# A Hedonic Assessment of Distance Decay in Willingness to Pay for Water Clarity Enhancements to Support Decision Making

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Abstract:

In the aftermath of Hurricane Sandy in 2012, new federal and state policies sought to increase community resilience by incorporating ecosystem services into long-term resilience planning. To provide information supporting the cost-benefit analysis of green infrastructure projects that can enhance resilience and water clarity, we estimate fixed effects and spatial econometric hedonic valuation models of residential real estate prices. We estimate these models using existing data from 31,973 sales transactions for 29,840 unique single-family properties from 2002 to 2015 within Hempstead Bay, NY along with water clarity measurements from the local government. The results indicate that despite increased variability and lower property values after Hurricane Sandy, willingness to pay for water clarity improvements and the pattern of distance decay in the effect size for properties closest to the water experienced little change. Applying a 3% discount rate, we estimate for households within 4km of the shore an average annual willingness to pay for a 1-foot increase in water clarity of $250/yr before Sandy and of $105/yr after Sandy.

Keywords: ecosystem service valuation; water quality valuation; water clarity valuation; hedonic valuation; ecosystem services

## 1. Introduction

On October 29th, 2012, Hurricane Sandy made landfall in New York State (NYS) affecting many coastal communities, with approximately $72.8 B total damages from storm surge and stormwater-related flooding (NOAA NCEI 2019). In the wake of this disaster, coastal communities across New York began a recovery process that included months of community engagement to inventory local projects that, when completed, might increase community resilience to future storms. Hurricane Sandy's extensive damage to coastal communities highlighted the need for long-term recovery solutions that could withstand the impacts of future storms. As such, integrating the concept of resilience, or "the ability of a system to withstand major shock or maintain or quickly return to normal function," (Leichenko 2011) within recovery planning became a top priority Recovery projects included green infrastructure in addition to grey as part of a renewed interest in incorporating ecosystem services, or the benefits derived from ecological functions and processes (Daily, 1997). In 2014, NYS passed the Community Risk and Resiliency Act (CRRA) prompting the consideration of the effects of climate change into certain elements of state infrastructure planning. Among other requirements CRRA instructs NYS DEC to partner with the NYS Department of State (DOS) to formulate guidance for incorporating natural resources and processes into resiliency planning (NYS DEC 2014).

"Natural resources and processes" relate to ecosystem services, or the "aspects of ecosystems utilized-- actively or passively-- to produce human well-being" (Fisher and Turner 2008; Boyd and Banzhaf 2007). Similar to CRRA but at the federal level, the Office of Management and Budget (OMB) issued Memorandum M-16-01 directing federal agencies to incorporate ecosystem services into planning and decision making. The National Ecosystem Services Partnership guidebook furthers this goal by providing assessment frameworks and methods that federal agencies and their partners can employ to weigh tradeoffs and assess the value of ES within natural resources management decisions (NESP, 2016).Incorporating ecosystem services into decision making has been heralded as a mechanism for advancing conservation and preservation of natural resources and for the promotion of human wellbeing (MEA 2005; Haines-Young and Potschin 2010; Hausmann et al. 2016). In particular, urban ES are critical for resilience especially those that provision stormwater absorption, recreational services, and food and drinking water (McPherason et al. 2014). Understanding the value of water clarity on housing values could allow local decision makers to further elucidate the many benefits of resilience projects to taxpayers and to justify public funding, in which improved water clarity is one of many benefits. Despite the growing body of literature on the benefits provided by ecosystem services, there are many challenges to integrating ecosystem services into decision making, including non-transferability of models to local contexts, failure to address relevant metrics for decision makers, and non-generalizability of results. (Daily et al. 2009; Fisher et al. 2008; De Groot et al. 2010, Olander et al. 2017).

### 1.1. Sandy Impacts in Town of Hempstead and Subsequent Legislation

During Hurricane Sandy, the storm surge (six to eleven feet in some areas) along with tidal flooding, inundated the south shore of the Town of Hempstead prompting electrical failure and stormwater system backups which subsequently extended flooded areas. (NYCRP 2014). The Town of Hempstead declared more than 521 homes “substantially damaged” and estimated another 500 homeowners would apply for funding from the state to elevate their homes (Winslow 2014). Waterfront communities along the south shore of Long Island were further impacted by the failure of the Bay Park Sewage Treatment Plant in East Rockaway, NY, which sustained extensive damage from a nine-foot storm surge. As a result, an estimated 100 million gallons of raw or partially treated sewage entered New York and New Jersey waterways in the 44 hours of power loss (Schwirtz 2012; Kenward et al. 2013; FEMA 2017), contaminating beaches, wetlands, and bays along the south shore of Long Island, including the coastal areas of the Town of Hempstead. Kenward et al. (2013) further estimated an additional 2.2 billion gallons of partially untreated sewage spilled into Hempstead Bay during the time it took to restore operations. Hurricane Sandy further compromised the coastal habitats along the south shore by breaching sand dunes, eroding beaches and barrier islands (Georgas et al. 2014), and even creating new inlets (Gobler et al. 2019).

After assessing the damage and gathering stakeholder input, municipalities across Long Island developed a list of projects that addressed critical infrastructure needs along with other community needs within the New York Rising Community Reconstruction Plans. While some plans featured larger, long-term projects such as sewer upgrades, other plans included aspects of green infrastructure (NYRCR 2014) that incorporated wetland restoration for surge protection and green space for stormwater retention and infiltration. Recovery funding is limited though, requiring a prioritization of projects slated to receive funding. Prioritization based on anticipated costs and benefits is particularly challenging for green infrastructure projects, for which the benefits are not necessarily immediate or readily understood or valued by the public and decision makers. When integrating ecosystem services into local policy, decision makers need information to explain and justify their choice of investment to constituents and fulfill the requirements for public funding given new NYS. However, economic valuation studies that could generate monetary measures of benefits present many barriers to implementation including cost, time, and skilled personnel (Olander et al. 2017). Conducting a study using existing data reduces some of the barriers towards integrating ecosystem services into resiliency planning. As such, our team, in consultation with the Nassau County Planning Department, chose to conduct a hedonic analysis with water clarity as the variable of inquiry.

### 1.2 Water Quality/Clarity Issues Post- Hurricane Sandy

Water quality and clarity have been longstanding concerns for communities on Long Island's south shore, especially nitrogen loading from septic tanks within the Great South Bay in Suffolk County (Swanson et al. 2010; Kinney and Valiela 2011; Foderaro 2017). In Nassau County, where the Town of Hempstead is, most home rely on sewers instead of septic systems

(Foderaro 2017), but the south shore of Nassau County is still impaired by nutrients, sediments, and pathogens (Fisher et al. 2018). After Hurricane Sandy and the failure of the Bay Park Wastewater Treatment Facility, the water discharging into Reynolds Channel (Hempstead Bay) contained untreated and partially treated sewage (Kenward et al. 2013; Fisher et al. 2018). Using a hedonic analysis, this study will examine how and to what magnitude water clarity played a role in influencing the sales price of single-family properties in the Town of Hempstead before and after Hurricane Sandy.

### 1.3 Hedonic Analysis and Impacts of Hurricanes on Housing Markets

Hedonic analysis is a revealed preferences method that decomposes real estate transactions into the implicit prices of the private amenities that make up the value of the house (Rosen 1974). Hedonic analyses are well demonstrated in the literature and have been applied to estimate household preferences for environmental quality such as water clarity (Leggett and Bockstael 2000; Michael et al. 2000; Poor, Pessagno, & Paul 2007; Walsh et al. 2011; Bin and Czajkowski 2013; Walsh et al. 2017; Liu et al. 2017). Various measures of water quality have been used, including turbidity, nitrate, nitrite, dissolved oxygen, and bacterial contamination. Our team selected secchi depth measurements as our variable of interest in consultation with the Nassau County planning department. Secchi depth is easily collected, low cost, and an intuitive measure of water clarity (Holmes, 1970; Preisendorfer, 1986). Water clarity as a measure of water quality is also sensible because hedonic values only capture values that homeowners are aware of. If homebuyers are unaware of more technically relevant measures of water quality, including them in the hedonic regression could introduce bias (Papenfus 2019).

