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BY

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Abstract

Global sea level rise is a known consequence of climate change. As predictions of sea level rise have grown in magnitude and certainty, coastal real estate assets face an increasing climate risk. I use a complete data set of repeated home sales from Long Island in New York State to estimate the appreciation discount caused by the threat of sea level rise. The repeat sale methodology allows for unobserved property characteristics to be controlled for. Between 2000 and 2017, I find that residential properties that were exposed to future sea level rise experienced annual price appreciation that was 0.8 percentage points below unexposed properties. I provide numerous robustness checks to confirm this result. I also find evidence of demand spillovers by estimating an appreciation premium for properties that are near the coast but are relatively safe from sea level rise.

Housing markets; Climate change; Sea level; Flooding
G10; R30; Q54

1 Introduction

Predictions of global sea level rise have become more dire (Chen et al., 2017). Current estimates suggest that by 2100 global sea level will be between 0.3 and 1.0 meters above 2000 levels (Church et al., 2013; Nicholls and Cazenave, 2010). The threat of sea level rise is compounded by the predicted increase in climate change induced extreme weather events that could cause water to surge into coastal areas (Seneviratne et al., 2012). Many real estate assets on the coast will experience climate change induced land erosion, flood events, or total inundation, all of which could decrease or eliminate the asset's value. I estimate the extent to which this climate risk has been priced into real estate transactions for the Long Island housing market in New York State.

Using repeated property sales, I compare the rate of price appreciation among properties at risk from sea level rise to other properties that are not at risk. The use of property level fixed effects allows for the price effect of coastal proximity to be controlled for and the use of detailed spatial coastline data allows for the control of unique appreciation trends for coastal properties. I calculate the sea level rise exposure of properties by combining transaction data with detailed elevation and flood map data. Results indicate that climate risk has reduced the value of exposed residential properties on Long Island.

How the risks of sea level rise influence real estate has been studied by a recent and growing literature. A starting point of the theoretical literature is the assumption that property markets are populated by forward-looking agents with information on future climate risk. Bunten and Kahn (2017) provided important theoretical work on the effect of climate change risk on property development and investment. If climate risk is included in the property valuation of buyers and sellers, financial incentives will shift investment decisions and partially insulate against sudden climate shocks. Kahn (2016) provided an important overview of how individuals adapt to climate change and

Kahn (2014) as well as Desmet and Rossi-Hansberg (2015) provided further discussion regarding adaptation in spatial location decisions. Severen et al. (2018) argued that much of the future costs of climate change in land markets are already accounted for due to pervasive information and beliefs about the probable effects of future climate change.

Some empirical work has been undertaken to estimate the effect of exposure to sea level rise on home prices. Bernstein et al. (2019) relied on Zillow home price data from across the US and found that homes exposed to sea level rise sell at a 7% discount relative to other homes that are similar, based on observable characteristics. Contrastingly, Murfin and Spiegel (2020) studied housing transaction data from US coastal states and found no evidence of climate risk being priced into home sales. The study made use of the fact that sea level rise affects different coastal areas differently due to local subsistence or uplift of continental landmasses partially offsetting or exacerbating sea level rise.

Buyers who personally believe climate change risk to be large are more likely to incorporate climate change risk into their purchase decisions. Some studies have found spatial heterogeneity in the US regarding to what extent climate change risk is priced into real estate assets, driven by spatial heterogeneity in personal beliefs about climate change risk. McNamara and Keeler (2013) supplied a model to study coastal climate change risk in the US Northeast, noting that heterogeneity in agent beliefs regarding climate change risk influence the overall support for climate mitigation measures. Bakkensen and Barrage (2018) as well as Baldauf et al. (2020) further extend theory and analysis of how belief heterogeneity affects the pricing of climate risk into coastal property assets. Both studies find that households that are skeptical regarding the risks posed by climate change are willing to pay relatively more for coastal assets that are in areas of significant risk, and this behavior leads to a difference in home

prices across local markets.

Informational issues are also addressed in studies of markets that have been exposed to an extreme weather or flood event. Results have shown that individual weather events can generate sudden shifts in how future climate risk is priced into real estate assets. Gibson and Mullins (2020) investigated price declines associated with climate risk in New York City. Results show significant price reductions for properties directly exposed to information shocks, including flooding from Hurricane Sandy, changes to federal flood insurance, and the updating of FEMA floodplain maps. Ortega and Taspinar (2018) looked specifically at the role of Hurricane Sandy on climate risk discounting in New York City. The authors found a significant price discount that increased over time in areas at risk of flooding. McCoy and Zhao (2018) analyzed a similar process in New York City, finding that homeowners' property investment decisions are influenced by perceived flood risk. Bin and Landry (2013) found that the price of homes in North Carolina reflected flood risk much more strongly after a nearby hurricane, despite long-term risk remaining constant. McKenzie and Levendis (2010) uncovered a similar informational effect for properties in New Orleans after Hurricane Katrina. For non-coastal flooding, Yi and Choi (2019) examined the effects of a flood event in Iowa, and Zhang and Leonard (2019) examined a flood event in the Fargo, North Dakota metropolitan area, both found that homes in flooded areas began discounting the future value of their homes more heavily after the flood.

The primary contribution of the current paper is to implement a repeat sales methodology to fully control for potential unobserved heterogeneity across properties. Access to a complete data set of housing transactions from Long Island for an 18 year period allows the repeat sales analysis to retain a large number of transactions. While the identification strategy followed by the prior literature has relied on controlling for observable characteristics, I am able to eliminate the effect of both observed and un-

observed, time-invariant heterogeneity between properties that may be correlated with the risk of sea level rise. It is likely the case that homes close to the ocean have unobserved characteristics that are different than homes that are further inland, suggesting that controlling for unobservable housing characteristics may be important. I also identify demand spillovers wherein properties in areas of high climate risk experience an appreciation penalty while properties close to the coast but with lower risk actually experience an appreciation premium as buyer demand for coastal properties shifts within the coastal housing market.

