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Modeling the Property Price Impact of Water Quality in 14 Chesapeake Bay Counties

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ABSTRACT

The Chesapeake Bay and its tributaries provide a range of recreational and aesthetic amenities, such as swimming, fishing, boating, wildlife viewing, and scenic vistas. Living in close proximity to the Bay improves access to these amenities and should be capitalized into local housing markets. We investigate these impacts in the largest hedonic analysis of water quality ever completed, with over 200,000 property sales across 14 Maryland counties. We use a spatially explicit water quality dataset, along with a wealth of landscape, economic, geographic, and demographic variables. These data allow a comprehensive exploration of the value of water quality, while controlling for a multitude of other influences. We also estimate several variants of the models most popular in current literature, with a focus on the temporal average of water quality. In comparing 1 year and 3 year averages, the 3 year averages generally have a larger implicit price. Overall, results indicate that water quality improvements in the Bay, such as those required by EPA's Total Maximum Daily Load, could yield significant benefits to waterfront and near-waterfront homeowners.

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1. Introduction

The Chesapeake Bay and its tributaries provide a range of recreational and aesthetic amenities, such as swimming, fishing, boating, wildlife viewing, and scenic vistas. Living in close proximity to the Bay improves access to these amenities and so should be capitalized into local housing markets. Indeed, homes near the waterfront command a premium in real estate markets across the country because of the unique services they provide (Brown and Polakowski, 1977; Lansford and Jones, 1995; Palmquist and Fulcher, 2006). This paper explores the value of water quality on homes near the waterfront, which should reflect several categories of recreational and aesthetic amenities.

Water pollution has been a chronic problem for the Chesapeake Bay over the last century, as agriculture, industry, and local populations have expanded. After a range of unsuccessful local and state efforts, in 2010 the US Environmental Protection Agency (hereafter EPA) passed the Chesapeake Bay Total Maximum Daily Load (TMDL), which assigns pollution limits to all areas of the watershed. The TMDL represents a substantial advance in combatting pollution since all states in the watershed—Maryland, Virginia, Pennsylvania, West Virginia, New York, and Delaware—and Washington, D.C. are now required to meet the assigned pollution limits by the year 2025. TMDL goals are tied to specific deadlines, and extensive measures have been taken to ensure accountability.[1] Since the TMDL is projected to improve water quality in the Bay and its tributaries, the subsequent improvements in recreational, aesthetic, and other amenities may be reflected in nearby property prices.

Hedonic property value analysis models the price of a home as a function of its characteristics. This approach has been used to value numerous types of environmental commodities. However, there are a variety of unresolved issues in the literature, particularly with respect to water quality. This is the largest hedonic analysis of water quality to date, with over 220,000 observations across 14 counties. Due to the size of the analysis, we are able to explore several important issues, in addition to reporting the main results of our preferred models. In particular, we focus on the representation of water quality in the hedonic equation. Most recent literature uses one year averages of the water quality indicator, frequently entering in natural log form. We compare one year averages to longer-term averages in both natural logs and levels and discuss the pros and cons of each approach. Finally, we also assess differences in spatial dependence and the spatial extent of water quality price impacts.

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[1] For further details on the TMDL, see http://www.epa.gov/chesapeakebaytmdl/

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2. Literature Review

2.1. Hedonic Studies of Water Quality

Hedonic property price analysis typically uses recorded real estate transactions, so estimates are based on actual behavior revealed in the market. Using statistical regression techniques, it is possible to estimate the price of a home as a function of its characteristics. Since local environmental conditions are relevant home characteristics, it is possible to estimate their value using hedonic analysis. Rosen (1974) derived the theoretical framework for hedonic analysis using a model of consumer bid and producer offer functions. Based on several assumptions about the market and interacting agents, Rosen demonstrated that in equilibrium the estimated marginal implicit prices equal the homebuyer's marginal willingness to pay, thus allowing for marginal welfare inferences from the estimated hedonic price function. Furthermore, even non-marginal welfare changes can be estimated in cases where certain assumptions hold, including that the hedonic price schedule remains constant.[2]

Hedonic analysis has been used to study the impact of a variety of local environmental commodities, including air pollution (Smith and Huang, 1995), property shoreline (Brown and Polakowski, 1977) and land contamination (Haninger et al., 2014), as well as green urban parks, open space, and noise pollution.[3] The literature also includes hedonic analyses of water quality, though until recently the limitations of water quality monitoring data have hindered large-scale studies.[4]

One of the earliest studies of the impact of water quality on property prices is an unpublished EPA report by David (1968), which analyzed variation in land values around sixty different lakes in Wisconsin. Since then there have been several hedonic studies focusing on water quality, with a first wave in the late 1990's/early 2000's focusing on waterfront homes around freshwater lakes, particularly those in the Northeast US (Young, 1984; Michael et al., 1996, 2000; Boyle et al., 1999; Boyle and Taylor, 2001; Poor et al., 2001, Gibbs et al., 2002). Other water bodies have been examined, with studies finding that waterfront home values are affected by the quality of local streams and rivers (Epp and Al-Ani, 1979; Bin and Czajkowski, 2013), and larger water bodies, such as the Great Lakes (Ara, 2007) and coastal harbors (Mendelsohn et al., 1992). More recent research has considered Florida (Walsh et al., 2011a, 2011b; Bin and Czajkowski, 2013), Oregon (Netusil et al., 2014), and Finland (Artell et al., 2013), among other study areas.

There are two previous hedonic studies of water quality in the Chesapeake Bay watershed. Leggett and Bockstael (2000) found that fecal coliform concentrations have a negative impact on Bayfront home values in Anne Arundel County, Maryland. Poor et al. (2007) explored the impact of ambient water quality on homes near the St. Mary's River, a tributary of the Chesapeake Bay. They found a negative impact of pollutant concentrations on both waterfront and non-waterfront homes.

Most of the hedonic property value studies of water quality focus solely on waterfront properties. Poor et al.'s (2007) study of the St. Mary's River was the first published paper to estimate water quality impacts on the value of non-waterfront homes. However, the authors include all homes within the study area and do not distinguish between waterfront and non-waterfront homes in their model. Walsh et al. (2011b) explicitly estimate separate implicit prices of water clarity for waterfront and non-waterfront homes around 146 lakes in Orange County, Florida. They find a statistically significant impact on non-waterfront homes that extends up to 1000 m from a lake.

There is currently no single accepted best practice for the representation of water quality in the hedonic equation. Clarity, represented by secchi disk measurement (SDM), is the most common measure used in the literature, with increases in lake clarity generally leading to appreciation in waterfront home values. However, a variety of other indicators have been used, and identifying appropriate measures of water quality has been the focus of much research in hedonics and other valuation methods (Griffiths et al., 2012). Other measures used in past hedonic studies include pH, dissolved oxygen, biochemical oxygen demand, acid from minerals and carbon dioxide, fecal coliform, total nitrogen, total phosphorus, chlorophyll *a*, dissolved inorganic nitrogen, and total suspended solids (Epp and Al-Ani, 1979; Poor et al., 2001; Leggett and Bockstael, 2000; Walsh et al., 2011a, Netusil et al., 2014). The early literature that examined different measures suggested that the indicators most visible to people, such as clarity, oil content and turbidity, were most likely to explain variation in property values (Feenberg and Mills, 1980; Brashares, 1985).

There is also no single approach for the temporal duration of the water quality measure included in the hedonic equation. Most recent papers use water quality values from a single year (for example, Walsh et al. (2011a), Netusil et al. (2014)). However, individual preferences and perceptions may be better captured by longer averages. Michael et al. (2000) suggest that historical trends in water quality might cause some stickiness in price, and that expectations of future water quality may be influenced by historical trends. On the other hand, the longer the average of water quality, the more likely it is that unobserved influences on property values could be correlated with the variable. Michael et al. (2000) explored several different ways of measuring water clarity, including historical means over one year and 10 years, historical minimums over one year and 10 years, and variables indicating a positive or negative recent trend. All of those variations were significant and of the expected sign, but exhibited a range of magnitudes that Michael et al. contend could lead to different policy outcomes.

