The Real Price to Pay for Waterfront Property: The Impact of Flood Zones and Spatial Proximity to Water on Property Prices in York County, Maine

A Thesis

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Lucy Faust

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Abstract

I employ a log-linear hedonic property price method to examine the effects of flood risk and spatial proximity to water on coastal property values. I use data from over 3,000 single-family home sales from 2010-2018 in York County, Maine. Results establish three main findings. Homes a half-mile from the ocean have a price premium (estimated at 7.6 percent in our model). Homes a half-mile closer to the river have a negative price premium, and homes in the flood zone are capturing an estimate price premium ranging from 27.1 to 66.2 percent in our models. Whereas most studies analyze flood risk after a major flooding event, this study explores perceived risk before a major flood. Future action is necessary to better inform homeowners and homebuyers of the flood risk in their community.

1. Introduction

According to an interactive map from the Union of Concerned Scientists, by 2045, 1,207 of today's home in Maine are at risk worth a collective $532 million dollars affecting about 1600 residents (2018).[1] In York County specifically, a partnership with Climate Central and Zillow find that by 2050, 1,438 homes are at risk of flooding at least once per year comprising almost $891 thousand dollars of home value. Even worse, growth of home building is occurring at the same rate in and out of flood zones.[2] Although predictions from these various sources vary in exact numbers, the increase in risk of flood damage over time is unquestioned.

Maine has one of the states with the worst erosion problems at Camp Ellis in Saco and severe flooding problems at Ocean Park, Old Orchard Beach. A formal sea level rise assessment completed for Saco, Biddeford, Old Orchard Beach, and Scarborough found that in my three communities of focus, there appears to be over 291 structures, with land and parcel values exceeding $1.06 billion dollars, already threatened by climate change impacts under existing conditions. Predictions for 2100 far exceed the 2011 estimates (Members of the Sea Level Adaptation Working Group (SLAWG) 2011). Maine's coastline has yet to make national headlines for severe flooding. Yet in the future, scientists find evidence that it will.

My research hopes to focus on these implications in a specific area in the Gulf of Maine: York County. I explore the impacts of flood zones and spatial proximity to the Atlantic Ocean

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[1] Union of Concerned Scientists. US Coastal Properties at Risk from Rising Seas. Retrieved from https://ucsusa.maps.arcgis.com/apps/MapSeries/index.html?appid=cf07ebe0a4c9439ab2e7e346656cb239

[2] Climate Central, Zillow, and ZTRAZ. Ocean at the Door: New Homes and the Rising Sea. Retrieved from http://www.climatecentral.org/news/ocean-at-the-door-new-homes-in-harms-way-zillow-analysis-21953?utm_medium=email&utm_campaign=SLR%20%20Stakeholders%20%20Zillow&utm_content=SLR%20%20Stakeholders%20%20Zillow+CID_492b862b4dd679a77d21743c7dd58f62&utm_source=Climate%20Central%20Email%20Campaign%20Monitor&utm_term=results, accessed on 11/27/18

and the Saco River on property values. I further explore community-level effects on either side of the Saco River.

Global climate change is causing sea levels to rise. According to the National Oceanic and Atmospheric Administration, oceans worldwide have been steadily rising since 1900 at a rate between .1 and .25 centimeters per year.[3] Specific to the northeast of the U.S., under low and high scenarios, the temperature is projected to rise more than 3.6°F on average by 2035.[4] Sea level rise is caused by two primary mechanisms. The first is that an increase in global temperatures leads to seawater expansion which takes up increased space in the ocean basin. The second is that an increase in global temperatures causes ice sheets and ice caps to melt. The introduction of freshwater from the melting ice sheets disrupts convection, the process by which surface water moves to the bottom of the ocean and travels along it. This then affects ocean currents and its distribution of warm and cold water globally. This second mechanism helps to explain why some parts of the world's oceans are warming at a faster rate than others.[5]

Pershing et al. (2015) notes that temperatures on the coastal Northeast are rising at least twice as fast as the global average. As Figure 1.1 from Pershing et al.'s work illustrates, the sea surface of the Gulf of Maine is rising significantly faster than anywhere else in the world. So why are sea surfaces in the Gulf of Maine rising so much faster?

The answer, in part, relies on the fact the east coast, and the Gulf of Maine in particular, is largely affected by the melting of the Greenland ice sheet and the warming of the Arctic Ocean. Due to positive feedback loops in the polar regions, in a process called arctic

[3] NOAA. How is sea level rise related to climate change?, National Ocean Service website, https://oceanservice.noaa.gov/facts/sealevelclimate.html, accessed on 10/18/18.
[4] NCA4. Chapter 18: Northeast, U.S. Global Change Research Program (USGCRP), https://nca2018.globalchange.gov/ assessed on 11/27/18.
[5] NOAA. How does sea ice affect global climate? National Ocean Service website, https://oceanservice.noaa.gov/facts/sea-ice-climate.html, accessed on 10/18/18.

amplification, the melting process is accelerating at an exponential rate (Stroeve et al., 2012). Pershing et al. (2015) explains that this ice melt flows into the Labrador Sea in Canada instead of the Gulf of Maine where it used to flow. This allows warm water from the Gulf Stream to come up from the South to replace the flow from ice melt. As a result, northern waters are warming rapidly, especially in the Gulf of Maine.

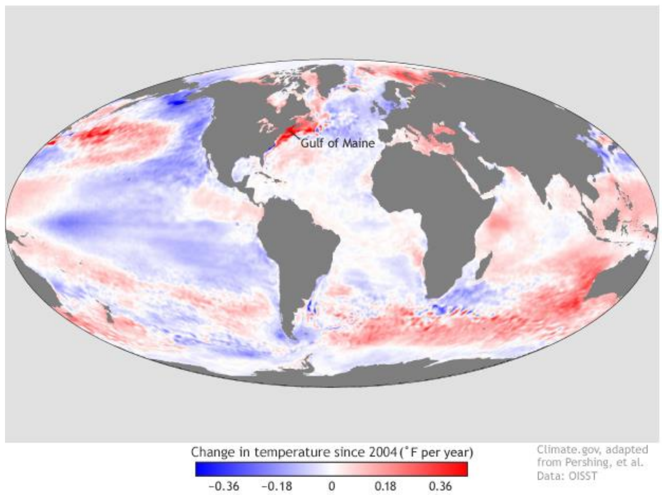

Figure 1.1 The Gulf of Maine has some of the highest rates of temperature change in the world.

Projections from the NCA4 suggest that sea level rise in the Northeast will increase by between 2 feet (low scenario) and 4.5 feet (high scenario) by 2100, greater than the global average. Ocean that are warmer and rising are anticipated to increase the probability of hurricanes to become more frequent and more intense in the future, flooding communities during future nor'easter type storms.[6] This data shows that climate change is causing an increase in risk for flood damage.

Many of the climate predictions that scientists make rely on a linear trajectory for rising sea-levels, rising temperatures, and the fate of biodiversity on our planet. What many predictions

[6] NCA4. Chapter 18: Northeast, U.S. Global Change Research Program (USGCRP), https://nca2018.globalchange.gov/ assessed on 11/27/18.

don't consider is the rate of arctic amplification, which could easily put areas close to the north and south pole on exponential trajectories for rising sea-levels and rising temperatures (Screen, 2010). This helps us emphasize the urgency of completing research to inform home-buyers, home-builders, and cities near polar coasts to act to prepare for future climate hazards. If they do so, it could minimize the likelihood of a full climate disaster. I hope that my research can positively impact these communities by quantifying the premium or discount homeowners are paying for flood risk which can more accurately inform homeowners and homebuyers.

This background information exemplifies the importance of identifying future dangers for coastal communities in regions close to the poles. This impact will affect thousands of Americans, their homes, and their businesses in the future as storms creep up the Eastern Coast of the U.S. Many studies look at the effects after a severe storm or flood. I hope my analysis to study the effects before a severe storm or flood can help to inform residents about flood risk before, rather than after, water arrives at their doorstep.

2. Literature Review

In this section I introduce the theory of the hedonic model. Then I will explore previous work that has applied the hedonic model to similar problems in other geographies and other time periods. Using this literature as a foundation, I further explore housing prices in relation to sea-level rise and flood zones in southern Maine.

2.1 Hedonic Models

The hedonic model was spearheaded by Lancaster who developed a consumer theory where he established that utility can be derived from the characteristics or properties of goods rather than the goods themselves. For example, he established that utility not only can come from having a car, but from the features of a car too. His paper on a consumer's demand and how an individual's utility of goods is based on a composite of attributes has led to the hedonic model that we know today (Lancaster, 1966). However, he never spoke of the pricing of these characteristics.

