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Abstract

This study conducts a meta-analysis of the value of water quality in the Chesapeake Bay derived from separate hedonic property value estimates in 14 Maryland counties. The meta-analysis allows us to: 1) investigate heterogeneity of estimates of the value of water clarity across counties based on socioeconomic and ecological factors, 2) understand the implication of econometric specification choices made in the original hedonic equations for benefit estimates, and 3) transfer the benefits out-of-sample to Bayfront counties in Washington, DC, Delaware, Virginia, and four additional counties in Maryland. 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. The results illustrate both the usefulness of meta-analysis and the challenges of benefit transfer even when estimates being transferred represent a common geographic area, environmental attribute, and policy instrument.

Key Words: meta-analysis, benefit transfer, water quality, Chesapeake Bay, hedonic property value analysis

JEL codes: Q51, Q53, Q57

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Explaining Variation in the Value of Chesapeake Bay Water Quality Using Internal Meta-analysis

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. Waterfront and near-waterfront residents are well-positioned to benefit from these ecosystem services, as reflected in property 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 in the Bay watershed, along with fish and shellfish disease and over-harvesting in the Bay waters, degraded water quality in the Bay and its tidal tributaries during much of the 20th century. Since the 1980s, the Chesapeake Bay has been the focus of numerous state and national restoration efforts. Due to limited progress, President Obama issued a 2009 Executive Order calling for coordinated 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).

Walsh et al. (2015) used hedonic property value analysis to estimate the value of water clarity improvements in the Chesapeake Bay from reduced nutrient pollution. They focused on property transactions in 14 Bayfront counties in Maryland; data limitations precluded developing original hedonic estimates in the remaining jurisdictions surrounding the Bay. However, quantifying only the benefits to Maryland residents of improvements in Bay water quality would underestimate the value of cleanup efforts, given that Maryland encompasses only about half of the total property value located near the Bay.

This study conducts a meta-analysis of the value of water quality derived from hedonic estimates in the 14 Maryland counties and a benefit transfer of these values to Bayfront counties in DC, Delaware, Virginia, and four additional counties in Maryland (Figure 1). Meta-analysis involves synthesizing multiple estimates, typically across several studies. In this case, we synthesize the results from the different study areas (i.e., counties) in the Walsh et al. analysis, undertaking an "internal meta-analysis" (Banzhaf and Smith 2007; Kuminoff, Zhang and Rudi 2010). Since the hedonic estimates are derived from similar datasets, using the same methods, it should be easier to isolate the determinants of variation than when the estimates come from different studies.

The meta-analysis allows us to: 1) explain heterogeneity of estimates across counties, 2) understand the implication of econometric specification choices made in the original hedonic equations for benefit estimates, and 3) transfer the benefits out-of-sample. We also investigate the in-sample and out-of-sample predictive power of simpler versus more complex transfer strategies. The results illustrate both the usefulness of meta-analysis and the challenges of benefit transfer even when estimates being transferred represent a common valuation measure, geographic area, environmental attribute, and policy instrument.

The meta-analysis, benefit transfer, and calculation of total property value impacts from improvements in water clarity involve several steps, covered in the sections below. First, we briefly discuss the use of meta-analysis for benefit transfer in the environmental economics literature. We summarize the methods and results from the Walsh et al. hedonic property value study, which provides the primary estimates used in this analysis. We then use meta-analysis to derive appropriate summary statistics for the elasticity of house prices with respect to light attenuation (K_D) from the hedonic regressions in 14 Maryland counties. These summary statistics provide a relatively simple estimate of how the elasticities change by distance buffer, give insight into how far beyond the waterfront to calculate benefits from improvements in water clarity, and provide point estimates for use in a unit value benefit transfer approach.

Next, we estimate a series of meta-regressions to explain the heterogeneity in property value impacts across counties. The parameter estimates from the meta-regressions allow us to conduct a benefit function transfer, which is a more complex transfer approach that accounts for variation in socioeconomic and environmental conditions throughout the Chesapeake Bay.[1] We also use the meta-regressions to examine the effect of econometric specification choices on the hedonic estimates. We then discuss the meta-regression results and calculate measures of transfer error. Finally, we sum the property value impacts from the 14 Maryland hedonic counties together with the benefit transfer results from Virginia, Delaware, DC, and the four additional Maryland counties to estimate the total appreciation in home values expected to result from improvements in water quality due to reduced pollution runoff. We find that the aggregate increase in home values for near-waterfront properties from a ten percent improvement in Bay clarity varies from about \$410 million to \$750 million, depending on the specification choice and benefit transfer approach.

Previous Meta-Analysis and Benefit Transfer Applications

[1] For additional information on the differences between unit value transfer and benefit function transfer, see EPA (2010a).

There have been numerous meta-analyses conducted in the environmental economic literature, including applications to air pollution, water quality, endangered species and biodiversity, recreational values, 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). However, a recent working paper included estimates from hedonic property value, travel cost, and stated preference studies (Ge et al. 2013). Several meta-analyses have also 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; and Mazzotta et al. 2014).

Despite the extensive use of meta-analytic methods in the environmental economics literature, Nelson and Kennedy note several common issues plaguing studies, including sample collection, data and treatment heterogeneity, and dependence among observations (multiple estimates) 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.

A major issue with any benefit transfer exercise is the need for 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 expected magnitude of the environmental change, and socioeconomic characteristics of the populations (EPA 2010a). If multiple original studies are used to develop the estimates, as is often the case with meta-analyses, consistency among the studies is also important. Ideally, the studies should use common outcome variables (usually measures of willingness to pay) and valuation methods, though analysts can adjust estimates *ex post* to account for conceptual and methodological heterogeneity (Smith and Pattanayak 2002, Bergstrom and Taylor 2006).

The meta-analysis and benefit transfer conducted here avoids many of these issues. In our study, the original empirical estimates and the target area for benefit transfer focus on the same environmental amenity, region, and policy change—the improvement in water clarity in the Chesapeake Bay resulting from pollution reduction efforts, such as the TMDL. The states directly bordering the Chesapeake and tidal tributaries all fall within the mid-Atlantic region of the US and share similar socioeconomic and locational characteristics. The analyses also employ the same data sources and methods. This methodological homogeneity ensures consistency in the welfare measure derived from the estimated change in property values, which is grounded in the hedonic property model (Rosen 1974).[2]

Property Value Impacts from Chesapeake Bay Cleanup 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 fourteen 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, socioeconomic, and other factors that influence a home's value.

[2] The measure of interest in this study is the price elasticity 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.

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). 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 "one-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 three years as a longer-term indicator of water clarity (termed "three-year average K_D").