3. Data

3.1. Property Data

Data on all residential transactions in Maryland from 1996 to 2008 were obtained from Maryland Property View (MDPV), which is a compilation of the tax assessment and sales databases from the tax assessor's office in each county. In order to better identify the effect of Bay water quality on the value of nearby residential properties, the sales data are limited to the 229,513 single family and townhouse transactions within four kilometers of the Chesapeake Bay tidal waters.[5] The Chesapeake Bay tidal waters include the main stem of the Bay, as well as the tidal portions of the tributaries entering the Bay, including fresh and brackish waters. Fig. 1 shows a map of the study area, illustrating the 14 counties in this study, as well as the nearby portions of the Bay and its major tributaries.

The MDPV data contain a wealth of variables describing the home structure and parcel including age, square footage, lot size, number of bathrooms, and the existence of a basement and garage; as well as the transaction price and date, whether the home is on the waterfront,

[2] Kuminoff and Pope (2014) demonstrate the conditions under which non-marginal welfare changes equal the change in price.

[3] See D'Acci (2014) for a useful and succinct summary of the hedonic literature on these and other urban commodities.

[4] Now that monitoring data is becoming more widely available, several organizations have recently started aggregating water quality data in a more comprehensive and accessible format, such as the university of South Florida's Water Quality Atlas: http://www.wateratlas.usf.edu/.

[5] More specifically, the analysis focuses on full property arms-length transactions of homes classified as standard single-family units and townhouses. In order to avoid the influence of outliers on our results, we omit homes with sales prices <\$30,000 and >\$4,000,000. Limiting the analysis to a 4 km buffer of waterfront and near-waterfront properties around the Bay helps ensure a more homogenous housing market in order to minimize omitted variable bias. Past hedonic studies (Walsh et al., 2011a, 2011b; Netusil et al., 2014) found that water quality price effects can extend up to one mile away in the context of freshwater lakes in Florida and streams in Washington and Oregon. To be conservative, we include homes out to 4 km.

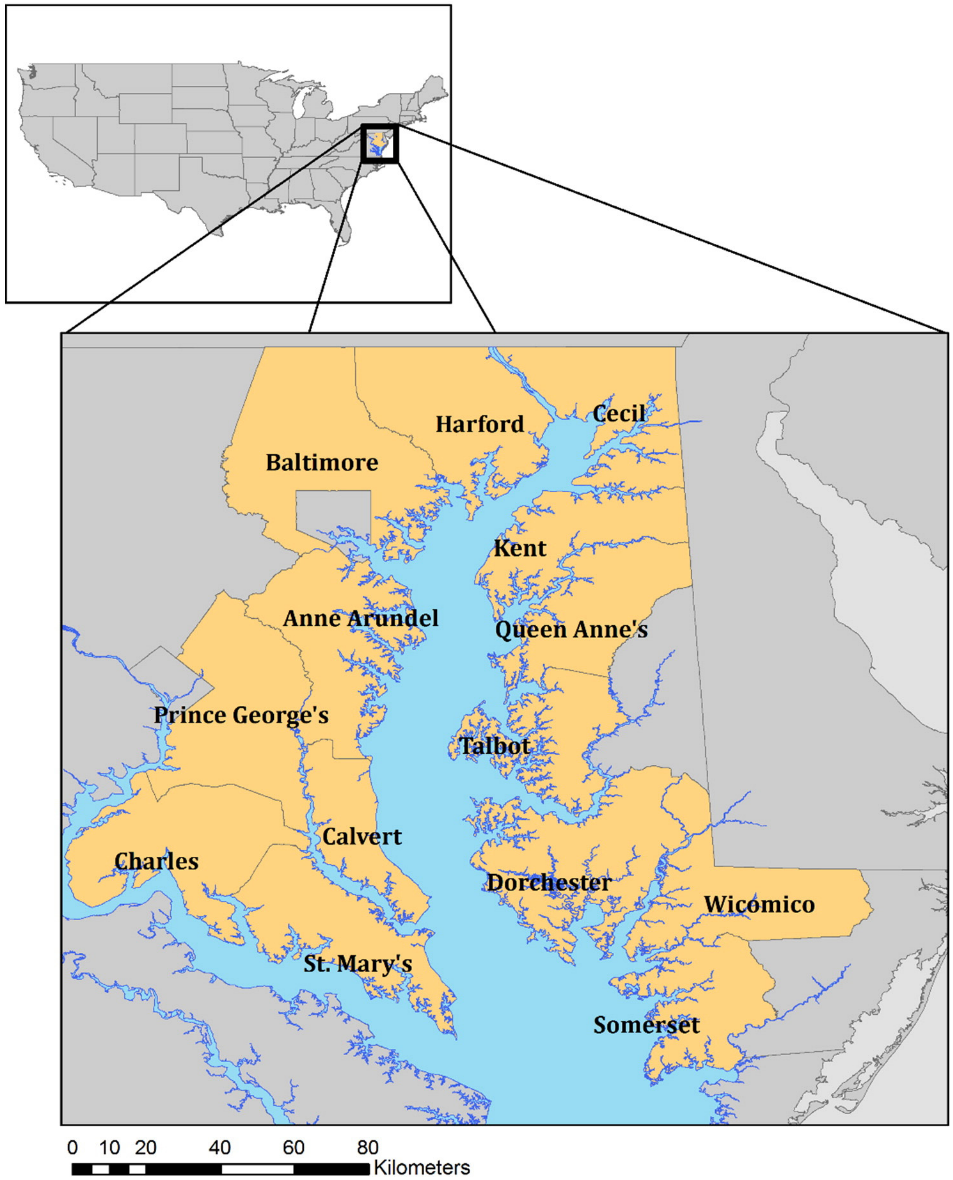

Fig. 1. Chesapeake Bay tidal waters and 14 Maryland Bay counties.

and its geographic coordinates, which we use to calculate proximity to the water (among other spatial variables). Table 1 contains a few descriptive statistics across all 14 counties, including the number of observations, mean sale price, and variables describing the distribution of sales near the water. Anne Arundel County has the highest average sales price, at $373,199, as well as the most observations (76,842). On the other hand, Somerset County has the lowest sales price ($158,194) and number of observations (1681). Talbot County has the largest share of waterfront homes in the sample, with almost 20% of homes in the data set. Prince George's County, which only has a small amount of frontage on a tributary, has the smallest share of waterfront properties, with only 0.6%.

In order to properly control for factors that influence housing prices, we match each parcel to a wealth of neighborhood, socioeconomic, and other variables that influence a home's value. State and local GIS maps were used to portray local land uses and proximity to a range of relevant variables, such as distance to Washington D.C., local water treatment plants,[6] beaches, and several other amenities and disamenities. Since

Table 1
Select Summary Statistics of Residential Transactions by County.

County	Obs	Mean sale price	% Waterfront properties	% 0 to 500 m buffer	% 500 to 1000 m buffer
Anne Arundel	76,842	373,199	10.4	43.6	23.2
Baltimore	34,781	167,766	9.4	40.3	23.1
Calvert	15,563	307,438	8.7	28.5	21.7
Cecil	10,816	250,576	8.8	28.2	21.3
Charles	5397	292,142	7.7	24.2	22.9
Dorchester	4358	217,662	16.8	38.3	26.6
Harford	17,483	230,199	3.5	18.9	20.8
Kent	3388	307,314	14.1	43.1	20.7
Prince George's	24,969	264,662	0.6	10.7	19.4
Queen Anne's	8674	392,945	16.6	46.1	26.4
Somerset	1681	158,194	18.7	34	33.4
St. Mary's	5966	278,967	10.8	24.1	15.8
Talbot	8227	507,353	19.6	34.4	13.2
Wicomico	11,368	194,521	2.4	34.9	29.4

[6] Following Leggett and Bockstael's (2000) concerns with potential omitted variable bias associated with proximity to pollution sources.

the bay is composed of brackish water, there are four different salinity regimes throughout the bay and its immediate tributaries. Different salinity regimes may present a different set of water-based amenities, and so we include dummy variables denoting each regime (when there is variation in these classifications within a county).[7] A full list of the right-hand side variables is provided in Table 2. These control variables represent a very comprehensive set of controls, capturing more potential influences than the majority of past hedonic studies. However, not all variables appear on the right-hand side for each county. For example, on the Western Shore of Bay, distance to DC or Baltimore (whichever is closest) is used. On the Eastern Shore, distance to the Bay Bridge—which gives access to DC and Baltimore, is used. To provide an idea of general magnitudes, Table 2 also contains summary statistics from the entire dataset—pooled across all counties.

