
Mean of Dependent Variable	3.0448304928
Std Error of Dependent Variable	0.3639053069
Standard Error of Estimate	0.2699919639
Sum of Squared Residuals	1020.1018743
Regression F(979,13994)	16.156
Significance Level of F	0.0000
Log Liklihood	-1210.6740

Regression VII: Panel Regression - Estimation by Fixed Effects	
Dependent Variable: Ln_GrossRent_PSF	
Panel (677) of Quarterly Data From 1//1988:10 to 900//2020.04	
Usable Observations	3654
Degrees of Freedom	2943
Skipped/Missing (from 608755)	605101
Centered R^2	0.575445
R-Bar^2	0.4730209
Uncentered R^2	0.9932753
Mean of Dependent Variable	3.2554705977
Std Error of Dependent Variable	0.4130573900
Standard Error of Estimate	0.2998521053
Sum of Squared Residuals	264.60891189
Regression F(710,2943)	5.6183
Significance Level of F	0.0000
Log Liklihood	-388.3300

Figure 29: Commercial Office Rent Regressions VI and VII Comparison

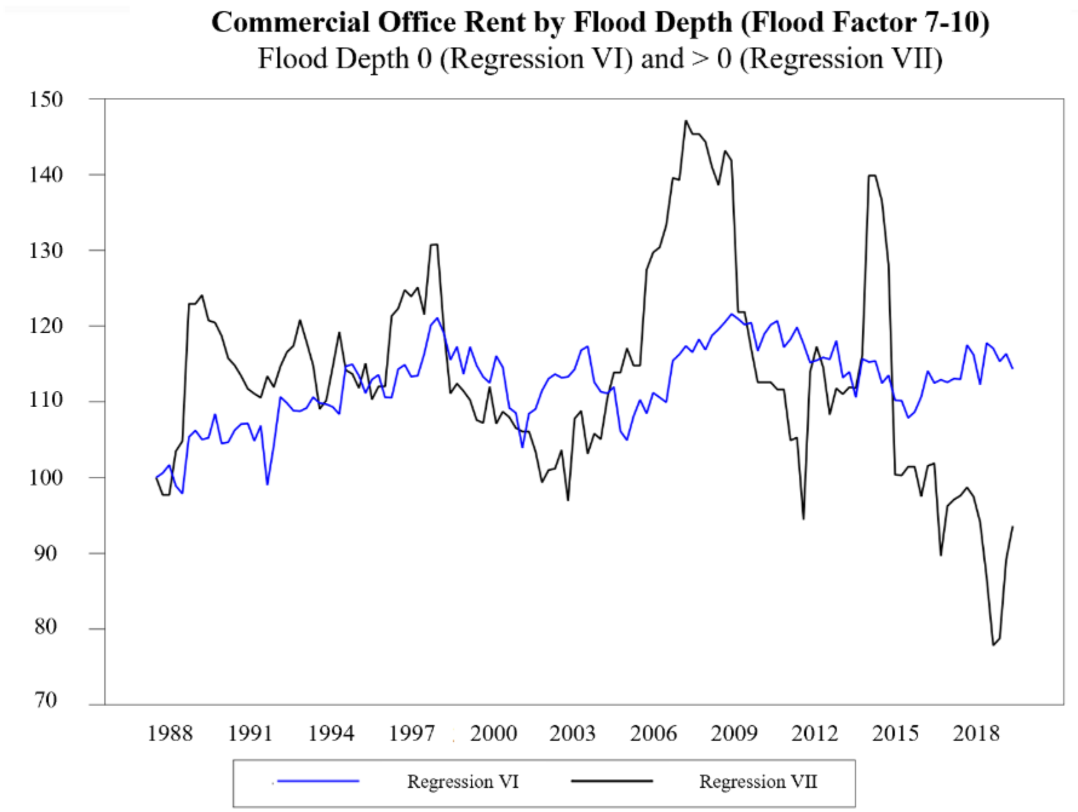
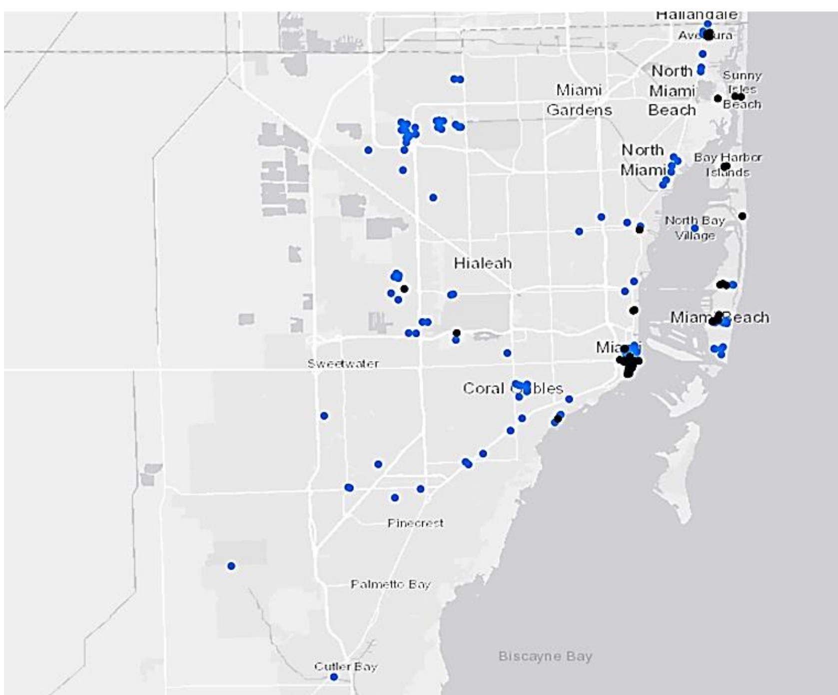