Using the “natural resources and processes” provision of CRRA and the OMB memo as guiding principles, our study aims to provide a practical example for local decision makers of the importance of ecosystem services and economic valuation. The Town of Hempstead was selected as the study area in partnership with the Nassau County Planning Department. Hempstead is a densely populated town in Nassau County, NY, whose coastal communities were impacted by flooding from storm surge and stormwater during Hurricane Sandy. Using only existing data, our team conducted a hedonic analysis to explore whether water clarity affected sales prices of single-family properties from 2002-2015. Water clarity is a measure of water quality that is appreciated by homeowners, swimmers, fishers, and boaters, and as such is an ecosystem service with potential economic value. For the remainder of the paper, we use these terms interchangeably. Our motivation in exploring this variable was to generate estimates of environmental quality to be used in cost benefit analysis for planned County expenditures focused on resilience, that would tend to enhance water clarity in addition to moderating flood risks. Understanding the influence of water clarity on housing values could allow local decision makers to further communicate the many benefits of resilience projects to taxpayers and to justify public funding, in which improved water clarity is one of many benefits.

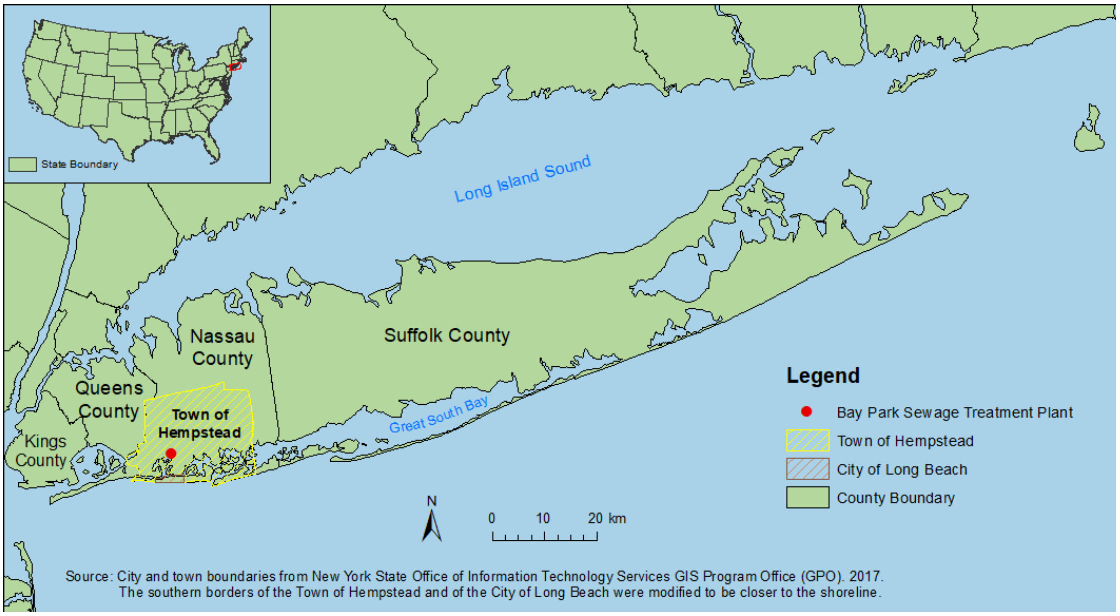
Our team used existing data amenable to ecosystem service valuation to provide additional data for benefit/cost analysis. We investigated how water clarity, measured as secchi depth, influenced sale prices of single-family properties in the Town of Hempstead in years preceding Hurricane Sandy (2002- October 29$^{th}$, 2012) and following Hurricane Sandy (October 30$^{th}$, 2012- 2015). This analysis aimed to quantify the relationship between water clarity and housing values. Making this connection could help justify municipal and county resilience investments like stormwater or drainage improvements for which water clarity is one of many public benefits.

## 2. Materials and Methods

2.1. Study Area

The Town of Hempstead is located in Nassau County, NY on the south shore of Long Island (Fig. 1). Hempstead is comprised of 22 incorporated villages and 34 unincorporated areas. In 2015, the last year considered in the analysis, the population was 771,018 with a median household income of $94,999 (U.S. Census Bureau) which is considerably higher than the national median household income ($55,775; Posey 2016). The Town of Hempstead is primarily developed (66.5%) with less wetland (10.1%) and agricultural/pastoral areas (8.3%; Yang et al., 2018, National Land Cover Dataset (https://www.mrlc.gov/national-land-cover-database-nlcd-2016). The Town of Hempstead is mostly sewered with the Bay Park Wastewater Treatment Facility nearby (Fig.1).

Figure 1: Map of the Town of Hempstead on Long Island, NY




## 2.2. Use of Existing Data

This study utilized existing datasets from national, state, and local sources to complete the hedonic analysis (Appendix A). We obtained sales transactions for single-family properties for Nassau County from the NYS SalesWeb (https://my.ny.gov/) from 2002-2015. We also obtained a dataset detailing parcel characteristics at the time of sale (e.g., number of bathrooms, total living area, sales areas sold, etc.) for 186,980 single-family properties from the Nassau County Land Records Viewer database (Sean Sallie, pers. comm.).Town of Hempstead socio-economic characteristics (e.g., educational attainment, income levels, etc.) were obtained from U.S. Census Bureau data at the block group level (Appendix A, https://www.census.gov/). Income measures from the US Census were adjusted to 2015 dollars using a Bureau of Labor Statistics (BLS) Consumer Price Index for all items for the New York-Newark-Jersey City area. A similar adjustment was made for sale prices using a housing price index for the same area from the BLS.

## 2.3 Interpolation of Secchi Depth Measurements

Georeferenced secchi depth measurements were obtained from the Town of Hempstead from 2002-2015 ($n$ = 4,289). Duplicate entries and entries with no data were removed from the analysis for a total of $n$ = 3,553 records. Within each year, the number of stations sampled varied. Across all of Hempstead Bay, 43 stations were sampled from 2007-2013 and 30 stations were sampled in 2005, 2014, and 2015. The Bay was divided into three sections: West, Middle and East Bay (Figure 2). Sixteen stations per year located in the West and Middle Bays were sampled from 2002 to 2004 and in 2006. The lowest secchi depths occurred in the South Shore estuary between 2000 and 2005 with a mean winter secchi depth of 1.2 m and a mean summer secchi depth of 1.1 m (New York SeaGrant, 2007). The similarity of mean values of secchi depth led us to use annual average secchi depth as our measure of water clarity.

With multiple secchi measurements per station per year, the average annual secchi depth per station was calculated, similar to Liu et al. (2017). The Inverse Path Distance Weighting (IPDW) R package was used to interpolate secchi measurements across the Bay each year. IPDW uses path distances instead of straight-line (Euclidean) distances as interpolation weights (Stachelek and Madden, 2015). The path distance calculations accounted for the main characteristics and obstructions (e.g. bays, islands, and channels) of the study area. The range of the interpolation neighborhood was set to 2,500 meters. Each property was assigned a secchi depth measurement corresponding to the year the property was sold. The interpolated raster values were attributed to a point at the center of each raster cell (cell size = 30m), and any points over land or in areas outside the interpolation neighborhood were removed. Spatial joins were performed to allocate the closest raster centroid secchi depth value to the center of each parcel within the analysis, also called the parcel centroid. This secchi value was then assigned to any home sold within that parcel during that time period. East Bay was not sampled from 2002 to 2004, or in 2006, causing parcel centroids that were roughly north of East Bay to be excluded from the analysis, as they did not receive a secchi depth value for this time period. Figures 2 and 3 show the interpolation of secchi measurements for 2002, a year with data sampling gaps in East Bay, and 2011, a year with no data sampling gaps. Each of the points on the map represents a sampling station within Hempstead Bay.