With the large number of right-hand side variables available, multicollinearity is a concern, especially in the smaller counties. To correct for these concerns, we start with the variance inflation factors (VIF) of each variable. Although several sources suggest using a threshold VIF of 10 or 20 (Kutner et al., 2004), others caution against VIF thresholds as a means to remove variables (O'Brien, 2007). We start by identifying if there are any non-interacted variables (which we would expect to be somewhat collinear) with a VIF > 15. If an examination of the correlation coefficients indicates that the variable is highly correlated with other important variables, it is dropped. In most cases, variables were correlated with fixed effects, and their removal never had more than a miniscule impact on the estimated water quality coefficients.

Since our data span the recent swings in the housing market, it is important to be mindful of disequilibrium behavior.[8] One sign of disequilibrium is an increase in the number of vacancies. (Boyle et al., 2012). Fig. 2 contains a graph of the percent of vacant sales over time in each county used in the present study. The majority of the counties actually show a decrease in vacancies after 2004–2005, with Prince George's County being the main exception. In addition, home prices are deflated using the seasonally adjusted Federal Housing Finance Agency's (FHFA) home price index,[9] and annual and quarterly dummies are included as control variables in the hedonic regressions.

3.2. Water Quality Data

The water quality data come from EPA's Chesapeake Bay Program Office (CBP), which collects samples twice a month from monitoring stations throughout the Bay tidal waters. CBP interpolates these water quality data, producing a spatial grid that covers the entire Bay and tidal tributaries. Each grid cell is a maximum of 1 km^2 in size (with smaller grid cells in the tributaries), and each cell has a unique value for water quality measures over time.

While CBP collects data on several indicators of water quality, we focus on light attenuation—represented by K_D, the water-column light attenuation coefficient—as the primary indicator of interest. K_D is essentially the inverse of water clarity; higher light attenuation is equivalent to cloudier water.[10] As discussed previously, the hedonic literature provides strong support for the notion that homebuyers value water clarity (Feenberg and Mills, 1980; Walsh et al., 2011a; Bin and Czajkowski, 2013). We match each home sale to the average light attenuation across the two closest grid cells. Each of the 14 Maryland Bay counties included in our analysis is covered by several monitoring stations, allowing us to capture spatial variation in water clarity.[11] On average, each county is bordered by 165 unique grid cells.

To reflect the temporal variation in water quality expected to be relevant for homebuyers, the past literature presents several temporal options. The majority of previous papers employ a water quality average from the year the property is sold. One popular approach is to use the average over the whole year. Gibbs et al. (2002) Leggett and Bockstael (2000), Poor et al. (2007), and Walsh et al. (2011b) match homes to the annual average of water quality in the year the home was sold. Other papers have used measures from a particular time of year. Boyle et al. (1999) and Boyle and Taylor (2001) use the minimum water clarity from the previous summer months. Netusil et al. (2014) compare wet season and dry season indicators (the study was done in the rainy Pacific Northwest). They prefer the dry season (summer) results, since residents are more likely to recreate on water during that time. In line with this second group of studies, we use average K_D from the spring and summer (March–September) during or immediately prior to the home sale.[12] In the Chesapeake Bay area, most water-based recreation activities occur during this time, and it is also when most adverse water clarity conditions—such as algae blooms—occur (along with related media coverage, which may be information sources for potential homebuyers) (EPA, 2003, 2007; MD DNR, 2013).

Table 3 presents summary statistics for water clarity in the 14 Maryland Bay counties. Mean light attenuation (K_D) is 2.53 m^{-1}, corresponding to a Secchi disk measurement of about 0.64 m. Figs. 3 and 4 illustrate patterns in water clarity over space and time, using 2002 (a year with good clarity) and 2003 (a year with poor clarity) as examples. While water clarity is worse in most areas in 2003, several hotspots of poor clarity are constant across the two years.

4. Hedonic Property Value Methods

4.1. Empirical Model

The hedonic property value equation postulates that the price of a home or housing bundle is a function of the individual attributes composing that bundle, including characteristics of the home and parcel (H_{it}), as well as its location and neighborhood (L_{it}). Distance to the Chesapeake Bay tidal waters (D_{it}) and local Bay water quality levels ($WQ_{i\tau}$), as represented by the light attenuation coefficient K_D, are of particular interest in this analysis, and so these variables are represented separately from the vector of other locational attributes.[13] D_i is a vector of dummy variables denoting different distance buffers, but this variable could also be represented as a scalar measure, such as linear or inverse distance. Lastly, p_{it} denotes the price of home i when it was sold in period t. For the time being, consider a single housing market. The hedonic price function is:

$$p_{it} = P(\mathrm{H}_{it}, \mathrm{L}_{it}, \mathrm{D}_i, WQ_{i\tau}, \mathrm{T}_t) \quad (1)$$

where T_t denotes a vector of year and quarter indicator variables to control for overall trends and seasonal cycles in the housing market.

The empirical model allows the influence of water quality on home prices to vary with proximity to the Bay by interacting water quality

[7] The zones are tidal fresh, olihohaline, mesohaline, and polyhaline. For an example map of salinity regimes in the Bay, see http://www.chesapeakebay.net/maps/map/sav_salinity_zones, as well as http://www.chesapeakebay.net/maps/map/chesapeake_bay_mean_surface_salinity_summer_1985_2006.

[8] Although some studies find implicit prices to be unaffected by swings in the housing market (Lueung et al., 2007), others find the opposite (Shimizu and Nishimura (2007), Chen and Hao (2008)). Also, Bin et al. (2016) examine the hedonic implicit price of water quality in Martin County, Florida, during the recent recession and find that the implicit price of water quality is still significant during the recession.

[9] http://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

[10] Light attenuation can be converted to SDM based on the following statistical relationship: $K_D = 1.45/\mathrm{SDM}$ (EPA, 2003).

[11] While the number of monitoring stations varied over the study period, water quality in each county in the hedonic analysis was monitored at an average of 14 stations in 2006, for example.

[12] Recognizing that most home sales take place several weeks after the buyer views the property and makes an offer, we assign home sales occurring during June–December to the same year's spring-summer average water quality. We assigned sales between January–May to the previous spring-summer average. Spring and summer light attenuation are highly correlated in our dataset ($\rho = 0.78$).

[13] Note that the water quality indicator is indexed by τ instead of t to reflect the use of the previous spring/summer average, which may not always align with t.

Table 2
RHS control variables and summary statistics (pooled across counties).

