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ABSTRACT: We conduct a meta-analysis using a comprehensive review of studies that examine the effects of water quality improvements on waterfront and non-waterfront housing values. Rather than conducting the meta-analysis using dollar values, this study estimates mean elasticity responses. We identify 36 studies that result in 656 unique observations. Mean property price elasticities with respect to numerous water quality measures are calculated (e.g., chlorophyll-a, fecal coliform, nitrogen, and phosphorous) for purposes of value transfer. In the context of water clarity, function transfers can be performed. We estimate numerous meta-regressions, and compare transfer performance across models using an out-of-sample transfer error exercise. The results suggest value transfers often perform just as well as more complicated function transfers. In our context, however, a simple function transfer that accounts for baseline water clarity performs best. We discuss the implications of these results for benefit transfer, and outline key limitations in the literature.

KEYWORDS: benefit transfer; hedonic; meta-analysis; property value; water pollution; water quality

JEL CODES: Q51 (Valuation of Environmental Effects); Q53 (Air Pollution; Water Pollution; Noise; Hazardous Waste; Solid Waste; Recycling)

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Property values and water quality:
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1. INTRODUCTION

The hedonic property value method is a popular nonmarket valuation technique to estimate how residents value local amenities and disamenities, including water quality and related ecosystem services. The basic notion is that a house and its location comprise a bundle of characteristics. Hedonic modeling allows analysts to estimate how each of those various characteristics contribute to the overall price of a home. Empirical applications of hedonic methods to property values date back to Hass (1922), who examined how agricultural land prices vary with distance to the city center. But it was not until Rosen's (1974) seminal paper that hedonic modeling was formally linked to welfare analysis. Since then there have been numerous empirical studies examining how local environmental commodities affect residential property prices.

Dating back to David's (1968) report, the hedonic literature examining the impacts of surface water quality on residential property values is fairly well-established. Our comprehensive literature review identified 36 unique studies in the published and grey literature. Many studies focus primarily on the price impacts of water quality among waterfront homes (Young 1984, Michael et al. 1996, Boyle et al. 1999, Leggett and Bockstael 2000), but recent studies have found price effects as far away as about one mile from a waterbody (Walsh et al. 2011a, Netusil et al. 2014, Liu et al. 2017, Klemick et al. 2018).

In order to generalize key conclusions from any literature, economists often turn to meta-analysis, which is a quantitative synthesis of multiple primary studies (Nelson, 2013). Nelson and Kennedy (2009) identified 140 meta-analyses in the environmental and resource economics field, about half of which were published since 2004. Although there are several meta-analyses of hedonic property value studies, including applications to air quality (Smith and Huang, 1993, 1995), contaminated

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sites (Messer et al., 2006; Kiel and Williams, 2007), open space (Mazzotta et al., 2014), and noise (Nelson, 2004), to our knowledge we conduct the first comprehensive meta-analysis of the hedonic literature examining surface water quality.[2]

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 study. In practice, 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).

Our objective is to synthesize the vast literature examining how water quality impacts home values, and estimate unit values and value-transfer functions. 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 then use Monte Carlo simulations to estimate the corresponding standard errors. Each study can yield numerous meta-observations due to multiple study areas, water quality metrics, and model specifications. Our meta-dataset contains n=665 unique observations, and for 656 of these observations sufficient information was reported to calculate the corresponding elasticity and/or semi-elasticity estimates.

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 the study examined. We often find it difficult to convert the disparate water quality measures to a common metric. Therefore, we conduct a separate meta-analysis for each water quality measure. In most cases this is limited to calculating mean elasticities with respect to each water quality measure. We calculate these unit values separately for waterfront and non-waterfront homes using a variety of different weighting schemes. Most notably, we propose a novel cluster-adjusted Random Effect Size (RES) weighting scheme that simultaneously gives more influence to more statistically precise primary study estimates and accounts for the cluster- (or panel-) nature of the meta-dataset.

In the context of water clarity specifically, a sufficient number of meta-observations (n=260) allows us to conduct a meta-regression analysis. In the absence of clear guidance on the most appropriate estimation approach and specification for these meta-regressions, a variety of specifications are estimated using different techniques, including Random Effects (RE) Panel models and the Mundlak (1978) regression model that was recently suggested by Boyle and Wooldridge (2018) as a possible alternative when estimating meta-regressions for purposes of benefit transfer.

[2] There are, however, two notable unpublished studies. In her Master's thesis, Fath (2011) conducts a limited meta-analysis of 13 hedonic studies. Abt Associates (2015) estimates the capitalization effects of large-scale changes in water clarity of lakes based on a simple weighted-average across nine hedonic studies.

We then statistically test the appropriateness of pooling estimates from different regions and types of waterbodies, and discuss the implications for benefit transfer. Benefit transfer performance across the different models for value function transfers are compared to each other, and to a simpler value transfer. This assessment entails an out-of-sample transfer error exercise. Although value transfers generally perform on par with more complicated function transfers, and sometimes even perform better, we do find that a transfer function accounting for baseline water clarity levels yields the lowest transfer error.

Along with recommendations to practitioners conducting benefit transfer, we provide some brief guidance on combining our results with available data to assess local, regional, and national policies affecting water quality. A key contribution of this study is in highlighting gaps in the literature regarding the types of waterbodies and regions covered, and the disconnect between the water quality metrics used by economists versus those currently examined 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 and our approach to format comparable elasticity estimates. Section 3 introduces the methodology for weighting and clustering meta-observations, and presents the meta-regression models used to predict values related to water clarity. We then present the results for the mean unit value and meta-regression models, including a comparison to determine which is more accurate for benefit transfer. We end with a discussion of the limitations and future research.

2. META-DATASET

2.1 Identifying Candidate Studies and Inclusion Criteria

Our search protocol included both peer-reviewed and grey literature sources. We focused on hedonic studies utilizing surface water quality measures or indices in the US, but we left criteria such as year published open under different combinations of keywords to capture the largest selection of studies. The search began with reviewing reports unrelated to this research effort (e.g., US EPA 2016; Van Houtven et al. 2008) or other literature reviews and meta-analyses on related topics (e.g., Abt Associates, 2015; Alvarez & Asci, 2014; Braden et al., 2011; Crompton, 2004; Fath, 2011). 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 on October 24, 2014 and January 21, 2016. Seven studies were provided from the 2014 request and one publication was added from the 2016 request. After this lengthy process, we attempted one final literature search through the US EPA's internal library system. This last step identified two studies that were not identified previously. 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). This provided additional reassurance that the identified set of studies fitting the outlined criteria is fairly comprehensive.

In total we identify 65 studies in the published and grey literature that are potentially relevant. To facilitate linkages between water quality models and economic valuation, and ultimately to perform more defensible benefit transfers to US policies, focus is drawn to the 36 unique primary studies that examined surface water quality in the US using objective water quality measures. More specifically, 29 studies are 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 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 are selected for inclusion in the final meta-dataset.

2.2 Meta-dataset Structure and Details

From the selected 36 studies, 26 are published studies in peer-reviewed academic journals, three are working papers, three are Master's level or PhD theses, two are government reports, one is a presentation, and one is a book chapter. The year of publication or study release 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 and midwest regions of the US, while the eastern and southern regions have the most studies. Some states even have as many as four (Maine, Maryland, Ohio), and even five studies (Florida).

[Insert Figure 1 about here.]

The meta-dataset consists of a panel or cluster structure, where each study can contribute multiple unique observations.[3] Individual studies may analyze multiple study areas, water quality metrics, and model specifications. Additionally, a unique dimension in the current context is that the primary hedonic studies sometimes examine how the property value effects of interest vary with distance from the waterbody. Distance is thus an important factor and should be accounted for when transferring water quality benefits to a new policy region. A novel contribution of this study is that the meta-dataset explicitly incorporates price effect estimates corresponding to different distances from the waterbody. This implies that even a single coefficient estimate from a primary study may be used to infer price effects for homes at different distances, each of which is represented as a separate observation in the meta-dataset.

[3] In the context of meta-analysis, Boyle and Wooldridge (2018) specify the distinction between a cluster versus a panel structure. The structures are similar, but with a cluster structure there is no natural ordering to the observations within a cluster, as is the case in this meta-analysis. We therefore continue with the cluster structure nomenclature, but believe making the connection to panel data analysis is useful given its prominence in econometrics

Across the 36 primary studies, there are 30 different measures of water quality examined. 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 price effect estimates with respect to different water quality measures, however, are examined separately in the meta-analysis. The pooling of estimates across different water quality measures is not 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 examining light attenuation (a measure of water clarity) in the Chesapeake Bay (Guignet et al., 2017; Walsh et al., 2017), where an appropriate conversion factor was available in the literature. 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 and Semi-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, hedonic property value methods, the outcome of interest itself is always the same – i.e., capitalization effects on residential property values. And as just discussed, elasticity estimates with respect to different water quality measures are never pooled and examined in a single meta-analysis, thus making the estimates that are examined together even more comparable. Two other sources deterring comparability of results across primary studies must still be accounted for, and both pertain to functional form assumptions in the original hedonic specifications.

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 across studies. In the hedonic literature, some studies estimate specifications like 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 (such as lake 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 derivations also sometimes include the mean transaction price and mean values of observed covariates, as reported in the primary study. Such variables enter into 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 account for the relationship between households' values for an environmental commodity and distance to the resource. Johnston et al. account for this relationship by proposing an approach to estimate the mean distance among the sample in each primary study, and then include that as a control variable in the right-hand side of their meta-regression models. In our study we are able take a different approach that explicitly incorporates such spatial heterogeneity into the structure of the meta-dataset itself. We include unique observations from the same primary study that account for the house price effects at different distances from the resource. Such an approach is possible due to the relatively fine spatial resolution associated with hedonic property value methods compared to other non-market valuation techniques.

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 (or panel) 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 so Klemick et al. (2018) and Guignet et al. (2018) had the luxury of assuming the initial functional forms of their hedonic regressions, and thus ensured that the distance gradients were specified the same way across all estimates. 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.

We make an overarching assumption to limit the meta-dataset and analysis to only housing value impacts within 500 meters. Although some hedonic studies have found that water quality impacts home values at farther distances (e.g., Walsh et al. 2011a, 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 due to 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 selection bias of elasticity estimates corresponding to farther distances, we limit the meta-data and analysis to only price effects within 500 meters.