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 quality 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 to 500; 500 to 1,000; 1,000 to 1,500; or 1,500 to 2,000 meters from the Bay. Interacting these terms with $\ln(WQ_{it})$ 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:

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

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 county to approximate separate real estate markets.

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 house prices with respect to one-year average K_D. The authors also considered three other specifications for the water clarity term: the log of three-year average K_D mentioned above, as well as one-year and three-year average K_D entered linearly in a semi-log hedonic functional form.

Figure 2 displays the pattern of the regression results across counties for the waterfront, 0-500m, and 500-1000m buffers for one illustrative specification—the log of one-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 with a p-value less than 0.10. Since K_D is inversely related to water clarity, a negative coefficient is expected and indicates that house prices decline as light attenuation increases. None of the positive waterfront coefficients are significant. Among the seven counties with significant coefficients, the estimates range from -0.033 to -0.156. In this model, the coefficients can be interpreted as elasticities, so a ten percent decrease in one-year average K_D (an improvement in clarity) yields a 0.33 to 1.56 percent increase in waterfront home values across these counties. For non-waterfront homes within 0 to 500 meters 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 estimates are positive but insignificant in four counties. 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 meter 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 at farther distances 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 quality are qualitatively similar.

Meta-analytic Summary Statistics

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 meters (m), 500 to 1000m, 1000 to 1500m, and 1500 to 2000m of the shore. 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 summary statistics using the Walsh et al. (2015) coefficient estimates for four alternate measures of water clarity: logged and linear one-year average K_D and logged and linear three-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 i^{th} county.[3] The significance levels are calculated using the average variance across the elasticity estimates.

As discussed by Nelson and Kennedy (2009), Borenstein et al. (2009), 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. However, 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 across all study areas, then the true unobserved elasticity is the same in all counties, and 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 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. This would point to the need for a Random Effect-Size (RES) model, reflecting both within-study and between-study variance.[4]

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 of

[3] 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.

[4] 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.

the 14 observations in any distance buffer is weighted by the inverse variance of the estimate. The variance of this mean FES elasticity is calculated as $V_{FES} = \frac{1}{\sum_{i=1}^{14} W_{FES,i}}$. In the FES setting, the weighted mean only accounts for within-study variance, which is appropriate if all estimates are drawn from the same distribution. The FES mean is interpreted as an estimate of the single true elasticity, assumed to be the same across all counties.

On the other hand, the RES meta-analysis model is built on the assumption that the true elasticity varies across counties. Such variation could be due to differences in preferences and income of local populations, the local housing markets, and the nature of the Bay and its features in a county. The RES weighted means presented in Table 1 are calculated as:

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

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, which are allowed to vary across counties. 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 one-year light attenuation leads to a statistically significant appreciation of about 0.6 percent, and the effect size is roughly doubled when the three-year clarity measure is used. The price gradient also appears to extend beyond waterfront properties, with home price increases of roughly 0.1 percent for a ten percent improvement in one-year or three-year light attenuation for non-bayfront homes extending out to 500 meters. (A ten percent improvement in light attenuation translates to approximately a two to four inch increase in water clarity on average, depending on the county.) There is no consistently statistically significant effect on home prices beyond 500 meters in the FES and RES weighted means, and no statistically significant effect beyond 1000 meters in the unweighted means for either the one-year or three-year clarity measures. Recent hedonic property value literature has found some home price appreciation from increases in water quality extending out beyond the waterfront to a similar distance (Walsh, Milon et al. 2011).

While all three sets of summary statistics produce consistent results out to 500 meters, 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 elasticity of K_D. We test the hypothesis of homogeneity of estimates across the 14 counties jointly 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 means the most appropriate summary of the data.

The RES mean elasticities could be used as point estimates in a benefit transfer using a unit value 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 latter approach is known as a function transfer and is often considered superior to a simpler unit value transfer. We estimate the function that we would transfer in the next section using meta-regression and then contrast it with a unit value transfer later in the paper.

Meta-Regression Approach

Statistically significant heterogeneity among the county-level estimates from the initial 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 try 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

$$\gamma_{ids} = \alpha_0 + L_i\alpha_1 + D_d\alpha_2 + D_s\alpha_3 + \varepsilon_{ids} \qquad (6)$$

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 econometric 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, Zhang and Rudi 2010). In particular, we examine the effect of a semi-log versus double-log functional form and using a one-year versus three-year average water quality. In equation (6), each county i at distance d has $S = 4$ elasticity estimates, each derived from a different specification of the hedonic model. D_s is a vector of dummy variables representing these different specifications.

We use the RES meta-regression model to estimate (6) (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 initial 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).[5]

[5] 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 component 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 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 AM-2. The results are extremely similar across the RES and panel data estimators.

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, 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 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 meters deep, and mean spring-summer K_D during the study period.

We rely on the 2000 US Census for data on housing values and other socioeconomic characteristics.[6] The Census block group is the finest level of disaggregation for which data are

[6] 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.

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 meters of the Chesapeake Bay, which are used to approximate the spatial extent of the study area.

As in the original hedonic analysis by Walsh et al. (2015), we use historic data on the light attenuation coefficient (K_D) provided by the EPA's Chesapeake Bay Program. Figure 3 shows average spring-summer K_D over 1996-2008, illustrating how water clarity varies over space. Within counties, there is substantial variation in light attenuation between Bay segments.

Meta-Regression Results

Table 3 presents the results of the RES meta-regressions. Models (1) through (6) 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), (4), and (6) 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. As shown in the lower portion of the tables, 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 (6).

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 meters 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 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.)

Model (3) is similar to Model (1), but it includes population density and the percent of the coastline that borders a tidal tributary rather than the main stem of the Bay as additional covariates. The results indicate that water clarity is more important for properties located along the tributaries and in areas with lower population density. Model (4), which includes non-waterfront interaction terms, suggests that these effects vary significantly depending on whether the property is located at the waterfront.

Model (5) adds several more covariates, including 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 $K_{D.}$ Only the water depth and median home value variables remain statistically significant in this model, and the adjusted R-squared is no higher than that for Model (3), suggesting that the additional covariates do not help explain variation in the elasticity of K_D. This is at least in part due to collinearity with the covariates in Model (3).[7] However, when the non-waterfront interaction terms for these variables are included in Model (6), the explanatory power of the model jumps considerably. Model (6) indicates that water clarity is more important in areas with 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 econometric specification variables, results across all six models indicate that the use of the double-log rather than the semi-log model has no significant effect on the elasticity of K_D for either waterfront or non-waterfront homes. Measuring water clarity using three-year average water quality yields a significantly larger effect on home values than the one-year average water quality measure and almost doubles the elasticity of K_D, though this relationship holds for waterfront homes only. This result suggests that waterfront homebuyers may be more aware of and concerned about longer term trends in water quality rather than short-term fluctuations. Alternatively, it could be that the three-year measure is more susceptible to biases from other unobserved local trends in housing

[7] These five covariates all had variance inflation factors greater than ten, justifying their exclusion from Models (1) through (4).