## 2.4 Hedonic Analysis Dataset Construction

To conduct the hedonic analysis, we merged components of the datasets in Appendix A into a single dataset that contained all variables of interest (property characteristics, socio-economic data, sales transactions, and water clarity data) We removed duplicate parcel record data (28 records) from our dataset obtained from the county. We removed 80,195 parcels to limit the master dataset to include only single-family homes and arm’s length sales transactions—transactions in which buyers and sellers have no relationship to one another and act only in their own self-interest, thereby representing fair market values. All parcels were assigned a secchi value that corresponded to the respective sale year (described in Section 2.3). Preliminary regression and correlation analyses showed that properties beyond 4km from the shoreline exhibited weak relationships with secchi depth., Therefore, properties located more than 4km from the shoreline were excluded (74,784 parcels) from the dataset. The final dataset included 31,973 single-family properties that are less than 4km from the shorelines and reflect, arm’s length transactions sold from 2002-2015 within the Town of Hempstead.

Figure 2: Map of Sampling Station across Hempstead Bay with Data Gaps (Year 2002)

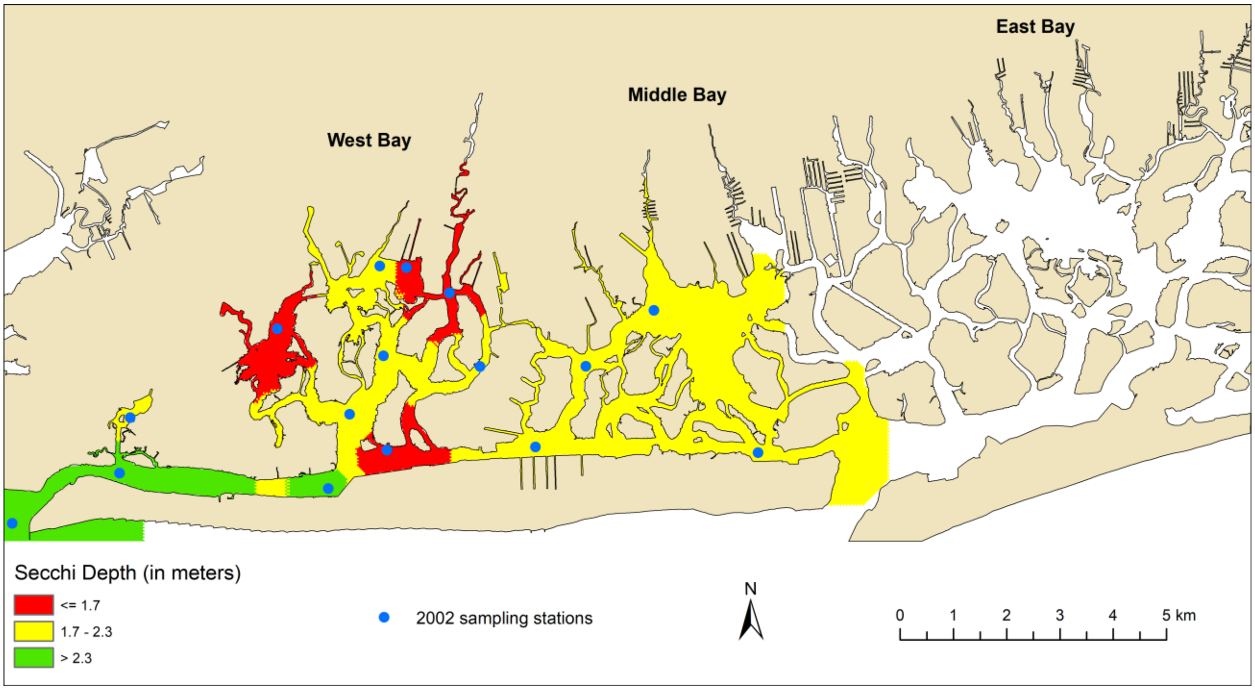
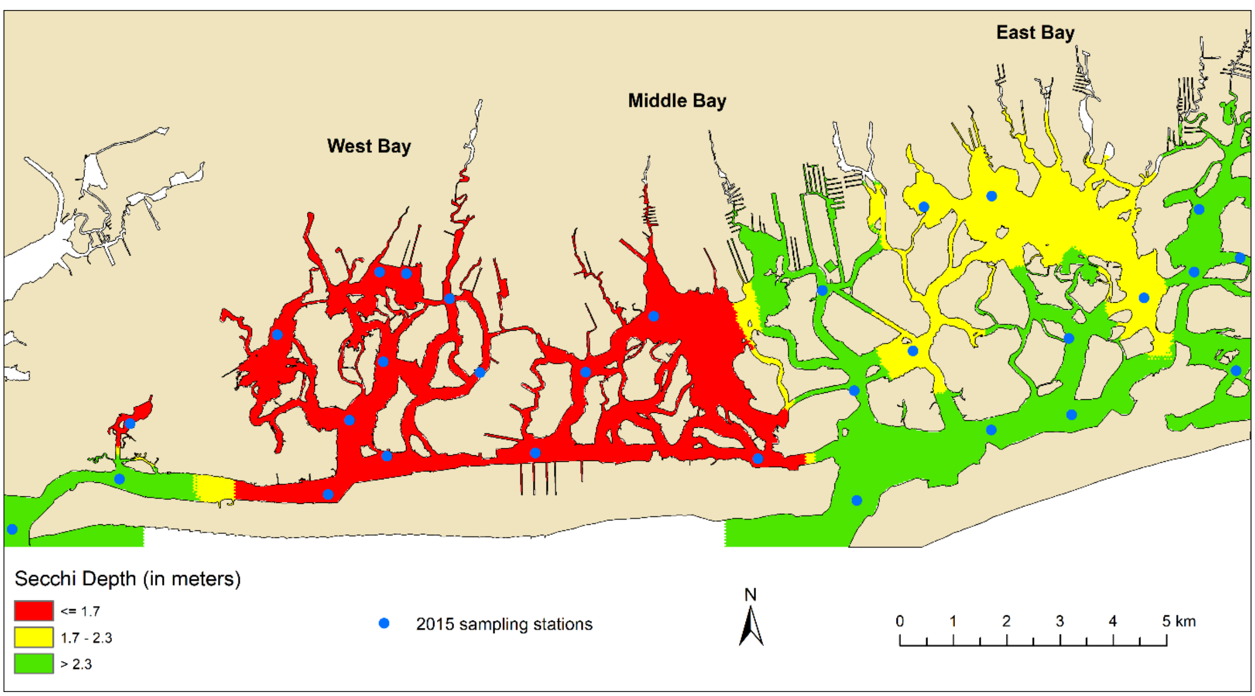



Figure 3: Map of Sampling Station across Hempstead Bay with no Data Gaps (Year 2015)




While constructing the dataset for the hedonic analysis, we distinguished between different types of waterfront properties because of prior evidence of price premiums for properties directly on the water (Benson et al. 1998; Bin et al. 2008; Wyman et al. 2014). Rather than just considering waterfront vs non-waterfront, we also differentiated the type of waterfront location for the parcel. The shoreline of the Town of Hempstead is characterized by many canals and inlets, which provide water access and frontage. However, these properties are distinct from properties located on the shoreline with an unobstructed scenic view of Hempstead Bay. We characterized properties located directly on Hempstead Bay as "Bayfront" property and properties located along the canals and inlets as "Water Access" properties. As in other hedonic analyses (Netusil et al. 2014; Wolf and Klaiber 2017; Liu et al. 2017), we used dummy variables and interaction terms to capture potentially non-linear and spatially variable impacts of water clarity on price. Walsh et al. (2015 and 2017) observed these impacts as far as 2km from the shoreline. We created bands for distance from shore for Bayfront, Water Access properties and remaining properties were grouped by thresholds at 0, 50, 75, 100, 150, 200, 300, 400, 600, 800, 1600, 3200, and 4000 meters. Results for models using alternative threshold are available in the online supplements.

