DETERMINING HOW WEALTH IMPACTS A HOUSEHOLD'S VALUE OF ENVIRONMENTAL AMENITIES DURING AN ECONOMIC BUST AND RECOVERY

By

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(Under the Direction of Genti Kostandini)

ABSTRACT

Hedonic modeling and quantile regressions were used to measure the impact of recessions on households of different wealth levels value environmental amenities. The value of amenities has been studied over time and over different wealth levels, but we believe we are the first to do so simultaneously. We studied the years 2008 through 2016 and our target amenities were distance to water, distance to the nearest park, mature landscaping, and FEMA flood zones. The environmental variables were intersected with yearly dummy variables and these were regressed against the log of house prices on the deciles with a set of control variables. This gives us a matrix of relative amenity values over time and for different wealth levels. We found that distance to water add the greatest value, environmental amenities impact households with greater wealth more, and amenities provide the greatest relative value at the bottom of a recession.

INDEX WORDS: Hedonic Modelling, Quantile Regression, Environment Valuation, Economic Cycles

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1 Introduction

The 2008 recession, caused by the burst of the housing bubble in the United States, had ripple effects around the world. The effects were severe enough that it has been dubbed the Great Recession. It caused the median income in the United States to decrease from $58,149 in 2007 to $53,331 in 2012, a decrease of 8.28% (FRED). In the same period the Case-Shiller Index (CSI), an index of house prices in metropolitan areas in the United States, dropped from 182 to a low of 134. The drop in the Orlando Metropolitan Statistical Area was even greater. It fell from a max of 281.09 in the first quarter (Q1) of 2008 to a min of 144.14 in the second quarter (Q2) of 2012 before starting to recover (FRED). This indicated the prices these houses sold for dropped dramatically in the 4-year period. After Q1 2012, the housing market started to recover. The cycle of boom-bust-recovery had a large effect on the supply and demand of houses on the market which greatly impacts their value (Fan et al. 2016, Chernobai and Chernobai 2013). Housing is an important sector of the economy with housing real estate adding 1.5 trillion USD every year on average from 2009 through 2016 (BEA 2018).

In the same period, green consumption slowed down (Flatters and Willmot 2009). In 2012, the Harris Poll found that people cared less about the environment after the recession started. From 2009 to 2012 green behavior measures including reusing products, using less water, and purchasing all-natural materials decreased by 3%. There was also a 10% decrease in the portion of people who are concerned about the condition the planet is left in for future generations. A new poll from The Harris Poll in 2014 surveyed 2,234 adults and found a reversal of the trends seen between 2009 and 2012. Compared to 2012, 5% more people were concerned about the condition of the planet we are leaving behind for future generations indicating peoples' opinions of the environment are not constant and can change from economic shocks.

Given that housing is a major component of the economy, it is important to examine how people's value environmental amenities that houses provide and how they change in the boom-bust-recovery cycle. In order to evaluate the value people put on environmental amenities we use housing transactions and hedonic modeling. It can be thought that each component of a house adds or detracts some value and adding all of the components together equals the price of the house. Hedonic models are used to breakdown the price of an object into the components that make up its value. Hedonic models are a common method used to approximate the value of environmental features using house market data (Sanders and Haight 2010, Cho et al. 2010, Boyle and Kiel 2001, Tse 2002, Luttik 2000, de Groot et al. 2002, Rosen 1974).

Traditionally, the value of a house is seen as the sum of the present value of the future rents (Buiter 2010). These rents come from three sources, the physical structure of the house, the characteristics of the parcel of land, and the location of the house. The value of the location of a house can be seen as the sum of the distances the occupants have to travel in order to use the goods and services around them as well as the services that are exclusive to the location. Examples of these services are shopping centers, school zones, and jobs.

There are also environmental services, that are less known, but are just as important in a household's decision making. Environmental features have value because of the ecosystem services they provide. Crossman et al. (2013) defines ecosystem services as various goods and services provided to society from the natural environment, which in turn contribute to human's well-being and economic wealth. There have been multiple attempts to classify ecosystem services. The most well-known classification is the Millennium Ecosystem Assessment (MEA) in 2003. The MEA splits ecosystem services into four categories: supporting, provisioning, regulating, and cultural. The regulating and cultural categories play the largest part in determining a house's price because they are the most visible to consumers who do not have intimate knowledge of ecosystem services. Regulating services keep the climate and environment and local climate habitable for humans and cultural services include beauty, aesthetics, and recreation. Both of these are provided by bodies of water and green spaces which are easily identifiable.

When put into the context of the housing market, ecosystem services can be seen as environmental amenities. In this paper we focus on the distance to water, parks, mature landscaping and examine how the value that households put on them changed during the Great Recession. Economic stress such as a recession changes a households's preferences because their income is reduced and their uncertainty about the future increases. The changes in preferences impact what households value and therefore what they will spend their money on especially for goods with a high price elasticity of demand such as environmental amenities (Flatter and Willmot 2009). Studies suggest that with economic recovery the value of environmental amenities will recover as well (Flatter and Willmot 2009, Cho et al. 2010). However, households of different wealth levels will respond differently to economic stress and to the value they put on environmental amenities. Previous papers have studied how the value of environmental amenities change over time but to our knowledge this is the first study to use a quantile model to study the effects across different economic wealth levels during the boom-bust-recovery cycle of the Great Recession. Fan et al. (2016) looked at the value of open spaces in the Fresno-Clovis metropolitan area in California from 2005 through 2012 and found that the recession caused a decrease of approximately 20% in value of proximity to parks and golf courses. Previous papers have modelled the change from the economic boom to the bust and a short recovery, but there is a gap in the literature examining a longer recovery as well as studying the value of proximity to water features over time (Cho et al. 2010, Fan et al. 2016, Du and Huang 2018, Kriesel 2016). This paper contributes to the literature by looking and how they change during an economic bust and recovery using both an aggregate and also a quantile model and looking at how the values of environmental amenities are affected by a recession. The quantile regression models and examines how people of different wealth values change the value they put on environmental amenities during the bust and recovery using data frame 2008 - 2016 as a proxy for wealth. This has implications for the housing market during future recessions because investors could use this information to better protect their assets during recessions by buying houses that retain their value during a recession. Policy makers could also use the results for policies meant to protect the value of houses and environmental amenities during recessions by encouraging developing in areas with more environmental amenities. We hypothesize that the value of the environmental amenities, modeled by the value they add to housing transactions, will decline from 2009 to 2011 and will show signs of recovery from 2011 to 2016 compared to our base year 2008.

2 Literature Review

2.1 Categorizing Environmental Amenities

There are multiple methods of categorizing ecosystem services depending on the framework that is needed. Bolound and Hunhammar (1999) identified six key services an urban ecosystem should provide. Four of these six have an impact at the household level and therefore should influence a house's value. These four are: micro-climate regulation, noise reduction, rainwater drainage, and recreation and cultural values. The micro-climate regulation come from the urban heat island effect, which is when the large, and often dark colored, structures and roads in an urban area cause the average temperature in a city to be 1-3 degrees Celsius warmer than the surrounding area (Bornstein 1968). Natural amenities like tree cover, green spaces, and large bodies of water can mitigate these changes and keep a house cooler. Trees planted on the west and southern sides of houses can also reduce the electricity bill of a house by blocking sunlight (Donovan and Butry 2009). Parks with trees are natural noise barriers and will contribute to a quieter neighborhood. Green spaces and bodies decrease rainwater damage because they allow water to flow natural through its cycle instead of being channeled through human infrastructure. Parks provide spaces for recreational activities as well as an aesthetic component. Bodies of water provide similar value but from different activities such as fishing and swimming.

De Groot et al. (2002) classified ecosystem services into 23 basic groups. Six of these are relevant to houses and their value: climate regulation, disturbance prevention, water regulation, soil retention, ornamental resources, aesthetic information, and recreation. These are similar to the values given by Bolound and Hunhammar (1999). Both include climate regulation, water regulation, and recreational values. The more urbanized an area becomes the fewer ecosystem services the area provides because more land is covered by concrete and man-made structures (Sander and Haight 2010).

Public parks provide ecosystem services from all four categories from the MEA classification. The ones most relevant to house prices are the cultural benefits from having a space where people can exercise and play and the aesthetic beauty that comes from the nature in a park. The closer a house is to a public park the lower the opportunity cost to use the park which should increase the value of a house the closer it is to a public park. However, not all public parks provide the same ecosystem services and may have different effects on housing amenity values. Previous papers have split parks into multiple categories (Fan et al. 2015, Panduro and Veie 2013). Panduro and Veie (2013) even found that some types of green spaces create negative value, especially if the green space is a buffer for a disamenity such as industrial zones or landfills. Parks also provide regulating services like climate regulation. In areas with hot climates like Florida this is valuable because it decreases the cost of cooling (Huang et al. 1989, Donovan and Butry 2009). Mature landscaping provides cultural ecosystem services from its aesthetic, and if it is used as a garden has provisional ecosystem services. Both of these are expected to increase the value of a house. Distance to nearest body of water and being located on the water provide similar services. They will provide cultural ecosystem services from all of the recreation activities that require water as well as provide regulating services. All of these should increase the price of a house.

2.2 Previous Hedonic Studies on Environmental Variables

Studies looking at environmental features have mostly found a positive relationship between availability of ecosystem services/ amenities and house prices. Luttik (2000) used data from three neighborhoods in Norway from 1989 - 1992 found that a house overlooking water sold for 8% more, near a park sold for 6% more and with a view of a park sold for 8% more, and a view of an open field sold for 9% more. Luttik (2000) used the residuals from an OLS model of the structural properties because they argued that the residuals contained the value from environmental features. Powe et al. (1997) used data from southern England and found that accessibility of wooded lands and house price were positively correlated. They used

GIS to find distances to forests and other amenities to create new environmental variables. One study looking at pollution effects on house prices found that environmental quality and house size are substitutes but environmental quality and lot size are not (Brasington and Hite 2003). A study of the value of open land in Minnesota used GIS and hedonic modelling to find house values increased with proximity to parks, trails, lakes, and streams (Sander and Polaski 2009). Liao and Wang (2011) found that distance to urban parks had a negative effect on house prices while distance to a natural park had a positive effect on house prices.

A study of houses in Dan Yang, China separated environmental amenities into two categories micro and macro ones (Liu et al. 2010). Macro amenities have an impact over a large area while micro amenities affect only a smaller local area. These are analogous to amenities that are *in-situ* or omnidirectional. They found that as distance to green spaces increases the value of a house decreases. Wu et al. (2003) created an equilibrium model based on the idea that the housing market is determined by three expressions for house price, development density and house size. They found that distance to the nearest park, river, and lake had a negative correlation with house price and that developers build larger, more spread out houses when further from the central business district.

Bastian et al. (2002) used GIS and a hedonic model to determine what aspects of undeveloped land made it more valuable than agricultural land. They found that having scenic views, being an elk habitat, and fishery production all had strong positive impacts on the price land sold for. In a large study of the entire UK with over one million observations, Gibbons et al. (2014) found that houses with private gardens, access to green space, and access to freshwater sold for significantly higher prices than those without these amenities.

Hamilton and Morgan (2010) use GIS, light imaging detecting and ranging (LIDAR), and hedonic modeling to differentiate how much people are willing to pay for beach access compared to ocean view in Pensacola Beach, FL. LIDAR was used to calculate the angular degrees of ocean view a house had. GIS was used to find the distance to the closest beach access point and LIDAR was used to determine the total angle that a house could see the oceanfront from. They found that access and view both significantly impacted house price with house price decreasing with decreased access and increasing with better views of the ocean. One study performed in a similar study area as ours, Orange County FL, looked at how water quality affected house prices for houses on the water and not on the water (Walsh et al. 2011). They used GIS to calculate the distance to the water bodies as well as the size of water bodies. They found that houses closer to cleaner lakes sold for higher prices than houses near more polluted lakes. Sirman et al. (2005) performed a meta-analysis of 125 hedonic models and found that amenities provided by having a "good view" or a lake view all had a positive correlation with house price. A study of houses in Hong Kong found that a view of water increased the price of houses by 9% (Tse 2002).

Environmental externalities have also been subject to many studies. A review paper of hedonic models focusing on environmental externalities found that air quality often was not statistically significant and was highly sensitive to the other variables put into the model (Boyle and Kiel 2001). This agrees with Smith and Huang's (1995) seminal paper that found that the marginal willingness to pay (MWTP) for air quality varies widely between housing markets. Water quality studies consistently showed the expected sign were significant with variables mostly easily seen by individuals like water clarity showing the strongest results. Distance to hazardous sites usually showed the expected sign and were significant but the estimated values differed greatly (Boyle and Kiel 2001).

The Federal Emergency Management Act (FEMA) flood zone is different from the other environmental features because it represents a disamenity from the environment. It is the only environmental feature that is hypothesized to have a negative effect on house prices. This is in direct conflict with distance to water which is expected to have a positive impact on house prices (Sander and Haight 2010, Daniel et al. 2009, Sirmans et al. 2005). To avoid either variable having the opposite sign from correlation, both were included. Zhang (2016) found that lower value homes are affected more by the presence of flood plains than higher valued homes, and that the effect of a flood shock creates an immediate change, but the effect diminishes quickly. A meta-analysis of 17 papers on flooding and house prices found that for every 1% increase in the probability of a flood the price a house sold for decreased by 0.6% (Daniel et al. 2009).

Foreclosures can also have a significant effect on the housing market equilibrium (Coulson and Zabel 2013, Chernobai and Chernobai 2013). There were three significant trends during the last recession: a fall in the general price of housing, a fall in the frequency of housing transactions, and an increase in the number of foreclosures and vacancies (Coulson and Zabel 2013). Foreclosures and vacancies can be sticky and can have an effect that lasts longer than the economic shock that caused them (Coulson and Zabel 2013). This can be countered with two different methods either adding a dummy variable for foreclosures or treating foreclosures as their own market and run a separate regression for them. They recommend at the very least that a foreclosure dummy is added to compensate for its effects on the equilibrium of the housing market.

Foreclosures can also have an effect on the value of houses in their immediate vicinity (Coulson and Zabel 2013, Harding and Rosenblatt 2009, Zhang and Leonard 2014). Harding and Rosenblatt (2009) using data from a proprietary mortgage database of houses from 296 zip codes in the US found that for every foreclosed house within 300ft the value of a house decreased by 1% and that the effect of foreclosures was insignificant beyond 500ft. Zhang and Loenard (2014) used a quantile regression to test the effects of foreclosures on different levels of the housing market for the period in Dallas County, TX from 2007 through 2009. They found that a foreclosure has the greatest effect on low value homes, houses within 250ft, and when the foreclosure happened within the past 12 month. Another paper that used a quantile regression with a hedonic model argued that people with different income levels will have different preferences when it comes to houses (Liao and Wang 2011). They found that distance to the nearest national park had a greater effect on the lower quantiles compared the higher ones.

In summary, there have not been many studies looking at how the value of amenities change over time let alone during a recession. Studies that have used data over multiple years have added time trends to control for time but have not crossed the time variable with other ones to see how the variable changes over time (Walsh et al. 2011, Gibbons et al. 2014, Hamilton and Morgan 2010, Daniel et al. 2009). We have identified five studies that study how the value of environmental amenities change over time and only three of the studies look at the change during a recession. The first study, by Cho et al. (2009), looked at how aggregate house prices from census block groups (CBGs) changed from 1990 to 2000 and connected it to changes in forest patch size and density. They found that shrinking forest patches was positively correlated with house prices in rural areas but in urban areas the effect was the opposite. The second study uses a spatial Durbin model to look at the temporal effects of a new urban wetland park on house prices in Hangzhou, China. They found that over time the value added to houses by proximity to the wetlands has increased and being 10% closer to the wetland increased the value of the house by 0.9% (Du and Huang 2018). The third study in Scotland from 2013-2017 found that tenants put a lower premium on locations with energy efficient properties during a recession compared to normal economic conditions. They did this by creating a break variable that separated the time period in pre and post-recession and used it to create interaction terms (Liu et al. 2018). The fourth study by Cho et al. (2010) looked at how landscape amenity values differed between the housing boom between 2000-2006 and housing market crash in 2008 differed. They found that people's willingness to pay for nearby forest cover was 20% lower during the recession than during the boom. The fifth study by Fan et al. (2016) using data from 2005 through 2012 in Clovis County, CA looked at the change in amenity values during the boom and bust of the Great Recession in California. They looked at five different types of open space (neighborhood parks, community parks, regional parks, seasonal parks, golf courses) and found that each types added less value after the recession.

