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Improving Water Quality in an Iconic Estuary: An Internal Meta-analysis of Property Value Impacts Around the Chesapeake Bay

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Abstract This study conducts a meta-analysis and benefit transfer of the value of water clarity in the Chesapeake Bay estuary to estimate the property value impacts of pollution reduction policies. Estimates of the value of water clarity are derived from separate hedonic property value analyses of 14 counties bordering the Bay. The meta-analysis allows us to: (1) estimate the average effect of water clarity in the Chesapeake Bay, (2) investigate heterogeneity of effects across counties based on socioeconomic and ecological factors, (3) evaluate different measures of water clarity used in the original hedonic equations, and (4) transfer the values to Bayfront counties in nearby jurisdictions to estimate the property value impacts of the total maximum daily load (TMDL), a policy to reduce nutrient and sediment pollution entering the Bay that is expected to improve water clarity and ecological health. We also investigate the in-sample and out-of-sample predictive power of different transfer strategies and find that a simpler unit value transfer can outperform more complex function transfers. We estimate that aggregate near-waterfront property values could increase by roughly $400–$700 million in response to water clarity improvements from the TMDL.

Keywords Meta-analysis · Benefit transfer · Water quality · Chesapeake Bay · Hedonic property value · Total Maximum Daily Load · TMDL

JEL Classification Q51 · Q53 · Q57

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Estuaries provide essential habitat for coastal and marine species globally. Many of the world's largest cities are located adjacent to estuaries, which makes these transition zones particularly vulnerable to degradation from human activities. At the same time, this proximity provides local residents with a host of ecosystem services, from food production to recreational opportunities to aesthetic values. Residents living on or near the waterfront are well-positioned to benefit from these ecosystem services, as reflected in price premiums for homes located near estuaries (Knight Frank 2014). Hedonic property value analysis thus offers a useful tool for researchers looking to quantify the value of estuary cleanup efforts.

The Chesapeake Bay is one of the largest estuaries worldwide and is adjacent to population centers in three US states—Maryland, Virginia, and Delaware—and the District of Columbia (DC). Urban and suburban development and agricultural runoff, along with fish and shellfish disease and over-harvesting, degraded water quality in the Bay and its tidal tributaries during the 20$^{\text{th}}$ century. Since the 1980s, the Chesapeake Bay has been the focus of numerous restoration efforts. Due to limited progress, President Obama issued a 2009 Executive Order calling for federal leadership to advance Bay restoration. In 2010, the U.S. Environmental Protection Agency (EPA) and all Bay watershed states agreed to a Total Maximum Daily Load (TMDL), or "pollution diet," to meet target reductions in nitrogen, phosphorus, and sediment by 2025 (EPA 2013a). These pollution reduction targets were developed to attain goals for water clarity, chlorophyll a, and dissolved oxygen, three ecological indicators that are critical to aquatic grasses, fish, and other wildlife in the Chesapeake Bay (EPA 2013a).

Such water quality issues are present in estuaries and other waterbodies worldwide, spurring similar policies. For example, the European Union and Member States have established management plans to address pollution in over 100 river basin districts, which include estuarine waters (European Commission 2010). Similar to the Chesapeake Bay, agricultural runoff and urban sewer overflows are the primary concerns (European Commission 2015). Efforts are guided by the EU's Water Framework Directive and Marine Strategy Framework Directive, which have the goal of achieving "good" ecological status for all waters.[1]

This study seeks to estimate the change in property values from water clarity improvements due to the Chesapeake Bay TMDL. In order to estimate this impact, we use a novel dataset to consider several related research questions. First, what is the effect of Chesapeake Bay water clarity on home prices, and how does this effect change with distance from the waterfront? Next, is the effect of water clarity on home prices heterogeneous across property markets surrounding the Bay? If so, what characteristics explain this heterogeneity? Finally, what benefit transfer approach is most appropriate to estimate home price impacts from improvements in water clarity in areas of the Bay where original hedonic price estimates are unavailable?

To address these questions, this study performs a meta-analysis of 70 estimates of the value of water clarity derived from a related study that conducted hedonic analyses of home sales in 14 Maryland counties (Walsh et al. 2015). This study then conducts a benefit transfer of these values to DC, Delaware, Virginia, and four additional counties in Maryland (Fig. 1). Meta-analysis involves synthesizing multiple estimates, typically across several studies. In this case we undertake an "internal meta-analysis" (Banzhaf and Smith 2007; Kuminoff et al. 2010), synthesizing the results from Walsh et al. (2015).

Before delving into our analysis, we discuss the use of meta-analysis for benefit transfer in past literature and summarize the Walsh et al. hedonic property value study. We then use meta-analysis to derive the mean effect on home prices of light attenuation (K_D)—a measure

[1] For additional information, see http://ec.europa.eu/environment/pubs/pdf/factsheets/water-framework-directive.pdf

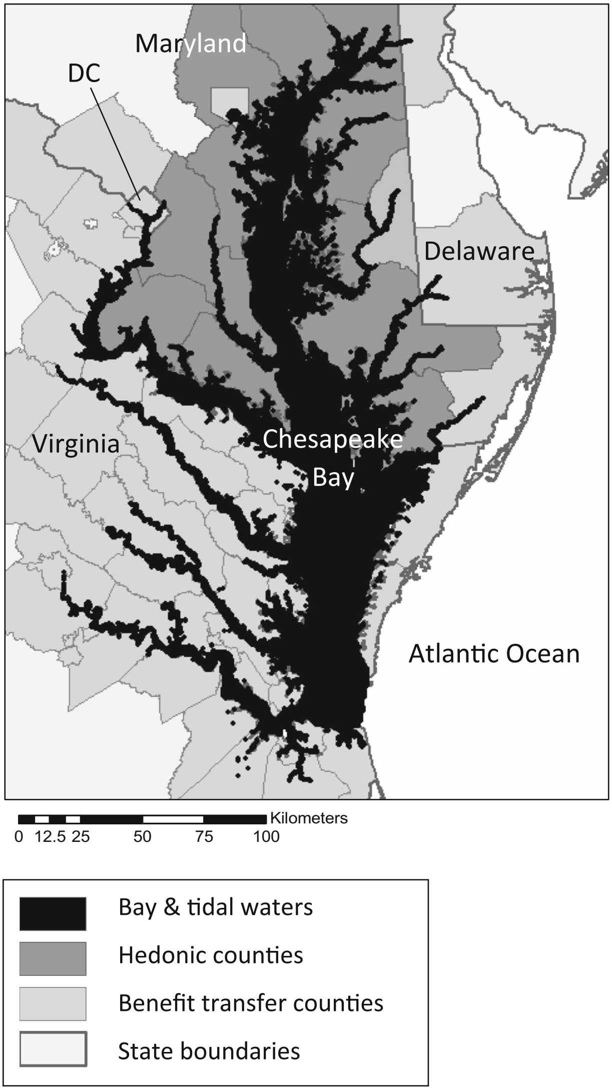

Fig. 1 Study area

of water clarity—which provides point estimates for use in a unit value benefit transfer. Next, we estimate a series of meta-regressions to explain the heterogeneity in property value impacts across counties. These results allow us to conduct a benefit function transfer and examine the effect of different water clarity measures on the hedonic estimates. We compare simpler versus more complex benefit transfer strategies and find that simple unit value transfers outperform more complex function transfers.

We combine our estimates of the value of water clarity with projections of the improvement in clarity anticipated under the TMDL to calculate the total property value impacts in Maryland, Virginia, Delaware, and DC. We find that aggregate near-waterfront property values could increase by roughly $400–$700 million. The results illustrate the usefulness of meta-analysis and the challenges of benefit transfer even when the estimates being transferred represent a common valuation measure, geographic area, environmental attribute, and policy instrument.

1 Previous Meta-analysis and Benefit Transfer Applications

There have been numerous meta-analyses in the environmental economic literature, including applications to air pollution, water quality, endangered species and biodiversity, recreation, land contamination, and mortality risks. Nelson and Kennedy (2009) analyzed 140 meta-analyses in environmental and resource economics, over half of which have been published since 2004. Most previous meta-analyses of the value of surface water quality have focused on estimates derived from stated preference and recreation demand studies (Johnston et al. 2003, 2005; Van Houtven et al. 2007; US EPA 2006, 2009, 2010b, 2013b), though a recent working paper also included estimates from hedonic property value studies (Ge et al. 2013). Several meta-analyses have used hedonic estimates in the context of other environmental commodities (Smith and Huang 1993, 1995; Nelson 2004; Messer et al. 2006; Debrezion et al. 2007; Kiel and Williams 2007; Mazzotta et al. 2014).