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, although the different point estimates could lead to different policy implications (Michael, Boyle, and Bouchard 2000).

Next we calculate measures of internal and external validity to determine which meta-regression model(s) might be most appropriate for transferring benefits outside of the 14 Maryland hedonic counties, following an approach similar to Stapler and Johnston (2009), Lindhjem and Navrud (2008), and Bateman et al. (2011). We compare the six meta-regression models presented in **Error! Reference source not found.**, 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 absolue 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 counties.[8] As a measure of external (out-of-sample) transfer error, we calculate a similar measure for each model by 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 counties. Both types of transfer error are calculated for the double log one-year and three-year average water quality elasticities for both the waterfront and 0-500m (non-waterfront) distance buffers. (We do not examine

[8] We use the absolute difference (rather than percent difference) as the measure of transfer error here 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.

transfer error for the semi-log models because the meta-regression results were not statistically different from the double log model results.)

The results in Table 4 show that the three-year average water quality measure always yields a higher absolute transfer error compared to the one-year measure (when comparing within a model and distance buffer). This holds across all models, for both in-sample and out-of-sample transfer errors, and for both waterfront and non-waterfront homes. While a longer-run average may better reflect steady-state changes in water quality likely to occur in response to long-term policies, this finding suggests that measures spanning broader temporal windows could potentially be picking up other unobserved local trends.

Table 1 also shows that the use of a meta-regression model incorporating socioeconomic and ecological covariates can improve in-sample forecasting performance. When using one-year average clarity, Models (1), (2), and (4) generate lower transfer errors than the RES mean when predicting the waterfront elasticity of K_D. However, Models (3), (5), and (6), which are among the more complex meta-regressions, yield comparable or higher transfer errors for the waterfront elasticity than the RES mean value transfer. All regression models using one-year average K_D perform poorly compared to the RES mean for the non-waterfront 0-500 m distance buffer elasticity. When using three-year average K_D, the meta-regression predicted values outperform the RES means across all models and both distance buffers.

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 0-500m distance buffers increase substantially with more complex regression models. In fact, only Model (1) outperforms the RES mean in predicting the waterfront elasticity for counties out of sample using both the one-year and three-year clarity measures. None of the meta-regression models outperform the RES mean for the one-year average K_D non-waterfront elasticity, although Models (1)-(4) yield lower transfer errors when using three-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.

Calculation of Benefits

In this section, we estimate the projected property value impacts of a ten percent improvement in water clarity 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 meters of the waterfront in these counties. We focus on calculating changes in home values within 500 meters of the Bay 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 benefits 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 coefficients from the hedonic equations is appropriate for this application because a ten percent change in mean water quality (corresponding to a two to four inch increase in water clarity) is well within the range of variation in the historic data.

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 0-500m, and a benefit 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 one-year and three-year average water quality specifications to calculate the value of improved water clarity to property owners. As already noted, the meta-regression model shows that the choice of a semi-log versus a double log specification has no significant effect on the results.

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

$$\Delta V_{icd} = \gamma_{cd} * \%\Delta WQ_i * V_{icd} \tag{7}$$

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*.[9] The data on assessed property values, which were available for the year 2009, were adjusted to 2010 values using the Federal Housing Finance Agency's Housing Price Index (HPI), which accounts for regional differences in appreciation in home prices over time.[10]

Table 2 shows that homes within 500 meters of the Bay are estimated to increase by $1397, on average, in response to a ten percent improvement in one-year water clarity. As expected, a much larger increase in value is expected at waterfront homes, amounting to an average of $6098 per home; non-waterfront homes within 500 meters of the water appreciate by $389. This difference occurs because waterfront homes both have 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 the adjusted average assessed value of non-waterfront homes within the 500-meter buffer of $ 234,684.) When the three-year water clarity measure is used, the results are roughly double: a $12,709 average increase for waterfront homes, and a $520 increase for non-waterfront homes within 500 meters of the water.

To calculate total benefits across these 14 counties, we sum the estimated house-specific price increases across all homes within the 500 meter and waterfront buffers. Table 7 presents these aggregated property value increases and 95 percent confidence intervals, based on both the one-year and three-year water clarity models. The aggregate increase in home values among these properties is $238 million using the one-year measure and is $456 million using the three-

[9] We apply the estimated elastiticites (and corresponding 95 percent 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.
[10] Federal Housing Finance Agency (FHFA), http://www.fhfa.gov/Default.aspx?Page=81, accessed January 13, 2013.

year measure. More than three-quarters of the increase accrues to waterfront properties, even though they make up only 18 percent of homes within 500 meters of the Bay.

A similar approach is used to calculate benefits in Virginia, Delaware, the District of Columbia, and the four additional counties in Maryland. Similar to expression (7) above, we calculate

$$\Delta \sum_{i}^{N} V_{icd} = \hat{\gamma}_{cd} * \sum_{i}^{N} \left(\% \Delta WQ_i * V_{icd} \right) \tag{8}$$

Here $\sum_i^N V_{icd}$ represents *total* housing stock value of all *N* homes within 500 meters 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*.[11]

For Baltimore City, Caroline County, Montgomery County, and Worcester County, 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. According to the HPI, depending on the metropolitan area home prices increased between 57 and 91 percent in the counties surrounding the Chesapeake Bay between 2000 and 2010.[12] 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

[11] Block groups in Virginia, Delaware, and DC, were matched to the single nearest grid cell to determine the change in water clarity rather than the two nearest grid cells.

[12] 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.

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 second approach uses a function transfer to estimate $\hat{\gamma}_{cd}$ for benefit transfer counties. Specifically, we use the coefficient estimates from the meta-regression models shown 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.

Table 6 compares the elasticities generated by the unit value approach, which are the same for all counties, with the mean elasticities yielded by the six meta-regression models for each state in the benefit transfer region using the one-year average K_D measure. It is apparent that the results are more variable across states and are larger in absolute value (seeming at times implausible) when the more complex meta-regression model results are used. When using the less complex models, the average results for DC, Delaware, and Virginia are roughly similar in magnitude to the RES means. The four Maryland benefit transfer counties pose an exception in that the meta-regression results for the 0-500m buffer across all six meta-regression models are counterintuitive in sign. These results are dominated 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). For the subsequent benefit transfer calculations, we use the results from Model (1) because it has the lowest out-of-sample transfer error.

