Appendix A: Meta-dataset details and study specific descriptions

This appendix provides details on the overall meta-dataset, and then gives a summary of each individual study and examples to illustrate the study-by-study derivations of the common elasticity and semi-elasticity estimates. The final meta-dataset is publicly available on the US EPA's Environmental Dataset Gateway.[1]

Appendix A.1: Meta-dataset details

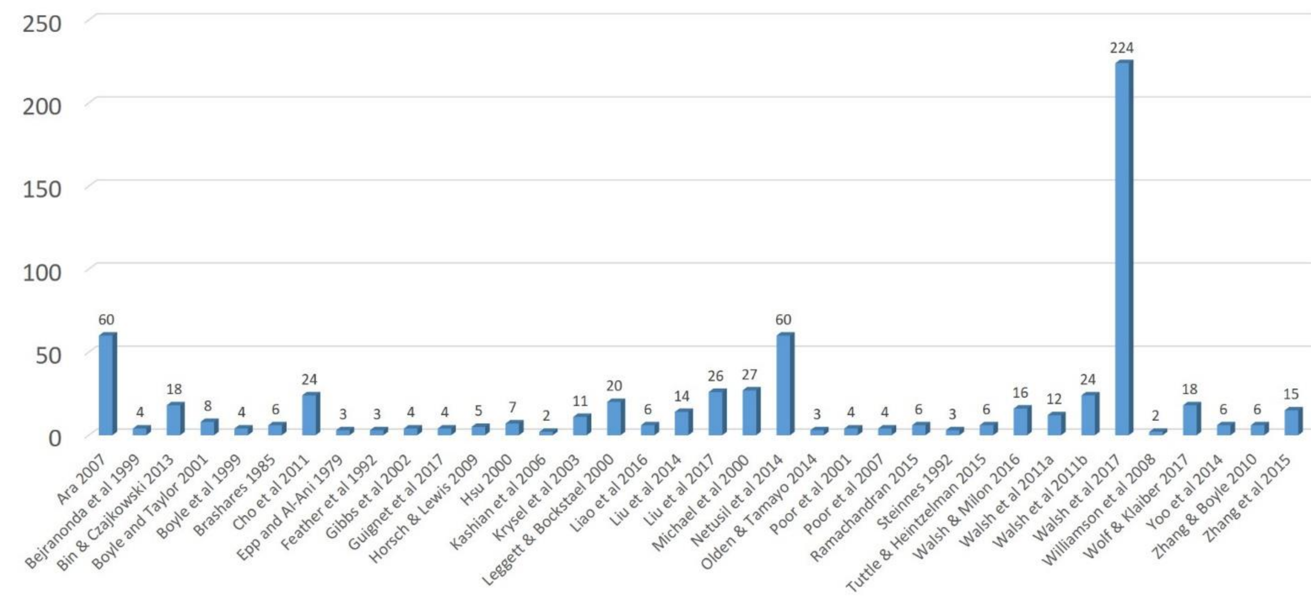
The set of 36 studies in the hedonic property value literature examining surface water quality in the United States provides 665 unique observations for the meta-dataset. Figure A1 displays the number of observations from each study, which ranges from just two observations from a single study to 224 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. Those nine observations are lost due to insufficient information in the primary study to estimate the elasticity, semi-elasticity, and/or the corresponding standard errors.[2] The corresponding water quality variable in 58 cases (across six studies) is a binary indicator (e.g., impaired vs. not impaired water), and although the percent change in price was

[1] US EPA's Environmental Dataset Gateway: "Meta-dataset for property values and water quality," https://doi.org/10.23719/1518489.

[2] Three of the missing elasticity estimates correspond to Steinnes (1992), who did not report the average price and average water quality values that are needed to calculate an elasticity. The other six missing elasticity estimates correspond to Liu et al. (2014). The coefficient estimates and standard errors needed for our elasticity calculations did not include a sufficient number of significant digits and were thus reported as zero. As such, the corresponding elasticity calculations were zero and the Monte Carlo simulations to infer a standard error could not be carried out (see study-specific details below).

calculated and labelled as a "semi-elasticity" in the meta-dataset for convenience, a parallel elasticity calculation is not applicable. In this study, we focus on the 598 unique house price elasticity estimates remaining in the meta-dataset.