Despite the extensive use of meta-analysis in environmental economics, Nelson and Kennedy note several common issues plaguing studies, including sample collection, data and treatment heterogeneity, and dependence among observations from the same primary study. Nelson and Kennedy (2009), Stapler and Johnston (2009), Borenstein et al. (2010), Boyle et al. (2013) and Nelson (2013) provide guidance for best practices when conducting meta-analysis and benefit transfer. Leon-Gonzalez and Scarpa (2008) propose a Bayesian alternative to traditional benefit function transfer that emphasizes selecting the appropriate subset of study sites for transferring to a policy site in order to improve the efficiency of estimates and determine when original benefit transfer is a robust alternative to original data collection.[2]

A major issue with any benefit transfer is the degree of consistency between the original studies and the new policy context. Important areas for consistency include the type of environmental amenity and metric used to quantify it, baseline conditions and magnitude of the environmental change, and socioeconomic characteristics of the populations (EPA 2010a). If multiple original studies are used to develop the estimates, consistency among the studies in terms of the outcome variable and valuation method is also important (Smith and Pattanayak 2002; Bergstrom and Taylor 2006), though studies using Bayesian techniques have demonstrated efficiency gains from pooling estimates across different welfare measures and contexts (Johnston and Moeltner 2014; Moeltner and Rosenberger 2014).

The meta-analysis and benefit transfer conducted here avoids many of these issues. In our study, the original estimates and the target area for benefit transfer focus on the same outcome variable, environmental amenity, region, and policy change. The states directly bordering the Chesapeake and tidal tributaries all fall within the mid-Atlantic region of the US and share similar socioeconomic and environmental characteristics. The analyses also employ

[2] The Bayesian Model Averaging technique is most useful when there are some data on the willingness to pay values for the sites to which values are being transferred. In this case, we do not have these data for counties in DC, Delaware, Virginia, and the four additional counties in Maryland. Leon-Gonzalez and Scarpa (2008) provide a method and assumptions for a case in which no data exists for these counties which could be used in an extension to this work, but is beyond the scope of this paper.

the same data sources and methods. This methodological homogeneity ensures consistency in the estimates, grounded in the hedonic property model (Rosen 1974).[3]

2 Property Value Impacts of Chesapeake Bay Water Clarity in Maryland

Primary estimates for this meta-analysis come from an original property value study of water clarity in Maryland (Walsh et al. 2015). The authors estimated separate hedonic price functions for 14 Maryland counties bordering the Chesapeake Bay and its tidal tributaries, using a dataset of over 200,000 residential property transactions and water quality from 1996 to 2008. The authors used an expansive set of controls to represent home, neighborhood, and other characteristics that influence a home's value.

Water quality was represented in the regressions by a measure of water clarity: the water-column light attenuation coefficient, or K_D, which is essentially the inverse of water clarity (i.e., higher light attenuation is equivalent to cloudier water). The analysis focused on water clarity for three reasons: its ecological significance as a determinant of aquatic grass habitat in the study area, its policy relevance given the water clarity criteria established under the TMDL, and its salience to homeowners. These data were provided by EPA's Chesapeake Bay Program, which collects monitoring data twice a month and interpolates the data to produce a spatial grid of cells with a maximum size of 1 km^2 that covers the entire Bay and tidal tributaries. The authors matched each home sale to average K_D over the two nearest grid cells during the most recent spring and summer (termed "1-year average K_D"), when algae blooms are most common and clarity is poor. They also used a measure that averaged spring and summer K_D over the most recent 3 years as a longer-term indicator of water clarity (termed "3-year average K_D"). Comparing the 1- and 3-year averages gives some indication of whether the persistence or variability of water clarity over time could be important to homebuyers in addition to mean water clarity.[4]

The hedonic property value equation posits that the price of a home is a function of its individual attributes, including characteristics of the home and parcel ($\boldsymbol{H_{it}}$), as well as its location and neighborhood ($\boldsymbol{L_{it}}$). Distance to the Chesapeake Bay tidal waters ($\boldsymbol{D_{it}}$) and local Bay water clarity levels (WQ_{it}), represented by K_D, are of particular interest. $\boldsymbol{D_i}$ is a vector of dummy variables denoting different distance buffers to the waterfront, namely whether a home is on the waterfront or is non-waterfront and within 0–500; 500–1000; 1000–1500; or 1500–2000 m from the Bay. Interacting these terms with WQ_{it} allows for estimation of separate water clarity coefficients for each distance buffer. The price (p_{it}) of home i sold in period t was estimated as:

$$\ln(p_{it}) = \beta_0 + \mathbf{H}_{it}\boldsymbol{\beta}_1 + \mathbf{L}_{it}\boldsymbol{\beta}_2 + \mathbf{T}_t\boldsymbol{\beta}_3 + \mathbf{D}_i\boldsymbol{\beta}_4 + \mathbf{D}_i \ln(WQ_{it})\boldsymbol{\gamma} + \varepsilon_{it} \quad (1)$$

where $\boldsymbol{T_t}$ is a vector of year and quarter indicator variables to control for broader trends and seasonal cycles in the housing market. 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 error term. A general spatial model with spatial error and autoregressive terms was used to account for spatial dependence among the prices of nearby properties (LeSage and Pace 2009). Hedonic models were estimated separately by

[3] The measure of interest in this study is the price elasticity of houses with respect to water clarity. Such capitalization effects may not necessarily be interpreted as formal welfare measures unless several conditions are met. See Kuminoff and Pope (2014) for details.

[4] A limitation of our study is that we do not explicitly estimate the effect of the variance of water clarity on home prices because projections of water clarity variability are not available from the water quality models that provide the basis for the TMDL policy analysis (Keisman and Shenk 2013; Wang et al. 2013).

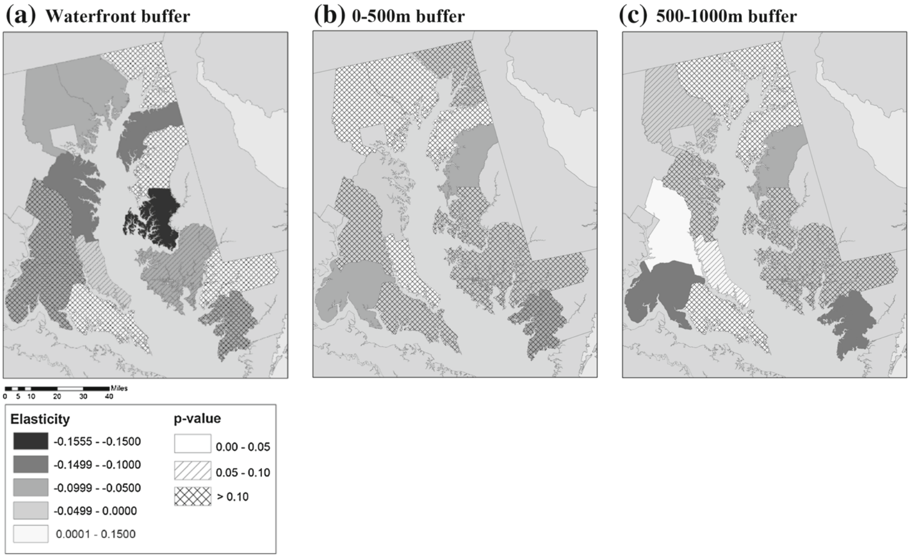

Fig. 2 K_D elasticity values and statistical significance in hedonic counties. Waterfront buffer (**a**), 0–500 m buffer (**b**), 500–1000 m buffer (**c**)

county to approximate separate real estate markets. While county administrative boundaries may not perfectly delineate real estate markets, counties represent a natural segmentation in this region due to common property tax rates and amenities. In particular, school districts in Maryland are run at the county level.[5]

The coefficients estimated were β_0, $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, $\boldsymbol{\beta_3}$, $\boldsymbol{\beta_4}$, and of particular interest, $\boldsymbol{\gamma}$. In this specification, $\boldsymbol{\gamma}$ can be interpreted as the elasticity of home prices with respect to 1-year average K_D. The authors also considered three other specifications for the water clarity term: the log of 3-year average K_D, as well as 1- and 3-year average K_D entered linearly.

Figure 2 displays the pattern of the regression results across counties for the waterfront, 0–500, and 500–1000 m buffers for one illustrative specification—the log of 1-year average K_D. Panel a shows that the coefficients for the waterfront buffer are negative in ten of the 14 counties; of those, seven are statistically significant (p value <0.10). Since K_D is inversely related to water clarity, a negative coefficient is expected and indicates that home prices decline as light attenuation increases. None of the positive waterfront coefficients are statistically significant. Among the seven counties with significant coefficients, the estimates range from −0.033 to −0.156. The coefficients can be interpreted as elasticities, so a ten percent

[5] We rejected the hypothesis that all counties in the analysis can be pooled in a single model with dummy variables for counties but a single coefficient for each of the other explanatory variables across counties using a likelihood ratio test ($p < 0.000$). We also estimated a model pooling only counties that fall within the same Metropolitan Statistical Area (MSA). MSAs are small groups of contiguous counties with overlapping labor markets, as defined by the US Office of Management and Budget (OMB Bulletin No. 15-01, 2015, "Revised Delineations of Metropolitan Statistical Areas, Micropolitan Statistical Areas, and Combined Statistical Areas, and Guidance on Uses of the Delineations of These Areas." https://www.whitehouse.gov/sites/default/files/omb/bulletins/2015/15-01.pdf). We rejected the hypotheses that coefficient estimates for the explanatory variables can be held constant across counties within each of the three MSAs that include multiple counties in our study area ($p < 0.000$). Together these results suggest that counties are appropriate for distinguishing separate housing markets in this region.

decrease in 1-year average K_D (an improvement in clarity) yields a 0.33–1.56 % increase in waterfront home values across these counties.