## 2.5. Regression Analysis- Fixed Effects and the Spatial Error Model

Our hedonic modeling approach includes the use of two separate models: (1) Ordinary Least Squares (OLS) with fixed effects and (2) the Spatial Error Model (SEM). We assume that the data generation process follows a standard linear regression model,

$$y = X\beta + u, \quad (1)$$

where $X = [X_{parcel}, X_{neighborhood}, X_{water}]$,

$$\text{and } \beta = \left[\beta_{parcel}, \beta_{neighborhood}, \beta_{water}\right]'.$$

Where $y$ is vector containing the natural logarithm of inflation adjusted sale prices, $\beta$ is a partitioned column matrix of parameters and $X$ is a partitioned matrix that includes variables common to hedonic analyses. $X_{parcel}$ contains variables such as parcel and transaction characteristics (e.g. number of bathrooms, year sold, and total living area). $X_{neighborhood}$ contains variables describing neighborhood characteristics such as census block data and distance to amenities (e.g. educational attainment, income, distance to park). $X_{water}$ contains a set of water clarity related variables specified to allow a non-linear pattern in water clarity impacts due to distance from the shoreline. These water clarity related variables include secchi depth, dummy variable spatial descriptors following Walsh et al. (2015 and 2017; e.g. property is <50m from the shoreline but not Bayfront or Water Access) and interactions between secchi depth and the dummy variable spatial descriptors. Secchi depth measures were centered using the mean from each time period to facilitate interpretation of the distance from shoreline fixed effects. Inference is made using Huber-Eicker-White heteroskedasticity robust standard errors.

Following the advice of Gibbons and Overman (2012) we avoid relying on spatial patterns alone for identification of causal effects. Instead, for econometric identification we include annual and spatial fixed effects. The fixed effects approach has also been called the dummy variable estimator (Greene 2012), and the approach can be thought of as a generalization of the intuitive differences-in-differences estimator. By defining two-way fixed effects for time and distance from shoreline, our model implicitly defines a group for each distance from shoreline for each year (e.g., bayfront-2003, 0m to 50m from shoreline-2004). We include time fixed effects and distance from shoreline fixed effects as constants, allowing each group to have a potentially unique regression parameter for the constant term. We also include interactions between each distance from shoreline fixed effects and water clarity to allow for potentially unique slope parameters on the water clarity variable for each distance from shoreline.

The inclusion of annual fixed effects helps control for correlations between the macroeconomy and water quality, which are likely to exist due to the increase in pollution that accompanies increased economic output (Fischer and Heutel 2013). Specifically, annual fixed effects effectively center each variable around its annual mean, just as a globally constant term effectively centers each variable around its global mean. With an annually centered measure of water quality, the estimated parameter measures how deviations from water quality around the annual mean cause price to vary around its annual mean. We employ a similar treatment across space by including dummy variables for distance from shore bands. Consequently, the model measures how a property's sale price differs from the average price for properties a similar distance from shore as a consequence of variations in water quality relative to properties in that same distance band. Because we include interaction terms between distance from shoreline groups and water clarity, the magnitude of the effect described above can vary by distance from shoreline group. These variables allow us to account for and measure distance decay (Sutherland and Walsh 1985; Johnston et al. 2019), while controlling for annual variability experienced within each group.

Because Hurricane Sandy may have impacted how people value related ecosystem services, we split the data and estimate separate models pre- and post- Hurricane Sandy. By estimating distinct models, we avoid restricting the scope of impact of a large event like Hurricane Sandy, which may alter the spatial dynamics estimated by the spatial models discussed below. To some extent, the annual fixed effect terms included in both models can accommodate changes in the market for single family homes in the years following the hurricane. This may be the case for changes in the housing market in the years preceding and following the collapse of financial markets in 2008.

A number of hedonic studies (e.g., Bin and Landry 2013; Wyman et al. 2014; Liu et al. 2017; Walsh et al. 2017), have identified spatial autocorrelation as a potential source of bias and inefficiency in regression models estimated with OLS. Spatial autocorrelation may result from properties in close proximity being more similar than properties further away because of similar location-based amenities not included in the model (e.g. school quality, public spaces, municipal services, etc.; Basu and Thibodeau 1998). Spatial autocorrelation violates the assumption of independence in the error term. We consider the SEM (Anselin 2001, LeSage and Pace 2009) to account for this source of bias. A correctly specified SEM model can account for autocorrelation (Wilhelmsson 2002; Wyman et al. 2014) by decomposing the error term into two components, a spatially uncorrelated error, $\epsilon$ , that satisfies normal regression assumptions, and $u$, the spatially autocorrelated component of the error term (Gleditsch and Ward 2008). The SEM starts with (1) and adds the following error term structure:

$$u = \lambda W u \ + \epsilon. \ (2)$$

where the spatial weighting matrix, $W$, effectively adjusts the autocorrelated error term, $u$ to explain more of the data. Without this spatial filtering, predictable patterns of heterogeneity due to omitted variables would be left in the error term, causing OLS to produce inflated standard errors (Anselin 2001). Importantly, for unbiased parameter estimates, as with OLS, the SEM requires that omitted variables not be correlated with observed variables. For the SEM, "the parameter, λ, indicates the extent to which the spatial component of the errors, $u$, are correlated with one another for nearby observations as given by the vector of connectivity, $W$." (Gleditsch and Ward 2008). We estimate the SEM model using the PYSAL's GM ErrorHet spatial regression tool, which implements a heteroskedasticity robust Generalized Method of Moments (GMM) estimator described in Anselin et al (2012). The assumptions required for estimating the GMM model are detailed in Kelejian and Prucha (2010) and in Arraiz et al. (2010). More details about the challenges associated with spatial econometric modeling can be found in Appendix B.

To estimate average marginal effects and average treatment effects in our log-linear regression models, we first create a merged dataset of all properties across all time periods. For properties sold more than once, only the most recent transaction was used. For time fixed effects regressor values in this merged dataset we assign equal weight to each year in each regression, or 1/11 for 2002-2012 and 1/4 for 2012 to 2015. Next we split the dataset by distance band and estimate and weight each marginal effect at the mean, $\partial E[y_i|d]/\partial x_k = \exp(\bar{X}_d\beta)\beta_k$, where $\bar{X}_d$ is the sample mean for distance band, $d$. The marginal effects for each split are combined with a weighted average with weights equal to the relative frequency of each split in the dataset. We also calculate average treatment effects for a non-marginal, 1 foot (0.305 m) increase in water clarity for all properties in the merged dataset. For each distance band, the sample average treatment effect can be calculated as, $E[y_{i1} - y_{i0}|d]$ = $(exp\ (\Delta X\beta) - 1)\bar{y}_d$, where 0 and 1 indicate treatment status and $\bar{y}_d$ is the sample mean for distance band, $d$. Additional details can be found in the appendix.

## 3. Results

### 3.1 Summary Statistics

Summary statistics for variables in the dataset of 31,973 single-family properties included in the hedonic regression analysis are provided in Table 2. The pre-Sandy analysis included single-family property sales transactions (*n*= 23,174) that occurred between 2002 and October 29th, 2012. Post-Sandy dataset contains single-family property transactions (*n*= 8, 799) after October 29th, 2012 through 2015. Mean values for variables were relatively stable across the pre-Sandy and post-Sandy analysis. Average secchi depth values in both the pre-Sandy (1.8 m) and the post-Sandy (1.5 m) analysis, both with standard deviation around 0.5, are not statistically different from each other. The earlier time period has a wider range of values, but only marginally higher variability.  Figure 4 displays the amount of properties sold per year with 2002 being the year with the lowest amount of transactions The year 2002 recorded the lowest number of property sales due to a data gap in the sales transactions data (*n*= 301), and the year 2015 recorded the higher number (*n*= 4,356). Figure 5 displays the breakdown of properties in each of the distance bands as well as those designated as Bayfront or Water Access Properties.