Figure 30: Commercial Office Rent Regressions VI and VII Map



8 Conclusion

In this paper, we provide evidence that high flood risk is a sufficient but not necessary condition for flooding, and that historic flood exposure from hurricanes has a tangible impact on commercial real estate sales prices and rental values. We regarded key measures of sea level rise exposure: a history of flooding in either or both 2005 and 2017 hurricanes and a measure of calculated flood risk on a scale of 1–10 and analyzed these variables in a series of regressions to determine the influence of flood exposure and risk on real estate values in Miami-Dade County. These regressions reveal a correlation between location and valuations as properties in superior, waterfront locations not only have higher sales and rental values over time, but also endure greater flood history and flood risk. Sales prices and rental values for high-risk or flood-exposed properties have declined since 2017 and 2015 respectively, while prices and values for low-risk, non-exposed properties have stabilized, perhaps reflecting escalating climate change awareness.

We then aspired to eliminate location as a confounding variable and only considered properties deemed high-risk, with associated flood factors of 6 or 7 and above. We found that commercial office sales pricing responds more rapidly than rental values to historic flood aversion. Sales values are greater for properties without historic flooding than for those with historic flooding across the past 20 years, and rental values for properties with flood exposure have declined in the past 7 years compared to properties in high-risk zones without flood histories. Why might rental markets be slower than sales markets to respond to historic flooding? In an efficient market, because prices are based on anticipated future rental changes, sales prices adjust before rents to any shock that will eventually have some impact on rental values[38].

Occupants of commercial offices in Miami-Dade County are at the risk of extreme weather events, flooding, and the associated harms. It is worth noting that historic flood events have a bona fide influence on commercial real estate valuations, while flood risk does not share this influence. While sea level rise is correlated with increased storm impacts, particularly with hurricanes, our results suggest that fewer buyers and renters are willing to bear these heightened risks at current market prices for commercial properties that have experienced genuine damage.

[38] Shiller, "Stock Prices, Earnings and Expected Dividends."

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