Variable	Source	Mean	Std dev	Min	Max
Current improved value	MDPV	116,816.5	88,632	10	2,396,310
Dummy: current improved value missing	MDPV	0.026	0.16	0	1
Age of structure	MDPV	28.8	27.3	0	359
Age squared	MDPV	1577	3015	0	128,881
Structure size (square feet)	MDPV	1544.6	734.3	16	13,940
Dummy: structure size missing	MDPV	0.030	0.171	0	1
Acres of parcel	MDPV	109.5	4064.8	0	871,200
Dummy: townhouse	MDPV	0.182	0.386	0	1
Dummy: basement	MPDV	0.432	0.495	0	1
Total # of bathrooms	MDPV	1.4	0.95	0	20.5
Dummy: garage	MDPV	0.247	0.431	0	1
Dummy: pool	MPDV	0.009	0.094	0	1
Dummy:pier	MDPV	0.007	0.086	0	1
Dummy: central air conditioning	MDPV	0.572	0.495	0	1
Dummy: high-density residential area	MDPV	0.180	0.384	0	1
Dummy: medium-density residential area	MPDV	0.515	0.500	0	1
Dummy: forested area	MDPV	0.078	0.268	0	1
Distance to primary road (m)	Federal highway administration	8447.2	9984.0	0.2	68,781.5
Distance to nearest wastewater treatment plant (m)	EPA FRS	8206.0	6251.5	41.2	39,642.5
Distance to Baltimore (m) if western shore	Derived using GIS data	41,123.3	28,429.6	5316.1	139,219.9
Distance to DC (m) if western shore	Derived using GIS data	56,519.1	26,833.7	6978.3	132,599.5
Distance to Bay Bridge if eastern shore	Derived using GIS data	41,562.9	24,240.8	690.3	126,724.8
Distance to nearest beach	Derived using GIS data	9753.3	9841.9	1.9	38,752.8
Distance to Military Base Gate (St Mary's only)	Derived using GIS data, following Poor et al. (2007)	13,342.4	11,183.3	6.8	36,389.9
Distance to Nearest urban area	Derived using GIS data	22,515.3	13,645.2	100.4	63,150.2
Distance to nearest urban cluster	Derived using GIS data	13,123.2	6576.6	7.8	33,332.0
Median household income	Census (1990, 2000 & 2010)	60,961.6	20,091.4	0	16,0694
% of total population black	Census (1990, 2000 & 2010)	0.174	0.222	0	0.987
% of total population Asian	Census (1990, 2000 & 2010)	0.018	0.024	0	0.223
% of families below the poverty line	Census (1990, 2000 & 2010)	0.053	0.056	0	0.488
% of total housing units that are vacant	Census (1990, 2000 & 2010)	0.070	0.060	0	0.555
Population growth rate, 1990–2000	Census (1990, 2000 & 2010)	0.169	0.707	−1	29.3
Population Density in 2000	Census 2000	0.0012	0.0014	0	0.0095
% of population age 25+ w/higher education	Census (1990 & 2000)	0.244	0.154	0	0.808
% of block group high-density residential	MDPV	0.098	0.197	0	1
% of block group industrial	MDPV	0.014	0.058	0	0.843
% of block group urban	MDPV	0.026	0.059	0	0.630
% of block group agriculture	MDPV	0.111	0.171	0	0.853
% of block group animal agriculture	MDPV	0.001	0.006	0	0.166
% of block group forest	MDPV	0.242	0.191	0	0.797
% of block group wetland	MDPV	0.018	0.057	0	0.900
% of block group beach	MDPV	0.0001	0.0028	0	0.074
Dummy: average home quality	MDPV	0.748	0.434	0	1
Dummy: good home quality	MDPV	0.035	0.185	0	1
Dummy: high home quality	MDPV	0.001	0.037	0	1
Dummy: home quality determination missing	MDPV	0.174	0.379	0	1
Water depth (m)	EPA CBP	1.29	1.46	0.5	18.5
Dummy: location in 1000–1500 m buffer	Derived using GIS data	0.142	0.349	0	1
Dummy: location in 1500–2000 m buffer	Derived using GIS data	0.100	0.300	0	1
Dummy: oligohaline (low) salinity	EPA CBP	0.208	0.406	0	1
Dummy: mesohaline (medium) salinity	EPA CBP	0.623	0.485	0	1
Dummy: tributary (versus Bay main stem)	Derived using GIS data	0.898	0.303	0	1
Dummy: location in a floodplain	FEMA Floodplain Maps (MDPV)	0.057	0.231	0	1
Dummy: location in nuclear evacuation zone	Derived using GIS data	0.042	0.201	0	1

with the Bay distance variables. The model can be written as:

$$\ln(p_{it}) = \beta_0 + \mathrm{H}_{it}\beta_1 + \mathrm{L}_{it}\beta_2 + \mathrm{T}_t\beta_3 + \mathrm{D}_i\beta_4 + \mathrm{D}_i WQ_{i\tau}\gamma + \varepsilon_{it} \quad (2)$$

where the dependent variable $\ln(p_{it})$ is the natural log of the price of home i sold in period t, and ε_{it} is an assumed normally distributed disturbance. The coefficient vectors to be estimated are β_k, for $k = 0, \ldots, 4$, and γ.

The implicit prices associated with characteristics of the house (e.g., interior square footage, number of bathrooms, lot size) and its location (e.g., proximity to nearest primary road, surrounding commercial or industrial land uses) are reflected in β_1 and β_2, respectively. The vector β_3 represents overall market and cyclical trends over time, and the combination of β_4 and its relevant interaction in γ express the influence of proximity to the Bay on the price of a home. The coefficients of particular interest are denoted by the vector γ, which is the percent change in home price with respect to water quality.

We measure proximity to the Bay using a vector of five indicator variables denoting whether a home is located on the Bayfront, or is a non-Bayfront home within 0 to 500, 500 to 1000, 1000 to 1500, or 1500 to 2000 m of the Chesapeake Bay.[14] This specification implicitly includes a restriction that water quality has no effect on homes more than 2000 m from the Bay. Although past papers have found that the implicit price gradient terminates earlier (Dornbusch and Barrager, 1973; Walsh et al., 2011b; Netusil et al., 2014), the size and prominence of the Bay may induce a longer gradient. Within 2000 m, we hypothesize that the implicit price of water quality declines with distance from the Bay,

[14] Other buffer sizes were explored, but smaller sized buffers in some counties had too few property sales for statistical analysis.

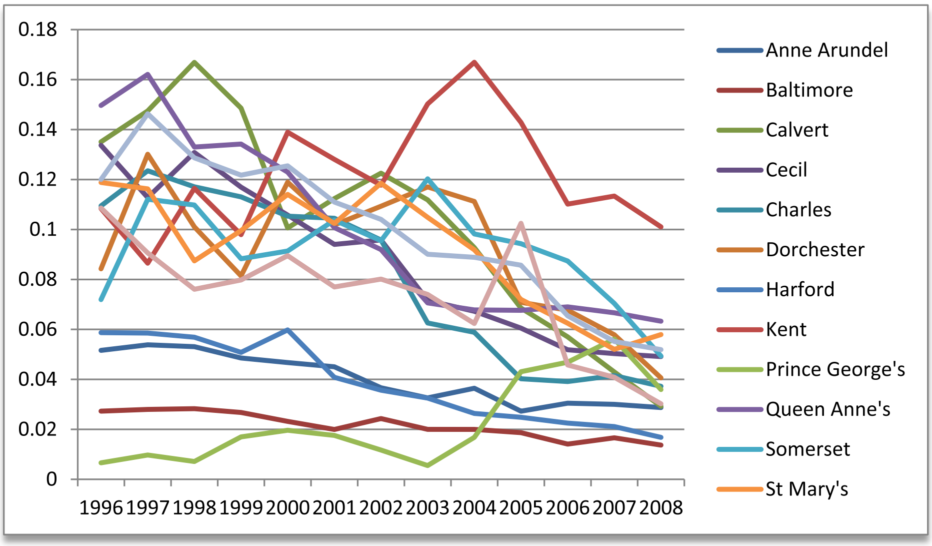

Fig. 2. Percent of vacant sales across counties.

but we do not impose this relationship when estimating the hedonic regressions.

Measuring proximity to the Bay using discrete “buffers,” or distance intervals, has the advantage over alternative specifications (such as linear or inverse distance gradients) in that it allows the influence of Bay proximity and water quality to vary freely across the Bay proximity buffer groups. This is particularly important since we are estimating the hedonic price equations for several different counties (or housing markets) with a variety of coastal and landscape features, and because there has been minimal guidance in the literature (with the exception of Walsh et al. (2011b) and Netusil et al. (2014)) as to the spatial extent and shape of this price gradient across different markets and water bodies. Our functional form follows similar applications in hedonic analyses of beach width, oceanfront access, and tree canopy and streams (Landry and Hindsley, 2011; Taylor and Smith 2000; Netusil 2005).[15]

Functional form assumptions and their impacts on implicit price estimates are prevalent concerns in the hedonic property value literature (Cropper et al., 1988; Kuminoff et al., 2010). The semi-log model (Eq. (2) above) is one of the most commonly assumed functional forms in the general hedonic literature. However, many studies also employ water quality variables in their natural log form (Michael et al., 2000; Gibbs et al., 2002; Walsh et al., 2011b), since the marginal implicit price of water quality may not be constant over different levels of water quality. For example, changes in water quality may be more visible at worse levels of quality.[16] More formally:

$$\ln(p_{it}) = \beta_0 + \mathrm{H}_{it}\beta_1 + \mathrm{L}_{it}\beta_2 + \mathrm{T}_t\beta_3 + \mathrm{D}_i\beta_4 + \mathrm{D}_i\ \ln(WQ_{i\tau})\gamma + \varepsilon_{it} \qquad (3)$$

In Eq. (3), γ can be interpreted as the elasticity of house prices with respect to water quality. In other words, γ denotes the percent change in the price of a home due to a 1% change in water clarity, expressed as K_D. The γ parameter in (2), on the other hand, yields the percent change in price due to a one *unit* change in K_D. For purposes of comparison, we estimate regressions for both (2) and (3) for each of the 14 counties in the analysis.