For non-waterfront homes within 0–500 m of the Bay, increases in K_D have a negative and statistically significant impact on property prices in three counties, and seven additional counties have a negative but statistically insignificant effect (panel b). The magnitude of the coefficient estimates is smaller in absolute value than those in the waterfront buffer, with significant coefficients ranging from −0.023 to −0.06. Results are mixed in the 500–1000 m buffer; four counties have negative and significant coefficients, and two counties have small positive and significant coefficients (panel c).

These results demonstrate that the impact of water clarity on home prices varies from county to county, sometimes extending beyond waterfront homes. In general, the magnitude of the price impact declines with distance from the Bay. Mixed results are also found in the remaining distance buffers. This is not necessarily surprising since landscape features and the density of homes varies across counties. The results for the other three specifications of water clarity are qualitatively similar.

3 Estimating the Effect of Water Clarity on Home Prices Using Meta-analysis

This section delves into our key research questions by assessing the effects of water clarity on home prices from the hedonic analysis in Walsh et al. (2015) and testing whether the estimated elasticities vary significantly across counties and with distance from the shore. For each county included in the hedonic analysis, we have estimates of the property value impact of water clarity at five different distances from the Bay: waterfront, and non-waterfront within 500, 500–1000, 1000–1500, and 1500–2000 m of the shore, yielding a total of 70 estimates. We synthesize the hedonic results across counties by calculating the unweighted and weighted means of the elasticities of K_D for each distance buffer. These elasticity measures represent the percent change in home value from a one percent change in light attenuation.

Table 1 presents these meta-analytic summary statistics using the Walsh et al. (2015) coefficient estimates for the four alternate measures of water clarity: logged and linear 1-year average K_D and logged and linear 3-year average K_D. Column (1) gives the unweighted arithmetic mean elasticities for each distance buffer across all 14 counties, or $\bar{\gamma}_{unweighted} = \frac{\sum_{i=1}^{14} \gamma_i}{14}$, where γ_i represents the elasticity estimate from the ith county.[6] The significance levels are calculated using the average variance across the elasticity estimates.

As discussed by Nelson and Kennedy (2009); Borenstein et al. (2010), and Nelson (2013), a more appropriate approach to estimating the mean effect size across multiple estimates is to weight each estimate by its inverse variance in order to give more weight to more precise estimates. The exact calculation of these weights depends on what we believe the variation in the primary estimates represents. If the elasticity estimates across the different counties reflect a single common elasticity of K_D, and the true unobserved elasticity is the same in all counties, then the variation in the primary estimates would simply be due to the random draw from that common distribution. This would indicate the use of a Fixed Effect-Size (FES) model reflecting the within-study variance of each estimate. Alternatively, different regions

[6] The coefficient estimate from the hedonic regression represents an elasticity when K_D is entered in log form; when K_D is entered linearly, unique elasticities are calculated for each property transaction by multiplying the coefficient estimate by K_D and dividing by the sale price. We then average these unique elasticities for each county and distance buffer.

Table 1 Mean elasticities of light attenuation (K_D) for in 14 Maryland counties

Distance from Bay	Specification	Unweighted mean elasticity	RES mean elasticity	FES mean elasticity
Waterfront	Semilog, 1 year	−0.051***	−0.056***	−0.057***
	Double log, 1 year	−0.060***	−0.063***	−0.067***
	Semilog, 3 year	−0.112***	−0.114***	−0.090***
	Double log, 3 year	−0.129***	−0.123***	−0.027***
0–500 m	Semilog, 1 year	−0.016***	−0.014**	−0.009***
	Double log, 1 year	−0.016**	−0.012*	−0.008**
	Semilog, 3 year	−0.001	−0.010	−0.015***
	Double log, 3 year	−0.005	−0.009	−0.013**
500–1000 m	Semilog, 1 year	−0.019***	−0.013	−0.004
	Double log, 1 year	−0.023***	−0.013	−0.003
	Semilog, 3 year	−0.011	−0.008	−0.011**
	Double log, 3 year	−0.017	−0.008	−0.010*
1000–1500 m	Semilog, 1 year	−0.008	0.002	0.008**
	Double log, 1 year	−0.013	0.001	0.012***
	Semilog, 3 year	−0.009	0.003	0.003
	Double log, 3 year	−0.015	0.002	0.010
1500–2000 m	Semilog, 1 year	0.004	0.001	0.001
	Double log, 1 year	0.007	0.003	0.004
	Semilog, 3 year	0.014	0.004	−0.001
	Double log, 3 year	0.018	0.011	0.006

The inverse variances of the elasticity estimates are used as weights in the RES and FES means. Standard errors calculated using Stata *metan* command (Harris et al. 2008)
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

surrounding the Bay, with different features and local housing markets, may have different underlying price elasticities. In this case, variation in the primary estimates would reflect differences in the true underlying price elasticities across counties. This would point to the need for a Random Effect-Size (RES) model, reflecting both within-study and between-study variance.[7]

For the FES model, mean elasticity estimates for each distance buffer presented in Table 1 are calculated as $\bar{\gamma}_{FES} = \frac{\sum_{i=1}^{14} W_{FES,i}\gamma_i}{\sum_{i=1}^{14} W_{FES,i}}$, where $W_{FES,i} = \frac{1}{V_i}$. In this model, the elasticity for each observation is weighted by the inverse variance of the estimate. The variance of this mean FES elasticity is calculated as $V_{FES} = \frac{1}{\sum_{i=1}^{14} W_{FES,i}}$.

The RES weighted means are calculated as

$$\bar{\gamma}_{RES} = \frac{\sum_{i=1}^{14} W_{RES,i}\gamma_i}{\sum_{i=1}^{14} W_{RES,i}}, \quad \text{where} \quad W_{RES,i} = \frac{1}{V_i + T^2},$$

[7] The Fixed Effect-Size (FES) model is also commonly called a fixed effect model or common-effect model. Similarly, the Random Effect-Size (RES) model is often called a mixed effect or random effect model. However, these models are conceptually different from the random effects and fixed effects panel data models commonly used in other branches of the econometrics literature. We adopt the FES and RES terminology used by Nelson and Kennedy (2009) and Nelson (2013) in order to avoid confusion.

$$T^2 = \frac{Q - 13}{\sum_{i=1}^{14} W_{FES,i} - \left(\frac{\sum_{i=1}^{14} (W_{FES,i})^2}{\sum_{i=1}^{14} W_{FES,i}} \right)}, \quad Q = \sum_{i=1}^{14} \frac{\gamma_i - \bar{\gamma}_{FES}}{V_i}.$$

This is an estimate of the mean elasticity weighted by two sources of variance, a within-study variance, V_i, and a between-study variance, T^2. The between-study variance is estimated with the DerSimonian and Laird method (DerSimonian and Laird 1986; Borenstein et al. 2010) using the inverse variance weights, $W_{FES,i}$, and the FES mean elasticity estimate, $\bar{\gamma}_{FES}$. The RES model is preferred if the elasticities from each county are from different distributions (Harris et al. 2008; Borenstein et al. 2010; Nelson 2013). In this framework the weighted mean is interpreted as an estimate of the mean of the true effects. All three types of means and associated standard errors were calculated using the *metan* command in Stata (Harris et al. 2008).

Across both unweighted and weighted means, it is apparent from the results in Table 1 that water clarity is most important to buyers of properties located closer to the Bay. Recall that a negative elasticity implies a positive premium for water clarity. For waterfront properties, a ten percent improvement in 1-year light attenuation leads to a statistically significant appreciation of about 0.6 %, and the effect size is roughly double for 3-year clarity. (A ten percent improvement in light attenuation translates to approximately an 11 cm increase in secchi depth on average.)

The price gradient extends beyond waterfront properties, with home price increases of roughly 0.1 % for a ten percent improvement in 1- or 3-year light attenuation for non-bayfront homes extending out to 500 m. There is no consistently statistically significant effect on home prices beyond 500 m in the FES and RES weighted means, and no statistically significant effect beyond 1000 m in the unweighted means for either the 1- or 3-year clarity measures.

As stressed in Walsh et al. (2015), few hedonic property value studies have incorporated non-waterfront home prices into analyses of water quality. Poor et al. (2007) found that average home prices—including both waterfront and non-waterfront homes—in a Chesapeake Bay county (St. Mary's County, Maryland) responded to water quality. Walsh et al. (2011) differentiated non-waterfront homes and found that water quality affected home prices out to approximately 1000 m in Florida. Netusil et al. (2014) found that stream water quality can affect Northwestern US home prices up to a mile ($\sim$1600 m) away. Therefore, the distance gradient identified by our study is within the range of previous literature.

While all three sets of summary statistics produce consistent results out to 500 m, variation in the preferences of local populations, features of the housing market, and other socioeconomic and geographic differences across Bay counties could lead to plausible variation in the true underlying elasticities of K_D. We test the hypotheses that the estimated elasticities in each distance buffer are homogenous across the 14 counties using a chi-squared test (Nelson 2013), and reject the null of no heterogeneity across county-level elasticities ($p = 0.000$ for all specifications and distance buffers out to 1500 m, beyond which elasticities across almost all counties are equal to zero). This result implies that the elasticities are not drawn from a single distribution, making the RES model the most appropriate.