Table 7 presents the benefit transfer results using the unit value and function transfer approaches from 10 percent improvements in one-year and three-year average K_D. The results show that the majority of property value increases in the benefit transfer areas occur in Virginia, regardless of the transfer approach. The unit value and function transfer approaches yield similar results for Delaware. However, the function transfer, which projects the elasticity of K_D based on median property values and water depth, generates substantially larger benefits for DC than the unit value approach because of DC's relatively high property values. In the four Maryland benefit transfer counties, the function transfer yields negative benefits (i.e., projected depreciation in home values) consistent with the predicted elasticities discussed above, again because Baltimore City, where a much larger proportion of the shoreline borders relatively deep water than in any of the 14 Maryland hedonic counties comprises most of the property value in the area.

Summing the results from the hedonic and benefit transfer areas yields a total net present value increase in property values of $411 to $749 million, depending on the benefit transfer approach and the temporal duration of the water clarity measure. The 95 percent confidence intervals around these point estimates are overlapping but are also fairly wide: $121 to $759 million and $210 to $1286 million, respectively. In particular, while the three-year average clarity values are considerably larger than the one-year clarity values, they also have a wider confidence interval, indicating that they are less robust.

The result that benefits 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 percent of owner-occupied property value in Census block groups within 500 meters 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 60 percent of the property value increase.

Conclusions

This study conducts an internal meta-analysis of results from the largest hedonic property value study of water quality conducted to date, which focused on Maryland counties bordering the Chesapeake Bay. Our approach allows us to examine the sources of variation in the estimated value of water quality across Maryland counties and to transfer those values to other states and counties bordering the Chesapeake tidal waters. The results can be useful to analysts, policymakers, and members of the public interested in evaluating the benefits to near-waterfront property owners of Bay pollution cleanup efforts such as the TMDL.

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. Including additional socioeconomic and ecological variables in the regression worsens its out-of-sample predictive power. Indeed, 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.

The comparison across water quality specifications shows that the functional form (semi-log versus double log) has negligible impacts on estimates of the value of water clarity. However, the duration of the water quality measure has impacts that are significant both statistically and economically: the estimated value of three-year average water clarity is roughly double the estimated value of one-year average water clarity for waterfront properties, which could indicate that residents are more aware of or concerned about longer term trends in water quality rather than annual variations. The three-year average results have a larger confidence interval and transfer error, however, suggesting that there is greater uncertainty about these estimates.

These results highlight the 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 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.

References

Banzhaf, H. S. and V. K. Smith (2007). "Meta-analysis in model implementation: choice sets and the valuation of air quality improvements." Journal of Applied Econometrics **22**(6): 1013-1031.

Bateman, I., R. Brouwer, S. Ferrini, et al. (2011). "Making benefit transfers work: deriving and testing principles for value transfer for similar and dissimilar sites using a case study of the non-market benefits of water quality improvements across Europe." Environment and Resource Economics 50: 365-387.

Barton, D. N. (2002). "The transferability of benefit transfer: contingent valuation of water quality improvements in Costa Rica." Ecological Economics **42**(1–2): 147-164.

Bergstrom, J. C. and L. O. Taylor (2006). "Using meta-analysis for benefits transfer: Theory and practice." Ecological Economics **60**(2): 351-360.

Borenstein, M., L. V. Hedges, J. P. T. Higgins and H. R. Rothstein (2010). "A basic introduction to fixed-effect and random-effects models for meta-analysis." Research Synthesis Methods **1**(2): 97-111.

Boyle, K., C. Parmeter, B. Boehlert and R. Paterson (2013). "Due Diligence in Meta-analyses to Support Benefit Transfers." Environmental and Resource Economics **55**(3): 357-386.

Buis, M., L., N. Cox, J. and S. Jenkins, P. (2003). BETAFIT: Stata module to fit a two-parameter beta distribution, Boston College Department of Economics.

Debrezion, G., E. Pels and P. Rietveld (2007). "The Impact of Railway Stations on Residential and Commercial Property Value: A Meta-analysis." The Journal of Real Estate Finance and Economics **35**(2): 161-180.

DerSimonian, R. and N. Laird (1986). "Meta-analysis in clinical trials." Controlled Clinical Trials **7**(3): 177-188.

EPA (2006). Regional Benefits Analysis for the Final Section 316(b) Phase III Existing Facilities Rule. Office of Water. Washington, DC.

EPA (2009). Environmental Impact and Benefits Assessment for Final Effluent Guidelines and Standards for the Construction and Development Category. Office of Water. Washington, DC.

EPA (2010a). Guidelines for Preparing Economic Analyses. Office of the Administrator. Washington, DC.

EPA (2010b). Economic Analysis of Final Water Quality Standards for Nutrients for Lakes and Flowing Waters in Florida. Office of Water. Washington, DC.

EPA (2013a). Fact Sheet – Chesapeake Bay: Total Maximum Daily Load (TMDL) http://www.epa.gov/reg3wapd/pdf/pdf_chesbay/BayTMDLFactSheet8_26_13.pdf (accessed Aug. 25, 2015)

EPA (2013b). Benefit and Cost Analysis for the Proposed Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category. Office of Water. Washington, DC.

Ge, J., C. L. Kling and J. A. Herriges (2013). "How Much is Clean Water Worth? Valuing Water Quality Improvement Using A Meta Analysis." Iowa State University Department of Economics Working Paper **13016.**

Harbord, R. M. and J. P. T. Higgins (2008). "Meta-regression in Stata." Stata Journal **8**(4): 493-519.

