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ABSTRACT: We conduct a comprehensive meta-analysis of 36 studies that examine the effects of water quality on housing values in the United States. The meta-dataset includes 656 unique estimates, and entails a cluster structure that accounts for property price effects at different distances from a waterbody. Focusing on water clarity, we estimate meta-regressions that account for within-cluster dependence, statistical precision, housing market and waterbody heterogeneity, publication bias, and best methodological practices. While we find evidence of systematic heterogeneity, the median out-of-sample transfer errors are relatively large. We discuss the implications for benefit transfer and identify future work to improve transfer performance.

1. INTRODUCTION

The hedonic literature examining the impacts of surface water quality on residential property values began over 50 years ago with David's (1968) report. Since then this literature has evolved significantly. To assess this literature's aptness for supporting water quality decisions, we use meta-analytic methods to synthesize and draw key conclusions from 36 unique studies in the United States (US). There are several existing meta-analyses of hedonic property value studies, including applications to air quality (Smith and Huang, 1993, 1995), contaminated sites (Messer et al., 2006; Kiel and Williams, 2007), open space (Mazzotta et al., 2014), and noise (Nelson, 2004). However, to our knowledge this study is the first comprehensive and rigorous meta-analysis of the hedonic literature examining surface water quality.[1]

The results from meta-analyses can help make predictions for benefit transfer – where an analyst uses the predicted outcomes to infer *ex ante* or *ex post* impacts of some policy action, in lieu of conducting a new original study. Benefit analyses of public policies often rely on benefit transfer because original studies require a lot of time and money, or are infeasible due to data constraints. In fact, benefit transfer is one of the most common approaches used to complete benefit-cost analyses at the US Environmental Protection Agency (US EPA, 2010; Newbold et al. 2018). Improving benefit transfer, as well as combining limited, but heterogeneous, information for surface water quality changes, remains a priority for policy makers (Newbold et al., 2018).

Addressing this priority, our study aggregates this literature and systematically calculates comparable within- and cross-study elasticity estimates by accounting for differences in functional forms, assumed price-distance gradients, and baseline conditions. We convert the primary study coefficient estimates to common elasticity and semi-elasticity measures for both waterfront and near-waterfront homes, and use Monte Carlo simulations to estimate the corresponding standard errors. Each study yields numerous meta-observations due to multiple study areas, water quality metrics, and model specifications, leading to a meta-dataset that contains over 650 unique observations.

We find considerable differences across the studies in the meta-dataset in terms of how studies quantified water quality, the type of waterbody studied, and the region of the US examined. We often find it difficult to convert the disparate water quality measures to a common metric. The meta-regression models in this study focus on water clarity, where there are sufficient meta-observations (n=260) for regression analysis. In the absence of clear guidance on the most appropriate estimation approach for meta-regressions, a variety of models are estimated. These include weighted least squares (WLS), Random Effects (RE) Panel models, and the Mundlak (1978) regression model that was recently suggested by Boyle and Wooldridge (2018) as an alternative when estimating meta-regressions for benefit transfer.

We test for systematic heterogeneity in the housing price elasticities across different regions and types of waterbodies, and account for best methodological practices and publication bias in the literature. Benefit transfer performance across the different models are compared using an out-of-sample transfer error exercise. We find that the simple WLS meta-regression models yield the lowest transfer error.

Along with recommendations to practitioners conducting benefit transfer, we provide brief guidance on combining our results with available data to assess local, regional, and national policies affecting water quality. We also highlight gaps in the literature regarding the types of waterbodies and regions covered, and the disconnect between the water quality metrics examined by economists versus those by water quality modelers and policy makers.

The remainder of the paper is organized as follows. First, we describe the meta-dataset, including how we identified studies, our approach to format comparable elasticity estimates, and the mean elasticity estimates. Section 3 describes the meta-regression models, and section 4 presents the results. We end with a discussion of the limitations of our analysis, implications for benefit transfer, and possible directions for future research.

2. META-DATASET

2.1 Identifying Candidate Studies and Inclusion Criteria

In developing the meta-dataset, we followed the "Meta-Analysis of Economics Research Reporting Guidelines" for searching and compiling the hedonic literature (Stanley et al., 2013).[2] We focused on studies examining the relationship between residential property values and measures of surface water quality.[3] In total, we identified 65 studies in the published and grey literature that were potentially relevant. To facilitate linkages between water quality models and economic valuation, and ultimately to perform more defensible benefit transfers for US policies, focus was drawn to the 36 unique primary studies that examined surface water quality in the US using objective water quality measures. More specifically, 29 studies were dropped after further screening because an objective water quality measure was not used, the study area was outside of the US, a working paper or other grey literature study became redundant with a later peer-reviewed publication that is in the meta-dataset, or the research was not a primary study (e.g., a literature review). The remaining 36 studies were selected for inclusion in the final meta-dataset.[4] Although it was published after the construction of the meta-dataset, the list of identified studies was compared to an extensive literature review by Nicholls and Crompton (2018), which provided additional assurance that our identified set of studies is comprehensive.

2.2 Meta-dataset Structure and Details

From the selected 36 studies, 26 are published in peer-reviewed academic journals, three are working papers, three are Master's or PhD theses, two are government reports, one is a presentation, and one is a book chapter. The year of publication ranges from 1979-2017. The majority of primary studies examine freshwater lakes (24 studies), followed by estuaries (6 studies), rivers (2 studies) and small rivers and streams (3 studies). One study examines both lakes and rivers. As shown in Figure 1, spatial coverage is limited in the southwest, west-central, and parts of the southern US, while the Northeast and some parts of the Midwest and South have the most studies (e.g., Maine, Maryland, and Ohio have four studies while Florida has five studies).

The meta-dataset consists of a panel or cluster structure, where each study can contribute multiple unique observations. Individual studies may analyze multiple study areas, water quality metrics, and model specifications. Additionally, some hedonic studies examine how the property value effects vary with distance from the waterbody. Therefore, distance can be an important factor when transferring the estimated capitalization effects to a new policy region. The incorporation of this distance dimension in our meta-dataset is a novel contribution (as described below).

There are 30 different measures of water quality examined in the literature. To be fully transparent and provide the most information for practitioners to choose from when conducting benefit transfers, the meta-dataset includes all water quality measures. The pooling of estimates across different water quality measures, however, is not necessarily appropriate. Even when converted to elasticities, a one-percent change in Secchi disk depth means something very different than a one-percent change in fecal coliform counts, pH levels, or nitrogen concentrations, for example. That said, when a valid approach could be found, the primary study estimates are converted to a common water quality measure. Such a conversion is only undertaken for two hedonic studies where an appropriate conversion factor for the corresponding study area was available in the literature (Guignet et al., 2017; Walsh et al., 2017). In these cases, the meta-dataset includes unique observations corresponding to the inferred water quality measure (Secchi disk depth), as well as the original measure (light attenuation). To our knowledge, valid conversion factors or other approaches are not currently available for other water quality measures and primary study areas included in the meta-dataset.

2.3 Formatting Comparable Elasticity Estimates

A key challenge in constructing any meta-dataset is to ensure that all the outcomes of interest are comparable across studies (Nelson and Kennedy, 2009). By focusing on a single methodology, the outcome of interest itself is always the same – capitalization effects on residential property values. However, we must still account for two other factors that would otherwise diminish the comparability of results across studies; both of which pertain to assumptions in the original hedonic regression models.

The first form of cross-study differences is a common obstacle for meta-analysts. Differences in functional form lead to coefficient estimates that have slightly different interpretations. In the hedonic literature, some studies estimate semi-log, double-log, and even linear models. Other primary studies include interaction terms between the water quality measure and various attributes of the waterbody (e.g., surface area) to model heterogeneity. To address these differences, we convert the coefficient estimates from the primary studies to common elasticity and semi-elasticity estimates based on study specific model-by-model derivations, which are carefully detailed in Appendix A. These calculations also sometimes include the mean transaction price and mean values of observed covariates, as reported in the primary study. Such variables sometimes enter the elasticity calculations due to interaction terms or other functional form assumptions in the primary study.

The second form of cross-study differences involves how (and if) the home price impacts of water quality are allowed to vary with distance to the waterbody. In a recent meta-analysis of stated preference studies on water quality, Johnston et al. (2019) point out that no published meta-regression studies in the valuation literature include a mechanism to incorporate the relationship between households' values for an environmental commodity and distance to the resource. Johnston et al. account for this relationship by estimating the mean distance among the sample in each primary study, and then include that mean distance as a control variable in the right-hand side of their meta-regression models.

We take a different approach that explicitly incorporates spatial heterogeneity into the structure of the meta-dataset itself. We include multiple unique observations from the same primary study, but that correspond to house price effects at different distances from the resource. The fine spatial resolution associated with hedonic property value methods compared to other non-market valuation techniques makes this approach possible.

In the hedonic literature, different primary studies make different functional form assumptions when it comes to the price-distance gradient with respect to water quality, including both discrete distance bins and continuous gradients (e.g., linear, inverse distance, polynomial). The consideration of how the outcome effects of interest vary with distance adds a unique and novel dimension to the cluster structure of our meta-dataset. Except for internal meta-analyses by Klemick et al. (2018) and Guignet et al. (2018), our meta-analysis is the first to incorporate this distance dimension into the meta-dataset. In an internal meta-analysis, the researchers estimate the primary regressions themselves, and thus Klemick et al. (2018) and Guignet et al. (2018) had the luxury of assuming consistent functional forms and distance gradients in their initial hedonic models. In the current meta-analysis, we do not have this luxury; and adapting the elasticity estimates to be comparable across different distance gradient specifications in different studies is a unique challenge.

Although some studies have found that water quality impacts home values at slightly farther distances (e.g., Walsh et al., 2011; Netusil et al., 2014; Klemick et al., 2018; Kung et al., 2019), 16 of the 36 studies in the literature exclusively analyze price impacts on waterfront homes. It is unknown whether some primary studies limited the spatial extent of the analysis because no significant price effects were found or believed to be present at farther distances, or because of other reasons (perhaps stakeholder interest, or to keep the analysis more tractable). The same reasoning applies to why other studies decided to limit the spatial extent of the analysis at a certain distance. To minimize any potential sample selection bias corresponding to farther distances, we limit the meta-data and analysis to only price effects within 500 meters of a waterbody.

To standardize the elasticities across different studies with different distance gradient functional form assumptions, we "discretize" distance into two bins – waterfront homes and non-waterfront homes within 500 meters. This allows us to calculate elasticities in a consistent fashion, no matter the form of the price gradient assumed in the original hedonic regressions. If a primary study only examined waterfront homes, then it only contributes observations to the meta-dataset corresponding to the waterfront distance bin. If a study examined both waterfront and non-waterfront homes, then it contributes separate observations for each distance bin, even if the observations are derived from the same underlying regression coefficients.

For elasticity estimates corresponding to waterfront homes, when applicable, a distance of 50 meters is plugged into the study-specific elasticity derivations. This assumed distance for a "representative" waterfront home is based on observed mean distances among waterfront homes across the primary studies. For non-waterfront homes within 0-500 meters, the midpoint of 250 meters is plugged into the study-specific elasticity derivations, when applicable. Details are provided in Appendix A.

Finally, meta-analysis often requires a measure of statistical precision around the outcome of interest, in our case the inferred elasticity estimates. To obtain the elasticity estimates of interest and the corresponding standard error of those estimates, we conduct Monte Carlo simulations. The meta-dataset contains intermediate variables representing all relevant sample means, coefficient estimates, variances, and covariances from the primary studies. Often only the variance for the single coefficient entering the study-specific elasticity calculations is needed for these simulations, and it is fairly standard in the economics literature to report coefficient standard errors in the results. However, some study-specific elasticity calculations include multiple coefficients, thus requiring both the variances and covariances among that set of coefficients. Hedonic studies do not usually report the full variance-covariance matrix. When needed, we contacted the primary study authors to obtain the necessary covariance estimates required to conduct the Monte Carlo simulations.[5] In the case of four studies, however, we assume the corresponding covariances are zero because we were unsuccessful in acquiring the information.

Using the primary study coefficient, variance, and covariance estimates, the Monte Carlo simulations entail 100,000 random draws from the joint normal distributions estimated by each primary study. The simulations are carried out separately for each observation in the meta-dataset. After each draw of the relevant coefficients, the inferred elasticity is re-calculated, resulting in an empirical distribution from which we obtain the inferred elasticity mean and standard deviation for each observation in the meta-dataset.

The set of 36 studies provide 665 unique observations for the meta-dataset. The number of observations from each study ranges from just two observations from a single study to over 224 observations (see Appendix A). There is sufficient information to infer 656 unique estimates of the price elasticity and/or semi-elasticity with respect to a change in an objective water quality measure. The current meta-analysis examines primary study estimates of elasticity, which decreases the sample to 607. Nine additional observations are lost due to insufficient information in the primary study to estimate the standard error of the elasticity estimates, leaving a final dataset of 598 unique elasticity estimates.

Water clarity is by far the most common water quality measure analyzed in the literature (with 260 unique elasticity estimates), followed by fecal coliform (56) and chlorophyll a (36). Several other water quality measures have been examined in the hedonic literature, and also contribute unique elasticity estimates to the meta-dataset (see Appendix B).

2.4 Mean Elasticity Estimates

Mean elasticity estimates provide useful summary measures, and can be utilized for benefit transfer when unit value transfers are deemed appropriate. Although the literature still generally finds function transfer approaches that explicitly account for various dimensions of heterogeneity preferable (Johnston and Rosenberger, 2010), simpler unit value transfers have performed better in some contexts (Barton, 2002; Lindhjem and Navrud, 2008; Johnston and Duke, 2010; Bateman et al., 2011; Klemick et al., 2018).

Column 1 of Table I displays the unweighted mean elasticity estimates for the three most common water quality measures examined in the literature – water clarity, chlorophyll a, and fecal coliform.[6] We present separate mean elasticities for waterfront homes and non-waterfront homes within 500 meters of a waterbody. Unweighted mean elasticities for chlorophyll a are counterintuitive, and marginally significant at best, suggesting if anything that property values increase in response to an increase in the concentration of chlorophyll a.

The unweighted mean elasticities with respect to fecal coliform counts are more in line with expectations, suggesting that a one-percent increase in fecal coliform corresponds to a statistically significant 0.018% and 0.020% decrease in the value of waterfront homes and non-waterfront homes, respectively. Although the unweighted mean elasticity with respect to water clarity among waterfront homes is positive, it is surprising that it is statistically insignificant. The estimated 0.028% increase in non-waterfront home prices for a one-percent increase in Secchi disk depth (i.e., how many meters you can see down into the water) is significant.

The above unweighted mean elasticity calculations can be misleading, however, because of the clustered nature of the meta-data. For example, a single primary study may include multiple regression specifications that are estimating the same underlying value, and so the weight given to those estimates must be reduced accordingly (Mrozek and Taylor, 2002). We define each cluster as a unique study and housing market combination. Meta-observations estimated from a common transaction dataset in terms of the study area and time period are really just different estimates of the same underlying "true" elasticity. No matter how many elasticity estimates are provided by a given study for a given location, each cluster as a whole is given the same overall weight. More formally, let $\hat{\varepsilon}_{idj}$ denote elasticity estimate i, at distance d, for cluster j, and k_{dj} is the number of elasticity estimates for distance bin d in each cluster j. The cluster weighted mean elasticity for each distance bin d is:

$$\bar{\varepsilon}_d = \sum_{i=1}^{n} \frac{\frac{1}{k_{dj}}}{\sum_{j=1}^{K_d} \sum_{i=1}^{k_{dj}} \frac{1}{k_{dj}}} \hat{\varepsilon}_{idj} \tag{1}$$

where the same $\frac{1}{k_{dj}}$ weight is given to each meta-observation i within cluster j. The total number of clusters in the meta-dataset for distance bin d is K_d. The denominator of equation (1) normalizes the weights so that they sum to one.

The cluster weighted mean elasticities are presented in column 2 of Table I. The results are generally similar, suggesting a counterintuitive increase in waterfront home values in response to an increase in the concentration of chlorophyll a, and again an insignificant effect on the value of non-waterfront homes. The negative price elasticity among waterfront homes with respect to fecal coliform is now insignificant. The mean elasticity with respect to fecal coliform counts for non-waterfront homes remains robust and is slightly larger in magnitude, suggesting a 0.059% decrease in value due to a one-percent increase in fecal coliform counts. The cluster weighted mean elasticities with respect to water clarity are similar to the unweighted means; suggesting a positive but insignificant effect on waterfront home prices, and a significant 0.042% increase in non-waterfront home prices due to a one-percent increase in Secchi disk depth.

Weights based on the inverse variance of the primary estimates are also often applied in meta-analyses in order to give more weight to more precise estimates (Nelson and Kennedy, 2009; Borenstein et al., 2010; Nelson, 2015). We propose an adjustment to the above cluster weights that re-distributes the weight given to each observation within a cluster based on the Random Effect Size (RES) weights commonly used in the meta-analysis literature (Nelson and Kennedy, 2009; Borenstein et al., 2010; Nelson, 2015). Our proposed RES-adjusted cluster (RESAC) weights give more weight to more precise primary study estimates, while also ensuring that equal influence is given to each study and housing market examined in the literature. A similar weighting scheme was proposed by Van Houtven et al. (2007), but they were forced to use primary study sample size as a proxy for statistical precision due to a lack of information on the estimated variances in their meta-dataset. For our study, we observe (or are able to infer) the variance for virtually all elasticity observations in our metadata. Weights based on the inverse variance or standard error are recommended over those based on the inverse of the study sample size (Van Houtven et al., 2007; Subroy et al., 2019).

Let w_{idj}^{RES} denote the commonly used Random Effect Size (RES) weights.[7] The normalized RESAC weights are calculated as:

$$\omega_{idj} = \frac{\frac{w_{idj}^{RES}}{k_{dj}}}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}}\left(\frac{w_{idj}^{RES}}{k_{dj}}\right)} \tag{2}$$

The RESAC weighted mean elasticity for distance bin *d* is calculated as shown in equation (3), and the corresponding results are shown in column 3 of Table I.

$$\bar{\bar{\varepsilon}}_d = \sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}} \omega_{idj}^{h}\, \hat{\varepsilon}_{idj} \tag{3}$$

The RESAC mean elasticities generally have the expected sign.[8] For example, in contrast to the earlier mean elasticity estimates, the RESAC mean elasticity with respect to chlorophyll a for waterfront homes is of the expected negative sign, suggesting a one-percent increase in chlorophyll a leads to a 0.026% decrease in home values. The non-waterfront mean elasticity, however, now suggests a small but statistically significant 0.009% increase in home values. The RESAC mean elasticities with respect to fecal coliform counts match expectations, suggesting a one-percent increase in fecal coliform corresponds to a 0.00013% and 0.052% decrease in waterfront and non-waterfront home values, respectively.