The RES mean elasticities could be used as point estimates in a unit value benefit transfer approach. Another approach to benefit transfer would involve examining and accounting for factors that contribute to the variation in the elasticities of K_D across counties. This is known as a function transfer and is often considered superior to a simpler unit value transfer (Johnston and Rosenberger 2010).

4 Examining Heterogeneity Across Counties Using Meta-regressions

Statistically significant heterogeneity among the county-level estimates from the hedonic regressions suggests that property value impacts might vary across counties in the Chesapeake Bay region based on socioeconomic characteristics, Bay ecology and associated amenities, and perhaps other unobserved sources of heterogeneity. We estimate a meta-regression model to identify such sources of heterogeneity across counties. This model is used as the basis for a subsequent benefit function transfer. The meta-regression allows us to evaluate the source of the variation among the elasticity estimates, and the function transfer accounts for this variation when transferring the estimates to out-of-sample counties in the Chesapeake Bay region.

The meta-regression equation can be written as

$$\gamma_{ids} = \alpha_0 + L_i\alpha_1 + D_d\alpha_2 + D_s\alpha_3 + \varepsilon_{ids} \quad (2)$$

Here γ_{ids} represents the estimated elasticity of light attenuation in county i at distance d from the waterfront estimated using specification $s = 1, \ldots, S$. L_i is a vector of locational variables representing socioeconomic and ecological attributes of each county; D_d is a vector of dummy variables denoting the five Bay distance buffers; α_0, α_1, and α_2 are vectors of coefficients to be estimated; and ε_{id} is a normally distributed error term.

The meta-regression approach also allows us to evaluate the implications of the different water clarity specifications used in the hedonic analysis. The use of meta-regression to assess and compare multiple estimates from the same study is termed "internal meta-analysis" (Banzhaf and Smith 2007; Kuminoff et al. 2010). In particular, we examine the effect of a semi-log versus double-log functional form and a 1-year versus 3-year water clarity average. In Eq. (2), each county i at distance d has $S = 4$ elasticity estimates. D_s is a vector of dummy variables representing these different specifications.

We use the RES meta-regression model to estimate (2) (Harbord and Higgins 2008). This estimator uses the RES weighting scheme described above to account for both within- and between-county variance of the elasticities derived from the hedonic regressions. This approach gives more weight to more precise estimates and addresses heteroskedasticity, while accounting for the fact that there could still be significant unexplained heterogeneity among elasticities even after controlling for several covariates (Nelson and Kennedy 2009; Nelson 2013).[8]

Previous meta-analyses of the value of water quality have included demographic characteristics like income, attributes of the amenity (waterbody type, water quality), and an indication of whether participants in stated preference studies are users of the resource (Johnston et al. 2005; Van Houtven et al. 2007; Johnston and Thomassin 2010; Ge et al. 2013). Meta-analyses including estimates from hedonic property models typically include some measure of proximity to the resource, and sometimes include median or mean home value instead of income as a demographic covariate (Debrezion et al. 2007; Nelson 2004; Kiel and Williams 2007;

[8] The use of multiple elasticity estimates per county based on different econometric specifications and distances from the Bay creates a panel structure in the data. Because estimates within each county are derived using the same data, they are not independent. As an alternative to the RES meta-regression, we also estimate a random effects panel data model with a county-specific error to address the correlation among elasticity estimates within each county. Nelson and Kennedy (2009) recommend this model to address correlation among estimates when multiple estimates per study are included. We use a weighted random effects panel model with clustered robust standard errors, again weighting each elasticity using the RES meta-analytic weighting scheme to address heteroskedasticity. These results are presented in the Appendix Table 9. The results from the RES and panel data estimators are extremely similar.

Mazzotta et al. 2014). In order to be useful for benefit transfer, all variables included in the meta-regression must be available for both the primary study and benefit transfer areas.

Table 2 shows summary statistics of socioeconomic and environmental characteristics in the hedonic and benefit transfer study areas, including median income and home value, population density, the proportion of housing units that are second homes, and boat ownership per household. Such factors could reflect heterogeneity in preferences for water clarity and determine the shape of the hedonic price function. We also present GIS-derived environmental variables, which may reflect differences in the amenities provided by different portions of the Bay. These variables include the percent of the county's Chesapeake shoreline that borders a tidal tributary (as opposed to the Bay main stem), less saline waters (represented by the tidal fresh and oligohaline salinity categories), waters at least 1.5 m deep, and mean spring-summer K_D during the study period. EPA's Chesapeake Bay Program provided historic data on the light attenuation coefficient (K_D), as well as projected improvements from the TMDL.

We rely on the 2000 US Census for data on housing values and other socioeconomic characteristics.[9] The Census block group is the finest level of disaggregation for which data are available. The 2000 Census is appropriate because (i) it falls within the time span of the hedonic analysis (1996–2008), and (ii) more recent American Community Survey data only provide total and median housing value at the more aggregate Census tract level. Relatively fine spatial resolution is important given the localized nature of the property value impacts from Bay water clarity. For each county we aggregate the Census data for all block groups falling at least partially within 500 m of the Chesapeake Bay to approximate the spatial extent of the study area.

Table 3 presents the results of the RES meta-regressions. Models (1) through (4) include different sets of explanatory variables in the meta-regression. The models increase in complexity moving from left to right, with more socioeconomic and ecological covariates. Models (2) and (4) include interaction terms between the socioeconomic/ecological covariates and a dummy variable representing the non-waterfront distance buffers. The non-waterfront interaction terms allow us to evaluate whether any of the socioeconomic or ecological variables have different effects on the elasticity of K_D for properties farther from the shore. All models include dummy variables denoting the econometric specification of the hedonic equation, as well as non-waterfront interaction terms with these variables. The adjusted R-squared statistics show that the explanatory power of the model generally increases as more covariates are added, rising from 0.39 in Model (1) to 0.68 in Model (4).

Model (1) is the most parsimonious model, including only the distance buffer dummy variables, median home value, and percent of the county's shoreline adjacent to waters more than 1.5 m deep. The positive coefficients on the distance buffer dummy variables illustrate how the property value impact declines with distance from the shore. (Since a negative elasticity of K_D indicates a positive premium for water clarity, coefficients with a positive sign suggest a lower premium for water clarity.) The water depth coefficient is positive and significant, indicating that water clarity is more important to homebuyers for properties adjacent to shallower water. This result makes sense if residents are more likely to dock boats at properties with deeper water, allowing them to travel easily to other parts of the Bay for recreation. The negative and significant coefficient on median home value indicates that water clarity is more important to homebuyers in wealthier areas. (Median household income

9 Data on housing values at the individual parcel level from Virginia, Delaware, and DC were either unavailable, incomplete, or cost prohibitive. We do have data on individual property assessed values for Baltimore City, Caroline County, Montgomery County, and Worcester County in Maryland, which we use in the benefit transfer for these counties.

Table 2 Chesapeake Bay region characteristics: benefit transfer and hedonic study areas

	Benefit transfer area				Primary study area
	Delaware	District of Columbia	Virginia	Maryland	Maryland
Socioeconomic characteristics[a]					
Total owner-occupied housing value (billion 2000$)	1.7	2.8	46.6	2.4	44.8
Median owner-occupied housing value (2000$)	134,372	174,974	122,809	172,600	135,340
Median income (2000$)	56,567	45,285	46,459	59,538	50,465
Population density (people per m^2)	0.0003	0.004	0.0007	0.001	0.0007
Second homes (% housing units)	0.5 %	1.7%	4.4 %	1.0 %	4.1 %
Number of registered boats per household	0.012	0.005	0.014	0.006	0.021
GIS-derived ecological variables					
% shoreline on a tidal tributary	100 %	100 %	86 %	100 %	78 %
% shoreline along tidal fresh water	50 %	100 %	40 %	45 %	15 %
% shoreline along oligohaline water	50 %	0 %	14 %	11 %	27 %
% shoreline bordering water at least 1.5 m deep	33 %	29 %	39 %	35 %	30 %
Mean K_D 1996–2008 (m^{-1})	3.3	2.9	2.4	3.0	2.7
Change in clarity from baseline to TMDL (cm)	11	15	11	11	12
Number of counties	2	1	44	4	14

[a] All socioeconomic characteristics are derived from the 2000 U.S. Census except for the number of boats per county. Information on the number of boats registered in each county by the U.S. Coast Guard in 2011 was downloaded from www.boatinfoworld.com (accessed Nov. 15, 2012); we then normalize boat registration by Census data on the number of households per county. We use Census data on the number of vacant homes for seasonal, recreational, or occasional use as a proxy for the number of second homes. Census-derived socioeconomic characteristics for each county are calculated using data on block groups within 500 m of the waterfront. Total owner-occupied housing value is calculated by summing across counties; all other summary statistics are calculated as simple averages across counties

was excluded from all of the regressions due to collinearity with median home value, but yielded similar results when used as an alternative to median home values.)