2.3 Relationship between House Value and Household Wealth

One important assumption in this study is that the value of a house is positively correlated to a households' wealth. Intuitively, this makes sense as a wealth and income are constraint by the amount a household can borrow to buy a house or spent to outright buy a house. As the value of a house increases people have been shown to increase consumption (Cooper 2013, Buiter 2010, Gan 2010, Slacalek 2009, Betsky and Prakken 2004, Benjamin et al. 2004). Attempts to determine the marginal propensity to consume from increases in housing wealth tentatively found that the marginal propensity to consume increase by 11 to 20 cents for every dollar increase in housing wealth (Benjamin et al. 2004, Case et al. 2005). However, the exact mechanics of why this happens and the total effect are still unknown. The effect seems to be constant across all households of different wealth levels (Cooper 2013).

One theory states that as the value of houses goes up households have additional collateral to use to obtain loans to spend more (Gan 2010, Slacalek 2009, Cooper 2010). Gan (2010) also found that as household wealth increased precautionary saving decreased and the income was moved to consumption. Betsky and Prakken (2004) estimated that from 2001 to 2004 that housing accounted for a quarter of the increase of consumer spending in the period. When the Federal Reserve Board lowered interest rates after the burst of the dotcom bubble in 2001, the rate of people borrowing against their home increased (Betsky and Prakken 2004). One other factor to note is that the effect may be asymmetric, theory dictates that households should decrease their spending when their house decreases in value, but the magnitude of this effect compared to when a household house increases in value is unknown (Cooper 2013). Houses make up a significant portion of most households' wealth, around 20%, and is the mostly commonly owned investment asset (Betsky and Prakken 2004, Benjamin et al. 2004).

3 Data

3.1 Study Site

The study area is a group of suburban neighborhoods to the east of Orlando in Orange county, FL. This site was chosen because Florida and the Orlando Metro statistical area were impacted hard by the recession. The houses are located in an area that is approximately 18.5 Km wide and 12.5 Km long. The study site is bordered by State Highway 50 to the north, State Highway 528 to the south, and State Highway 436 to the west. Orange County is on the east side of Florida towards the middle of the state. There are hundreds of bodies of water scattered across the county including: lakes, ponds, and man made canals. Orange county is densely populated with an population density of 3808 people per square mile according to the 2010 US census.

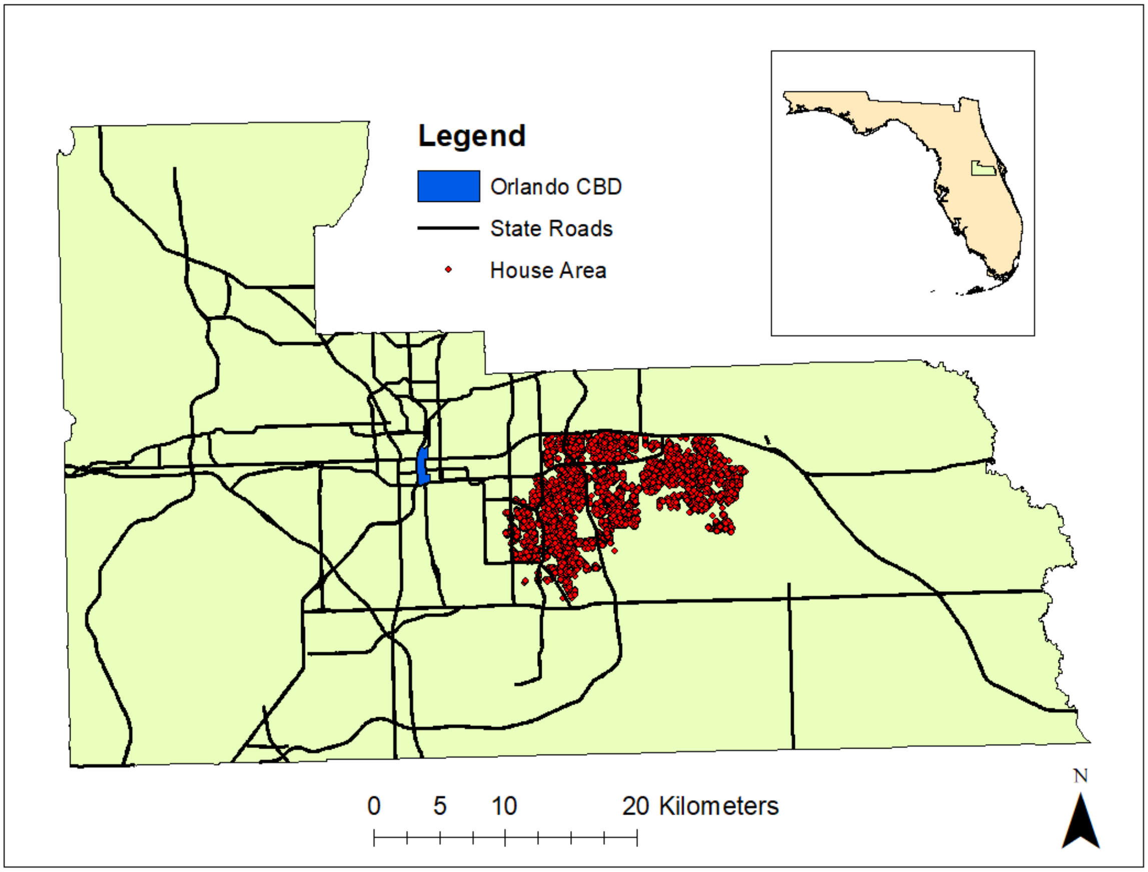

Figure 1: Study Site in Orange County, FL.

3.2 Data Manipulation and Description

The housing data was obtained from the Multiple Listing Service (MLS) in Florida. It includes all the houses listed for sale in the study are from Q1 2008 though Q1 2016. Before cleaning the data there was a total of 33530 observations. The first operation was to drop any houses that did not have a closing price, the dependent variable in our study. The Florida GIS clearinghouse was used to source data for some of the environmental variables. The ability to overlay house location data and environmental features data in ArcMAP is instrumental in determining the relationship between the two. These are the variables related to ecosystem services that were used in the regression: FEMA Flood Zones (floodzone), distance to nearest water body (allwatdist), distance to nearest park (parkdist), mature landscaping (landscapemature), and if the house has access to a lake, a canal, or a pond (lakedum, canaldum, and ponddum).

Dummy variables for common physical amenities in houses were created as well as dummy variables for the different styles of houses: single family, duplex, town house, condo, and mobile. A variable for the year sold was also created so that intersect variables could be created to show how the variable changed between 2008 and 2016 as well as to control for the effect of the recession. Table 1 illustrates the variables and their description and Table 2 presents the summary stats for the variables.

The average 2009 normalized price was $136,665.60 and the median price was $130,000.00. The house at the 0.1 decile was valued at $43,246.84 and the house at the 0.9 decile was valued at $237,107.30. The difference between deciles was on average $24,000. The average house was approximately 18 years old and the size of the average house was 1726 square feet. The square feet heated was strongly correlates with number of bedrooms, number of full bathrooms, and the multiple story dummy. We expect this because all these factors should increase the size of a house. The breakdown of the house styles was as follows: 68% are single family style, 20% are condo style, 9% are town house style, 2% are duplex style, and 1% are mobile house style. The average house had 3 bedrooms, 2 full bathrooms, and 0 half baths. Approximately 18% of houses had security systems. Most of the houses are single story and only 23% have more than one level. Most houses (68.5%) have a garage but only a few (3.2%) have a carport. A large majority (80%) of houses are located within a home owners association. Approximately 1 out of 7 (16%) houses have a private pool and a little under half (41%) have access to a community pool. Houses without access to a community pool are twice as likely to own a private pool. Over half (54%) of the house sold were a short sale or under foreclosure because of the recession. 7% of the houses were located within a FEMA 100-year flood zone[1]. Houses were on average 1.41 Km away from

[1]The FEMA 100 year flood zone denotes an area where the probability of flood each year is 1%

the nearest park. Most houses were near bodies of water like a lake, pond, or canal. The houses were on average 350 meters away from the nearest body of water and the maximum distance from a water body was 1.25 km. Approximately 8% of houses were located on a body of water.

Table 1: Variable Descriptions

Variable	Description
normprice	Price houses sold for normalized to 2009 USD
logprice	Log of normprice
houseage	Age of physical structure in years
houseagesq	houseage squared
sqftheated	Area of the indoor floor plan of the house
lotsizesqf	Size of the lot in sq ft
condostyle	Dummy variable. 1 for condo style
mobilestyle	Dummy variable. 1 for mobile home
singlefamstyle	Dummy variable. 1 for single family home
townstyle	Dummy variable. 1 for town house
duplexstyle	Dummy variable. 1 for duplex style
bedstotal	Number of bedrooms advertised
bathsfull	Number of full bathrooms advertised
bathshalf	Number of half bathrooms advertised
security	Dummy variable. 1 if a security system is installed
storydum	Dummy variable. 1 if more than one story
fireplacedum	Dummy variable. 1 if at least one fireplace
carportdum	Dummy variable. 1 if there is a carport
garagedum	Dummy variable. 1 if there is a garage
hoa	Dummy variable. 1 if the house is located within an HOA
pantry	Dummy variable. 1 if the house has a pantry
breakbar	Dummy variable. 1 if the house has a breakfast bar
kitchenisland	Dummy variable. 1 if the house has a kitchen island
pooldum	Dummy variable. 1 if the house has a private pool
communitypooldum	Dummy variable. 1 if house has access to a community pool
shortsale	Dummy variable. 1 if house was part of a short sale.
foreclosure	Dummy variable. 1 if house was sold under foreclosure.
floodzone	Dummy variable. 1 if house is in a FEMA 100yr floodzone
parkdist	Distance to nearest park in Km
allwatdist	Distance to nearest body of water in Km
ponddum	Dummy Variable. 1 if house is adjacent to a pond
lakedum	Dummy Variable. 1 if house is adjacent to a lake
canaldum	Dummy Variable. 1 if house if adjacent to a canal
orlcbddist	Distance to Orlando, FL central business district in Km
airportdist	Distance to nearest airport in Km

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
normprice	136655.689	76803.228	6707.966	634760.688
logprice	11.639	0.659	8.811	13.361
houseage	17.889	12.334	0	88
houseagesq	472.163	625.621	0	7744
sqftheated	1726.347	717.558	455	8626
lotsizeac	0.396	1.744	0	18
condostyle	0.196	0.397	0	1
mobilestyle	0.006	0.08	0	1
singlefamstyle	0.683	0.465	0	1
townstyle	0.091	0.288	0	1
duplexstyle	0.019	0.136	0	1
bedstotal	3.162	0.97	0	7
bathsfull	2.102	0.59	0	7
bathshalf	0.255	0.445	0	5
security	0.176	0.381	0	1
storydum	0.23	0.421	0	1
fireplacedum	0.111	0.314	0	1
carportdum	0.032	0.175	0	1
garagedum	0.685	0.464	0	1
hoa	0.803	0.397	0	1
pantry	0.433	0.496	0	1
breakbar	0.293	0.455	0	1
kitchenisland	0.091	0.287	0	1
pooldum	0.162	0.368	0	1
communitypooldum	0.409	0.492	0	1
landscapemature	0.29	0.454	0	1
shortsale	0.213	0.41	0	1
foreclosure	0.329	0.47	0	1
floodzone	0.071	0.257	0	1
parkdist	1.422	1.169	0	5.074
ALLWATDIST	0.355	0.231	0	1.254
ponddum	0.074	0.262	0	1
lakedum	0.01	0.098	0	1
canaldum	0.002	0.045	0	1
ORLCBDDIST	13.898	4.849	6.239	23.91
airportdist	7.06	1.801	3.136	11.875
N		20934		

4 Methods

As mentioned this data is a random sample of houses sold between 2008 and 2016 in the suburbs to the east of Orlando, FL. The data came from the Multiple Listing Services, an online database of houses for sale and that have sold. The X and Y coordinates were geocoded and the distance to each different environmental amenity was calculated and any houses that could not be geocoded were dropped from the data. The number dropped was equal to less than 0.1% of our final sample. Any houses that were missing important variables such as the closing price were removed. The final number of observations was 20,934, so 12,596 observations were dropped. A vast majority of observations were dropped because they did not have a closing price which indicates that the houses did not sell and therefore was not part of the market.

In this study we rely on hedonic models which have been used since the 1960s. In a hedonic model, the value of an object is decomposed into the components that make it up. The most common variables used in housing hedonic property models are physical characteristics such as house size, lot size, age, room count, and house style (Sirmans et al. 2005). Hedonic models with house values are usually calculated with a semi-log transformation because the value added by a feature will vary depending on the price of a house, but the magnitude of the change is similar (Sirmans et al. 2005, Fletcher et al. 2004, Xiao 2017, Diewert 2003). Physical characteristics are not the only factors people care about when buying a house. The location of the house also plays a large role in what people want to buy, and more importantly, how much they are willing to pay for it. When using a hedonic model to look at housing markets only houses in the same market should be compared (Luttik 2000).

Quantile regression differs from OLS because it minimizes the absolute value of the residuals as opposed to the square of the residuals. This means it can be used to find the values for the median or any other percentile. Quantile regressions have gained popularity in recent years as a method for hedonic models because they are robust to heteroscedasticity (Ebru and Eban 2011). We chose to use deciles as our percentiles to get a finer look at the housing market compared to what the traditional quartiles or quintiles would show. The households buying houses are not homogenous. They have different preferences and have different wealth constraints. Quantile hedonic models can be used to parse out the different wealth levels to reveal their different preferences (Liao and Wang 2011). It has been shown that households of higher and lower wealth will sort themselves into houses with different amenities (Malpezzi 2003, Bayer et al. 2004). Bayer et al. (2004) created a general equilibrium model to determine how households with different preferences will sort themselves in a housing market. They found that households with more wealth exhibited higher willingness to pay for housing attributes.

A benefit quantile models have over OLS in hedonic property models is that they can model how different house price levels value an amenity. This is important because people of different wealth level will value amenities differently and they will create different sub-markets (Farmer and Lipscomb 2010). For instance if people with lower wealth dislike an amenity and people with higher wealth enjoy an amenity then the implicit price from the OLS hedonic model would have an opposite sign quantile effect and the calculated price would not represent the whole sample or may be falsely insignificant (Liao and Wang 2011).

Heteroskedasticity is commonly found in housing market data (Goodman and Thibodeau 2010, Flecther et al. 2004, Brasington and Hite 2003). It is especially important to test for heteroskedasticity over time, age, and price (Fletcher et al. 2004, Goodman and Thibodeau 1995). Age can have a negative or positive effect on house prices and is nonlinear and potentially non-monotonic because the older a house is there is a greater chance of a major renovation which could increase the price (Goodman and Thibodeau 1995, Sirman et al. 2005). In a meta-analysis of 125 hedonic models Sirman et al. (2005) found that age was the most common variable used in hedonic regressions and it has been both positive, negative, and not significant but is most often negative. Heteroskedasticity in housing data can be minimized by using the semilog form (Fletcher et al. 2004, Xiao 2017, Diewert 2003, Sirman et al. 2005).