The estimated RESAC mean elasticities with respect to water clarity best match expectations. We now see a positive effect among waterfront homes, suggesting that a one-percent increase in Secchi disk depth leads to a 0.105% increase in value. As expected among homes in closer proximity to the resource, this effect is larger than the corresponding 0.026% increase in the value of non-waterfront homes.

2.5. Water Clarity: Descriptive Statistics and Publication Bias

Water clarity is the most common water quality measure in the meta-dataset, with 260 unique house price elasticity estimates, from 18 studies, covering 63 different housing markets. This relatively large sample allows us to estimate meta-regressions for purposes of function transfers, and go beyond providing simple mean elasticities for benefit transfer.

Descriptive statistics of the elasticity observations with respect to water clarity are in Table II. Of the 260 estimates, 56% correspond to water clarity in freshwater lakes or reservoirs, while the other 44% correspond to estuaries. About 68% of the observed elasticity estimates are for waterfront homes. The average of the mean baseline clarity levels reported in the primary studies is a Secchi disk depth of 2.34 meters. Of course, this varies by waterbody type. Estuaries have a mean Secchi disk depth of only 0.64 meters, whereas freshwater lakes have a mean Secchi disk depth of 3.68 meters. Most estimates correspond to the South (49%) or Northeast (29%) regions of the US, with the remainder corresponding to the Midwest (19%) or West (4%).[9]

Socio-demographics of the primary study areas were obtained from the US Census Bureau by matching each observation to data for the corresponding jurisdiction and year of the decennial census. Median household income (2017$ USD) is, on average, $59,080 in the areas examined by these primary studies. Interestingly, the percent of the population with a college degree is fairly low (only 13.7% on average), as is population density, suggesting an average of only 50 households per square kilometer. These statistics suggest that homes near lakes and estuaries generally tend to be in more rural areas. Finally, mean house prices as reported in the primary studies were, on average, $211,314.

In terms of methodological choices, the assumed functional form of the primary study hedonic regressions varies considerably. Most use double log specifications (43%), followed by linear-log (31%), log-linear (22%), and even linear (4%). As can be seen by the "no spatial methods" variable, 38% of the elasticity estimates with respect to water clarity were derived from models that did *not* utilize econometric methods to account for spatial dependence (i.e., spatial fixed effects, spatial lag of neighboring house prices, and/or account for spatial autocorrelation via a formal spatial autocorrelation coefficient or cluster robust standard errors). A time trend variable, as reflected by the last year of transaction data in the primary study, is also included, and ranges from 1994 to 2014. This is converted into an index representing the number of years since 1994, which corresponds to the first study in the meta-dataset.

We were able to identify and include three unpublished hedonic studies examining water clarity (15% of the observations), but publication bias is still a concern given our goal of obtaining an accurate estimate of the true underlying capitalization effects for purposes of benefit transfer. As suggested by Stanley and Doucouliagos (2012), we first create "funnel plots" of the elasticity estimates against the inverse of the corresponding standard errors. Visual inspection of these funnel plots suggests that the meta-data may suffer from publication bias (see Appendix B). We next implement the more formal funnel-asymmetry test (FAT) and precision-effect test (PET) following Stanley and Doucouliagos (2012). We estimate the following FAT-PET weighted least squares regression

$$\hat{\varepsilon}_{idj} = \theta_0 + \theta_1 SE_{idj} + u_{idj} \tag{4}$$

where $\hat{\varepsilon}_{idj}$ is elasticity estimate i for distance bin d in cluster j. SE_{idj} is the standard error of that estimate, and the weights used are the inverse variance of $\hat{\varepsilon}_{idj}$ $\left(\frac{1}{v_{idj}}\right)$.

The null hypothesis under FAT is $H_0\colon \theta_1 = 0$, which would suggest no evidence of publication bias. As can be seen in column 1 of Table III, we reject the null hypothesis due to the statistically significant coefficient on the standard error term, suggesting that publication bias is in fact a concern with the meta-data collected from this literature. Nonetheless, the statistically significant constant implies that we fail to reject the PET null hypothesis $H_0\colon \theta_0 = 0$. In other words, even after adjusting for publication bias, we find evidence of a statistically significant true effect of water clarity on home values.

Simulation studies have suggested that including the elasticity variances v_{idj} on the righthand side of equation (4), instead of SE_{idj} provides a better estimate of the true empirical effect of interest (Stanley and Doucouliagos, 2012, 2014). Referred to as the precision-effect estimate with standard error (PEESE), $\hat{\theta}_0$ can be interpreted as the true elasticity estimate purged of any selection bias. As shown in column 2 of Table III, the significant constant term or PEESE estimate reveals a significant and positive elasticity of 0.0237.

With such tests, it is important to control for sources of high heterogeneity (Stanley and Doucouliagos, 2019). The model in column 3 includes a *waterfront* dummy denoting meta-observations corresponding to homes in the closest waterfront distance bin, as opposed to non-waterfront homes within 500 meters. The constant term suggests a statistically significant and positive 0.0130 elasticity for non-waterfront homes, and the sum of the constant term and waterfront coefficient suggest a significant and positive elasticity of 0.0386. Even after adjusting for publication bias, the literature suggests that a one-percent increase in Secchi disk depth (an average increase of 2.34 centimeters, or a little less than one inch) leads to an average increase in waterfront home values of 0.0386%, and an increase of 0.0130% in the value of non-waterfront homes within 500 meters.

These estimates are noticeably smaller than the mean elasticity estimates presented earlier in Table I. This is partly due to the publication-bias correction, but we caution against such a direct comparison because the publication corrected estimates in Table III do not account for the clustered nature of the meta-dataset. The meta-regression models discussed next account for the clustered nature of the dataset, control for other potential sources of heterogeneity, and include the elasticity variances as a covariate to minimize publication bias.

3. META-REGRESSION METHODOLOGY

Function transfers based on meta-regressions can be a useful approach for benefit transfer (Nelson, 2015). The approach takes advantage of the full amount of information provided by the literature, while also accounting for key dimensions of heterogeneity in the outcome effect of interest. Consider the following meta-regression model:

$$\hat{\varepsilon}_{idj} = \beta_0 + \boldsymbol{\beta_1 x_{idj}} + \boldsymbol{\beta_2 z_{idj}} + e_{idj} \qquad (5)$$

where the parameters to be estimated are β_0, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$. The right-hand side moderator variables include a vector of characteristics of the primary estimate, study area, and corresponding waterbody $(\boldsymbol{x}_{idj})$, and a vector of methodological variables $(\boldsymbol{z}_{idj})$, which describe attributes of the primary study and model assumptions. We discuss the error term e_{idj} at the end of this section.

The vector $\boldsymbol{x}_{idj}$ includes attributes like an indicator of whether the observed elasticity estimate corresponds to the value of homes on the waterfront (as opposed to non-waterfront homes), whether the elasticity estimate corresponds to water quality in an estuary (as opposed to freshwater lakes)[10], and the mean baseline water clarity level corresponding to the respective waterbody, or portion of the waterbody. The vector $\boldsymbol{x}_{idj}$ also includes characteristics of the study area and housing market, such as median income, proportion of the population with a college degree, mean house prices, and a series of indicator variables denoting one of the four broad US regions – the Northeast, Midwest, South, or West.

The vector $\boldsymbol{z}_{idj}$ is meant to capture differences in elasticities due to estimate quality and methodological choices made by the primary study authors. If particular values of $\boldsymbol{z}_{idj}$ denote better modelling choices, then such information can be exploited when predicting values for purposes of benefit transfer (Boyle and Wooldridge, 2018). The vector $\boldsymbol{z}_{idj}$ includes the variance of the corresponding elasticity estimate. The implicit assumption is that a better-quality estimate has a lower variance. The "true" elasticity would not be an estimate, and thus have a variance of zero. Therefore, this attribute should be set to zero in any subsequent benefit transfer exercise (Stanley and Doucouliagos, 2012, 2014).

In addition, $\boldsymbol{z}_{idj}$ includes indicator variables denoting unpublished studies, whether a study used assessed values (as opposed to data on actual transaction prices), and different functional forms. Most importantly, an indicator is included that denotes when the corresponding primary study regression model did *not* account for spatial dependence among housing observations in the primary data. If a model did not include spatial fixed effects, a spatial lag of housing prices, nor account for spatial autocorrelation in some fashion, then the *no spatial methods* indicator is set to one, and is zero otherwise.

We also include a study year trend variable to reflect changes in empirical methods, data, tastes and preferences, and/or awareness of water quality over time (Rosenberger and Johnston, 2009). Time trends in meta-analyses of stated preference studies are typically based on the year the primary study survey was conducted, which is different from the year of publication (e.g., Van Houtven et al., 2007; Rosenberger and Johnston, 2009; Johnston et al. 2019). For a hedonic meta-analysis, the choice is not as clear because the observed revealed preference data in a primary study often spans several years. To capture changes over time, we use the last year of transaction data in the primary study sample. This proxy is not without possible error, however. For example, Zhang et al. (2015) conduct a more recent analysis using older transaction data, and so our trend variable may not reflect methodological trends well in that case.

When estimating equation (5), the observations are weighted according to the same RESAC weights, but an additional complication arises from the cluster structure of the meta-data. There may be cluster-specific effects associated with a particular housing market and the waterbodies examined in that housing market. Any residual cluster-specific effect c_j would be reflected in the error term of equation (5), i.e., $e_{idj} = c_j + u_{idj}$, where u_{idj} is an independent and normally distributed error term. This implies that when estimating equation (5) the error terms (e_{idj}) are correlated for observations pertaining to the same cluster.

Conventional Random Effects (RE) Panel models are sometimes recommended in cases when a meta-regression model is estimated using multiple estimates from a primary study (Nelson and Kennedy, 2009). However, the cluster-specific effect c_j could be correlated with observed right-hand side variables, which would lead to inconsistent estimates (Wooldridge, 2002). Stanley and Doucouliagos (2012) point out that the necessary assumptions for consistent estimates in a RE Panel model will often be violated, especially when a measure of precision (e.g., estimate variance) is included on the right-hand side to control for publication bias. They recommend a simple weighted-least squares (WLS) meta-regression that allows for cluster-robust standard errors. We follow this recommendation in our base meta-regression analysis.

A fixed effect (FE) panel meta-regression model to directly estimate c_j and isolate it from the error term could also be implemented, but this is not a viable approach in the current context. First, the site-specific fixed effects would absorb much of the variation of interest. Many of the modifiers in the meta-regression do not vary within a cluster. Even when there is some within-cluster variation, it is often only seen among a subset of the observations. A FE Panel model would thus disregard a lot of observations and variation of interest. Second, out of sample inference for purposes of benefit transfer would not be valid because we cannot estimate the corresponding fixed effects for housing markets and waterbodies that are not in the current meta-dataset.

When benefit transfer is the primary objective, Boyle and Wooldridge (2018) suggest estimating a regression model first proposed by Mundlak (1978). The Mundlak model parametrically estimates the cluster-specific effects by including the cluster average of the relevant modifier variables in the right-hand side of the meta-regression:

$$\hat{\varepsilon}_{idj} = \beta_0 + \boldsymbol{\beta_1} \boldsymbol{x_{idj}} + \boldsymbol{\beta_2} \boldsymbol{z_{idj}} + \boldsymbol{\gamma_1} \boldsymbol{\bar{x}_j} + \boldsymbol{\gamma_2} \boldsymbol{\bar{z}_j} + e^*_{idj} \quad (6)$$

The variables $\boldsymbol{\bar{x}_j}$ and $\boldsymbol{\bar{z}_j}$ are the cluster-specific means for the study area and methodological attributes, respectively.[11]

A portion of the cluster-specific effect that was previously assumed to be random in equation (5) is now explicitly estimated in equation (6), as follows: $e_{idj} = \boldsymbol{\gamma_1} \boldsymbol{\bar{x}_j} + \boldsymbol{\gamma_2} \boldsymbol{\bar{z}_j} + e^*_{idj}$, where $e_{idj}^{*} = c_{j}^{*} + u_{idj}$. The coefficients $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$ capture the portion of the cluster-specific effects that are correlated with the other right-hand side modifier variables. The remaining portion of the cluster-specific effect c_j^* is assumed to be uncorrelated with the observed right-hand side variables and can thus be modelled as random. The Mundlak model in equation (6) relaxes the assumption that c_j be uncorrelated with observed right-hand side variables, as is the case with a conventional RE Panel model, and now only requires that c_j^* be uncorrelated. The model also has an advantage over a FE Panel model because it does not disregard variation with respect to cluster-invariant variables, and allows for out-of-sample inference (Boyle and Wooldridge, 2018).

A priori, the most appropriate meta-regression estimation approach remains unclear. In the next section we present estimation results first using a simple WLS meta-regression that allows for cluster-robust standard errors, and then using the Mundlak model. We then conduct an out-of-sample prediction exercise to compare modelling approaches for benefit transfer.

4. RESULTS

4.1. Meta-regression Results

We estimate the first set of meta-regressions as a series of simple Weighted Least Squares (WLS) models using the RESAC weights. As discussed above, this weighting scheme gives more within-cluster weight to more precise primary study estimates, and ensures that equal influence is given to each study and housing market examined in the literature.[12] The clusters are defined according to the 63 unique study-housing market combinations.

The WLS results are presented in Table IV. Model 1 includes key variables defining the elasticity estimate (e.g., *waterfront*), waterbody examined (e.g., *estuary* and *mean clarity* levels), and the surrounding population (e.g., *median income*), as well as methodological attributes. As expected, and in line with the earlier unit value estimates, the price elasticity with respect to clearer waters is significantly higher among waterfront homes (0.0525 percentage points).

The positive 0.0225 coefficient corresponding to baseline mean water clarity implies that homes surrounding waterbodies with already relatively clear waters experience larger increases in value in response to further clarity improvements. This "pristine premium" seems to be isolated to freshwater lakes, however; as suggested by the statistically insignificant -0.0294 ($p=0.633$) sum of the *mean clarity* and corresponding *estuary* interaction term coefficient estimates. Such a finding seems reasonable given that surrounding residents may not generally expect the water to be clear in estuaries because brackish waters are often naturally opaque.

Median income of the primary study area and whether a waterbody is an estuary (as opposed to a freshwater lake, the omitted category), have no significant effect on the estimated elasticities. The methodological variable coefficients are largely insignificant, including that corresponding to the elasticity variance, which is meant to account for potential publication bias. The *unpublished* dummy is marginally significant, however, suggesting that elasticity estimates from unpublished studies tend to be 0.0643 percentage points higher.[13]

To illustrate the implications of the WLS model 1 results, consider the "average" elasticity observation, where we plug in the cluster weighted mean values for most of the covariates and use the estimated coefficients to predict an illustrative elasticity.[14] With respect to *elasticity variance, assessed values,* and *no spatial methods*, we plug in zero to reflect best practices (Stanley and Doucouliagos, 2012; Boyle and Wooldridge, 2018). In order to infer an elasticity estimate that is based on the most recent methods and data possible, the value for the time trend index is set to 20 (which corresponds to 2014, the most recent year observed in the metadata). The "average" elasticity for waterfront homes is 0.1347, suggesting that a one-percent increase in Secchi disk depth (an increase of 2.34 centimeters, on average) leads to a 0.1347 percent increase in home values (*p=0.002*). A slightly smaller 0.0821 elasticity is estimated for the "average" non-waterfront home (*p=0.058*). Overall, the literature yields plausible and statistically significant elasticity estimates of how water clarity is capitalized in surrounding home values, even after empirically controlling for key dimensions of heterogeneity, publication bias, and subpar empirical methods.

Model 2 in Table IV includes indicator variables denoting each of the four regions of the US, with the Northeast being the omitted category. After accounting for heterogeneity across US regions in this fashion, we see that baseline mean clarity is no longer statistically significant, but the premium associated with waterfront homes is robust. The region coefficients suggest that housing price elasticities with respect to water clarity in the Midwest, South, and West tend to be significantly less than those in the Northeast. For example, a one-percent increase in water clarity for that "average" illustrative waterfront (non-waterfront) home in the Northeast would lead to a 0.3635% (0.3170%) increase in value. That same waterfront (non-waterfront) home would experience a 0.2129% (0.1664%) increase in value if it were in the Midwest, or a 0.1802% (0.1338%) increase in value if it were in the South, all else constant. Although these "average" elasticity estimates for the Northeast, Midwest, and South are all statistically significant at the *p=0.000* level, we find positive but statistically insignificant "average" elasticities corresponding to waterfront and non-waterfront homes in the West. Together, these results suggest that regional heterogeneity must be accounted for in any benefit transfer exercise. The inclusion of the regional dummies in model 2 also leads to the positive time trend variable becoming significant; suggesting that elasticity estimates have been increasing over time, all else constant.

The waterfront premium, and highly significant regional indicators and time trend are robust to the inclusion of additional methodological attributes in model 3. The premium associated with mean baseline water clarity is again (marginally) significant after accounting for additional variation in specification choices made by the primary study authors. The largely insignificant coefficients for the methodological variables added in model 3 suggest no significant differences in estimated elasticities based on functional form assumptions, nor based on whether a study controlled for spatial dependence using neighborhood fixed effects, spatial lags, or by modelling spatial autocorrelation. The one exception is that models using a linear-log specification to define the relationship between house prices and water clarity tend to yield smaller elasticity estimates relative to a double-log specification.[15]

We next compare our meta-regression results to the Mundlak model (Table V) suggested by Boyle and Wooldridge (2018). The positive and significant coefficient on the waterfront dummy reveals a similar finding to earlier models – an improvement in clarity leads to a statistically larger price increase among waterfront homes. The finding that price effect estimates for waterbodies and homes in the Midwest, South, and West tend to be lower than those for the Northeast is also robust. In agreement with the WLS models, Mundlak models 2 and 3 suggest a positive trend over time after controlling for regional heterogeneity. Otherwise, as before we find limited evidence of systematic variation in the elasticity estimates from this literature.

The Mundlak models suggest no statistical differences in the estimated elasticities based on baseline water clarity levels, at least not when considering within or across cluster variation separately. In conjunction, however, model 1 suggests a 0.0327 elasticity premium when baseline Secchi disk depth is one meter greater ($p=0.026$).[16] This result does not hold in the Mundlak variants of models 2 and 3, which suggest a statistically insignificant 0.0240 ($p=0.132$) and 0.0261 (*p=0.120*) increase in elasticity associated with a one meter increase in baseline water clarity. In that sense, we consistently find mixed evidence of a "pristine premium" when comparing within and across the WLS and Mundlak models.