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. If a primary study only examined waterfront homes, then it only contributes observations to the meta-dataset corresponding to waterfront homes. But 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 set of coefficients.[4] 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. Overall, this approach allows us to derive comparable elasticity estimates across studies based on the form of the distance gradient assumed in each primary study.

Finally, meta-analysis often requires a measure of statistical precision around the estimates of 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 consisting of 100,000 iterations. 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 include the coefficient standard errors when reporting 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 the primary study authors did not respond or could no longer provide the requested information.

Using the primary study coefficient estimates, variances, and covariances, the Monte Carlo simulations entail 100,000 random draws from the joint normal distributions estimated by the primary studies. The simulations are carried out separately for each observation in the meta-dataset. After each draw 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.

2.4 Meta-data Descriptive Statistics

After considering these multiple dimensions, the set of 36 studies provide 665 unique observations for the meta-dataset. Figure 2 displays the number of observations from each study, which ranges from just two observations from a single study to over 224 observations. 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

[4] In a couple of studies (Poor et al., 2007; Tuttle and Heintzelman, 2015) the distance gradient was essentially assumed to be flat. In those cases, the resulting elasticity observations for waterfront and non-waterfront homes in the meta-dataset are identical.

[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).

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 for analysis.

[Insert Figure 2 about here.]

With 260 unique elasticity estimates, water clarity is by far the most common water quality measure analyzed in the literature; followed by fecal coliform (56), chlorophyll a (36), nitrogen (20), pH (19), and phosphorous (12). Several other water quality measures have been examined by one or two studies in the hedonic literature, and also contribute unique elasticity estimates to the meta-dataset (see Table B2 in Appendix B for a full list).

The elasticities with respect to different water quality measures are examined separately in the meta-analysis methodology discussed in the next section. In particular, the meta-regression analysis focuses on water clarity, where there is currently enough studies and observations to conduct such an analysis. The 260 unique house price elasticity estimates with respect to water clarity are estimated from 18 separate studies, and cover 63 different housing markets. About 56% of these estimates correspond to water clarity in freshwater lakes or reservoirs, while the other 44% correspond to estuaries.

A few additional descriptive statistics of the elasticity observations with respect to water clarity are provided in Table 1. About 68% of the observed elasticity estimates corresponding to water clarity are for waterfront homes. The average of the mean clarity levels reported in the primary studies is a Secchi disk depth of 2.343 meters. Of course, as one may expect this varies by waterbody type. Estuaries have a mean Secchi disk depth of only 0.635 meters, whereas freshwater lakes have a mean Secchi disk depth of 3.677 meters. The majority of estimates correspond to the southern (48.5%) or northeastern (28.8%) quadrants of the US, with the remainder of this set of elasticity estimates corresponding to the midwest (19.2%) or west (3.5%) US.[6] As can be seen by the "no spatial methods" variable, 38% of the 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 in some fashion). Although admittedly imperfect, this is the only observed variable that reflects quality of the primary study models, and so it is intended to proxy for *potentially* poorer quality studies.

[Insert Table 1 about here.]

Socio-demographics corresponding to the primary study areas and time period were also obtained from the US Census Bureau by matching each observation to data for the corresponding jurisdiction and year from the decennial census most closely corresponding to the primary study time period. Median household income (2017$ USD) is on average $59,080 in the areas examined by the 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 only 50 households per square

[6] Regions of the US are defined following the US Census Bureau's "Census Regions" (https://www.census.gov/geo/reference/gtc/gtc_census_divreg.html, accessed 18 Mar. 2019).

kilometer. These statistics may reflect the fact that homes near lakes and estuaries generally tend to be in more rural areas.

3. METHODOLOGY

3.1 Mean Unit Values

We next calculate mean elasticity values for each water quality measure examined in the hedonic literature. These unit values provide a useful summary measure, and can be utilized for benefit transfer when value transfers are deemed appropriate or are the only transfer approach available. In fact, although the literature still generally finds function transfer approaches that explicitly account for various dimensions of heterogeneity preferable (Johnston and Rosenberger, 2010), it has been found that simpler unit value transfers may perform better in some contexts (Klemick, 2018; Bateman et al., 2011; Johnston and Duke, 2010; Lindhjem and Navrud, 2008; Barton, 2002).

When calculating the mean values in a meta-analysis it is often appropriate to weight each observation by its inverse variance in order to give more weight to more precise estimates (Nelson, 2013; Borenstein et al., 2010; Nelson and Kennedy, 2009). Two weighting schemes are generally used. We refer to the first as the Fixed Effect Size (FES) model, in order to avoid confusion with the frequently used fixed effects models in panel data analysis. Under the FES framework each meta-observation is considered a draw from the same underlying population distribution (even if from different studies), and the estimated weighted mean is interpreted as an average of that single true distribution. In other words, sampling error is the only driver of differences in the observed estimates across studies. The second weighting scheme is a variant of the above, and is sometimes referred to as the Random Effects Size (RES) model. The RES model 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 2013). In the RES framework the weighted mean is interpreted as an estimate of the average of the different average elasticities across the different distributions.

An additional complication in the current meta-dataset is that primary studies often report multiple estimates based on the same underlying property transaction data. If such dependence is not accounted for, some 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 "true" value. We propose the following cluster-adjusted FES and RES weights to account such dependence in the meta-dataset.

One can think of the clustering (or panel nature) of the meta-data at different levels, such as by study, or by groups of studies, that rely on the same primary data, researchers, etc., but our preferred definition of a cluster is by "housing market." Meta-observations estimated from a common transaction dataset in terms of study area and time period are grouped together. The intuition is that these are common estimates of the same underlying elasticity. Under this clustering scheme, we are agnostic towards who conducted the primary study. Whether from the same study or not, we are interested in the "true" elasticity in a given area and time period. For example, consider a primary study that estimated four hedonic regressions and contributed four elasticity estimates to the meta-dataset. If each elasticity pertained to a different study area (e.g., a different county in the same state), then these estimates would not be grouped as a cluster. Each observation in this case is an estimate of the elasticity in a different housing market, and pertaining to a different waterbody (or set of waterbodies). In contrast, if these four different regressions were just different functional forms and estimated from the same sample of transactions in the same county, then the estimates would be grouped as a single cluster. The four meta-observations in that case would basically just be four different estimates of the same underlying elasticity.

The starting point is the standard Fixed Effect Size (FES) and Random Effects Size (RES) weighting schemes (Nelson and Kennedy, 2009; Borenstein et al., 2010; and Nelson, 2013), which are slightly manipulated to account for the distance dimension that is incorporated into the meta-dataset. For the FES model, the weight for elasticity estimate *i*, at distance *d*, in cluster j $\left(\hat{\varepsilon}_{idj}\right)$ is:

$$w_{idj}^{FES} = \frac{1}{v_{idj}} \tag{1}$$

where v_{idj} is the variance of the estimate $\hat{\varepsilon}_{idj}$ from the primary study. We could also add subscripts denoting estimates from model *m* of study *s*, but these are omitted for notational ease, as are subscripts denoting different water quality measures. The FES mean elasticity for a given water quality parameter and distance bin *d* is thus,

$$\bar{\varepsilon}_{d}^{FES} = \sum_{i=1}^{n} \frac{w_{idj}^{FES}}{\sum_{i=1}^{n} w_{idj}^{FES}} \hat{\varepsilon}_{idj} \tag{2}$$

where *n* is the number of observed estimates in the meta-dataset for distance bin *d* and the water quality measure of interest.

The RES weights can be calculated in a similar fashion:

$$w_{idj}^{RES} = \frac{1}{v_{idj}+T^{2}} \tag{3}$$

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

$$T^2 = \frac{Q-(n-1)}{\sum_{i=1}^{n} w_{idj}^{FES} - \left(\frac{\sum_{i=1}^{n}\left(w_{idj}^{FES}\right)^2}{\sum_{i=1}^{n} w_{idj}^{FES}}\right)} \tag{4}$$

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:

$$Q = \sum_{i=1}^{n} \frac{\left(\hat{\varepsilon}_{idj} - \bar{\varepsilon}_{d}^{FES}\right)^2}{v_{idj}} \tag{5}$$

The RES weighted means are thus calculated as

$$\bar{\varepsilon}_{d}^{RES} = \sum_{i=1}^{n} \frac{w_{idj}^{RES}}{\sum_{i=1}^{n} w_{idj}^{RES}} \hat{\varepsilon}_{idj} \tag{6}$$

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. 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).

Our proposed cluster-adjusted FES and RES weights adapt equations 1 and 3 in order to account for the dependence of meta-observations within a cluster. Let k_{dj} denote the number of elasticity estimates in cluster *j*, for homes in distance bin *d*. Since a cluster does not necessarily correspond to a study, subscript *s* is not necessarily equivalent, and is thus again omitted for notational ease. The proposed adjustment to the weights simply involves multiplying the original FES or RES weights, which we now denote as $w_{idj} = w_{idj}^{RES}\ or\ w_{isj}^{FES}$, by the inverse of k_{dj}. This is done for all clusters $j = 1, \ldots, K_d$.

The intuition is that the RES or FES weighted elasticity corresponding to each meta-observation is weighted such that $w_{idj}\hat{\varepsilon}_{idj}$ sums to the weighted elasticity for a single synthetic meta-observation of distance bin *d* for each cluster. The new weights are $\frac{1}{k_{dj}} w_{idj}$. This can be illustrated mathematically. First consider the normalized weights based on just the statistical precision of observation *i*, for distance bin *d*, and from cluster *j*, $\frac{w_{idj}}{\sum_{i=1}^{n} w_{idj}}$. The summation in the denominator can be re-written as two separate summations. In other words, summing over all meta-observations in the sample is equivalent to summing over all meta-observations in each cluster, and then over all clusters in the sample; more formally: $\frac{w_{idj}}{\sum_{j=1}^{K_d} \sum_{i=1}^{k_{dj}} w_{idj}}$.