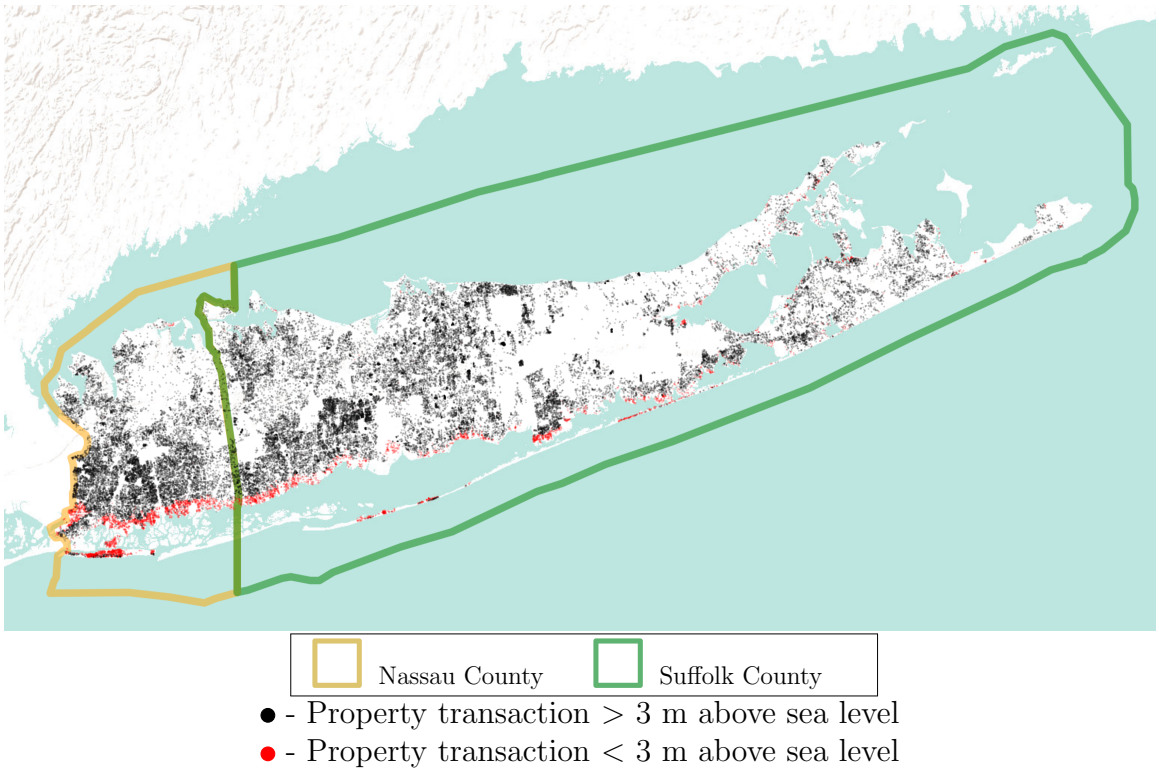
The paper will proceed as follows. The next section discusses details of the Long Island property market. The third section introduces data sources. The fourth section provides the methodology. The fifth section provides primary results and numerous robustness tests and the final section concludes.

2 The Long Island Property Market

The study area includes Nassau and Suffolk counties in New York State. These counties comprise all of Long Island, outside of New York City. Figure 1 provides a map indicating the study area. The numerous coastal communities on Long Island provide an excellent opportunity to study the impact of sea level rise on a real estate market with significant coastal exposure. A significant portion of real estate assets on Long Island are within a few meters of current sea levels, and coastal areas are at risk of damage due to storm events, particularly hurricanes.

Table 1 provides demographic summary statistics for the study area and compares the demographics of Long Island to the US as a whole. Nassau and Suffolk counties have higher income and education levels than the US average. The racial composition of the counties are relatively representative of the national population. Nassau and Suffolk have a high rate of homeownership, with 81.3% of residents being owner-occupiers,

Figure 1: Long Island Study Area



Each of the 52,085 unique properties in the repeat sales transaction data are represented as a point on the map. Red dots indicate properties that are within three meters of sea level. The large majority of properties that are close to sea level are on the southern coast of Long Island.

compared to the national rate of 66.1%.

Coastal erosion and flooding are long-term issues faced by coastal landowners on Long Island. An important event for real estate assets in Long Island was Hurricane Sandy, which struck the area in October 2012. The storm event caused significant property damage on Long Island, in New York City, and neighboring states. In addition to the direct damage caused by the storm, Hurricane Sandy may have impacted the perceptions of local homeowners as to the risk of climate change related property damage (McCoy and Zhao, 2018; Ortega and Taspinar, 2018).

Table 1: Demographic Characteristics of Study Area

	Nassau and Suffolk Counties	**USA**
Population	2,820,124	306,603,772
Median household income	89,947	52,762
College education rate (%)	36.6	28.2
Median Age	39.8	37.0
White (%)	78.2	74.1
Black (%)	9.1	12.5
Asian (%)	5.4	4.7
Hispanic (%)	15.1	16.1
Owner-occupancy rate (%)	81.3	66.1

Data from the 2007-2011 American Community Survey.

3 Data

I use housing data provided by the New York State Department of Taxation and Finance (NYSDTF), Office of Real Property Tax Services. The data covers all real estate transactions within the state of New York between 2000 and mid-2017. I trim the data to only Suffolk and Nassau counties.

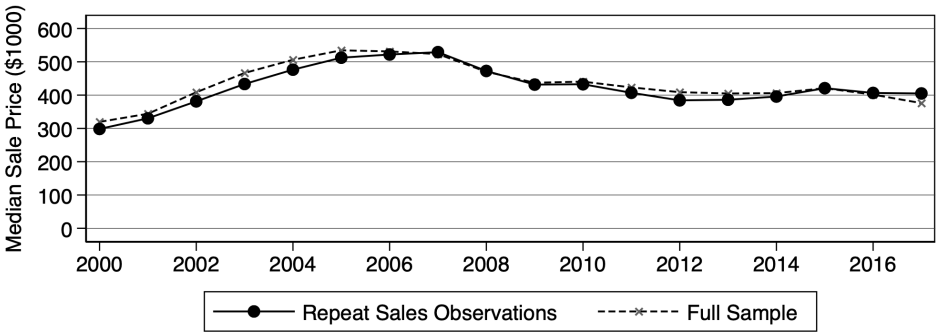
I drop a number of observations to focus analysis on reliable data and to enable the repeat sales methodology. I drop any observation that sold for less than $5,000. I also drop observations with incomplete street address information. I keep only sales that are classified by the NYSDTF as "arms-length." I exclude sales of individual condominium units. In part, I exclude condominium units because the unit number of condominiums are not reliably recorded in all cases, preventing the matching of specific units through time. I further limit the sample to the following property types as defined by the NYSDTF: One Family Year-Round Residences, Two Family Year-Round Residences, Three Family Year-Round Residences, Apartments, and Multiple Residences. These property types cover 92.4% of property sales in Suffolk and Nassau counties. The excluded property types include commercial, industrial and agricultural land uses.