Multicolinearity is also prevalent in housing market data (Powe et al. 1997, Berry and Bednarz 1975, Sirman et al. 2005). There are thousands of potential variables that can be put into a hedonic housing model and many of them are correlated. Many location variables will have strong collinearity because amenities are often grouped together. Aquatic variables in particular are affected by this. Houses located in flood zones have several factors influencing them. They are located near or on the water which can increase the value of a house, but the risk of a flood can decrease the value of the house (Sander and Haight 2010, Daniel et al. 2009). Some studies have found that being in a flood zone increases the value of a house while others have found that it decreases the value of a house (Sirmans et al. 2005, Sander and Haight 2010). Logically being in a flood zone should decrease the value of a house because a rational person would buy flood insurance to minimize their risk and many banks will not loan money without it, so the value of the house will decrease. If a study finds that being in flood zone increases the value of a house it is probably missing a variable to control for the positive aspect of living near water (Daniel et al. 2009).

Another common issue in hedonic property modeling is omitted variable bias (Harding and Rosenblatt 2009). This occurs because there are thousands of variables that can have an impact on house price and are correlated with the variables of interest. This can be corrected by using repeated sales of houses and testing for the differences in sales price but this would severely limit our sample size as only 10% of our data represented repeat sales.

There are many different methods of performing a regression on a hedonic model with housing market data. OLS is a commonly used method, however it has some downfalls when it comes to spatial autocorrelation and heteroskedasticity because there is no method to control for them (Osland 2010). In this study a semi-log OLS and a semi-log quantile regression is used. The quantile regressions are used because as mentioned it is robust to heteroskedasticity and because it can look at the effects of variables at different quantiles

(Ebru and Eban 2011). Quantile regressions were also chosen because they can be used to look at how households across different quantiles changed their value of different amenities changed over time. This allows the change in variables to be viewed over two dimensions, over time and over different quantiles. This was done by creating intersect variables between yearly dummies and the target variables.

5 Model

First, an OLS model was constructed using only the structural variables as well as variables for short sales and foreclosure. The dependent variable for these regressions was the log of the house prices with the prices normalized for 2009 USD. This is shown in equation 1:

$$ln(p_i) = \Sigma X_i \beta_k + \varepsilon \tag{1}$$

Where $ln(p_i)$ is the natural log of the real price the house sold for, X_i is a matrix of the house characteristics, and β_k is a vector of the beta coefficients each variables. ε_i is a vector of random error terms. Then a second model was constructed including all of the environmental variables that provide ecosystem services. These variables included distance to the nearest water body, dummy variables for houses located on different types of water bodies, distance to the nearest park, a variable for mature landscaping, and a dummy variable for location in a 100-year flood zone. This is shown in equation 2:

$$ln(p_i) = \Sigma X_i \beta_k + \Sigma Z_i \beta_k + \varepsilon \tag{2}$$

Where we add Z_i a matrix of environmental amenity variables for each house. Then quantile regressions were used to study how environmental variables effect houses across different quantiles. We chose to use deciles for the different quantiles as used by Liao and Wang (2012) to obtain a finer distinction between households of different wealth levels. Equation 3 is a quantile model similar to equation 2. τ is the quantile being regressed at. In this model it ranges from 0.1 through 0.9. X_i are structural and lot variables.

$$ln(p_i) = \Sigma X_i \beta_k(\tau) + \Sigma Z_i \beta_k(\tau) + \varepsilon \tag{3}$$

Lastly, intersect variables were created between the environmental variables and years sold to show how the coefficients different over the recession and recovery as well as over the quantiles. In equation 4 γ_i is a matrix of dummy variables for the year sold.

$$ln(p_i) = \Sigma X_i \beta_k(\tau) + \Sigma Z_i \gamma_i \beta_k(\tau) + \varepsilon \tag{4}$$

We are studying the bust and recovery cycle by adding dummy variables for each year. The years 2008 through 2011 are the recession years and the years 2012 through 2016 are the recovery years. Separating by year will allow us to look at how the variables were effected each year from the beginning of the recession (2008) to the end of the recovery (2016). Recent literature suggests that weight matrices based on house proximity should be used to control for small regional effects that are difficult to identify (Osland 2010, Sanders and Haight 2010, Brasington and Hite 2003, Liao and Wang 2011, Tse 2002). A weight matrix like this was not included in this study because we believe the study area is small enough that there are few regional effects. We also perform robustness checks for spatial effects by clustering based on neighborhoods.

6 Results and Discussion

6.1 OLS Regressions

We start by discussing Table 3 which presents the baseline OLS regression results of the housing data set with log of the normalized price as the dependent variable. This is the regressions from equations 1 and 2. Table 3 is separated into three columns. The first column is a simple regression that only includes house age, house age squared, the area of the house in square feet, and the area of the lot in square feet. The second column contains all of the variables from the first model along with physical features of the house such as the number of bedrooms, a fireplace dummy variable and a pool dummy variable. Dummy variables for short sales and foreclosure are also included. The third column has all of the variables from the second OLS regression as well as the environmental and distance variables. Adding the environmental and distance variables does not significantly affect the rest of the control variables compared to the regression with only the physical variables. The only variable to change signs or loose significance was house age squared. Most variables had the expected signs across all the specifications, however several variables had signs that were the opposite of what was expected. The story dummy variable for example was negative when it was expected to be positive. This could be from Florida's larger than normal elderly population who would not want a house with stairs. The dummy variable for a security system is negative. This could be because owning a security system could be an indicator of a house located in a less safe area with more crime.

Single family homes were the most valuable type of housing and mobile style was the least value type. Duplexes and town house styles provided similar value. The most valuable physical features of the houses were owning a garage and owning a private pool. Both of these can increase the value of a house by around 15%. Fireplaces and access to a community pool both also add a large amount of value to the house. The variables with the largest negative impact on house price were the dummy variables for short sales and foreclosures. Houses that had been a foreclosure or a short sale sold for about 25% less than other houses. Over half of the houses sold in this period were foreclosed or on short sale. This mounts to millions of dollars of property value.

Turning to the environmental amenity variables, houses in a flood zone sold for 2.5% less than houses outside of the flood zone. Living adjacent to a water body has a positive effect on house price ranging from 1.6% to 11.5% depending on the type of water body. Distance to the nearest body of water has no effect in the OLS regression, but when we separate it into quantiles later an effect appears. Park distance was positive for all regressions (meaning increasing value with distance) while we would expect being closer to the park to be an amenity and be positive. Distance to the Orlando Central Business District was positive while we would have expected it to be negative for the same reason as park distance. We will go further into why these variables have opposite signs from what we initially expected later on.

The results from the OLS regression are mostly in line with the results from Sirmans et al. (2005). They compiled 125 hedonic house price models to compare the most commonly used variables and whether they are significantly positive or negative. We included 12 from their list of the 20 most common variables. The other 8 were not important to our study area for example a basement dummy variable. Houses in Florida are not built with basements due to the shallow water tables. Sirman et al. (2005) found that there is not consistency in the value of multiple stories. They found that approximately one third of the hedonic models they studies had a negative value for multiple stories in living residences. This suggests that the value of stories is dependent on the region and the region in our study has a preference for single story homes.

Table 3: OLS Regressions

	Simple	Physical	Distance
houseage	-.005***	-.018***	-.012***
	(0.0007)	(0.0005)	(0.0006)
houseagesq	-.00004***	0.0001***	0.00006***
	(1.00e-05)	(1.00e-05)	(1.00e-05)
sqftheated	0.0007***	0.0003***	0.0002***
	(4.34e-06)	(5.66e-06)	(5.62e-06)
lotsizeac	-.005***	0.018***	0.021***
	(0.002)	(0.001)	(0.001)
condostyle		-.252***	-.196***
		(0.027)	(0.026)
mobilestyle		-.445***	-.465***
		(0.035)	(0.034)
singlefamstyle		0.409***	0.384***
		(0.027)	(0.026)
townstyle		0.139***	0.113***
		(0.028)	(0.027)
duplexstyle		0.11***	0.111***
		(0.029)	(0.029)
bedstotal		0.031***	0.031***
		(0.004)	(0.004)
bathsfull		0.079***	0.08***
		(0.005)	(0.005)
bathshalf		0.021***	0.015***
		(0.005)	(0.005)
security		-.010**	-.013***
		(0.005)	(0.005)
storydum		-.011**	-.013**
		(0.005)	(0.005)
fireplacedum		0.047***	0.061***
		(0.006)	(0.006)
carportdum		0.089***	0.084***
		(0.011)	(0.011)
garagedum		0.159***	0.15***
		(0.006)	(0.006)
hoa		0.026***	0.009
		(0.006)	(0.006)
pantry		0.025***	0.025***
		(0.004)	(0.004)
breakbar		-.007	-.008*
		(0.004)	(0.004)
kitchenisland		-.003	-.008
		(0.007)	(0.006)

pooldum		0.142***	0.136***
		(0.005)	(0.005)
communitypooldum		0.068***	0.058***
		(0.004)	(0.004)
shortsale		-.309***	-.307***
		(0.005)	(0.005)
foreclosure		-.286***	-.284***
		(0.004)	(0.004)
landscapemature		0.052***	0.049***
		(0.004)	(0.004)
floodzone			-.024***
			(0.007)
parkdist			0.023***
			(0.002)
ALLWATDIST			0.001
			(0.008)
ponddum			0.015**
			(0.007)
lakedum			0.052***
			(0.017)
canaldum			0.109***
			(0.037)
ORLCBDDIST			0.014***
			(0.0005)
airportdist			0.014***
			(0.001)
Obs.	20934	20934	20934
e(r2-a)	0.622	0.856	0.863
e(df-a)			

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01

6.2 Quantile Regressions

As mentioned we make the assumption that the value of houses bought has a strong correlation with household consumption and therefore wealth (Cooper 2013, Buiter 2010). We use this in conjunction with hedonic models to examine how households of different wealth levels change in their valuation of environmental amenities both across quantiles and across time. Tables 4 and 5 are the results from the decile regressions for the physical features of the house and the decile regressions 0.1 through 0.9 with the environmental amenity's variables, respectively. House age squared is positive and significant in every decile in Table 4, but in Table 5 it is only significant in deciles five through nine and is positive in each. We expected age squared to be positive due to the vintage effect. The vintage effect is that older houses are more likely to receive renovations which would increase their price (Goodman and Thibodeau 1995). Half bathrooms only has significance in a few deciles in both tables while it had significance in the OLS regression. The multi-story dummy variable only had significance in the lower quantiles in both tables and was negative. This shows a difference in preference between households of high and low amounts of wealth. Households with lower amounts of wealth see multiple stories as a negative feature, while people of higher wealths are indifferent to multiple stories and single stories.

There are some notable patterns for some variables from deciles one through nine. The relative value of a carport and garage decreases over the quantiles, providing about half the relative value in decile nine as it did in decile one. The value of living in a neighborhood with an HOA has a similar decreasing pattern. The value of a breakfast bar is constant between one and five but starts to decrease and loose significance after that. The value of pool access depends on if the pool is a private pool located on the property or a community pool. The value of a private pool is approximately 1.5 times that of a community pool. Private pools require maintenance, which increases the annual cost of household maintenance while providing the same amenities as a community pool. Across the quantiles short sale and foreclosure continue to be the largest negative impact of house prices. Both have the largest negative effect in decile three and are decreasing after with the smallest effect in decile nine. This is consistent with the findings of Zhang and Leonard (2014).

Turning to the environmental amenity's value, the three water body dummy variables about whether a house has access to a body of water or not had more significance in the higher quantiles and of the three being by a canal adds the most value. The distance to the nearest body of water variable also shows the most significance in the upper deciles. Distance to water shows the greatest effect of the environmental variables, which is consistent with the findings of Luttik (2000). However, Luttik (2000) found that houses along a lake were more valuable than houses along a canal, which is the opposite of what we found. This could arise from differences in preferences between the study sites, a difference in quality of lakes and canals in the two sites, or a change of preferences over time. We believe the difference arises also from differences in preferences in the two areas because there is no evidence of a drastic difference in quality between the two sites and we cannot think of a reason that preferences would have changed from lakes to canals in the time between the two studies. Previous studies have found that the quality of the water body is correlated with the partial effect the water body has on house prices (Boyle and Kiel 2001, Walsh et al. 2011, Poor et al. 2007). The large positive impact of water bodies on house prices suggests that the water bodies in the study site are clean or the buyers are unaware of any contamination.

The park distance variable is decreasing from the one to nine decile, but it is positive in all quantiles which is unexpected, which indicates that parks do not add value and are a disamenity. Previous studies have found that distance to the nearest park has a positive effect on house value (Gibbons et al. 2014, Sander and Haight 2010, Sander and Polasky 2009, Fan et al. 2015). Sander and Haight (2010) found that households with greater wealth are more effected by park distance. In our results we find the opposite effect. One possible explanation for this effect could be the general safety of the parks. Part of the reason parks have positive value is the cultural ecosystem services we can obtain from them from recreation services. If the parks are seen as unsafe because vandalism or violent crimes occur in them then they can be viewed as a liability. However, we were unable to find literature of the effect of park's safety on house prices.

The flood zone variable is negative for all deciles, but it only significant for deciles four through eight. The effect of the flood zone is greater for the higher deciles. The differences between high and low deciles could be from the knowledge between the two group or differences between expectations of floods and flood damage. Flood zones decrease a house's value from two mechanisms (Coulson and Zabel 2013). One is the cost of flood insurance, and the other is though expected losses from floods. Flood insurance costs increase as the value of a house increases, so it could be that the cost of flood insurance does not have a significant impact on household expenditures until it reaches a certain point. On the other hand, there is a limit to how much coverage is provided by the National Flood Insurance Program (NFIA). It caps at \$250,000 for structures and \$100,000 for belongings. Private insurers can insure for greater amounts, however. This the opposite of what was found in a previous study by Zhang (2016), who found that the effect of being in a flood plain effected lower priced houses more than higher prices houses.

Table 6 presents the results of the F-tests for equality between all of the deciles from the regression results in Table 5. The null hypothesis is that every quantile is equal. Equation 5 is an example using house age.

$$H_0 : \beta_{houseage}(\tau = 0.1) = \beta_{houseage}(\tau = 0.2) = ... = \beta_{houseage}(\tau = 0.9) \tag{5}$$

This was done for two reasons. First to see if the coefficients were constant across deciles and second as further support for using a quantile regression for our analysis. If none or very few of the variables were significantly different across the quantiles then there is little to be learned from running a quantile regression, but a significant difference means there is more to be learned by running a quantile regression. There are 33 different variables in the regression and as results in Table 6 indicate only 6 of them were constant across quantiles when using a significance level of 0.1. They are square feet heated, the carport dummy, mature landscaping dummy, the flood zone dummy, the lake dummy, and the airport distance. For every variable that is not constant across the quantiles there is a pattern. These patterns were discussed previously and Table 6 provides support of their existence.

Table 4: Quantile Regression with Only Physical Features.