We next discount all weights corresponding to elasticity estimates for distance bin *d*, and within cluster *j*, by multiplying it by the inverse of the number of primary estimates in that cluster. This yields $\frac{1}{k_{dj}} \frac{w_{idj}}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}} w_{idj}}$, which we must then re-normalize such that the new combined weights sum to one. More formally:

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

This can then be rearranged as:

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

and then after cancelling out the common term $\frac{1}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}} w_{idj}}$, we are left with the normalized cluster-adjusted weight:

$$\omega_{idj}^{h} = \frac{\frac{w_{idj}}{k_{dj}}}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}}\left(\frac{w_{idj}}{k_{dj}}\right)} \qquad (7)$$

where *h* simply denotes the FES or RES weight depending on which was used to calculate w_{idj}. As a result, the cluster-adjusted FES or RES unit value mean elasticities for each distance bin *d* are calculated as:

$$\bar{\varepsilon}_{d}^{h} = \sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}} \frac{\frac{w_{idj}}{k_{dj}}}{\sum_{j=1}^{K_d}\sum_{i=1}^{k_{dj}}\left(\frac{w_{idj}}{k_{dj}}\right)}\ \hat{\varepsilon}_{idj} \qquad (8)$$

We prefer the cluster-adjusted RES weights over the corresponding FES weights. There is no reason to suspect that the true home price elasticities with respect to water quality are the same at different waterbodies and housing markets across the US. 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, likely vary as well. We estimate the cluster-adjusted FES weights and other weighting schemes mainly as a sensitivity analysis.

3.2 Meta-regression Models

Function transfers based on meta-regressions can be a useful approach for benefit transfer (Nelson, 2013). Such an approach involves first estimating a meta-regression model, and then using the estimated parameters to predict outcome values for a policy site. 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. The meta-regression model description below is kept general, but in the current study we limit the meta-regressions to just water clarity (i.e., Secchi disk depth). In our opinion, this is the only water quality measure analyzed frequently enough in the current literature to allow for a defensible meta-regression analysis.

The dependent variable $\hat{\varepsilon}_{idj}$ is elasticity estimate *i* for distance bin *d* in cluster (i.e., housing market) *j*. The most comprehensive model is:

$$\hat{\varepsilon}_{idj} = \beta_0 + wf_{idj}\beta_1 + estuary_j\beta_2 + WQ_{ij}\beta_3 + \boldsymbol{region}_j\boldsymbol{\beta}_4 + z_{ij}\beta_5 + e_{idj} \qquad (9)$$

where wf_{idj} is a dummy variable denoting that the observed elasticity estimate corresponds to the value of homes on the waterfront, as opposed to non-waterfront homes within 0 to 500 meters of the waterbody. The dummy variable $estuary_j$ equals one if the elasticity estimate corresponds to water quality in an estuary, as opposed to freshwater lakes (the omitted category).[7] In theory, different waterbody types in the same housing market could be examined, but in the current meta-dataset this variable is invariant within each cluster, and so the *i* subscript is omitted. The variable WQ_{ij} is the mean baseline water quality level corresponding to the respective waterbody, or portion of the waterbody, for observation *i* in cluster (or housing market) *j*. In the case of water clarity, WQ_{ij} is measured as Secchi disk depth in meters. The next variable denotes the region of the US from which the estimates in housing market *j* are located – the northeast, south, midwest, and west.

The final variable z_{ij} represents study attributes or model assumptions made by the primary study authors. As described by Boyle and Wooldridge (2018), such variables are helpful because $\hat{\varepsilon}_{idj}$ is merely an estimate of the true elasticity, and that estimate is dependent on modelling assumptions made in the primary studies. These assumptions could be correlated with other variables in equation (9), and so inclusion of z_{ij} helps avoid a potential omitted variable bias. Additionally, if particular values of z_{ij} denote better modelling choices, then such information can be exploited when predicting values for purposes of benefit-transfer (Boyle and Wooldridge, 2018). For this meta-analysis z_{ij} is a dummy variable equal to one if elasticity *i* for housing market *j* was estimated

[7] 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 or estuaries.

from a primary study model that did *not* account for spatial dependence among housing observations in the primary data. In other words, if a model did *not* include spatial fixed effects, a spatial lag of housing prices, or account for spatial autocorrelation in some fashion, then $z_{ij} = 1$; and $z_{ij} = 0$ otherwise. This is meant as a proxy for potentially poorer quality estimates, and so β_4 absorbs potential effects that could otherwise bias the other meta-regression coefficients.[8] The omitted category is thus potentially better-quality estimates from models that did account for spatial dependence, and so the remaining meta-regression coefficients can be used directly for benefit-transfer in practice. The parameters to be estimated are $\beta_0, \ldots, \beta_5$, and e_{idj} is an error term that we discuss in more detail below.[9]

As was the case when calculating the mean elasticities, when estimating the meta-regressions the cluster structure of the meta-dataset must be accounted for so that studies reporting multiple elasticity estimates from the same housing market are not given an unwarranted amount of influence. When estimating equation (9), the observations are weighted according to the same cluster-adjusted RES weights described in section 3.1.

An additional complication that arises from the cluster structure of the meta-dataset is that there may be cluster-specific effects associated with a particular housing market and the waterbodies examined in that housing market. In equation (9), we assume that this cluster-specific effect c_j is reflected in the error term, i.e., $e_{idj} = c_j + u_{idj}$, where u_{idj} is an assumed independent and normally distributed error term. This implies that the error terms (e_{idj}) when estimating equation (9) are correlated for observations pertaining to the same housing market. To account for such correlation, we estimate equation (9) as a Random Effects (RE) Panel model (see, for example, Wooldridge, 2002). A RE Panel regression model is recommended when more than one estimate is taken from a primary study (Nelson and Kennedy, 2009).

An issue with modelling the cluster (or housing market) specific effect in this fashion is that c_j could be correlated with observed right-hand side variables, which would lead to inconsistent estimates (Wooldridge, 2002). In the current context, it may very well be the case that the necessary assumptions for consistent estimates from the RE panel model are violated. Unobserved variables associated with a particular housing market and waterbody (or set of waterbodies) may likely be correlated with observed right-hand side variables. In such cases, a fixed effect (FE) panel model is often estimated. But the FE Panel model is not a viable approach in the current context. First, the site specific fixed effect would absorb much of the variation of interest because most of the modifiers in the meta-regression do not vary within a cluster. Even if there is some within-cluster variation, it is often only seen among a small subset of the observations, and would thus disregard a lot of observations and variation of interest. Second, out of sample inference for

[8] The later meta-regression results are robust if a dummy denoting results from an unpublished study are used instead.

[9] Subsequent regression models are estimated that include characteristics of the population corresponding to housing market *j* (i.e., median income, percent of population with a college degree, and population density), but the coefficients on these variables are found to be statistically insignificant. See Table B1 in Appendix B for details.

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) recently suggested estimating a regression model first proposed by Mundlak (1978), as an alternative to a FE Panel meta-regression. The Mundlak model estimates the cluster-specific effects by including the cluster average of the relevant modifier variables in the right-hand side of the meta-regression:

$$\hat{\varepsilon}_{idj} = \beta_0 + wf_{idj}\beta_1 + estuary_j\beta_2 + WQ_{ij}\beta_3 + \boldsymbol{region}_j\boldsymbol{\beta}_4 + z_{ij}\beta_5 \\ +\overline{wf}_j\gamma_1 + \overline{WQ}_j\gamma_3 + \bar{z}_j\gamma_5 + e^*_{idj} \qquad (10)$$

The variables $\overline{wf}_j$, $\overline{WQ}_j$, and $\bar{z}_j$ are the cluster-specific means for the waterfront, baseline water quality, and model attribute variables, respectively. The corresponding cluster-mean for $estuary_j$ and $\boldsymbol{region}_j$ could also be included, in theory, but in the current meta-dataset these variables do not vary within a cluster.

A portion of the cluster-specific effect that was previously assumed to be random in equation (9) is now explicitly estimated in equation (10). More formally,

$$e_{idj} = \overline{wf}_j\gamma_1 + \overline{WQ}_j\gamma_3 + \bar{z}_j\gamma_5 + e^*_{idj} \qquad (11)$$

where $e^*_{idj} = c^*_j + u_{idj}$. The coefficients γ_1, γ_3 and γ_5 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 (10) does not require the assumption that c_j be uncorrelated with other right-hand side variables, as is the case with a conventional RE Panel model. 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. In this particular context, however, it is unclear what the gains from the Mundlak model are, or if it is even appropriate, due to limited within-cluster variation. In this specific application the model hinges primarily on the dummy variable denoting whether an observed elasticity estimate corresponds to waterfront (versus non-waterfront) home values. There is within cluster-variation of wf_{idj} among 19 (of the 63 housing markets), this corresponds to 160 observations from six different studies. There is some within cluster-variation in WQ_{ij}, but this is limited to just six housing markets, corresponding to 95 observations from three different studies. There is also little within-cluster variation in the model attribute variable $\bar{z}_{ij}$, with only two housing markets, examined by two studies, showing variation in models that do and do not account for spatial dependence (17 and 18 observations, respectively).

A priori, the most appropriate meta-regression estimation approach and model remains unclear. In the next section we present estimation results for all meta-regression model variants. Then we conduct an out-of-sample prediction exercise to compare which modelling approach performs best in terms of benefit transfer.

4. RESULTS

4.1. Mean Unit Value Estimates

We estimate mean elasticities for each water quality measure used in the hedonic literature. When available, we present separate mean elasticities for waterfront homes and for non-waterfront homes within 500 meters of a waterbody. The results in Table 2 display the mean values only for water quality measures that were used in at least three studies (but the full set of mean elasticity estimates can be found in Table B2 of Appendix B).

[Insert Table 2 about here.]

Our preferred estimates are the cluster-adjusted RES means, which give more weight to more precise primary study estimates, and also ensure that equal influence is given to each housing market examined in the literature. The cluster-adjusted RES means in Table 2 generally have the expected sign, and the relative magnitude is often larger for waterfront versus non-waterfront homes, as one would expect. For example, a one-percent increase in nitrogen concentrations leads to a 0.220% decline in waterfront home values, and a 0.136% decline in the value of non-waterfront homes that are within 500 meters of the waterbody. A one-percent increase in phosphorous concentrations leads to a 0.107% decrease in waterfront home values, but has a statistically insignificant impact on non-waterfront homes. A similar insignificant impact on non-waterfront home values is found in the context of pH, but a one-percent decrease in pH levels (i.e., more acidic waters) does lead to a 0.779% decrease in waterfront home values.