I conduct analysis only on properties that sold at least twice during the study period. Limiting the sample to repeat sales will be important to the methodology wherein I introduce fixed effects at the property level, which partials out the effect of all time-invariant housing characteristics. The NYSDTF flags observations that have undergone significant renovations between sales. Homes that underwent significant renovations can not be reasonably assumed to represent the same asset so I consider the post-renovation property as a unique property in the repeat sales method. Only 0.5% of the properties in the sample underwent a significant renovation between sales.

The final repeat sales data set contains 112,716 transactions spanning 52,085 unique properties. 44,745 properties sold exactly twice, 6,347 properties sold three times, and the remainder sold more than three times. The most transacted property in the data set was sold eleven times. 97.2% of transactions in the final sample are classified as "One Family Year-Round Residences." The median sale price among the repeat sales properties is $436,590. Figure 2 graphs the change in median sale price over time within the repeat sales sample. Home prices on Long Island climbed significantly along with the national US housing market during the 2000-2007 period, with the median property price rising by 77.3%. The 2007-2017 period corresponds to a significant decline in home prices on Long Island, with the median home value dropping by 23.4%. The average property within the sample appreciated at a rate of 0.7% annually in real terms (2.9% in nominal terms) across the 2000-2017 study period. Figure 2 also displays annual median sales prices for the full sample of properties (N=511,110), including those that sold only once over the study period. The two series track very closely to one another, suggesting that the repeat sales data is fairly representative of the overall market.

Figure 3 shows the distribution of sale prices across the sample of 112,716 repeat sale observations. Panel A shows the sale prices in 2017 USD. I use the log of the sale

Figure 2: Trend in Repeat Sale Median Property Price



Among homes that sold multiple times on Long Island, the median sale price rose between 2000 and 2007. Prices declined beginning with the Great Recession. Between 2012 and 2017 prices were relatively stable. All prices are in 2017 USD.

price in analysis. Panel B shows the distribution of logged sale prices, which provides an approximately normally distributed dependent variable for analysis.

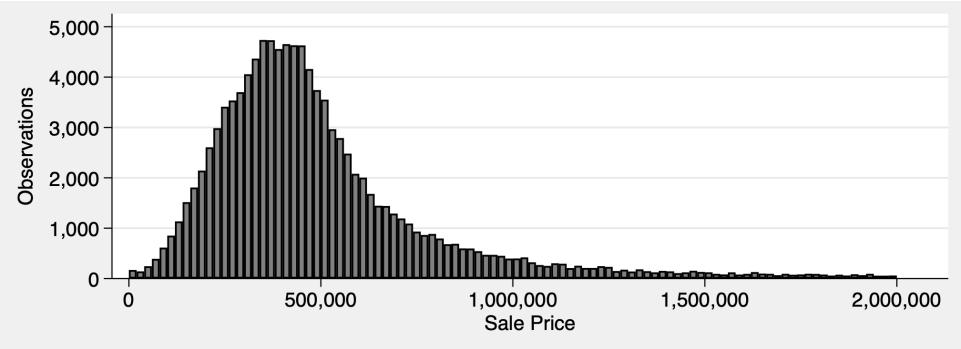
I use the street address of each property in the NYSDTF data in order to calculate the latitude and longitude coordinates of the property's centroid. I rely on the geocoding web service HERE to convert street addresses into precise latitude and longitude coordinates.

Two separate data sources will be used to evaluate the extent to which a property is exposed to the risk of sea level rise. First, I make use of the Federal Emergency Management Agency (FEMA) flood maps. In particular, I use the FEMA National Flood Hazard Layer for Nassau and Suffolk counties. The maps classify all land into zones of various flood risk. I use FEMA defined 100-year flood zones, which correspond to areas that have at least a 1% chance of flooding during a given year. I assign each property transaction as being either inside or outside of a 100-year flood zone through spatial mapping software.

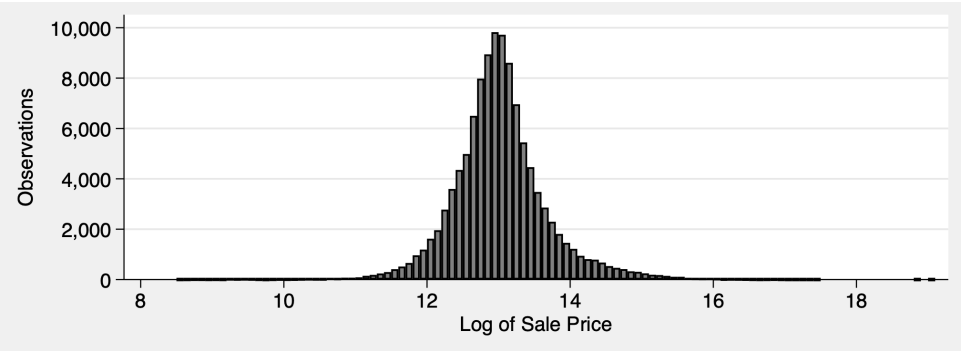
The second definition I use for sea level rise exposure is the elevation at the centroid of the property. Using the latitude and longitude coordinates of each property's

Figure 3: Sale Price Distribution

A. Sale Prices



B. Logged Sale Prices



Panel A shows the distribution of sale prices, across all years in the sample. Panel A truncates the data at $2,000,000. Panel B shows the distribution of logged sale prices, which will be the variable used in analysis. All prices are in 2017 USD.

centroid, I make use of the United States Geological Survey (USGS) online Elevation Point Query Service. The web service can return the elevation of any set of latitude and longitude points for the US. I generate an individual query for all 52,085 unique properties, creating precise elevation estimates. The elevation estimates from USGS are interpolated from the 1/3 arc-second 3D Elevation Program DEM dataset. For Long Island, USGS elevation points are measured approximately every 8 meters and interpolated between these points, providing highly accurate elevation estimates.

Figure 4A provides an elevation map of Long Island. Most areas that are within three meters of sea level are located along the southern coast of Long Island. Figure 1 provides the locations of all the transactions in the data set that are within three meters of sea level. The elevation profile of Long Island is such that coastal areas are the only locations that have an elevation that is close to sea level. There are no inland areas of low elevation that do not extend to the coast. This fact is important to justify using elevation as a proxy for exposure to sea level rise. Figure 4B maps the location of FEMA defined 100-year flood zones. The location of FEMA flood zones are highly correlated with areas of low elevation.