Figure 4: Pre- and Post- Sandy Properties Sold in Each Year of the Analysis

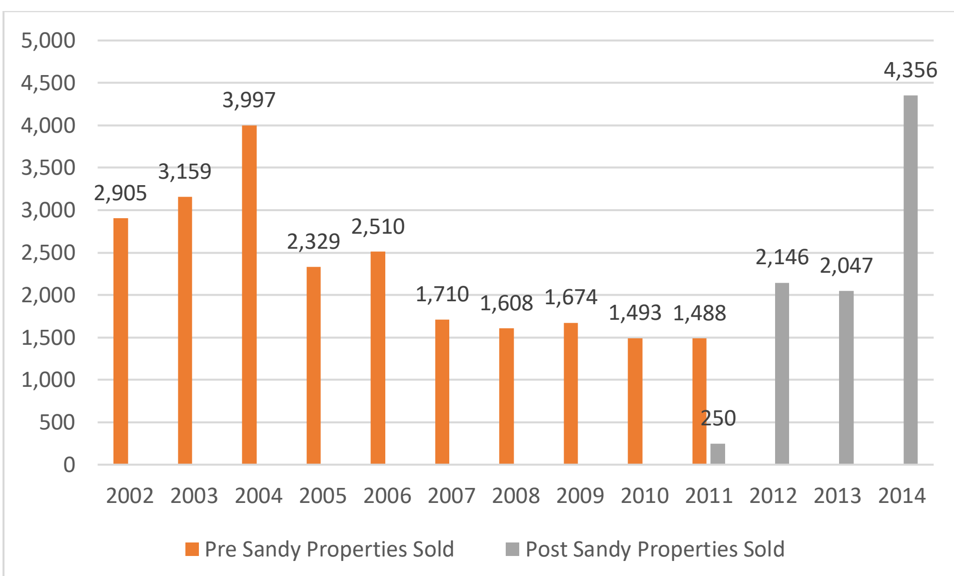



Figure 5: Pre- and Post-Sandy Property Designations by Distance Characteristics

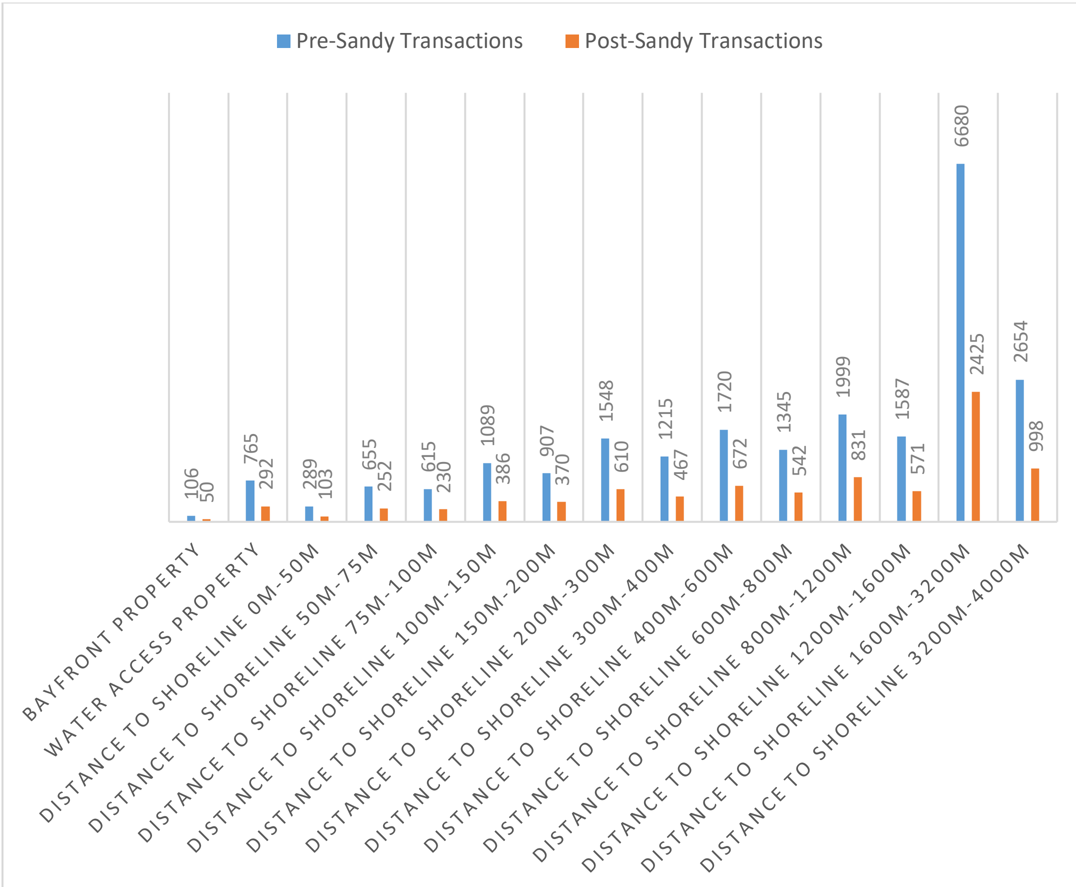



Table 2. Pre- and Post-Sandy Summary Statistics of Variables Analyzed

| Variable Name | Variable Description | Pre-Sandy | | | | Post- Sandy | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Min | Max | Mean | SD | Min | Max |
| **Secchi** | Annual average secchi depth measurement | 1.8 | 0.5 | 0.6 | 4.1 | 1.5 | 0.47 | 1 | 3.5 |
| **Total Bathrooms** | # of full & half baths | 1.9 | 0.8 | 1 | 13 | 2.0 | 0.8 | 1 | 8 |
| **Total Living Area** | Total living area (sqft) | 1791.6 | 742.5 | 360.0 | 12661.0 | 1816.6 | 741.0 | 376.0 | 11982.0 |
| **Parcel Area** | Lot/Parcel area (sqft) | 6653.5 | 3578.6 | 447.6 | 87563.1 | 6948.9 | 3895.6 | 933.1 | 80247.7 |
| **Distance to Public Parks** | Property distance (m) to public parks | 756.4 | 513.3 | 0 | 3026.6 | 758.2 | 515.6 | 0 | 2814.9 |
| **Distance to NYC** | Property distance (m) to NYC border | 7991.4 | 5296.3 | 9.4 | 20128.3 | 8856.6 | 5656.9 | 5.5 | 20192.3 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Distance to Golf/Country Clubs** | Property distance (m) to golf courses/ country clubs | 2461.7 | 1627.5 | 0 | 8370.4 | 2548.8 | 1736.2 | 0 | 8391.1 |
| **Educational Level** | % bachelor's degree or higher by block group | 40.1 | 17 | 0 | 92.6 | 46.4 | 16.4 | 5.2 | 92.6 |
| **Income** | Median HH income by block group | 108730 | 34132 | 13395 | 281130 | 113880 | 36708 | 19565 | 257890 |
| **Poverty level** | % of HHs below poverty level by block group | 4.5 | 5.2 | 0 | 64.6 | 5 | 6.2 | 0 | 47.4 |
| **Pct White** | % white householder by block group | 80.2 | 25.7 | 0 | 100 | 81.3 | 24 | 0 | 100 |

## 3.2. Hedonic Regression Results

Table 3 displays the results of both OLS and pre-Sandy SEM with 3 nearest neighbor (NN) spatial weighting matrices for the Pre-Sandy and Post-Sandy datasets. Coefficient estimates for parcel-related hedonic variables have the expected sign with more bathrooms, a larger lot, and a larger living space contributing positively to home value, though inference is weaker in the post-Sandy dataset. Coefficients for income, education, and percent white are positive and significant in both models, while poverty level is significant and positive but only in the Pre-Sandy regression. The coefficients for distance to Parks and NYC are negative and significant in the Pre-Sandy regression while distance to parks is not significant in the Post-Sandy regression. In contrast, the coefficient for distance to golf courses was positive and significant in all but the Pre-Sandy SEM model. Annual fixed effects (year dummy coefficients) indicate rising impacts on prices from 2002 to 2005, with a pattern of declining prices beginning in 2006 and extending through the end of the pre-Sandy period. In the post-Sandy period, annual fixed effects fall and then rise with a sharp increase in 2015, the year omitted from the regression.