As shown in the subsequent columns of Table 2, these results are generally robust across alternative weighting schemes, including the FES cluster-adjusted counterpart, as well as more standard approaches – the conventional RES mean (e.g., Borenstein et al., 2010), a cluster weighted mean that does not account for statistical precision of the primary estimates, and a completely unweighted average where all observations are given equal weight. The estimated mean elasticities with respect to water clarity, at least for waterfront homes, do however appear sensitive to weighting schemes that do not account for statistical precision of the primary estimates and/or clustering of estimates from the same housing market. This may be at least partly driven by the fact that just three studies (Walsh et al., 2017; Ara, 2007; and Michael et al., 2000) contribute 65% of the observed elasticities with respect to water clarity. In any case, we believe the cluster-adjusted RES means are the most valid for the reasons previously discussed. The other mean elasticity calculations are presented mainly as a sensitivity analysis.

There are some examples where the cluster-adjusted RES means yield somewhat counterintuitive results. For example, although a one-percent increase in chlorophyll-a concentrations suggests a 0.026% decline in waterfront home values, the mean elasticity estimate for non-waterfront home values suggests a small but statistically significant 0.009% increase in home values. This result is sensitive to the weighting scheme. In the other mean elasticity calculations, we see no significant impact of chlorophyll-a on non-waterfront home values, which at least does not run counter to expectations. The home price effects of increased fecal coliform concentrations are also somewhat odd. The price impact among non-waterfront homes is larger in magnitude than that for waterfront homes. At first, we thought that this result might be driven by the fact that the set of studies used to calculate these averages differ slightly. Leggett and Bockstael's (2000) hedonic analysis of fecal coliform in the Chesapeake Bay examines only waterfront property prices. However, even if we omit that study, the cluster-adjusted RES waterfront mean elasticity is -0.003, which is still less in absolute value than the -0.052 price elasticity corresponding to non-waterfront homes within 500 meters. Although the relative magnitudes of the price elasticities are against expectations, it is reassuring that both suggest the expected negative effect of increased fecal coliform counts on nearby home values.

Due to the limited number of studies, and to our knowledge an inability to defensibly convert elasticities across different water quality parameters to a common measure, it seems that value transfers are generally the only viable option available if one is interested in using benefit transfer to estimate the capitalization effects of water quality changes on home values. In the case of water clarity, however, there are a sufficient number of observations to estimate limited meta-regressions and pursue a function transfer approach.

4.2. Meta-regression Results

The meta-regression analysis focuses on just a subset of the meta-dataset, only examining the n=260 observed elasticity estimates with respect to water clarity (i.e., Secchi disk depth measurements). All meta-regressions utilize the same weights as the preferred cluster-adjusted RES mean elasticity estimates. This is the preferred weighting scheme for the same reasons discussed above – it gives more weight to more precise estimates and ensures that no single study or analyzed housing market unduly influences the results. The clusters are defined according to the 63 unique housing markets.[10]

We first estimate a series of RE Panel meta-regression models following equation (9). The results are presented in Table 3. The first model (1A) includes only a dummy variable equal to one when the elasticity estimate corresponds to waterfront home values, and zero otherwise. As expected, and in line with the earlier unit value estimates, the price elasticity with respect to clearer waters is significantly higher (0.0791) among waterfront homes. The constant term reflects the price elasticity with respect to non-waterfront homes within 500 meters (the omitted category). And so,

[10] Although the unique housing market-based cluster-adjusted RES weights are preferred, the results are generally robust to simple OLS models where all observations are given equal weight, and to models where estimates from the same study (instead of housing market) are defined as a cluster (see Tables B3 through B5 in Appendix B).

a one-percent increase in water clarity corresponds to a 0.0257% increase in non-waterfront home values and a statistically higher 0.1048% (=0.0791+0.0257) increase in the value of waterfront homes.

[Insert Table 3 about here.]

Model 2A in Table 3 adds a dummy variable denoting elasticity estimates corresponding to clarity improvements in an estuary; the omitted category is freshwater lakes. The coefficient is negative and statistically significant, suggesting that water clarity changes in an estuary have a lesser impact on home values. The results suggest that a one-percent increase in water clarity of a lake leads to a 0.1211% (=0.0498+0.0713) and 0.0713% appreciation in the value of lakefront and non-lakefront homes, respectively. In contrast, a one-percent increase in water clarity of an estuary leads to a respective increase of 0.0665% (=0.0498+0.0713-0.0546) and 0.0167% (=0.0713-0.0546) in the value of waterfront and non-waterfront homes. One potential explanation for this difference is that surrounding residents do not generally expect the water to be as clear in estuaries. Estuaries have brackish waters that are often naturally more opaque. The unweighted mean Secchi disk depths reported by the primary studies in the meta-dataset is 3.68 meters for lakes, but only 0.64 meters for estuaries.

To examine whether baseline water clarity matters, the RE Panel Model 3A includes the mean water clarity level (i.e., Secchi disk depth in meters). The results suggest that water clarity improvements in waterbodies that already have relatively clear waters lead to larger increases in home values. For example, a one-percent increase in clarity leads to a 0.0937% increase in the value of waterfront homes around a waterbody that has a Secchi disk depth equal to the unweighted mean of 2.343 meters. But a one-percent increase in the clarity of a waterbody that has a baseline Secchi disk depth of 4.311 meters (a one standard deviation increase) suggests a statistically higher 0.1224% increase in waterfront home values. This result could be evidence of a premium to maintain or further improve relatively clear waters, which would run counter to the idea of diminishing marginal utility with respect to water clarity. A more likely explanation is that it may reflect differences in perceptions and expectations across different waterbodies or types of waterbodies (i.e., freshwater lakes versus estuaries), as discussed above. Model 4A shows that when conditional on the waterbody type, the mean clarity coefficient becomes much smaller and statistically insignificant.

Model 5A in Table 3 includes dummy variables denoting different regions of the US. The results suggest that hedonic studies examining waters in the midwest and western US seem to yield statistically similar results as studies examining waters in the northeast (the omitted category). This lends some confidence to potentially performing benefit transfers across regions. We do, however, see that studies examining water clarity in the southern US yield systematically lower elasticity estimates on average. Model 6A includes all covariates, and although some of the results are robust, the inclusion of all covariates leads to losses in statistical significance for some variables. We posit that such a comprehensive model is too taxing on the currently available n=260 observations in the metadata, especially given the correlation across many of the modifier variables. We see, conditional on region of the US, the mean clarity coefficient actually becomes negative; which although it is statistically insignificant, this is at least in line with the notion of diminishing marginal utility. The same holds true in the later Mundlak models, which controls for such housing market and waterbody specific effects.

We next re-estimate all six of the RE Panel models, but now also add the model attribute variable *no spatial methods*, which denotes elasticity estimates that were derived from primary study models that did *not* account for spatial dependence of the original housing transaction data. The omitted category is thus elasticity estimates from models that did account for such spatial dependence, and that could thus be interpreted as potentially more accurate estimates. The results from models 1B through 4B in Table 4 are similar to the earlier meta-regressions. The statistically insignificant coefficients corresponding to *no spatial methods* suggest that modelling assumptions by the primary study authors did not systematically affect the elasticity estimates.

This finding is not robust however, in models 5B and 6B, where we condition on regions of the US. The significant -0.1308 and -0.1412 coefficient estimates corresponding to *no spatial methods* suggest that studies not utilizing modelling techniques to account for spatial dependence tend to yield significantly lower elasticity estimates; implying that modelling choices made by the primary study authors may be important to control for in a benefit-transfer exercise. The results also suggests that modelling choices are correlated with where a primary study focused. The *midwest* coefficient is now statistically significant, at least in model 5B, implying that that after conditioning on model attributes, the housing price effects in the midwest are systematically lower compared to price effects in the northeast. Differences between price effects in the south and the northeast are also now much larger in magnitude, as seen by the large negative coefficient corresponding to *south* in models 5B and 6B. In contrast to some of the earlier meta-regression results, this suggests that heterogeneity across regions may be important to account for when conducting benefit transfers.

[Insert Table 4 about here.]

As an alternative to the RE Panel meta-regression models we next implement the Mundlak (1978) regression model that was recently suggested by Boyle and Wooldridge (2018) for estimating meta-regressions. The results are presented in Table 5. First looking at model 1A, the positive and significant coefficient on the waterfront dummy reveals a similar finding to earlier models – that an improvement in clarity leads to a statistically significant increase in waterfront home values, and that effect is statistically larger than the price impact on non-waterfront homes. More specifically, the model suggests that a one percent increase in water clarity leads to a 0.1135% (=0.0640+0.0471+0.0024) increase in waterfront home values, which is very similar to the results of earlier models. In contrast, however, the Mundlak variant of model 1A suggests a one-percent increase in clarity leads to a 0.0495% (=0.0471+0.0024) increase in the value of non-waterfront homes within 500 meters. Based on the overlapping confidence intervals, this effect is likely not statistically different from that of earlier models, but the point estimate is twice as large.

[Insert Table 5 about here.]

The Mundlak variants of models 2A through 6A in Table 5 reveal somewhat similar results to the earlier models. As shown in model 2A, the price elasticities with respect to water clarity are still lesser in the context of estuaries (compared to lakes), although this difference is no longer statistically significant. And model 3A again suggests higher price elasticities with respect to water clarity when baseline water clarity levels are higher. A baseline clarity level of one additional meter suggests an *additional* 0.0325% (=0.0597-0.0273) increase in home values for a one-percent improvement in clarity, an effect that is statistically significant at conventional levels (p=0.020).[11] As before, elasticity estimates corresponding to housing markets and waterbodies in the southeastern US are systematically lower than those for the northeast (the omitted category). One difference compared to the RE Panel models is that the Mundlak variants of models 5A and 6A suggest that the elasticity estimates corresponding to the midwest are also systematically lower.

Finally, in Table 6 we present the same six Mundlak meta-regression models, but now again include the model attributes variable, *no spatial methods*. The results are fairly similar to the previous meta-regressions. The small and insignificant coefficients on *no spatial methods* suggests that such modelling choices do not systematically affect the within-cluster variation in the inferred elasticities. Interpretation of this variable warrants caution in the Mundlak models, however, because as discussed in section 3.2 there is limited within-cluster variation. Only two studies, examining water clarity in two different housing markets, estimated hedonic regressions with different model assumptions regarding spatial dependence (Ara, 2007; Horsch and Lewis, 2009). Both of these studies examined waters in the Midwest. The corresponding *no spatial methods* cluster mean, however, is in agreement with earlier results. Some models, and in particular models controlling for study region (5A and 6A), suggest that primary studies not accounting for spatial dependence tend to yield lower elasticity estimates.

[Insert Table 6 about here.]