Rosen (1974) built on Lancaster's consumer model to define hedonic pricing, where any good is assigned a hedonic, or implicit price. More specifically, he acknowledged that a total price can be seen as the sum price of each homogeneous attribute, and each attribute has an implicit price in an equilibrium market where supply equals demand. He finds that a good can be regressed on its characteristics to determine how each characteristic contributes to the overall price an individual is willing to pay for a good. The hedonic price function is typically represented as:

$$Y = Y(z) \tag{1}$$

For example, the price of a car is a function $Y(z)$ where (z) is a vector of characteristics completely describing the choices in purchasing a car. These characteristics could include make, model, color, fuel efficiency, airbags, cruise control, a sun roof, aux and charging capabilities, among many others, of a car. These (z) characteristics determine the price that consumers pay when they purchase a car. In many situations, the data on prices can allow us to estimate the price of $Y(z)$ directly. This model is powerful because it can help us estimate the price people are willing to pay for an extra MPG of fuel efficiency or an added sunroof; characteristics that don't usually have known or specific price tags on them. The environmental economics literature specifically utilizes a hedonic model that either takes an exact or a slight variation of the following form adapted from Xiao's Hedonic Housing Price Theory Review (2017):

$$Y = Y(H, N, E) \tag{2}$$

In this case, Y is the natural log of a sales price which is a function of (z)'s vector of characteristics: $(H, N, E\ )$. The structural characteristics of a home are represented in H, neighborhood characteristics are represented in N, and environmental characteristics are represented in E. A household's utility will therefore be expressed as:

$$U = U(X, K, N, E) \tag{3}$$

where X is a composite commodity with price equal to one. These composite commodities are the implicit prices the hedonic model will estimate. The homebuyer's goal then, is to maximize utility, or U, based upon:

$$I = X + Y \tag{4}$$

where I equals the household income. For each specific environmental attribute, E, it is assumed a household will choose to buy a house based on their marginal willingness to pay for that characteristic with the following form:

$$\frac{\left(\frac{\partial U}{\partial E}\right)}{\left(\frac{\partial U}{\partial X}\right)} = \frac{\partial Y}{\partial E} \tag{5}$$

As Xiao (2017) notes, this first derivative represents the marginal willingness to pay for an additional unit of that specific environmental attribute. My model will use a similar variation of this model according to my specific variables and data set using the exact mathematical process to analyze my results.

Hedonic models have three main assumptions that need to be met for its implicit prices to accurately represent the cost of a set of characteristics through a stable price function of (z). First, there needs to be completeness where all products in the market are on the market to be bought and sold. Second, availability is necessary so that all of the complete products in the market are available to all consumers. Third, there needs to be equal power in the market where consumers are price-takers and no consumer or producer has un-just market power (Gilbert, 2013).

As Rothenberg (1991) describes, there are two primary insights the hedonic model can provide to economics. One is that a hedonic model avoids biases because it is constructed with homogenous attributes all together in one regression instead of in multiple regressions. The other is that hedonic models can capture the multiple and implicit marginal trade-offs buyers and sellers face in the marketplace when they looking to buy or invest in a product.

Housing largely contributes to the welfare of individuals. Purchasing a home is one of the biggest decisions an individual or family may make. As this decision is not made lightly, many hedonic studies have looked into the willingness to pay of housing characteristics. Prices of properties are driven by macro-economic trends, changes in consumer preferences and incomes, and exogenous shocks (Xiao, 2017). However, this paper will primarily look at consumer preferences.

The hedonic model is useful in determining whether or not environmental variables with no traditional prices are reflected in housing markets. Thus, the hedonic model is widely used in public, environmental, and natural resource economics to estimate the consumer willingness to pay for amenities that typically don't have a specific price, like clean air, high quality schools, or a scenic view.

2.2 The Hedonic Model Applied

Many economic studies examine the hedonic prices of different structural characteristics of a home. Common price indicators in these models have been lot size, square feet, age of the house and number of bathrooms and bedrooms (Atreya, Ferreira, & Kriesel, 2013; Bin, Kruse, & Landry, 2008; Bohlen & Lewis, 2009; Brookshire, Thayer, Tschirhart, & Schulze, 1985; Hallstrom & Smith, 2005; Lewis & Landry, 2017; MacDonald, 1990; Michaels & Smith, 1990; Morgan, 2007; Paterson & Boyle, 2002; Rabassa & Zoloa, 2016; Sirmans, Macpherson, & Zietz, 2005; Votsis & Perrels, 2016). Other studies have also seen the value of shower stalls, types of roofs, fireplaces, cooling, as well as garages and pools (Atreya et al., 2013; Bin & Landry, 2013; Bohlen & Lewis, 2009; Hui, Zhong, & Yu, 2012; Lewis & Landry, 2017; MacDonald, 1990; McKenzie & Levendis, 2010; Samarasinghe & Sharp, 2010).

In recent years, literature on models that research proximity to environmental amenities like schools, police stations, and parks as well as qualitative neighborhood characteristics like crime rates and school quality is increasing. (Atreya et al., 2013; Bin & Landry, 2013; Bohlen & Lewis, 2009; Hite, Chern, Hitzhusen, & Randall, 2001; Hui et al., 2012; Lewis & Landry, 2017; Votsis & Perrels, 2016). Further, there is heightened attention towards the value of the visibility of one's surroundings and the configuration of landscape as a major contributor to the quality of life, and therefore, a strong contributor in price. This could include a scenic view or comparing a backyard with a natural landscape versus developed property (Bockstael, 1996; Bohlen & Lewis, 2009; Daniel, Florax, & Rietveld, 2009; Lewis & Landry, 2017; Paterson & Boyle, 2002; Samarasinghe & Sharp, 2010).

The idea of considering spatial risk in the context of the hedonic model has become more common and utilized in the last 20 years as many studies have utilized GIS and other mapping software to put a price on the distance, and sometimes direction to amenities and hazards as well as to explore the spatial pattern and distribution of land use. These studies have revealed important economic, societal, and environmental consequences (Bockstael, 1996; Bohlen & Lewis, 2009; Cameron, 2006; Geoghegan, Wainger, & Bockstael, 1997; Lewis & Landry, 2017; Paterson & Boyle, 2002).

There is also an increasing number of studies exploring the effect of hazards on property values and exogenous shocks as a result of natural disasters over the past 15 years. In single family homes, these papers find negative price impacts on homes as proximity to landfills and earthquake zones increases (Brookshire et al., 1985; Hite et al., 2001; Michaels & Smith, 1990; Sirmans et al., 2005). A recent study looked at long-term impacts of sea level rise to find that homes exposed to sea level rise sell for approximately 7 percent less than homes not exposed to sea level rise (Bernstein, A., Gustafson, M., & Lewis, R., 2018)

Considering flooding and severe storms specifically, the literature includes a growing number of studies. Some literature focuses only on housing prices and perceived risk. In an area of Argentina, for example, where there is no flood insurance, Rabassa and Zoloa (2016) find that property values in flood-prone areas are reduced by 3.5 percent, revealing that houses prices on the coast of Argentina do account for the possible risk of damage from flooding and storms.

However, most of the literature refers to studies where FEMA flood maps, flood insurance premiums, or individualized community flood zones that can help homeowners perceive the potential damage from flood risk in house pricing. Atreya, Ferreira, & Kriesel (2013) show using a difference in differences model, with single-family homes in Georgia, that flood risk discounts in price only lasts between 4-9 years before going up again. Bin & Landry (2013) similarly find that after Hurricane Fran and Hurricane Floyd in the 1990's there was a 6.0%-20.2% risk discount for homes sold in flood zone for between 5-7 years before the effects diminished. Morgan (2007) argues that Hurricane Ivan in 2004 increased expected flood loses by 75% and raised flood risk perceptions for only a relatively small period of time. McKenzie & Levendis (2010) compare insurance flood premiums and find a 1.4 percent increase per foot before and a 4.6 percent increase per foot after Hurricane Katrina in 2005. Daniel et al. (2009) investigates the impact of exposure to flood risk and conclude that the marginal effect of a 1% increase in the probability of flood risk amounts to a decrease in a house price of 0.6%.

Although all of these studies differ in their definition and quantification of flood risk, they all point to a statistically significant price discount after a major flooding event. Additionally, these studies show two main trends. Flood risk shown in housing prices are primarily reactive to a flood or storm instead of proactive to risk of flooding and storm damage. Second, many of the effects of flood risk discounts are short-lived and don't "stick" from storm to storm. In my analysis, I will be looking at the proximity of homes to the Atlantic Ocean and the Saco River (which feeds into the Atlantic Ocean) and its effect on the price of single family home sales in an attempt to do a unique proactive study on proximity to the ocean and its associated flood risk rather than the large body of reactive literature.