The overall elasticity predictions from the Mundlak model are similar to those from the WLS regressions. For example, after accounting for best methodological practices and publication bias, model 1 in Table V suggests a statistically significant 0.1391 and 0.0792 elasticity for the same illustrative "average" waterfront and non-waterfront home, respectively, compared to the WLS elasticity predictions of 0.1347 and 0.0821.[17]

4.2. Best Performing Model for Benefit Transfer

To examine out-of-sample transfer error, we iteratively leave out observations corresponding to each of the 63 housing market-study clusters, and then re-estimate the meta-regression models using the remaining sample. The predicted elasticities are estimated for the excluded cluster. This is repeated by excluding each of the 63 clusters one at a time. After completing all 63 iterations we calculate the median absolute transfer error. Similar out-of-sample transfer error exercises have been implemented in the literature (e.g., Lindhjem and Navrud, 2008; Stapler and Johnston, 2009).

We carry out this out-of-sample transfer exercise in two ways. In the first approach, we construct a synthetic observation for each distance bin *d*, in cluster *j*, and then compare the elasticity value for this synthetic observation to the predicted elasticity from the meta-regression models. The synthetic observation is simply an inverse variance weighted mean across all elasticity estimates for distance bin d in cluster j: $\hat{\varepsilon}_{dj}^{s} = \sum_{i=1}^{k_{dj}} \left(\frac{\frac{1}{v_{idj}} \hat{\varepsilon}_{idj}}{\sum_{i=1}^{k_{dj}} \frac{1}{v_{idj}}} \right)$. The corresponding right-hand side variables for the synthetic observations are calculated in the same fashion. Those variable values are then plugged into the estimated meta-regressions to yield a predicted elasticity $\hat{\hat{\varepsilon}}_{dj}^{s}$ for houses in distance bin d of cluster j, which is then compared to the "actual" elasticity for each synthetic observation $\hat{\varepsilon}_{dj}^{s}$. The transfer error is calculated as the absolute value of the percent difference:

$$\left|\%TE_{dj}\right| = \left| \left(\frac{\hat{\hat{\varepsilon}}_{dj}^{s} - \hat{\varepsilon}_{dj}^{s}}{\hat{\varepsilon}_{dj}^{s}} \right) \times 100 \right| \tag{7}$$

Our synthetic observation approach for measuring out-of-sample transfer error weights the "actual" observed elasticity estimates and the sample used to parameterize the meta-regression models in the same fashion. When dealing with a panel- or cluster-structured meta-dataset, the more common practice of comparing predicted and observed elasticity estimates for all left out observations within each iteration (e.g., Londoño and Johnston, 2012; Fitzpatrick et al., 2017; Subroy et al., 2019) potentially inflates the transfer error. The parameterized meta-regressions, and hence the predicted elasticities $\hat{\hat{\varepsilon}}_{idj}$, would appropriately discount less precise estimates, but the excluded elasticity observations $\hat{\varepsilon}_{idj}$ that these are compared to in each iteration would all be treated equally. This inconsistent weighting across the predicted and observed elasticities automatically puts the predictive performance of the meta-regression models at a disadvantage. We carry out the out-of-sample transfer error exercise using both approaches for comparison and find similar results.

The median absolute transfer error results for each model are presented in Table VI. The top row shows the median transfer errors using our out-of-sample synthetic observation approach.

The second row shows the median transfer errors when all excluded observations are treated equally and used for comparison. The results suggest a median absolute transfer error of 95% to 131% under the synthetic comparison approach, versus 93% to 163% when comparing all excluded observations.[18]

Although errors of this size are not unheard of, the transfer errors for this study are in the high range for function transfers. In a recent study evaluating modeling decisions that affect benefit transfer errors, Kaul et al. (2013) examined 1,071 transfer errors reported by 31 studies and report that the absolute value of the transfer errors ranged from 0% to 7,496%, with a median of 39%. Rosenberger (2015) summarized the results for 38 studies that statistically analyzed transfer errors, and reported a median transfer error of 36% for function transfers. In their leave-one-study-out transfer error analysis, Londoño and Johnston (2012) report a 59% median transfer error using all available studies. Similar to our study, Subroy et al. (2019) used a leave-one-cluster-out approach, and estimated a median transfer error of 21% for non-market values of threatened species.

Overall, we find that the simple WLS models slightly outperform the more complex Mundlak models that try to better account for cluster-specific effects. We favor the WLS model 2 for purposes of function transfer because (i) the model accounts for regional heterogeneity, which was shown to be a large and significant predictor of elasticity, and (ii) it results in the lowest median transfer error (95%) under our preferred synthetic observation comparison.[19] The additional methodological variables added in WLS model 3 do not improve predictive performance.

5. DISCUSSION

A primary objective of this study is to help practitioners exploit the fairly large literature of hedonic property value studies examining surface water quality, and ultimately to facilitate *ex ante* and *ex post* assessments to better inform local, regional, and national policies impacting water quality. Based on the constructed meta-dataset, limited unit value transfers could be conducted to assess policies impacting one of several different water quality measures (e.g., chlorophyll a and fecal coliform). Given the limited number of studies on any one water quality measure, value transfers are often the only viable option for practitioners examining the property capitalization effects from changes in water quality.

In the context of water clarity, a function transfer using meta-regression results can improve transfers by catering the estimates to a particular policy context, and by adjusting for best methodological practices and publication bias. Our WLS meta-regression results can be combined with spatially explicit data of the relevant surface waterbodies, housing locations, baseline housing values, and the number of homes, in order to project the total capitalization effects of a policy or project affecting water quality. Ideally, such a benefit transfer exercise can be carried out using detailed, high-resolution data on waterbodies and individual residential properties from local or state governments. In the absence of such data, one can combine our results with waterbody location data provided by the National Hydrography Dataset (NHD), along with aggregated data on housing and land cover, from the US Census Bureau and National Land Cover Dataset (NLCD).[20]

As with any benefit transfer exercise, however, the results must be appropriately caveated. The out-of-sample transfer error of our meta-regressions is among the upper-end of errors found in the meta-analytic literature valuing environmental commodities. Despite our best attempts to parameterize systematic heterogeneity, many of our right-hand side moderator variables turned out to not provide much explanatory power. The capitalization of water quality changes in surrounding housing values is a very local phenomenon. Surely local unobserved factors remain that affect the accuracy of any transferred estimates.

In future work we hope to expand this meta-dataset in two ways. First, for tractability we decided early in the development of the meta-dataset to limit the distance bins to waterfront homes and non-waterfront homes within 500-meters of a waterbody. But the hedonic literature has increasingly expanded this focus, finding significant impacts on home prices up to a few kilometers away (e.g., Walsh et al., 2011; Netusil et al., 2014; Klemick et al., 2018; Kung et al., 2019). Adding meta-observations that pertain to farther distance bins will provide a more comprehensive meta-analysis in the future (although one must also consider the sample selection concerns discussed in section 2.3).

Second, new studies should be periodically added to the meta-dataset as they emerge. When conducting new hedonic studies, we encourage researchers to consider some of the gaps in the current literature. Our review reveals limitations in the types of waterbodies studied and the geographic areas covered. More hedonic studies examining surface water quality in the mountain states in the West, parts of the Midwest, and the South-central portions of the US are needed; as are studies examining how property values respond to water quality changes in estuaries, rivers, and streams. Such primary studies will facilitate truly nationwide coverage and ultimately more robust benefit transfers.

Our review of the literature also highlights a critical disconnect between the water quality metrics used by economists and those by water quality modelers and policy makers. Water clarity is the most common metric in the hedonic literature. It is a convenient measure for non-market valuation because households are able to directly perceive and understand it. In certain cases, it also can act as a reasonable proxy for other measures of water quality (e.g., nutrients or sediments). That said, water clarity is not a good measure of quality across all contexts (Keeler et al., 2012). For example, waters with low pH levels due to acid rain or acid mine drainage may be very clear, but of poor quality. This disconnect between water clarity and quality is an issue in the non-market valuation literature more broadly (Abt Associates, 2016).

Although the majority of hedonic studies focus on water clarity, water quality models, such as the Soil and Water Assessment Tool (SWAT), Hydrologic and Water Quality System (HAWQS), and SPAtially Referenced Regressions On Watershed Attributes (SPARROW), tend to focus on changes in nutrients, sediments, metals, dissolved oxygen, and organic chemicals (Tetra Tech, 2018). There are some process-based water quality models and estimated conversion factors that can be used to calculate changes in Secchi disk depth, but such approaches require location-specific relationships and waterbody characteristics as an input (Hoyer et al., 2002; Wang et al. 2013; Park and Clough, 2018); thus deterring the broader application of these existing approaches to project water clarity changes resulting from a policy.

Further research is necessary to improve the link between water quality and economic models, and ultimately to better inform policy decisions. Closing this gap can entail one of two things, or some combination of both. First, when choosing the appropriate water quality metric, economists conducting future studies should keep the application of their results in mind. Doing so will allow economic results to be more readily used to monetize the quantified policy changes projected by water quality models. It will also facilitate more robust transfer approaches by adding observations to our meta-dataset that focus on water quality measures other than water clarity.

Second, water quality modelers could develop models that directly project changes in water clarity, or perhaps develop more robust conversion factors. Such a call is not a new idea. Desvousges et al. (1992, p. 682) recommended that, at the very least, statistical analyses establish "… the correlation between policy variables and variables frequently used as indicators of water quality." Developing such conversion factors would be challenging, and would likely need to be watershed, and perhaps even waterbody, specific.

6. CONCLUSION

Despite the large number of studies of the capitalization of local surface water quality into home values, this literature has not generally been used to inform decision-making in public policy. For example, hedonic property value studies have yet to be used in regulatory analyses of regional and nationwide water quality regulations enacted by the US Environmental Protection Agency. Heterogeneity in local housing markets, the types of waterbodies examined, the model specifications estimated, and the water quality metrics used, are key reasons why the results of these local studies have not been applied to broader policies. This meta-analysis overcame these obstacles through the meticulous development of a detailed and comprehensive meta-dataset.

The relative out-of-sample transfer performance of our estimated meta-regressions suggests caution when conducting benefit transfers to inform water quality policy. The proper use of this study will depend on the relative accuracy necessary for decision-making (Bergstrom and Taylor, 2006). Nonetheless, in the absence of resources for an original study, and if there is no single study that closely matches the policy context at hand, then this meta-analysis provides a path for practitioners to conduct benefit transfer, and assess how improvements in water quality from local, regional, and even national policies are capitalized into housing values.

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TABLES

Table I. Mean Elasticity Estimates of Three Most Frequently Examined Water Quality Measures.

Water quality measure	Unweighted Mean (1)	Cluster Weighted Mean (2)	RES-Adjusted Cluster (RESAC) Weighted Mean (3)	n	Studies
Chlorophyll a (mg/L)					
waterfront	0.737*	0.324*	-0.026***	18	3
	[-0.044, 1.517]	[-0.036, 0.685]	[-0.031, -0.021]		
non-waterfront w/in 500 m	0.005	0.010	0.009***	18	3
	[-0.201, 0.211]	[-0.085, 0.105]	[0.006, 0.012]		
Fecal coliform (count per 100 mL)					
waterfront	-0.018***	-0.037	-1.3E-4***	36	4
	[-0.026, -0.011]	[-0.088, 0.014]	[-1.8E-4, -0.7E-4]		
non-waterfront w/in 500 m	-0.020***	-0.059*	-0.052***	20	3
	[-0.034, -0.006]	[-0.090, -0.005]	[-0.096, -0.008]		
Water clarity (Secchi disk depth, meters)					
waterfront	0.155	0.182	0.105***	177	18
	[-6.102, 6.413]	[-17.398, 17.762]	[0.095, 0.114]		
non-waterfront w/in 500 m	0.028***	0.042***	0.026***	83	6
	[0.020, 0.036]	[0.025, 0.059]	[0.017, 0.034]		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Confidence intervals at the 95% level are displayed in brackets. Only elasticity estimates pertaining to the three most commonly examined water quality measures in the hedonic literature are presented, but the full suite of mean elasticity estimates are presented in Appendix B.2. We present the respective units for each water quality measure in parentheses just as a reference but emphasize that the elasticity estimates presented in the table are unit-less.

Table II. Descriptive Statistics of Observations Pertaining to Water Clarity.

Variable	Mean	Std. Dev.	Min	Max
Dependent variable:				
Elasticity	0.1147	0.2549	-0.6499	1.7191
Study area variables:				
Waterfront[a]	0.6808	0.4671	0	1
Mean clarity (secchi disk depth, meters)	2.34	1.97	0.38	6.45
Lake or Reservoir[a]	0.5615	0.4972	0	1
Estuary[a]	0.4385	0.4972	0	1
Median income (thousands, 2017$)	59.080	14.142	37.865	91.174
College degree (% population)	0.1367	0.0414	0.0768	0.2734
Population density (households /sq. km.)	49.91	58.38	1.41	227.96
Mean house price (thousands, nominal$)	211.314	131.341	31.287	675.364
Northeast[a]	0.2885	0.4539	0	1
Midwest[a]	0.1923	0.3949	0	1
South[a]	0.4846	0.5007	0	1
West[a]	0.0346	0.1832	0	1
Methodological variables:				
Elasticity variance	1228.1590	18704.5200	9.03E-06	301448.5
Unpublished[a]	0.1500	0.3578	0	1
Assessed values[a]	0.0538	0.2261	0	1
Time Trend (0=1994 to 20=2014)	8.59	6.17	0	20
No spatial methods[a]	0.3808	0.4865	0	1
Double-log[a]	0.4308	0.4961	0	1
Linear-log[a]	0.3077	0.4624	0	1
Linear[a]	0.0385	0.1927	0	1
Log-linear[a]	0.2231	0.4171	0	1

Unweighted descriptive statistics presented for n=260 unique elasticity estimates in meta-dataset pertaining to water clarity. Estimates based on 18 primary hedonic studies, corresponding to 63 unique study-housing markets clusters. All variables are dummy variables unless indicated otherwise.
(a) Denotes independent variables that are dummy variables.

Table III. Simple Meta-regression Models Testing for Publication Bias.

VARIABLES	(1)	(2)	(3)
Elasticity std error	1.5738***		
	(0.249)		
Elasticity variance		0.0001	0.0001
		(0.006)	(0.006)
Waterfront			0.0256***
			(0.006)
Constant	0.0088**	0.0237***	0.0130***
	(0.004)	(0.003)	(0.004)
Observations	260	260	260
R-squared	0.135	0.000	0.064

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Weighted least squares estimated using the "regress" routine in Stata 14 and defining analytical weights equal to the inverse variance of each of the corresponding elasticity estimates.

Table IV. Weighted Least Squares (WLS) Meta-regression Results.

VARIABLES[a]	(1)	(2)	(3)
Waterfront[a]	0.0525**	0.0465**	0.0574***
	(0.021)	(0.021)	(0.019)
Mean clarity	0.0225**	0.0104	0.0292*
	(0.010)	(0.015)	(0.017)
Estuary[a]	-0.0014	-0.0301	0.0057
	(0.055)	(0.044)	(0.045)
Mean clarity × estuary	-0.0519	-0.0395	-0.0568
	(0.063)	(0.064)	(0.063)
Median income	0.0015	0.0015	0.0013
	(0.001)	(0.001)	(0.001)
Midwest[a]		-0.1506***	-0.1645***
		(0.043)	(0.041)
South[a]		-0.1832***	-0.2544***
		(0.052)	(0.069)
West[a]		-0.3055***	-0.4551***
		(0.067)	(0.084)
Elasticity variance	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Unpublished[a]	0.0643*	0.0548*	0.0104
	(0.037)	(0.029)	(0.048)
Assessed values[a]	-0.0090	0.0491	0.0523*
	(0.055)	(0.047)	(0.029)
Time trend	0.0038	0.0137***	0.0127***
	(0.004)	(0.003)	(0.002)
No spatial methods[a]			-0.0090
			(0.015)
Linear-log[a]			-0.1349**
			(0.065)
Linear[a]			0.0473
			(0.058)
Log-linear[a]			0.0016
			(0.004)
Constant	-0.1215	-0.0461	0.0112
	(0.075)	(0.107)	(0.105)
Observations	260	260	260
Adjusted R-squared	0.153	0.204	0.226

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Clustered-robust standard errors in parentheses; clustered according to the K=63 unique study-housing market combinations. Weighted least squares regressions estimated using the "regress" routine in Stata 14 and defining analytical weights equal to the RESAC weights (see equation 2 in section 2.4).

(a) Denotes independent variables that are dummy variables.

Table V. Mundlak Model Meta-regression Results.

VARIABLES	(1)	(2)	(3)
Waterfront[a]	0.0599***	0.0613***	0.0616***
	(0.019)	(0.019)	(0.019)
Waterfront cluster mean	-0.1122	-0.3344***	-0.3946*
	(0.144)	(0.101)	(0.220)
Mean clarity	-0.0289	-0.0206	-0.0175
	(0.066)	(0.062)	(0.061)
Clarity cluster mean	0.0616	0.0446	0.0436
	(0.069)	(0.064)	(0.064)
Estuary[a]	-0.0020	-0.0115	-0.0117
	(0.062)	(0.044)	(0.046)
Mean clarity × estuary	-0.0616	-0.0510	-0.0516
	(0.062)	(0.061)	(0.060)
Median income	0.0014	0.0012	0.0011
	(0.001)	(0.001)	(0.001)
Midwest[a]		-0.1988***	-0.2144***
		(0.043)	(0.056)
South[a]		-0.3173***	-0.2878***
		(0.064)	(0.071)
West[a]		-0.3486***	-0.3987***
		(0.039)	(0.099)
Elasticity variance	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Unpublished[a]	0.0454	-0.0275	0.0018
	(0.050)	(0.044)	(0.045)
Assessed values[a]	-0.0143	-0.0106	-0.0102
	(0.009)	(0.010)	(0.010)
Assessed values cluster mean	0.0067	0.0902*	0.0805*
	(0.070)	(0.047)	(0.042)
Time trend	0.0038	0.0151***	0.0181***
	(0.004)	(0.002)	(0.005)
No spatial methods[a]			0.0128
			(0.015)
No spatial methods cluster mean			0.0160
			(0.060)
Linear-log[a]			0.0482
			(0.128)
Linear[a]			0.1195*
			(0.067)
Log-linear[a]			0.0011
			(0.003)

Log-linear cluster mean			-0.0175
			(0.044)
Constant	-0.0612	0.2271*	0.2011
	(0.123)	(0.122)	(0.150)
Observations	260	260	260
ll	1.5529	1.6705	1.6846

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Mundlak (1978) regressions estimated by first calculating cluster means for independent variables that vary within each of the K=63 study-housing market clusters, and then by using the "mixed" routine in Stata 14 where the cluster-specific residual is allowed to be correlated. Observations weighted following the RESAC weights (see equation 2 in section 2.4). If there is no within cluster variation for a given variable, then a companion cluster mean term is not included in the above results. The one exception is the elasticity variance term, which does vary within clusters, but the corresponding cluster mean term was dropped by Stata due to multicollinearity.
(a) Denotes independent variables that are dummy variables.