	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
houseage	-.016***	-.016***	-.016***	-.015***	-.014***	-.014***	-.014***	-.014***	-.013***
	(0.001)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
houseagesq	0.00007***	0.00007***	0.00008***	0.00007***	0.00007***	0.00007***	0.00009***	0.00009***	0.00009***
	(0.00002)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)
sqftheated	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(1.00e-05)	(8.49e-06)	(7.28e-06)	(6.48e-06)	(6.85e-06)	(6.60e-06)	(6.43e-06)	(7.38e-06)	(7.84e-06)
lotsizeac	0.021***	0.019***	0.019***	0.018***	0.018***	0.017***	0.015***	0.017***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
condostyle	-.331***	-.287***	-.237***	-.216***	-.197***	-.250***	-.311***	-.328***	-.283***
	(0.051)	(0.04)	(0.035)	(0.031)	(0.032)	(0.031)	(0.03)	(0.035)	(0.037)
mobilestyle	-.584***	-.475***	-.437***	-.422***	-.402***	-.490***	-.530***	-.498***	-.289***
	(0.066)	(0.052)	(0.044)	(0.04)	(0.042)	(0.04)	(0.039)	(0.045)	(0.048)
singlefamstyle	0.434***	0.456***	0.484***	0.48***	0.475***	0.413***	0.325***	0.274***	0.259***
	(0.051)	(0.04)	(0.034)	(0.031)	(0.032)	(0.031)	(0.03)	(0.035)	(0.037)
townstyle	0.163***	0.215***	0.241***	0.231***	0.228***	0.163***	0.077**	0.047	0.037
	(0.052)	(0.041)	(0.035)	(0.032)	(0.033)	(0.032)	(0.031)	(0.036)	(0.038)
duplexstyle	0.126**	0.149***	0.172***	0.149***	0.142***	0.057*	-.014	-.043	-.069*
	(0.056)	(0.044)	(0.038)	(0.034)	(0.035)	(0.034)	(0.033)	(0.038)	(0.041)
bedstotal	0.034***	0.025***	0.02***	0.021***	0.022***	0.022***	0.022***	0.022***	0.019***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
bathsfull	0.036***	0.053***	0.051***	0.06***	0.058***	0.061***	0.06***	0.053***	0.052***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
bathshalf	0.015	0.017**	0.006	0.014**	0.012*	0.012*	0.017***	0.005	-.002
	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
security	0.004	-.004	-.007	-.005	-.008	-.008	-.007	-.006	-.003
	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
storydum	-.031***	-.030***	-.021***	-.017***	-.013**	-.008	-.010*	-.009	0.006
	(0.01)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)
fireplacedum	0.036***	0.032***	0.044***	0.051***	0.053***	0.054***	0.054***	0.054***	0.062***
	(0.011)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
carportdum	0.123***	0.097***	0.084***	0.103***	0.099***	0.083***	0.085***	0.075***	0.076***

	(0.021)	(0.017)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.015)
garagedum	0.238***	0.199***	0.178***	0.162***	0.152***	0.13***	0.125***	0.111***	0.087***
	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
hoa	0.087***	0.069***	0.057***	0.055***	0.041***	0.04***	0.036***	0.024***	0.012
	(0.011)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
pantry	0.034***	0.02***	0.023***	0.023***	0.028***	0.027***	0.025***	0.024***	0.021***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
breakbar	0.014*	0.006	0.005	0.005	-.004	-.007	-.010**	-.016***	-.020***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
kitchenisland	0.027**	0.013	0.005	-.006	-.012	-.008	-.006	-.008	-.006
	(0.012)	(0.01)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
pooldum	0.152***	0.149***	0.147***	0.151***	0.151***	0.142***	0.136***	0.133***	0.129***
	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
communitypooldum	0.088***	0.077***	0.074***	0.065***	0.066***	0.061***	0.056***	0.049***	0.043***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
shortsale	-.298***	-.318***	-.327***	-.319***	-.315***	-.302***	-.291***	-.275***	-.258***
	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
foreclosure	-.308***	-.313***	-.310***	-.296***	-.278***	-.261***	-.245***	-.220***	-.191***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)									
e(df-a)									

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01

Table 5: Quantile Regressions with Distance Variable.

	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
houseage	-.009***	-.009***	-.009***	-.009***	-.010***	-.010***	-.011***	-.011***	-.011***
	(0.001)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
houseagesq	-3.29e-06	2.52e-06	1.00e-05	0.00002*	0.00004***	0.00005***	0.00007***	0.00008***	0.00008***
	(0.00002)	(0.00002)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)
sqftheated	0.0002***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(1.00e-05)	(8.65e-06)	(7.11e-06)	(6.53e-06)	(6.77e-06)	(6.41e-06)	(6.81e-06)	(7.23e-06)	(7.43e-06)

lotsizeac	0.024***	0.022***	0.023***	0.022***	0.022***	0.02***	0.02***	0.02***	0.016***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
condostyle	-.214***	-.234***	-.185***	-.147***	-.158***	-.160***	-.249***	-.299***	-.272***
	(0.049)	(0.04)	(0.033)	(0.03)	(0.032)	(0.03)	(0.032)	(0.034)	(0.035)
mobilestyle	-.621***	-.531***	-.470***	-.425***	-.436***	-.436***	-.513***	-.527***	-.273***
	(0.063)	(0.052)	(0.043)	(0.039)	(0.041)	(0.039)	(0.041)	(0.043)	(0.045)
singlefamstyle	0.43***	0.404***	0.443***	0.462***	0.442***	0.425***	0.319***	0.232***	0.222***
	(0.048)	(0.04)	(0.033)	(0.03)	(0.032)	(0.03)	(0.032)	(0.034)	(0.035)
townstyle	0.145***	0.135***	0.189***	0.212***	0.198***	0.18***	0.075**	0.006	0.005
	(0.05)	(0.041)	(0.034)	(0.031)	(0.032)	(0.031)	(0.033)	(0.035)	(0.036)
duplexstyle	0.134**	0.131***	0.149***	0.155***	0.131***	0.107***	-.005	-.058	-.072*
	(0.053)	(0.044)	(0.036)	(0.033)	(0.034)	(0.033)	(0.035)	(0.037)	(0.038)
bedstotal	0.039***	0.024***	0.022***	0.022***	0.024***	0.023***	0.022***	0.023***	0.019***
	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
bathsfull	0.05***	0.056***	0.056***	0.062***	0.06***	0.062***	0.056***	0.057***	0.056***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
bathshalf	0.019**	0.01	0.006	0.003	0.005	0.007	0.004	0.007	0.001
	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
security	0.0002	-.005	-.010	-.010*	-.009	-.011*	-.012*	-.012*	-.005
	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
storydum	-.033***	-.022***	-.022***	-.016**	-.016**	-.009	-.005	-.014**	-.0005
	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
fireplacedum	0.045***	0.049***	0.052***	0.059***	0.064***	0.063***	0.07***	0.073***	0.074***
	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
carportdum	0.111***	0.098***	0.074***	0.08***	0.091***	0.082***	0.077***	0.068***	0.065***
	(0.02)	(0.017)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.014)
garagedum	0.224***	0.196***	0.168***	0.156***	0.136***	0.124***	0.113***	0.108***	0.087***
	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)
hoa	0.063***	0.052***	0.034***	0.03***	0.021***	0.012*	0.004	-.001	-.007
	(0.011)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
pantry	0.027***	0.015**	0.019***	0.021***	0.026***	0.026***	0.024***	0.022***	0.018***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
breakbar	0.011	0.009	0.008	0.002	-.004	-.009**	-.012**	-.016***	-.022***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

kitchenisland	0.012	0.008	-.007	-.010	-.009	-.012	-.013*	-.012	-.007
	(0.012)	(0.01)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
pooldum	0.141***	0.136***	0.137***	0.141***	0.144***	0.143***	0.136***	0.129***	0.122***
	(0.01)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
communitypooldum	0.072***	0.062***	0.061***	0.059***	0.056***	0.054***	0.048***	0.041***	0.036***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
shortsale	-.289***	-.310***	-.318***	-.316***	-.315***	-.302***	-.290***	-.278***	-.261***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
foreclosure	-.296***	-.309***	-.306***	-.292***	-.277***	-.261***	-.242***	-.213***	-.192***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
landscapemature	0.044***	0.042***	0.041***	0.04***	0.039***	0.041***	0.037***	0.038***	0.033***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
floodzone	-.003	-.013	-.008	-.018**	-.014*	-.020***	-.021**	-.028***	-.016*
	(0.013)	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
parkdist	0.028***	0.027***	0.024***	0.02***	0.019***	0.017***	0.013***	0.013***	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
allwatdist	-.013	-.007	-.016*	-.013	-.018*	-.019**	-.011	-.018*	-.015
	(0.014)	(0.012)	(0.01)	(0.009)	(0.009)	(0.009)	(0.009)	(0.01)	(0.01)
ponddum	0.02*	0.005	0.01	0.007	0.008	0.015**	0.023***	0.034***	0.03***
	(0.012)	(0.01)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
lakedum	0.031	0.032	0.025	0.036*	0.038*	0.024	0.037*	0.058***	0.087***
	(0.032)	(0.027)	(0.022)	(0.02)	(0.021)	(0.02)	(0.021)	(0.022)	(0.023)
canaldum	0.12*	0.068	0.044	0.022	0.062	0.038	0.111**	0.156***	0.15***
	(0.069)	(0.057)	(0.047)	(0.043)	(0.045)	(0.042)	(0.045)	(0.048)	(0.049)
orlcbd	0.018***	0.017***	0.015***	0.014***	0.013***	0.011***	0.01***	0.011***	0.009***
	(0.001)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
airportdist	0.016***	0.016***	0.015***	0.015***	0.015***	0.014***	0.014***	0.014***	0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01

Table 6: F-test for Differences across Quantiles.

Variable	F-score	Probability
houseage	1.80	0.0719
houseagesq	4.28	0.0000
sqftheated	1.21	0.2867
lotsizeac	9.44	0.0000
condostyle	2.51	0.0101
mobilestyle	4.23	0.0000
singlefamstyle	10.34	0.0000
townstyle	5.28	0.0000
duplexstyle	5.53	0.0000
bedrooms	10.15	0.0000
bathsfull	1.71	0.0908
bathshalf	1.13	0.3383
security	1.73	0.0862
storydum	4.10	0.0001
fireplacedum	2.65	0.0067
carportdum	0.86	0.5484
garagedum	10.95	0.0000
HOA	11.00	0.0000
pantry	3.06	0.0019
breakbar	7.15	0.0000
kitchenisland	2.22	0.0231
pooldum	2.49	0.0106
communitypooldum	6.73	0.0000
landscapemature	1.21	0.2903
shortsale	23.73	0.0000
foreclosure	43.65	0.0000
floodzone	1.21	0.2853
allwatdist	0.65	0.7399
ponddum	5.54	0.0000
lakedum	1.03	0.4076
canaldum	1.84	0.0654
orlcbddum	14.87	0.0000
airportdist	0.92	0.4998

6.3 Effects of Recession and Recovery

Next we examine whether all deciles were impacted by the recession the same or not and whether higher quantiles suffered more than the lower quantiles. For this purpose dummy variables were created for the years the transactions took place. When regressed at the 9 different deciles two clear patterns emerge. First is that 2011 was the worst year of the recession for house prices in this area. Second is that houses at the lower quantiles were less affected by the recession. Both of these can easily be observed in Figure 2, which illustrates the effect of the recession and recovery on the nine deciles and the OLS regressions from 2008 through 2016. The base year was 2008 so all of the effects are relative to that year. In 2011, house prices were 33.5% lower for houses in decile one and 39.6% lower for houses in decile nine relative to their house prices in 2008. In 2016, house prices were 11.2% higher in decile one compared to houses sold in 2008, however houses decile nine were still 11.2% lower than the 2008 value. The recovery for houses in in the higher quantiles has been slower than those in the lower of the quantiles. The difference in recovery between the deciles could be from more expensive houses being more over-valued than less expensive houses. Also, houses with higher values have access to more amenities, so when the recession hit they have more value to loose than houses at lower deciles. A clear break between the bust and recovery can be seen in Figure 2. From 2008 though 2011 house prices are decreasing indicating a bust and from 2012 through 2016 house prices are increasing indicating a recovery.

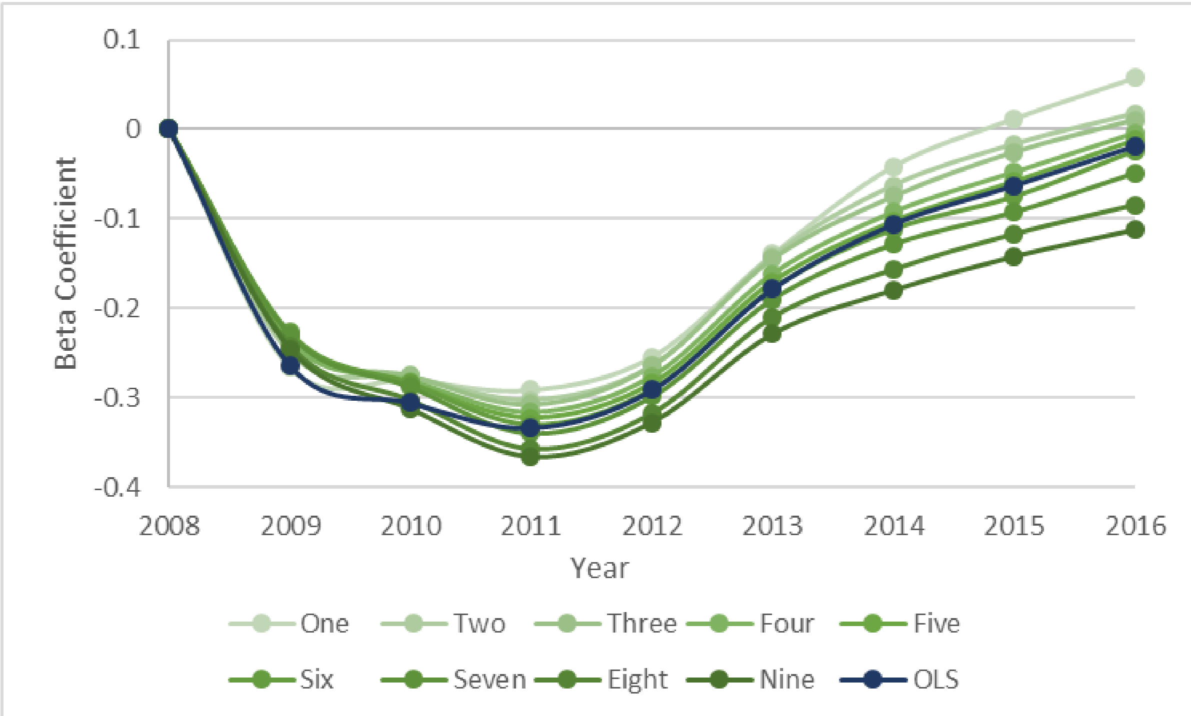

Figure 2: Effect of Recession and Recovery
Graph comparing how the recession affected the deciles. As line color darkens deciles increase and the blue line is from the OLS regression.

Next we investigate how the value households place on each environmental amenity changes over time from 2008 through 2016 and from quantiles 0.1 through 0.9. As mentioned, the years 2008 through 2011 are the bust years and the years 2012 through 2016 are the recovery years.

6.4 Distance to Water

In Table 3, water distance did not have any significance, however in Table 7 in the first column where intersect variables between water distance and the yearly dummies shows that there is significance for distance to water bodies. There is more significance at the higher quantiles and the greatest effect is found from 2010 through 2014. This period is the bottom of the recession curve in Figure 2 where house prices were the lowest. This could indicate that houses located close to water are more resistant to recessions. Water distance has a large change in effect from 2008 through 2009 and from 2014 through 2016. It is expected that distance to water will have a negative coefficient since that indicates that being closer to water is more valuable. This is not the case in 2008 and 2016. This same trend is found in Table 15 but the signs are flipped. This could be from systemic bias from the correlation between distance to water bodies and flood zones (Daniel et al. 2009). However, we included the flood zone variable in these regressions to reduce omitted varaible bias. Proportionally the distance to water can change from less than 10% to an almost 70% change. The year with the greatest change is 2014. There is strong evidence that the quantile regression elucidates more information about the temporal and recession effects on value of water distance. There is significance for every year in the OLS regression but in the lowest four deciles there is little significance expect from 2011 through 2013. Decile One has no significance except for 2011 where it is only significant at a p of 0.1. The largest impact on house prices in the OLS regression came in 2010 where there was a 7.9% increase per km closer to water. This is lower than the greatest effect found in the lower quantiles (15.7%) and the effect found in the upper quantile (10.3%). The OLS regression cannot accurately model how the upper and lower deciles behave in relation to distance to water.