As mentioned above, we also explore the temporal representation of water quality in the hedonic equation. To probe the issue of the temporal duration of effects, we use a 3 year average of the spring/summer water clarity variable in addition to the one year spring/summer average described above. To be consistent with the other measure, we use a 3 year average of the spring/summer measure, so winter and fall measurements are excluded.[17]

The hedonic models are estimated separately by county to approximate separate real estate markets. It is highly unlikely that the 14 counties we analyze are viewed as one real estate market by consumers. Although the counties in our study may not perfectly capture individual real estate markets, they are probably a close approximation. Furthermore, the shared amenities, taxes, school systems and other county services represent a natural distinction between areas.

4.2. Spatial Econometric Models

Spatial dependence is an issue in most hedonic analyses. It arises when the prices or characteristics of nearby homes are more alike than more distant homes (Anselin and Lozano-Gracia, 2008). There may also be other geographically clustered omitted variables that are not easily observable or quantifiable. Although all these influences can be difficult to represent using traditional methods, nearby home prices can improve the explanatory power of a regression model (LeSage and Pace, 2009), and help absorb any residual spatially correlated unobserved influences, which could otherwise confound the coefficient estimates of interest (Anselin and Lozano-Gracia, 2008).

We employ several spatial econometric models to account for spatial dependence. Since the structure of dependence can vary between counties, we use a multi-step procedure to identify the appropriate spatial econometric model in each county. The two most common models in the hedonic literature are the spatial error model (SEM) and spatial autoregressive (SAR) model (Lesage and Pace, 2009). The SEM allows for spatial autocorrelation of the disturbance terms, whereas the SAR includes a spatial lag of the dependent variable (i.e., neighboring home prices) on the right-hand side of the hedonic equation. Both forms of spatial dependence can be accounted for using the general spatial

[15] We also estimated regressions with the linear functional form for distance on each specification discussed below. The implicit prices for waterfront and non-waterfront homes were quite similar between the linear and buffer approaches. Additionally, comparing adjusted R^2 values, the buffer model showed marginally better fit in 52 of 56 specifications. To further explore, we split each dataset into 60%/40% subsamples and re-estimated each model on both. The buffer model again indicated better fit in the vast majority of estimated models.

[16] Unfortunately, a Box—Cox specification was not a useful guide in selecting the functional form due to the zeros in the interacted water quality/distance terms. To be used in a Box—Cox model, a variable's values must be strictly greater than 0.

[17] The 3 year average is calculated similarly to the 1 year average, so if the home is sold in June–December, it is assigned the spring/summer average of that year and the previous two. If it is sold in January–May, it receives the average of the previous 3 years.

Table 3
Water clarity in MD Bay counties, March–September 1996–2008.

County	K_D mean (m^{-1})	K_D std. dev (m^{-1})	Secchi depth (m)	Number of unique interpolator cells
Anne Arundel	1.91	0.47	0.76	564
Baltimore county	3.07	1.42	0.47	185
Calvert	1.56	0.86	0.93	149
Cecil	3.07	1.07	0.47	193
Charles	2.60	0.83	0.56	80
Dorchester	1.99	0.75	0.73	186
Harford	3.82	1.23	0.38	26
Kent	3.57	1.50	0.41	115
Prince George's	3.08	1.20	0.47	57
Queen Anne's	1.85	1.24	0.78	222
Somerset	2.12	1.00	0.69	116
St. Mary's	1.74	0.73	0.83	102
Talbot	1.42	0.54	1.02	182
Wicomico	3.63	0.78	0.40	138
Average	2.53	0.97	0.64	165.36

Notes: Summary statistics calculated for nearest two grid cells to each property in the county sales dataset located within 500 m of the Bay. Secchi depth measurement calculated by the formula SDM = 1.45/K_D.

model (referred to as the SAC model in Lesage and Pace, 2009), which we estimate for each county, as shown below.

$$P = \rho W_1 P + \beta_0 + H\beta_1 + L\beta_2 + T\beta_3 + D\beta_4 + Q\gamma + e,$$
$$e = \lambda W_2 e + u \tag{4}$$

Letting n denote the number of observed transactions, P is an $n \times 1$ vector of logged sales prices. The vectors previously denoting home and parcel characteristics, neighborhood attributes, time, and distance to the Bay, are now represented by the matrices H, L, T, and D, respectively. The elements of matrix Q correspond to the interactions between water quality and distance to the Bay, more formally $D_i f(WQ_{i\tau})$, where f(•) could be either linear or logged versions of the water quality parameter. As before, the coefficient vectors to be estimated include β_k, for $k = 0, \ldots, 4$ and γ.

The W_1 and W_2 terms denote row standardized $n \times n$ spatial weight matrices (SWMs) that exogenously define neighbor relations among observations. When used in a spatial lag term ($\rho W_1 P$), it produces a spatially weighted average of the home price of neighbors. The SWM in the error term, W_2, defines the dependence among the disturbances. The $n \times 1$ vector u is assumed to be iid and u ~ $N(0,\sigma^2 I_n)$. The scalars λ and ρ are spatial coefficients to be estimated.

A variety of SWMs have been used in the literature; we employ four different variations that define neighbor relations over space and based on the relative timing of transactions.[18] To identify the spatial model and SWM combination that is most appropriate for each county, the SAC model is first run with all combinations of SWMs. Following recommendations from LeSage and Pace (2009), the model with the highest likelihood value is selected. Given these models, the spatial coefficients λ and ρ are examined for statistical significance. If both are significant, the SAC model is selected as the preferred spatial model. If λ is significant but not ρ, the SEM model is used. In the opposite situation the SAR model is selected.

This approach represents a flexible way to account for the spatial influences within each county. Based on the results of the spatial regressions, as well as likelihood ratio tests that confirmed the existence of spatial dependence in every county, the spatial model is appropriate because it addresses spatial dependence among the error terms and/or unobserved spatially correlated (potentially confounding) price influences. Results also indicate that the general spatial (SAC) model is preferred in each county, as the spatial error and lag coefficients were both significant in all counties.[19,20]

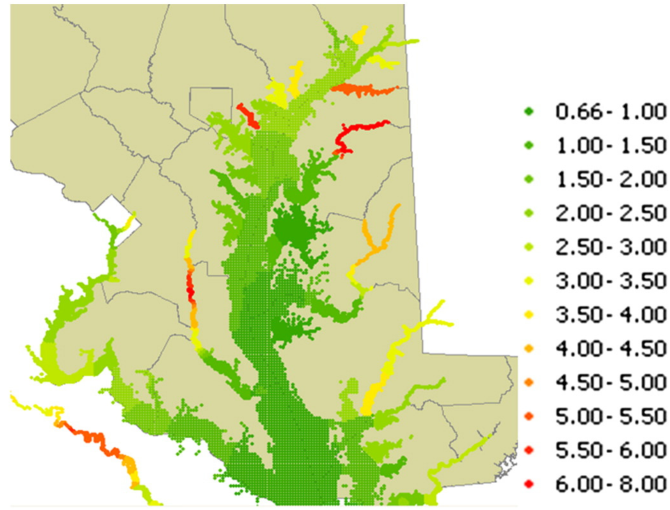

Fig. 3. Spring-Summer average light attenuation (K_D) in MD Bay counties, 2002.