Model (2) uses these same covariates but also includes the non-waterfront interaction terms. The results of this model suggest that the effect of the water depth variable is no different for waterfront versus non-waterfront homes. However, the effect of median home value does vary; the total effect is negative and statistically significant in both locations, but for waterfront homes the effect is roughly double what it is for non-waterfront homes. (The net impact of a variable on non-waterfront homes is obtained by summing the non-interacted with the interacted coefficient estimates.)

Table 3 Meta-regression results (dependent variable: elasticity of K_D from Walsh et al. (2015) spatial hedonic regressions)

	(1)	(2)	(3)	(4)
Socioeconomic and ecological covariates				
Non-waterfront distance buffer	0.041**	−0.063	0.041**	−0.098
	(0.018)	(0.046)	(0.018)	(0.12)
≥500 m distance buffer	0.0088	0.0087	0.0079	0.0085
	(0.0095)	(0.0094)	(0.0092)	(0.0079)
% coastline water depth ≥1.5 m	0.13***	0.18***	0.23***	0.28***
	(0.020)	(0.048)	(0.042)	(0.087)
Median home value	−5.7e−7***	−1.3e−6***	−1.1e−6***	−2.2e−6***
	(1.3e−7)	(3.0e−7)	(3.1e−7)	(6.2e−7)
% coastline along tributary			−0.052	0.099
			(0.049)	(0.11)
Population density			4.6	−97.6***
			(12.8)	(27.6)
% second homes			−0.81	−4.0***
			(0.65)	(1.3)
Boats per household			1.1	4.1*
			(1.2)	(2.3)
% tidal fresh salinity			0.031	−0.0086
			(0.050)	(0.10)
% oligohaline salinity			0.022	0.11
			(0.058)	(0.12)
Mean K_D (1996–2008)			−0.011	0.008
			(0.019)	(0.039)
Covariates interacted with non-waterfront dummy variable				
% coastline water depth ≥1.5 m		−0.057		−0.083
* non-waterfront		(0.053)		(0.096)
Median home value		8.5e−7**		1.5e−6**
* non-waterfront		(3.4e−7)		(6.9e−7)
% coastline along tributary				−0.19*
* non-waterfront				(0.12)
Population density				123***
* non-waterfront				(30.3)
% second homes				3.9***
* non-waterfront				(1.5)
Boats per household				−4.0
* non-waterfront m				(2.6)
% tidal fresh salinity				0.033
* non-waterfront				(0.11)
% oligohaline salinity				−0.11
* non-waterfront				(0.13)

Table 3 continued

	(1)	(2)	(3)	(4)
Mean K_D (1996–2008)				−0.017
* non-waterfront				(0.044)
Specification variables				
3-year average water clarity	−0.046**	−0.047**	−0.047***	−0.043***
	(0.018)	(0.018)	(0.018)	(0.016)
Double log model	−0.0010	−0.0032	−0.0016	−0.008
	(0.0181)	(0.018)	(0.018)	(0.016)
3-year average water clarity	0.056***	0.056***	0.055***	0.048***
* non-waterfront	(0.020)	(0.020)	(0.020)	(0.018)
Double log model	0.0015	0.0039	0.0019	0.0089
* non-waterfront	(0.020)	(0.020)	(0.019)	(0.017)
Constant	−0.018	0.067	0.087*	0.19*
	(0.023)	(0.041)	(0.051)	(0.11)
Adjusted R-squared	0.39	0.40	0.44	0.68
N = 280				

Standard errors in parentheses
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Model (3) adds several more covariates, including the percent of coastline that borders a tidal tributary rather than the main stem of the Bay, population density, the percent of housing units that are second homes, boat ownership per household, percent of the coastline bordering water of tidal fresh and oligohaline salinity, and mean K_D.[10] While the additional variables are jointly significant at the one percent level, only the water depth and median home value variables remain individually significant in this model. The additional covariates do not help explain a substantial amount of variation in the elasticity of K_D, though this is in part due to collinearity.[11] However, when the non-waterfront interaction terms for these variables are included in Model (4), the explanatory power of the model jumps considerably. Model (4) indicates that water clarity is more important in areas with higher population density, more second homes and with lower boat ownership, but that these effects only hold for waterfront properties.

Turning now to the coefficient estimates for the water clarity specification variables, results across all four models indicate that the use of the double-log rather than the semi-log model has no significant effect on the estimated elasticity of K_D for either waterfront or non-waterfront homes. Measuring water clarity using a 3-year average produces a significantly larger effect on home values than the 1-year average measure and almost doubles the elasticity of K_D, though this relationship holds for waterfront homes only. This result indicates that waterfront homebuyers may be more aware of and concerned about longer term trends in water clarity rather than short-term swings. The premium that homebuyers place on water clarity that

[10] In previous drafts of the paper, we considered two intermediate models: a model similar to Model (1) but adding just population density and the percent of the coastline that borders a tidal tributary, and a model that also included non-waterfront interaction terms for these variables. The results were similar to Models (3) and (4) but are omitted here for brevity.

[11] These covariates all had variance inflation factors greater than those for the variables included in Models (1) and (3), justifying their exclusion.

persists over multiple years suggests that they prefer average water clarity improvements that fluctuate less over time, all else constant. Alternatively, it could be that the 3-year measure is more susceptible to biases from other unobserved local trends in housing markets. It also contrasts with the results of a hedonic property analysis of Maine lakes, which found no significant difference between the price premiums for water clarity measured using current year, previous year, or 10-year average data (Michael et al. 2000).

5 Evaluating Approaches for Benefit Transfer to Other Areas of the Chesapeake

Next we calculate measures of internal and external validity to determine which meta-regression models are most appropriate for transferring benefits outside of the 14 Maryland counties included in the original hedonic analysis (herein referred to as the "Maryland hedonic counties"), following an approach similar to Stapler and Johnston (2009), Lindhjem and Navrud (2008), and Bateman et al. (2011). We compare the four meta-regression models presented in Table 3, as well as the RES mean elasticities from Table 1, which provide point estimates for a unit value transfer of the waterfront and non-waterfront elasticities of K_D. As a measure of internal (within-sample) transfer error, we examine the absolute value of the difference between each county's elasticity estimate from the hedonic models and the predicted value from the RES mean or meta-regression models, averaged over all 14 Maryland hedonic counties.[12] As a measure of external (out-of-sample) transfer error, we calculate a similar measure for each model by iteratively re-estimating the meta-regression models, but leaving out all elasticity estimates from one county at a time, getting the predicted value for the excluded county, and taking the absolute value of the difference between the excluded county's elasticity and its predicted value. We then average this measure across all 14 Maryland hedonic counties. Both types of transfer error are calculated for the double log 1- and 3-year average water clarity elasticities for both the waterfront and 0–500 m (non-waterfront) distance buffers. (We do not examine transfer error for the semi-log models because the meta-regression results were not statistically different from the double log model results.)

Table 4 shows that the use of a meta-regression model incorporating socioeconomic and ecological covariates sometimes improves in-sample forecasting. When using 1-year average clarity, Models (1) and (2) generate lower transfer errors than the RES mean when predicting the waterfront elasticity of K_D. (Transfer errors from the meta-regression models that are lower than those from the RES mean are shown in bold text.) Models (3) and (4), the more complex meta-regressions, yield comparable or higher transfer errors. All regression models using 1-year average K_D perform poorly compared to the RES mean for the non-waterfront 0–500 m distance buffer elasticity. When using 3-year average K_D, the meta-regression predicted values outperform the RES means across all models and both distance buffers. In addition, the 3-year average water clarity measure always yields a higher absolute transfer error compared to the 1-year measure when comparing within a model and distance buffer. While a longer-run average may better reflect steady-state changes in water clarity likely to occur in response to

[12] We use the absolute difference (rather than percent difference) as the measure of transfer error because it allows for symmetric treatment of elasticities regardless of whether they are above or below the predicted values. The percent difference yields substantially larger transfer errors when the actual elasticity is close to zero than when the elasticity is larger in absolute value than the predicted value, even if the differences are equal in absolute terms.

Table 4 Internal and external absolute transfer error

	RES mean	Meta-regression model			
		(1)	(2)	(3)	(4)
In-sample transfer error					
1-year average log K_D					
Waterfront	0.051	**0.046**	**0.047**	0.051	0.053
0–500 m (non-waterfront)	0.018	0.024	0.023	0.025	0.022
3-year average log K_D					
Waterfront	0.125	**0.116**	**0.110**	**0.120**	**0.100**
0–500 m (non-waterfront)	0.052	**0.036**	**0.039**	**0.039**	**0.042**
Out-of-sample transfer error					
1-year average log K_D					
Waterfront	0.055	**0.053**	0.069	0.129	0.304
0–500m (non-waterfront)	0.019	0.026	0.027	0.106	0.080
3- year average log K_D					
Waterfront	0.135	**0.127**	0.136	0.179	0.348
0–500 m (non-waterfront)	0.056	**0.040**	**0.043**	0.115	0.087

Transfer errors from the meta-regression models that are lower than those from the RES mean are shown in bold

long-term policies, this finding suggests that measures spanning broader temporal windows could potentially be reflecting other unobserved local trends.