4.3. Best Performing Model for Benefit Transfer

In this section we attempt to shed light on whether a value or function transfer approach is more accurate for benefit transfer, at least in this particular context of water clarity and housing values. Focusing on water clarity, the cluster-adjusted RES means and all meta-regression models are evaluated by taking the absolute value of the percent difference between the initial elasticities from the primary studies $(\hat{\varepsilon}_{idj})$ and the predicted elasticities from the corresponding unit value means or meta-regressions $(\hat{\hat{\varepsilon}}_{idj})$. Note that we distinguish between waterfront and non-waterfront homes when estimating the mean elasticities and conducting the value transfer. More formally, the absolute value of the percent transfer error is calculated as:

$$|\%TE| = \left|\left(\frac{\hat{\hat{\varepsilon}}_{idj}-\hat{\varepsilon}_{idj}}{\hat{\varepsilon}_{idj}}\right) \times 100\right| \tag{12}$$

To examine out-of-sample transfer error, we iteratively leave out observations corresponding to one of each of the 63 housing markets and then re-estimate the mean values and meta-regressions using the remaining a sub-sample. The predicted values $(\hat{\hat{\varepsilon}}_{idj})$ and $|\%TE|$ are then estimated for

[11] The overall marginal effect with respect to mean water clarity levels is calculated by summing the coefficients corresponding to the baseline water clarity level and the associated cluster mean water clarity level, yielding 0.0325. The standard error of 0.0139 is estimated via the delta method.

the excluded observations. This is repeated by excluding each of the housing market clusters one at a time. After completing all 63 iterations we then calculate the mean $|\%TE|$ to evaluate out-of-sample transfer performance. We prefer an out-of-sample transfer error exercise like this over a simpler in-sample comparison that would directly use the full sample results presented in Tables 2-6 because an out-of-sample transfer error comparison is more indicative of how a value or function transfer would perform in policy settings.

The results in Table 7 suggest that the unit value transfer often performs on par with the more complicated function transfers. The value transfer even performs better than some of the most comprehensive models (e.g., 6A and 6B) and many of the more complicated Mundlak models.

In general, the RE Panel estimation procedures seem superior to the Mundlak approach, at least within the context of property value capitalization effects with respect to water clarity. Only in the case of model 1A does the Mundlak model perform slightly better. The superior transfer performance of the RE Panel model should minimize concerns regarding the validity of the assumption that the cluster-specific effects be uncorrelated with observed right-hand side variables.

[Insert Table 7 about here.]

Of most relevance is the answer to the question – which transfer approach performs best? In all cases model specification 3, which includes mean water clarity as a right-hand side moderator yields the lowest transfer error. Accounting for baseline water clarity levels improves transfer accuracy. And in particular, the RE Panel variant of model 3A performs the best, yielding a mean transfer error of 256% (median of 81%). Overall, in the context of water clarity the results suggest that practitioners perform a function transfer approach based on the RE Panel variant of model 3A.[12]

Although this model yields the lowest transfer error, it is concerning that the magnitude of the transfer error is large. This is unfortunately not unheard of given the current state of benefit-transfer methods, at least in the context of environmental applications. 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 mean of 172% (median of 39%). This is similar to the finding by Rosenberger (2015), who reports median absolute transfer errors between 36% – 45%. Notably, across all of the observations included in both of these studies, there are only three hedonic property values studies (which appear in Rosenberger (2015)), and none of these hedonic studies examined surface water quality.

[12] One can use the point estimates in Table 3 for purposes of benefit-transfer. The full variance-covariance matrix is presented in Appendix C. This is needed to derive the corresponding confidence intervals via the delta method (Greene, 2003, page 70) or Monte Carlo simulations.

5. DISCUSSION

The 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 value transfers can be conducted to assess policies impacting chlorophyll-a, fecal coliform, nitrogen, phosphorous, water clarity, and pH in waterbodies. Our findings, at least in the context of water clarity, suggest that simpler value transfers perform on par with (and sometimes better than) more complicated function transfers. This is in line with other recent findings in the literature (Klemick, 2018; Bateman et al., 2011; Johnston and Duke, 2010; Lindhjem and Navrud, 2008; Barton, 2002), and is a promising result for practitioners. Given the limited number of studies on any one water quality measure, value transfers are really the only viable option for examining the property capitalization effects from changes in water quality (with the exception of water clarity, which we discuss further below).

To conduct a unit value transfer, one would need to select the water quality measure that is most appropriate for the policy site, and/or based on the available water quality data and projection models. Policies generally result in changes in many water quality measures, but the hedonic literature often focuses on a single measure within a hedonic regression.[13] We recommend practitioners do the same when transferring results from this literature, and so when conducting benefit transfers one should not add up the price impacts across changes in multiple water quality measures. Our mean elasticity estimates can be combined with spatially explicit data of the relevant surface waterbodies, housing locations and number of homes, and baseline housing values, in order to project how a water quality policy impacts residential property values. 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 estimated elasticities 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).[14]

In the context of water clarity, our results suggest that a function transfer accounting for baseline water clarity levels can improve transfer performance. In addition to the data needs discussed above, one would also need to have information on baseline water clarity levels. Such information is likely needed anyway to quantify the change in water clarity resulting from a policy.

In future work we hope to expand this meta-dataset in two ways to increase its utility in informing policy. First, for tractability we decided early in the development of the meta-dataset to limit the

[13] Of the 598 observations analyzed in this meta-analysis, 444 (74%) are derived from hedonic regressions that included a single water quality measure. The remaining 156 elasticity observations were estimated from hedonic regressions that included two or more water quality measures directly on the right-hand of the same hedonic regression (Ara, 2007; Bin and Czajkowski, 2013; Brashares, 1985; Liao et al., 2016; Liu et al., 2014; Netusil et al., 2014; and Walsh and Milon, 2016).

[14] Website links to these 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).

distance bins to waterfront homes and non-waterfront homes within 500-meters of a waterbody. The hedonic literature has increasingly expanded this focus, however, finding significant impacts on home prices up to a few kilometers away (e.g., Walsh et al. 2011a, Netusil et al. 2014, Klemick et al. 2018, Kung et al. 2019). Adding meta-observations that pertain to farther distance bins, even within the context of the currently included studies, will provide a more comprehensive meta-analysis in the future (although one must also consider the sample selection concerns discussed in section 2).

Second, new studies should be periodically added to the meta-dataset as they emerge in the hedonic literature. 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 hedonic studies examining how property values respond to water quality changes in estuaries, rivers, and streams. Such primary studies are needed to provide truly nationwide coverage and ultimately more robust benefit-transfer procedures for assessing policies.

Another disconnect pertains to the types of water quality metrics used by economists versus those used by water quality modelers and policy-makers. Water clarity is the most common metric used in the hedonic literature. It is a convenient measure for non-market valuation because households are able to 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), which may be more difficult for households to observe. With that said, water clarity is not always a good measure of quality across all contexts (Keeler et al. 2012). For example, waters with low pH levels due to acid rain or 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 and aquatic ecosystem models that can calculate Secchi disk depth, but they require waterbody-specific characteristics as an input (Park and Clough, 2018). There are other studies that estimate relationships or correlations between water quality parameters and water clarity, but such relationships are also often very location specific (e.g., Wang et al. 2013; Hoyer et al. 2002). Due to the location or waterbody specific nature of the existing approaches to project changes in water clarity, such methods generally cannot be broadly applied without more information.

Further research is necessary to improve the link between water quality and economic models. 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 hedonic studies should keep the application of their results for policy analysis in mind. Doing so will allow their results to be used to monetize the quantified policy changes projected by water quality models. It will also help facilitate more robust transfer approaches by adding observations to our meta-dataset that focus on other water quality measures besides 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.

If relationships between policy-relevant water quality measures and clarity can be made more often, then such translations could be directly incorporated into the meta-dataset in a similar fashion to some of the conversions already made when "standardizing" the primary study estimates (for example, see Walsh et al. (2017) and Guignet et al. (2017) in Appendix A). Instead of conducting a separate meta-analysis for each water quality measure, as we do in this study, more primary studies could be combined into a single more robust meta-analysis that focuses on whatever water quality measure is most relevant for the policy at hand.

6. CONCLUSION

Despite the large literature of the capitalization of local surface water quality in 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 existence of this meta-dataset and our subsequent meta-analysis provides a means 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.

FIGURES AND TABLES

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

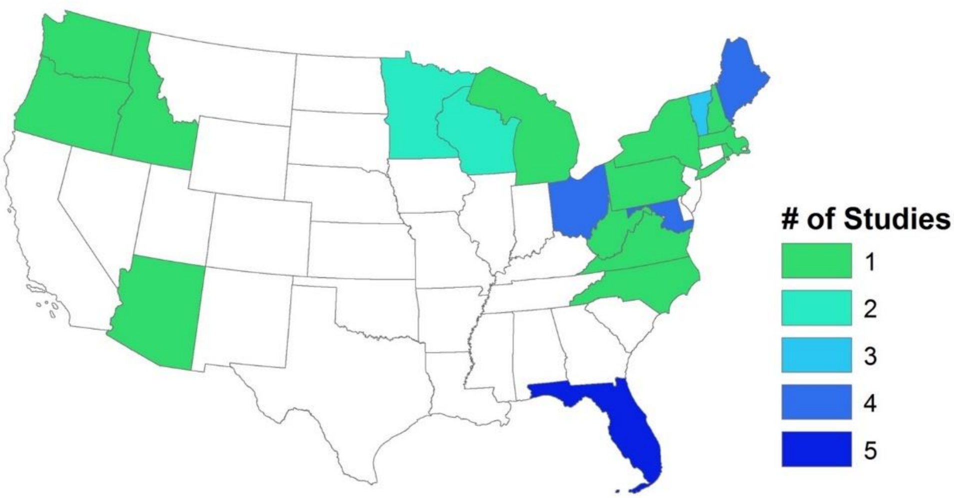

Figure 2. Number of Meta-dataset Observations by Study.