5. Hedonic Regression Results

5.1. One Year Model

To simplify our discussion, we start with the model that uses the 1 year K_D variable in natural-log form in Table 4, which presents the water quality-related coefficient estimates for all 14 Maryland Bay counties.[21] As depicted in Eq. (3), ln(K_D) is interacted with dummy variables denoting whether a home is located on the waterfront, or is non-

[18] The first is the nearest-neighbor specification, where the 20 nearest neighbors (for example) are given nonzero weights based on the inverse distance from the parcel of interest to each neighbor. We set the number of neighbors to 20, although other larger and smaller values were used and produced only minimal differences. The three other SWMs use variations of the inverse distance SWM, where the number of neighbors given a nonzero weight is not directly constrained. These variations are intended to mimic the comparable sales method of real estate appraisal. One SWM uses a distance cutoff of 400 m, and a time cutoff of 6 months back and 3 months forward. The next uses a radius of 800 m. The final SWM is a hybrid approach that applies the 800 m boundary and the same time constraints, but keeps the 10 closest, to prevent irrelevant home sales from entering the SWM. For background on the comparable sales method, see Appraisal Foundation (2013). Vandell (1991) describes the comparable sales approach as finding a set of properties that are "closest" in terms of "time, locational, or structural amenity differences." Besner (2002)—who also use a 400 m distance cutoff for a SWM, discusses the importance of using temporal constraints in SWMs. Similar discussions on comparable sales and modeling can also be found in Lentz and Wang (1998), and Kummerow and Galfalvy (2002). Finally, the MD Department of Assessments and Taxation discusses the comparable sales approach typically used in MD here: http://dat.maryland.gov/realproperty/Pages/Questions-and-Answers-About-Real-Property-Assessments.aspx.

[19] For the preferred spatial weights matrices, all counties use the 20 nearest neighbor specification for the spatial lag term. For the spatial error term, Baltimore, Prince George's, and Somerset Counties favored the SWM that uses a distance radius of 800 m. All other counties use the same distance boundary, but with the additional restriction that only the nearest 10 observations are kept. All SWMs use temporal boundaries of 6 months back and 3 months forward.

[20] Since W_2 defines neighboring sales based on distance over space and the relative timing of sales, our models account for spatio-temporal autocorrelation among the error terms. However, as recommended by an anonymous reviewer, there are alternative models to address spatial autocorrelation, particularly over longer timer periods. Kelejian and Prucha (2010) highlight this issue while developing the theoretical implications of the general spatial two-stage least squares (GS2SLS) model, and find that model to have several superior qualities. Unfortunately, that model is not yet implementable for large datasets (so cannot be used for many of our counties) and current programs are unable to deal with datasets involving multiple transactions of the same parcel (Ateya et al., 2013).

[21] For an expanded example, the full set of estimated coefficients for Anne Arundel County are posted online in a previous working paper version: http://yosemite.epa.gov/ee/epa/eed.nsf/WPNumber/2015-07?OpenDocument.

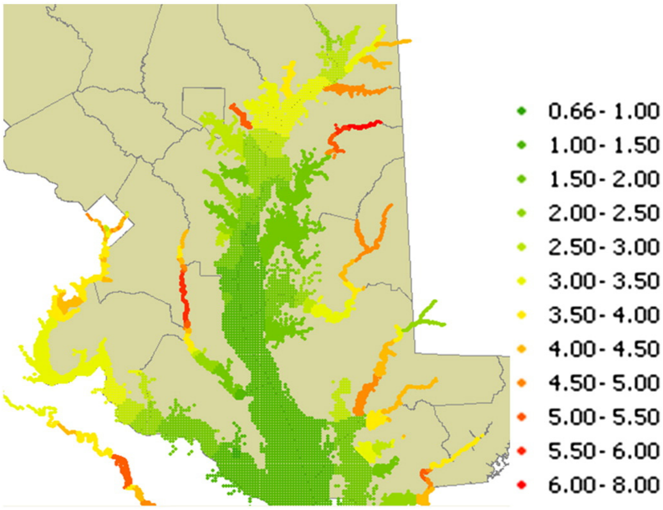

Fig. 4. Spring-Summer average light attenuation (K_D) in MD Bay counties, 2003.

waterfront and within one of the Bay proximity buffers. As there was only limited significance beyond 1000 m, the Table contains coefficients out to that buffer.

For the RHS variables not included in the table, in general the signs on these variables are as anticipated and they are mostly statistically significant. An expected suite of characteristics improve a home's value, including the interior square footage, a basement, a garage or carport, higher education level in the Census block group, and, importantly, a waterfront location. The age of the home, townhouses (relative to single-family homes), increased residential density, and an industrial setting are all negatively correlated with home prices. A few variables, such as land area, number of bathrooms, median household income in the block group, proportion of families below the poverty line, and housing vacancy have mixed results across counties. The R-squared values range from approximately 0.7 to 0.9, suggesting a fairly good statistical fit in all counties.

The coefficient estimates corresponding to the interaction term between $\ln(K_D)$ and the waterfront buffer are negative in 10 of the 14 counties (indicating a positive impact of water clarity since K_D is inversely related); of those, seven are statistically significant. Among these seven counties, the spatial Bayfront coefficient estimates range from -0.03 to -0.16. In these double-log models, the coefficient estimates can be interpreted as elasticities, so a 10% decrease in K_D (an improvement in clarity) would be expected to yield approximately a one third to a one and a half percent increase in waterfront home values across these seven counties. In the four counties with positive waterfront-K_D interaction terms, none of the coefficients are significant.

Turning to the non-waterfront results, the magnitude of the price impact generally declines at farther distances from the Bay, as one might expect. However, there is considerable heterogeneity across counties. For example, Anne Arundel and Charles demonstrate a price gradient extending out to 2 km and 1.5 km, respectively. In other counties, this negative price impact does not extend beyond Bayfront homes (e.g., Dorchester, Kent, Talbot), or there is no monotonic trend with distance.

Focusing on non-waterfront homes within 0 to 500 m, in three counties increases in K_D have a negative and statistically significant impact on residential property prices, with a smaller range of impacts from 0.02–0.06. Seven additional counties show a negative but statistically insignificant effect. Mixed results are also found in the farther distance buffers. This is not necessarily surprising since landscape features and the density of homes vary across counties. The previous journal articles to find price gradients extending past waterfront homes (Walsh et al., 2011b; Netusil et al., 2014) studied urban areas, probably most similar to Anne Arundel County. The 500–1000 distance buffer has six significant estimates, with two of them yielding counter-intuitive signs.[22]

In an extension paper, Klemick et al. (2016) investigated the sources of variation in the water quality coefficients across counties and distance buffers using a series of meta-regressions.[23] They considered several environmental and socioeconomic covariates as potential variables explaining the spatial heterogeneity in the home price premium associated with proximity to clearer water. They found that two factors are significantly associated with a higher price premium for clear water across counties: median home value and proximity to shallow water (no more than 1.5 m deep). The result that water clarity is more important to homebuyers in wealthier counties with higher home values in not surprising. The finding that clarity matters more for properties in counties adjacent to shallow water might be explained by the fact that boat docks typically require water of at least 1.5 m. If residents are more likely to dock boats at properties with deeper water, local water quality is less important since they can travel easily to other parts of the Bay for recreation. The effect of median home value on the value of water clarity is more pronounced for waterfront homes than for homes farther from the water, while the effect of water depth is roughly the same for both waterfront and non-waterfront homes.

Table 5 shows the estimated implicit prices for a 10% increase in light attenuation (K_D) for the model that uses the natural log of the one year average of spring/summer K_D. This 10% change translates into roughly a 4 to 10 cm decrease in SDM, depending on the location, where the actual changes in K_D appear in the final column of the table. Among waterfront homes, this 10% decrease in water clarity can lead to declines in property values by as much as $26,497 (in Talbot County), or as low as $2576 in Calvert County. The price premium for a 10% improvement in light attenuation in the 0–500 m buffer is smaller in magnitude, with implicit prices up to $3233 in Queen Anne's County, but generally smaller and less significant.

5.2. Alternate Models

We now proceed to some of the additional models we considered. First, the second set of values in Table 4 contains the results of the models that use K_D in levels instead of logs. Although there is general agreement in sign and significance with most of the previous results, there are some notable differences. Calvert County's waterfront coefficient is no longer significant, while St. Mary and Charles Counties' now are. Calvert County has relatively better water clarity (lower light attention) than most other counties in the data set, while Charles County has about average clarity, so forcing the relationship between K_D and price to be linear may be worse in that County. St. Mary's County has a

[22] Both of these Counties have unique aspects that may be worth exploring in future research. Calvert County is the smallest MD County, and is just one long peninsula between the Bay and the Patuxent River, around 14 km wide. Prince George's County only has a small amount of water frontage on the Potomac River, so effects beyond the waterfront may be confounded by other influences.