Because Secchi depths are centered in each regression model, coefficients for the uninteracted distance bands indicate the effect of housing location relative to the shoreline when secchi depth is at its average. Many of the uninteracted distance from shoreline coefficients are significant and nearly all switch from positive to negative and become more significant after Sandy. In comparison, the interacted (with Secchi) distance from shoreline coefficients are estimated less precisely. The larger, significant interaction coefficients increase substantially after Sandy. These patterns are more consistent and inference on the interacted coefficients is stronger when comparing the OLS and SEM models. Bayfront and Water Access cause the highest positive impact on sale price before Sandy, but this is only true for Bayfront after Sandy. The parameter for Secchi depth, representing the outermost distanceband, is not significant at the 5% level for any of the models

The spatial correlation coefficient, $\lambda$, is significant in both regressions. Pseudo $R^2$ is lower and the constant is higher for the SEM models in comparison to the OLS models. Generally, OLS and SEM coefficients and standard errors are close in value for most coefficients. As can be seen in the appendix, $\lambda$ and the regression constant rise substantially while Pseudo $R^2$ falls as more nearest neighbors are included.

Table 3. Hedonic Regression Results [1]

| | Pre-Sandy | | Post-Sandy | |
|---|---|---|---|---|
| | OLS | SEM | OLS | SEM |
| Constant | 12.29*** | 12.35*** | 11.9*** | 11.98*** |
| Secchi | 0.0194* | 0.0208 | -0.0244 | -0.0259 |
| Total Bathrooms | 0.0155*** | 0.0106*** | 0.0142** | 0.00591 |
| Total Living Area | 1.23e-05*** | 5.38E-06 | 1.62e-05* | 1.32e-05* |
| Parcel Area | 2.84e-05*** | 2.7e-05*** | 2.89e-05*** | 2.85e-05*** |
| Distance Park | -1.37e-05*** | -8.5e-06* | -9.76E-06 | -5.65E-06 |
| Distance Nyc | -7.57e-06*** | -7.64e-06*** | -1.41e-05*** | -1.37e-05*** |
| Distance Golf | 2.75e-06** | -1.02E-06 | 1.07e-05*** | 6.73e-06** |

[1] *** indicates p < 0.01, ** indicates p < 0.05, and *indicates p < 0.10

| | | | | | |
|---|---|---|---|---|---|
| | Education | 0.00727*** | 0.00655*** | 0.00798*** | 0.00759*** |
| | Income Real-2015 | 9.33e-07*** | 8.66e-07*** | 1.43e-06*** | 1.14e-06*** |
| | Poverty Level | 0.00318*** | 0.0025*** | -0.00118 | -0.00119 |
| | Pct White | 0.00346*** | 0.00351*** | 0.00474*** | 0.00467*** |
| | 2002 | -0.096*** | -0.0929*** | - | - |
| | 2004 | 0.0817*** | 0.0817*** | - | - |
| | 2005 | 0.143*** | 0.145*** | - | - |
| | 2006 | 0.12*** | 0.126*** | - | - |
| | 2007 | 0.0127 | 0.0232* | - | - |
| | 2008 | -0.065*** | -0.0553*** | - | - |
| | 2009 | -0.156*** | -0.143*** | - | - |
| | 2010 | -0.176*** | -0.165*** | - | - |
| | 2011 | -0.234*** | -0.22*** | - | - |
| | 2012 | -0.317*** | -0.302*** | -0.0619*** | -0.0605** |
| | 2013 | - | - | -0.0928*** | -0.0962*** |
| | 2014 | - | - | -0.0487*** | -0.0512*** |
| | Bayfront | 0.667*** | 0.639*** | 0.472*** | 0.431*** |
| | Water Access | 0.123*** | 0.154*** | -0.101*** | -0.093*** |
| Distance to Shoreline | 0m-50m | 0.0241 | 0.0354** | -0.227*** | -0.18*** |
| | 50m-75m | 0.0317*** | 0.0286** | -0.163*** | -0.164*** |
| | 75m-100m | 0.0256** | 0.0205 | -0.0791*** | -0.0773*** |
| | 100m-150m | 0.00204 | 0.00798 | -0.06*** | -0.0649*** |
| | 150m-200m | 0.00453 | 0.0161 | -0.101*** | -0.0873*** |
| | 200m-300m | 0.0241*** | 0.0234** | -0.0769*** | -0.0775*** |
| | 300m-400m | 0.0232*** | 0.0245** | -0.0381* | -0.0516** |
| | 400m-600m | 0.00318 | 0.0172* | -0.0416*** | -0.033* |
| | 600m-800m | 0.0243*** | 0.0259** | 0.016 | 0.000783 |
| | 800m-1200m | 0.00731 | 0.00778 | 0.00895 | 0.0127 |
| | 1200m-1600m | -0.00482 | -0.00254 | 0.016 | 0.0102 |
| | 1600m-3200m | 0.014*** | 0.0126* | 0.00425 | -0.00293 |
| | Secchi * Bayfront | 0.239*** | 0.212*** | 0.275*** | 0.265*** |
| | Secchi * Water Access | 0.0877*** | 0.0914*** | 0.125*** | 0.146*** |
| Secchi * Distance to Shoreline | 0m-50m | 0.104*** | 0.11*** | 0.282*** | 0.184** |
| | 50m-75m | 0.0823*** | 0.0819*** | 0.156** | 0.132* |
| | 75m-100m | 0.0667*** | 0.0513** | 0.0739 | 0.0942 |
| | 100m-150m | 0.0331 | 0.0364 | 0.0378 | -0.00322 |
| | 150m-200m | 0.0125 | 0.00228 | -0.0457 | 0.000858 |
| | 200m-300m | 0.0541*** | 0.0445** | 0.0888** | 0.0838* |
| | 300m-400m | 0.0328 | 0.016 | 0.147*** | 0.123** |
| | 400m-600m | 0.0265 | 0.0167 | 0.056* | 0.0437 |
| | 600m-800m | -0.0144 | -0.012 | 0.0091 | -0.0121 |
| | 800m-1200m | 0.0189 | 0.0197 | 0.0572** | 0.0657* |
| | 1200m-1600m | 0.0321* | 0.0239 | 0.0286 | 0.0195 |
| | 1600m-3200m | 0.0302** | 0.0302* | 0.00358 | 0.00316 |
| | Lambda | - | 0.32*** | - | 0.294*** |
| | $R^2$ | 0.518 | 0.517 | 0.45 | 0.448 |

## 4. **Discussion**

4.1. OLS vs SEM

We consider a couple of ideas from the spatial econometrics literature to help narrow down our choice of model for each time period. Parameter estimates were fairly stable across the OLS and SEM models presented. However, a strong pattern exists where including more neighbors drives down the fit of the model, as measured by pseudo-$R^2$. Following LeSage and Pace (2014), we conclude that the divergence of parameter estimates from the OLS results are indicative of bias, which happened for SEM models with large numbers of nearest neighbors in the spatial weights matrix (see appendix). On the other hand, the estimated OLS models and SEM models with few neighbors summarized in Table 3 are quite similar to each other, which Pace and LeSage (2008) suggest supports the conclusion that the data generating process is consistent with the regression specification. Finally, because model fit and efficiency was superior for the OLS model and because the OLS model does not require assumptions about the patterns of spatial interactions, we conclude that the OLS results are most reliable and focus our discussion accordingly.