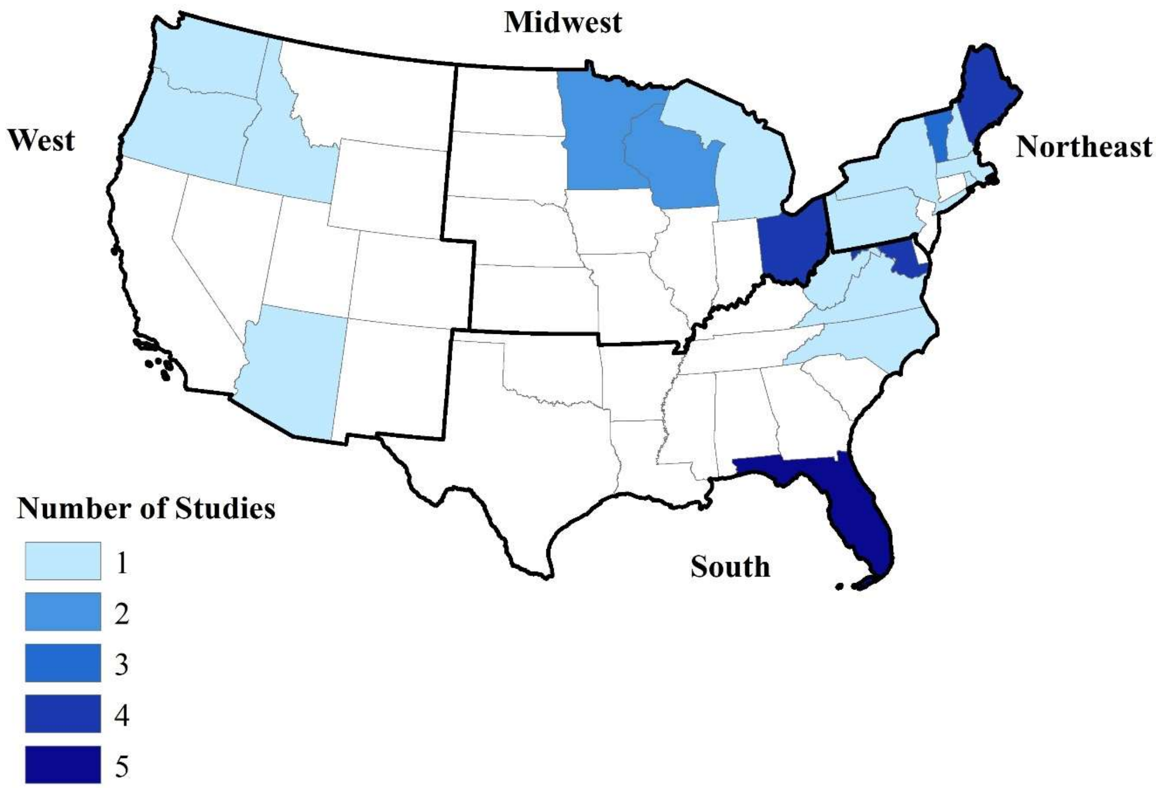
Table VI. Out-of-Sample Transfer Error: Median Absolute Value of the Percent Difference in Predicted Elasticities.

WLS 1	WLS 2	WLS 3	Mundlak 1	Mundlak 2	Mundlak 3
Comparison with Synthetic Observations for Excluded Cluster (n=82)					
101%	95%	103%	109%	102%	131%
Comparison with Excluded Cluster Observations (n=260)					
93%	110%	116%	103%	94%	163%

The out-of-sample transfer error is calculated by iteratively leaving out each of the K=63 clusters, estimating the model with the remaining clusters, and then calculating the predicted elasticities and resulting transfer error for the synthetic observation or the actual observations corresponding to the excluded cluster.

FIGURES

Figure 1. Number of Water Quality Hedonic Studies in each State.



[1] There are three notable unpublished studies. In her Master's thesis, Fath (2011) conducted a limited meta-analysis of 13 hedonic studies. Ge et al. (2013) conducted a meta-analysis that combined contingent valuation, travel cost, and hedonic studies. They also estimated one meta-regression using only hedonic studies (10 studies with 127 observations) for comparison. Abt Associates (2015) estimated the capitalization effects of large-scale changes in water clarity of lakes using a simple weighted-average across nine hedonic studies. Finally, we are aware of one recent published study that focused on urban rivers and property values, but it did not examine measures of surface water quality (Chen et al. 2019).

[2] The first author developed how the data would be coded with feedback from all authors. The fourth author did most of the data entry with quality checks by all authors throughout the process.

[3] The search began with reviewing reports (e.g., Van Houtven et al., 2008; US EPA, 2016) or other literature reviews and meta-analyses on related topics (e.g., Crompton, 2004; Braden et al., 2011; Fath, 2011; Alvarez and Asci, 2014; Abt Associates, 2015). The next step was to search a variety of databases and working paper series which included Google Scholar, Environmental Valuation Reference Inventory, JSTOR, AgEcon Search, EPA's National Center for Environmental Economics Working Paper Series, Resources for the Future (RFF) Working Paper Series, Social Science Research Network (SSRN), and ScienceDirect, among many others. Keywords when searching these databases included all combinations of the terms: house, home, property, value, price, or hedonic with terms such as water quality, water clarity, Secchi disk, pH, aquatic, and sediment. Requests also were submitted to ResEcon and Land and Resource Economics Network. Seven additional studies were provided from the first request on October 24, 2014. And one additional study was added from a second request on January 21, 2016. After this lengthy process, we attempted one final literature search through the US EPA's internal library system.

[4] See Appendix A for the full list of included studies. No later than one year after publication of this manuscript, the meta-dataset will be made publicly available on the US EPA's Environmental Dataset Gateway: https://edg.epa.gov/, "Metadata for property values and water quality", DOI: 10.23719/1503693.

[5] We are extremely grateful and thank Okmyung Bin, Allen Klaiber, Tingting Liu, Patrick Walsh, and James Yoo for providing the variance-covariance estimates needed to complete the Monte Carlo simulations. We also thank Kevin Boyle for providing details on the functional form assumptions in Michael et al. (2000).

[6] Mean elasticity estimates for all 30 water quality measures examined in the literature are provided in Appendix B.

[7] Details on the interpretation and derivation of the standard RES weights and our proposed RESAC weights are provided in Appendix B.

[8] The standard RES weighted mean elasticities are similar, and are presented in Appendix B.

[9] Regions of the US are displayed in Figure 1 and are defined following the US Census Bureau's "Census Regions" (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf, accessed 11 June 2019).

[10] Initially, a vector of dummy variables denoting different waterbody types was to be included in the meta-regression. As described in section 2.4, the meta-dataset includes price elasticities corresponding to freshwater lakes, estuaries, rivers, and small rivers and streams. However, the primary hedonic studies in the current literature that examine water clarity focus solely on freshwater lakes and estuaries.

[11] The mean values for some attributes, by definition, do not vary within clusters (e.g., indicators denoting Northeast, South, Midwest, and West regions; whether a study is unpublished; study year trend;). The mean values for such attributes are excluded in the subsequent meta-regressions due to multicollinearity.

[12] Some of the WLS meta-regression results are not as robust when comparing across models that use the conventional cluster-based $\frac{1}{k_{dj}}$ weights (Mrozek and Taylor, 2002). See Table C1 in Appendix C for details. When comparing across weighting schemes, the coefficient corresponding to the elasticity variance variable, which is intended to correct for publication bias (Stanley and Doucouliagos, 2012, 2014), becomes significant in the models using conventional cluster-based weights. This coefficient is insignificant in our main set of meta-regression models, however, suggesting that the RESAC weights in the main analysis help minimize selection bias.

[13] Models including the average transaction price reported in the primary study, population density, and percent of population with a college education revealed statistically insignificant results.

[14] The mean covariate values can be found in Appendix C, Table C2.

[15] As a robustness check, we compare the WLS models in Table IV to the corresponding set of RE Panel models. As described above, the necessary assumptions for consistent estimates from a RE Panel model are often violated in

practice (Stanley and Doucouliagos, 2012). Nonetheless, we find virtually identical results (see Table C3 in Appendix C).

[16] This estimate is calculated as the sum of the mean clarity and mean clarity cluster average coefficient estimates. The standard error of 0.0147 is estimated via the delta method.

[17] These "average" elasticities were predicted using the same procedure as described for the WLS model 1 "average" home illustration. The cluster-weighted average values for each attribute are plugged in (see Table C2 in appendix C). A value of zero is plugged in for the *elasticity variance, assessed values,* and *no spatial methods* variables, and a value of 20 is used for the time trend variable. The averages of the cluster means are also plugged in for the corresponding cluster average variables.

[18] The transfer error medians are reported, as opposed to the means, because the transfer error means are heavily influenced by a single outlier. The mean transfer errors range from 3,508% to 11,955%, but this is greatly affected by a single observation that has a variance that is orders of magnitude larger than the rest of the sample. Although the meta-regression coefficient corresponding to the elasticity variance is very small and insignificant, the large variance corresponding to this single outlying observation pushes its predicted elasticity up considerably. Thanks to our RESAC weighting scheme, excluding this outlier from the estimating sample does not affect our main meta-regression results. But excluding it from the mean transfer error calculation does make a substantial difference. Excluding this outlier results in a mean transfer error ranging from 255%% to 492%. For comparison, Kaul et al. (2013) find a mean transfer error of 172% across a variety of valuation methods, Stapler and Johnson (2009) report a best case mean of 80.5% (outliers removed), and Lindhjem and Navrud (2015) report means ranging from 26% to 258% depending how their data were screened.

[19] One can use the coefficient estimates in Table IV for purposes of benefit transfer. The full variance-covariance matrix for WLS model 2 is presented in Appendix D. This is needed to derive the corresponding confidence intervals via the delta method (Greene, 2003, page 70) or Monte Carlo simulations.

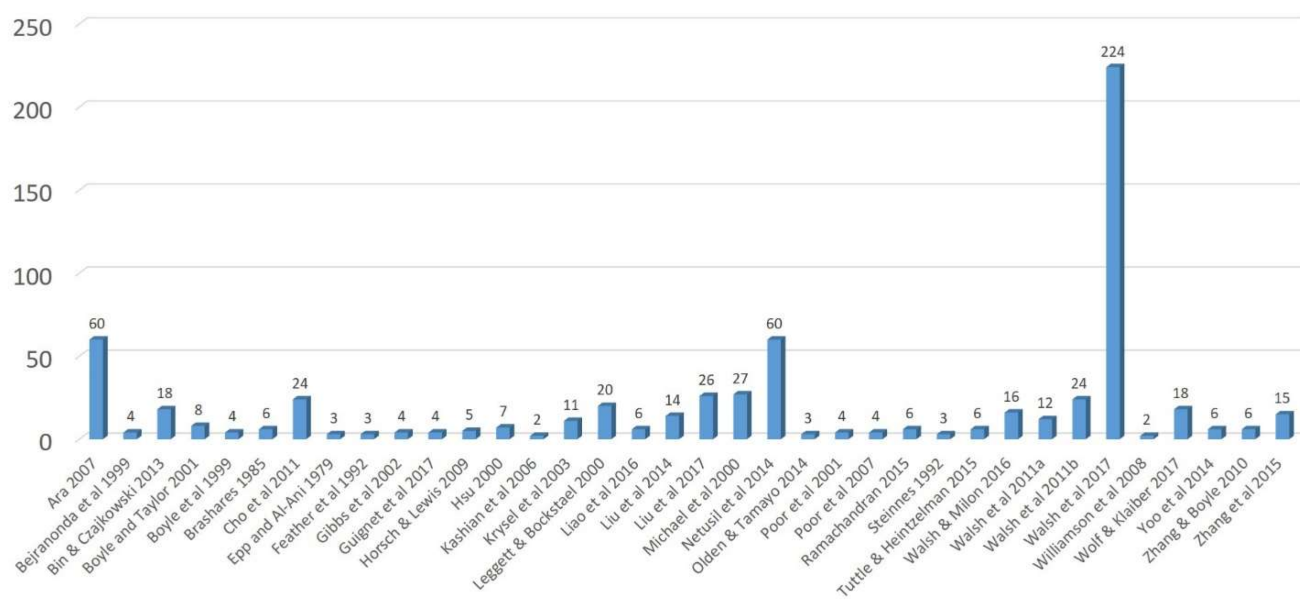
[20] Website links to these publicly available data sources are as follows: National Hydrography Dataset (NHD), https://www.usgs.gov/core-science-systems/ngp/national-hydrography/; US Census Bureau, https://www.census.gov/; National Land Cover Dataset (NLCD), https://www.mrlc.gov/ (accessed 20 Feb. 2019).

ONLINE APPENDICES

Appendix A: Meta-dataset details and study specific description.

The set of 36 studies in the hedonic property value literature examining surface water quality in the United States provides 665 unique observations for the meta-dataset. Figure A1 displays the number of observations from each study, which ranges from just two observations from a single study to over 224 observations.

Figure A1. Number of Meta-dataset Observations by Study.



This appendix provides a brief summary of each study in the meta-dataset and examples to illustrate the study-by-study derivations of the common elasticity and semi-elasticity estimates in the meta-dataset. The final meta-dataset will be publicly available on the US EPA's

Environmental Dataset Gateway no later than one year after publication of this manuscript.[1] The below textbox introduces the standardized notation used.

p = sales price (or alternative measure of house value)

WQ = water quality variable of interest. If multiple water quality parameters are included, then they are denoted using subscripts. Letter subscripts denote differences in units (e.g., meters (m) versus feet (ft)).

$area$ = surface area of waterbody

X = vector for all other variables not of primary interest

$dist_{WF}$ = waterfront dummy variable

$dist$ = continuous variable measuring distance to waterbody

$dist_{e\text{-}f}$ = distance dummy variable ranging from e to f (e.g., distance buffer between zero and 200 meters would be $dist_{0\text{-}200}$)

γ = coefficients on X

β = coefficient on WQ

D = coefficient on WQ dummy variable

Ara (2007)

This study examined water clarity and fecal coliform in Lake Erie. The study used several clustering algorithms to define submarkets along Lake Erie. This clustering led to eight submarkets for which hedonic price equations are estimated for Secchi disk depth and fecal coliform. Equations are estimated for both waterfront and non-waterfront homes. The authors

[1] US EPA, Environmental Dataset Gateway: https://edg.epa.gov/ , "Metadata for property values and water quality", DOI: 10.23719/1503693.

estimated each model using both OLS and spatial error models. The study contributed 60 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. All models have a double-log specification:

$$\ln(p) = \gamma X + \beta \ln(WQ) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \beta \frac{p}{WQ}$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{\beta}{WQ} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \quad (3)$$

The relevant sample means for WQ are then plugged in as needed to calculate the estimated semi-elasticities.

Bejranonda et al. (1999)

This study examined sediment inflow rates for state park lakes and reservoirs within 4,000 feet (1219.2 meters) of homes in Ohio. The counties are not identifiable based on the information provided in the primary study. The hedonic models examined the effect of sedimentation rates on property values for homes near lakes/reservoirs with regulations limiting boating horse-power to 10 (Limited HP) versus unlimited horse-power lakes (Unlimited HP).

The dependent variable is the annual rental value which is obtained from a transformation on the total assessed housing value. The authors excluded homes near lakes that had a water surface area less than 100 acres (one acre equals 4046.86 square meters). The study estimated two models (one for the Limited HP lakes and one for the Unlimited HP lakes) each yielding a waterfront and non-waterfront estimate. Therefore, four observations are included in the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model (1) as an example.

$$\ln(p) = \gamma X + \beta \ln(WQ) \tag{1}$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \beta \frac{p}{WQ}$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{\beta}{WQ} \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \tag{3}$$

The relevant sample means for WQ are then plugged in as needed to calculate the estimated semi-elasticities.

Bin and Czajkowski (2013)

This study examined a variety of water quality variables including visibility, salinity, pH, and dissolved oxygen (DO) in the St. Lucie River, St. Lucie Estuary, and Indian River Lagoon of Florida. The study estimated eight hedonic regression models, but only four included an objective and usable set of water quality parameters (e.g., water visibility, pH, dissolved oxygen). The four models not included used a subjective location-based grade to measure water quality. The study contributed a total of 18 observations to the meta-dataset.

For 12 observations, water quality variables were actual measures. The derivation of our standardized elasticity and semi-elasticity estimates for these 12 observations is as follows. Consider a simplified representation of Table 3's Model I as an example.

$$\ln(p) = \gamma X + \beta_1 WQ + \beta_2 WQ^2$$

Rearranging for *p*,

$$p = \exp\left(\gamma X + \beta_1 WQ + \beta_2 WQ^2\right) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta_1 WQ + \beta_2 WQ^2) \cdot (\beta_1 + 2\beta_2 WQ)$$

Substituting for in p from equation (1) yields: $\frac{\partial \mathrm{p}}{\partial \mathrm{WQ}} = p \cdot (\beta_1 + 2\beta_2 WQ)$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = (\beta_1 + 2\beta_2 WQ) \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = (\beta_1 + 2\beta_2 WQ) \cdot WQ \quad (3)$$

The relevant sample means for WQ are then plugged in as needed to calculate the estimated elasticities and semi-elasticities.

Six observations are based on dummy variables for WQ. The dummy variables were equal to one for water visibility fair, water visibility good, and salinity good. Consider a simplified representation of Model III in Table 3 of the primary study as an example.

$$\ln(p) = \gamma X + DWQ$$

Rearranging to isolate *p* on the left-hand side yields,

$$p = \exp\,(\gamma X + DWQ)$$

Let p_0 denote the price when $WQ = 0$, and p_1 denote when $WQ = 1$. These can be written out, respectively, as:

$$p_0 = \exp\,(\gamma X)$$

$$p_1 = \exp\,(\gamma X + D)$$

Because the functional form is log-linear, we use the transformation first outlined by Halvorsen and Palmquist (1980) for calculating the percent change in price: $\%\Delta p = \frac{p_1 - p_0}{p_0}$.

Plugging in the above equations yields:

$$\%\Delta p = \frac{p_1 - p_0}{p_0} = \frac{\exp(\gamma X + D) - \exp(\gamma X)}{\exp\,(\gamma X)}$$

Some rearranging and simplification yields:

$$\%\Delta p = \frac{\exp(\gamma X)\exp\,(D) - \exp(\gamma X)}{\exp(\gamma X)}$$

$$\%\Delta p = \exp\,(D) - 1$$

The relevant coefficient estimate for *D* is then plugged in as needed to calculate the percent change in price. The percent change in price enters the meta-dataset as a "semi-elasticity" estimate for observations like this, and the corresponding elasticity variables are not applicable and are left as null.