[23] In that paper, we conduct a Random Effect-Size (RES) meta-regression of the elasticity of the water quality variable on socioeconomic and ecological covariates and our econometric model specification. Because the RES model weights the elasticity by the inverse variance of the estimate as well as the estimated between-study variance across counties, significant elasticity estimates are given greater weight than insignificant elasticity estimates. In other words, we control for significance and model choice. The counties in these regressions that consistently have significant water quality variables, such as Anne Arundel, Baltimore County, Calvert, Dorchester, Harford, Kent, and Talbot, are in areas with a history of boating and high boat ownership, and hence water-based recreation. Other counties are more rural and have less water-based activities. Some of this can be seen in the summary statistics with the % waterfront homes measure. Unfortunately, data on things like local boat ownership and local recreation are only available at aggregate levels, such as the county, so cannot be incorporated into the home-specific regressions.

Table 4
Regression results: 1 year (Spring/Summer) average.***

	One year $\ln(K_D)$				One year K_D			
	Waterfront	0–500 m	500–1000 m	R^2	Waterfront	0–500 m	500–1000 m	R^2
Anne Arundel	-0.126^{***}	-0.023^{***}	-0.009	0.755	-0.0585^{***}	-0.0249^{***}	-0.0089^{**}	0.789
Baltimore county	-0.090^{***}	0.009	-0.015^{*}	0.781	-0.0293^{***}	0.0032^{*}	-0.0060^{***}	0.736
Calvert	-0.033^{*}	0.001	0.021^{*}	0.839	-0.0088	0.0174^{***}	0.0196^{***}	0.783
Cecil	0.010	-0.001	0.003	0.803	0.0024	0.0086^{*}	0.0012	0.771
Charles	-0.058	-0.056^{**}	-0.107^{***}	0.796	-0.041^{**}	-0.0252^{***}	-0.0335^{***}	0.710
Dorchester	-0.078^{*}	-0.008	-0.013295	0.820	-0.0557^{**}	-0.0076	-0.0079	0.796
Harford	-0.096^{***}	0.001	0.012	0.907	-0.0243^{***}	0.0022	-0.0022	0.860
Kent	-0.142^{***}	0.008	0.002	0.828	-0.0289^{**}	0.0120	0.0049	0.811
Prince George's	-0.062	-0.001	0.022^{**}	0.772	-0.0093	-0.0018	-0.0023	0.699
Queen Anne's	0.017	-0.060^{***}	-0.068^{***}	0.824	-0.0151	-0.041422^{***}	-0.0470^{***}	0.775
Somerset	-0.091	-0.055	-0.141^{***}	0.721	-0.0300	-0.0207	-0.0498^{***}	0.705
St Mary's	0.014	-0.015	0.017	0.803	0.0375^{*}	-0.0082	0.0115	0.750
Talbot	-0.156^{***}	-0.014	-0.031	0.859	-0.0631^{***}	-0.0122	-0.0190	0.845
Wicomico	0.046	-0.015	-0.010	0.847	-0.0018	-0.0130^{*}	-0.0116	0.837

*** , **, and * denote significance at the 99%, 95%, and 90% levels, respectively.

positive coefficient, counter to expectations, which is significant at the 10% level in this model. Previous work in St. Mary's County (Poor et al., 2007) noted the confounding impact of a large military base, which is the largest employer as well as the location of significant impervious surface—which is negatively related to water quality (Poor et al., 2007). Although we use a variable indicating distance to the nearest gate of the base (as done in Poor et al. (2007)), it may be better to employ different water quality variables in this county (Poor et al. used stormwater-related variables).

Table 6 contains the results of the models that use 3 year averages of (spring/summer) water clarity. The waterfront coefficients are now much larger, on average. In some areas, these are implausibly large, with Charles County having an elasticity of 0.64, so that a 10% improvement in clarity is associated with a 64% increase in home price. The first column of values contains the coefficients for the model with logged K_D, where the waterfront coefficients for Dorchester and Kent Counties are no longer significant, while Wicomico and Queen Anne's Counties now have significant waterfront coefficients of the expected sign. Additionally, Talbot County, which has a large number of valuable waterfront homes and had the highest implicit price in Table 5, no longer has a significant waterfront coefficient.

In addition, The Table also illustrates much different behavior beyond the waterfront, with 6 counties now having positive and significant coefficients at the 0–500 m buffer. These results could indicate that these longer term measures are capturing more than just the impact of water clarity, and may, at least partially, reflect very local trends in the housing market that are not captured by our county-wide annual time dummies.

Finally, the second column of Table 6 contains results from the last model that uses a 3 year average of spring/summer non-logged K_D. Similar to the first column of $\ln(K_D)$ results, the average waterfront coefficients here are also usually larger than the parallel one year averages. The non-waterfront results also include several counterintuitive (positive and significant) results, again raising questions about the robustness of the 3 year average water quality measure, particularly for non-waterfront homes. The Klemick et al. (2016) meta-regression analysis again found that median home value and water depth help explain the varying results across counties for the three-year measure of water quality.

To better compare across specifications, the remaining implicit prices are presented in Table 7. While the size of the implicit prices for the 1 year K_D model are roughly comparable to those in Table 5, the implicit prices for some of the 3 year models are considerably larger. Anne Arundel County's waterfront implicit price is approximately $50,000 dollars in both 3 year models, compared to around $17,000–$20,000 in the 1 year models. Charles County goes from approximately $3000 and insignificant to $29,000 and significant in the 3 year $\ln(K_D)$ model. On the other hand, the implicit prices for Baltimore and Calvert Counties stay fairly consistent. Overall, the differences in magnitude between these differences in functional form could induce different recommendations in a benefit-cost policy context, similar to the findings of Michael et al. (2000).

The much larger average implicit prices from the 3 year models are troubling, since the longer averages may allow for additional omitted variable bias, as compared to the one year averages. Furthermore, weather patterns and other events can induce wide variation in clarity across years, so that a 3 year average may deviate from what a potential homeowner actually sees when they visit the property. The Klemick et al. (2016) meta-analysis examined differences caused by the functional form variations in these hedonic regressions. They found that the benefit transfers based on the 3 year models exhibit larger confidence intervals and larger transfer errors than the 1 year models, further supporting the use of the one year averages.

Table 5
Implicit price estimates for a 10% increase in K_D.(2010$).

1 year $\ln(K_D)$	Distance from shore			Mean 10% change
County	Waterfront	500	1000	K_D
Anne Arundel	$-20{,}001.0^{***}$	-1604.7^{***}	-544.5	0.1919
	(2946.4)	(528.1)	(634.5)	
Baltimore	-4247.1^{***}	217.8	-296.6^{*}	0.3284
	(724.8)	(161.2)	(163.8)	
Calvert	-2575.9^{*}	18.8	847.1^{*}	0.1764
	(1424.0)	(406.7)	(434.3)	
Cecil	888.3	-52.6	123.5	0.2979
	(3340.2)	(542.4)	(629.7)	
Charles	-3055.6	-2159.2^{**}	-3572.1^{***}	0.2775
	(2760.4)	(1016.1)	(977.4)	
Dorchester	-5289.3^{*}	-215.3	-321.1	0.209
	(3205.7)	(970.5)	(904.6)	
Harford	-6399.6^{***}	43.8	463.0	0.3735
	(1993.1)	(369.0)	(377.7)	
Kent	$-12{,}589.4^{***}$	302.5	81.9	0.3755
	(3473.7)	(1183.5)	(1210.8)	
Prince George's	-5058.6	-27.3	849.1^{**}	0.3287
	(5230.1)	(564.1)	(413.8)	
Queen Anne's	2263.5	-3232.6^{***}	-3337.4^{***}	0.1923
	(2829.3)	(815.9)	(916.2)	
Somerset	-2968.9	-999.8	-1996.6^{*}	0.2188
	(2001.0)	(837.4)	(658.2)	
St. Mary's	942.7	-586.6	656.6	0.1692
	(2373.0)	(883.0)	(969.3)	
Talbot	$-26{,}497.2^{***}$	-949.6	-1912.4	0.1688
	(6460.6)	(1971.8)	(2170.2)	
Wicomico	3671.9	-515.1	-273.0	0.3644
	(5235.3)	(818.5)	(674.5)	

Standard errors appear in parentheses.