Some studies have recently come out that highlight the positive impact of informing communities about risk. In New Zealand and Finland respectively, as residents got more information about flooding and flood zones, sales prices were discounted in a flood zone than out of a flood zone for a period of a few years (Samarasinghe & Sharp, 2010; Votsis & Perrels, 2016). This shows promise that informing homeowners and communities can help reduce risk in geographically vulnerable locations. In addition, the Union of Concerned Scientists recently released a brochure to inform home-buyers about the questions they should ask regarding tiding flooding and their possible new home, many questions homebuyers currently do not ask (Union of Concerned Scientists 2018).

This information, as well as the increased frequency of flooding disasters is creating urgency to start a dialogue of risk in flood-prone areas. These studies show how my analysis, a preemptive study, could positively impact and inform communities at risk about the risks of owning waterfront property in this era.

3. **Data**

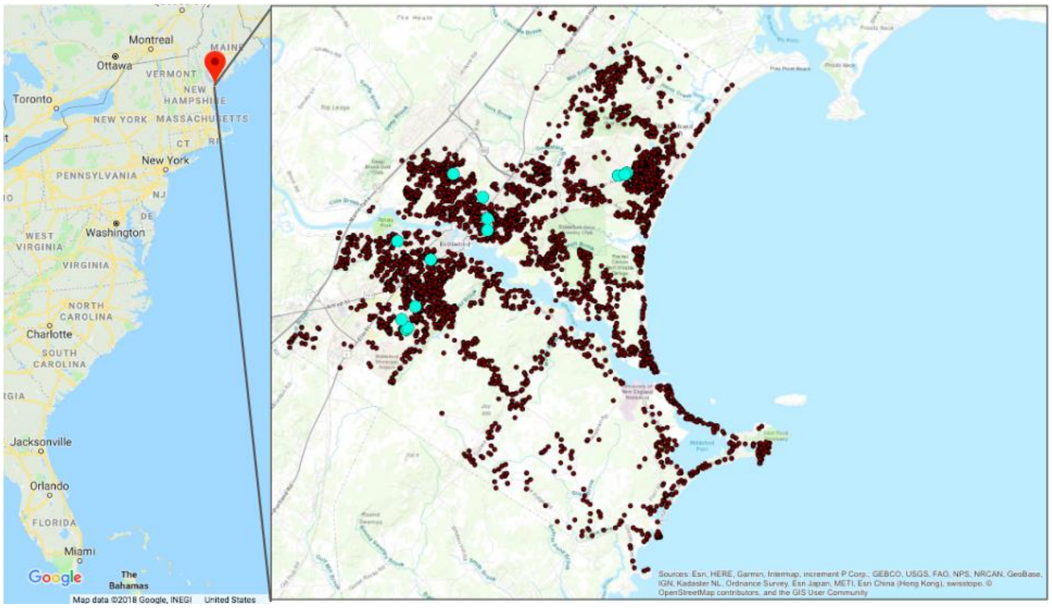

Figure 3.1 Study Area - York County communities of Biddeford, Saco, and Old Orchard Beach on the southern coast of Maine, U.S.A. The figure includes 13 Schools (teal circles) and over 3,000 properties (maroon dots).

Data comes from Multiple List Service (MLS) data of single-family home sales from 2006-2018.[7] 5,053 single family homes sold during this period in York County, Maine. All houses were contained in the cities of Biddeford and Saco, and the town of Old Orchard Beach. These three communities surround the longest stretch of continuous sand beaches in Maine and are particularly vulnerable to the effects of climate change, particularly from sea-level rise, storm surge, and erosion. York County contains 991 square miles of land and 279 square miles of water (22% of the total) highlighting the strong influence of sea-level rise on the county. Census data on York county and community specific data is shown in Table 3.1.

Saco and Biddeford have comparable populations although Saco has more wealth, more space and less than half as much poverty. Old Orchard Beach has the smallest population but is the densest with the lowest median household income, and a poverty rate higher than the county

[7] I eliminated data prior to 2009 to account for the housing market crash between 2007 and 2009. I took these sales out because during these years, one can hypothesize that the market was not in equilibrium, implying that the hedonic price of a good would not be strictly equal to the marginal willingness to pay. This would disrupt a fundamental assumption in the model. This decision eliminated over 500 homes from our data set.

average. When thinking about flood risk, density can be important in finding new spaces for people than may need in an emergency situation. In general, the cities of Biddeford and Saco, and the towns of Old Orchard Beach make up York County's biggest communities so they are highly representative of York County as a whole.

Table 3.1[8]
Census QuickFacts For Our Area of Focus

	Population	Median Household Income	Poverty Level	Population/mi^2
York County	204,191	$59,132	7.8%	199.0
City of Biddeford	21,488	$47,265	18.1%	707.2
Old Orchard Beach Town	8,855	$43,523	11.7%	1,160.1
City of Saco	19,485	$59,740	7.6%	480.5

Table 3.2 defines all of the variables in the model. Variables of interest include housing structural characteristics such as the lot size of the property and the square feet above ground of the house. I include the age of the home, the number of bedrooms, the number of bathrooms and the amount of water frontage owned in meters. I assume that 0.5 equals a half bath while 1.0 equals a full bathroom. Therefore, a house with 1 full bath and 2 half baths equaled 2 total bathrooms. I also look at real estate purchasing characteristics like the days on market, the price, the type of payment used, and what year it was sold.

The data set also includes several dummy variables constructed from qualitative variables. These dummy variables include the presence of a fireplace, the presence of cooling capabilities, seasonality capabilities, the quality of scenery (as defined by the listing agent or the seller). These dummy variables may not capture the exact realized utility of these features in

[8] U.S. Census Bureau QuickFacts Data, York County, City of Biddeford, City of Saco, Town of Old Orchard Beach, https://www.census.gov/quickfacts/yorkcountymaine, accessed 12/03/18

Table 3.2

Variable	Description	Type
Age	Age of the house in years	Home
Lotsize	Lot size in acres	Home
Sqftabove	Square feet of living space above ground	Home
Bedstotal	Number of bedrooms	Home
Bathstotal	Number of bathrooms	Home
Cooling	Mechanism for home cooling = 1	Home
Fireplace	Working fireplace =1	Home
Seasonal	Can only live in home in the summer = 1	Home
Cash	Bought solely with cash =1	Purchase
Mortgage	Bought with some type of mortgage =1	Purchase
Price2000	Sale price of the house	Purchase
Price2010	Adjusted price of the house to 2010 dollars	Purchase
Logprice	The log of *Price2010*	Purchase
Dom	The number of days the house was on the market	Purchase
Yr2010	House sale in 2010 =1	Purchase
Yr2011	House sale in 2011 =1	Purchase
Yr2012	House sale in 2012 =1	Purchase
Yr2013	House sale in 2013 =1	Purchase
Yr2014	House sale in 2014 =1	Purchase
Yr2015	House sale in 2015 =1	Purchase
Yr2016	House sale in 2016 =1	Purchase
Yr2017	House sale in 2017 =1	Purchase
Yr2018	House sale in 2018 =1	Purchase
Biddeford	In the city of Biddeford = 1	Environment
Oldorchard	In the town of Old Orchard Beach =1	Environment
Saco	In the city of Saco = 1	Environment
Neighbor	In a neighborhood association =1	Environment
Schooldist	Distance to a school in meters	Environment
Scenic	Home is scenic =1	Environment
Amtwater	Amount of waterfront owned in meters	Environment
Oceandist	Distance to the Atlantic Ocean in meters	Environment
Riverdist	Distance to the Saco River in meters	Environment
Oneftflood	House in 2015 high tide + 1ft flood zone =1	Zone
Threeftflood	House in 2015 high tide + 3.3ft flood zone =1	Zone
Sixftflood	House in 2015 high tide + 6ft flood zone =1	Zone
Oceansaco	Oceandist*Saco	Interaction Term
Riversaco	Riverdist*Saco	Interaction Term
SixFloodSaco	Sixftflood*Saco	Interaction Term

each home because when constructing several dummies like cooling and scenery the quality of scenery or cooling could have varied. These potentially qualitative measures of scenery or cooling could have been different from one real estate agent to the next. Similarly, the quality of the fireplace in one house could vary from the next. For my model, I assume that if it was labeled scenic or cooling, I take that as given with Scenic = 1 or Cooling =1 if designated as such. Other quantitative dummy variables include whether a home is in a neighborhood association, if it was bought strictly with cash or with a loan, what city the home is located in, and whether or not the home was in one of the three flood zones. Flood zones are explained subsequently.