Boyle and Taylor (2001)

This study examined water clarity in 34 lakes of Maine that are divided into four groups. The study estimated four hedonic regression models based on the groupings and each model is estimated with two different datasets of property characteristics. The first was labeled as town data and utilized tax-assessor records, and the second used survey responses from buyers and sellers. Each model contributed a waterfront estimate to the meta-dataset, yielding a total of eight observations. Waterbody surface area was measured in acres in the original study (one acre equals 4046.86 square meters).

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of Group 1, town data model as an example.

$$p = \gamma X + \beta \cdot area_{acres} \cdot \ln(WQ) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \left(\beta \cdot area_{acres} \cdot \frac{1}{WQ}\right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{(\beta \cdot area_{acres})}{WQ \cdot p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \frac{(\beta \cdot area_{acres})}{p} \quad (3)$$

The relevant sample means for WQ, price, and *area* are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities. Because Boyle and Taylor did not include lake area or the specific lakes that are used for the different groups, we use the 3,515 mean acreage estimate (14,224,713 sq. meters) from Michael et al. (2000), who used a similar, but not the exact same, data set.

Boyle et al. (1999)

This study examined water clarity (secchi depth) of lakes in four different housing markets in Maine. The study estimated four hedonic regression models, one for each market, and each yielding one observation for waterfront homes. Therefore, the study contributed a total of four observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the linear-log model.

$$p = \gamma X + \beta \cdot area \cdot \ln{(WQ)} \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ and some rearrangement yields the semi-elasticity and elasticity calculations, equations (2) and (3) respectively:

$$\frac{\partial p}{\partial WQ} = \beta \cdot area \cdot \frac{1}{WQ}$$

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot \frac{area}{WQ \cdot p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot \frac{area}{p} \qquad (3)$$

One complication for the study is only the mean implicit prices $\left(\frac{\partial p}{\partial WQ}\right)$ are reported, not the actual regression coefficients β (see Table 1 in Boyle et al., 1999). Therefore, we back out the relevant elasticities and semi-elasticities using the available estimates and the implicit price equation preceding equation (2) above. In addition, the relevant sample means for WQ and p are plugged in as needed for each of the four study areas in order to calculate the estimated elasticities and semi-elasticities.

Brashares (1985)

This study examined the effect of turbidity and fecal coliform on lakeshore home values in southeast Michigan. The study estimated several hedonic price functions each using different subsets of the data. One model examined homes with lake frontage only, one with lake or canal frontage, and one with selected homes on lakes with public access. With three different subsets of the housing data and two water quality variables, this study contributed 6 observations to the meta-dataset. All the models followed a log-quadratic specification, where the water quality variables entered as squared values of the mean.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. All models have the following log-quadratic specification:

$$\ln(p) = \gamma X + \beta WQ^2 \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = 2\beta WQ \cdot p$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = 2\beta WQ \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = 2\beta WQ^2 \qquad (3)$$

Elasticities and semi-elasticities are then computed using the summer mean values for the water quality variables as reported in table v.3 of the primary study.

Cho et al. (2011)

This study examined impairment in streams and the river in the Pigeon River Watershed of North Carolina and Tennessee. The impairment source was identified as a paper mill. The study estimated six hedonic regression models (four for NC and two for TN), each yielding a waterfront and non-waterfront estimate for two impairment dummy variables. Therefore, the study contributed a total of 24 observations to the meta-dataset.

The derivation of our standardized semi-elasticity estimates is as follows. Consider a simplified representation of the North Carolina Thiessen Polygon (TP) model as an example, where $WQ_{impairriver}$ and $WQ_{impairstreams}$ are dummy variables denoting that the nearby river and contributing streams, respectively, are considered impaired.

$$\ln(p) = \gamma X + D_1 WQ_{impairriver} + D_2 WQ_{impairstreams}$$

Rearranging for p,

$$p = \exp\,(\gamma X + D_1 WQ_{impairriver} + D_2 WQ_{impairstreams}) \qquad (1)$$

Because the functional form is log-linear, we use the Halvorsen and Palmquist (1980) equation for calculating the percent change in price which can then be expressed as $\%\Delta p = \frac{p_1 - p_0}{p_0}$.

As an example, the percent change in price due to a river being classified as impaired is expressed as follows. Let p_0 denote the price when the dummy variable is turned off, and p_1 denote when it is turned on. These can be written out, respectively, as:

$$p_0 = \exp\,(\gamma X)$$

$$p_1 = \exp\,(\gamma X + D_1)$$

Plugging in the above equations yields:

$$\%\Delta p = \frac{p_1 - p_0}{p_0} = \frac{\exp(\gamma X + D_1) - \exp(\gamma X)}{\exp\,(\gamma X)}$$

Some rearranging and simplification produces:

$$\%\Delta p = \frac{\exp(\gamma X)\exp\,(D_1) - \exp(\gamma X)}{\exp(\gamma X)}$$

$$\%\Delta p = \exp\,(D_1) - 1$$

The relevant coefficient estimate for D_1 is then plugged in as needed to calculate the percent change in price. The percent change in price enters the meta-dataset as a “semi-elasticity” estimate for observations like this, and the corresponding elasticity variables are not applicable and are left as null.

Epp and Al-Ani (1979)

This study examined pH levels in small rivers and streams in Pennsylvania. The study estimated four hedonic regression models, but only three included an objective water quality parameter for waterfront properties. The excluded model focused on a subjective water quality measure based on property owners' perceptions. Therefore, the study contributed a total of three observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model *1* as an example.

$$\ln(p) = \gamma X + \beta_1 \ln(WQ) + \beta_2[\ln(WQ)\, popchange]$$

$$\ln(p) = \gamma X + [\beta_1 + \beta_2 popchange]\ln(WQ)$$

where *popchange* denotes the change in population in that area. Rearranging for *p*,

$$p = e^{\gamma X \quad [\beta_1 + \beta_2 popchange]\ln(WQ)} \tag{1}$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = e^{\gamma X + [\beta_1 + \beta_2 popchang \quad]\ln(WQ)} \cdot [\beta_1 + \beta_2 popchange]\frac{1}{WQ}$$

Substituting for *p* from equation (1) yields: $\frac{\partial \mathrm{p}}{\partial W} = p \cdot [\beta_1 + \beta_2 popchange]\frac{1}{WQ}$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = [\beta_1 + \beta_2 popchange]\frac{1}{WQ} \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = [\beta_1 + \beta_2 popchange] \tag{3}$$

The relevant sample means for pH and population change are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Feather et al. (1992)

This study examined the effect of water quality -- as proxied by a trophic status index (TSI) -- on the sale of vacant lots on lakes in Orange County, Florida between 1982-84. TSI theoretically ranges from 0 (good water quality) to 100 (very poor). The study estimated two hedonic regression models. The first used a linear model specification for waterfront properties only and the second model, for both waterfront and non-waterfront properties, was log-linear based on Box-Cox procedures for estimating functional form. Therefore, the study contributed a total of three observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of Table V-4 as an example.

$$p = \gamma X + \beta WQ \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \beta$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta\frac{1}{p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta\frac{WQ}{p} \quad (3)$$

For the log-linear specification, consider the simplified representation of the model in Table V-8 of the primary study.

$$\ln(p) = \gamma X + \beta WQ \tag{1}$$

Rearranging for p,

$$p = \exp\,(\gamma X + \beta WQ)$$

Taking the partial derivative with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta WQ) \cdot \beta$$

Substituting in for p yields: $\frac{\partial \mathrm{p}}{\partial \mathrm{WQ}} = p\beta$

The semi-elasticity and elasticity are respectively:

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta WQ \tag{3}$$

The relevant sample means for TSI and price are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Gibbs et al. (2002)

This study examined water clarity (secchi depth) of lakes in four different housing markets in New Hampshire. The study estimated four hedonic regression models, one for each market, and each yielding one observation for waterfront homes. Therefore, the study contributed a total of four observations to the meta-dataset. The derivation of our standardized elasticity and semi-elasticity estimates is similar to that reported for Boyle et al. (1999) in this appendix. Consider a simplified representation of the linear-log model.

$$p = \gamma X + \beta \cdot area \cdot \ln{(WQ)} \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ and some rearrangement yields the semi-elasticity and elasticity calculations, equations (2) and (3) respectively:

$$\frac{\partial p}{\partial WQ} = \beta \cdot area \cdot \frac{1}{WQ}$$

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot \frac{area}{WQ \cdot p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot \frac{area}{p} \quad (3)$$

The relevant sample means for lake area, Secchi disk depth, and price are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Guignet et al. (2017)

This study examined water clarity (light attenuation coefficient) in the Chesapeake Bay. The study estimated several hedonic regression models but only one included a water quality parameter of interest, yielding a waterfront and non-waterfront observation. Two additional observations are derived from the same regression results by converting the estimates to correspond to Secchi disk depth (instead of the light attenuation coefficient). Therefore, the study contributed a total of four observations to the meta-dataset. The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model 2.C as an example.

$$\ln(p) = \gamma X + \beta_1(\ln(WQ_{KD}) \cdot dist_{WF}) + \beta_2(\ln(WQ_{KD}) \cdot dist_{0-200})$$

$$+\beta_3(\ln(WQ_{KD}) \cdot dist_{200-500})$$

where $dist_{WF}$ is a dummy variable equal to one for waterfront homes, $dist_{0-200}$ is a dummy variable equal to one for non-waterfront homes within 0-200 meters of the water, and $dist_{200-500}$ is a dummy variable equal to one for non-waterfront homes within 200-500 meters of the water. The above equation can be simplified to:

$$p = e^{\gamma X + (\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \ln(WQ_{KD})}$$

Calculating the elasticities and semi-elasticities with respect to the light attenuation coefficient (WQ_{KD}) is straight forward and follows similar derivation as that below. Here we focus on converting those estimates to secchi depth in meters (WQ_m), using the following inverse relationship estimated for this particular study area and referenced in the primary study: $WQ_{KD} = 1.45/WQ_m$. Plugging this into the above hedonic regression yields:

$$p = e^{\gamma X \quad (\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \ln\left(\frac{1.45}{WQ_m}\right)} \tag{1}$$

To calculate the semi-elasticity and elasticity estimates (equations 2 and 3 below, respectively), we take the derivative with respect to WQ_m and then do some slight rearranging:

$$\frac{\partial p}{\partial WQ_m} = e^{\gamma X + (\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \ln\left(\frac{1.45}{WQ_m}\right)}$$

$$\cdot -(\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \frac{WQ_m}{1.45} (1.45) {WQ_m}^{-2}$$

$$\frac{\partial p}{\partial WQ_m} = -\frac{p}{WQ_m}(\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-5}\quad)$$

$$\frac{\partial p}{\partial WQ_m}\frac{1}{p} = -\frac{1}{WQ_m}(\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \tag{2}$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = -(\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-5}\quad) \tag{3}$$

After plugging in the appropriate value of zero or one for the corresponding distance bin dummy variables, the elasticities and semi-elasticities for waterfront homes are simply $-\beta_1$and $-\frac{\beta_1}{WQ_m}$, respectively. For non-waterfront observations, the representative non-waterfront home distance of 250 meters is assumed, and so $dist_{0-200} = 0$ and $dist_{200-500} = 1$ is plugged in. The corresponding elasticities and semi-elasticities are $-\beta_3$ and $-\frac{\beta_3}{WQ_m}$. The relevant sample mean for WQ_m is then plugged in as needed in order to calculate the estimated semi-elasticities.

Horsch and Lewis (2009)

Although the authors' primary focus was on Eurasian milfoil (an invasive aquatic vegetation), this study also examined water clarity (secchi depth) of lakes in Vilas County, Wisconsin. The study estimated nine hedonic regression models, five of which included water clarity. Each model only used waterfront homes in the estimations. Therefore, the study contributed a total of five observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the primary study's linear model.

$$p = \gamma X + \beta WQ_{ft}$$

The primary study WQ is expressed in terms of Secchi disk depth in feet, which we re-express as Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28084\, ft}{1\, m}$. Plugging this into the hedonic regression yields:

$$p = \gamma X + \beta(WQ_m \cdot 3.28084) \tag{1}$$

Taking the partial derivative with respect to WQ_m and then multiplying both sides by $1/p$ and WQ_m/p yields the semi-elasticity and elasticity calculations, respectively.

$$\frac{\partial p}{\partial WQ_m}\frac{1}{p} = \frac{\beta}{p} \cdot 3.28084 \tag{2}$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = \beta \cdot 3.28084 \cdot \frac{WQ_m}{p} \tag{3}$$

The relevant sample means for price and the converted mean Secchi depth in meters are then plugged in as needed.

Hsu (2000)

This study examined the effect of lake water clarity and aquatic plants on lakefront property values across twenty lakes grouped into three distinct markets in Vermont. The metadata includes seven observations from this study. Three of the observations are from model specifications which exclude the aquatic plant variables and include only water clarity. The other four observations on water clarity come from model specifications that include the aquatic plant variables. All of the water clarity variables are specified as the interaction of the natural log of the minimum water clarity in the year the property was sold multiplied by the total lake surface area. The derivation of the standardized elasticity and semi-elasticity is as follows.

The lin-log specification can generally be expressed as:

$$p = \gamma X + \beta \cdot area \cdot \ln(WQ) \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \left(\beta \cdot \frac{area}{WQ}\right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \left(\beta \cdot \frac{area}{WQ}\right) \cdot \frac{1}{p} \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot area \cdot \frac{1}{p} \qquad (3)$$

The relevant sample means for lake area, water clarity, and price are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Kashian et al. (2006)

This study examined water clarity in the lake community of Delavan, Wisconsin. The study estimated three hedonic models, but only one included a water quality parameter, yielding a waterfront and a non-waterfront observation. Therefore, the study contributed a total of two observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model 3 from the primary study as an example.

$$p = \gamma X + \beta WQ \qquad (1)$$

In this case, WQ is expressed in terms of Secchi disk depth in feet, which we re-express as

Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28084\,ft}{1\,m}$.

Substituting this conversion into equation (1), we have

$p = \gamma X + \beta(WQ_m \cdot 3.28084)$

Taking the partial derivative with respect to WQ yields:

$$\frac{\partial p}{\partial WQ_m} = \beta \cdot 3.28084$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial W \quad _m}\frac{1}{p} = \frac{\beta}{p} \cdot 3.28084 \qquad (2)$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = \beta \cdot 3.28084 \cdot \frac{WQ_m}{p} \qquad (3)$$

The relevant sample means for WQ_m and price are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Krysel et al. (2003)

This study examined the effect of lake water clarity on lakefront property values across thirty-seven lakes grouped into six distinct markets in Minnesota. There are two estimates based on different model specifications for five of the groups and one estimate for the Bemidji group. Thus, this study contributes 11 observations to the meta-dataset. The water quality variable used in the study is the natural log of water clarity multiplied by lake size.

The lin-log specification can generally be expressed as:

$$p = \gamma X + \beta \cdot area \cdot \ln (WQ) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \left(\beta \cdot \frac{area}{WQ}\right)$$

Rearranging produces the formulas for the semi-elasticity equation (2) and elasticity equation (3).

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot \frac{area}{WQ} \cdot \frac{1}{p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot area \cdot \frac{1}{p} \quad (3)$$

The relevant sample means for WQ, p, and $area$ are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Leggett and Bockstael (2000)

This study examined fecal coliform counts in the Chesapeake Bay. The study estimated 20 different hedonic regression models, all of which focused on waterfront homes in Anne Arundel county, Maryland, and each yielded one observation. Therefore, the study contributed a total of 20 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. The primary study considered several different functional forms, but the fecal coliform count variable of interest (WQ) always entered linearly. Consider a simplified representation Leggett and Bockstael's linear model as an example.

$$p = \gamma X + \beta WQ \qquad (1)$$

Taking the derivative and dividing by p yields the semi-elasticity:

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{\beta}{p} \qquad (2)$$

The elasticity can then be expressed by taking equation (2) and multiplying by WQ, as follows:

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \frac{\beta WQ}{p} \qquad (3)$$

The relevant sample means for WQ and price from Table I of the primary study are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Liao et al. (2016)

This study examined water clarity in the Coeur d'Alene Lake, Idaho. The study estimated six hedonic regression models, but only four included an objective water quality parameter of interest for waterfront properties. Two of the hedonic models include two water quality parameters (one for northern division of the lake and one for southern division of the lake). Therefore, the study contributed a total of six observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model 1 in Table 2 of the primary study as an example. The hedonic double-log specification can generally be specified as:

$$\ln(p) = \gamma X + \beta \ln(WQ)$$

Rearranging for p,

$$\text{p} = \exp\left(\gamma X + \beta \ln(WQ)\right) \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial \text{p}}{\partial WQ} = \exp\left(\gamma X + \beta \ln(WQ)\right) \frac{\beta}{WQ}$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial \text{p}}{\partial WQ}\frac{1}{p} = \frac{\beta}{WQ} \qquad (2)$$

$$\frac{\partial \text{p}}{\partial WQ}\frac{WQ}{p} = \beta \qquad (3)$$

The relevant coefficient and sample means for WQ are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Liu et al. (2014)

This working paper examined sediment loads, dissolved oxygen, nitrogen and phosphorous levels, and Secchi disk depth in the Hoover Reservoir, as well as nitrogen and phosphorous in rivers, focusing on the Upper Big Walnut Creek watershed in Ohio. The study estimated a single hedonic regression model, that included interaction terms for each specific water quality measure and waterbody combination listed above, yielding seven observations corresponding to waterfront homes and seven corresponding to non-waterfront homes. Therefore, the study contributed a total of 14 observations to the meta-dataset. Only eight of these observations, however, can be included in any subsequent meta-analysis. Standard errors for all the relevant coefficient estimates in the other six cases lacked the necessary number of significant digits and were essentially listed as zero. This prevented us from simulating the corresponding standard errors associated with our standardized elasticity and semi-elasticity estimates.[2]

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the model that focuses on nitrogen levels in the Hoover Reservoir as an example. Note that although numerous water quality measures are included in the single hedonic regression from this study, they will cancel out when taking the partial derivative with respect to each water quality measure of interest. The hedonic regression can be represented as:

$$\ln(p) = \gamma X + \beta_1 WQ + \beta_2 (WQ \cdot dist_{miles})$$

where $dist_{miles}$ is distance to the Hoover Reservoir, measured in miles. Since the distances for the standardized waterfront and non-waterfront estimates in the meta-dataset are noted in meters, we must convert the distance measure by applying the following conversion factor: $dist_{miles} = {dist_m}/{1609.34}$. Plugging this into the hedonic equation yields:

$$\ln(p) = \gamma X + \beta_1 WQ + \beta_2 \left(WQ \cdot \frac{dist_m}{1609.34}\right) \qquad (1)$$

Taking the partial derivative and rearranging yields the semi-elasticity and elasticity calculations (equations (2) and (3) below, respectively).