Harris, R., M. Bradburn, J. Deeks, R. Harbord, D. Altman and J. Sterne (2008). "metan: fixed- and random-effects meta-analysis." Stata Journal **8**(1): 3-28.
Johnston, R. J., E. Y. Besedin, R. Iovanna, C. J. Miller, R. F. Wardwell and M. H. Ranson (2005). "Systematic Variation in Willingness to Pay for Aquatic Resource Improvements and Implications for Benefit Transfer: A Meta-Analysis." Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie **53**(2-3): 221-248.
Johnston, R. J., E. Y. Besedin and R. F. Wardwell (2003). "Modeling relationships between use and nonuse values for surface water quality: A meta-analysis." Water Resources Research **39**(12): 1363.
Johnston, R. J. and J. M. Duke (2010). "Socioeconomic adjustments and choice experiment benefit function transfer: Evaluating the common wisdom." Resource and Energy Economics **32**(3): 421-438.
Johnston, R. J. and R. S. Rosenberger (2010). "METHODS, TRENDS AND CONTROVERSIES IN CONTEMPORARY BENEFIT TRANSFER." Journal of Economic Surveys **24**(3): 479-510.
Johnston, R. J. and P. J. Thomassin (2010). "Willingness to Pay for Water Quality Improvements in the United States and Canada: Considering Possibilities for International Meta-Analysis and Benefit Transfer." Agricultural and Resource Economics Review **39**(1): 114-131.
Kiel, K. A. and M. Williams (2007). "The Impact of Superfund Sites on Local Property Values: Are all Sites the Same?" Journal of Urban Economics **61**: 170-192.
Knight Frank (2014). “A Premium You Can Bank On: Knight Frank Waterfront Index 2014.” Residential Research Report. http://www.knightfrank.co.uk/resources/research/knight-frank-waterfront-index-aug-2014.pdf (accessed Aug. 25, 2015)
Kuminoff, N. V., J. C. Pope (2014). “Do ‘Capitalization Effects’ For Public Goods Reveal the Public’s Willingness to Pay?” International Economic Review **55**(4): 1227-1250.
Kuminoff, N. V., C. Zhang and J. Rudi (2010). "Are Travelers Willing to Pay a Premium to Stay at a “Green” Hotel? Evidence from an Internal Meta-Analysis of Hedonic Price Premia." Agricultural and Resource Economics Review **39**(3): 468 - 484.
LeSage, J. and R. K. Pace (2009). Introduction to Spatial Econometrics. Boca Raton, Florida, Chapman & Hall/CRC Press.
Lindhjem, H. and S. Navrud (2008). "How reliable are meta-analyses for international benefit transfers?" Ecological Economics **66**(2–3): 425-435.
Mazzotta, M., E. Besedin and A. Speers (2014). "A Meta-Analysis of Hedonic Studies to Assess the Property Value Effects of Low Impact Development." Resources **3**(1): 31-61
Messer, K., W. Schulze, K. Hackett, T. Cameron and G. McClelland (2006). "Can Stigma Explain Large Property Value Losses? The Psychology and Economics of Superfund." Environmental and Resource Economics **33**(3): 299-324.
Michael, H. J., K. J. Boyle and R. Bouchard (2000). "Does the Measurement of Environmental Quality Affect Implicit Prices Estimated from Hedonic Models?" Land Economics **76**(2): 283-298.
Nelson, J. P. (2004). "Meta-Analysis of Airport Noise and Hedonic Property Values: Problems and Prospects." Journal of Transport Economics and Policy **38**(1): 1-27.
Nelson, J. P. (2013). Meta-Analysis: Statistical Methods. Benefit Transfer of Environmental and Resources Values. R. Johnston, R. Rosengerger and e. al., Springer.

Nelson, J. P. and P. r. Kennedy (2009). "The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment." Environmental and Resource Economics **42**(3): 345-377.

Rosen, S. (1974). "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." The Journal of Political Economy **82**(1): 34-55.

Smith, V. K. and J. Huang (1995). "Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models." Journal of Political Economy **103**(1): 209-227.

Smith, V. K. and J. Huang (1993). "Hedonic models and air pollution: Twenty-five years and counting." Environmental and Resource Economics **3**(4): 381-394.

Smith, V. K. and S. Pattanayak (2002). "Is Meta-Analysis a Noah's Ark for Non-Market Valuation?" Environmental and Resource Economics **22**(1-2): 271-296.

Stapler, R. and R. Johnston (2009). "Meta-Analysis, Benefit Transfer, and Methodological Covariates: Implications for Transfer Error." Environmental and Resource Economics **42**(2): 227-246.

Van Houtven, G., J. Powers and S. K. Pattanayak (2007). "Valuing water quality improvements in the United States using meta-analysis: Is the glass half-full or half-empty for national policy analysis?" Resource and Energy Economics **29**(3): 206-228.

Walsh, P., C. Griffiths, D. Guignet, and H. Klemick (2015) “Modeling the Property Price Impact of Water Quality in 14 Chesapeake Bay Counties.” NCEE Working Paper, forthcoming.

Walsh, P. J., J. W. Milon and D. O. Scrogin (2011). "The Spatial Extent of Water Quality Benefits in Urban Housing Markets." Land Economics **87**(4): 628-644.