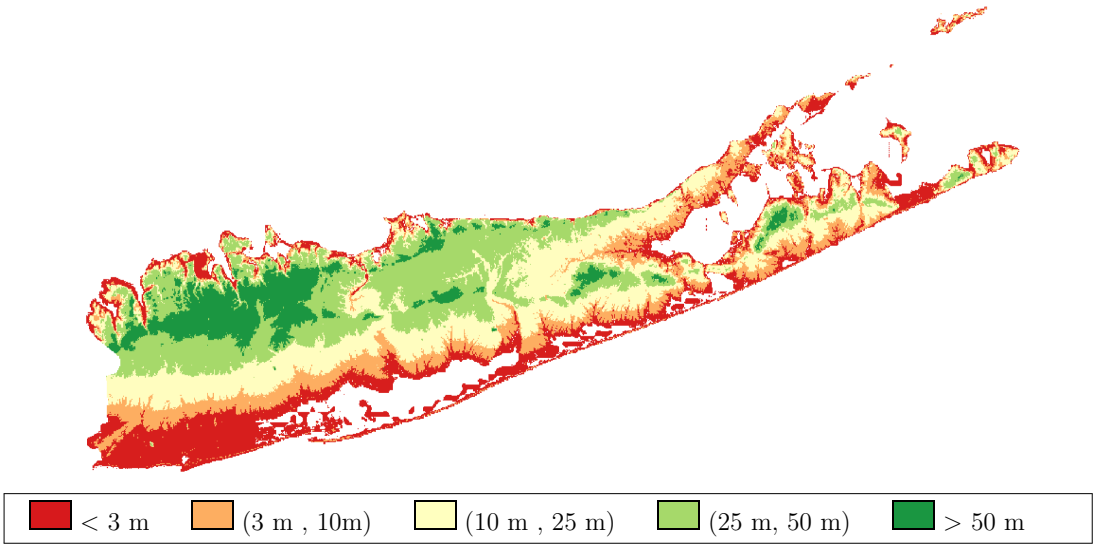
Figure 5 provides a histogram of the elevation of properties in the repeat sales sample. A large share of properties are close to sea level. 10.4% of properties are within three meters of current sea level and 4.6% are within two meters.

I measure the distance of each property to the coast. I use the publicly available New York State Civil Boundaries Shoreline shapefile. I calculate the shortest straight line distance, in meters, from every property observation to the nearest coastline. I make use of these measurements to control for potentially differential price appreciation for properties with coastal proximity. By combining data on elevation with data on coastal proximity, the proposed methodology will be able to separately identify the price appreciation effects of coastal proximity from the appreciation effects of sea level risk exposure.

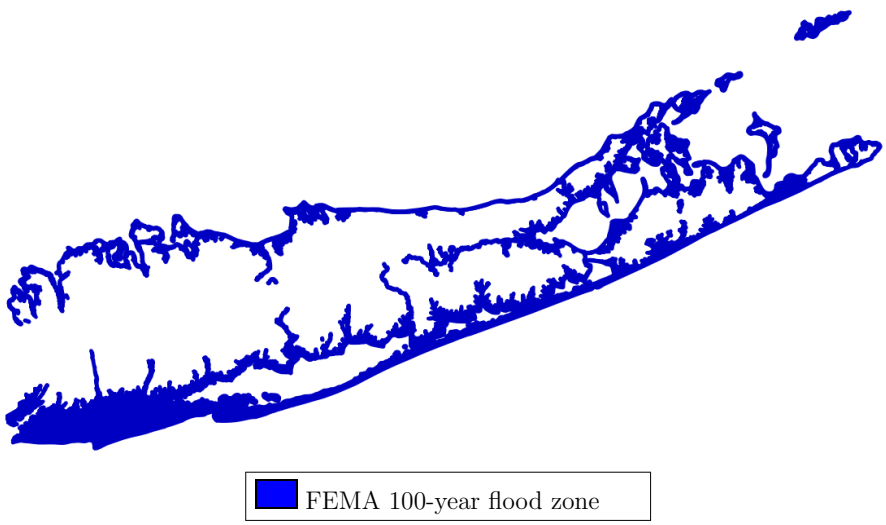
Finally, I use the FEMA National Flood Insurance Act Redacted Claims Data Set. The data provides census tract level information on insurance payments made by FEMA. I assign each property to a census tract using the US Census TIGER shapefile. I generate a time-invariant dummy variable for each property that takes a value of one if the property is located in a tract that collected a high value of FEMA insurance

Figure 4

A. Elevation Map of the Study Area



B. FEMA Flood Map

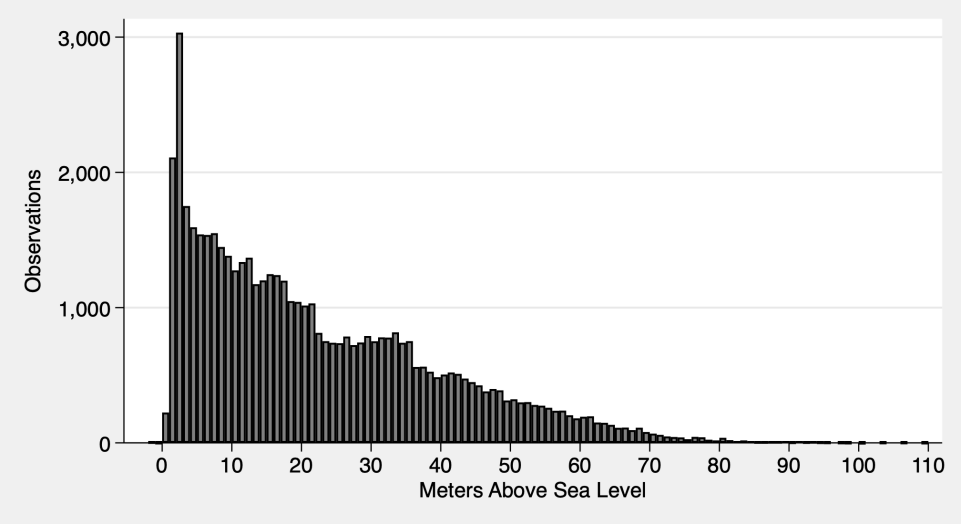


Panel A displays the elevation across Nassau and Suffolk counties. Most areas close to sea level are on the south coast. Panel B displays all areas that are classified by FEMA as being within a 100-year flood zone.

payments during the study period.[1] I use high insurance payouts to proxy for high

[1] I elect not to use a continuous measure of FEMA payouts because a majority of the observations are in a tract with zero storm damage payments, and the remainder of the sample is highly skewed,

Figure 5: Elevation of Repeat Sale Properties



The plot shows the frequency of properties at each elevation level, using one meter bins. For example, there are 3,033 properties in the data set that are at an elevation of between three and four meters.

levels of storm damage. I make use of this variable to test whether storm damage affects climate risk discounting.