We found that the marginal value of distance to water was highest during the height of the recession. This is similar to the results of Cho et al. (2010). They found that the marginal value of water was higher during the recession compared to the boom before it. Our study is looking at a similar situation but the boom/ recovery happens after the recession. These studies together point to the idea that the marginal value of distance to water may be cyclical with the boom, bust, and recovery cycle of the economy. However, longer term studies are needed to test this theory further.

Table 7: Water Distance Quantile Regressions

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
allwatdist	0.104***	-.022	0.061	0.07**	0.037	0.056*	0.048*	0.133***	0.141***	0.148***
	(0.027)	(0.053)	(0.042)	(0.035)	(0.033)	(0.029)	(0.029)	(0.031)	(0.03)	(0.033)
allwatdist09	-.055*	0.102	0.01	-.053	-.060	-.092***	-.078**	-.158***	-.154***	-.130***
	(0.033)	(0.064)	(0.051)	(0.042)	(0.039)	(0.035)	(0.035)	(0.038)	(0.036)	(0.04)
allwatdist10	-.115***	0.027	-.058	-.107***	-.070*	-.078**	-.076**	-.172***	-.181***	-.222***
	(0.032)	(0.062)	(0.05)	(0.041)	(0.038)	(0.034)	(0.034)	(0.037)	(0.035)	(0.039)
allwatdist11	-.178***	-.110*	-.157***	-.141***	-.099**	-.105***	-.087**	-.188***	-.215***	-.242***
	(0.032)	(0.062)	(0.05)	(0.041)	(0.038)	(0.034)	(0.034)	(0.037)	(0.035)	(0.039)
allwatdist12	-.183***	-.084	-.157***	-.161***	-.112***	-.112***	-.113***	-.210***	-.226***	-.227***
	(0.033)	(0.064)	(0.051)	(0.042)	(0.039)	(0.035)	(0.035)	(0.038)	(0.036)	(0.04)
allwatdist13	-.169***	-.014	-.099*	-.129***	-.103***	-.125***	-.114***	-.226***	-.244***	-.247***
	(0.033)	(0.063)	(0.051)	(0.042)	(0.039)	(0.035)	(0.035)	(0.037)	(0.036)	(0.04)
allwatdist14	-.127***	-.055	-.086*	-.091**	-.047	-.062*	-.048	-.143***	-.169***	-.202***
	(0.033)	(0.064)	(0.051)	(0.042)	(0.039)	(0.035)	(0.035)	(0.038)	(0.036)	(0.04)
allwatdist15	-.112***	-.046	-.079	-.062	-.022	-.048	-.048	-.135***	-.150***	-.172***
	(0.032)	(0.062)	(0.05)	(0.041)	(0.038)	(0.034)	(0.034)	(0.037)	(0.035)	(0.039)
allwatdist16	-.087*	-.066	-.125*	-.064	0.028	0.002	-.003	-.130**	-.140***	-.144**
	(0.047)	(0.092)	(0.074)	(0.061)	(0.056)	(0.051)	(0.05)	(0.054)	(0.052)	(0.058)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)	0.893									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01. All variables in the physical regression were included as controls as well as the FEMA flood zone variable.

Table 8 has the results for the F-tests of equality across the deciles for every year. We find that the effect of distance to water is significantly different across the deciles for every year. This means that the full effect of distance to a water body can be better explained when using a quantile regression and when the effect is split by years. When the effect is not split into quantiles then distance to water is not significant as in Table 3 and when it the effect is not split into years as in Table 5 there is a lack of significance. The effect of the recession and recovery is not constant and can lead to missing important effects of variables. Using a quantile regression with multiple quantiles should be included as a robustness check for studies looking at distance to water as an important variable, so that they do not miss out on effects that may differ depending on a household's wealth.

Figure 3 shows the total effect of water distance for the nine quantiles and OLS from 2008 through 2016. In 2008, the total effect is equal to the variable allwatdist, and for every other year it equal to that year's variable plus allwatdist. The OLS regression as well as deciles three through nine all behave in a similar manner. They form a "U" shape with minimum in 2011 or 2012. Deciles one and two, however, behave more erratically and do not follow the "U" shape. This is further evidence that quantile regressions are better at modelling lower value houses than OLS.

Table 8: F-test for Difference in Yearly Change of Water Distance between Deciles.

Variable	F-Score	Probability
allwatdist	3.84	0.0002
allwatdist09	2.75	0.0049
allwatdist10	5.99	0.0000
allwatdist11	3.63	0.0005
allwatdist12	4.48	0.0000
allwatdist13	4.10	0.0001
allwatdist14	3.34	0.0008
allwatdist15	4.10	0.0001
allwatdist16	5.78	0.0000

Table 9: F-test for Differences in Total Effect of Water Distance

Year	F-Score	Probability
2008	3.84	0.0002
2009	2.60	0.0076
2010	5.37	0.0000
2011	4.63	0.0000
2012	1.17	0.3147
2013	3.22	0.0012
2014	4.52	0.0000
2015	1.88	0.0592
2016	4.15	0.0001

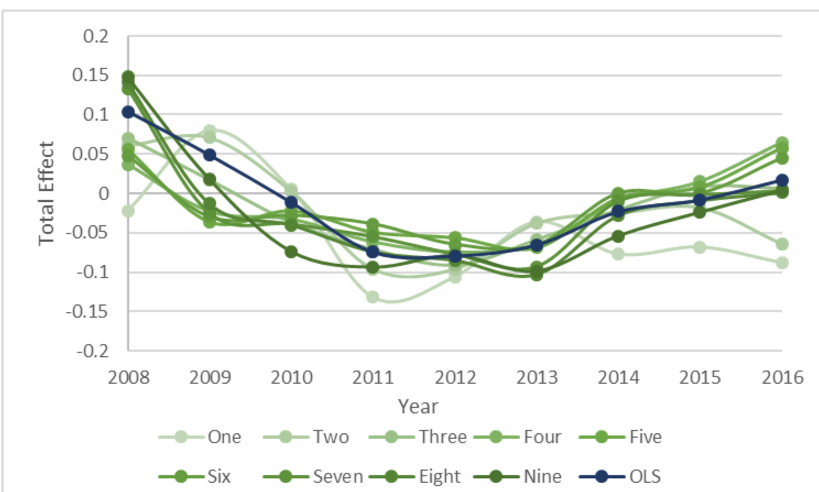

Figure 3: Total Effect of Water Distance.
Total effect of water distance on the deciles and OLS from 2008 to 2016.

6.5 Mature Landscaping

Table 10 shows the quantile regressions for mature landscaping. These results are different from the previous results because the variable has been split by every year (2008-2016) instead of 2009 through 2016 and 2008 as a base year to measure the change from. There is a sharp positive increase from 2008 to 2009 for the OLS and all the deciles then a decline in beta coefficient. The lower deciles (one - six) and OLS have a second peak in 2013 while the higher deciles decrease from 2009 through 2016. In 2015 and 2016 there is no significance in the quantile regressions. This is around the time that the recession had ended and house prices had mostly recovered to their previous levels. This shows that in a non-recession house market mature landscaping does not capture a significant premium. With normal purchasing power households may feel they can afford to pay for landscaping of their own design. The OLS regression shows that mature landscaping has a significant positive effect from 2008 through 2015. In 2008, deciles one, two, and three did not have any significance, in 2014 deciles eight and nine did not have any significance, and lastly in 2015 the OLS regression had significance at p value of 0.1 while none of the rest had significance. Figure 4 shows the total effect mature landscaping has on house price. From 2008 to 2009 there is an increasing trend, from 2009 to 2012, there is a decreasing trend, from 2012 to 2013 there is an increasing trend, and from 2013 there is a decreasing trend. Overall the trend is decreasing. The two years with the positive trends, 2009 and 2013, are also the years with the largest change in house prices but 2009 was a negative change and 2013 is a positive change. However this could be a coincidence and we are only capturing variation from a long term downward trend. One explanation for the shape is the shock of the beginning of the recession caused the value of mature landscaping to increase quickly then that value decreases slowly as the bust and recovery play out.

Table 11 has the results from the F-tests for equality over the deciles. The difference in quantiles was only significant for three years, 2012-2014. These years are the beginning of the recovery period. The other six years there was no statistical difference across the quantiles.

This shows households of different wealth levels value mature landscaping the same most years, but when coming out of a recession their value of mature landscaping changes. The premiums garnered by mature landscaping in our study are higher than the values found previously for private green spaces such as gardens. Gibbons et al. (2014) found that private gardens in the UK increase that value of a house by around 1%, which is much smaller than the 3.8% to 8.8% impact we find.

Table 10: Mature Landscaping Quantile Regressions.

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
landscapemature08	0.04***	0.039	0.02	0.023	0.038**	0.04***	0.036**	0.036**	0.033**	0.03*
	(0.013)	(0.024)	(0.02)	(0.017)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
landscapemature09	0.084***	0.085***	0.088***	0.061***	0.072***	0.073***	0.069***	0.06***	0.059***	0.054***
	(0.011)	(0.02)	(0.016)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
landscapemature10	0.07***	0.054***	0.043***	0.044***	0.063***	0.059***	0.072***	0.07***	0.062***	0.052***
	(0.01)	(0.018)	(0.015)	(0.012)	(0.012)	(0.01)	(0.01)	(0.01)	(0.011)	(0.012)
landscapemature11	0.061***	0.046***	0.061***	0.053***	0.051***	0.044***	0.046***	0.05***	0.048***	0.052***
	(0.009)	(0.017)	(0.014)	(0.012)	(0.011)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
landscapemature12	0.037***	0.015	0.05***	0.038***	0.031***	0.03***	0.026**	0.021**	0.035***	0.029**
	(0.009)	(0.018)	(0.014)	(0.012)	(0.012)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
landscapemature13	0.053***	0.073***	0.056***	0.06***	0.05***	0.042***	0.039***	0.038***	0.03***	0.028**
	(0.009)	(0.017)	(0.014)	(0.012)	(0.011)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
landscapemature14	0.039***	0.039**	0.041***	0.03***	0.021*	0.017*	0.02**	0.017*	0.013	0.017
	(0.009)	(0.017)	(0.014)	(0.012)	(0.011)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
landscapemature15	0.014*	0.015	0.006	0.007	0.009	0.008	0.009	0.003	0.006	0.009
	(0.008)	(0.015)	(0.012)	(0.01)	(0.01)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
landscapemature16	0.007	0.008	0.014	-.0007	0.003	-.003	0.009	-.0003	-.014	-.005
	(0.018)	(0.034)	(0.028)	(0.023)	(0.023)	(0.02)	(0.02)	(0.02)	(0.02)	(0.024)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)	0.892									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01. All variables in the physical regression were included as controls

Table 11: F-test for Differences across Quantiles of Mature Landscaping.

Variable	F-Score	Probability
landscapemature08	1.33	0.2230
landscapemature09	1.10	0.3579
landscapemature10	1.10	0.3622
landscapemature11	0.98	0.4529
landscapemature12	3.13	0.0015
landscapemature13	1.67	0.0991
landscapemature14	3.72	0.0002
landscapemature15	0.67	0.7192
landscapemature16	0.72	0.6698

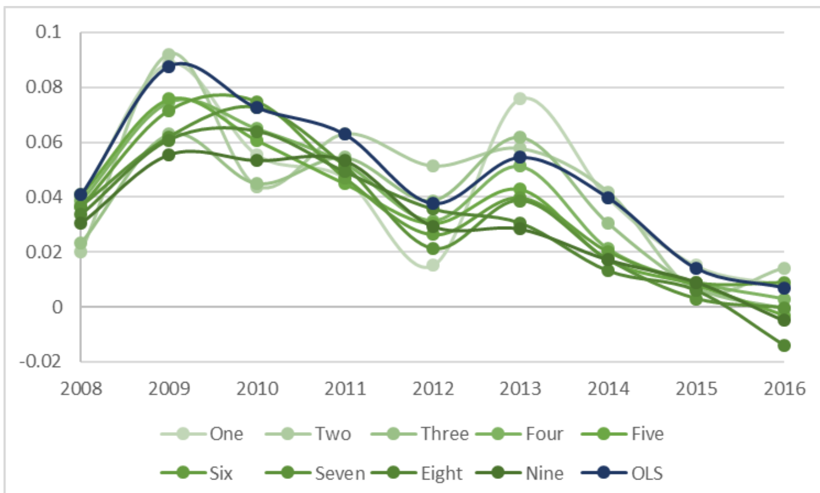

Figure 4: Total Effect of Mature Landscaping.
Total effect of mature landscaping on the deciles and OLS from 2008 to 2016

6.6 Park Distance

Table 12 shows the quantile regressions for park distance and the OLS regression. The OLS regression is in column 1. In the OLS regression the only year that living closer to a park provides positive value is 2008 and during all other years park distance is negatively correlated with house value. In 2008, deciles two through nine show significant negative correlation between park distance and house price. The other years have a mix of positive and negative values, but there is no trend or pattern. There are no other clear trends over the quantiles or over time. Proportionally the change in effect of park distance varies. The proportional change in significant variables varies from an increase of 100% in decile nine from 2011 to 2012 to a 0% change in decile five from 2009 to 2010. Decile nine also shows the large amount of variance in changes from year to year. It is expected that distance to parks would be negative in correlation to price because of the amenities it provides along with travel costs as well as previous literature findings (Sander and Haight 2012, Gibbons et al. 2014, Sander and Polasky 2009, Fan et al. 2015, Luttik 2000). The study area may have contributed to the unexpected findings. To the east there are state parks that are much bigger than the parks in the study. The amenities from these parks may decrease the value households put on the closer but smaller parks. Pandura and Veie (2013) provide a possible explanation. They found that depending on the type of green space it can have a positive or negative impact. They specifically found that green spaces that act as buffers for negative disamenities provide negative values themselves. Unfortunately we did not have enough parks in our study area for this level of granularity. Another potential explanation of the negative value of park distance is a perception of a lack if safety in the parks. If parks are seen as a place crimes are likely to occur they will be willing to pay more to avoid them. Albouy et al. (2018) found that parks with high crime risks decrease the value of a house and parks with low crime risks increase the value of a house. They also found that a spike in crime can "lock in" the negative value of parks even if they currently safer. As in the previous environmental amenity variables there is evidence that the OLS regression fails to capture the effects on the lower deciles. Decile one only had significance from 2009 through 2012, and in 2013 and 2016 the OLS has significance while deciles one through five do not.

Figure 5 illustrates the total effect of park distance from 2008 through 2016. The X-axis is the total effect which is calculated that same way as for water distance. The green lines are the different deciles with darker meaning higher quantile and the blue line is the OLS results. There is an odd pattern to the graph of a wide spread in 2009 and a reconverges by 2012. We have no definite explanation for this trend. There could have been some event in 2009 or late 2008 that lead people to believing that parks were less safe and caused a large shock. This would not explain why such a large difference developed between the deciles however. Between 2012 and 2013 there is a flip between the low decile and the high decile value of park distance. High decile households valued parks more from 2008 through 2012 and low decile households valued parks more from 2013 through 2016.