Figure 1: Hedonic and Benefit Transfer Counties

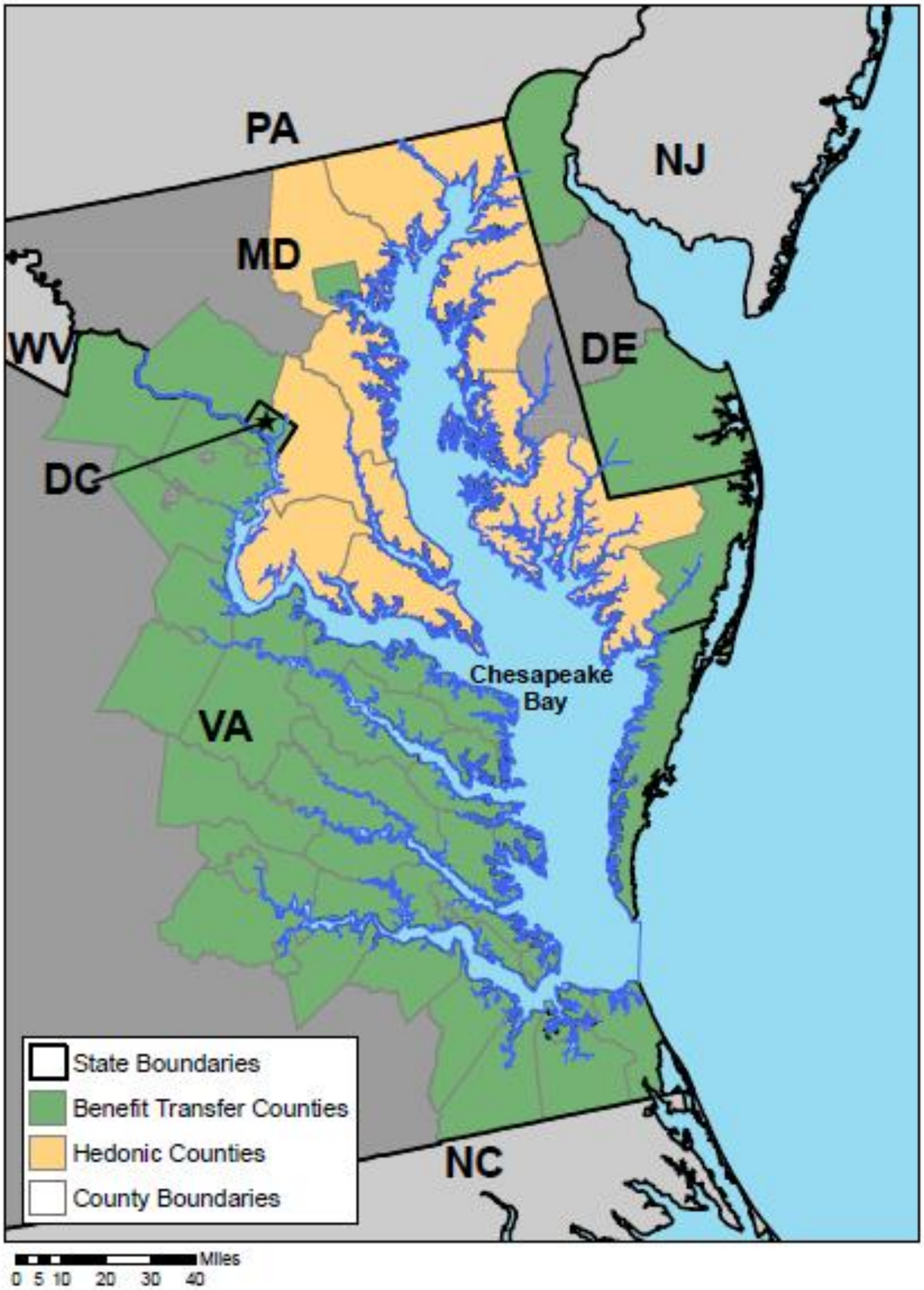

Figure 2a - c: K_D Elasticity Values and Statistical Significance by County

Waterfront buffer (a) **0-500m buffer (b)** **500-1000m buffer (c)**

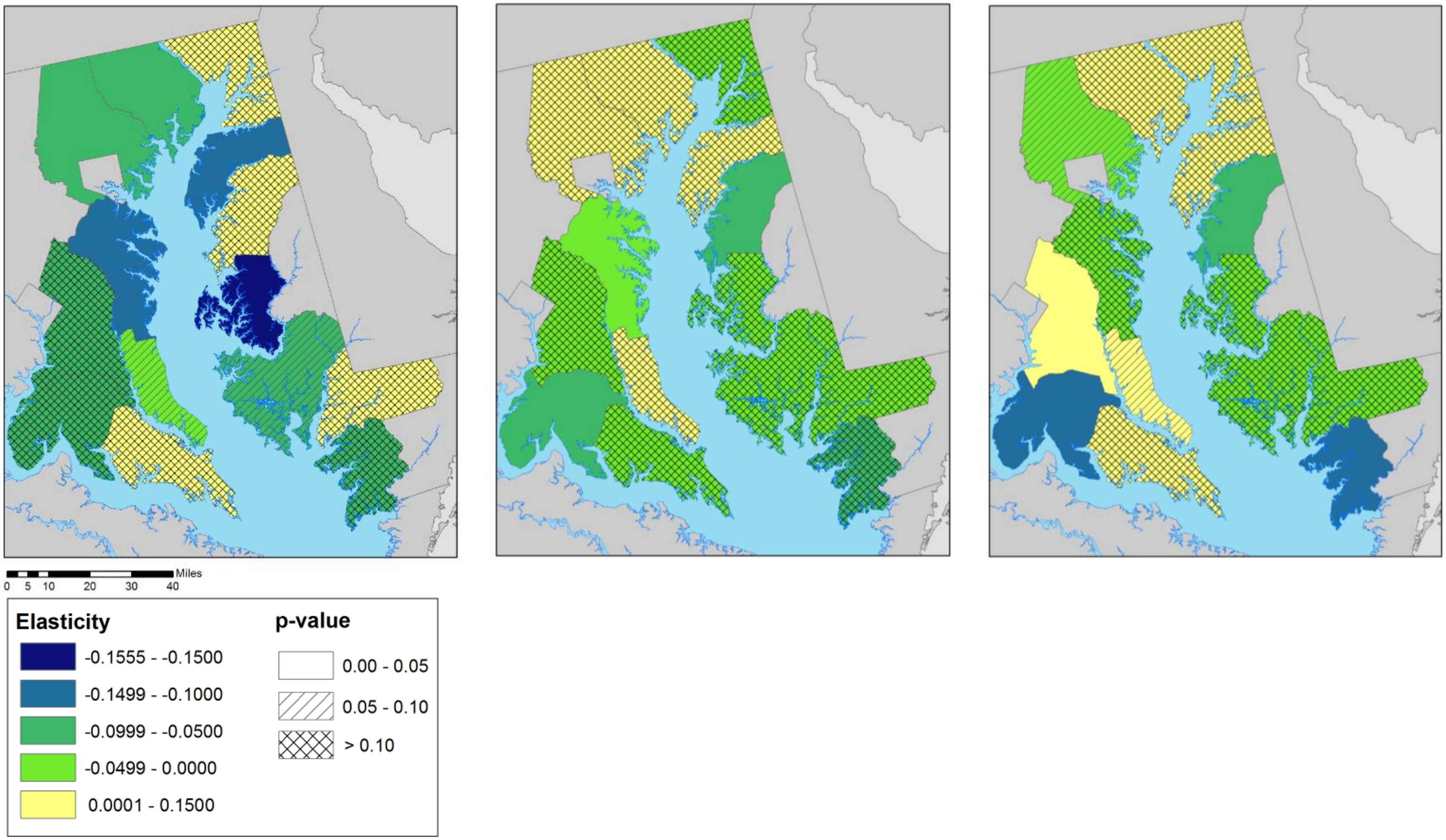

Figure 3: Chesapeake Bay Spring-Summer Average Light Attenuation (K_D), 1996-2008