When considering the out-of-sample transfer errors, the meta-regression results look considerably worse. Transfer errors for both measures of clarity at the waterfront and 0–500 m distance buffers increase substantially with more complex regression models. In fact, only Model (1) outperforms the RES mean in predicting the waterfront elasticity for out-of-sample counties using both the 1- and 3-year clarity measures. None of the meta-regression models outperform the RES mean for the 1-year average K_D non-waterfront elasticity, although Models (1) and (2) yield lower transfer errors when using 3-year average K_D. The contrast between the internal and external transfer errors may initially seem surprising, but it suggests that meta-regression models that control for many socioeconomic and ecological covariates may not be generalizable, even to locations with similar characteristics. Given the relatively small number of counties in the dataset, the models with more covariates may even be overfitting the data rather than describing true underlying relationships among variables.

These results run counter to a near-consensus that benefit function transfer is preferable to unit value transfer (Johnston and Rosenberger 2010). However, a small but growing number of studies support the contention that "simplicity can beat complexity when forecasting" (Nelson 2013). Such studies have highlighted cases in which unit value transfers outperformed function transfers and socioeconomic controls heightened rather than reduced transfer error (Johnston and Duke 2010; Lindhjem and Navrud 2008; Barton 2002; Bateman et al. 2011; Nelson 2013). Our results echo the finding that simple benefit transfer models—even unit value transfers—can outperform complex function transfers including numerous covariates. They are also consistent with Bateman et al.'s (2011) hypothesis that mean value transfers dominate value function transfers when the policy site has similar characteristics to the study site.

6 Calculating the Property Value Impacts of the TMDL

In this section, we estimate the property value impacts from the projected improvements in water clarity from the TMDL in both the 14 Maryland hedonic counties and the remaining counties adjacent to the Chesapeake Bay and its tidal tributaries. For the 14 Maryland hedonic counties, we apply the estimated elasticities from the hedonic analyses to all residential properties within 500 m of the waterfront in these counties. We focus on calculating changes in home values within this boundary because all three approaches for calculating mean elasticities suggest that there are increases in home values up to, but not beyond, this distance. We then use the meta-analysis results to transfer the estimates to properties in waterfront counties in Virginia, Delaware, the District of Columbia, and four Maryland counties that were excluded from the original hedonic analysis due to data limitations.

Using the light attenuation (K_D) elasticity estimates from the hedonic regressions is reasonable for this application because the anticipated change in water clarity resulting from the TMDL is relatively small—11 % on average—and well within the range of variation in the historic data. However, it is important to note that the geographic scale of the projected water clarity changes is widespread and the water clarity improvements under the TMDL could potentially be considered non-marginal. The use of hedonic coefficients to project changes in property values from water clarity improvements under the TMDL rests on the assumption that the hedonic price function does not shift. Such shifts could occur if non-marginal improvements in water clarity spur households to relocate, which could then lead to changes in community demographics and other features, ultimately resulting in a new equilibrium in the housing market (Bartik 1988; Kuminoff et al. 2013). If such sorting occurs, our projections could either over- or under-estimate the gains to property owners from the TMDL. Another limitation of our analysis is that we do not account for potential shifts in the housing market equilibrium caused by the stormwater management practices or other costs and ancillary benefits of the TMDL policy that may affect homeowners.

In the calculations that follow, we conduct the benefit transfer to out-of-sample counties using two approaches: a unit value transfer using the RES means as point estimates for the elasticity of K_D at the waterfront and 0–500 m buffers, and a function transfer using the meta-regression results to predict unique elasticities of K_D for each out-of-sample county and distance buffer. We use the double log 1- and 3-year average water clarity specifications to calculate the value of improved water clarity to property owners.[13]

First we calculate in-sample price impacts in the 14 Maryland hedonic counties. We match each residential property within 500 m of the Bay with a light attenuation elasticity based on its county and distance from the Bay. We write this expression as:

$$\Delta V_{icd} = \gamma_{cd} {}^{*} \% \Delta WQ_i {}^{*} V_{icd} \tag{3}$$

where V_{icd} is the assessed value of property i in county c at distance d. The change in value at the property is denoted as ΔV_{icd}, $\% \Delta WQ_i$ is the percent change in water clarity closest to property i, and γ_{cd} is the light attenuation elasticity estimate corresponding to county c in distance buffer d.[14] The data on assessed property values, which were available for the year 2009, were adjusted to 2010 values using the US Federal Housing Finance Agency's

13 As already noted, the choice of a semi-log versus a double log specification has no significant effect on the results.

14 We apply the estimated elasticities (and corresponding 95 % confidence intervals) in the calculation of net benefits for all counties and distance buffers regardless of the statistical significance and sign of the estimated elasticity of K_D; in some cases these elasticities are positive, though not significantly different from zero.

Housing Price Index (HPI), which accounts for regional differences in appreciation in home prices over time.[15]

To estimate the improvement in water clarity from the TMDL, EPA's Chesapeake Bay Program uses its Chesapeake Bay Estuary Model to project light attenuation for grid cells throughout the Bay and tidal tributaries as a function of nitrogen, phosphorus, and sediment runoff under two scenarios: a baseline accounting for pollution reduction actions undertaken before the TMDL was enacted and other actions that would be implemented in the future in the absence of the TMDL; and a policy scenario in which the TMDL is fully implemented according to the States' and the District of Columbia's Watershed Implementation Plans, but where all other socioeconomic factors (such as population) are held constant.[16] Figure 3 illustrates the estimated percent decline in K_D (i.e., improvement in water clarity) between the baseline and the TMDL scenarios due to the modeled reduction in nutrient and sediment runoff. The average decrease in K_D across all grid cells is 11 %, corresponding to an 11 cm increase in secchi depth. The largest gains in water clarity are expected in the upper Bay and tidal tributaries, with smaller improvements occurring closer to the mouth of the Bay.

Focusing first on the 14 Maryland counties included in the original hedonic analysis, Table 5 shows that the value of each home within 500 m of the Bay is estimated to increase by $1299 on average in response to the TMDL when using the 1-year water clarity measure.[17] A much larger appreciation is expected among waterfront homes, amounting to an average of $5571 per home; non-waterfront homes within 500 m of the water appreciate by only $366. This difference occurs because waterfront homes have both larger light attenuation elasticities (in absolute value) and higher assessed values. (The HPI-adjusted average assessed value of waterfront homes in the dataset is $645,194, compared to $234,684 for non-waterfront homes within the 500-m buffer.) When the 3-year water clarity measure is used, the results are roughly double: a $11,901 average increase for waterfront homes, and a $575 increase for non-waterfront homes within 500 m of the water.

To calculate the total increase in property values across these 14 counties, we sum the estimated house-specific price increases across all homes within the waterfront and 500 m buffers. The first row of Table 6 presents these aggregated property value increases, based on both the 1- and 3-year water clarity models. The aggregate increase in home values among these properties is $213 million using the 1-year measure and is $427 million using the 3-year measure. More than three-quarters of the increase accrues to waterfront properties, even though they make up only 18 % of homes within 500 m of the Bay.

A similar approach is used to calculate the residential property value impacts in Virginia, Delaware, the District of Columbia, and the four additional counties in Maryland. Similar to expression (3) above, we calculate

$$\Delta \sum_{i}^{N} V_{icd} = \hat{\gamma}_{cd}{}^{*} \sum_{i}^{N} \left(\% \Delta W Q_i{}^{*} V_{icd}\right) \tag{4}$$

[15] Federal Housing Finance Agency (FHFA), http://www.fhfa.gov/Default.aspx?Page=81, accessed January 13, 2013.

[16] Shenk and Linker (2013) provide further details about the baseline and TMDL scenarios (which they label the "2009" and "TMDL WIP" scenarios). Wang et al. (2013) and Keisman and Shenk (2013) describe the Estuary Model. The Estuary Model's projections are missing or unreliable for three Bay segments denoted in Fig. 3 (Shenk, personal communication). We exclude properties matched to grid cells in these segments in our calculations. The Watershed Implementation Plans (WIPs) for each jurisdiction are available at http://www2.epa.gov/chesapeake-bay-tmdl/chesapeake-bay-watershed-implementation-plans-wips (accessed November 30, 2015). The Phase II WIPs were used for these projections.

[17] This and subsequent calculations adopt the simplifying assumption that the improvement in water clarity occurs instantaneously, rather than gradually over time.