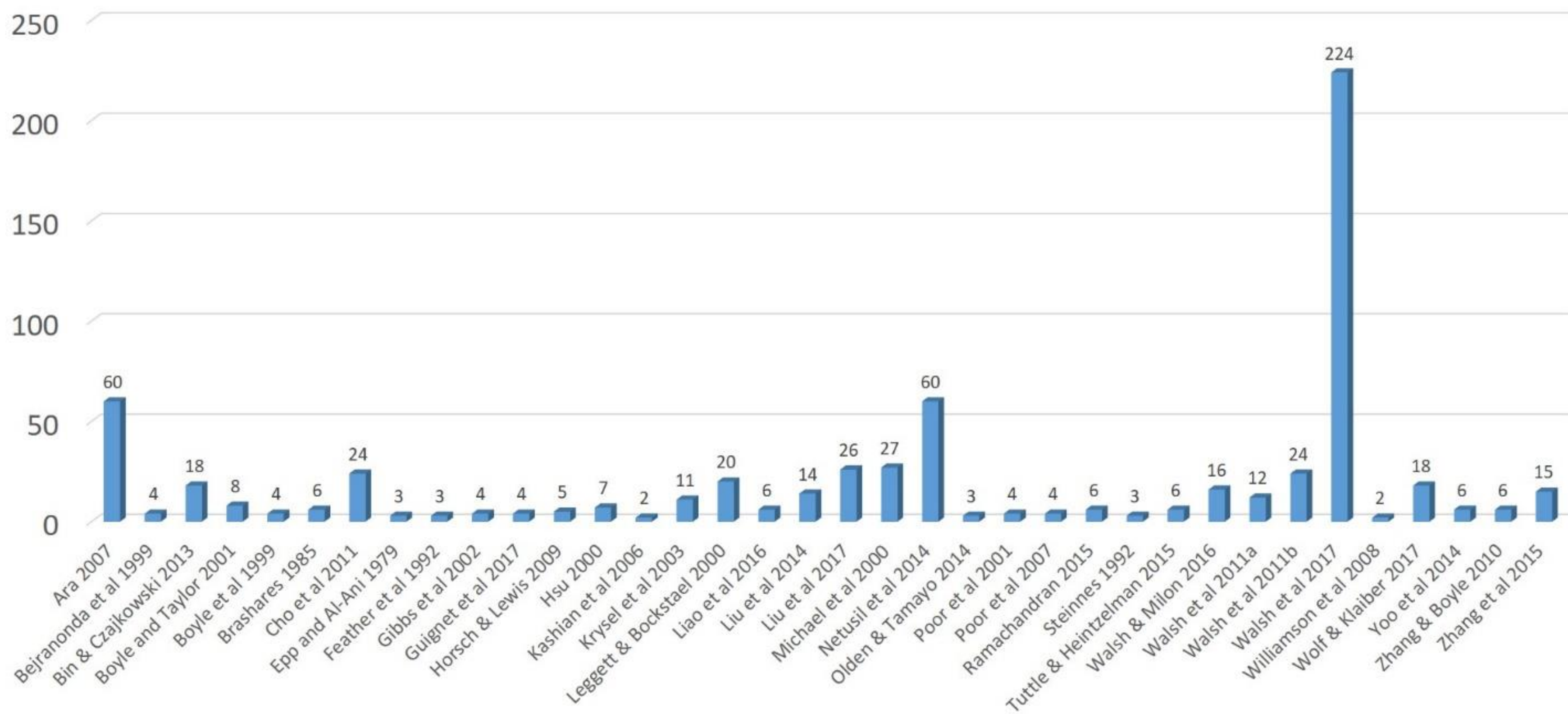

Table 1. Descriptive Statistics of Elasticity Observations with respect to Water Clarity.

Variable	Mean	Std. Dev.	Min	Max
waterfront	0.681	0.467	0	1
estuary	0.438	0.497	0	1
mean clarity (Secchi disk depth in meters)	2.343	1.968	0.380	6.450
northeast	0.288	0.454	0	1
midwest	0.192	0.395	0	1
south	0.485	0.501	0	1
west	0.035	0.183	0	1
no spatial methods	0.381	0.183	0	1
median income (2017$ USD)	59,080	14,142	37,865	91,174
college degree (% population)	0.137	0.041	0.077	0.273
population density (households /sq. km.)	49.908	58.378	1.410	227.963

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 housing markets (as defined by the primary studies). All variables are dummy variables unless indicated otherwise.

Table 2. Unit value mean elasticity estimates.

Water quality measure	Cluster Adjusted RES Mean	Cluster Adjusted FES Mean	Standard RES Mean	Cluster Weighted Mean	Unweighted Mean	n	Studies
Chlorophyll a (mg/L)							
waterfront	-0.026***	-0.027***	-0.022***	0.324*	0.737*	18	3
	(-0.031, -0.021)	(-0.032, -0.021)	(-0.031, -0.013)	(-0.036, 0.685)	(-0.044, 1.517)		
non-waterfront w/in 500 m	0.009***	-0.001	0.001	0.010	0.005	18	3
	(0.006, 0.012)	(-0.003, 0.001)	(-0.006, 0.009)	(-0.085, 0.105)	(-0.201, 0.211)		
Fecal coliform (count per 100 mL)							
waterfront	-1.3E-4***	-2.2E-5***	-0.2E-4	-0.037	-0.018***	36	4
	(-1.8E-4, -0.7E-4)	(-2.8E-5, -1.6E-5)	(-0.6E-4, 0.1E-4)	(-0.088, 0.014)	(-0.026, -0.011)		
non-waterfront w/in 500 m	-0.052***	-0.036***	-0.024***	-0.059*	-0.020***	20	3
	(-0.096, -0.008)	(-0.046, -0.027)	(-0.036, -0.011)	(-0.090, -0.005)	(-0.034, -0.006)		
Nitrogen (mg/L)							
waterfront	-0.220***	-0.131***	-0.245***	-0.242***	-0.292***	10	5
	(-0.244, -0.196)	(-0.149, -0.113)	(-0.321, -0.170)	(-0.271, -0.215)	(-0.326, -0.257)		
non-waterfront w/in 500 m	-0.136***	-0.030***	-0.130***	-0.184***	-0.221***	10	5
	(-0.156, -0.116)	(-0.036, -0.023)	(-0.184, -0.077)	(-0.210, -0.157)	(-0.254, -0.187)		
Phosphorous (mg/L)							
waterfront	-0.107***	-0.093***	-0.114***	-0.107***	-0.115***	6	3
	(-0.122, -0.092)	(-0.106, -0.081)	(-0.154, -0.074)	(-0.123, -0.092)	(-0.130, -0.100)		
non-waterfront w/in 500 m	-0.005	0.003	-0.002	-0.019***	-0.016**	6	3
	(-0.012, 0.003)	(-0.002, 0.008)	(-0.015, 0.010)	(-0.032, -0.005)	(-0.029, -0.003)		
Water clarity (Secchi disk depth, meters)							
waterfront	0.105***	0.031***	0.090***	0.182	0.155	177	18
	(0.095, 0.114)	(0.028, 0.034)	(0.078, 0.102)	(-17.398, 17.762)	(-6.102, 6.413)		
non-waterfront w/in 500 m	0.026***	0.012***	0.018***	0.042***	0.028***	83	6
	(0.017, 0.034)	(0.010, 0.015)	(0.008, 0.028)	(0.025, 0.059)	(0.020, 0.036)		
pH (pH scale, 0 [acidic] to 14 [basic])							
waterfront	0.779**	0.419***	0.424	1.986***	2.173***	13	3
	(0.019, 1.540)	(0.183, 0.654)	(-0.285, 1.133)	(-.840, 3.133)	(1.015, 3.331)		
non-waterfront w/in 500 m	-0.188	-0.188	-0.379	0.008	-0.334	6	1
	(-1.086, 0.711)	(-1.086, 0.711)	(-1.084, 0.326)	(-1.405, 1.422)	(-1.126, 0.457)		

*** p<0.01, ** p<0.05, * p<0.1. Confidence intervals at the 95% level are displayed in parentheses. Observations weighted by cluster-adjusted RES weights, where each cluster defined at the housing market level as defined in the primary studies. Only elasticity estimates pertaining to water quality measures used in at least 3 studies are presented here, but the full suite of mean elasticity estimates are presented in Appendix B, Table B2. We present the respective units for each water quality measure in parentheses, but emphasize that the elasticity estimates presented in the table are unit-less.

Table 3. Random Effects Panel (RE Panel) Meta-regression Results.

VARIABLES	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
waterfront	0.0791***	0.0498**	0.0457**	0.0443**	0.0347	0.0381*
	(0.018)	(0.024)	(0.020)	(0.021)	(0.022)	(0.021)
estuary		-0.0546*		-0.0395		-0.0015
		(0.030)		(0.053)		(0.024)
mean clarity			0.0146**	0.0059		-0.0103
			(0.007)	(0.013)		(0.019)
midwest					-0.0318	-0.0513
					(0.039)	(0.053)
south					-0.0865***	-0.1239*
					(0.032)	(0.067)
west					-0.0622	-0.0609
					(0.097)	(0.108)
constant	0.0257*	0.0713**	0.0138	0.0538	0.1065***	0.1517
	(0.016)	(0.031)	(0.017)	(0.060)	(0.033)	(0.096)

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 n=260 observations are weighted by the cluster-adjusted Random Effect Size (RES) weights and the cluster specific effects are defined according to the K=63 unique housing market clusters.

Table 4. RE Panel Meta-regression Results with Model Attributes.

VARIABLES	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)
waterfront	0.0654***	0.0612***	0.0552***	0.0553***	0.0524***	0.0514***
	(0.017)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
estuary		-0.0788		-0.0535		0.0168
		(0.053)		(0.059)		(0.022)
mean clarity			0.0299**	0.0213		0.0077
			(0.013)	(0.013)		(0.016)
midwest					-0.0695**	-0.0579
					(0.029)	(0.043)
south					-0.2003***	-0.1958***
					(0.058)	(0.060)
west					-0.0582	-0.0588
					(0.097)	(0.089)
no spatial methods	0.0227	-0.0405	-0.0739	-0.0890	-0.1308**	-0.1412**
	(0.025)	(0.051)	(0.050)	(0.057)	(0.054)	(0.066)
constant	0.0252	0.0925*	0.0031	0.0552	0.2156***	0.1904***
	(0.016)	(0.053)	(0.018)	(0.062)	(0.057)	(0.073)

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 n=260 observations are weighted by the cluster-adjusted Random Effect Size (RES) weights and the cluster specific effects are defined according to the K=63 unique housing market clusters.

Table 5. Mundlak Model Meta-regression Results.