The weight matrices for the SEM models were all constrained to have same- year nearest neighbors to avoid price shocks traveling backwards in time. The analyst's choice for treatment of time as well as other variables that may be important to the definition of neighbor is rarely discussed in the spatial econometric literature. Because we included annual fixed effects in our model to control for annual variations shared across groups, it seems consistent to restrict the definition of a nearest neighbor to transactions in the same year. However, the simultaneous spatial reverberations of spatial econometric models could indeed be due to unobserved heterogeneity that is invariant to time; lacking compelling evidence of time invariant spatial interactions, we default to assuming interactive heterogeneity results from new information or shocks which potentially change from year to year. Expanding the definition of neighbor to not only include geographic and time variables but other variables of interest is also sensible, but like with kernel regression, this expansion is also likely to face issues with the curse of dimensionality (Frölich 2006).

## 4.2. Pre- and Post-Sandy Analysis

The pattern of strongly significant and declining coefficients for water clarity interacted with distance bands matches intuition. However, the larger values for many of these coefficients in the post-Sandy analysis is an unexpected result. Further analysis of marginal and treatment effects below help clarify how home prices in our models respond to changes in water clarity. As can be seen in Figure 6, up to a distance of around 100m in both pre- and post-Sandy datasets water clarity impacts are significant. The coefficients in both time periods rise again and become significant around 200-400m and again before Sandy at 800m-1600m.  The pre-Sandy pattern is plausibly consistent with a smoothly declining water quality effect; the pattern is similar but much more dramatic in the post-Sandy analysis, suggesting something other than random variability is responsible. One possibility is that residents of houses closer to the shoreline use and value water differently than residents further from the shoreline and our non-monotonic estimates are the result of variations in these preferences.

Figure 7 tells a more complete story than Figure 6. Figure 7 contains estimates of the marginal effect of water clarity improvements conditional on distance from shore band. Because the uninteracted Secchi coefficient is small and insignificant, we set it to zero for calculating marginal effects and confidence intervals for the included distance bands, Bayfront, and Water Access properties. Remarkably, the higher post-Sandy coefficients in Figure 4 are attenuated by the lower average prices of homes in each distance band in Figure 5. This seems to suggest that willingness to pay for water quality enhancements are fairly consistent across the time periods. Average treatment effects tell a somewhat different story. The average treatment effect for a 1-foot increase in water clarity from a weighted average of each distance band's effect (including water access properties omitted from Figure 7) is about $8,400 per property before Sandy, and this effect falls to about $3,500 after Sandy. Annualized in perpetuity at a discount rate of 3%, these values translate to an average benefit to the residents of each property for a 1foot increase in water clarity of $250/yr before Sandy, falling to $105/yr after Sandy.

Figure 6: Fixed Effects Estimates of Water Quality Coefficients

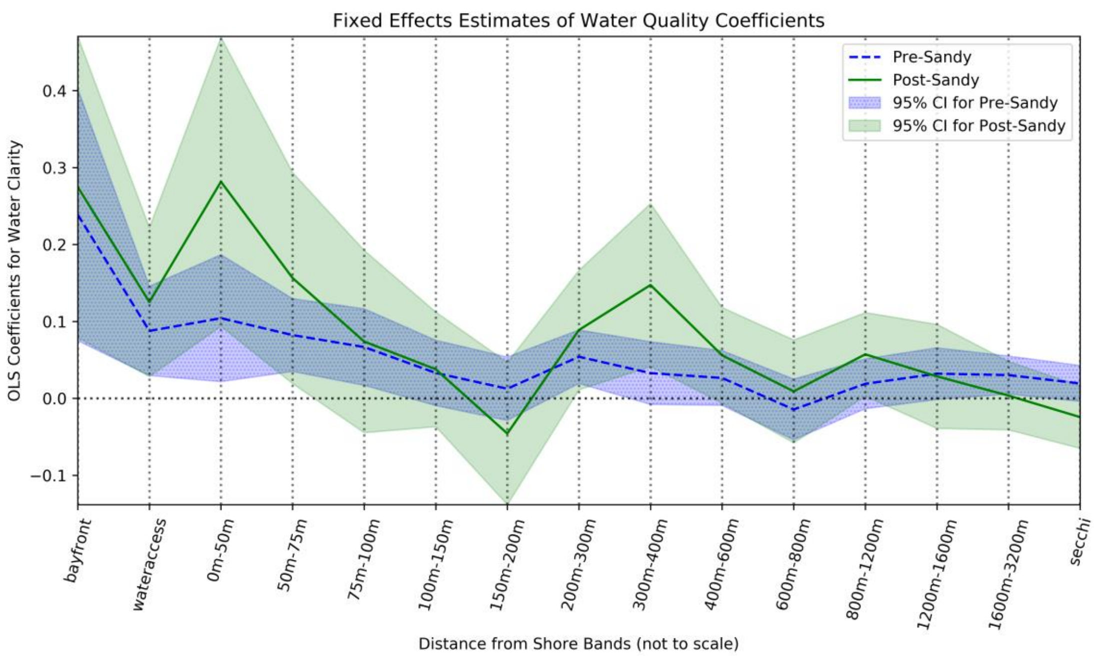



Figure 7: Marginal Effects for Water Clarity by Distance Band

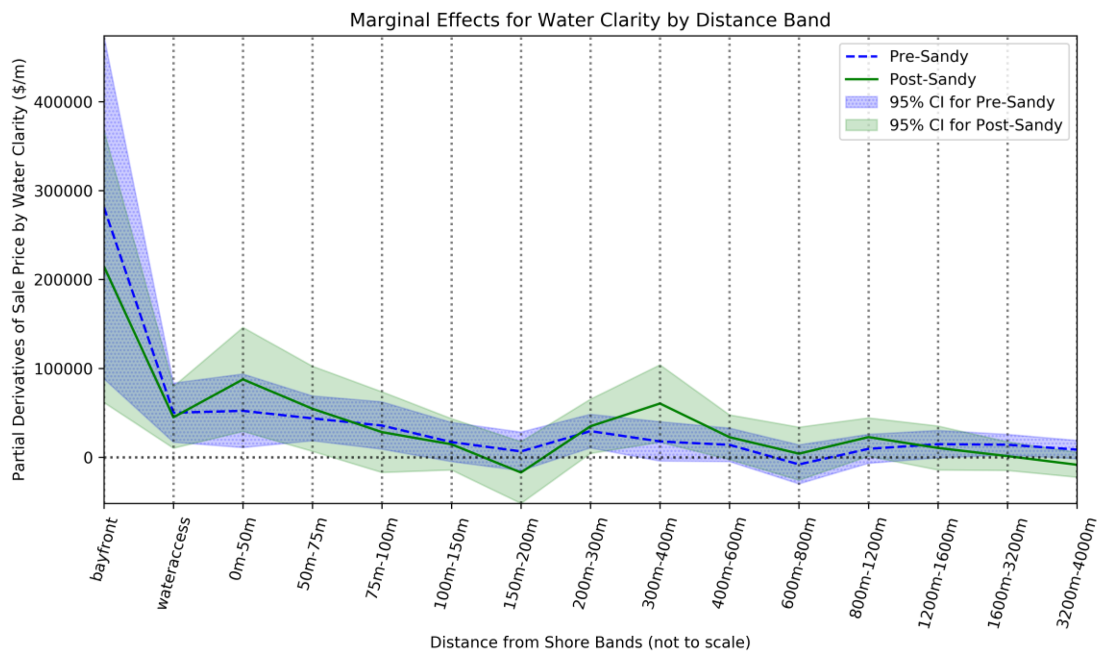



Table 4 shows the average treatment effect conditional on distance band for the pre- and post-Sandy OLS models. Much of the substantial difference between the estimated average treatment effects above are a consequence of low or negative values for treatment effects estimated for distance bands further from shore in the post-Sandy model. The negative coefficient for Secchi in the post-Sandy model overwhelms some of the small and positive coefficients estimated for the impact of secchi in these further from shoreline distance bands. Bayfront, Water Access, and the 200m-300m band had similar treatment effects between the two time periods. In contrast, the remaining distance bands have substantial differences with four negative estimates in the Post-Sandy column. Those distance bands with the most dramatically diverging treatment effects are also less precisely estimated in the regressions models; the true population coefficients may have high variances. The negative yet insignificant coefficient for the constant term in the post-Sandy models is also an important part of the story, as it is responsible for three of the four negative signs.