Table 6
Coefficients from models with 3 year K_D averages.

	3 year $\ln(K_D)$				3 year K_D			
	Waterfront	0–500 m	500–1000 m	R^2	Waterfront	0–500 m	500–1000 m	R^2
Anne Arundel	-0.3058^{***}	-0.1020^{***}	-0.0123	0.789	-0.1660^{***}	-0.0586^{***}	-0.0103^{*}	0.789
Baltimore County	-0.05560^{***}	0.0386^{***}	-0.0077	0.736	-0.0191^{***}	0.0117^{***}	-0.0015	0.736
Calvert	0.0134	0.0779^{***}	0.0653^{***}	0.783	-0.0133	0.0247^{***}	0.0237^{***}	0.783
Cecil	-0.0010	0.1257^{***}	0.0362	0.771	-0.0023	0.0329^{***}	0.0128	0.771
Charles	-0.6413^{***}	-0.1764^{**}	-0.3021^{***}	0.710	-0.2421^{***}	-0.0670^{***}	-0.1037^{***}	0.0.711
Dorchester	-0.0607	0.0429	0.0053	0.796	-0.0309	0.0284	0.0040	0.796
Harford	-0.2600^{***}	0.0213	0.0370^{**}	0.861	-0.0760^{***}	0.0066	0.0109^{**}	0.861
Kent	-0.0745	0.1147^{***}	0.1083^{**}	0.811	-0.0277^{*}	0.0349^{**}	0.0306^{**}	0.812
Prince George's	0.0090	-0.1411^{***}	-0.1427^{***}	0.700	0.0227	-0.0399^{***}	-0.0439^{***}	0.699
Queen Anne's	-0.1310^{***}	-0.1838^{***}	-0.1983^{***}	0.775	-0.0402^{***}	-0.0633^{***}	-0.0664^{***}	0.775
Somerset	-0.0839	-0.0632	-0.1635^{***}	0.705	-0.0547^{*}	-0.0499^{**}	-0.0761^{***}	0.705
St Mary's	0.1265^{***}	0.0855^{***}	0.1324^{***}	0.751	0.0839^{***}	0.0476^{***}	0.0665^{***}	0.751
Talbot	-0.0793	0.1082^{**}	0.0984	0.846	-0.0473	0.0149	0.0226	0.845
Wicomico	-0.0751^{***}	-0.0869^{**}	-0.0878^{**}	0.837	-0.0053	-0.0187	-0.0190	0.837

***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.

6. Conclusions

The Chesapeake Bay area has a long history of water-related culture and recreation, involving boating, fishing, and a range of other exploits. To the extent that these activities are bundled with local housing decisions, affected water quality should be capitalized into home prices. This study conducts the largest hedonic analysis of water quality ever undertaken, using over 225,000 property sales across fourteen Maryland counties. These data are combined with spatially explicit water clarity data, as well as an extensive set of other home, neighborhood, socio-economic, and location-based characteristics. These data are explored using a variety of econometric models and specifications.

For our specification that uses the log of water clarity averaged over the spring and summer of the sale year, which best represents the most common functional form in past literature, we find a positive impact of water clarity on waterfront property prices in ten of the 14 counties, seven of which are statistically significant. In the four other counties, the waterfront impact was insignificant. Although the results are more mixed in the non-waterfront areas, we still find evidence that the impact of water quality stretches past the waterfront.

We explore several different representations of water clarity during estimation, with emphasis on the length of the temporal average and alternative functional forms. Although similar hedonic analyses of air quality have focused on the spatial extent of averaging (Anselin and Le Gallo, 2006), there has been much less attention on temporal aspects. Only one other paper investigates this issue in the water quality literature (Michael et al., 2000). We compare a 3 year average of spring and summer water quality to a one year average, which is much more prevalent in the literature. Results indicate that the 3 year averages yield larger estimates (implausibly large in some cases), although they are much more variable. Beyond the waterfront, the 3 year averages are characterized by counterintuitive signs and magnitudes, suggesting that the broader temporal window may capture more than just the impact of water quality.

Utilizing our sizable dataset, we find significant price impacts for water quality across multiple property markets in Maryland. Since almost all past hedonic papers on water quality focus on narrow areas, such as a county or municipality, we believe this provides a broader look at the wider potential impacts of water quality, or conversely water pollution, on home prices in other areas. There have been a wealth of local, state, and federal water quality regulations passed in recent years. In the benefit-cost analyses of these rules, there has been no use of hedonic property price analysis, which is partly due to the narrow geographic scope of the previous literature. Our results suggest that property price impacts may represent an important benefit category to be considered in future regulatory analysis. Furthermore, existing efforts to improve water quality, such as the Chesapeake Bay TMDL, could yield significant benefits to local property owners.

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Table 7
Implicit prices for 1 year K_D, 3 year K_D, and, 3 year $\ln(K_D)$ models.

	1 year K_D			3 year K_D			3 year $\ln(K_D)$		
	Waterfront	0–500 m	500–1000 m	Waterfront	0–500 m	500–1000 m	Waterfront	0–500 m	500–1000 m
Anne Arundel	$-16{,}506.9^{***}$	-1356.6^{***}	-647.3	$-50{,}662.4^{***}$	-3394.0^{***}	-743.9	$-49{,}523.3^{***}$	-2890.6^{***}	-302.1
Baltimore County	-4375.3^{***}	192.4	-279.8^{*}	-4871.9^{***}	350.7^{**}	-435.3^{***}	-4704.1^{***}	380.7^{**}	-474.5^{***}
Calvert	-4053.5^{***}	-295.7	477.2	-5678.8^{***}	-827.0^{***}	-0.6	-5686.6^{***}	-710.3	61.7
Cecil	860.2	-251.3	210.3	-4275.6	499.1	930.8	-4196.2	1287.0	823.6
Charles	-3462.7	-2408.6^{***}	-3253.1^{***}	$-27{,}258.3$	-2967.2^{**}	-8293.4^{***}	$-29{,}351.1^{***}$	-2848.6	-8662.0^{***}
Dorchester	-3900.6	90.1	-427.5	-2449.5	2673.1^{**}	-111.5	-4503.2	1529.3	-513.8
Harford	-5680.8^{***}	283.4	544.1	$-19{,}064.3^{***}$	-1338.8^{**}	533.2	$-19{,}147.8^{***}$	-1559.8^{***}	255.6
Kent	$-12{,}990.8^{***}$	763.8	73.8	$-15{,}041.7^{***}$	3628.3^{**}	2768.3	$-14{,}960.6^{***}$	2766.3	2258.0
Prince George's	-3019.2	18.8	876.5^{**}	-9627.6^{***}	-1262.2	862.5	-8663.4^{***}	-1291.8	1107.5
Queen Anne's	378.1	-2882.6^{***}	-2759.3^{***}	-1751.2	-3776.2^{***}	-3435.0^{***}	-3204.7	-5431.8^{***}	-5249.2^{***}
Somerset	-2332.7	-1161.0	-1489.9^{***}	-2803.1	-2048.9^{**}	-2206.4^{***}	-2807.6	-1596.5^{**}	-2248.7^{***}
St Mary's	2286.4	-520.1	691.7	4588.4^{**}	2155.5^{**}	3095.5^{***}	3529.1^{**}	2175.4^{**}	3440.1^{***}
Talbot	$-19{,}288.8^{***}$	-1439.6	-2017.6	$-18{,}594.1^{***}$	-499.7	41.6	$-34{,}565.0^{***}$	89.0	1455.5
Wicomico	4875.1	-670.3	-525.7	$17{,}988.2^{**}$	3939.4^{**}	3230.0^{**}	$14{,}140.6^{***}$	3511.7^{***}	2953.5^{***}

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