There were several qualitative variables I decided to eliminate from the raw data for two reasons. One reason was that these variables were too difficult to classify. These variables included various added appliances or amenities that would describes unique aspects of a home such as an "elegant staircase." Another reason was that based on past literature, these characteristics were not shown to greatly influence housing prices anyways. Some of these variables included type of flooring, gas, heat system, electricity, roof, driveway and parking, color of home, style of home, and foundation materials.

Although many of these characteristics are attributes that contribute to the total price of a home, it is hard to incorporate the overall quality of every home into the model when every detail about each home in the data set is unknown. This idea captures a flaw of the hedonic model that is difficult to adjust for.

Using the close price of the home as my home price variable, noted as *Price2000* in Table 3.2, I deflated the price to adjust for the change in price overtime to 2010 dollars using monthly Case-Schiller U.S. National Home Price Index data from FRED noted as *Price2010* in Table 3.2.[9] I took the log of that price and used it as my dependent variable, *logprice*, in the

[9] S&P Dow Jones Indices LLC, S&P/Case-Shiller U.S. National Home Price Index [CSUSHPINSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CSUSHPINSA, October 3, 2018.

model. To capture any linear trends in housing market conditions, I included dummy variables for the year each home sold (2010-2018) (year fixed effects). The summary statistics for the variables we use in our hedonic model are shown in Table 3.3 below.

TABLE 3.3

Variable	Mean	Std. Dev.	Minimum	Maximum
Age	58.981	44.515	0	283
Lotsize	0.624	2.518	0.008	56
Sqftabove	1625.421	708.472	444	11659
Bedstotal	3.156	0.867	1	14
bathstotal	1.795	0.800	0	12.5
Cooling	0.138	0.345	0	1
Fireplace	0.069	0.295	0	1
Seasonal	0.028	0.166	0	1
Cash	0.211	0.408	0	1
Mortgage	0.612	.489	0	1
Price2000	162959	144171.3	14543	3848766
Price2010	236295	209052.7	21087.79	5580826
Logprice	12.197	0.547	9.956	15.535
Dom	155.378	155.490	0	2132
Yr2010	0.159	0.365	0	1
Yr2011	0.074	0.262	0	1
Yr2012	0.089	0.280	0	1
Yr2013	0.106	0.308	0	1
Yr2014	0.111	0.314	0	1
Yr2015	0.120	0.324	0	1
Yr2016	0.141	0.348	0	1
Yr2017	0.126	0.332	0	1
Yr2018	0.079	0.270	0	1
Biddeford	0.408	0.492	0	1
Oldorchard	0.241	0.428	0	1
Saco	0.351	0.477	0	1
Neighbor	0.178	0.382	0	1
Schooldistance	472.5851	473.742	0	1608.756
Scenic	0.072	0.258	0	1
Waterfront	0.067	0.249	0	1
Amtwater	8.508	49.362	0	1260
Oceandist	3180.82	2216.014	4.824	9548.834
Riverdist	2121.37	1676.515	0	7443.888
Oneftflood	0.018	0.131	0	1
Threeftflood	0.043	0.202	0	1
Sixftflood	0.107	0.310	0	1
Oceansaco	1385.914	1901.468	0	6870.19
Riversaco	506.793	822.256	0	7223.601
Sixfloodsaco	0.0452	0.208	0	1

I plot the longitude and latitude of each home into ArcGIS, a GIS software program to calculate other amenities and spatially quantity our area of focus. With GIS, I eliminated 835 homes due to their location on the west side of highway 95, a distance so far from the ocean, that there is a low probability that rising sea-levels and flooding would have an impact on those homes. Figure 3.1 highlights the homes in the dataset from York County after deleting homes on the other side of the highway through GIS. The maroon dots represent the 3,707 homes I use for analysis.

Using this group of homes, I measured their distance to the Atlantic Ocean, their distance to the Saco River, and the distance to the closest elementary, middle, and high schools. The data on schools comes from the Maine School Geolibrary online database[10]. The teal circles in Figure 3.1 represent the 13 schools I use in my analysis.

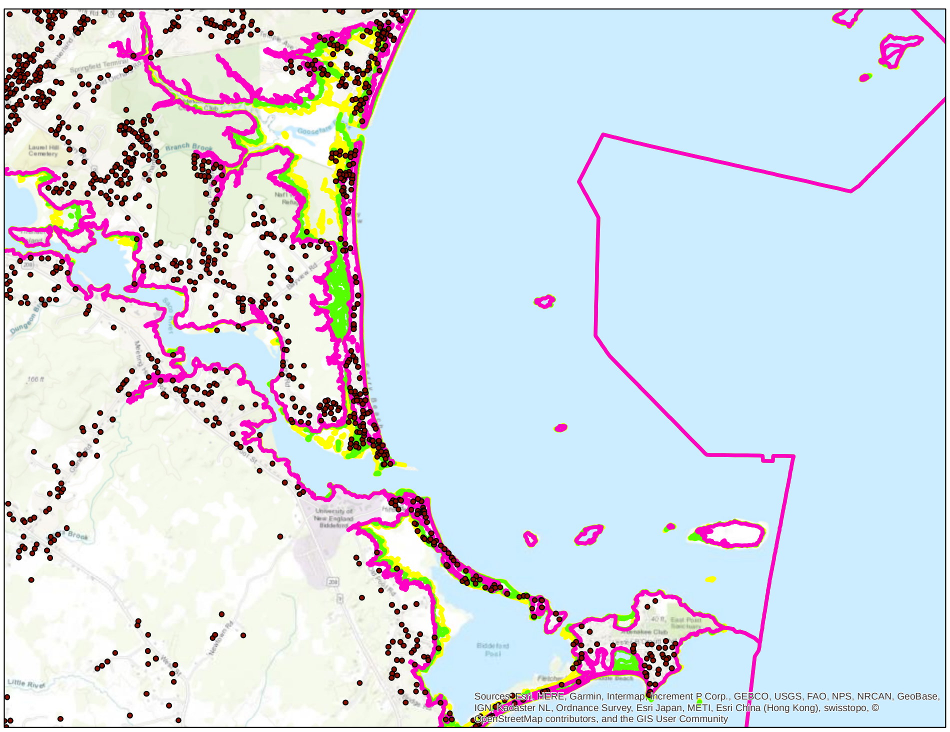

Figure 3.2- The green line represents 1 foot of flooding, the yellow line represents 3.3 feet of flooding, and pink line represents 6 feet of flooding.

[10] Maine GeoLibrary (Open Data), Maine Schools Geolibrary, retrieved from gis.maine.gov; https://geolibrary-maine.opendata.arcgis.com/datasets/maine-schools-geolibrary, October 3, 2018.

Figure 3.2 shows a close-up picture of Figure 3.1. I chose to focus on this area because as it includes the Biddeford Pool (bottom center of Figure 3.2), the Saco River (left center of Figure 3.2) and the Atlantic Ocean, (right side of Figure 3.2) the area has historically been more vulnerable to flooding than other areas in the data set.

Using GIS files from the Maine Geological Survey, the yellow line represents 2015's high tide plus 1 foot of flood water, the green line displays 2015's high tide plus 3.3 feet of flood water, and the pink line shows 2015's high tide plus 6 feet of flood water. Many homes in this area have a high risk of damage when flooding occurs. We created dummy variables for each of these scenarios. The green 1-foot flood scenario would include 65 homes, the yellow 3.3-foot flood scenario would include 158 homes and the pink 6-foot flood scenario would include 398 homes.[11] I keep the flood zone dummies separate in each model to avoid multi-collinearity as homes in the green 1-foot flood scenario are likely in the 6-foot flood scenario too.

[11] Maine Department of Agriculture, Conservation, and Forestry, Maine Geological Survey, Sea Level Rise/Storm Surge, https://www.maine.gov/dacf/mgs/hazards/slr_ss/index.shtml, accessed on 11/10/18.

4. Methods

I chose to utilize a log-linear model to be consistent with recent literature. The log-linear model I use in my analysis for the base model is shown below:

$$\ln(price) = \beta_0 + \beta_1 H + \beta_2 P + \beta_3 E + \beta_4 Z + \mathcal{E} \qquad (6)$$

The natural log of the sales price is the dependent variable and the variables in Table 3.2 are the explanatory variables. The model incorporates the housing characteristics in $\beta_1 H$, the purchasing characteristics in $\beta_2 P$, the environmental characteristics in $\beta_3 E$ and the flood zone dummies in $\beta_4 Z$. The error term follows the explanatory variables. To limit heteroskedasticity, I use robust standard errors in all models.

I run one group of log-linear regressions with this base model to test for two primary results. One result I look for is the relationship between the price of a home and its proximity to the Atlantic Ocean and the Saco River. This is the model I primarily use for the analysis. When I run this regression, I will omit the flood variables from this model so I can isolate the effects of spatial proximity on price.