Table 4. Average Treatment Effects for a 1-foot increase in secchi depth by distance band

| Distance Band | Pre-Sandy | Post-Sandy |
|---|---|---|
| Bayfront | $3,064 | $2,967 |
| Water Access | $600 | $564 |
| Distance to Shoreline 0m-50m | $582 | $1,236 |
| Distance to Shoreline 50m-75m | $516 | $673 |
| Distance to Shoreline 75m-100m | $447 | $256 |
| Distance to Shoreline 100m-150m | $266 | $67 |
| Distance to Shoreline 150m-200m | $159 | -$344 |
| Distance to Shoreline 200m-300m | $388 | $340 |
| Distance to Shoreline 300m-400m | $283 | $673 |
| Distance to Shoreline 400m-600m | $239 | $164 |
| Distance to Shoreline 600m-800m | $27 | -$83 |
| Distance to Shoreline 800m-1200m | $187 | $160 |
| Distance to Shoreline 1200m-1600m | $229 | $19 |
| Distance to Shoreline 1600m-3200m | $225 | -$93 |
| Distance to Shoreline 3200m-4000m | $82 | -$102 |

One explanation for increased variability of the water quality interaction coefficients in the post-Sandy model is that the physical locations of the water pertinent to each property (i.e., where each property's secchi measure is located) may have changed due to Hurricane Sandy even if preferences for water clarity remain unchanged. It seems reasonable that this effect would be stronger for properties further from shore that must travel away from home in order to observe water clarity and be affected by it directly.

Another hypothesis is that the consistency between the two time periods of the treatment effects for the Bayfront and Water Access properties indicates that these segments of the market have quickly regained their ability to efficiently use information to allow buyers and sellers to accurately price these assets. Episodic storm surge is expected for properties in these segments. Because Hurricane Sandy likely had effects that were less expected by market segments further from the shore, these segments may be processing information less efficiently so asset prices and thus water quality effects on asset prices are less predictable as a consequence. It is also notable that many more properties are found in the distance bands further from shore than in the

Bayfront and Water Access categories, so relatively more information about those market segments is available. On one hand, these numerous properties would contribute more to the loss function being optimized; on the other hand, higher value properties closer to the shoreline potentially have larger errors even after the log transformation, so those properties would contribute relatively more to the loss function. The similarity of the OLS and GMM results suggest heteroskedasticity does not have a large impact on standard errors, so these opposing influences on the loss function may be balancing each other out.

The Distance to Golf coefficient had a significant and positive relationship with the sale prices variable suggesting people may prefer to live far from country clubs or perhaps that the location of golf courses was constrained by availability of suitably large tracts of land. The other significant distance coefficients have the expected negative sign: greater distance from amenities lowers prices. The estimated models indicate that socio-economic characteristics, like Education Level and Income, behave in an expected way; sales prices increased within U.S. census block groups with higher incomes and higher educational attainment, but as with other neighborhood related variables the effect on the dependent variable is relatively small. The Percent White variable displayed statistical significance in the pre- and post-Sandy models which may be due to wealth and income sources (e.g., inheritance) not captured by the census measure.

### 4.4. Study Limitations and Future Considerations

Although water clarity measured by secchi depth was selected in consultation with the Nassau County Planning Department, considerable uncertainty exists regarding how people and their homes are affected by water quality and clarity. Michael et al. (2000) make a case for cautious selection in water clarity variables in hedonic analyses because this choice can affect the outcome, which may in turn alter policy outcomes. Furthermore, while using existing data reduces costs associated with data collection, the limitations imposed by relying solely on existing data also restrict the types of analyses that can be explored, as well as policy recommendations. For example, the primary goal of this project was to provide county decision makers with monetary estimates for ES that could be used in CBA analysis to justify green infrastructure spending within disaster resilience projects. When assessing the data available, our team decided that a hedonic analysis that estimates the value of changes in water clarity was our most feasible path forward. We justified this research plan by acknowledging that increased water clarity is a co-benefit of many green infrastructure improvements that also have stormwater management components (e.g. wetland restoration). Therefore, interpretations of the results of this analysis and its communication is limited to water clarity as *one benefit* of green infrastructure projects, and *not a comprehensive valuation of specific* green infrastructure projects. Stated preferences techniques such as discrete choice experiments or contingent valuation can provide more contextually relevant and localized monetary estimates than our approach. The tradeoff is, of course, money for data collection and skilled personnel to administer these types of studies.

We encountered gaps in the secchi data which required censoring some sales transactions from the analysis as a result of incomplete data records. If secchi measurements avoided areas with particularly clear or unclear water, then results may be biased through both interpolation and through censoring. Also, because the analysis only extended to 2015, future analyses should consider additional years post-Sandy to assess changes in the observed effects.

We control for spatial and temporal autocorrelation in our final models with two-way fixed effects and interaction terms. A more granular approach to defining groups more finely with fixed effects for census block and interactions between fixed effects, for example. Similarly, water access properties may differ by their distance to the bay. The large number of new dummy variables may be problematic for inference, but many coefficients are significant in our models at 1% or better, so this is a potential avenue for future research.

A limitation of this study is the lack of controls for variations in flood risk. Variations in flood risk are controlled for in this study to the extent that those variations cluster around the fixed effect groupings implied by the regression models we estimate. It is likely that some of the variability in flood risk does cluster around the grouping in this study because of the 3 categories that properties near the shoreline may fall into: Water Access, Bayfront, or neither (i.e., Distance from Shoreline 0m-50m). The SEM can also control for variations in flood risk that are uncorrelated with included variables such as water clarity. The results of both OLS and SEM are biased if flood risk is correlated with included explanatory variables in ways not captured by the specification of our model. However, the similarity of coefficients and standard errors between OLS and the robust GMM results from the SEM models may indicate our models are correctly specified.

The ability of applied researchers to utilize and interpret results from more complex spatial econometric models is hindered by complexity that has not been fully explored in analytical or empirical studies. For example, the definition of neighbors in the context of real estate transactions typically depends on which properties were sold in the same year. Alternatively, if time is ignored in specifying neighbors, the definition relies on assuming the spatial component of the error does not vary over time, which is a strong assumption when the dependent variable and many explanatory variables do vary over time. Interpolating sale prices to every year with matrix completion techniques (e.g. Athey et al. 2018) may be a path to resolving this issue while providing a balanced panel of observations.

## 5. Conclusion:

This study has shown that the impact of changes in water quality on real estate prices are substantial, particularly for properties near the shore or with access to water. Increased public expenditures on green infrastructure for storm water management and other resilience improvements that result in improvements in water clarity may be justified in the context of cost-benefit analysis when these private benefits are considered. Changes in water quality would also affect the distribution of tax revenues, allowing the properties that benefit from water quality enhancements the most to pay more for them, an enhancement of economic efficiency. Improvements in water clarity would also likely enhance active-use values for boaters, anglers, and swimmers as well as passive values for users and non-users. Primary valuation studies or benefit transfers may be useful for establishing public ecosystem service values associated with green infrastructure improvements and water quality enhancements. Importantly, this study estimates only a private component of water quality values; other contributions of water quality to economic value and human well-being could be much larger.

Because of the potentially large effects of an event like Hurricane Sandy on housing values, we divided the analysis into pre-and post-Sandy datasets to avoid restrictive assumptions about how the hurricane might affect both spatial and conventional regression parameters. Despite increases in many of the coefficients for interactions of water clarity with geographic fixed effects (i.e., distance from shore, Bayfront, and Water Access bands) from the pre-Sandy to post-Sandy models, the average value of water clarity enhancements to home falls substantially between the two time periods. Additional research using transaction data for years after 2015 could help determine if the value of water clarity reflected by the housing market recovers to pre-Sandy levels.

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Data Availability Statement:

The dataset used in the regression models as well as the code necessary to implement as well as modify these models is available through our github page.