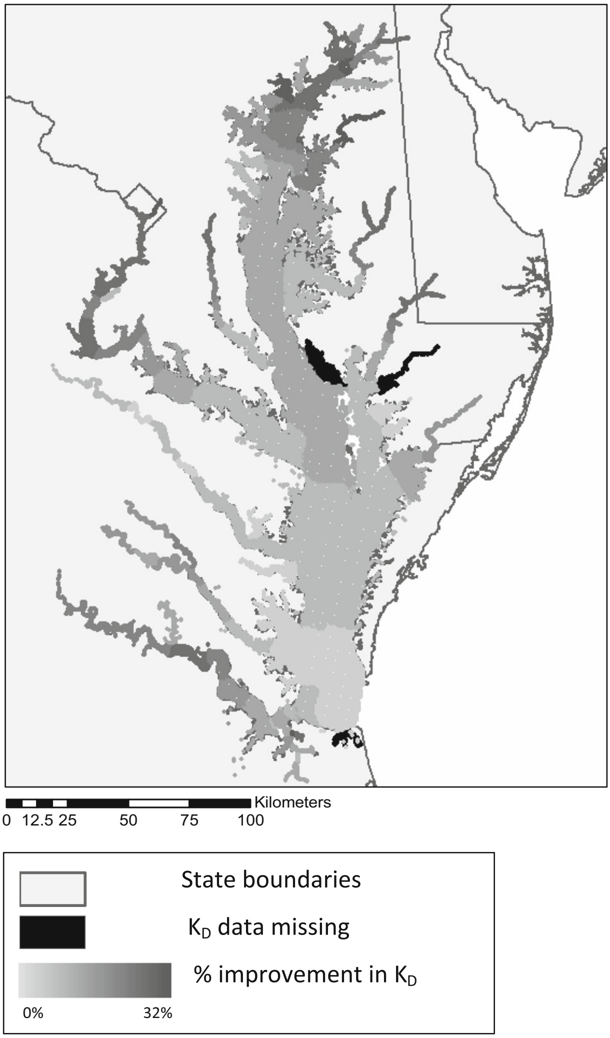

Fig. 3 Projected reduction in Chesapeake Bay spring–summer average light attenuation (K_D) from baseline to TMDL (%)

Table 5 Mean property value increases from TMDL water clarity improvements in 14 Maryland counties

Distance from Bay	Mean home price increase (2010$), 1-year K_D	Mean home price increase (2010$), 3-year K_D
Waterfront	$5571	$11,901
0–500 m (non-waterfront)	$366	$575
All homes within 500 m	$1299	$2606

Table 6 Total property value increases from TMDL water clarity improvements

	Aggregate home price increase, 1-year K_D (million 2010$) (95% confidence interval[a])		Aggregate home price increase, 3-year K_D (million 2010$) (95% confidence interval[a])	
Hedonic study area				
Maryland (14 counties)	$213		$427	
	($40–385)		($178–676)	
Benefit transfer area	Unit value transfer	Function transfer	Unit value transfer	Function transfer
Delaware	$5	$4	$9	$6
	($2–$8)	($2–$7)	($1–$16)	($3–10)
District of Columbia (DC)	$19	$36	$30	$41
	($6–$32)	($18–$54)	(−$2 to $63)	($23–$59)
Virginia	$144	$179	$243	$235
	($51–$236)	($42–$316)	($7–$479)	($97–$373)
Maryland (4 counties)	$5	–$26	$6	−$29
	($3–$10)	(−$43 to $10)	(−$6 to $17)	(−$46 to $12)
Total	$386	$406	$715	$680
	($102–$671)	($59–$752)	($178–$1251)	($255–$1106)

[a]The confidence interval only accounts for uncertainty in the predicted elasticity of K_D. Estimates of uncertainty in water clarity improvements or in baseline property values were unavailable. Function transfer estimates based on Model (1)

Here $\sum_i^N V_{icd}$ represents *total* housing stock value of all N homes within 500 m of the Bay in county c, ΔWQ_i is still the change in water clarity experienced by home i, and $\hat{\gamma}_{cd}$ is the predicted value of the elasticity of light attenuation for homes in county c and distance buffer d.[18]

For the four remaining Bayfront counties in Maryland, we calculate total housing value by simply summing the assessed values of all properties within each Bay distance buffer and adjusting from 2009 to 2010 values using the HPI. Calculating housing stock value within each distance buffer for block groups in Virginia, Delaware, and DC is more complicated because we do not have parcel-level data. We use block-group level housing data from the 2000 Census, updated for appreciation in home values from the year 2000 to 2010 using the HPI.[19] We also make additional adjustments to the data because (i) the Census only provides data on the value of owner-occupied housing but not rental or vacant properties, (ii) the number of households in each county changed from 2000 to 2010 and (iii) Census block groups do not fall neatly within the Bay distance buffers used in our analysis. The "Appendix" provides more detail on these adjustments.

We use two approaches to estimate $\hat{\gamma}_{cd}$. The first corresponds to the unit value transfer approach and uses the RES mean elasticity for each distance buffer as the estimate of the value of improved water clarity in each out-of-sample distance buffer (reported in Table 1). The

[18] Block groups in Virginia, Delaware, and DC, were matched to the single nearest grid cell to determine the change in water clarity.

[19] The HPI is not available for a few areas surrounding the Chesapeake Bay that are outside of a Metropolitan Statistical Area (MSA) or Metropolitan Statistical Area Division (MSAD). For these areas, we impute the change in housing prices by taking the HPI from the nearest MSA or MSAD on the same side of the Bay as the corresponding block group.

second approach uses a function transfer to estimate $\hat{\gamma}_{cd}$ for the transfer counties. Specifically, we use the coefficient estimates from Model (1) in Table 3 and then plug into the right-hand side the covariate values specific to each individual county and bay distance buffer. This yields predicted values for the individual elasticities corresponding to each county and distance buffer. We rely on Model (1) because it has the lowest out-of-sample transfer error of the meta-regression models.

Table 6 presents the benefit transfer results from improvements in water clarity under the TMDL using the unit value and function transfer approaches and the 1- and 3-year measures. The results show that the majority of property value increases in the transfer areas occur in Virginia, regardless of the transfer approach. Calculations using the value of 3-year average water clarity yield higher impacts than those using the value of 1-year average clarity. The unit value and function transfer approaches yield similar results for Delaware, as well as for Virginia. However, the function transfer, which projects the elasticity of K_D based on median property values and water depth, generates substantially larger price impacts for DC than the unit value approach because of DC's relatively high property values. In the four Maryland transfer counties, the function transfer yields a projected depreciation in home values. This counterintuitive result is driven by Baltimore City, which is bordered entirely by deep water. (Recall that the deep water dummy variable is associated with a smaller premium for water clarity.)

As noted above, we calculate the increase in property values under the assumption that that the hedonic price function for water clarity does not shift in response to the TMDL policy. Summing the results from the hedonic and transfer areas yields a total net present value gain of \$386 to \$715 million, depending on the benefit transfer approach and the temporal duration of the water clarity measure. The 95 % confidence intervals around these point estimates are overlapping but are also fairly wide: \$102 to \$671 million and \$255 to \$1106 million, respectively. While the 3-year average clarity values are larger than the 1-year clarity values, they also have a wider confidence interval, indicating that they are less robust.

The result that property value impacts nearly double when the benefit transfer results are added to the property value increases from the 14 Maryland hedonic counties is sensible given the distribution of total owner-occupied housing value across the different areas (Table 2). The 14 Maryland hedonic counties comprise 46 % of owner-occupied property value in Census block groups within 500 m of the waterfront along the Chesapeake Bay. Property value increases in the 14 Maryland hedonic counties are somewhat larger as a percent of total benefits, representing roughly 55–60 % of the property value increase.

7 Conclusions

This study projects the change in property values from pollution reduction policies in the Chesapeake Bay using an internal meta-analysis of results from the largest hedonic property value study of water clarity to date. We examine the mean value of water clarity to homebuyers, identify sources of variation in the implicit value of water clarity across counties, and transfer those values to other states and counties bordering the Chesapeake tidal waters. The results are useful for analysts, policymakers, and members of the public interested in evaluating the impacts to near-waterfront property owners of Chesapeake Bay pollution cleanup efforts. The results could also inform policies to reduce pollution in other estuaries and iconic waterbodies. For instance, Artell and Huhtala (2015) assert that property value impacts could assist in evaluating the goals of the EU Water Framework Directive.

The results also provide some insights about methods for estimating the property value impacts of water quality and for benefit transfer. The meta-regression results suggest that the value of water clarity is greater in areas with shallower water and higher property values, suggesting that it could be important to control for these factors in a benefit transfer. At the same time, including additional socioeconomic and ecological variables in the meta-regression worsens its out-of-sample predictive power. A simple benefit transfer approach using the RES mean of the water clarity elasticities as a point estimate for the value of water clarity outperforms most of the meta-regression based function transfers that we evaluate.

In addition, the duration of the water clarity measure has impacts that are significant both statistically and economically: the value of 3-year average water clarity is roughly double the value of 1-year average water clarity for waterfront properties, which could indicate that residents are more aware of or concerned about longer term trends in water clarity rather than annual variations. The 3-year average results have a larger confidence interval and transfer error, however, suggesting that there is greater uncertainty about these estimates.

These results highlight questions that remain about the best approaches for estimating the value of water quality improvements in policy contexts where analysts rely on benefit transfer. Adjusting property value estimates to account for local socioeconomic and ecological variation is intuitively appealing, but our analysis does not provide strong empirical support for doing so, at least not in the context of relatively homogenous environmental commodities and housing markets. Mean values may perform somewhat better, but we urge caution when considering the transfer of values estimated here far-afield of the study region given the iconic nature of the Chesapeake Bay. Further meta-analyses incorporating cross-regional estimates of the value of water quality using the hedonic property value approach would shed light on these issues.