The other results I am looking for is the relationship between the price of a home and its location in or out of a flood zone. I will run my model with $\beta_4 R$ but without the two proximity variables to isolate the effects of flood zones on price. I run a model with 2015's high tide plus 1 foot of flood water, another model with 2015's high tide plus 3.3 feet of flood water, and a final model with 2015's high tide plus 6 feet of flood water.

In my second group of log-linear regressions, I run the same model but I eliminate all data from Old Orchard Beach. I eliminate these houses to focus on the relationship between houses on either side of the Saco River in Biddeford and Saco respectively. Old Orchard Beach has many large hotel and apartment complexes, as well as shops and amusement parks in oceanfront space. As a result, many single-family homes in Old Orchard Beach are farther away from the Atlantic Ocean and the Saco River compared to Biddeford and Saco (see Figure 3.1). This will make our results city-level specific.

With this more isolated group of data, I re-run my initial four models with the purpose of reconfirming my results with and without Old Orchard Beach data. Then, I add three different interaction terms to three separate models to expand understanding about the relationships discovered previously. Each of these three models will take the following form:

$$\ln(price) = \beta_0 + \beta_1 Oceandist + \beta_2 Saco + \beta_3 Oceansaco + \beta_4 \text{"}all\ other\ vars\text{"} + \mathcal{E} \quad (7)$$

$$\ln(price) = \beta_0 + \beta_1 Riverdist + \beta_2 Saco + \beta_3 Riversaco + \beta_4 \text{"}all\ other\ vars\text{"} + \mathcal{E} \quad (8)$$

$$\ln(price) = \beta_0 + \beta_1 Sixftflood + \beta_2 Saco + \beta_3 sixfloodsaco + \beta_4 \text{"}all\ other\ vars\text{"} + \mathcal{E} \quad (9)$$

The estimation of β_3 will increase the understanding of each community's relationship to key variables of our analysis (variable definitions are in Table 3.2). The *"all other vars"* refers to all the variables listed in Table 3.2 that I continue to keep in the model.

When constructing the model, multicollinearity tests were completed to ensure that independent variables were not correlated with each other. In my models, the degree of correlation was never above 50 percent, which is considered reasonable in hedonic models. After running the complete regressions for my analysis, I perform heteroskedasticity tests through Breusch-Pagan and White tests as well as an omitted variable bias test to address possible biases in the results.

5. Results

I predict that over the 8 years of data, from 2010-2018, single-family home sale prices do not account for flood risk and potential flood damage. Instead of a risk discount for homes closer to waterfront property, I predict a price premium on homes due to easy water access and scenery, common in coastal housing markets.

The estimation results of the log-linear hedonic model are reported in Table 5.1 in Base Model (1). In this model, I am primarily focusing on the relationship between the price of a house and the straight-line distance to the Atlantic Ocean and the Saco River. I take the mean price of the 3,696 properties in the model and multiply it by each explanatory variable's coefficients to estimate the dollar value of the attributes that make up the total price of a home.

TABLE 5.1

VARIABLES	(1) Base Model	(2) One Ft Flood	(3) Three Ft Flood	(4) Six Ft Flood
lotsize	0.000736	0.00296	0.00285	0.00653*
	(0.00291)	(0.00373)	(0.00375)	(0.00361)
sqftabove	0.000165***	0.000174***	0.000178***	0.000209***
	(2.07e-05)	(2.24e-05)	(2.23e-05)	(1.99e-05)
age	-0.00257***	-0.00246***	-0.00250***	-0.00286***
	(0.000160)	(0.000169)	(0.000168)	(0.000164)
bedstotal	0.0473***	0.0457***	0.0451***	0.0295***
	(0.0114)	(0.0125)	(0.0124)	(0.0113)
bathstotal	0.118***	0.126***	0.127***	0.112***
	(0.0163)	(0.0195)	(0.0193)	(0.0161)
cooling	0.0920***	0.0859***	0.0822***	0.0621***
	(0.0144)	(0.0162)	(0.0160)	(0.0139)
fireplace	0.0654***	0.0899***	0.0859***	0.0619***
	(0.0214)	(0.0242)	(0.0239)	(0.0214)
mortgage	0.0975***	0.0927***	0.0920***	0.105***
	(0.0121)	(0.0135)	(0.0134)	(0.0119)
dom	2.67e-05	0.000169***	0.000156***	5.89e-06
	(4.64e-05)	(5.66e-05)	(5.66e-05)	(4.45e-05)
neighbor	0.158***	0.188***	0.181***	0.107***
	(0.0163)	(0.0190)	(0.0192)	(0.0154)
schooldist	-6.70e-06	-0.000158***	-0.000158***	-0.000113***
	(1.27e-05)	(1.26e-05)	(1.25e-05)	(1.15e-05)
seasonal	0.243***	0.342***	0.305***	0.106**
	(0.0498)	(0.0599)	(0.0602)	(0.0483)
scenic	0.229***	0.355***	0.331***	0.178***

	(0.0294)	(0.0363)	(0.0361)	(0.0306)
amtwater	0.000947**	0.00130***	0.00126***	0.000941**
	(0.000379)	(0.000492)	(0.000485)	(0.000420)
oceandist	-9.39e-05***			
	(4.14e-06)			
riverdist	6.68e-05***			
	(6.38e-06)			
oldorchard	-0.481***	0.0112	0.00557	0.0140
	(0.0306)	(0.0159)	(0.0157)	(0.0141)
saco	-0.0374**	0.0712***	0.0700***	0.0663***
	(0.0146)	(0.0138)	(0.0138)	(0.0119)
yr2011	0.0242	0.0246	0.0278	0.0279
	(0.0261)	(0.0284)	(0.0281)	(0.0247)
yr2012	0.0336	0.0351	0.0422*	0.0401*
	(0.0226)	(0.0255)	(0.0254)	(0.0218)
yr2013	-0.0499**	-0.0578**	-0.0553**	-0.0652***
	(0.0227)	(0.0253)	(0.0251)	(0.0222)
yr2014	-0.0839***	-0.0816***	-0.0808***	-0.0852***
	(0.0211)	(0.0234)	(0.0232)	(0.0205)
yr2015	-0.108***	-0.117***	-0.112***	-0.116***
	(0.0219)	(0.0238)	(0.0237)	(0.0209)
yr2016	-0.0954***	-0.105***	-0.108***	-0.111***
	(0.0198)	(0.0217)	(0.0216)	(0.0193)
yr2017	-0.0643***	-0.0761***	-0.0769***	-0.0870***
	(0.0201)	(0.0214)	(0.0212)	(0.0194)
yr2018	-0.0775***	-0.0946***	-0.0893***	-0.0765***
	(0.0225)	(0.0241)	(0.0239)	(0.0217)
oneftflood		0.271***		
		(0.0587)		
threeftflood			0.286***	
			(0.0379)	
sixftflood				0.662***
				(0.0276)
Constant	11.92***	11.60***	11.60***	11.62***
	(0.0411)	(0.0378)	(0.0375)	(0.0354)
Observations	3,696	3,696	3,696	3,696
R-squared	0.643	0.566	0.572	0.664

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Most structural housing characteristics are statistically significant and have expected signs that are stable across all specifications. For every 100 square-foot increase in a home, price increases by $3,892 dollars. For every decade older a home is, its value decreases by $6,073 dollars. An additional bedroom increases the price by 4.7 percent and an additional bath raises the price by 11.8 percent or $ 27,831 dollars. Similarly, a fireplace adds 6.5 percent in value to a home. If a home can be lived in for all four seasons in Maine, including a cold winter and a humid summer, value increases by $57,372 dollars. Adding a cooling mechanism to provide comfort in warmer months bumps the price up by 9.2 percent or $21,716 dollars.

Most environmental characteristics are statistically significant and have expected signs as well. If a home is in an official neighborhood association, its value rises by 15.8 percent or $37,335 dollars. Similarly, as distance to a school increases by a half mile, prices go up by $1,274 or 0.7 of a percentage point. Although in this base model the school distance coefficient is statistically insignificant, in models (2), (3), and (4), it is statically significant to $p<0.01$. If a home is designated as scenic, price increases by $53,996 dollars, demonstrating that scenery in this area is very valuable to homebuyers. In a similar fashion, for every 100 meters of waterfront property owned, price increases by 9.5 percent or $22,372 dollars.

Base model results indicate that traditional amenities to homes and their surroundings, such as more bedrooms, bathrooms, square-feet and neighborhood associations add significant value to a home. In this particular data set however, property values are most emphasized by scenery, seasonality, and the amount of waterfront owned.