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta_1 + \beta_2 \frac{dist_m}{1609.34} \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \left(\beta_1 + \beta_2 \frac{dist_m}{1609.34}\right) WQ \qquad (3)$$

[2] Subsequent correspondence with the primary study authors to obtain the necessary estimates, as well as the covariances, were unsuccessful as the available working paper was said to be undergoing revisions.

The relevant sample means for WQ are then plugged in as needed in order to calculate the estimated elasticity and semi-elasticities. The mean distance for waterfront homes was not reported, and so in calculating the waterfront estimates a distance of 50 meters was assumed (as done for other studies where such information was needed but unavailable), and an assumed 250 meters was used for the representative non-waterfront home.

Liu et al. (2017)

This study examined chlorophyll in Narragansett Bay, Rhode Island. The study estimated 13 hedonic regression models, each yielding a waterfront and non-waterfront estimate. Therefore, the study contributed a total of 26 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. As an example, consider a simplified representation of the "well-informed" model for waterfront properties, which used the 99th percentile for chlorophyll concentration as the relevant water quality measure.

$$\ln(p) = \gamma X + \beta_1 WQ + \beta_2 WQ \cdot dist_{0-100}$$

Rearranging for *p*,

$$p = \exp(\gamma X + \beta_1 WQ + \beta_2 WQ \cdot dist_{0-100}) \qquad (1)$$

In this case, WQ is expressed in terms of micrograms per liter, which we re-express as milligrams per liter using the following conversion factor: $WQ_{\mu g/L} = WQ_{mg/L} \cdot \frac{1000\mu g}{1\, mg}$.

$dist_{0-100}$ is a dummy variable representing waterfront properties within 100m of the Bay.

Substituting this conversion into equation (1), we have

$$p = \exp(\gamma X + \beta_1 WQ_{mg/L} \cdot 1000 + \beta_2 WQ_{mg/L} \cdot 1000 \cdot dist_{0-100} \;)$$

Taking the partial derivative with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta_1 WQ_{mg/L} \cdot 1000 + \beta_2 WQ_{mg/L} \cdot 1000 \cdot dist_{0-100m})(\beta_1 \cdot 1000 + \beta_2 \cdot 1000 \cdot dist_{0-100m})$$

Plugging in p from equation (1) yields:

$$\frac{\partial p}{\partial WQ} = p \cdot (\beta_1 \cdot 1000 + \beta_2 \cdot 1000 \cdot dist_{0-100m})$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = 1000(\beta_1 + \beta_2 dist_{0-100m}) \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = WQ_{mg/L} \cdot 1000(\beta_1 + \beta_2 dist_{0-100m}) \tag{3}$$

For waterfront properties, we set $dist_{0-100} \;= 1$. The relevant coefficients and sample means for WQ are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Michael et al. (2000)

This study examined water clarity in 22 lakes of Maine that are divided into three groups. The study estimated nine hedonic regression models per group, each yielding one waterfront observation. Therefore, the study contributed a total of 27 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of Group 1's CMIN model as an example. CMIN represents the minimum water clarity for the year the property was sold.

The lin-log specification can generally be expressed as:

$$p = \gamma X + \beta \ln(WQ) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial W} = \left(\beta \frac{1}{WQ}\right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \left(\beta \frac{1}{WQ}\right)\frac{1}{p} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \left(\beta \frac{1}{p}\right) \quad (3)$$

The relevant coefficient and sample means for WQ and price are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

The functional form of WQ varied across specifications. Table 4 in Michael et al. presents CMAX/CMIN or CMAX/CMIN% as additional water clarity specifications. However, in Table 7, the specification is presented as CMIN/CMAX and CMIN/CMAX%. For models 6 and 7, we estimate the elasticities as presented in Table 4, as suggested by the primary study authors.[3]

As an example, Model 6 from the primary study has the following form:

[3] Personal communication with K. Boyle, December 8, 2017.

$$p = \gamma X + \beta \frac{\ln(CMAX)}{\ln(WQ)} \quad (1)$$

where ln(CMAX) is an interaction term.

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = - \beta \left(\frac{\ln(CMAX)}{WQ \cdot \ln(WQ)^2} \right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ} \frac{1}{p} = - \beta \left(\frac{\ln(CMAX)}{WQ \cdot \ln(WQ)^2} \right) \cdot \frac{1}{p} \quad (2)$$

$$\frac{\partial p}{\partial WQ} \frac{WQ}{p} = - \beta \left(\frac{\ln(CMAX)}{\ln(WQ)^2} \right) \cdot \frac{1}{p} \quad (3)$$

As another example, Model 7 from the primary study has the following form:

$$p = \gamma X + \beta \frac{\ln(CMAX) - \ln(WQ)}{\ln(CMAX)} \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \left(\frac{- \beta}{WQ \cdot \ln(CMAX)} \right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ} \frac{1}{p} = \left(\frac{- \beta}{WQ \cdot \ln(CMAX)} \right) \cdot \frac{1}{p} \quad (2)$$

$$\frac{\partial p}{\partial WQ} \frac{WQ}{p} = \frac{- \beta}{\ln(CMAX)} \cdot \frac{1}{p} \quad (3)$$

Netusil et al. (2014)

This study examined a variety of water quality parameters including dissolved oxygen, E. coli, fecal coliform, pH, temperature, and total suspended solids in Johnson Creek, Oregon, and Burnt Bridge Creek, Washington. The study estimated five hedonic regression models for Johnson Creek and one model for Burnt Bridge Creek, each yielding five water quality measures for waterfront and non-waterfront properties. For this study, the dummy variable, $dist_{0\text{-}0.25}$, representing properties within a 0.25 mile (402.34 meters) of the creeks includes both waterfront and non-waterfront homes. Therefore, the study contributed a total of 60 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the Johnson Creek (Dry) OLS model from the primary study as an example.

$$\ln(p) = \gamma X + \beta WQ \cdot dist_{0-0.25}$$

$$p = \exp(\gamma X + \beta WQ \cdot dist_{0-0.25}) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta WQ \cdot dist_{0-0.25})\, \beta \cdot dist_{0-0.25}$$

Substituting in p from equation (1), the formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot dist_{0-0.25} \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta WQ \cdot dist_{0-0.25} \quad (3)$$

For both waterfront and non-waterfront properties, we set $dist_{0-0.25}$=1. The relevant coefficient and sample means for WQ are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Olden and Tamayo (2014)

This study examined water clarity in lakes located in King County, Washington. The study estimated three hedonic regression models, each yielding a waterfront observation. Therefore, the study contributed a total of three observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of Model 1 from the primary study as an example.

$$p = \gamma X + \beta WQ \tag{1}$$

Taking the partial derivative with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \beta$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{\beta}{p} \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta\frac{WQ}{p} \tag{3}$$

The relevant sample means for WQ and p are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Poor et al. (2001)

This study estimated several hedonic regression models that included both objective and subjective measures of water clarity (i.e., Secchi disk depth) in lakes in Maine. The meta-dataset focuses solely on objective measures of water quality, and so we examine the four hedonic regression models that included objective Secchi disk depth measurements as an explanatory variable. Each model corresponded to one of four different housing markets in Maine and provided one waterfront observation. Therefore, the study contributed a total of four observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is similar to Boyle et al. (1999) and is briefly re-summarized here. Consider a simplified representation of the linear-log model presented in the primary study.

$$p = \gamma X + \beta \cdot area \cdot \ln(WQ) \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ and some rearrangement yields the semi-elasticity and elasticity calculations, equations (2) and (3) respectively:

$$\frac{\partial p}{\partial WQ} = \beta \cdot area \cdot \frac{1}{WQ}$$

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot \frac{area}{WQ \cdot p} \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot \frac{area}{p} \qquad (3)$$

The relevant sample means for WQ, $area$, and p are plugged in as needed for each of the four study areas in order to calculate the estimated elasticities and semi-elasticities.

Poor et al. (2007)

This study examined concentrations of total suspended solids and dissolved inorganic nitrogen in rivers throughout the St. Mary's watershed in Maryland. The study presented two hedonic regression models, one for each of the two water quality measures. The focus was on ambient water quality, and so the sample encompassed both waterfront and non-waterfront homes (although the distance gradient with respect to water quality was essentially assumed to be flat). Therefore, each model contributed a waterfront and non-waterfront observation, implying that the study provided a total of four observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the model as follows:

$$\ln(p) = \gamma X + \beta WQ$$

$$p = e^{\gamma X + \beta WQ} \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ and some rearrangement yields the semi-elasticity and elasticity calculations, equations (2) and (3), respectively:

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \quad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta WQ \quad (3)$$

The relevant sample means for WQ (either total suspended solids or dissolved inorganic nitrogen depending on the model) are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Ramachandran (2015)

This study examined nitrogen concentrations in the Three Bays area of Cape Cod, Massachusetts. The study estimated and presented four hedonic regression models, but only three of these models included the relevant water quality measure as a control variable. Each model yielded a waterfront and non-waterfront observation. Therefore, the study contributed a total of six observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates from the double-log specification in the primary study is as follows.

$$\ln(p) = \gamma X + \beta \ln(WQ)$$

$$p = e^{\gamma X+\beta \mathrm{l}\ \ (WQ)} \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ and some rearrangement yields the semi-elasticity and elasticity calculations, equations (2) and (3) respectively:

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{\beta}{WQ} \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \qquad (3)$$

The relevant sample mean for WQ is then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Steinnes (1992)

This study examined the effect of water clarity across 53 lakes in Northern Minnesota. The study used several measures of the appraised value of land as the dependent variable in the hedonic price equation. However, the study did not report the average price nor the summary statistics for the water clarity variable so neither the elasticity nor the semi-elasticity are computed for this study.

Tuttle and Heintzelman (2015)

This study examined numerous ecological and water quality measures in lakes in the Adirondacks Park in New York, including the presence of milfoil (an invasive species), loons (an aquatic bird and indicator species of ecological health), and lake acidity (i.e., pH levels). The only objective measure of water quality for inclusion in this meta-dataset is lake acidity, which is measured as an indicator equal to one if pH levels are below 6.5. The study estimated and presented four hedonic regression models that included the poor pH indicator as a control variable. Two of these models included only lakefront homes, and thus contributed only a single observation each to the meta-dataset. The other two models included waterfront and non-waterfront homes in the estimating sample and thus provided two observations each. This study contributed a total of six observations to the meta-dataset.

The relevant water quality measures are binary indicator variables in this case, and so the percent change in price ($\%\Delta p$) is calculated for the "semi-elasticity" variable in the meta-dataset. The elasticity estimates are not applicable and are left as null. Consider a simplified representation of Tuttle and Heintzelman's hedonic model.

$$\ln(p) = \gamma X + DWQ$$

$$p = e^{\gamma X + DWQ} \tag{1}$$

where D is the coefficient of interest corresponding to the poor pH dummy variable. Note that the distance gradient with respect to water quality was assumed to be flat in this study, and so, when appropriate, the calculations for waterfront and non-waterfront $\%\Delta p$ are the same. Let the price for a representative home when the nearest lake does not and does have poor pH be denoted as p_0 and p_1, respectively. These can be expressed as:

$$p_0 = \exp(\gamma X)$$

$$p_1 = \exp(\gamma X + D)$$

Plugging the above two equations into the percent change in price calculation yields:

$$\%\Delta p = \frac{p_1 - p_0}{p_0} = \frac{\exp(\gamma X + D) - \exp(\gamma X)}{\exp(\gamma X)}$$

And with some rearranging and simplification yields:

$$\%\Delta p = \frac{\exp(\gamma X)\exp(D) - \exp(\gamma X)}{\exp(\gamma X)}$$

$$\%\Delta p = \exp(D) - 1$$

The relevant coefficient estimate for D is then plugged in as needed to calculate the percent change in price.

Walsh and Milon (2016)

This study examined the effect of nutrients on properties on and/or near lakes in Orange County, Florida. The study estimated several singular indicators of nutrients including Total Nitrogen (TN), Total Phosphorus (TP), and chlorophyll a (CHLA). The study also examined several composite indicators – the trophic status index (TSI) and what the authors label as the one-out, all-out (OOAO) indicator that equals one if all the US EPA criteria for TN, TP, and CHLA are achieved. Each model yields a waterfront and non-waterfront observation which contributes ten observations, plus an additional model which includes TN, TP, and CHLA in a single model yielding six more observations for a total of 16 observations from this study.

The derivation of the standardized elasticity and semi-elasticity estimates is as follows. Consider simplified version of the basic specification used (see EQ1 on pg. 647 of the primary study):

$$\ln(p) = \gamma X + \beta_0 dist_{WF} + \beta_1 \ln(WQ) + \beta_2(\ln(WQ) \cdot dist_{WF}) + \beta_3(\ln(WQ) \cdot \ln(dist)) + \beta_4(\ln(WQ) \cdot \ln(area)) + \beta_5(\ln(WQ) \cdot ClearLow)$$

where *ClearLow* is a dummy variable indicating that a lake is considered a clear lake with low alkalinity. This equation can be simplified to:

$$\ln(p) = \gamma X + \beta_0 dist_{WF} + [\beta_1 + \beta_2\, dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow] \ln(WQ)$$

$$p = \exp(\gamma X + \beta_0 dist_{WF} + [\beta_1 + \beta_2\, dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow] \ln(WQ)) \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta_0 dist_{WF} + [\beta_1 + \beta_2\, dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow] \ln(WQ)) \cdot [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow] \cdot \frac{1}{WQ}$$

Plugging in *p* from equation (1), and then rearranging yields the formulas for the semi-elasticity and elasticity estimates, equations (2) and (3), respectively.

$$\frac{\partial p}{\partial WQ} = p[\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow]\frac{1}{WQ}$$

$$\frac{\partial p}{\partial W\ _m}\frac{1}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow]\frac{1}{WQ} \qquad (2)$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area) + \beta_5 ClearLow] \qquad (3)$$

For waterfront observations, the relevant sample mean values for *area* are plugged in to equations (2) and (3), the representative waterfront home distance of 50 meters is plugged in for *dist*, and $dist_{WF}$ is set equal to one. For non-waterfront observations, the corresponding sample mean values are plugged in, but $dist_{WF}$ is set equal to zero and the representative non-waterfront home distance of 250 meters is plugged in for *dist*. The dummy variable *ClearLow* indicates clear lakes with low alkalinity is set to one for model specifications that include that variable.

Walsh et al. (2011a)

This study examined water clarity (secchi depth) in lakes in Orange County, Florida. The study estimated six hedonic regression models that varied in terms of the independent variables and how they address spatial dependence. Each model yields a waterfront and a non-waterfront observation. Therefore, the study contributed a total of 12 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation model 3 or 3S in the primary study as an example.

$$\ln(p) = \gamma X + \beta_1 \ln(WQ_{ft}) + \beta_2(\ln(WQ_{ft}) \cdot dist_{WF}) + \beta_3(\ln(WQ_{ft}) \cdot \ln(dist)) +$$

$\beta_4(\ln(area) \cdot \ln(WQ_{ft}))$

which can be simplified to:

$$\ln(p) = \gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ_{ft})$$

In this case, WQ is expressed in terms of Secchi disk depth in feet, which we re-express as Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28084\, ft}{1\, m}$. Plugging the conversion factor into the hedonic price function and re-arranging so that p is on the on the left-hand side yields:

$$p = e^{\gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ_m \cdot 3.28084)} \quad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial W\ \ _m} = e^{\gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ_m \cdot 3.28084)}$$

$$\cdot [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ_m \cdot 3.28084} \cdot 3.28084$$

Notice that the re-scaling factor of 3.28084 will cancel out in the derivative. Plugging in p from equation (1), and then rearranging yields the formulas for the semi-elasticity and elasticity estimates, equations (2) and (3), respectively.

$$\frac{\partial p}{\partial WQ_m} = p[\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ_m}$$

$$\frac{\partial p}{\partial WQ_m} \frac{1}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ_m} \quad (2)$$

$$\frac{\partial p}{\partial WQ_m} \frac{WQ_m}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \quad (3)$$

For waterfront observations, the relevant sample mean value for *area* is plugged into equations (2) and (3), the representative waterfront home distance of 50 meters is plugged in for *dist,* and $dist_{WF}$ is set equal to one. The mean water quality value (from table 2 of the primary study) is converted to meters and plugged in for WQ_m. For non-waterfront observations, the corresponding sample mean values are plugged in, but $dist_{WF}$ is set equal to zero and the representative non-waterfront home distance of 250 meters is plugged in for *dist.*

Walsh et al. (2011b)

This study examined four water quality measures (chlorophyll a, nitrogen, phosphorous, and a trophic state index) for lakes in Orange County, Florida. The study estimated 12 hedonic regression models, three for each of the four water quality measures, which varied in terms of how the functional form accounted for spatial dependence. Each model yielded two observations, one for waterfront homes and another for non-waterfront homes.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of the Walsh et al.'s double-log hedonic model.

$$\ln(p) = \gamma X + \beta_1 \ln(WQ) + \beta_2(\ln(WQ) \cdot dist_{WF}) + \beta_3(\ln(WQ) \cdot \ln(dist)) + \beta_4(\ln(area) \cdot \ln(WQ))$$

Which can be simplified to:

$$\ln(p) = \gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ) \quad (1)$$

where WQ denotes the corresponding measure of interest.

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \mathrm{e}^{\gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ)}$$

$$\cdot [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ}$$

Plugging in p from equation (1), and then rearranging yields the formulas for the semi-elasticity and elasticity estimates, equations (2) and (3), respectively.

$$\frac{\partial p}{\partial WQ} = p[\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ}$$

$$\frac{\partial p}{\partial WQ} \frac{1}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ} \quad (2)$$

$$\frac{\partial p}{\partial WQ} \frac{WQ}{p} = [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \quad (3)$$

For waterfront observations, the relevant sample mean value for *area* is plugged in to equations (2) and (3), the representative waterfront home distance of 50 meters is plugged in for *dist,* and $dist_{WF}$ is set equal to one. The corresponding mean water quality values are plugged in for WQ. For non-waterfront observations, the corresponding sample mean values are plugged in, but $dist_{WF}$ is set equal to zero and the representative non-waterfront home distance of 250 meters is plugged in for *dist.*

Walsh et al. (2017)

This study examined water clarity (light attenuation coefficient) in the Chesapeake Bay tidal waters for 14 adjacent counties in Maryland. The study estimated 56 separate hedonic regression models; four for each county, where the functional form (double-log versus semi-log) and period for which the water quality measure is averaged over (one versus three years) varied.

Each model in turn yields a waterfront and non-waterfront estimate, implying 112 observations. Furthermore, an additional 112 observations are derived from the same regression results by converting the estimates to correspond to Secchi disk depth (instead of the light attenuation coefficient). Therefore, the study contributed a total of 224 observations to the meta-dataset.