4 Methodology

A major empirical challenge to identifying the price effect of coastal climate risk is untangling the effect of exposure to sea level rise with the amenity effect of coastal proximity. Homes closer to the beach are likely to sell at a premium to other homes, independent of climate risk (Atreya and Czajkowski, 2019; Conroy and Milosch, 2011). Rather than compare prices in cross-section, which has generally been the approach of prior literature, I perform a repeat sales analysis and study how property appreciation differs during a period of increasing projections of sea level rise. By focusing only on homes that sold multiple times I am able to control for all property characteris-

with a few tracts having sustained very high levels of damage.

tics, including nearness to the beach as well as unobserved home quality that may be correlated with coastal proximity.

While I can control for the level effect of coastal proximity through fixed effects, it may be the case that homes closer to the coast are appreciating at different rates for reasons unrelated to climate risk. For example, home buyer preferences for coastal proximity may vary through time. To deal with this potential source of bias I control for the time trend of coastal proximity's relationship to price, absorbing potential changes in coastal preference. I test for the effect of adding several metrics of coastal proximity trends, including linear distance and vectors of dummy variables for various coastal proximity distances. I find that these controls are important to results and that the price premium for coastal proximity appears to be increasing over the study period. Controlling for the effect of coastal proximity means that I am effectively comparing homes that are at similar distances to the coast, but face different climate risk due to their elevation or location within flood zones. Results are robust to various alternative methods to control for coastal proximity time trends.

Equation 1 represents the main estimation equation. P is the log of the sale price. R is a dummy variable indicating whether the property is at risk due to sea level rise. Y indicates the year of sale. Y is a continuous variable generated from the date of sale. For example, a sale occurring exactly halfway through 2008 takes a value of 2008.5. U is a property level fixed effect. M is a fixed effect for year-month of sale. D indicates the distance of the property to the nearest coastline, while W^d is a dummy variable that takes a value of one if the property's centroid is within d meters of the coast. C is the county where the property is located. In alternative specifications, I will replace the county time trends with other levels of geography. i and t subscripts index the particular property and time of sale respectively.

$$P_{it} = \beta_0 + \beta_1(R_i \times Y_t) + \Phi U_i + \Psi M_t + \alpha_1(D_i \times Y_t) + \alpha_2(W_i^{100} \times Y_t) \\ + \alpha_3(W_i^{250} \times Y_t) + \alpha_4(W_i^{500} \times Y_t) + \kappa(C_i \times Y_t) + \varepsilon_{it} \tag{1}$$

The coefficient of interest (β_1) corresponds to the average difference in annual price appreciation between properties that are located in areas at risk from sea level rise relative to properties that are not at risk. I will test multiple definitions of "at risk."

Homes with coastal exposure are more likely to have experienced damage from past storm events. Additionally, considering past research on storm damage and risk perceptions (McKenzie and Levendis, 2010; Ortega and Taspinar, 2018), areas that have experienced past damage may price future climate risk into current prices more aggressively. The presence of storm damage over the study period may influence the above estimates through two distinct processes. First, some properties may have sustained real damage to their structure which was not repaired before resale and therefore resulted in a diminished sales price. Second, the storm events may have increased the awareness of potential buyers and sellers regarding local flood risk, and caused them to reduce their evaluation of the asset's value.

I test for a differential price appreciation effect between properties located in areas that experienced different degrees of storm damage over the study period. The estimation strategy follows a triple difference model setup, captured in Equation 2. I add a term to the model that captures the interaction between a property being at risk (R), a dummy variable for whether that property's census tract suffered a high level of storm damage over the study period (F), and time (Y). F is measured using FEMA insurance claim data. In the main specification, I define high-storm damage tracts as those above the 95th percentile in terms of FEMA storm damage insurance payouts over

the study period. I also control for the possibility that high-damage areas appreciated at a different rate in general with a high-storm damage (F) by time (Y) interaction term. The form and notation of Equation 2 is otherwise consistent with Equation 1. A negative coefficient on the triple interaction term (γ_2) would indicate that properties in areas of high-storm damage suffered a larger price penalty from sea level rise exposure. The estimate of γ_1 will correspond to the annual appreciation penalty of exposure that accrues to a property that is in a neighborhood that did not experience a high level of storm damage. $\gamma_1 + \gamma_2$ will equal the annual price appreciation penalty of exposure for properties that are in a high-storm damage area.

$$\begin{aligned} P_{it} = \beta_0 + \gamma_1(R_i \times Y_t) + \gamma_2(R_i \times F_i \times Y_t) + \gamma_3(F_i \times Y_t) + \Phi U_i + \Psi M_t + \\ \alpha_1(D_i \times Y_t) + \alpha_2(W_i^{100} \times Y_t) + \alpha_3(W_i^{250} \times Y_t) + \alpha_4(W_i^{500} \times Y_t) + \\ \kappa(C_i \times Y_t) + \varepsilon_{it} \end{aligned} \tag{2}$$

5 Results

Table 2 presents estimates of the effect of being exposed to coastal climate risk on property appreciation. The estimation strategy corresponds to Equation 1. The first definition of exposure is whether a home is within two meters of current sea level, shown in column 1. I find that, conditional on distance to the coast, properties within two meters of sea level experienced average annual price appreciation that was 0.8 percentage points below properties at higher elevations. I find the same result when increasing the treatment definition to three meters (column 2) and a reduced but still highly significant effect of 0.5 percentage points when the definition is increased to four meters (column 3). The declining estimate is consistent with a more severe effect for properties at higher risk. Column 4 considers a property at risk to sea level rise if it

is located within a FEMA defined 100-year flood risk zone. I estimate a similar and significant effect of an annual reduction in price appreciation of 0.6 percentage points. The estimated effects of sea level rise exposure across Table 2 are all precisely estimated and highly significant.

Table 2: Effect of Sea Level Exposure on Price Appreciation

	(1)	(2)	(3)	(4)
At risk × Year	-0.008**	-0.008**	-0.005**	-0.006**
	(0.002)	(0.001)	(0.001)	(0.001)
Distance to coast × Year	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Within 100 m of coast × Year	0.003	0.004	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Within 250 m of coast × Year	0.003	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Within 500 m of coast × Year	0.010**	0.011**	0.010**	0.010**
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
County time trends	Y	Y	Y	Y
At risk definition	2 m	3 m	4 m	FEMA Zone
R^2	0.884	0.884	0.884	0.884
N	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The coefficient estimates for At risk × Year correspond to the difference in annual price appreciation attributable to sea level rise exposure. The variable "Distance to coast" is in units of 10 kilometers.

Compared to the typical price appreciation on Long Island over the study period, the estimated effects of sea level rise exposure are economically sizable. For example, a home purchased on Long Island for $500,000 in nominal dollars in 2000 appreciated, on average, to $761,000 by 2017. However, if the same home was within three meters of sea level it would have only appreciated to $689,000 by 2017, on average.