Distance variables of statistical significance reveal mixed results for property sales and proximity to water. For every half-mile a home is closer to the Atlantic Ocean, home values increase by $17,854 dollars or 7.6 percent suggesting a waterfront premium as predicted. However, for every half-mile a home is closer to the Saco River, home values decrease by $12,701 dollars or 5.4 percent, suggesting a price discount. This could mean that property values along the Saco River are accounting for flood risk or that proximity to the river is not valued as much as the proximity to the ocean and homes closer to the Saco River are bought for reasons other than water accessibility. This second hypothesis is probably more likely as major flooding affects have not yet hit this area. Most of the literature notes a price discount after a major flooding event not before a major flooding event.

Models (2), (3), and (4) in Table 5.1 looks at the isolated effects of the presence of a home in or out of the various flood zone scenarios with a primary focus on the relationship between the price of a house and the location in or out of one of the three flood zones. Results show strong positive coefficient estimates of statistical significance. If a home is in the 2015 high tide plus 1 foot flood zone, it has a 27.1 percent value premium of $64,035 dollars. Similarly, if a home is in the 2015 high tide plus 3.3 feet flood zone, it has a 28.6 percent value premium of $67,580 dollars. Even more drastically, if a home is in the 2015 high tide plus 6 feet flood zone, it has a 66.2 percent value premium of $156,427, amounting to about two-thirds the price of an average home in the data set.

It is logical to think that homes most immediately vulnerable to flooding in the “One Ft Flood” zone would add the highest premium to housing values because that zone contains the homes with the most premier beachfront property. However, the 10 percent increase in R-squared in Model (4) and Figure 3.2’s pink flood zone could explain more of the story as to why the “Six Ft Flood” zone adds more of a value premium for homes. As there are only 65 homes in the 2015 high tide plus 1 foot flood zone, versus 398 in the 2015 high tide plus 6 feet of flooding, the “Six Ft Flood” coefficient could capture more waterfront homes, especially up the Saco River. Spatial proximity results, especially distance to the Atlantic Ocean, compliments flood zone results to confirm that water accessibility is highly desirable in coastal housing markets.

When comparing the base models in Table 5.1 with data from Old Orchard Beach compared to the base model without Old Orchard Beach data in Table 5.2, the housing, environmental, and neighborhood characteristics do not vary drastically and coefficients remain largely statistically significant with expected coefficient signs for the communities of Biddeford and Saco combined.

Table 5.2 exhibits both the base models for comparative purposes and the three models with interaction terms to highlight community-level results. In both models, proximity and amount of waterfront owned variables are relatively comparable. The premium of the proximity to the ocean, at 7.4 percent is smaller in data from Table 5.2 by about $2,500 dollars at an increase of $15,360 for every half-mile closer to the ocean. Interestingly, as a home gets close to the Saco River by a half-mile, home values from Table 5.2 decreases by about $5,500 dollars more at $18,260 dollars compared to homes from Table 5.1. This demonstrates that homes in Old Orchard Beach value proximity to the ocean more and proximity to the Saco River less. Amount of waterfront only changes by 1/10 of a percentage point suggesting no remarkable change. Regardless of the difference of the percent change between the two sets of models, the importance of distance to the river is relatively small compared to the other variables in the base model, suggesting that other characteristics about a house and its surroundings are more important than proximity to the Saco River for homes in Biddeford and Saco.

One reason for the magnified decrease in the relationship between home value and distance to the Saco River for Saco and Biddeford could be that these two areas are more residential with less summer beach-goers and more full-time residents who choose to buy homes with distances to other preferred amenities. These residents may choose a home closer to schools or the workplace rather than having a scenic second home to relax in. Many other spatial

TABLE 5.2

VARIABLES	(1) Base Model	(2) One Ft Flood	(3) Three Ft Flood	(4) Six Ft Flood	(5) Ocean*Saco	(6) River*Saco	(7) Six Ft Flood*Saco
lotsize	0.000840	0.00625	0.00638	0.0124***	0.000696	-0.000338	0.0132***
	(0.00422)	(0.00498)	(0.00497)	(0.00475)	(0.00419)	(0.00432)	(0.00467)
sqftabove	0.000139***	0.000140***	0.000143***	0.000191***	0.000139***	0.000138***	0.000186***
	(2.18e-05)	(2.29e-05)	(2.29e-05)	(2.08e-05)	(2.19e-05)	(2.18e-05)	(2.00e-05)
age	-0.00231***	-0.00253***	-0.00254***	-0.00281***	-0.00234***	-0.00234***	-0.00281***
	(0.000171)	(0.000181)	(0.000181)	(0.000182)	(0.000171)	(0.000170)	(0.000180)
bedstotal	0.0359***	0.0323**	0.0329**	0.0158	0.0363***	0.0334***	0.0179
	(0.0126)	(0.0139)	(0.0140)	(0.0121)	(0.0126)	(0.0126)	(0.0118)
bathstotal	0.151***	0.161***	0.162***	0.138***	0.151***	0.147***	0.138***
	(0.0146)	(0.0169)	(0.0168)	(0.0146)	(0.0146)	(0.0145)	(0.0143)
cooling	0.0724***	0.0654***	0.0642***	0.0544***	0.0757***	0.0694***	0.0734***
	(0.0165)	(0.0189)	(0.0189)	(0.0165)	(0.0166)	(0.0165)	(0.0165)
fireplace	0.0680***	0.103***	0.0998***	0.0575**	0.0682***	0.0642***	0.0515**
	(0.0242)	(0.0273)	(0.0271)	(0.0238)	(0.0242)	(0.0239)	(0.0233)
mortgage	0.0822***	0.0737***	0.0727***	0.0929***	0.0824***	0.0848***	0.0963***
	(0.0140)	(0.0157)	(0.0157)	(0.0137)	(0.0140)	(0.0139)	(0.0135)
dom	5.71e-05	0.000233***	0.000223***	-1.01e-05	4.85e-05	5.12e-05	-6.62e-05
	(5.49e-05)	(6.47e-05)	(6.50e-05)	(5.25e-05)	(5.51e-05)	(5.51e-05)	(5.20e-05)
neighbor	0.157***	0.216***	0.213***	0.117***	0.161***	0.171***	0.119***
	(0.0193)	(0.0231)	(0.0232)	(0.0182)	(0.0193)	(0.0190)	(0.0178)
schooldist	-6.19e-08	-0.000215***	-0.000211***	-0.000119***	-6.75e-06	-2.09e-07	-0.000124***
	(1.53e-05)	(1.55e-05)	(1.54e-05)	(1.32e-05)	(1.51e-05)	(1.51e-05)	(1.31e-05)
seasonal	0.267***	0.410***	0.409***	0.230***	0.265***	0.257***	0.197***
	(0.0726)	(0.0881)	(0.0884)	(0.0714)	(0.0722)	(0.0716)	(0.0682)
scenic	0.244***	0.409***	0.389***	0.154***	0.242***	0.232***	0.142***
	(0.0362)	(0.0443)	(0.0446)	(0.0387)	(0.0362)	(0.0361)	(0.0374)
amtwater	0.000961**	0.00130**	0.00124**	0.000851*	0.000928**	0.000969**	0.000763
	(0.000437)	(0.000516)	(0.000532)	(0.000473)	(0.000437)	(0.000431)	(0.000477)
oceandist	-9.26e-05***				-9.71e-05***	-9.07e-05***	
	(4.84e-06)				(5.64e-06)	(4.72e-06)	
riverdist	7.79e-05***				7.51e-05***	0.000108***	
	(7.51e-06)				(7.51e-06)	(9.63e-06)	
saco	-0.0252	0.0789***	0.0773***	0.0693***	-0.0806**	0.0878***	0.106***
	(0.0154)	(0.0138)	(0.0138)	(0.0120)	(0.0344)	(0.0227)	(0.0119)
yr2011	0.0334	0.0226	0.0257	0.0279	0.0337	0.0300	0.0283
	(0.0291)	(0.0323)	(0.0321)	(0.0273)	(0.0290)	(0.0286)	(0.0266)