Table 12: Park Distance Quantile Regressions

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
parkdist	-.023***	-.012	-.019**	-.020***	-.013**	-.013**	-.021***	-.021***	-.025***	-.036***
	(0.005)	(0.01)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
parkdist09	0.062***	0.081***	0.081***	0.067***	0.047***	0.038***	0.035***	0.027***	0.022***	0.023***
	(0.006)	(0.012)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist10	0.056***	0.053***	0.059***	0.057***	0.046***	0.038***	0.043***	0.034***	0.028***	0.031***
	(0.006)	(0.012)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist11	0.029***	0.03**	0.033***	0.034***	0.024***	0.02***	0.025***	0.022***	0.017**	0.014*
	(0.006)	(0.012)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist12	0.032***	0.028**	0.032***	0.026***	0.017**	0.017**	0.022***	0.022***	0.021***	0.028***
	(0.006)	(0.013)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist13	0.027***	-.0003	0.008	0.01	0.006	0.01	0.02***	0.029***	0.036***	0.041***
	(0.007)	(0.013)	(0.01)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist14	0.039***	0.018	0.025**	0.025***	0.022***	0.022***	0.029***	0.031***	0.038***	0.048***
	(0.007)	(0.013)	(0.01)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist15	0.031***	0.01	0.018*	0.017**	0.014*	0.015**	0.024***	0.028***	0.031***	0.043***
	(0.006)	(0.012)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
parkdist16	0.031***	0.007	0.019	0.016	0.006	0.011	0.022**	0.029***	0.035***	0.049***
	(0.009)	(0.018)	(0.014)	(0.012)	(0.011)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)	0.894									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01. All variables in the physical regression were included as controls.

Table 13: F-test for Difference across Quantiles of Park Distance.

Variable	F-Score	Probability
parkdist	3.92	0.0001
parkdist09	7.88	0.0000
parkdist10	4.44	0.0000
parkdist11	2.80	0.0042
parkdist12	2.78	0.0045
parkdist13	2.60	0.0076
parkdist14	1.44	0.1729
parkdist15	3.86	0.0002
parkdist16	2.74	0.0052

Table 14: F-test for Differences in Total Effect of Park Distance

Year	F-Score	Probability
2008	3.92	0.0001
2009	46.64	0.0000
2010	19.24	0.0000
2011	13.77	0.0000
2012	2.28	0.0196
2013	3.20	0.0012
2014	1.20	0.2970
2015	0.86	0.5489
2016	1.36	0.2071

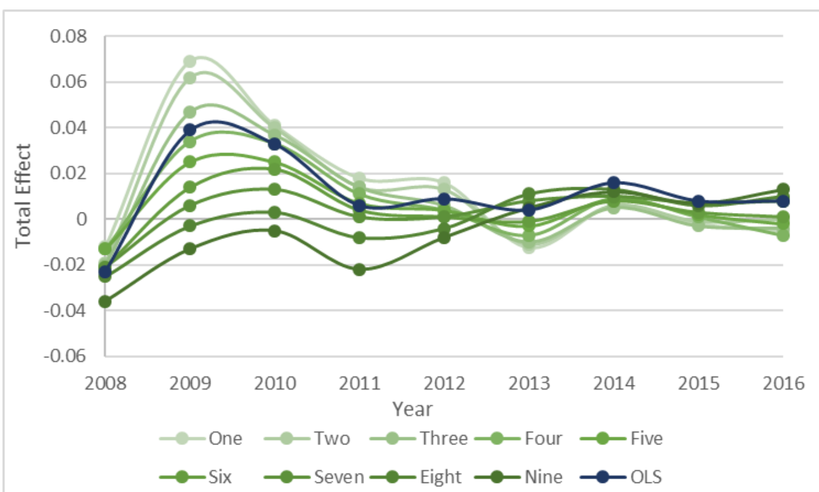

Figure 5: Total Effect of Park Distance.
Total effect of park distance on the deciles and OLS from 2008 to 2016.

6.7 Flood Zones

Table 15 presents the results from the decile regressions with the floodzone and year dummy intersect variables. We included the water distance variable to prevent omitted variable bias since flood zones and water distance are highly correlated. When interpreting the tables with the variables intersected with the yearly dummies there are two things to keep in mind. The first is that the non-intersected variable is equal to the year 2008 and the second is that the intersect variables are the change since that year, so effect for each year after 2008 is the non-intersect variable summed with the corresponding year variable. There are two notable trends in the data. The first one is that houses in the high quantiles are more sensitive to being located in a flood zone. They have higher significance and larger values. The second trend is that there is a U-shaped trend from 2008 to 2016 with 2012 as the minimum for the higher quantile regressions. The proportional effect of a flood zone is about 30% stronger in 2012 compared to the beginning of the bust and the end of the recovery. Previous studies have found that large changes in the impact of flood zones will occur after a major flooding event, but there were none in Orange county during our time period. There can be large significant changes from year to year. Proportionally the effect of flood zones can change up to 40%. This can been seen in decile seven from 2014 to 2015. The OLS regression and the lower quantile regressions are bimodal with minimums in 2011 and 2014. The lower quantile regressions, however, do not show much significance. The reason for the bimodal shape is unclear. Previous research has found that the shock of a flood can cause a sharp increase in sensitivity to flood zones for a short period, which could create a bimodal distribution, but no major floods occurred in the area during the time period (Zhang 2016). In 2008 and 2016, there is a significant positive effect for living near a FEMA flood zone. This is not expected because living in a flood zone should decrease the value of a house because of the extra cost of flood insurance. As with the earlier environmental variables the OLS regression is a poor representation of the houses in the lower quantiles. The OLS regression shows significance in almost every year while deciles one through four have no significance except for deciles two, three, and four in 2010 and three in 2014. In 2009 the OLS regression did not show any significance, but deciles six through eight had significance.

The F-tests in Table 16 show that the flood zones do not have a statistically different changes from 2008 across the deciles at a p-level of 0.1 except for in 2012 and 2016. In 2012, deciles one, two, and four have a positive total effect while the higher deciles have a significant negative total effect. A similar effect is seen in 2016 but its deciles one, three, and four that have the positive coefficient. Figure 6 shows the total effect of the FEMA flood zone from 2008 through 2016 for each decile and the OLS regression and Table 17 has the F-test for the total effects. Figure 6 has a similar U-shape as we observed in the water distance graph in the higher deciles and the OLS regression. The lower regressions have peaks in 2012 and 2013 but none of these effects are statistically significant. The F-tests for the total effect are similar to the F-test for the changes from 2008, but 2010 is significantly different at a p-level of 0.1.

Other studies have found a positive coefficient for floods zones like we have in 2008 and 2016, but this was probably from omitted variable bias. Sanders and Haight (2010) also used the FEMA 100-year floods zones for a study on cultural ecosystem services in urban areas. They found that flood zones had a positive effect on house price, but they believe it was because they did not control for the positive value of living near water bodies. In our study we still found a positive effect in two years even when accounting for the positive effects of water bodies. 2008 was the beginning of the recession and 2016 is five years after the recession was at its worst. This could indicate in times without the shock of a recession the costs of living in a floodplain are negligible or people are willing to put up with the cost for the benefit of living near water.

Table 15: FEMA Flood Zone Quantile Regressions

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
floodzone	0.049*	0.02	0.048	0.048	0.031	0.047*	0.074***	0.063**	0.094***	0.058*
	(0.025)	(0.047)	(0.04)	(0.031)	(0.03)	(0.027)	(0.027)	(0.028)	(0.028)	(0.033)
floodzone09	-.040	-.034	-.074	-.044	-.013	-.027	-.073**	-.067**	-.091***	-.052
	(0.03)	(0.057)	(0.048)	(0.038)	(0.036)	(0.033)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone10	-.078***	-.051	-.082*	-.079**	-.069*	-.094***	-.103***	-.078**	-.099***	-.104***
	(0.03)	(0.056)	(0.048)	(0.037)	(0.035)	(0.032)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone11	-.093***	-.057	-.060	-.048	-.034	-.047	-.094***	-.083**	-.127***	-.094**
	(0.03)	(0.056)	(0.048)	(0.037)	(0.035)	(0.032)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone12	-.064**	0.047	-.025	-.060	-.025	-.061*	-.106***	-.107***	-.144***	-.111***
	(0.03)	(0.056)	(0.048)	(0.037)	(0.036)	(0.032)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone13	-.095***	-.018	-.060	-.037	-.040	-.066**	-.089***	-.091***	-.109***	-.077**
	(0.03)	(0.056)	(0.048)	(0.038)	(0.036)	(0.032)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone14	-.106***	-.041	-.065	-.067*	-.051	-.079**	-.116***	-.103***	-.121***	-.090**
	(0.03)	(0.056)	(0.048)	(0.038)	(0.036)	(0.032)	(0.032)	(0.033)	(0.034)	(0.039)
floodzone15	-.068**	-.032	-.053	-.059	-.049	-.056*	-.070**	-.064**	-.104***	-.067*
	(0.029)	(0.055)	(0.047)	(0.037)	(0.035)	(0.032)	(0.031)	(0.032)	(0.033)	(0.038)
floodzone16	-.017	0.005	-.024	0.052	0.03	-.032	-.054	-.027	-.026	-.036
	(0.04)	(0.075)	(0.064)	(0.05)	(0.048)	(0.043)	(0.043)	(0.044)	(0.045)	(0.052)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)	0.893									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01. All variables in the physical regression were included as controls as well as water distance.

Table 16: F-test for Differences across Quantiles of Flood Zone

Variable	F-score	Probability
floodzone	1.03	0.4130
floodzone09	1.12	0.3456
floodzone10	0.29	0.9862
floodzone11	0.86	0.5540
floodzone12	2.05	0.0369
floodzone13	0.77	0.6299
floodzone14	1.99	0.0432
floodzone15	0.77	0.6260
floodzone16	1.76	0.0804

Table 17: F-test for Differences in Total Effect of Flood Zone

Year	F-Score	Probability
2008	1.03	0.4130
2009	1.12	0.3466
2010	1.86	0.0609
2011	1.21	0.2896
2012	3.12	0.0016
2013	1.44	0.1745
2014	0.41	0.9136
2015	0.37	0.9391
2016	3.20	0.0013

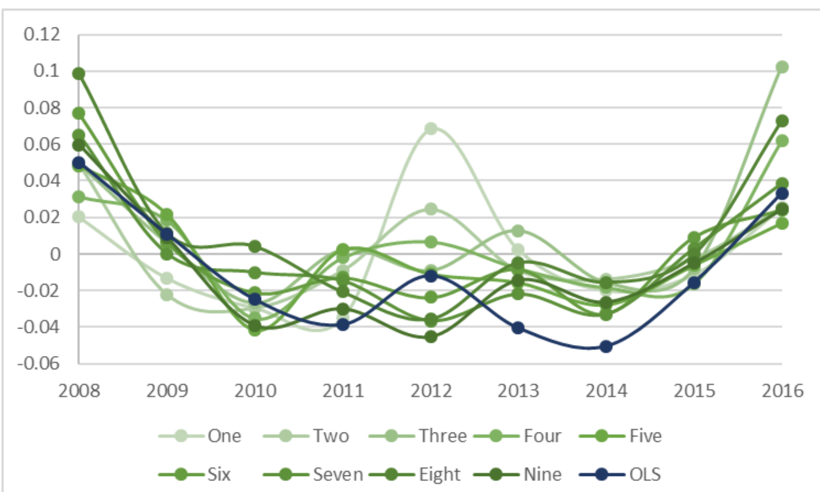

Figure 6: Total Effect of Flood Zones.
Total effect of FEMA flood zones on the deciles and OLS from 2008 to 2016.

7 Robustness Checks

We performed three robustness checks to help show that our estimators are unbiased and consistent. The three checks were run with the same variables as the ones used in Table 5. The first check splits the data into two groups, houses sold under foreclosure and short sale and those that did not. Previous literature studying the effects of foreclosures and short sales has warned that houses sold under these conditions may be a separate market from other houses (Coulson and Zabel 2013). Tables 18 and 19 in the appendix show the results from the regressions that split the observations into sales that were foreclosure or short sale and those that were not. The physical variables do not show much difference between the foreclosure and short sales, non foreclosures and short sales, and all house regressions. There is a difference in the implied value of water though. The regressions with the foreclosures and short sales did not show much significance for water distance or house on bodies of water. There is not a significant difference in distance from water or the proportion of house located on water bodies between foreclosed and short sales and non foreclosed and short sale houses. Houses sold under foreclosure or short sale are sold for significantly less than houses that are not. This is because they are sold to cover debts owned to banks. Savvy home buyers will recognize this and buy houses for less than their true worth, so they can obtain amenities for a discount.

The second robustness check is dropping all of the observations where houses sold for less than $35,000 nominal dollars because they might not be arms-length transactions. This amounted to 5.6% of the observations or about half of one decile. The results are reported in the appendix in Table 20. Water distance was significant in all deciles when the lower observations were dropped while it was only significant in some with all of the observations. We did not believe this change was enough to justify remove half of one decile of the observations.

The final robustness check was adding variables to control for neighborhoods. Using state roads as barriers we identified four different clusters of houses. Figure 7 is a map showing the four clusters created. We used census blocks to create the clusters. We added dummy variables to see if the neighborhoods had large difference between them. Table 21 shows the results from this regression. Houses in cluster 1, the East-most cluster sold for a higher price than the houses in the other three clusters on average. This shows that there may be spatial variation in the house prices we have not accounted for. However, none of the variables differed significantly, so it does not seem like there is a strong collinearity between our environmental variables and the unaccounted for spatial variables.

8 Conclusions

This study contributes to the literature by examining how households of different wealth levels value of environmental amenities changed over the bust and recovery of the Great Recession using a quantile hedonic property model of houses sold in Orange county, Florida. We found that there was a large change in values between 2008 and 2009. This was also the time when there was the largest shock to the housing market in our study area as seen in Figure 2. We found that households with more wealth were more effected by the presence of environmental amenities and disamenities. This is in line with previous studies (Sander and Height 2010). Our findings indicate environmental amenities have a large amount of elasticity, which is consistent with the findings of Flatter and Willmot (2009). Our original hypothesis for environmental amenities was not supported. We believed that that an economic shock would cause people to place less value on environmental amenities, but we found that distance to water provided that largest amount of value at the bottom of the recession in 2011. Mature landscaping value was not impacted by the recession, and distance to parks had a trend that was not consistent with the recession. However, our hypothesis for environmental disamenities was supported by our findings. People were more sensitive to the risk from FEMA flood zones during the end of the recession and beginning of the recovery.

The effect that bodies of water have on house is not constant over the deciles or time. We have strong evidence that distance varies between all of the deciles as present in the F-tests for the years in Table 8. Our results are consistent with the prediction The F-tests for the FEMA flood zones did not show statistical significance for most years. The curve of the total effects from 2008 through 2016 was a U-shaped for both distance to water and location in a FEMA flood zone. At its peak in 2012, distance to water added between 6-10% per km to a houses value. In the same year houses in a flood zone sold for 2-6% less than houses not in a flood zone. The shock and stress of a prolonged recession caused people to see more value in house that were near water, but houses that were also in a FEMA flood zone sold for less.

Distance to the nearest park did not show the expected sign except for in 2008. Multiple previous studies have found that parks provide positive value to houses (Sander and Height 2010, Gibbons et al. 2014, Sander and Polasky 2009, Fan et al. 2015). One previous study by Liao and Wang (2012) found that urban parks will decrease that value of houses while natural parks will increase the value. All the parks in our study area were urban parks, so our findings are in line with their findings. The estimators also showed an unusual trend where some years had estimators that were similar while others had estimators that were very different. We have three possible explanations for why parks had a negative value from 2009 - 2016. The first is that large state parks to the west of the study site offer so many amenities that they crowd out the effect of small local parks. The second is a lack of park safety may cause the parks to be viewed as a disamenity. The third is that parks could represent areas with higher congestion, which would negatively impact house prices.

Mature landscaping seems to have a stronger correlation with the shock of the recession opposed to the recession itself. It garnered the greatest premium in 2009 where it added about 7% to a houses value for all quantiles and the OLS regression. From 2009 there were two different trends depending on the decile. Lower deciles and the OLS regression had a second peak in 2013 while the higher deciles decreased from 2009 through 2016. The F-test for 2013 show that this is a significant difference. In 2015 and 2016, when the housing market had recovered, mature landscaping did not command a significant premium.