An important component of the identification strategy is to control for the possibility that there had been differential appreciation of properties close to the coast

for reasons unrelated to climate change. For example, home buyer tastes may have changed over the study period. I address this in the main specification by including several controls that capture differential time trends for coastal properties (Equation 1). The distances from the coast I select to construct control variables are somewhat arbitrary. In Table 3, I evaluate the robustness of the main result to different sets of coastal proximity time trends. I repeat the Table 2, column 3 estimate, which used the three meter definition of exposure, in Table 3 but alter the coastal time trends controls.

In Table 3 column 1, I remove all coastal proximity time trends. In this specification, I estimate a small positive effect of sea level exposure on price appreciation. The positive effect suggests that the price appreciation trend of properties close to the coast outperformed properties further from the coast, and the exposure variable is proxying for this amenity value of coastal access. In columns 2-5 I increase the number of time trend controls that capture differential appreciation for properties with coastal proximity. Column 2 adds only a linear time trend of distance to the coast, column 3 also includes a unique time trend for properties within 500 meters of the coast, column 4 repeats the main (equation 1) specification for comparison and column 5 includes a vector of 11 unique coastal time trends using 100 meter buckets. Column 5 is potentially guilty of overfitting the relationship as there is little reason to think that there would be significant shifts in demand across such narrow definitions of coastal proximity. However, the main estimate of interest changes little between columns 3-5, suggesting the main model is able to control for changing market preferences for coastal proximity and isolate the partial effect of climate risk. The change in the β_1 estimate between columns 4 and 5 suggests that my main estimate of climate risk's price effect may be somewhat conservative.

In addition to coastal proximity time trends, I include time trends at the county level. In Table 4 I test for the sensitivity of results to time trends implemented at

Table 3: Effect of Coastal Proximity Time Trend Controls on Results

	(1)	(2)	(3)	(4)	(5)
At risk × Year	0.002*	0.001	-0.007**	-0.008**	-0.011**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Distance to coast × Year		-0.004*	-0.003*	-0.003*	-0.003*
		(0.002)	(0.001)	(0.001)	(0.001)
Within 100 m of coast × Year				0.004	0.001
				(0.003)	(0.003)
Within 200 m of coast × Year					0.006**
					(0.002)
Within 250 m of coast × Year				0.003	
				(0.002)	
Within 300 m of coast × Year					-0.003
					(0.002)
Within 400 m of coast × Year					0.004
					(0.002)
Within 500 m of coast × Year			0.013**	0.011**	0.001
			(0.001)	(0.001)	(0.002)
Within 600 m of coast × Year					0.001
					(0.003)
Within 700 m of coast × Year					-0.002
					(0.003)
Within 800 m of coast × Year					0.005
					(0.003)
Within 900 m of coast × Year					0.006**
					(0.002)
Within 1 km of coast × Year					-0.000
					(0.000)
Time fixed effects	Y	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y	Y
County time trends	Y	Y	Y	Y	Y
At risk definition	3 m	3 m	3 m	3 m	3 m
R^2	0.880	0.884	0.884	0.884	0.884
N	112,716	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The coefficient estimates for At risk × Year correspond to the difference in annual price appreciation attributable to sea level rise exposure. The variable "Distance to coast" is in units of 10 kilometers.

alternative geographic units. Column 1 shows the estimate when county time trends are removed, column 2 repeats the main specification, column 3 includes time trends

unique to local school districts and column 4 includes zip code level time trends. There are 124 school districts and 172 zip codes with at least one repeated sale property. The main estimate is essentially unchanged in columns 1-3. With the inclusion of 172 unique time trend controls by zip code in column 4 the estimated effect of sea level exposure remains statistically significant but is reduced by half. The inclusion of so many time trends in column 4 is absorbing much of the identifiable statistical variation and attenuating estimates towards zero.

Table 4: Effect of Local Time Trend Controls on Results

	(1)	(2)	(3)	(4)
At risk × Year	-0.007**	-0.008**	-0.007**	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to coast × Year	-0.003*	-0.003*	-0.003*	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Within 100 m of coast × Year	0.003	0.004	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
Within 250 m of coast × Year	0.003	0.003	0.003	0.003*
	(0.002)	(0.002)	(0.002)	(0.001)
Within 500 m of coast × Year	0.011**	0.011**	0.011**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
At risk definition	3 m	3 m	3 m	3 m
Time trends	None	County	School Dist.	Zip Code
R^2	0.884	0.884	0.885	0.890
N	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The coefficient estimates for At risk × Year correspond to the difference in annual price appreciation attributable to sea level rise exposure. The variable "Distance to coast" is in units of 10 kilometers.

In the above analysis, I include all repeat sales occurring within Nassau and Suffolk counties. However, properties far from the coast may represent a different sub-market and may therefore be relatively poor control observations. Limiting control observations to properties that are somewhat close to the coast may provide a cleaner estimate. As

a robustness check, I repeat the analysis while limiting the observations to include only those properties within two kilometers of the coast. This strategy substantially reduces the number of transactions in the sample from 112,716 to 43,220. If demand for properties close to the coast had a differential trend over the study period for uncontrolled for reasons this could potentially be a source of bias for the full sample specification, but this bias should be reduced in the coastal sample analysis.

Coastal sample results are provided in Table 5. I find results that are very similar to the main estimates when I limit the sample to properties within two kilometers of the coast. The result demonstrates that coefficient estimates are not driven by observations far from the coast.