yr2012	0.0446*	0.0395	0.0437	0.0376	0.0451*	0.0400	0.0442*
	(0.0254)	(0.0290)	(0.0289)	(0.0241)	(0.0253)	(0.0251)	(0.0235)
yr2013	-0.0561**	-0.0646**	-0.0633**	-0.0735***	-0.0562**	-0.0619**	-0.0664***
	(0.0252)	(0.0285)	(0.0284)	(0.0241)	(0.0252)	(0.0252)	(0.0236)
yr2014	-0.0750***	-0.0741***	-0.0753***	-0.0983***	-0.0762***	-0.0832***	-0.0969***
	(0.0241)	(0.0273)	(0.0271)	(0.0233)	(0.0241)	(0.0239)	(0.0227)
yr2015	-0.119***	-0.128***	-0.126***	-0.133***	-0.121***	-0.123***	-0.129***
	(0.0250)	(0.0276)	(0.0275)	(0.0238)	(0.0251)	(0.0248)	(0.0234)
yr2016	-0.108***	-0.112***	-0.114***	-0.133***	-0.108***	-0.111***	-0.132***
	(0.0230)	(0.0252)	(0.0252)	(0.0218)	(0.0230)	(0.0228)	(0.0214)
yr2017	-0.0940***	-0.0961***	-0.0967***	-0.115***	-0.0953***	-0.0944***	-0.111***
	(0.0231)	(0.0245)	(0.0244)	(0.0217)	(0.0231)	(0.0227)	(0.0212)
yr2018	-0.0665***	-0.0775***	-0.0744***	-0.0809***	-0.0687***	-0.0652**	-0.0766***
	(0.0255)	(0.0275)	(0.0273)	(0.0244)	(0.0256)	(0.0255)	(0.0238)
oneftflood		0.00880					
		(0.110)					
threeftflood			0.133**				
			(0.0567)				
sixftflood				0.734***			0.922***
				(0.0346)			(0.0422)
oceansaco					1.55e-05**		
					(7.37e-06)		
riversaco						-8.69e-05***	
						(1.24e-05)	
sixfloodsaco							-0.388***
							(0.0530)
Constant	11.90***	11.66***	11.65***	11.65***	11.93***	11.86***	11.64***
	(0.0464)	(0.0428)	(0.0428)	(0.0375)	(0.0502)	(0.0464)	(0.0369)
Observations	2,805	2,805	2,805	2,805	2,805	2,805	2,805
R-squared	0.675	0.600	0.601	0.697	0.676	0.681	0.707

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

proximities to amenities like grocery stores, major roads, and places of employment, in addition to others mentioned in the literature, could help explain this result.

When comparing the flood variables, results from the “One Ft Flood” variable in Model (2) of Table 5.2 are not significant with too few homes to do a proper analysis due to the decrease in observations. The “Three Ft Flood” variable results in Model (3) of Table 5.2 show that there is a 15 percent reduction of a premium to be in a 2015 high tide plus a 3.3 feet flood zone. This is encouraging to see as it could suggest that Biddeford and Saco are more appropriately accounting for flood risk. However, when examining the Six Ft Flood variable and its roughly 11 percent increase in Biddeford and Saco in Model (3) of Table 5.2, with a more comprehensive group of homes, it helps shed light on the fact that this comprehensive set of homes may have an even higher premium than homes in Old Orchard Beach. Unbeknownst to homeowners, in long term flood models, with rising sea levels and higher storm surge levels, their home is at risk of flood and the premium they pay for their location could be a future cost.

Models (5), (6), and (7) in Table 5.2 highlight the discoveries made from the interaction terms of spatial proximity and flood variables to Saco in the three separate equations using Biddeford and Saco data. These interaction terms demonstrate that Biddeford has a higher premium for ocean front property than Saco, Biddeford sees less of a price discount in proximity to the Saco River, and Biddeford accounts for more flood risk, or values homes in flood zones less, than in Saco. As Saco has a higher median income, a lower poverty rate, and a lower density, it is concerning that Biddeford’s citizens have less to lose but unknowingly, they value areas of future flood risk more highly than areas of little to no flood risk.

When analyzing results from these hedonic models, there are potential econometric biases that can occur including multi-collinearity, heteroskedasticity, and omitted variable bias

(Xiao, 2017). It was necessary to test all models for bias. The tests for multi-collinearity were performed before the models were created to ensure that no two explanatory variables were highly related linearly. The tests for heteroscedasticity and omitted variable bias were performed after the models were created.

One major caveat in these results is that they did not pass heteroscedasticity or omitted variable bias tests. In hedonic analyses, omitted variable bias is difficult to overcome and I find no reason this will over bias and inaccurately affect the estimated results. Another caveat to discuss is our assumption that there is completeness in our dataset to ensure every consumer gets their optimal bundle. We likely took a subset of properties instead of all properties in this housing market. Incompleteness can be safety ignored as this is common in hedonic housing studies (Gilbert 2013).

Heteroskedasticity however, is important to correct for. Stevenson (2004) and Goodman and Thibodeau (1995) find evidence of heteroskedasticity in hedonic housing models based on the age of the house. One explanation for this occurrence is that property age depreciation is not linear due to remodels and upgrades. These authors adjust for heteroscedasticity from the age variable by adding age^2 and age^3 to the model to account for the nonlinearity. Goodman and Thibodeau (1995) further perform a semi-log hedonic price function and include age^4 in their model.

In Table 5.3, I square and cube “age” and include it in base models from Table 5.1 hoping to correct for heteroskedasticity. My results show inconsistencies in the significance of age, age squared, and aged cubed among all four models unlike the results found in the literature.[12] In addition, this did not remedy the heteroskedasticity in the data after performing tests on the models shown in the table.

TABLE 5.3

VARIABLES	(1) Base Model	(2) One Ft Flood	(3) Three Ft Flood	(4) Six Ft Flood
lotsize	0.000164	0.00286	0.00271	0.00580
	(0.00302)	(0.00373)	(0.00376)	(0.00376)
sqftabove	0.000157***	0.000174***	0.000177***	0.000200***
	(2.04e-05)	(2.27e-05)	(2.25e-05)	(1.92e-05)
age	-0.00315***	-0.000422	-0.000682	-0.00444***
	(0.000732)	(0.000821)	(0.000816)	(0.000702)
age2	-5.33e-06	-2.91e-05***	-2.70e-05***	2.58e-06
	(8.27e-06)	(9.18e-06)	(9.12e-06)	(8.14e-06)
age3	4.97e-08**	1.00e-07***	9.59e-08***	3.76e-08
	(2.49e-08)	(2.74e-08)	(2.72e-08)	(2.48e-08)
bedstotal	0.0496***	0.0460***	0.0455***	0.0321***
	(0.0113)	(0.0126)	(0.0125)	(0.0112)
bathstotal	0.114***	0.129***	0.129***	0.106***
	(0.0162)	(0.0198)	(0.0195)	(0.0157)
cooling	0.0910***	0.0842***	0.0806***	0.0602***
	(0.0143)	(0.0163)	(0.0161)	(0.0138)
fireplace	0.0667***	0.0894***	0.0856***	0.0638***
	(0.0213)	(0.0243)	(0.0240)	(0.0213)
mortgage	0.0945***	0.0922***	0.0914***	0.101***
	(0.0120)	(0.0134)	(0.0133)	(0.0117)
dom	2.46e-05	0.000173***	0.000159***	4.43e-07
	(4.61e-05)	(5.65e-05)	(5.66e-05)	(4.40e-05)
neighbor	0.146***	0.191***	0.183***	0.0855***
	(0.0168)	(0.0197)	(0.0199)	(0.0154)
schooldist	8.42e-07	-0.000157***	-0.000157***	-0.000104***
	(1.26e-05)	(1.27e-05)	(1.26e-05)	(1.12e-05)
seasonal	0.254***	0.350***	0.313***	0.115**
	(0.0501)	(0.0602)	(0.0605)	(0.0488)
scenic	0.227***	0.350***	0.327***	0.175***
	(0.0292)	(0.0361)	(0.0359)	(0.0304)
amtwater	0.000933**	0.00126***	0.00122**	0.000936**
	(0.000374)	(0.000487)	(0.000480)	(0.000416)
oceandist	-9.63e-05***			
	(4.12e-06)			
riverdist	6.58e-05***			
	(6.38e-06)			
oldorchard	-0.484***	0.0167	0.0107	0.0139
	(0.0305)	(0.0159)	(0.0157)	(0.0142)
saco	-0.0457***	0.0716***	0.0701***	0.0601***
	(0.0146)	(0.0137)	(0.0137)	(0.0118)
yr2011	0.0227	0.0256	0.0285	0.0252
	(0.0261)	(0.0283)	(0.0280)	(0.0246)

[12] Both of these authors find age, age^2, and age^3 significant in their models.

yr2012	0.0291	0.0311	0.0382	0.0351
	(0.0224)	(0.0253)	(0.0252)	(0.0214)
yr2013	-0.0559**	-0.0635**	-0.0610**	-0.0723***
	(0.0226)	(0.0253)	(0.0251)	(0.0219)
yr2014	-0.0879***	-0.0829***	-0.0823***	-0.0908***
	(0.0210)	(0.0232)	(0.0230)	(0.0204)
yr2015	-0.110***	-0.117***	-0.113***	-0.118***
	(0.0218)	(0.0238)	(0.0237)	(0.0208)
yr2016	-0.0961***	-0.103***	-0.107***	-0.113***
	(0.0198)	(0.0216)	(0.0215)	(0.0193)
yr2017	-0.0663***	-0.0742***	-0.0753***	-0.0913***
	(0.0202)	(0.0214)	(0.0212)	(0.0195)
yr2018	-0.0819***	-0.0943***	-0.0894***	-0.0831***
	(0.0225)	(0.0241)	(0.0239)	(0.0217)
oneftflood		0.273***		
		(0.0583)		
threeftflood			0.287***	
			(0.0381)	
sixftflood				0.687***
				(0.0280)
Constant	11.98***	11.57***	11.57***	11.70***
	(0.0474)	(0.0445)	(0.0442)	(0.0404)
Observations	3,696	3,696	3,696	3,696
R-squared	0.646	0.568	0.574	0.670

6. Discussion

Results establish three main findings. Homes a half-mile from the ocean have a price premium (estimated at 7.6 percent in our model). Homes a half-mile closer to the river have a negative price premium and finally, homes in the flood zone are capturing an estimate price premium ranging from 27.1 to 66.2 percent in our models, suggesting that homebuyers are not correctly accounting for risk. Additionally, interaction terms illustrate that Biddeford puts a higher premium on oceanfront and riverfront property compared to Saco but Saco puts a higher premium on houses in flood zones.