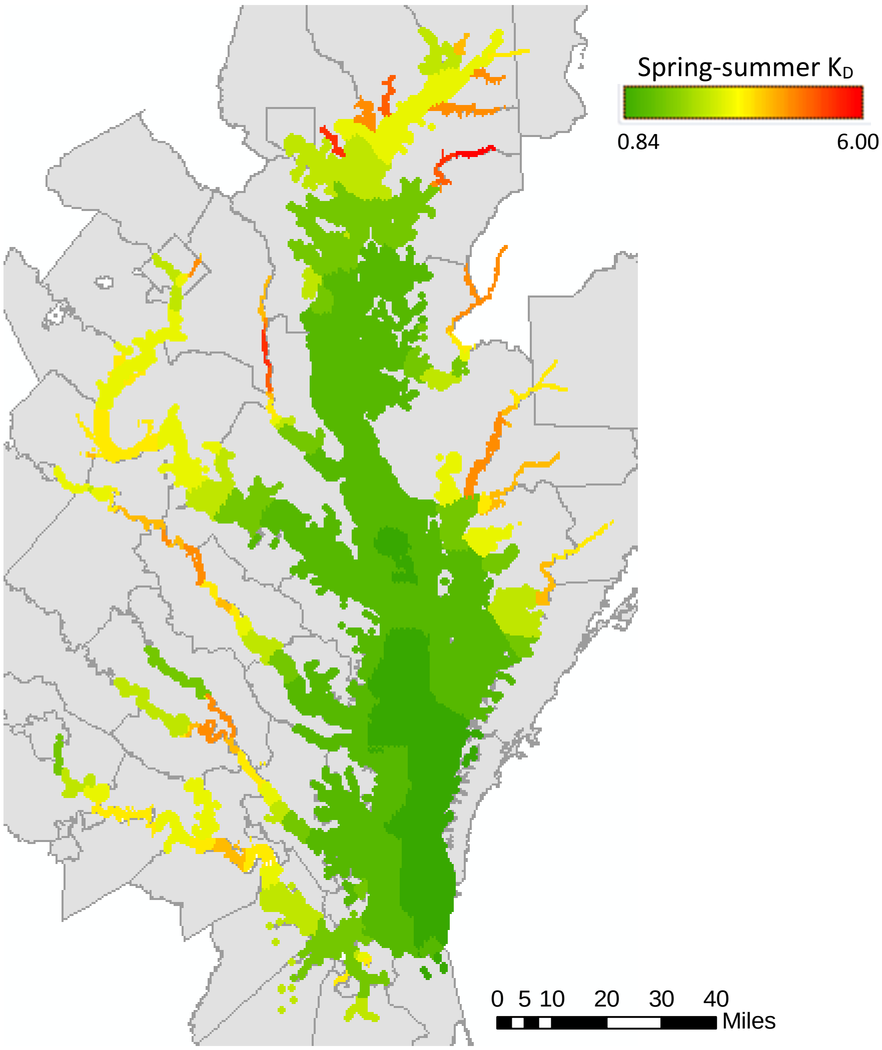

Table 1. Mean K_D Elasticities for Properties within 2,000 m of the Bay across 14 Maryland Counties

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

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

Table 2: Chesapeake Bay Region Characteristics by State: Benefit Transfer and Hedonic Study Areas

	Benefit transfer area				Primary study area
	Delaware	**District of Columbia**	**Virginia**	**Maryland**	**Maryland**
*Socioeconomic characteristics**					
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
Number of counties	2	1	44	4	14

*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 meters 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Socioeconomic & ecological covariates						
Non-waterfront distance buffer	0.041**	-0.063	0.041**	-0.0022	0.041**	-0.098
	(0.018)	(0.046)	(0.018)	(0.066)	(0.018)	(0.12)
≥ 500 m distance buffer	0.0088	0.0087	0.0079	0.0075	0.0079	0.0085
	(0.0095)	(0.0094)	(0.0092)	(0.0086)	(0.0092)	(0.0079)
% coastline water depth ≥	0.13***	0.18***	0.19***	0.12**	0.23***	0.28***
1.5 m	(0.020)	(0.048)	(0.024)	(0.053)	(0.042)	(0.087)
Median home value	-5.7e-7***	-1.3e-6***	-7.1e-7***	-1.3e-6***	-1.1e-6***	-2.2e-6***
	(1.3e-7)	(3.0e-7)	(1.37e-7)	(3.1e-7)	(3.1e-7)	(6.2e-7)
% coastline along tributary			-0.086***	0.050	-0.052	0.099
			(0.022)	(0.054)	(0.049)	(0.11)
Population density			15.8***	-31.8***	4.6	-97.6***
			(5.2)	(11.6)	(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						
Water depth ≥ 1.5 m		-0.057		0.078		-0.083
* non-waterfront		(0.053)		(0.059)		(0.096)
Median home value		8.5e-7**		7.1e-7**		1.5e-6**
* non-waterfront		(3.4e-7)		(3.4e-7)		(6.9e-7)
% coastline along tributary				-0.16***		-0.19*
* non-waterfront				(0.058)		(0.12)
Population density				57.5***		123***
* non-waterfront				(12.8)		(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)
Mean K_D (1996-2008)						-0.017
* non-waterfront						(0.044)
Specification variables						
3-year average water quality	-0.046**	-0.047**	-0.046***	-0.041**	-0.047***	-0.043***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.016)
Double log model	-0.0010	-0.0032	-0.00083	-0.0012	-0.0016	-0.008

	(0.0181)	(0.018)	(0.018)	(0.017)	(0.018)	(0.016)
3-year average water quality	0.056***	0.056***	0.053***	0.047**	0.055***	0.048***
* non-waterfront	(0.020)	(0.020)	(0.019)	(0.018)	(0.020)	(0.018)
Double log model	0.0015	0.0039	0.0012	0.0018	0.0019	0.0089
* non-waterfront	(0.020)	(0.020)	(0.019)	(0.018)	(0.019)	(0.017)
Constant	-0.018	0.067	0.039	0.071	0.087*	0.19*
	(0.023)	(0.041)	(0.029)	(0.061)	(0.051)	(0.11)
Adjusted R-squared	0.39	0.40	0.44	0.55	0.44	0.68
Observations	280	280	280	280	280	280

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

Table 1: Internal and External Absolute Transfer Error across Meta-Analysis Models of 14 Maryland Counties

	RES	Meta-regression model					
	mean	(1)	(2)	(3)	(4)	(5)	(6)
1-year average log K_D							
In-sample transfer error							
Waterfront	0.051	0.046	0.047	0.053	0.046	0.051	0.053
0-500m (non-waterfront)	0.018	0.024	0.023	0.021	0.021	0.025	0.022
Out-of-sample transfer error							
Waterfront	0.055	0.053	0.069	0.067	0.084	0.129	0.304
0-500m (non-waterfront)	0.019	0.026	0.027	0.028	0.026	0.106	0.080
3-year average log K_D							
In-sample transfer error							
Waterfront	0.125	0.116	0.110	0.121	0.111	0.120	0.100
0-500m (non-waterfront)	0.052	0.036	0.039	0.037	0.041	0.039	0.042
Out-of-sample transfer error							
Waterfront	0.135	0.127	0.136	0.137	0.155	0.179	0.348
0-500m (non-waterfront)	0.056	0.040	0.043	0.046	0.048	0.115	0.087

Table 2: Net Present Value Mean Home Price Increases for Near-waterfront Residential Properties in 14 Maryland Hedonic Counties from 10 Percent Water Clarity Improvement

Distance from Bay	**Mean home price increase (2010\$) - 1-year K_D**	**Mean home price increase (2010\$) – 3-year K_D**	**Number of properties**
Waterfront	\$6,098	\$12,709	30,113
0-500m (non-waterfront)	\$389	\$520	140,332
All homes within 500m	\$1,397	\$2,674	170,445