Housing is a major sector of the US economy and houses are heterogenous in regards to physical structure and location. We find that environmental amenities have a significant impact on the value of house so it is important to continue studying them. We further confirm the findings that water based amenities provide more value than other environmental amenities and we show that the value they provide is influenced by outside economic conditions. Between 2008 and 2009 there was a large shift in the value of all of the amenities and this effect warrants further study. Lastly, Quantile regressions should be run when hedonic modeling is used because we found that OLS regressions do not model the lower quantiles of the housing market well and may under estimate the impact of environmental amenities on houses in the higher quantiles.

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Appendix

Table 18: Foreclosure and Shortsale Robustness Check.

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
houseage	-.012***	-.015***	-.014***	-.011***	-.009***	-.009***	-.008***	-.007***	-.006***	-.007***
	(0.0008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
houseagesq	0.00003*	0.00006**	0.00003*	-2.45e-06	-.00002	-.00002	-.00004*	-.00004**	-.00004**	-6.59e-06
	(1.00e-05)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
sqftheated	0.0002***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0002***
	(7.90e-06)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(9.65e-06)	(9.97e-06)	(1.00e-05)	(1.00e-05)	(1.00e-05)
lotsizeac	0.029***	0.028***	0.032***	0.032***	0.031***	0.029***	0.031***	0.029***	0.026***	0.02***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
condostyle	-.202***	-.297***	-.303***	-.229***	-.173***	-.124***	-.141***	-.207***	-.285***	-.298***
	(0.034)	(0.06)	(0.046)	(0.045)	(0.044)	(0.042)	(0.043)	(0.046)	(0.044)	(0.053)
mobilestyle	-.648***	-.791***	-.699***	-.565***	-.518***	-.500***	-.555***	-.633***	-.743***	-.797***
	(0.047)	(0.081)	(0.063)	(0.062)	(0.06)	(0.057)	(0.059)	(0.062)	(0.06)	(0.072)
singlefamstyle	0.38***	0.349***	0.352***	0.42***	0.456***	0.47***	0.434***	0.349***	0.249***	0.206***
	(0.034)	(0.059)	(0.046)	(0.045)	(0.044)	(0.042)	(0.043)	(0.046)	(0.044)	(0.053)
townstyle	0.076**	0.042	0.053	0.128***	0.165***	0.181***	0.145***	0.063	-.018	-.044
	(0.035)	(0.061)	(0.047)	(0.046)	(0.046)	(0.043)	(0.045)	(0.047)	(0.046)	(0.054)
duplexstyle	0.101***	0.08	0.066	0.126**	0.141***	0.161***	0.122**	0.011	-.057	-.144**
	(0.037)	(0.065)	(0.05)	(0.049)	(0.048)	(0.046)	(0.047)	(0.05)	(0.048)	(0.058)
bedstotal	0.04***	0.052***	0.036***	0.024***	0.025***	0.022***	0.024***	0.028***	0.026***	0.029***
	(0.005)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
bathsfull	0.085***	0.042***	0.054***	0.067***	0.07***	0.073***	0.072***	0.072***	0.073***	0.071***
	(0.007)	(0.012)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)
bathshalf	0.008	0.012	0.005	0.001	-.006	-.005	-.008	-.005	-.005	-.00004
	(0.007)	(0.013)	(0.01)	(0.01)	(0.009)	(0.009)	(0.009)	(0.01)	(0.009)	(0.011)
security	-.021***	0.012	-.007	-.013	-.018*	-.021**	-.027***	-.037***	-.038***	-.043***
	(0.008)	(0.014)	(0.011)	(0.011)	(0.011)	(0.01)	(0.01)	(0.011)	(0.011)	(0.013)
storydum	0.0009	-.041***	-.028***	-.015	-.007	-.006	0.006	0.019*	0.022**	0.021*

	(0.008)	(0.013)	(0.01)	(0.01)	(0.01)	(0.009)	(0.01)	(0.01)	(0.01)	(0.012)
fireplacedum	0.039***	0.002	0.037***	0.029**	0.036***	0.05***	0.054***	0.065***	0.059***	0.069***
	(0.009)	(0.015)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)
carportdum	0.109***	0.135***	0.089***	0.113***	0.102***	0.097***	0.116***	0.105***	0.109***	0.096***
	(0.016)	(0.028)	(0.022)	(0.021)	(0.021)	(0.02)	(0.021)	(0.022)	(0.021)	(0.025)
garagedum	0.15***	0.209***	0.166***	0.147***	0.128***	0.125***	0.123***	0.112***	0.115***	0.104***
	(0.008)	(0.013)	(0.01)	(0.01)	(0.01)	(0.009)	(0.01)	(0.01)	(0.01)	(0.012)
hoa	0.006	0.05***	0.054***	0.033***	0.023**	0.022**	0.011	0.0002	-.008	-.018
	(0.008)	(0.014)	(0.011)	(0.011)	(0.011)	(0.01)	(0.01)	(0.011)	(0.011)	(0.013)
pantry	0.014**	0.017*	0.016**	0.008	0.012	0.013*	0.011	0.01	0.008	0.011
	(0.006)	(0.01)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
breakbar	-.009	0.016	0.005	0.002	0.003	-.008	-.011	-.011	-.015*	-.019**
	(0.006)	(0.011)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
kitchenisland	-.004	-.002	-.005	-.009	-.004	-.002	-.009	-.014	0.0002	0.004
	(0.01)	(0.018)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.016)
pooldum	0.134***	0.129***	0.132***	0.129***	0.136***	0.145***	0.142***	0.13***	0.132***	0.127***
	(0.008)	(0.014)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
communitypooldum	0.051***	0.062***	0.054***	0.049***	0.045***	0.044***	0.044***	0.039***	0.036***	0.039***
	(0.006)	(0.01)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
landscapemature	0.059***	0.048***	0.045***	0.05***	0.053***	0.054***	0.059***	0.06***	0.051***	0.043***
	(0.006)	(0.01)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
floodzone	-.022**	0.011	-.003	-.009	-.014	-.014	-.010	-.008	-.029**	-.029*
	(0.01)	(0.017)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)
parkdist	0.032***	0.03***	0.031***	0.035***	0.034***	0.029***	0.029***	0.028***	0.028***	0.026***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
allwatdist	0.02*	0.007	0.008	-.00003	0.002	0.004	0.007	0.019	0.011	0.016
	(0.011)	(0.019)	(0.015)	(0.014)	(0.014)	(0.013)	(0.014)	(0.015)	(0.014)	(0.017)
ponddum	0.011	0.01	0.01	0.014	0.013	0.014	0.014	0.013	0.009	0.006
	(0.01)	(0.018)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.016)
lakedum	0.025	0.029	0.005	-.027	-.030	-.048	-.014	0.015	0.089**	0.06
	(0.029)	(0.051)	(0.039)	(0.039)	(0.038)	(0.036)	(0.037)	(0.039)	(0.038)	(0.045)
canaldum	0.104*	0.073	0.086	0.13	0.098	0.119	0.107	0.07	0.056	0.085
	(0.062)	(0.108)	(0.083)	(0.082)	(0.081)	(0.076)	(0.079)	(0.083)	(0.081)	(0.096)
orlcbd	0.017***	0.018***	0.017***	0.018***	0.018***	0.016***	0.016***	0.016***	0.017***	0.016***

	(0.0008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
airportdist	0.017***	0.02***	0.018***	0.018***	0.018***	0.018***	0.017***	0.016***	0.015***	0.017***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	11354	11354	11354	11354	11354	11354	11354	11354	11354	11354
e(r2-a)	0.853									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01.

Table 19: Non Foreclosure and Shortsale Robustness Check.

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
houseage	-.011***	-.001	-.004***	-.007***	-.009***	-.010***	-.011***	-.011***	-.013***	-.014***
	(0.0007)	(0.002)	(0.001)	(0.001)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
houseagesq	0.00008***	-.0001***	-.00004*	0.00003*	0.00006***	0.00007***	0.00009***	0.0001***	0.0001***	0.0001***
	(1.00e-05)	(0.00003)	(0.00002)	(0.00002)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(0.00002)	(0.00002)
sqftheated	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(7.67e-06)	(0.00002)	(1.00e-05)	(1.00e-05)	(8.17e-06)	(8.26e-06)	(7.94e-06)	(7.95e-06)	(8.71e-06)	(9.46e-06)
lotsizeac	0.012***	0.014***	0.012***	0.013***	0.014***	0.012***	0.013***	0.012***	0.011***	0.01***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
condostyle	-.158***	-.086	-.070	-.119**	-.145***	-.195***	-.186***	-.310***	-.255***	-.169***
	(0.04)	(0.085)	(0.062)	(0.053)	(0.042)	(0.043)	(0.041)	(0.041)	(0.045)	(0.049)
mobilestyle	-.263***	-.337***	-.344***	-.321***	-.269***	-.335***	-.282***	-.315***	-.164***	-.095
	(0.048)	(0.103)	(0.075)	(0.064)	(0.051)	(0.052)	(0.05)	(0.05)	(0.055)	(0.059)
singlefamstyle	0.413***	0.529***	0.548***	0.513***	0.496***	0.427***	0.396***	0.235***	0.242***	0.295***
	(0.04)	(0.085)	(0.062)	(0.053)	(0.042)	(0.043)	(0.041)	(0.041)	(0.045)	(0.049)
townstyle	0.182***	0.291***	0.329***	0.314***	0.3***	0.223***	0.185***	0.025	0.028	0.077
	(0.04)	(0.087)	(0.064)	(0.054)	(0.043)	(0.044)	(0.042)	(0.042)	(0.046)	(0.05)
duplexstyle	0.154***	0.239***	0.273***	0.214***	0.179***	0.106**	0.104**	-.033	-.0001	0.112**
	(0.043)	(0.092)	(0.067)	(0.058)	(0.046)	(0.046)	(0.044)	(0.045)	(0.049)	(0.053)
bedstotal	0.024***	0.023**	0.02***	0.022***	0.025***	0.023***	0.023***	0.023***	0.021***	0.008
	(0.005)	(0.01)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
bathsfull	0.064***	0.045***	0.045***	0.044***	0.044***	0.043***	0.037***	0.039***	0.047***	0.048***

	(0.006)	(0.014)	(0.01)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
bathshalf	0.013*	0.003	0.005	0.004	0.002	0.006	0.005	0.01	0.017**	0.021**
	(0.007)	(0.015)	(0.011)	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
security	0.00006	0.01	0.001	0.002	-.001	-.003	-.002	0.002	0.002	0.007
	(0.006)	(0.012)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
storydum	-.018***	-.025	-.007	-.007	-.012	-.018**	-.013*	-.019**	-.029***	-.027***
	(0.007)	(0.015)	(0.011)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
fireplacedum	0.074***	0.061***	0.059***	0.061***	0.056***	0.061***	0.061***	0.068***	0.068***	0.074***
	(0.007)	(0.015)	(0.011)	(0.01)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
carportdum	0.042***	0.085***	0.059***	0.038**	0.024*	0.032**	0.048***	0.055***	0.037**	0.039**
	(0.014)	(0.029)	(0.022)	(0.018)	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.017)
garagedum	0.135***	0.21***	0.179***	0.157***	0.139***	0.125***	0.12***	0.105***	0.086***	0.059***
	(0.008)	(0.018)	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.01)
hoa	0.016**	0.081***	0.066***	0.048***	0.044***	0.025***	0.025***	0.017**	0.013	-.006
	(0.008)	(0.018)	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.01)
pantry	0.041***	0.027**	0.033***	0.031***	0.028***	0.035***	0.034***	0.032***	0.031***	0.04***
	(0.005)	(0.011)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
breakbar	-.004	0.014	0.016*	0.014**	0.006	0.0009	-.008	-.010*	-.020***	-.025***
	(0.005)	(0.011)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
kitchenisland	-.005	0.02	0.016	0.01	-.0006	-.003	-.004	-.017**	-.013	-.019**
	(0.008)	(0.016)	(0.012)	(0.01)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
pooldum	0.144***	0.141***	0.145***	0.14***	0.147***	0.145***	0.141***	0.139***	0.138***	0.137***
	(0.006)	(0.014)	(0.01)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
communitypooldum	0.066***	0.084***	0.078***	0.071***	0.067***	0.062***	0.056***	0.053***	0.046***	0.032***
	(0.006)	(0.012)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
landscapemature	0.036***	0.035***	0.028***	0.034***	0.032***	0.029***	0.025***	0.021***	0.026***	0.033***
	(0.005)	(0.01)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
floodzone	-.019**	-.010	-.003	-.013	-.013	-.015	-.017*	-.009	-.007	-.010
	(0.009)	(0.019)	(0.014)	(0.012)	(0.01)	(0.01)	(0.009)	(0.009)	(0.01)	(0.011)
parkdist	0.01***	0.021***	0.015***	0.01***	0.008***	0.007***	0.006**	0.003	-.001	-.006*
	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
allwatdist	-.021**	-.011	-.037**	-.053***	-.035***	-.035***	-.024**	-.028**	-.024**	-.020
	(0.011)	(0.023)	(0.017)	(0.014)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)
ponddum	0.024***	0.025	0.013	0.014	0.017*	0.016*	0.017**	0.031***	0.041***	0.036***

	(0.008)	(0.018)	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.01)
lakedum	0.069***	0.058	0.044	0.065**	0.063***	0.057***	0.053**	0.062***	0.058**	0.067***
	(0.02)	(0.042)	(0.031)	(0.027)	(0.021)	(0.021)	(0.02)	(0.02)	(0.022)	(0.024)
canaldum	0.096**	0.088	0.024	0.027	0.034	0.014	0.022	0.123***	0.125**	0.161***
	(0.043)	(0.093)	(0.068)	(0.058)	(0.046)	(0.047)	(0.045)	(0.045)	(0.049)	(0.053)
orlcbd	0.01***	0.016***	0.013***	0.012***	0.01***	0.009***	0.008***	0.007***	0.006***	0.005***
	(0.0007)	(0.001)	(0.001)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)
airportdist	0.012***	0.015***	0.012***	0.012***	0.011***	0.01***	0.01***	0.011***	0.011***	0.01***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	9580	9580	9580	9580	9580	9580	9580	9580	9580	9580
e(r2-a)	0.851									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01.

Table 20: Only Houses sold for over $35,000 Robustness Check.