VARIABLES	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
waterfront	0.0640***	0.0602***	0.0607***	0.0595***	0.0581***	0.0579***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
waterfront cluster mean	0.0471	-0.0571	-0.1744	-0.1791	-0.2279*	-0.2566
	(0.052)	(0.093)	(0.112)	(0.122)	(0.134)	(0.158)
estuary		-0.0693		-0.0399		0.0183
		(0.046)		(0.058)		(0.025)
mean clarity			-0.0273	-0.0305		-0.0378
			(0.067)	(0.068)		(0.070)
clarity cluster mean			0.0597	0.0548		0.0469
			(0.066)	(0.068)		(0.070)
midwest					-0.0806***	-0.0693*
					(0.030)	(0.042)
south					-0.1832***	-0.1781**
					(0.070)	(0.075)
west					-0.0622	-0.0633
					(0.097)	(0.087)
constant	0.0024	0.1118	0.0856*	0.1282	0.3109**	0.2969**
	(0.034)	(0.088)	(0.052)	(0.094)	(0.132)	(0.136)

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. Regressions estimated using n=260 observations. Observations are weighted by the cluster-adjusted Random Effect Size (RES) weights, where each cluster is defined as one of the K=63 unique housing markets. Mundlak (1978) regressions estimated by first calculating cluster (primary study) means for independent variables that vary within each cluster, and then by running the subsequent model via the "mixed" routine in Stata 14, where the residual cluster-specific effect is maintained.

Table 6. Mundlak Model Meta-regression Results with Model Attributes.

VARIABLES	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)
waterfront	0.0637***	0.0613***	0.0621***	0.0609***	0.0598***	0.0596***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
waterfront cluster mean	0.0248	0.0531	-0.0828	-0.0385	-0.0146	-0.0526
	(0.041)	(0.070)	(0.072)	(0.095)	(0.141)	(0.146)
estuary		-0.0860		-0.0569		0.0281
		(0.059)		(0.065)		(0.022)
mean clarity			-0.0243	-0.0280		-0.0363
			(0.060)	(0.061)		(0.060)
clarity cluster mean			0.0631	0.0575		0.0550
			(0.064)	(0.064)		(0.065)
midwest					-0.0849***	-0.0622
					(0.029)	(0.039)
south					-0.2441***	-0.2311***
					(0.053)	(0.054)
west					-0.0569	-0.0589
					(0.097)	(0.078)
no spatial methods	0.0129	0.0135	0.0124	0.0129	0.0137	0.0135
	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)
no spatial methods cluster mean	-0.0005	-0.0890	-0.0879*	-0.1252	-0.1877**	-0.2050**
	(0.033)	(0.073)	(0.049)	(0.081)	(0.085)	(0.098)
constant	0.0131	0.0731	0.0370	0.0711	0.2648***	0.2316**
	(0.022)	(0.055)	(0.031)	(0.059)	(0.081)	(0.092)

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. Regressions estimated using n=260 observations. Observations are weighted by the cluster-adjusted Random Effect Size (RES) weights, where each cluster is defined as one of the K=63 unique housing markets. Mundlak (1978) regressions estimated by first calculating cluster (primary study) means for independent variables that vary within each cluster, and then by running the subsequent model via the "mixed" routine in Stata 14, where the residual cluster-specific effect is maintained.

Table 7. Out-of-Sample Transfer Error: Average of the Absolute Value of Percentage Difference in Predicted Elasticities.

	Cluster-adjusted RES Mean	Meta-regression Model					
	286%						
Original Models		(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
RE Panel		286%	265%	**256%**	262%	267%	294%
Mundlak		276%	293%	281%	301%	355%	391%
Models w/ Methodological Variable		(1B)	(2B)	(3B)	(4B)	(5B)	(6B)
RE Panel		280%	278%	261%	265%	278%	306%
Mundlak		280%	299%	272%	296%	354%	386%

Bold text denotes the model that yields the lowest transfer error, in absolute terms. Absolute value of the percentage transfer error is calculated as the absolute value of the percentage difference between the predicted elasticity from the corresponding meta-regression model or mean value and the original elasticity estimate from the primary studies. Observations in all unit value mean and meta-regression estimates weighted following the cluster-adjusted RES scheme. The out-of-sample absolute transfer error is calculated by iteratively leaving out each of the K=63 unique housing market clusters, estimating the model with the remaining clusters, and then calculating the predicted elasticities and resulting transfer for the excluded cluster.

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APPENDICES

Appendix A: Study specific description and meta-dataset details.

This appendix provides a brief summary of each study in the meta-dataset, and provides examples to illustrate the study-by-study derivations of the common elasticity and semi-elasticity estimates in the meta-dataset. 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 depth and fecal coliform. Equations are estimated for both waterfront and non-waterfront homes. The authors 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

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

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

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.

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

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

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

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

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*,

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

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

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.

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

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:

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

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

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

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

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

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = 2\beta WQ^2 \tag{3}$$

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*,

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

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*,

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

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

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

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

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

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

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

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.

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

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

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

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

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

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

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:

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

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

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 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:

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

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:

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

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

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

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

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = -(\beta_1 dist_{WF}+\beta_2 dist_{0-200}+\beta_3 dist_{200-500}) \qquad (3)$$

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 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:

$$p = \gamma X + \beta(WQ_m \cdot 3.28084) \quad (1)$$

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.

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

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

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:

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

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

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

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

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

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

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.

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

In this case, WQ is expressed in terms of secchi 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

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

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

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).

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

$$\frac{\partial p}{\partial WQ}\frac{WQ}{p} = \beta \cdot area \cdot \frac{1}{p} \tag{3}$$

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.

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

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

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

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

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

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,

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

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

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

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 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.[15]

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

[15] 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 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:

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

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

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

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

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.

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

Rearranging for p,

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

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: $WQ_{\mu g/L} = WQ_{mg/L} \cdot \frac{1000\mu g}{1\ mg}$.

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

Substituting this conversion into equation (1), we have

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

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

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

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

For waterfront properties, we set $dist_{0-100m} = 1$. 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:

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

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

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

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

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.[16]

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

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

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

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

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

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

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.

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

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

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

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

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

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.

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

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

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

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

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 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 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.

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

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 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:

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

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

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:

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

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

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.

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

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

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:

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

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

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:

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

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

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.

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

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

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

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 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:

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

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 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:

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

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

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

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

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

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.

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

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:

$$p = \exp(\gamma X + D_1 Algae + D_2\big(Algae \cdot (dist_{0-20m} + dist_{20-600m})\big) + D_3(Algae \cdot dist)) \quad (1)$$

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:

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

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:

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

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:

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

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

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

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

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: Supplemental meta-analysis results.

Table B1. Meta-regression Results Examining Heterogeneity by Study Area Demographics.

VARIABLES	RE Panel 1	Mundlak 1	RE Panel 2	Mundlak 2	RE Panel 3	Mundlak 3
waterfront	0.0807***	0.0644***	0.0812***	0.0643***	0.0863***	0.0643***
	(0.020)	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)
waterfront cluster mean		0.0632		0.0541		0.0762
		(0.052)		(0.052)		(0.055)
median income (2017$ USD)	0.0000	0.0000				
	(0.000)	(0.000)				
college degree (% population)			0.1538	0.1908		
			(0.290)	(0.298)		
population density (households /sq. km.)					0.0002	0.0003
					(0.000)	(0.000)
Constant	0.0166	-0.0382	0.0020	-0.0305	0.0112	-0.0316
	(0.056)	(0.074)	(0.045)	(0.059)	(0.020)	(0.042)

Dependent variable: home price elasticity with respect to water clarity (secchi depth). *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Regressions estimated using n=260 observations, from K=63 unique housing market clusters. Random Effects Panel (RE Panel) regressions estimated using the "mixed" routine in Stata 14, where the n=260 observations are weighted by the cluster-adjusted Random Effect Size (RES) weights and the cluster specific effects are defined according to the K=63 unique housing market clusters. Mundlak (1978) regressions estimated by first calculating cluster means for independent variables that vary within each cluster, and then by running the subsequent model via the "mixed" routine in Stata 14, where the residual cluster-specific effect is maintained.

Table B2. Unit value mean elasticity estimates.

Water quality measure	Cluster Adjusted RES Mean	Cluster Adjusted FES Mean	Standard RES Mean	Cluster Weighted Mean	Unweighted Mean	n	# studies
Chlorophyll a							
waterfront	-0.026***	-0.027***	-0.022***	0.324*	0.737*	18	3
	(-0.031, -0.021)	(-0.032, -0.021)	(-0.031, -0.013)	(-0.036, 0.685)	(-0.044, 1.517)		
non-waterfront w/in 500 m	0.009***	-0.001	0.001	0.010	0.005	18	3
	(0.006, 0.012)	(-0.003, 0.001)	(-0.006, 0.009)	(-0.085, 0.105)	(-0.201, 0.211)		
Dissolved oxygen							
waterfront	-0.010	0.064	0.098	-0.014	0.089	10	2
	(-0.257, 0.237)	(-0.217, 0.345)	(-0.669, 0.865)	(-0.262, 0.235)	(-0.207, 0.384)		
non-waterfront w/in 500 m	0.642***	0.209	0.992***	0.666***	1.063***	6	1
	(0.374, 0.910)	(-0.095, 0.513)	(0.343, 1.641)	(0.395, 0.937)	(0.708, 1.419)		
E-coli							
waterfront	-0.081***	-0.094***	-0.089***	-0.073***	-0.073***	5	1
	(-0.129, -0.032)	(-0.140, -0.048)	(-0.147, -0.031)	(-0.124, -0.021)	(-0.124, -0.021)		
non-waterfront w/in 500 m	-0.081***	-0.094***	-0.089***	-0.073***	-0.073***	5	1
	(-0.129, -0.033)	(-0.140, -0.048)	(-0.147, -0.031)	(-0.125, -0.022)	(-0.125, -0.022)		
Fecal coliform							
waterfront	-1.3E-4***	-2.2E-5***	-0.2E-4	-0.037	-0.018***	36	4
	(-1.8E-4, -0.7E-4)	(-2.8E-5, -1.6E-5)	(-0.6E-4, 0.1E-4)	(-0.088, 0.014)	(-0.026, -0.011)		
non-waterfront w/in 500 m	-0.052***	-0.036***	-0.024***	-0.059*	-0.020***	20	3
	(-0.096, -0.008)	(-0.046, -0.027)	(-0.036, -0.011)	(-0.090, -0.005)	(-0.034, -0.006)		
Lake trophic state index							
waterfront	-0.797***	-0.797***	-0.797***	-0.920***	-0.920***	2	1
	(-1.330, -0.264)	(-1.330, -0.264)	(-1.330, -0.264)	(-1.545, -0.295)	(-1.545, -0.295)		
non-waterfront w/in 500 m	-0.682**	-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)	(-1.296, -0.068)		
Light attenuation							
waterfront	-0.082***	-0.071***	-0.070***	-0.086***	-0.086***	57	2
	(-0.093, -0.070)	(-0.078, -0.064)	(-0.076, -0.063)	(-0.099, -0.074)	(-0.099, -0.073)		