These results could indicate multiple findings. It could suggest that homes along the Saco River are adjusting for flood risk, or that river have a negative value for homeowners while homes along the Atlantic Ocean and in the flood zones do not (Lewis & Landry, 2017). These results are slightly contradictory in the sense that many homes along the Saco river see a price discount for risk using spatial proximity measures but see a price premium when they are in a flood zone. It is also possible that the distance variables do not account for risk because flood risk from the Saco River compared to the Atlantic Ocean is less detrimental after a certain distance away from the river compared to a certain distance away from the ocean.

When the various amenities of the hedonic model are put into context, it can further signify the risk that citizens in York County face everyday. As Table 5.3 emphasizes, homebuyers spend upwards of $60,000 to be closer to the waterfront. However, homebuyers, sometimes unknowingly, and also paying for the risk to be in a flood zone. As census data shows, this premium is greater than the median household income in York County for an entire year. Hazardous nor'easters have frequented the Maine coastline and with rising sea-levels, they will only get more damaging. Once a major flooding event occurs, the resources required to recover from such an event would negatively impact individuals and their families. Home prices do not seem to be capitalizing the value of this risk.

The spatial proximity results show opposite results to the literature. My results estimate a price premium for property in a flood zone while literature finds a price discount ranging from 6 to 20 percent in multiple areas of the U.S (Atreya et al., 2013; Bin & Landry, 2013; Daniel et al., 2009; McKenzie & Levendis, 2010; Morgan, 2007). However, as this is a preemptive study and the literature analyzes property values following a major hurricane or storm, results are unsurprising. The current high premium for houses in the flood zone in York County compared to the literature can help encompass the severity of the need for action to help change perceptions of risk.

Homebuyers should be more informed before purchasing a home, and existing homeowners should prioritize the need for flood insurance of their properties. Although there are currently more than 6,900 flood insurance policies in effect in the state totaling more than $899 million, it is not fully encompassing of homes in potential flood zones.[13] Since FEMA released new flood maps in 2017 for York County, there has been great resistance from the community as "nobody wants to be mapped into a flood zone" as Richard Verville, the acting risk analysis branch chief for FEMA Region 1, explained last summer (Dion 2017).

Many existing homeowners do not want to pay for flood insurance as their perceived risk of flooding is less than the actual risk of flooding. Additionally, some homebuyers may not know that their new home is in a flood zone. I hope these results further incentivize homeowners to see why it is beneficial for them to buy flood insurance.

[13] Maine Department of Agriculture, Conservation, and Forestry, Maine Floodplain Management Program, Flood Insurance, https://www.maine.gov/dacf/flood/flood_insurance.shtml, accessed on 12/04/18.

Another possible solution so that individuals can both have the added amenity of scenery and proximity to the water but reduced risk from flooding would be to build a home that is made to last severe storms. For example, Joint homeowners Russell King and his nephew Dr. Lebron Lackey built their home in Mexico Beach, FL at double the cost per square foot as they prepared for high wind and water speeds by building “breakaway walls that would tear free without ripping off anymore of the structure,” hurricane resistant windows, and stormproof stilts to elevate their home (Mazzei, 2018).

While homeowners in York County could take King and Lackey’s advice, it is easier said than done. The resources to be able to storm proof homes are expensive and can take many years to accomplish. Most homeowners would not be incentivized to do so, nor could they afford to do so, especially when risk is unclear and a real threat of flooding can feel far away.

A recent study from Harvard published a paper on the idea of climate gentrification, and used a county in Florida as a case study. They find that property values for homes in higher elevations for optimal climate longevity are much higher than in lower elevations susceptible to risk of flooding (Jesse, Thomas, & Anurag, 2018). This suggests that damage from Hurricanes and storms in the Southeast can provide a model for how the Northeast can act proactively to adjust property values for risk and ensure property value can appreciate, rather than depreciate overtime.

In the past two decades, significantly more zoning laws have been put in place to limit new land development in existing flood plains and FEMA mapped regions. In 2013 for example, after hardships following Hurricane Sandy, Mayor Bloomberg of New York City proposed major changes to building codes in the city that were approved to make buildings more sustainable during environmental emergencies (Navarro 2013). In 2015, Obama signed an executive order to establish the first ever federal flood risk management standards that set goals for defining flood plains and mitigating construction in them to align with climate research[14]. The order gave federal agencies three ways to address flood risk in design and construction. They could use methods informed by climate scientists, build two feet above 100-year flood elevation predictions or build to the 500-year elevation plans.

However, just 10 days before Hurricane Harvey hit Texas, Trump signed an executive order in August of 2017 which rolled back Obama's order (Capps 2017). Obama's executive order would have helped minimize the destruction of Hurricane Harvey and help reconstruction efforts to be backed by climate scientists to ensure that future development would be sustainable.

While this executive order will cause severe flood damage in the future, some cities are still electing to enact stricter zoning laws. Norfolk City Council in Virginia unanimously voted to adopt a new zoning ordinance to help address their city become more flood resilient as sea-levels rise earlier this year (O'Bier 2018). York County does have varying zoning laws for new development, especially on shorelines, but it could still be improved to be more fully-encompassing of climate predictions.

[14] Exec. Order No. 13690, C. F. R. 6428 (2015)

7. Conclusion

According to the IPCC-AR5 and summarized by the GFDL of NOAA, in the future, sea level rise will cause higher storm surge levels and effects of climate change will lead to more intense tropical cyclones and rainfall.[15] Because of the steadily increasing influence of climate change, I hoped results would show that property values account for risk of flood and that property values would increase as distance increased from the water increased too. Instead, I found the results I predicted, the exact opposite effect. As distance to the waterfront increases, with the exception of the Saco River, property values increase. If a home is in a flood zone scenario, property values are sold at even higher prices. This is not surprising given that hedonic models are not forecasting models. They can only tell us about current and past home sales and the conditions that existed at the time of the purchase.

If I were to do a similar analysis again, I would change my model slightly. Fist I would construct a more dynamic risk variable instead of the static ones like the current flood zone dummy variables. This would help to calculate the exact risk for every house to help further identify areas that are at most risk of flooding in the future. Second, I would seek to address omitted variable bias by including individual household flood insurance in the model. This would increase the R-squared and adjust for homes that are fully-insured for flooding to help illuminate the impact of risk on the individual household level.

I would predict that if this same study was done 5 years after a major storm and flooding event, home sales would more accurately represent the perceived risk in this vulnerable area and results would align with the literature. Additionally, if this study was done in another decade or two as sea-levels rise and storms frequent the coast more often, I would hope that the premium

[15] NOAA. Global Warming and Hurricanes: An Overview of Current Research Results, Geophysical Fluid Dynamics Laboratory, https://www.gfdl.noaa.gov/global-warming-and-hurricanes/, accessed on 11/09/18.

for risky homes decreases and that property development and construction growth is located more inland over time.

This study adds to the literature by adding a preemptive study that has the possibility to proactively address flood damage in Maine. Whereas most studies study flood risk after a flood, this study explores perceived risk rather than actualized risk in popular vacation communities to find that potential risk is not communicated or realized by homebuyers. The analysis proves this idea and finds that homes with higher risk have higher values. In the meantime, perhaps the lower housing prices inland incentivizes homebuyers to buy homes in protected neighborhoods instead of in flood zones.

The Northeast is being impacted by climate change at a higher rate than other areas in the world as U.S. Government agencies take no action to prevent public and private infrastructure developments in flood plains. As a result, climate studies continually need to be published to raise awareness and transform the course of housing to align with the rapidly changing earth.

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