Table 6: Weighted mean predicted elasticities in benefit transfer counties, by state* (1-year K_D)

		RES mean	(1)	(2)	(3)	(4)	(5)	(6)
Delaware	Waterfront	-0.06	-0.05	-0.05	-0.07	-0.03	-0.03	0.20
	0-500m	-0.01	-0.01	-0.01	-0.03	-0.05	0.01	-0.04
DC	Waterfront	-0.06	-0.08	-0.11	-0.05	-0.21	-0.08	-0.49
	0-500m	-0.01	-0.04	-0.03	-0.00	0.03	-0.03	0.05
Virginia	Waterfront	-0.06	-0.06	-0.07	-0.06	-0.08	-0.06	-0.16
	0-500m	-0.01	-0.02	-0.02	-0.01	-0.00	-0.01	0.01
Maryland (4 counties)	Waterfront	-0.06	-0.07	-0.09	-0.07	-0.12	-0.07	-0.16
	0-500m	-0.01	0.08	0.07	0.16	0.19	0.17	0.20

*Predicted elasticities are weighted by the value of the housing stock in each county and distance buffer.

Table 7: Property Value Increases from Ten Percent Water Clarity Improvement

	Aggregate home price increase, 1-year K_D (million 2010$) (95% confidence interval*)		**Aggregate home price increase, 3-year K_D (million 2010$) (95% confidence interval*)**	
<u>Hedonic study area</u>				
Maryland (14 counties)	$238 ($58-419)		$456 ($203-708)	
<u>Benefit transfer area</u>	<u>Unit value transfer</u>	<u>Function transfer</u>	<u>Unit value transfer</u>	<u>Function transfer</u>
Delaware	$3 ($1 - $4)	$2 ($1 - $4)	$5 ($1 - $8)	$3 ($1 – 5)
DC	$9 ($3 - $16)	$18 ($9 - $27)	$15 (-$1 - $31)	$20 ($11 - $29)
Virginia	$157 ($57 - $258)	$181 ($42 - $320)	$269 ($12 - $526)	$246 ($105 - $386)
Maryland (4 counties)	$4 ($2 - $8)	-$24 (-$37 - -$11)	$4 (-$5 - $13)	-$26 (-$40 - -$13)
Total	$411 ($121 - $705)	$415 ($73 - $759)	$749 ($210 - $1,286)	$699 ($280 - $1,115)

*Note: The confidence interval only accounts for uncertainty in the predicted elasticity of K_D. It does not account for uncertainty in baseline property values.

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 house 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 percent (in Delaware) to 60 percent (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:

$$\sum_{i}^{n_i+n_2} V_{i,2010} = \beta_1 \sum^{n_1} V_{i,2010} + \beta_2 n_2 \overline{v}_{2010} + \varepsilon_b \qquad (1)$$

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. $\overline{v}_{2010}$ 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 A-1 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 to 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 meters 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 meters (as a proxy for waterfront area) and 500 meters of the waterfront, and the distance of the block group to the Bay (all calculated using GIS tools). We also include the median 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 A-2 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 meters 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 meters 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.

Table A-1: Total assessed housing value in Maryland block groups (MDPV), OLS regression

	Total assessed housing value (MDPV)
Total owner-occupied housing value (U.S. Census)	0.87***
	(0.014)
Average owner-occupied housing value x number of non-owner-occupied units (U.S. Census)	0.12***
	(0.028)
Observations	1,214
R-squared	0.85
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1	

Table A-2: **Percent Census block group housing value within each Bay distance buffer, two-parameter beta distribution model**

	Bayfront	0-500m (non-waterfront)
% land area within 50 meters of Bay	4.6***	-0.57
	(0.95)	(1.3)
% land area within 500 meters 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 A-3: Random effects panel data estimation (dependent variable: elasticity of K_D from hedonic regressions)

	(1)	(2)	(3)	(4)	(5)	(6)
Socioeconomic & ecological covariates						
Non-waterfront distance buffer	0.042**	-0.06	0.042**	-0.0036	0.041**	-0.089
	(0.019)	(0.10)	(0.019)	(0.14)	(0.019)	(0.23)
Distance from shore ≥ 500 m	0.0087	0.008	0.0082	0.0070	0.0083	0.0072
	(0.0086)	(0.0087	(0.0089)	(0.0089)	(0.0087)	(0.0086)
Water depth ≥ 1.5 m	0.13***	0.18	0.19***	0.13	0.23**	0.30**
	(0.042)	(0.17)	(0.06)	(0.17)	(0.096)	(0.15)
Median home value	-5.4e-07**	-1.2e-06	-7.00e-07**	-1.3e-06	-1.1e-06*	-2.2e-06*
	(2.6e-07)	(1.0e-06)	(2.7e-07)	(9.3e-07)	(6.5e-07)	(1.2e-06)
% coastline along tributary			-0.086*	0.046	-0.047	0.087
			(0.050)	(0.12)	(0.12)	(0.22)
Population density			16.5	-29.1	3.4	-86.6
			(12.2)	(22.2)	(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)
% 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						
Water depth ≥ 1.5 m		-0.058		0.071		-0.070
* non-waterfront		(0.17)		(0.16)		(0.10)
Median home value		8.5e-07		7.2e-07		1.4e-06
* non-waterfront		(1.0e-06)		(8.9e-07)		(1.1e-06)
% coastline along tributary				-0.16		-0.16
* non-waterfront				(0.12)		(0.22)
Population density				56.1***		109*
* non-waterfront				(21.7)		(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 quality	-0.045*	-0.046*	-0.045*	-0.042	-0.046*	-0.049*
	(0.027)	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)
Double log model	3.7e-05	-0.0026	-2.8e-05	-0.0015	-0.00062	-0.0082

	(0.012)	(0.0092)	(0.012)	(0.0092)	(0.012)	(0.0061)
3-year average water quality	0.053**	0.053**	0.052**	0.048**	0.053**	0.052**
* non-waterfront	(0.021)	(0.021)	(0.02`)	(0.021)	(0.021)	(0.021)
Double log model	0.00044	0.0032	0.00046	0.0020	0.0011	0.0089
* non-waterfront	(0.012)	(0.0092)	(0.012)	(0.0092)	(0.012)	(0.0065)
Constant	-0.0238	0.061	0.036	0.069	0.088	0.19
	(0.032)	(0.098)	(0.051)	(0.15)	(0.086)	(0.23)
Log pseudolikelihood	138.25	139.63	140.29	145.46	141.12	150.78
Number of groups	14	14	14	14	14	14
Observations	280	280	280	280	280	280

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