non-waterfront w/in 500 m	-0.013***	-0.011***	-0.011	-0.014***	-0.014***	57	2
	(-0.020, -0.006)	(-0.014, -0.007)	(-0.014, -0.007)	(-0.022, -0.006)	(-0.022, -0.006)		
Nitrogen							
waterfront	-0.220***	-0.131***	-0.245***	-0.242***	-0.292***	10	5
	(-0.244, -0.196)	(-0.149, -0.113)	(-0.321, -0.170)	(-0.271, -0.215)	(-0.326, -0.257)		
non-waterfront w/in 500 m	-0.136***	-0.030***	-0.130***	-0.184***	-0.221***	10	5
	(-0.156, -0.116)	(-0.036, -0.023)	(-0.184, -0.077)	(-0.210, -0.157)	(-0.254, -0.187)		
Percent Water Visibility							
waterfront	-1.659***	-1.659***	-1.659***	-1.655***	-1.655***	2	1
	(-1.900, -1.418)	(-1.900, -1.418)	(-1.900, -1.418)	(-1.896, -1.414)	(-1.896, -1.414)		
non-waterfront w/in 500 m	-	-	-	-	-	0	0
Phosphorous							
waterfront	-0.107***	-0.093***	-0.114***	-0.107***	-0.115***	6	3
	(-0.122, -0.092)	(-0.106, -0.081)	(-0.154, -0.074)	(-0.123, -0.092)	(-0.130, -0.100)		
non-waterfront w/in 500 m	-0.005	0.003	-0.002	-0.019***	-0.016**	6	3
	(-0.012, 0.003)	(-0.002, 0.008)	(-0.015, 0.010)	(-0.032, -0.005)	(-0.029, -0.003)		
Salinity							
waterfront	0.552***	0.552***	0.552***	0.553***	0.553***	2	1
	(0.279, 0.824)	(0.279, 0.824)	(0.279, 0.824)	(0.281, 0.826)	(0.281, 0.826)		
non-waterfront w/in 500 m	-	-	-	-	-	0	0
Sediment							
waterfront	-0.003	4.9E-6**	4.9E-6**	-0.012	-0.018	4	2
	(-0.008, 0.001)	(0.2E-6, 9.7E-6)	(0.2E-6, 9.7E-6)	(-0.059, 0.035)	(-0.088, 0.052)		
non-waterfront w/in 500 m	-0.006	4.9E-6**	4.9E-6**	-0.012	-0.018	4	2
	(-0.014, 0.003)	(0.2E-6, 9.7E-6)	(0.2E-6, 9.7E-6)	(-0.059, 0.035)	(-0.088, 0.052)		
Sedimentation Rate							
waterfront	-0.113***	-0.113***	-0.113***	-0.132***	-0.132***	2	1
	(-0.134, -0.091)	(-0.134, -0.091)	(-0.134, -0.091)	(-0.183, -0.082)	(-0.183, -0.082)		
non-waterfront w/in 500 m	-0.113***	-0.113***	-0.113***	-0.132***	-0.132***	2	1
	(-0.134, -0.091)	(-0.134, -0.091)	(-0.134, -0.091)	(-0.183, -0.082)	(-0.183, -0.082)		

Temperature							
waterfront	-0.164 (-0.688, 0.361)	-0.118 (-0.603, 0.366)	-0.164 (-0.226, 0.533)	-0.177 (-0.720, 0.366)	0.138 (-0.240, 0.516)	6	1
non-waterfront w/in 500 m	-0.164 (-0.687, 0.360)	-0.119 (-0.602, 0.365)	-0.164 (-0.226, 0.532)	-0.177 (-0.719, 0.365)	0.137 (-0.240, 0.515)	6	1
Total Suspended Solids							
waterfront	-0.032** (-0.064, -0.000)	-0.039** (-0.073, -0.005)	-0.013 (-0.055, 0.029)	-0.026 (-0.057, 0.005)	0.002 (-0.31, 0.036)	7	2
non-waterfront w/in 500 m	-0.032** (-0.064, -0.000)	-0.039** (-0.073, -0.005)	-0.013 (-0.055, 0.029)	-0.026 (-0.057, 0.005)	0.002 (-0.31, 0.036)	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)	-0.036*** (-0.057, -0.016)	2	1
non-waterfront w/in 500 m	-	-	-	-	-	0	0
Water clarity							
waterfront	0.105*** (0.095, 0.114)	0.031*** (0.028, 0.034)	0.090*** (0.078, 0.102)	0.182 (-17.398, 17.762)	0.155 (-6.102, 6.413)	177	18
non-waterfront w/in 500 m	0.026*** (0.017, 0.034)	0.012*** (0.010, 0.015)	0.018*** (0.008, 0.028)	0.042*** (0.025, 0.059)	0.028*** (0.020, 0.036)	83	6
pH							
waterfront	0.779** (0.019, 1.540)	0.419*** (0.183, 0.654)	0.424 (-0.285, 1.133)	1.986*** (-.840, 3.133)	2.173*** (1.015, 3.331)	13	3
non-waterfront w/in 500 m	-0.188 (-1.086, 0.711)	-0.188 (-1.086, 0.711)	-0.379 (-1.084, 0.326)	0.008 (-1.405, 1.422)	-0.334 (-1.126, 0.457)	6	1
Trophic state index							
waterfront	-0.158*** (-0.181, -0.136)	-0.135*** (-0.160, -0.110)	-0.177*** (-0.229, -0.124)	-1.60*** (-0.184, -0.137)	-0.181*** (-0.209, -0.154)	4	2
non-waterfront w/in 500 m	0.015** (0.001, 0.029)	-0.001 (-0.011, 0.010)	0.022 (-0.007, 0.051)	0.018** (0.003, 0.034)	0.029*** (0.007, 0.050)	4	2

*** p<0.01, ** p<0.05, * p<0.1. Confidence intervals at the 95% level are displayed in parentheses. Observations weighted by cluster-adjusted RES weights, where each cluster defined at the housing market level as defined in the primary studies.

Table B 3. Unweighted OLS Meta-regression Results.

VARIABLES	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
waterfront	0.1279***	0.0972***	0.0908**	0.0911**	0.0547	0.0602*
	(0.033)	(0.035)	(0.037)	(0.037)	(0.036)	(0.036)
estuary		-0.0841**		-0.0653		-0.0486
		(0.033)		(0.048)		(0.075)
mean clarity			0.0195**	0.0068		-0.0504***
			(0.009)	(0.013)		(0.019)
midwest					-0.1485***	-0.2673***
					(0.046)	(0.064)
south					-0.1705***	-0.3242***
					(0.040)	(0.095)
west					-0.1212	-0.0856
					(0.085)	(0.085)
constant	0.0276	0.0854**	0.0071	0.0653	0.1928***	0.4247***
	(0.027)	(0.035)	(0.029)	(0.051)	(0.046)	(0.098)
R-squared	0.055	0.079	0.073	0.080	0.122	0.146

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. Regressions estimated using n=260 unweighted observations and the OLS regression routine "regress" in Stata 14.

Table B 4. Random Effect (RE) Panel Meta-regression Results: Clustered at Study Level.

VARIABLES	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
waterfront	0.0954***	0.0539**	0.0461*	0.0440*	0.0334	0.0350
	(0.023)	(0.026)	(0.024)	(0.026)	(0.031)	(0.029)
estuary		-0.0767**		-0.0509		0.0073
		(0.032)		(0.056)		(0.024)
mean clarity			0.0210***	0.0102		-0.0053
			(0.006)	(0.014)		(0.024)
midwest					-0.0415	-0.0520
					(0.056)	(0.087)
south					-0.1183***	-0.1452*
					(0.030)	(0.082)
west					-0.0915	-0.0906
					(0.097)	(0.103)
constant	0.0308*	0.0938***	0.0131	0.0639	0.1397***	0.1631
	(0.018)	(0.036)	(0.015)	(0.065)	(0.036)	(0.121)

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 n=260 observations are weighted by the cluster-adjusted Random Effect Size (RES) weights and the cluster specific effects are defined according to the K=18 primary studies.

Table B 5. Mundlak Model Meta-regression Results: Clustered at Study Level.

VARIABLES	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)
waterfront	0.0681***	0.0631***	0.0632***	0.0619***	0.0601***	0.0599***
	(0.006)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
waterfront cluster mean	0.0828	-0.0471	-0.2119	-0.1985	-0.2553*	-0.2817
	(0.066)	(0.113)	(0.162)	(0.170)	(0.147)	(0.186)
estuary		-0.0884*		-0.0457		0.0224
		(0.052)		(0.067)		(0.028)
mean clarity			0.0166	0.0156		0.0133
			(0.024)	(0.024)		(0.025)
clarity cluster mean			0.0270	0.0160		-0.0035
			(0.030)	(0.034)		(0.031)
midwest					-0.1044***	-0.0914*
					(0.027)	(0.048)
south					-0.2260***	-0.2210***
					(0.073)	(0.078)
west					-0.0915	-0.0931
					(0.097)	(0.087)
constant	-0.0102	0.1267	0.0989	0.1399	0.3683**	0.3487**
	(0.044)	(0.105)	(0.070)	(0.109)	(0.145)	(0.144)

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. Regressions estimated using n=260 observations. Observations are weighted by the cluster-adjusted Random Effect Size (RES) weights, where each cluster is defined as one of the K=18 unique primary studies. Mundlak (1978) regressions estimated by first calculating cluster (primary study) means for independent variables that vary within each cluster, and then by running the subsequent model via the "mixed" routine in Stata 14, where the residual cluster-specific effect is maintained.

Appendix C: Variance-Covariance Matrix for Random Effects Panel Model 3A.

Table C1. Variance-Covariance Matrix for Random Effects Panel Model 3A (from Table 3).

	waterfront	mean clarity	constant
waterfront	0.00040212		
mean clarity	-0.00006911	0.00004695	
constant	-0.00008892	-0.00005674	0.00029653