Table 5: Effect of Sea Level Exposure on Price Appreciation, Coastal Sample

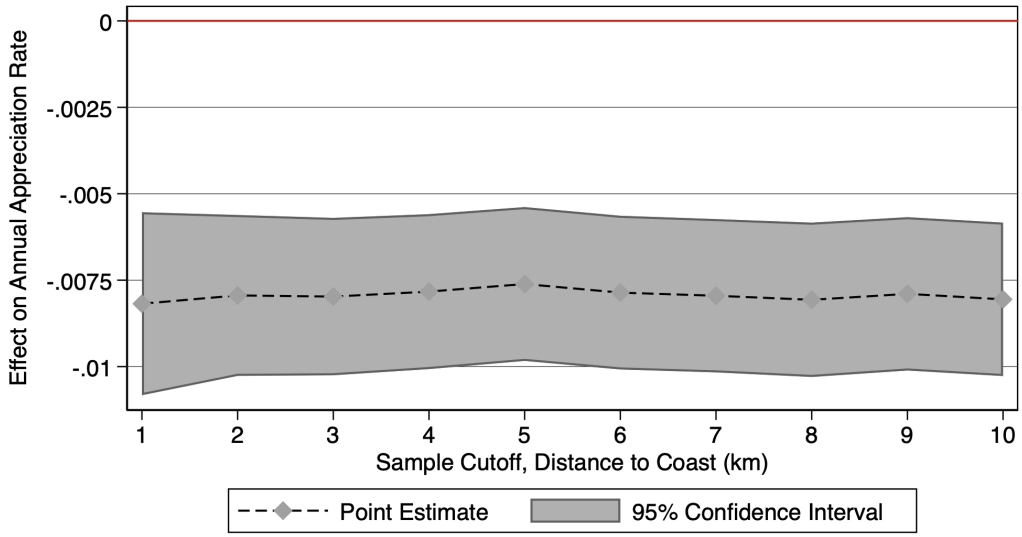
	(1)	(2)	(3)	(4)
At risk × Year	-0.009**	-0.008**	-0.006**	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)
Distance to coast × Year	-0.000	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Within 100 m of coast × Year	0.002	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Within 250 m of coast × Year	0.003*	0.004*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Within 500 m of coast × Year	0.004**	0.005**	0.005**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
County time trends	Y	Y	Y	Y
At risk definition	2 m	3 m	4 m	FEMA Zone
R^2	0.907	0.908	0.907	0.907
N	43,220	43,220	43,220	43,220

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The coefficient estimates for At risk × Year correspond to the difference in annual price appreciation attributable to sea level rise exposure. The variable "Distance to coast" is in units of 10 kilometers.

In Table 5 estimates, I choose a cutoff of two kilometers to limit the sample. Figure

6 shows β_1 estimates (using the three meter exposure definition) but varies the distance to coast cutoff value used for filtering observations. I test alternative values ranging from one to 10 kilometers. I find the negative price effect is highly robust to truncating the sample at any of these distances.

Figure 6: Effect of Sample Selection on Main Estimate (β_1)



The dotted line plots the estimated partial effect of sea level rise exposure on annual property appreciation (β_1). I use the three meter elevation definition of exposure. The sample cutoff is varied along the horizontal axis, with the sample size increasing from left to right.

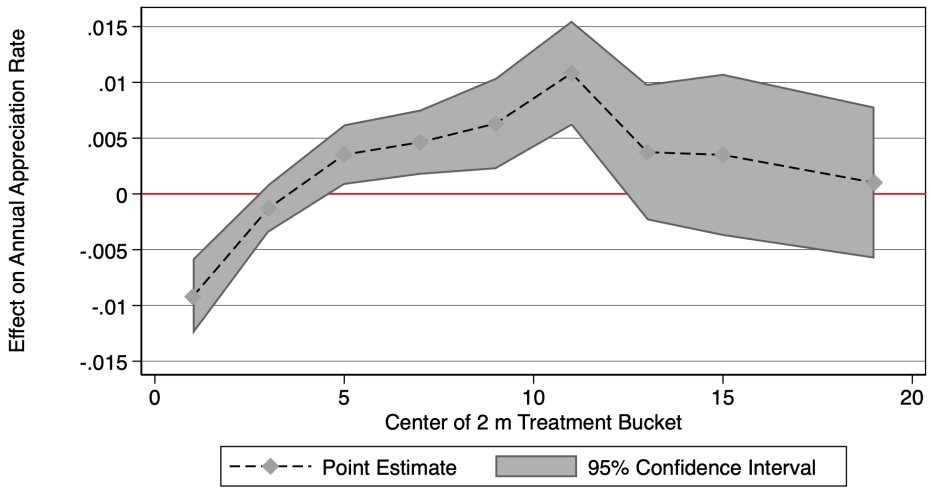
I expect that the direct relationship between climate risk and elevation is only relevant for properties fairly close to sea level, as properties at relatively high altitudes face no risk from rising seas. However, while climate risk should clearly reduce demand for at risk properties, it may increase demand for properties that are good substitutes for at risk properties. Properties that have good coastal access, but face a low risk from sea level rise may experience an increase in demand. I test for the presence of demand spillovers by estimating unique price appreciation premiums for sets of properties in various elevation buckets. I limit this analysis to properties within two kilometers of

the coast to focus on the coastal real estate market. Figure 7 shows the results of 15 unique estimates of β_1 (Equation 1) as the "at risk" definition is changed. The leftmost data point corresponds to the effect of being within two meters of sea level, which is equivalent to the Table 5, column 1 estimate. Moving rightwards, the subsequent point shows the estimated effect of being within 2-4 meters of sea level and the elevation buckets similarly increase by two thereafter.

Conditional on coastal proximity, climate risk seems to have significantly diminished the demand for low elevation properties, but increased the demand for higher elevation properties. Figure 7 shows the strong negative price appreciation effect of being within two meters of sea level. For the estimates that span the elevation buckets from 4 to 12 meters, I estimate a price appreciation premium relative to the rest of the coastal market. I find a null effect when testing the effect of being in the two meter buckets spanning 12 to 20 meters above sea level. I interpret this pattern as representing demand substitution within the coastal real estate market, away from the riskiest locations and towards relatively less risky locations. Because the estimates are controlling for distance to the coast, the effect estimated is essentially comparing homes that are the same distance from the coast but face different risk exposure due to elevation. Properties within two kilometers of the coast but at elevations greater than 12 meters may have comparatively poor coastal access and are therefore comparatively poor substitutes for at risk properties.

The expectations of future climate change induced property risk will be incorporated into present prices by forward-looking buyers. However, storm events that may have been induced by climate change have already affected Long Island during the study period. The most severe event being Hurricane Sandy in 2012. Past storm damage may affect home prices either through actual structural damage or from changing the expectations of buyers and sellers regarding the likelihood of future damage. I use

Figure 7: Estimating Demand Spillovers in the Coastal Market



The dotted line plots the estimated partial effect of a property being within a specific two meter elevation bucket. For example, the leftmost point estimate is the partial effect of being within two meters of sea level and the subsequent point estimate shows the effect of being within two to four meters of sea level. I report the β_1 estimates according to Equation 1.

equation 2 to test for a heterogeneous effect of coastal exposure in areas that have been subjected to high levels of past storm damage. I present results of this specification in Table 6.