Appendix: Census Housing Value Data Adjustments for Benefit Transfer

Housing value data from the Census have several limitations that we address through a series of adjustments. As already noted, we use data from the 2000 Census because housing value is available at the relatively spatially refined block group level. However, use of data from 2000 could lead to a misrepresentation of property value impacts in 2010 (the reference year chosen for the analysis) because both the number of housing units and the average value of housing units changed over time. We use the HPI to adjust for region-specific changes in home prices over time, and we use county-level Census data on the change in the number of households from 2000 to 2010 to adjust for population growth. (Because Census block group and tract boundaries change over time, it was only feasible to determine the change in the number of households at the county level.) In addition, the Census only provides data on housing values for owner-occupied houses. Rental and vacant properties (including second homes) comprise a substantial proportion of the housing stock in counties bordering the Chesapeake Bay —from 15 % (in Delaware) to 60 % (in DC).

We use a regression-based approach to make these adjustments, relying on the fact that we have a more complete dataset of property values for the Maryland counties in our analysis from MDPV that includes the assessed values of all residential properties (owner-occupied and otherwise) in 2009. We use an ordinary least squares regression to estimate the relationship between MPDV data on total assessed property values, which we aggregate up from individual home assessed values to the Census block group level, and Census data on owner-estimated housing values, also at the block group level. Specifically, we estimate the following relationship:

Table 7 Total assessed housing value in Maryland block groups, OLS regression

	Total assessed housing value (MDPV)
Total owner-occupied housing value (U.S. Census)	0.87***
	(0.014)
Average owner-occupied housing value × number of non-owner-occupied units (U.S. Census)	0.12***
	(0.028)
Observations	1214
R-squared	0.85

Standard errors in parentheses
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

$$\sum_{i}^{n_i+n_2} V_{i,2010} = \beta_1 \sum^{n_1} V_{i,2010} + \beta_2 n_2 \bar{v}_{2010} + \varepsilon_b \tag{5}$$

In this equation, $\sum_i^{n_i+n_2} V_{i,2010}$ is the sum of the value of all n_1 owner-occupied and n_2 non-owner-occupied properties in the Census block group, calculated using MDPV data updated to 2010 values with the HPI. $\sum^{n_1} V_{i,2010}$ is the sum of the value of only the n_1 owner-occupied properties in the block group, taken from the 2000 Census data and updated to 2010 values. $\bar{v}_{2010}$ is the average value of owner-occupied properties in each Census block group, again updated to 2010 values, which is multiplied by n_2 to obtain a proxy for the total value of non-owner occupied properties. β_1 and β_2 are coefficients to be estimated, and ε_b is a normally distributed error term. β_1 will be equal to one if total owner-reported home values documented by the Census are roughly equal to the total of the assessed home values used by Maryland counties for tax assessments. β_2 will be equal to one if both owner-reported values are equal to county assessed values and if rental and vacant properties have home values equal to owner-occupied properties. The model is estimated without a constant term.

Table 7 reports the estimates of the relationship between total MDPV assessed home values and Census home values in Maryland block groups. The R-squared of 0.85 indicates that the Census data are highly correlated with the MDPV data. Both coefficients are significantly greater than zero. β_1 is 0.87, suggesting that home values reported by owners to the Census are somewhat higher than those recorded by county assessors. β_2 is much smaller, at 0.12, which indicates that rental and vacant properties have a much lower average value than owner-occupied properties. Assuming these relationships estimated from the Maryland data also hold in DC, Delaware, and Virginia, we predict the total value of the housing stock in each block group in 2010 in these other states for non-owner-occupied properties and the change in population over 2000 to 2010.

Next we adjust the data to account for the fact that Census block groups do not neatly correspond to the Bay distance buffers over which the estimated price impact of water clarity varies. We again rely on the MDPV data on the assessed values of residential properties to calculate the fraction of the housing stock value in each block group in Maryland that lies either along the waterfront or within 500 m of the Bay. We regress the percent of block group housing stock in each of the two distance buffers on several geographic variables in two separate equations. Independent variables include the percent land area in each block group within 50 m (as a proxy for waterfront area) and 500 m of the waterfront, and the distance of the block group to the Bay (all calculated using GIS tools). We also include the median

Table 8 Percent census block group housing value within each Bay distance buffer, two-parameter beta distribution model

	Bayfront	0–500 m (non-waterfront)
% land area within 50 m of Bay	4.6***	−0.57
	(0.95)	(1.3)
% land area within 500 m of Bay	0.62**	3.5***
	(0.27)	(0.26)
Block group distance from Bay	−0.00087	−0.0019***
	(0.00083)	(0.00052)
Median housing value	3.4e−06***	1.9e−06**
	(6.4e−07)	(6.4e−07)
% second homes	5.5***	6.7***
	(0.81)	(0.96)
Population density	−384.0***	48.4*
	(72.0)	(27.6)
Constant	−2.5***	−1.9***
	(0.15)	(0.14)
Log likelihood	272.23	313.70
Prob > chi2	0.00	0.00
Observations	388	537

Table 9 Random effects panel data estimation (dependent variable: elasticity of K_D from hedonic regressions)

	(1)	(2)	(3)	(4)
Socioeconomic and ecological covariates				
Non-waterfront distance buffer	0.042**	−0.06	0.041**	−0.089
	(0.019)	(0.10)	(0.019)	(0.23)
Distance from shore ≥500 m	0.0087	0.008	0.0083	0.0072
	(0.0086)	(0.0087	(0.0087)	(0.0086)
% coastline water depth ≥1.5 m	0.13***	0.18	0.23**	0.30**
	(0.042)	(0.17)	(0.096)	(0.15)
Median home value	−5.4e−07**	−1.2e−06	−1.1e−06*	−2.2e−06*
	(2.6e−07)	(1.0e−06)	(6.5e−07)	(1.2e−06)
% coastline along tributary			−0.047	0.087
			(0.12)	(0.22)
Population density			3.4	−86.6
			(34.3)	(73.4)
% second homes			−0.89	−3.76
			(1.6)	(2.84)
Boats per household			1.23	4.05
			(2.7)	(4.72)
% tidal fresh salinity			0.037	−0.01
			(0.12)	(0.21)

Table 9 continued

	(1)	(2)	(3)	(4)
% oligohaline salinity			0.030	0.093
			(0.15)	(0.27)
Mean K_D (1996–2008)			−0.013	0.0066
			(0.042)	(0.077)
Covariates interacted with non-waterfront dummy variable				
% coastline water depth ≥1.5 m		−0.058		−0.070
* non-waterfront		(0.17)		(0.10)
Median home value		8.5e−07		1.4e−06
* non-waterfront		(1.0e−06)		(1.1e−06)
% coastline along tributary				−0.16
* non-waterfront				(0.22)
Population density				109*
* non-waterfront				(63.7)
% second homes				3.40
* non-waterfront				(2.59)
Boats per household				−3.29
* non-waterfront m				(3.98)
% tidal fresh salinity				0.055
* non-waterfront				(0.18)
% oligohaline salinity				−0.07
* non-waterfront				(0.23)
Mean K_D (1996–2008)				−0.023
* non-waterfront				(0.071)
Specification variables				
3-year average water clarity	−0.045*	−0.046*	−0.046*	−0.049*
	(0.027)	(0.026)	(0.027)	(0.026)
Double log model	3.7e−05	−0.0026	−0.00062	−0.0082
	(0.012)	(0.0092)	(0.012)	(0.0061)
3-year average water clarity	0.053**	0.053**	0.053**	0.052**
* non-waterfront	(0.021)	(0.021)	(0.021)	(0.021)
Double log model	0.00044	0.0032	0.0011	0.0089
* non-waterfront	(0.012)	(0.0092)	(0.012)	(0.0065)
Constant	−0.0238	0.061	0.088	0.19
	(0.032)	(0.098)	(0.086)	(0.23)
Log pseudolikelihood	138.25	139.63	141.12	150.78
Number of groups = 14				
N = 280				

Standard errors in parentheses
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

housing value, percent of housing units that are second homes, and population density to control for the fact that population and housing values may not be evenly distributed over space and could be correlated with these socioeconomic characteristics. We estimate each equation using a two-parameter beta distribution model that yields predicted values bounded by zero and one (Buis et al. 2003).

Table 8 reports the results from the regressions explaining the percent of block-group housing stock within each distance buffer. As expected, the percent of the block group's land area contained within the relevant distance buffer is positive and highly significant in predicting the percent of housing stock across both equations. Block groups located farther from the water also have less property value in the two distance buffers. Holding geographic variables constant, the results show that block groups with more property value along the waterfront and within 500 m of the water have higher housing values and more second homes. Block groups with lower population density have more waterfront homes, while those with higher population density have more homes within 500 m of the water.

We apply the results from these regressions to DC, Delaware and Virginia to predict the proportion of each block group's housing stock value that falls within each distance buffer, again making the assumption that relationships estimated using the Maryland data are applicable to these nearby states. In addition, we set the predicted percent housing stock in a particular distance buffer equal to zero if the block group contains no land within that distance buffer and alternately, set the percent housing stock equal to one hundred if the entirety of the land area falls within the distance buffer.

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