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
houseage	-.009***	-.008***	-.007***	-.008***	-.008***	-.008***	-.008***	-.009***	-.009***	-.010***
	(0.0005)	(0.0009)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
houseagesq	0.00004***	-1.00e-05	-1.00e-05	2.17e-06	1.75e-06	0.00002**	0.00002*	0.00004***	0.00006***	0.00008***
	(9.03e-06)	(0.00002)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)
sqftheated	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(5.04e-06)	(9.08e-06)	(7.77e-06)	(6.28e-06)	(6.24e-06)	(5.98e-06)	(6.16e-06)	(6.39e-06)	(6.90e-06)	(6.42e-06)
lotsizeac	0.012***	0.012***	0.013***	0.012***	0.012***	0.014***	0.014***	0.015***	0.015***	0.013***
	(0.0009)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
condostyle	-.096***	-.006	-.043	-.043	-.041	-.079***	-.136***	-.225***	-.255***	-.242***
	(0.024)	(0.043)	(0.036)	(0.029)	(0.029)	(0.028)	(0.029)	(0.03)	(0.032)	(0.03)
mobilestyle	-.233***	-.237***	-.260***	-.223***	-.244***	-.273***	-.365***	-.366***	-.277***	-.199***
	(0.033)	(0.06)	(0.051)	(0.041)	(0.041)	(0.039)	(0.041)	(0.042)	(0.045)	(0.042)
singlefamstyle	0.373***	0.43***	0.43***	0.449***	0.464***	0.436***	0.378***	0.288***	0.217***	0.196***
	(0.023)	(0.042)	(0.036)	(0.029)	(0.029)	(0.028)	(0.029)	(0.03)	(0.032)	(0.03)
townstyle	0.142***	0.182***	0.195***	0.224***	0.244***	0.215***	0.156***	0.065**	0.023	-.005

	(0.024)	(0.044)	(0.037)	(0.03)	(0.03)	(0.029)	(0.03)	(0.031)	(0.033)	(0.031)
duplexstyle	0.09***	0.147***	0.145***	0.151***	0.15***	0.103***	0.044	-.034	-.085**	-.107***
	(0.026)	(0.046)	(0.039)	(0.032)	(0.032)	(0.03)	(0.031)	(0.032)	(0.035)	(0.033)
bedstotal	0.014***	0.018***	0.014***	0.012***	0.012***	0.011***	0.01**	0.009**	0.015***	0.011***
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
bathsfull	0.031***	0.013	0.022***	0.027***	0.027***	0.027***	0.027***	0.027***	0.031***	0.041***
	(0.004)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
bathshalf	-.002	0.002	-.003	-.006	-.009	-.007	-.002	-.002	0.00005	-.002
	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
security	-.003	0.004	0.005	-.002	-.005	-.006	-.004	-.006	-.008	0.0008
	(0.004)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
storydum	-.008*	-.031***	-.018**	-.017***	-.013**	-.008	-.006	-.007	-.013**	-.002
	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
fireplacedum	0.059***	0.047***	0.047***	0.052***	0.056***	0.056***	0.059***	0.065***	0.07***	0.068***
	(0.005)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
carportdum	0.06***	0.079***	0.061***	0.049***	0.062***	0.069***	0.067***	0.065***	0.045***	0.049***
	(0.01)	(0.017)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
garagedum	0.133***	0.199***	0.169***	0.163***	0.142***	0.123***	0.109***	0.098***	0.09***	0.075***
	(0.005)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
hoa	0.046***	0.103***	0.082***	0.069***	0.056***	0.048***	0.035***	0.031***	0.018**	0.017**
	(0.005)	(0.01)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
pantry	0.027***	0.02***	0.022***	0.024***	0.024***	0.026***	0.025***	0.023***	0.024***	0.022***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
breakbar	-.006	0.01	0.01*	0.006	0.003	-.002	-.006	-.009**	-.018***	-.022***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
kitchenisland	0.002	0.018*	0.016*	0.005	-.002	0.002	-.001	-.006	-.005	-.004
	(0.006)	(0.01)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
pooldum	0.132***	0.132***	0.134***	0.134***	0.142***	0.14***	0.139***	0.131***	0.126***	0.121***
	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
communitypooldum	0.043***	0.057***	0.048***	0.048***	0.05***	0.048***	0.043***	0.043***	0.038***	0.028***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
landscapemature	0.036***	0.029***	0.031***	0.034***	0.034***	0.036***	0.032***	0.032***	0.031***	0.03***
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
shortsale	-.286***	-.275***	-.282***	-.294***	-.300***	-.300***	-.288***	-.275***	-.267***	-.252***

	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
foreclosure	-.243***	-.257***	-.256***	-.257***	-.257***	-.250***	-.236***	-.216***	-.194***	-.173***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
floodzone	-.023***	-.015	-.018*	-.007	-.008	-.014*	-.022***	-.022***	-.021**	-.012
	(0.006)	(0.011)	(0.01)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)
parkdist	0.01***	0.011***	0.014***	0.012***	0.011***	0.011***	0.009***	0.008***	0.005**	-.0003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
allwatdist	-.027***	-.038***	-.025**	-.031***	-.035***	-.035***	-.037***	-.036***	-.031***	-.024***
	(0.007)	(0.013)	(0.011)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.01)	(0.009)
ponddum	0.021***	0.023**	0.013	0.013*	0.014*	0.016**	0.017**	0.027***	0.035***	0.032***
	(0.006)	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
lakedum	0.05***	0.035	0.03	0.013	0.039**	0.035*	0.032*	0.045**	0.062***	0.072***
	(0.015)	(0.027)	(0.023)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.021)	(0.019)
canaldum	0.097***	0.127**	0.066	0.054	0.022	0.031	0.065	0.115***	0.124***	0.146***
	(0.033)	(0.06)	(0.051)	(0.042)	(0.041)	(0.04)	(0.041)	(0.042)	(0.046)	(0.042)
orlcbd	0.011***	0.015***	0.014***	0.013***	0.012***	0.011***	0.01***	0.009***	0.009***	0.007***
	(0.0005)	(0.0009)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
airportdist	0.013***	0.015***	0.014***	0.014***	0.014***	0.013***	0.012***	0.013***	0.014***	0.013***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	19656	19656	19656	19656	19656	19656	19656	19656	19656	19656
e(r2-a)	0.851									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01.

Table 21: Neighborhood Cluster Robustness Check.

	OLS	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
houseage	-.012***	-.009***	-.009***	-.010***	-.011***	-.011***	-.011***	-.011***	-.012***	-.012***
	(0.0006)	(0.001)	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)
houseagesq	0.00007***	-1.00e-05	7.88e-06	0.00003**	0.00004***	0.00005***	0.00006***	0.00008***	0.00009***	0.00009***
	(1.00e-05)	(0.00002)	(0.00002)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(1.00e-05)	(0.00002)
sqftheated	0.0002***	0.0002***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***

	(5.70e-06)	(1.00e-05)	(8.50e-06)	(7.33e-06)	(6.69e-06)	(6.70e-06)	(6.55e-06)	(6.95e-06)	(7.05e-06)	(8.53e-06)
lotsizeac	0.021***	0.024***	0.022***	0.023***	0.022***	0.022***	0.021***	0.02***	0.02***	0.015***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
condostyle	-.205***	-.231***	-.248***	-.195***	-.150***	-.174***	-.186***	-.237***	-.315***	-.281***
	(0.026)	(0.05)	(0.039)	(0.034)	(0.031)	(0.031)	(0.03)	(0.032)	(0.032)	(0.039)
mobilestyle	-.473***	-.642***	-.546***	-.462***	-.430***	-.436***	-.461***	-.492***	-.550***	-.280***
	(0.034)	(0.064)	(0.05)	(0.043)	(0.04)	(0.04)	(0.039)	(0.041)	(0.042)	(0.05)
singlefamstyle	0.369***	0.412***	0.374***	0.425***	0.444***	0.418***	0.396***	0.328***	0.219***	0.21***
	(0.026)	(0.05)	(0.039)	(0.034)	(0.031)	(0.031)	(0.03)	(0.032)	(0.032)	(0.039)
townstyle	0.109***	0.136***	0.113***	0.182***	0.209***	0.189***	0.162***	0.1***	-.001	-.0002
	(0.027)	(0.051)	(0.04)	(0.035)	(0.031)	(0.032)	(0.031)	(0.033)	(0.033)	(0.04)
duplexstyle	0.106***	0.116**	0.11***	0.147***	0.156***	0.119***	0.092***	0.021	-.065*	-.083*
	(0.028)	(0.054)	(0.042)	(0.037)	(0.033)	(0.033)	(0.033)	(0.035)	(0.035)	(0.043)
bedstotal	0.033***	0.039***	0.026***	0.023***	0.024***	0.025***	0.026***	0.022***	0.023***	0.019***
	(0.004)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
bathsfull	0.081***	0.051***	0.058***	0.056***	0.059***	0.061***	0.062***	0.06***	0.061***	0.062***
	(0.005)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
bathshalf	0.014***	0.019*	0.011	0.004	-.0005	0.002	0.005	0.003	0.01	0.002
	(0.005)	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
security	-.013***	-.001	-.004	-.009	-.010*	-.012**	-.011*	-.010*	-.010	-.008
	(0.005)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
storydum	-.013**	-.034***	-.025***	-.023***	-.018***	-.016**	-.009	-.005	-.012*	0.0004
	(0.005)	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
fireplacedum	0.059***	0.046***	0.049***	0.055***	0.056***	0.057***	0.064***	0.069***	0.07***	0.074***
	(0.006)	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
carportdum	0.084***	0.119***	0.09***	0.061***	0.077***	0.085***	0.079***	0.081***	0.064***	0.068***
	(0.011)	(0.021)	(0.016)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.016)
garagedum	0.147***	0.216***	0.191***	0.161***	0.153***	0.134***	0.123***	0.112***	0.107***	0.085***
	(0.006)	(0.011)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
hoa	-.0005	0.056***	0.043***	0.026***	0.021***	0.012*	0.003	-.0003	-.012	-.017*
	(0.006)	(0.011)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
pantry	0.025***	0.028***	0.017***	0.018***	0.023***	0.023***	0.026***	0.024***	0.022***	0.019***
	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
breakbar	-.008**	0.011	0.006	0.005	0.0004	-.004	-.008*	-.014***	-.017***	-.019***

	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
kitchenisland	-.003	0.015	0.013	-.002	-.011	-.003	-.006	-.008	-.009	-.003
	(0.006)	(0.012)	(0.01)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.01)
pooldum	0.135***	0.138***	0.137***	0.135***	0.141***	0.141***	0.14***	0.133***	0.129***	0.122***
	(0.005)	(0.01)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
communitypooldum	0.061***	0.073***	0.068***	0.064***	0.062***	0.057***	0.055***	0.048***	0.043***	0.036***
	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
landscapemature	0.048***	0.041***	0.042***	0.04***	0.041***	0.041***	0.039***	0.037***	0.037***	0.033***
	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
shortsale	-.307***	-.288***	-.310***	-.320***	-.315***	-.311***	-.301***	-.287***	-.279***	-.261***
	(0.004)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
foreclosure	-.283***	-.294***	-.306***	-.307***	-.291***	-.276***	-.261***	-.241***	-.216***	-.190***
	(0.004)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
floodzone	-.017**	0.006	0.004	-.007	-.011	-.011	-.013	-.020**	-.026***	-.018*
	(0.007)	(0.013)	(0.01)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.01)
parkdist	0.035***	0.035***	0.038***	0.037***	0.034***	0.032***	0.028***	0.027***	0.022***	0.012***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
allwatdist	-.007	-.008	-.003	-.015	-.019**	-.021**	-.027***	-.017*	-.025***	-.022*
	(0.008)	(0.015)	(0.012)	(0.01)	(0.009)	(0.009)	(0.009)	(0.01)	(0.01)	(0.012)
ponddum	0.011*	0.018	0.0008	0.009	0.004	0.008	0.009	0.022***	0.027***	0.031***
	(0.007)	(0.013)	(0.01)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.01)
lakedum	0.048***	0.043	0.039	0.017	0.021	0.037*	0.029	0.033	0.045**	0.085***
	(0.017)	(0.033)	(0.026)	(0.022)	(0.02)	(0.02)	(0.02)	(0.021)	(0.021)	(0.026)
canaldum	0.111***	0.099	0.082	0.036	0.052	0.075*	0.048	0.128***	0.154***	0.127**
	(0.037)	(0.071)	(0.055)	(0.048)	(0.044)	(0.044)	(0.043)	(0.045)	(0.046)	(0.056)
orlcbd	0.005***	0.012***	0.01***	0.006***	0.004***	0.003**	0.002	0.0006	0.003*	0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
airportdist	0.009***	0.012***	0.011***	0.011***	0.013***	0.012***	0.011***	0.012***	0.011***	0.011***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
cluster2	-.057***	-.054**	-.047***	-.058***	-.064***	-.063***	-.068***	-.076***	-.062***	-.051***
	(0.011)	(0.021)	(0.016)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.017)
cluster3	-.041***	-.025	-.034*	-.053***	-.066***	-.060***	-.057***	-.069***	-.043***	-.018
	(0.013)	(0.025)	(0.019)	(0.017)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.019)
cluster4	-.119***	-.093***	-.111***	-.130***	-.133***	-.130***	-.120***	-.127***	-.099***	-.062***

	(0.014)	(0.027)	(0.021)	(0.018)	(0.017)	(0.017)	(0.016)	(0.017)	(0.018)	(0.021)
Obs.	20934	20934	20934	20934	20934	20934	20934	20934	20934	20934
e(r2-a)	0.864									
e(df-a)										

*: significant at p=0.1, **: significant at p=0.05, ***: significant at p=0.01.

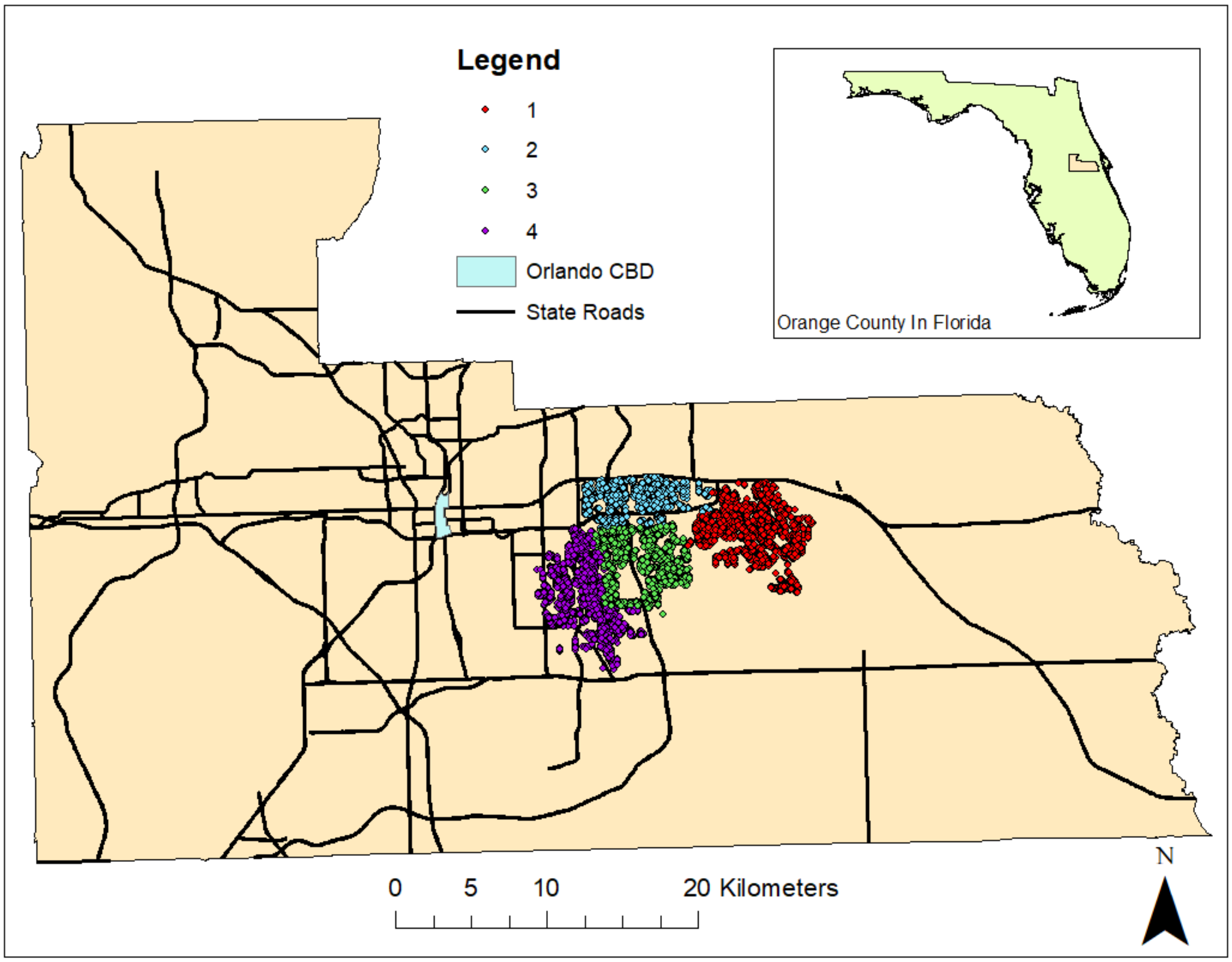

Figure 7: Map Showing Partition of Clusters.