I find some evidence that properties located in areas of high-storm damage over the study period also suffered the greatest appreciation penalty. For example, for properties within three meters of sea level and located within a tract that was in the top 5% of tracts in terms of FEMA storm damage insurance payouts, I find an annual price appreciation penalty of 1.6%. For properties within three meters of sea level but not located in a high-storm damage tract, I estimate an annual effect of only 0.5%, though the effect remains statistically significant. I find an insignificant effect of local storm damage on the appreciation penalty when using the two meter definition of exposure or the FEMA flood zone definition. I find a highly significant difference when using the

Table 6: Triple Difference Estimates, Heterogeneous Effects by Local Storm Damage

	(1)	(2)	(3)	(4)
At risk × Year	-0.007*	-0.005**	-0.002*	-0.003
	(0.003)	(0.001)	(0.001)	(0.002)
At risk × Year × High-damage area	0.002	-0.011**	-0.019**	-0.002
	(0.004)	(0.004)	(0.007)	(0.003)
Year × High-damage area	-0.007**	0.005	0.012	-0.005*
	(0.002)	(0.003)	(0.007)	(0.002)
Distance to coast × Year	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Within 100 m of coast × Year	0.002	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Within 250 m of coast × Year	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Within 500 m of coast × Year	0.011**	0.011**	0.011**	0.011**
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
County time trends	Y	Y	Y	Y
At risk definition	2 m	3 m	4 m	FEMA Zone
R^2	0.884	0.884	0.884	0.884
N	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The variable "Distance to coast" is in units of 10 kilometers.

four meter definition of exposure. I estimate a 0.2% appreciation penalty for low-storm damage areas but a 2.1% penalty for high-storm damage areas. In Appendix A, I also test the robustness of results to alternative cutoff values for which tracts I consider to be high-storm damage areas. The appendix provides additional evidence of a discrepancy in the partial effect of sea level rise exposure on home price appreciation based on the history of local storm damage. Overall I find evidence that the negative effect of sea level rise exposure on price appreciation is concentrated in areas that experienced storm damage, consistent with past research showing an information effect of storm events.

6 Conclusion

Sea level rise poses a significant and growing threat to coastal real estate. Over recent decades, climate research has increased predictions regarding the extent of future sea level rise and extreme coastal weather events. Current real estate prices will reflect not only the current utility of the asset but future monetary and utility flows. Because expectations of sea level rise became both more dire and less far into the future over the study period, properties exposed to sea level rise should sell at an increased discount if the market is populated by agents who are forward-looking, profit-maximizing and have full information on climate risk.

Implementing a repeat sales method on a complete set of housing transactions from Long Island, I find that properties exposed to the risks of sea level rise suffered a significant appreciation penalty over the 2000-2017 study period. Properties within three meters of current sea level were found to have annual price appreciation that was 0.8 percentage points per year lower than unexposed homes. I can control for observable and unobservable housing characteristics through property level fixed effects. I subject estimates to a battery of robustness checks to confirm the magnitude and significance of results. I also find evidence that the demand for high risk coastal properties has been diverted to lower risk coastal properties. Additionally, I provide evidence that the appreciation penalty of sea level exposure is larger in areas that experienced significant storm damage during the study period.

The declining value of high risk real estate suggests that the housing market is able to price, at least a portion, of the cost of climate risk. A gradual decline in the value of coastal real estate will help to buffer property owners from the costs of sudden climate event shocks, such as coastal floods and storm damage. However, some literature has suggested that the US housing market sets prices in ways that systematically reflect incomplete information on risk. Chivers and Flores (2002), Atreya and Ferreira (2015)

as well as Hino and Burke (2020) provided empirical evidence that home buyers do not fully understand flood risk. Bakkensen and Barrage (2018) estimated that the US market for coastal homes in the 2007-2016 study period exceeded fundamental values by 10% because the market failed to fully account for flood risk. An initiative to increase information on flooding among home buyers in Finland was analyzed in Votsis and Perrels (2016), finding that the initiative was successful in closing the information gap and led to reduced prices among homes at risk of flooding. The possibility that US buyers are making real estate purchases with incomplete information about future climate risk suggests that the appreciation penalty I estimate is possibly less than what would arise in a market with perfect information. Government initiatives to ensure the availability and salience of climate risk information during the purchase process could be important in overcoming issues of incomplete information.

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Appendix A

In Section 5 I test for a heterogeneous effect of sea level rise exposure between properties located in tracts that have and have not experienced significant storm damage over the study period (Table 6). In the Table 6 specification I define a high-storm damage tract as one above the 95th percentile of all tracts in terms of FEMA claims payments made. In this appendix I test the sensitivity of results to alternative definitions of high-storm damage tracts. Table A1 shows results when I adopt a cutoff threshold at the 90th percentile and Table A2 shows results with a 99th percentile threshold. Point estimates in both specifications suggest that the appreciation penalty was larger in areas of high-storm damage. In the 90th percentile specification the appreciation penalty is primarily driven by properties in high-storm damage areas. In the 99th percentile specification the difference in price penalty between properties in high and low-storm damage tracts is not statistically significant. The ability to identify a heterogeneous effect for the 99th percentile specification is more difficult because there are only 1,298 transactions in the 99th percentile tracts.

Table A1: Triple Difference Estimates, Heterogeneous Effects by Local Storm Damage, 90th Percentile Definition of High-Damage Area

	(1)	(2)	(3)	(4)
At risk × Year	-0.005	-0.002	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.003)
At risk × Year × High-damage area	-0.003	-0.013**	-0.019**	-0.009**
	(0.004)	(0.003)	(0.003)	(0.003)
Year × High-damage area	-0.003*	0.005**	0.009**	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Distance to coast × Year	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Within 100 m of coast × Year	0.003	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Within 250 m of coast × Year	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Within 500 m of coast × Year	0.010**	0.011**	0.011**	0.011**
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
County time trends	Y	Y	Y	Y
At risk definition	2 m	3 m	4 m	FEMA Zone
R^2	0.884	0.884	0.884	0.884
N	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The variable "Distance to coast" is in units of 10 kilometers.

Table A2: Triple Difference Estimates, Heterogeneous Effects by Local Storm Damage, 99th Percentile Definition of High-Damage Area

	(1)	(2)	(3)	(4)
At risk × Year	-0.008**	-0.008**	-0.005**	-0.006**
	(0.002)	(0.001)	(0.001)	(0.001)
At risk × Year × High-damage area	-0.005	-0.007	-0.025	-0.019
	(0.007)	(0.009)	(0.018)	(0.012)
Year × High-damage area	0.004	0.006	0.022	0.017
	(0.006)	(0.008)	(0.018)	(0.011)
Distance to coast × Year	-0.003*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Within 100 m of coast × Year	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Within 250 m of coast × Year	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Within 500 m of coast × Year	0.009**	0.011**	0.010**	0.009**
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y
County time trends	Y	Y	Y	Y
At risk definition	2 m	3 m	4 m	FEMA Zone
R^2	0.889	0.889	0.889	0.889
N	112,716	112,716	112,716	112,716

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis. The variable "Distance to coast" is in units of 10 kilometers.