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of Walsh et al.'s double-log models as an example.

$$\ln(p) = \gamma X + \beta_1(\ln(WQ_{KD}) \cdot dist_{WF}) + \beta_2(\ln(WQ_{KD}) \cdot dist_{0-500})$$
$$+\beta_3(\ln(WQ_{KD}) \cdot dist_{500-1000})$$

where $dist_{WF}$ is a dummy variable equal to one for waterfront homes, $dist_{0-500}$ is a dummy variable equal to one for non-waterfront homes within 0-500 meters of the water, and $dist_{500-1000}$ is a dummy variable equal to one for non-waterfront homes within 500-1000 meters of the water. The above equation can be simplified to:

$$p = e^{\gamma X + (\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000}) \ln(WQ_{KD})}$$

Calculating the elasticities and semi-elasticities with respect to the light attenuation coefficient (WQ_{KD}) is straight forward and follows similar derivation as that below. Here we focus on converting those estimates to Secchi depth in meters (WQ_m), using the following inverse relationship estimated for this particular study area and noted in the primary study: $WQ_{KD} = 1.45/WQ_m$. Plugging this into the above hedonic regression yields:

$$p = e^{\gamma X + (\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000}) \ln\left(\frac{1.45}{WQ_m}\right)} \quad (1)$$

To calculate the semi-elasticity and elasticity estimates (equations 2 and 3, respectively), we take the derivative with respect to WQ_m and then do some slight rearranging:

$$\frac{\partial p}{\partial WQ_m} = e^{\gamma X \quad (\beta_1 dist_{WF}+\beta_2 dist_{0-500}+\beta_3 dist_{500-1000}) \ln\left(\frac{1.45}{WQ_m}\right)}$$

$$\cdot -(\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000}) \frac{WQ_m}{1.45} (1.45) WQ_m{}^{-2}$$

$$\frac{\partial p}{\partial WQ_m} = -\frac{p}{WQ_m} (\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000})$$

$$\frac{\partial p}{\partial WQ_m}\frac{1}{p} = -\frac{1}{WQ_m} (\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000}) \quad (2)$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = -(\beta_1 dist_{WF} + \beta_2 dist_{0-500} + \beta_3 dist_{500-1000}) \quad (3)$$

After plugging in the appropriate value of zero or one for the corresponding dummy variables, the elasticities and semi-elasticities for waterfront homes are simply $-\beta_1$and $-\frac{\beta_1}{WQ_m}$, respectively. For non-waterfront observations, representative non-waterfront home distance of 250 meters is plugged in for *dist*, and so the corresponding elasticities and semi-elasticities are $-\beta_2$ and $-\frac{\beta_2}{WQ_m}$. The relevant county specific sample means for WQ_m and p are then plugged in as needed in order to calculate the estimated semi-elasticities.

Williamson et al. (2008)

This study examined acid mine drainage impairment in the Cheat River Watershed in West Virginia. The study estimated one hedonic regression model, yielding a waterfront and non-waterfront observation. For this study, the dummy variable, $WQ_{impair0.25}$ representing properties within a 0.25 mile (i.e., 402.34 meters) of the acid mine drainage impaired stream includes both waterfront and non-waterfront. Therefore, the study contributed a total of two observations to the meta-dataset.

Consider a simplified representation of Table 3 as an example.

$$\ln(p) = \gamma X + D_1 WQ_{impair0.25} + D_2 WQ_{impair0.50} \quad (1)$$

Rearranging for p,

$$p = \exp\,(\gamma X + D_1 WQ_{impair0.25} + D_2 WQ_{impair0.50})$$

Because the functional form is log-linear, we use the following equation for calculating the percent change in price, as first outlined by Halvorsen and Palmquist (1980): $\%\Delta p = \frac{p_1 - p_0}{p_0}$.

Estimating the percent change for impaired river, let p_0 denote the price when the dummy variable is turned off, and p_1 denote when it is turned on. These can be written out, respectively, as:

$$p_0 = \exp\,(\gamma X)$$

$$p_1 = \exp\,(\gamma X + D_1)$$

Plugging in the above equations yields:

$$\%\Delta p = \frac{p_1 - p_0}{p_0} = \frac{\exp(\gamma X + D_1) - \exp(\gamma X)}{\exp\,(\gamma X)}$$

Some rearranging and simplification yields:

$$\%\Delta p = \frac{\exp(\gamma X)\exp\,(D_1) - \exp(\gamma X)}{\exp(\gamma X)}$$

$$\%\Delta p = \exp\,(D_1) - 1$$

The relevant coefficient for D_1 is then plugged in as needed to calculate the percent change in price.

Wolf and Klaiber (2017)

This study examined the effect of the density of harmful algae (as proxied by microsystin concentrations) on properties across six counties surrounding four inland lakes in Ohio. The study estimated nine hedonic models, each yielding a waterfront and non-waterfront estimate. Therefore, the study contributed a total of 18 observations to the meta-dataset. The algae concentrations are converted to a binary water quality dummy variable (*Algae*) that is set equal to one when the algae density is above the World Health Organization's standard of 1ug/L for drinking water for a period of time matching individual housing transactions data.

The derivation of the standardized elasticity and semi-elasticity estimates is as follows. Consider simplified version of the basic specification used.

$$\ln(p) = \gamma X + D_1 Algae + D_2\big(Algae \cdot (dist_{0-20m} + dist_{20-600m})\big) + D_3(Algae \cdot dist)$$

This can then be rewritten as:

$$p = \exp\,(\gamma X + D_1 Algae + \ D_2\big(Algae \cdot (dist_{0-20m} + dist_{20-60} \quad)\big) + D_3(Algae \cdot dist)) \ (1)$$

Let p_0 denote the price when the algae dummy is turned off, and p_1 denote when it is turned on. These can be written out, respectively, as:

$$p_0 = e^{\gamma X}$$

$$p_1 = e^{\gamma X + D_1 + D_2 + D_3(dist)}$$

The percent change in price can then be expressed as $\%\Delta p = \frac{p_1 - p_0}{p_0}$. Plugging in the above equations yields:

$$\%\Delta p = \frac{p_1 - p_0}{p_0} = \frac{e^{\gamma X + D_1 + D_2 + D_3(dist)} - e^{\gamma X}}{e^{\gamma X}}$$

Some rearranging and simplification yields:

$$\%\Delta p = \frac{e^{\gamma X} e^{D_1 + D_2 + D_3(dist)} - e^{\gamma X}}{e^{\gamma X}}$$

$$\%\Delta p = e^{D_1 + D_2 + D_3(dist)} - 1$$

The relevant coefficients and the appropriate representative home distance for *dist* (50 meters for waterfront homes, 250 meters for non-waterfront homes) are then plugged in as needed in order to calculate the estimated percent change in price.

Yoo et al. (2014)

This study examined the effect of sediment loads on five lakes in Arizona. The sediment loading observations are derived from a watershed level sediment delivery model. The sediment load is interacted with the travel time from each property to the nearest lake in all models. Three semi-log model specifications are estimated – OLS, spatial lag model, and spatial error model – for both waterfront and non-waterfront homes. There are six observations from this study. Derivation of the elasticity and semi-elasticity is as follows – recall that WQ in this study is measured as sediment load. The primary study WQ is expressed in terms of tons/acre, which we re-express as kg/sq. meters using the following conversion factor: $WQ_{\frac{tons}{acre}} = WQ_{\frac{kg}{sqm}} \cdot 4.461$.

Plugging this into the hedonic regression yields:

$$\ln(p) = \gamma X + \beta_1 WQ_{\frac{kg}{sqm}} \cdot 4.461 + \beta_2 WQ_{\frac{kg}{sqm}} \cdot 4.461 \cdot Time + \beta_3 WQ_{\frac{kg}{sqm}} \cdot 4.461 \cdot Time^2$$

which is rewritten as:

$$\mathrm{p} = \exp\left(\gamma X + \beta_1 WQ_{\frac{kg}{sqm}} \cdot 4.461 + \beta_2 WQ_{\frac{kg}{sqm}} \cdot 4.461 \cdot Time + \beta_3 WQ_{\frac{kg}{sqm}} \cdot 4.461 \cdot Time^2\right) \tag{1}$$

Now, the derivative with respect to WQ is:

$$\frac{dp}{dWQ} = p \cdot (\beta_1 \cdot 4.461 + \beta_2 \cdot 4.461 \cdot Time + \beta_3 \cdot 4.461 \cdot Time^2)$$

and the semi-elasticity (equation 2) and elasticity (equation 3) are given by:

$$\frac{dp}{dWQ}\frac{1}{p} = 4.461(\beta_1 + \beta_2 \cdot Time + \beta_3 \cdot Time^2) \tag{2}$$

$$\frac{dp}{dWQ}\frac{WQ}{p} = WQ_{\frac{kg}{sqm}} \cdot 4.461(\beta_1 + \beta_2 \cdot Time + \beta_3 \cdot Time^2) \tag{3}$$

The relevant sample means for WQ and $Time$ are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Zhang and Boyle (2010)

This study examined the interaction of water clarity and surface area of waterbody in the four lakes and one pond in Rutland County, Vermont. The study estimated ten hedonic regression models, but only six included a water quality parameter. These six models focused only on waterfront homes, and therefore the study contributed a total of six observations to the meta-dataset. Waterbody surface area was measured in acres in the original study (one acre equals 4046.86 square meters).

The derivation of our standardized elasticity and semi-elasticity estimates is as follows. Consider a simplified representation of model Total Macrophytes-Quadratic as an example. The hedonic double-log specification can generally be specified as:

$$\ln(p) = \gamma X + \beta \cdot area_{acres} \cdot \ln(WQ)$$

Rearranging for *p*,

$$p = \exp(\gamma X + \beta \cdot area_{acres} \cdot \ln(WQ)) \qquad (1)$$

Taking the partial derivative of equation (1) with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \exp(\gamma X + \beta \cdot area_{acres} \cdot \ln(WQ)) \cdot (\beta \cdot area_{acres}) \frac{1}{WQ}$$

Substituting in *p* from equation (1) and rearranging, the formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \frac{(\beta \cdot area_{acres})}{WQ} \qquad (2)$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = (\beta \cdot area_{acres}) \qquad (3)$$

The relevant sample means for WQ and *area* are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Zhang et al. (2015)

This study examined the effect of water clarity on lakefront homes across 15 markets in Maine, Vermont, and New Hampshire. The water quality variable used in the study is the natural log of water clarity multiplied by lake size. There is one observation per market, thus this study contributed 15 observations to the meta-dataset.

The specification used in all the models is:

$$p = \gamma X + \beta \cdot area \cdot \ln{(WQ)} \tag{1}$$

Taking the partial derivative of the price equation with respect to WQ yields:

$$\frac{\partial p}{\partial WQ} = \left(\beta \cdot \frac{area}{WQ}\right)$$

The formulas for the semi-elasticity equation (2) and elasticity equation (3) follow

$$\frac{\partial p}{\partial WQ}\frac{1}{p} = \beta \cdot \frac{area}{WQ} \cdot \frac{1}{p} \tag{2}$$

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot \frac{area}{p} \tag{3}$$

The relevant sample means for WQ, price, and *area* are then plugged in as needed in order to calculate the estimated elasticities and semi-elasticities.

Appendix B: Meta-analytic Weights, Mean Elasticity Calculations, and Funnel Plots of Publication Bias.

Appendix B.1: Meta-analytic Weights

When calculating the mean values in a meta-analyses, researchers often wish to account for the clustered nature of the meta-data (Mrozek and Taylor, 2002). As in this study, meta-datasets often contain multiple meta-observations from the same study and dataset. If such dependence is not accounted for, meta-observations would be unduly weighted, counting as a single observation when they should be discounted appropriately because there are multiple observed estimates of the same unobserved "true" value. We define each cluster as a unique study and "housing market" combination. Meta-observations estimated in the same study and from a common transaction dataset in terms of the study area and time period are in fact estimates of the same underlying elasticity.

Let $\hat{\varepsilon}_{idj}$ denote elasticity estimate *i*, for homes at distance *d*, in cluster or housing market *j* $\left(\hat{\varepsilon}_{idj}\right)$. The number of elasticity estimates in each cluster *j* is denoted by k_{dj}. The cluster weighted mean elasticity for each distance bin *d* is calculated as:

$$\bar{\varepsilon}_d = \sum_{i=1}^{n} \frac{\frac{1}{k_{dj}}}{\sum_{j=1}^{K_d} \sum_{i=1}^{k_{dj}} \frac{1}{k_{dj}}} \hat{\varepsilon}_{idj} \qquad \text{(B1)}$$

where the same $\frac{1}{k_{dj}}$ weight is given to each meta-observation i within cluster *j*. The denominator of equation (1) normalizes the weights so that they sum to one. The inner summation in the denominator sums to one for each cluster, and then the outer summation sums to the total number of clusters in the meta-dataset for distance bin d (K_d). Under this weighting scheme, no matter how many elasticity estimates are provided in the literature, each cluster as a whole is given the same weight.

Weights based on the inverse variance of the primary estimates are also often applied in meta-analyses in order to give more weight to more precise estimates (Nelson, 2015; Borenstein et al., 2010; Nelson and Kennedy, 2009). In particular, we re-distribute the weight given to each observation within a cluster based on the Random Effect Size (RES) weights commonly used in the meta-analysis literature (Nelson and Kennedy, 2009; Borenstein et al., 2010; and Nelson, 2015). Estimates from each cluster are still given the same overall weight, but more precise estimates of the underlying "true" elasticity for that cluster are given more weight than less precise estimates.

Before presenting our RES-adjusted cluster (RESAC) weights, we review the two conventional precision-based weighting schemes commonly used in meta-analyses. The first is the Fixed Effect Size (FES) model.[4] Under the FES framework each meta-observation is considered a draw from the same underlying population distribution (even if from different studies examining different areas), and the estimated weighted mean is interpreted as an estimate of the average from that single true distribution. In other words, under the FES framework sampling error is the only driver of differences in the observed estimates across studies. The FES weight for elasticity estimate *i*, at distance *d*, in cluster j $\left(\hat{\varepsilon}_{idj}\right)$ is:

$$w_{idj}^{FES} = \frac{1}{v_{idj}} \qquad \text{(B2)}$$

where v_{idj} is the variance of the estimate $\hat{\varepsilon}_{idj}$ from the primary study. Note that these weights are not yet normalized to sum to one.

[4] The FES weighting scheme is also sometimes called a fixed effects model. We use the FES terminology to avoid confusion with the frequently used fixed effects model in panel data analysis.

The second weighting scheme is a variant of the above and is sometimes referred to as the Random Effects Size (RES) model. The RES weighting scheme is preferred if the meta-observations are believed to be estimates of *different* "true" elasticities from different distributions (Harris et al. 2008, Borenstein et al. 2010, Nelson 2015). In the RES framework the weighted mean is interpreted as an estimate of the average of the different average elasticities across the different distributions. There is no reason to suspect that the true home price elasticities with respect to water quality are the same at different waterbodies in different housing markets. These waterbodies differ in size, baseline water quality levels, and the provision of recreational, aesthetic and ecosystem services, among other things. The housing bundles, and preferences and income of buyers and sellers, are heterogeneous as well. Therefore, weights based on the RES model are applied in this meta-analysis.

The conventional RES weights are calculated as:

$$w_{idj}^{RES} = \frac{1}{v_{idj}+T^2} \quad \text{(B3)}$$

where T^2 is the between study variance, and is calculated as:

$$T^2 = \frac{Q-(n-1)}{\sum_{i=1}^{n} w_{idj}^{FES} - \left(\frac{\sum_{i=1}^{n}\left(w_{idj}^{FES}\right)^2}{\sum_{i=1}^{n} w_{idj}^{FES}}\right)} \quad \text{(B4)}$$

The numerator of T^2 entails the weighted sum of squares of the elasticity estimates around the FES mean, denoted as Q, minus the available degrees of freedom (i.e., the number or meta-observations minus one). Q is calculated as:

$$Q = \sum_{i=1}^{n} \frac{\left(\hat{\varepsilon}_{idj} - \bar{\varepsilon}_d^{FES}\right)^2}{v_{idj}} \quad \text{(B5)}$$

The conventional RES weighted means are thus calculated as

$$\bar{\varepsilon}_d^{RES} = \sum_{i=1}^{n} \frac{w_{idj}^{RES}}{\sum_{i=1}^{n} w_{idj}^{RES}} \hat{\varepsilon}_{idj} \quad \text{(B6)}$$

where n is the number of observed estimates in the meta-dataset for distance bin d and the water quality measure of interest. The between-study variance is estimated via the DerSimonian and Laird (1986) method using the inverse variance weights $\left(w_{ij}^{FES}\right)$ and the FES mean elasticity estimate $\bar{\varepsilon}_{d}^{FES}$. Following Borenstein et al. (2010), the between study variance T^2 is set to zero for a few observations where it was originally negative.[5]

The normalized RESAC weights that we use in this study are calculated as:

$$\omega_{idj} = \frac{\frac{w_{idj}^{RES}}{k_{dj}}}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}}\left(\frac{w_{idj}^{RES}}{k_{dj}}\right)} \tag{B7}$$

These weights re-distribute the influence given to each observation within a cluster based on the RES weights such that each cluster (study-housing market combination) is still given the same overall weight, but that more precise estimates of the underlying "true" elasticity for that cluster are given more weight than less precise estimates in that cluster. The RESAC weighted mean elasticity for distance bin d is calculated as:

$$\bar{\bar{\varepsilon}}_d = \sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}} \omega_{idj}^{h}\, \hat{\varepsilon}_{idj} \tag{B8}$$

Appendix B.2: Mean Elasticities

Table BI displays the unweighted mean elasticity estimates, as well as the cluster-adjusted, standard RES, and RESAC weighted mean elasticity estimates, for all water quality measures examined in the hedonic property value literature. When represented in the literature, separate mean elasticity estimates are provided for two distances bins – waterfront homes and non-waterfront homes within 500 meters of a water body. The number of observations and contributing studies for each water quality measure are displayed in the rightmost columns.

[5] Any such instances in the current meta-datset seem reasonable because they always entail just a single study (and so there is no between study variation).

Appendix B.2: Mean Elasticities

Table BI. Unit value mean elasticity estimates.

Water quality measure	Unweighted Mean (1)	Cluster Weighted Mean (2)	Standard RES Mean (3)	RES-Adjusted Cluster (RESAC) Weighted (4)	n	# studies
Chlorophyll a						
waterfront	0.737*	0.324*	-0.022***	-0.026***	18	3
	(-0.044, 1.517)	(-0.036, 0.685)	(-0.031, -0.013)	(-0.031, -0.021)		
non-waterfront w/in 500 m	0.005	0.010	0.001	0.009***	18	3
	(-0.201, 0.211)	(-0.085, 0.105)	(-0.006, 0.009)	(0.006, 0.012)		
Dissolved oxygen						
waterfront	0.089	-0.014	0.098	-0.010	10	2
	(-0.207, 0.384)	(-0.262, 0.235)	(-0.669, 0.865)	(-0.257, 0.237)		
non-waterfront w/in 500 m	1.063***	0.666***	0.992***	0.642***	6	1
	(0.708, 1.419)	(0.395, 0.937)	(0.343, 1.641)	(0.374, 0.910)		
E-coli						
waterfront	-0.073***	-0.073***	-0.089***	-0.081***	5	1
	(-0.124, -0.021)	(-0.124, -0.021)	(-0.147, -0.031)	(-0.129, -0.032)		
non-waterfront w/in 500 m	-0.073***	-0.073***	-0.089***	-0.081***	5	1
	(-0.125, -0.022)	(-0.125, -0.022)	(-0.147, -0.031)	(-0.129, -0.033)		
Fecal coliform						
waterfront	-0.018***	-0.037	-0.2E-4	-1.3E-4***	36	4
	(-0.026, -0.011)	(-0.088, 0.014)	(-0.6E-4, 0.1E-4)	(-1.8E-4, -0.7E-4)		
non-waterfront w/in 500 m	-0.020***	-0.059*	-0.024***	-0.052***	20	3
	(-0.034, -0.006)	(-0.090, -0.005)	(-0.036, -0.011)	(-0.096, -0.008)		
Lake trophic state index						
waterfront	-0.920***	-0.920***	-0.797***	-0.797***	2	1
	(-1.545, -0.295)	(-1.545, -0.295)	(-1.330, -0.264)	(-1.330, -0.264)		

non-waterfront w/in 500 m	-0.682**	-0.682**	-0.682**	-0.682**	1	1
	(-1.296, -0.068)	(-1.296, -0.068)	(-1.296, -0.068)	(-1.296, -0.068)		
Light attenuation						
waterfront	-0.086***	-0.086***	-0.070***	-0.082***	57	2
	(-0.099, -0.073)	(-0.099, -0.074)	(-0.076, -0.063)	(-0.093, -0.070)		
non-waterfront w/in 500 m	-0.014***	-0.014***	-0.011	-0.013***	57	2
	(-0.022, -0.006)	(-0.022, -0.006)	(-0.014, -0.007)	(-0.020, -0.006)		
Nitrogen						
waterfront	-0.292***	-0.242***	-0.245***	-0.220***	10	5
	(-0.326, -0.257)	(-0.271, -0.215)	(-0.321, -0.170)	(-0.244, -0.196)		
non-waterfront w/in 500 m	-0.221***	-0.184***	-0.130***	-0.136***	10	5
	(-0.254, -0.187)	(-0.210, -0.157)	(-0.184, -0.077)	(-0.156, -0.116)		
Percent Water Visibility						
waterfront	-1.655***	-1.655***	-1.659***	-1.659***	2	1
	(-1.896, -1.414)	(-1.896, -1.414)	(-1.900, -1.418)	(-1.900, -1.418)		
non-waterfront w/in 500 m	-	-	-	-	0	0
Phosphorous						
waterfront	-0.115***	-0.107***	-0.114***	-0.107***	6	3
	(-0.130, -0.100)	(-0.123, -0.092)	(-0.154, -0.074)	(-0.122, -0.092)		
non-waterfront w/in 500 m	-0.016**	-0.019***	-0.002	-0.005	6	3
	(-0.029, -0.003)	(-0.032, -0.005)	(-0.015, 0.010)	(-0.012, 0.003)		
Salinity						
waterfront	0.553***	0.553***	0.552***	0.552***	2	1
	(0.281, 0.826)	(0.281, 0.826)	(0.279, 0.824)	(0.279, 0.824)		
non-waterfront w/in 500 m	-	-	-	-	0	0
Sediment						
waterfront	-0.018	-0.012	4.9E-6**	-0.003	4	2
	(-0.088, 0.052)	(-0.059, 0.035)	(0.2E-6, 9.7E-6)	(-0.008, 0.001)		
non-waterfront w/in 500 m	-0.018	-0.012	4.9E-6**	-0.006	4	2

	(-0.088, 0.052)	(-0.059, 0.035)	(0.2E-6, 9.7E-6)	(-0.014, 0.003)		
Sedimentation Rate						
waterfront	-0.132*** (-0.183, -0.082)	-0.132*** (-0.183, -0.082)	-0.113*** (-0.134, -0.091)	-0.113*** (-0.134, -0.091)	2	1
non-waterfront w/in 500 m	-0.132*** (-0.183, -0.082)	-0.132*** (-0.183, -0.082)	-0.113*** (-0.134, -0.091)	-0.113*** (-0.134, -0.091)	2	1
Temperature						
waterfront	0.138 (-0.240, 0.516)	-0.177 (-0.720, 0.366)	-0.164 (-0.226, 0.533)	-0.164 (-0.688, 0.361)	6	1
non-waterfront w/in 500 m	0.137 (-0.240, 0.515)	-0.177 (-0.719, 0.365)	-0.164 (-0.226, 0.532)	-0.164 (-0.687, 0.360)	6	1
Total Suspended Solids						
waterfront	0.002 (-0.31, 0.036)	-0.026 (-0.057, 0.005)	-0.013 (-0.055, 0.029)	-0.032** (-0.064, -0.000)	7	2
non-waterfront w/in 500 m	0.002 (-0.31, 0.036)	-0.026 (-0.057, 0.005)	-0.013 (-0.055, 0.029)	-0.032** (-0.064, -0.000)	7	2
Turbidity						
waterfront	-0.036*** (-0.057, -0.016)	-0.036*** (-0.057, -0.016)	-0.036*** (-0.057, -0.016)	-0.036*** (-0.057, -0.016)	2	1
non-waterfront w/in 500 m	-	-	-	-	0	0
Water clarity						
waterfront	0.155 (-6.102, 6.413)	0.182 (-17.398, 17.762)	0.090*** (0.078, 0.102)	0.105*** (0.095, 0.114)	177	18
non-waterfront w/in 500 m	0.028*** (0.020, 0.036)	0.042*** (0.025, 0.059)	0.018*** (0.008, 0.028)	0.026*** (0.017, 0.034)	83	6
pH						
waterfront	2.173*** (1.015, 3.331)	1.986*** (-.840, 3.133)	0.424 (-0.285, 1.133)	0.779** (0.019, 1.540)	13	3
non-waterfront w/in 500 m	-0.334 (-1.126, 0.457)	0.008 (-1.405, 1.422)	-0.379 (-1.084, 0.326)	-0.188 (-1.086, 0.711)	6	1
Trophic state index						
waterfront	-0.181***	-1.60***	-0.177***	-0.158***	4	2

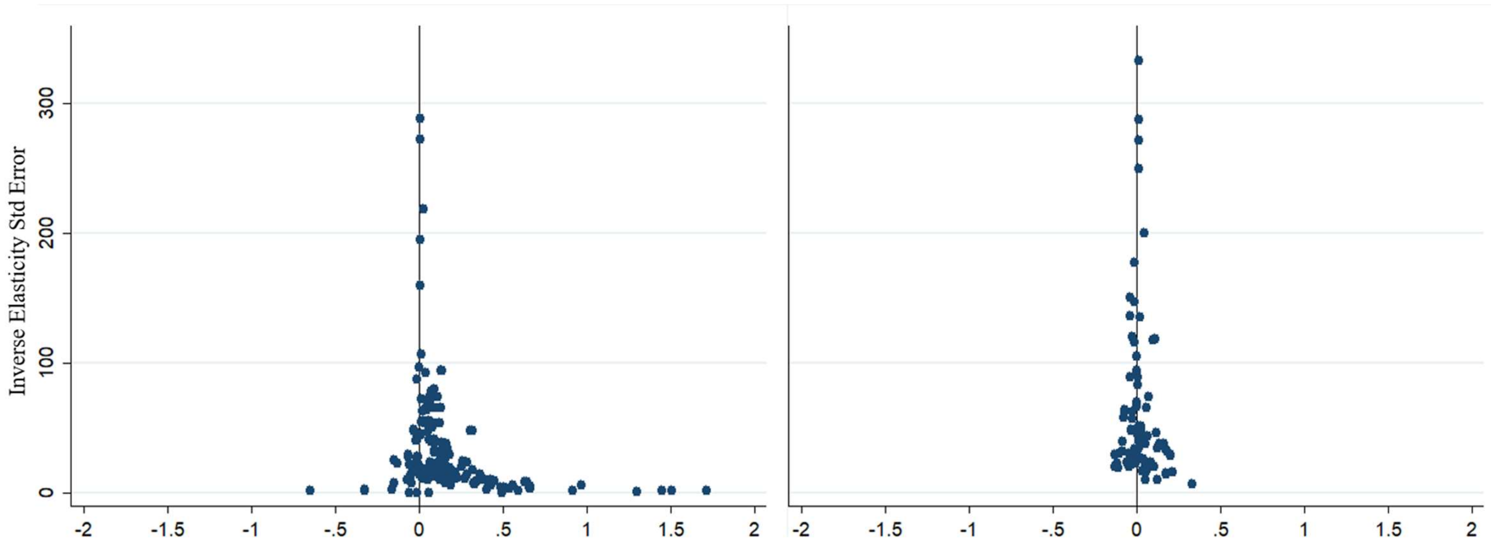
	(-0.209, -0.154)	(-0.184, -0.137)	(-0.229, -0.124)	(-0.181, -0.136)		
non-waterfront w/in 500 m	0.029***	0.018**	0.022	0.015**	4	2
	(0.007, 0.050)	(0.003, 0.034)	(-0.007, 0.051)	(0.001, 0.029)		

*** p<0.01, ** p<0.05, * p<0.1. Confidence intervals at the 95% level are displayed in parentheses.

Appendix B.3: Funnel Plots of Publication Bias

As a first step to examine possible selection concerns, we create a "funnel plot" of the elasticity estimates with respect to water clarity against the inverse of the corresponding standard errors. If the plot exhibits a symmetric inverted funnel shape, then this provides an informal signal that the meta-data does not suffer from publication bias (Stanley and Doucouliagos, 2012). As can be seen in Figure B1, the funnel plots of the price elasticity estimates with respect to water clarity for waterfront and non-waterfront homes exhibit some asymmetries. The left funnel plot (panel (a)) suggests that lower precision elasticity estimates for waterfront homes tend to be positive, and in some cases rather large. This suggests that publication selection or some other mechanism is causing an upward bias in the meta-data. The right funnel plot (panel (b)) suggests a similar, but less pronounced, selection among the non-waterfront elasticity observations. We provide formal tests and correction methods to address this possible selection bias in Section 2.5 of the main text.

Figure B1. Funnel Plots of Housing Price Elasticities with respect to Water Clarity (Secchi disk depth).



(a) Elasticity: Waterfront homes

(b) Elasticity: Non-waterfront homes within 500 meters

Appendix C: Supplemental meta-regression results and descriptive statistics.

Table C1. WLS Meta-regression Results using Conventional Cluster-Based Weights.

VARIABLES[a]	(1)	(2)	(3)
Waterfront[a]	0.0555*	0.0354	0.0325
	(0.030)	(0.025)	(0.027)
Mean clarity	0.0054	-0.0347	-0.0345
	(0.026)	(0.044)	(0.046)
Estuary[a]	-0.0777	-0.0843	-0.0853
	(0.106)	(0.072)	(0.082)
Mean clarity × estuary	-0.0470	-0.0058	-0.0034
	(0.082)	(0.090)	(0.090)
Median income	0.0026	0.0025	0.0022
	(0.002)	(0.002)	(0.002)
Midwest[a]		-0.3312***	-0.3045**
		(0.120)	(0.126)
South[a]		-0.4367***	-0.3101
		(0.152)	(0.209)
West[a]		-0.4354***	-0.3194
		(0.118)	(0.259)
Elasticity variance	-0.0000***	-0.0000***	-0.0000**
	(0.000)	(0.000)	(0.000)
Unpublished[a]	0.0022	-0.0127	0.0743
	(0.081)	(0.055)	(0.120)
Assessed values[a]	0.0285	0.1649*	0.1195
	(0.100)	(0.093)	(0.084)
Time trend	-0.0061	0.0094*	0.0102
	(0.008)	(0.005)	(0.007)
No spatial methods[a]			-0.0638
			(0.103)
Linear-log[a]			0.1916
			(0.219)
Linear[a]			0.1908
			(0.161)
Log-linear[a]			-0.0007
			(0.007)
Constant	0.0280	0.2664	0.1471
	(0.193)	(0.296)	(0.312)
Observations	260	260	260
Adjusted R-squared	0.110	0.155	0.153

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** p<0.01, ** p<0.05, * p<0.1. Clustered-robust standard errors in parentheses; clustered according to the K=63 unique study-housing market combinations. Weighted least squares regressions estimated using the "regress" routine in Stata 14 and defining analytical weights according to the inverse of the number of primary estimates from the corresponding study-housing market cluster. (a) Denotes independent variables that are dummy variables.

Table C2. Cluster-weighted Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Dependent variable:				
Elasticity	0.1113	0.2595	-0.6499	1.7191
Study area variables:				
Waterfront[a]	0.4961	0.5009	0	1
Mean clarity (secchi disk depth, meters)	2.16	1.92	0.38	6.45
Estuary[a]	0.5160	0.5007	0	1
Median income (thousands, 2017$)	61.446	14.567	37.865	91.174
College degree (% population)	0.1455	0.0406	0.0768	0.2734
Population density (households /sq. km.)	54.70	63.59	1.41	227.96
Mean house price (thousands, nominal$)	222.789	120.383	31.287	675.364
Midwest[a]	0.1662	0.3730	0	1
South[a]	0.5504	0.4984	0	1
West[a]	0.0157	0.1247	0	1
Methodological variables:				
Elasticity variance	2514.3190	26702.0700	9.03E-06	301448.5
Unpublished[a]	0.0924	0.2902	0	1
Assessed values[a]	0.0738	0.2619	0	1
Time Trend (0=1994 to 20=2014)	9.64	5.980	0	20
No spatial methods[a]	0.3448	0.4762	0	1
Linear-log[a]	0.3150	0.4654	0	1
Linear[a]	0.0501	0.2187	0	1
Log-linear[a]	0.2752	0.4475	0	1
Last year of transaction data	2003.64	5.98	1994	2014

Cluster weighted descriptive statistics for n=260 unique elasticity estimates in meta-dataset pertaining to water clarity. Weighted by study-housing market clusters (K=63).
(a) Denotes independent variables that are dummy variables.

Table C3. Random Effects (RE) Panel Meta-regression Results.

VARIABLES[a]	(1)	(2)	(3)
Waterfront[a]	0.0525**	0.0465**	0.0574***
	(0.021)	(0.021)	(0.019)
Mean clarity	0.0225**	0.0104	0.0292*
	(0.010)	(0.015)	(0.016)
Estuary[a]	-0.0014	-0.0301	0.0057
	(0.054)	(0.043)	(0.044)
Mean clarity × estuary	-0.0519	-0.0395	-0.0568
	(0.062)	(0.062)	(0.061)
Median income	0.0015	0.0015	0.0013
	(0.001)	(0.001)	(0.001)
Midwest[a]		-0.1506***	-0.1645***
		(0.042)	(0.040)
South[a]		-0.1832***	-0.2544***
		(0.051)	(0.067)
West[a]		-0.3055***	-0.4551***
		(0.065)	(0.081)
Elasticity variance	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Unpublished[a]	0.0643*	0.0548*	0.0104
	(0.037)	(0.029)	(0.047)
Assessed values[a]	-0.0090	0.0491	0.0523*
	(0.054)	(0.046)	(0.028)
Time trend	0.0038	0.0137***	0.0127***
	(0.004)	(0.003)	(0.001)
No spatial methods[a]			-0.0090
			(0.014)
Linear-log[a]			-0.1349**
			(0.063)
Linear[a]			0.0473
			(0.056)
Log-linear[a]			0.0016
			(0.004)
Constant	-0.1215	-0.0461	0.0112
	(0.074)	(0.104)	(0.102)
Observations	260	260	260
ll	1.5445	1.6191	1.6634

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Random Effects Panel (RE Panel) regressions estimated using the "mixed" routine in Stata 14, where the cluster specific effects are defined according to the K=63 unique study-housing market clusters. Observations weighted following the RESAC weights (see equation 2 in section 2.4).
(a) Denotes independent variables that are dummy variables.

Appendix D: Variance-Covariance Matrix for Weighted Least Squares (WLS) Meta-regression Model 2.

Table D1. Variance-Covariance Matrix for WLS 2 Meta-regression.

	Waterfront	Mean clarity	Estuary	Mean clarity × estuary	Median income	Midwest
Waterfront	4.5665E-04					
Mean clarity	-1.7039E-05	2.2389E-04				
Estuary	-2.7068E-04	2.5750E-04	1.9709E-03			
Mean clarity × estuary	3.7960E-04	-2.4875E-04	-2.5313E-03	4.0880E-03		
Median income	2.2328E-06	2.8977E-06	-1.2469E-05	5.3594E-06	1.1345E-06	
Midwest	4.6048E-05	3.8895E-04	5.4929E-04	-3.3254E-04	6.2228E-06	1.8246E-03
South	2.9903E-04	5.3809E-04	6.8063E-04	-3.2271E-04	2.9702E-06	1.9009E-03
West	1.7073E-04	-2.6609E-04	1.6246E-04	3.2173E-04	-1.7593E-05	8.4662E-04
Elasticity variance	-1.0967E-08	-3.2775E-09	-4.3966E-09	-1.3272E-08	8.4489E-10	-3.2815E-08
Unpublished	1.7767E-04	1.1686E-04	1.6351E-04	3.0563E-05	-2.0086E-06	2.7453E-04
Assessed values	-3.2116E-04	-1.0685E-04	-2.6897E-04	4.9478E-05	7.3989E-06	-5.1677E-04
Time trend	-6.9604E-07	2.2725E-05	1.5459E-05	-2.9965E-05	-1.3719E-07	-3.8581E-06
Constant	-5.1956E-04	-1.2940E-03	-4.7040E-04	6.1872E-04	-7.1785E-05	-2.8698E-03

	South	West	Elasticity variance	Unpublished	Assessed values	Time trend	Constant
Waterfront							
Mean clarity							
Estuary							
Mean clarity × estuary							
Median income							
Midwest							
South	2.6933E-03						
West	9.8456E-04	4.4636E-03					
Elasticity variance	-5.6400E-08	-6.5956E-08	2.8479E-10				
Unpublished	9.1739E-04	5.0955E-04	-2.3739E-08	8.6437E-04			
Assessed values	-6.5136E-04	-1.2047E-03	4.3330E-08	-6.0920E-05	2.1784E-03		
Time trend	1.0246E-05	-1.0347E-04	3.0762E-10	-8.7010E-06	6.2301E-06	6.7973E-06	
Constant	-3.9335E-03	1.4444E-03	1.3528E-08	-9.5751E-04	4.3208E-04	-1.0754E-04	1.1381E-02

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