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



Appendix A.2: Study specific descriptions and calculations

This appendix provides a brief summary of each study in the meta-dataset, and examples to illustrate the study-by-study derivations of the common elasticity and semi-elasticity estimates. 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 two sets of cluster analysis to define different submarkets around Lake Erie, one based on individual house transactions and the other on census block groups. Of the 21 defined submarkets, twelve were completely outside of our 500-meter range for non-waterfront homes; and are thus excluded from the meta-dataset. The study estimated hedonic price equations using both OLS and spatial error models, and examined both Secchi disk depth and fecal coliform. Considering the nine included submarkets, the study contributed a total of 60 observations to our meta-dataset. Hedonic estimates for most of the identified submarkets contributed both waterfront and non-waterfront meta-observations, but three submarkets only contributed non-waterfront price estimates because the corresponding sets of observed transactions fell completely outside of our assumed 50-meter distance for a representative waterfront home.

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

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

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

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

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

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

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

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

Bejranonda et al. (1999)

This study examined sediment inflow rates for state park lakes and reservoirs within 4,000 feet (1219.2 meters) of homes in Ohio. The counties are not identifiable based on the information provided in the primary study. The hedonic models examined the effect of sedimentation rates on property values for homes near lakes/reservoirs with regulations limiting boating horse-power to 10 (Limited HP) versus unlimited horse-power lakes (Unlimited HP). The dependent variable is the annual rental value which is obtained from a transformation on the total assessed housing value. The authors excluded homes near lakes that had a water surface area less than 100 acres (one acre equals 4046.86 square meters). The study estimated two models (one for the Limited HP lakes and one for the Unlimited HP lakes) each yielding a waterfront and non-waterfront estimate. Therefore, four observations are included in the meta-dataset.

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

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

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

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

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

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

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

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

Bin and Czajkowski (2013)

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

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

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

Rearranging for *p*,

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

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

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

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

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

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

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

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 different market regions. 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 for house and property characteristics, and the second used survey responses from buyers and sellers for house and property characteristics. 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.

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

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

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

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

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

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

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:

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

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

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

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:

$$\ln(p) = \gamma X + \beta WQ^2 \tag{1}$$

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*,

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

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

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

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

$$p_1 = \exp\left(\gamma X + D_1\right)$$

Plugging in the above equations yields:

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

Some rearranging and simplification produces:

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

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

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*,

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

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: $\frac{\partial \mathrm{p}}{\partial WQ} = p \cdot [\beta_1 + \beta_2 popchange]\frac{1}{WQ}$

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

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

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

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.

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

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

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

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

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

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

Rearranging for p,

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

Taking the partial derivative with respect to WQ yields:

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

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

The semi-elasticity and elasticity are respectively:

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

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

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.

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

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

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

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

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

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

Guignet et al. (2017)

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

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

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

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

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

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

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

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:

$$\frac{\partial p}{\partial WQ_m} = e^{\gamma X + (\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \ln\left(\frac{1.45}{WQ_m}\right)} \cdot -(\beta_1 dist_{WF} + \beta_2 dist_{0-200} + \beta_3 dist_{200-500}) \frac{WQ_m}{1.45}(1.45) WQ_m{}^{-2}$$

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

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

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

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

Horsch and Lewis (2009)

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

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

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

The primary study WQ is expressed in terms of Secchi disk depth in feet, which we re-express as Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28\,ft}{1\,m}$. Plugging this into the hedonic regression yields:

$$p = \gamma X + \beta(WQ_m \cdot 3.28) \quad (1)$$

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.

$$\frac{\partial p}{\partial WQ_m}\frac{1}{p} = \frac{\beta}{p} \cdot 3.28 \quad (2)$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = \beta \cdot 3.28 \cdot \frac{WQ_m}{p} \quad (3)$$

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:

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

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

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

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

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.

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

In this case, WQ is expressed in terms of Secchi disk depth in feet, which we re-express as Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28\ ft}{1\ m}$.

Substituting this conversion into equation (1), we have

$$p = \gamma X + \beta(WQ_m \cdot 3.28)$$

Taking the partial derivative with respect to WQ yields:

$$\frac{\partial p}{\partial WQ_m} = \beta \cdot 3.28$$

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

$$\frac{\partial p}{\partial WQ_m}\frac{1}{p} = \frac{\beta}{p} \cdot 3.28 \tag{2}$$

$$\frac{\partial p}{\partial WQ_m}\frac{WQ_m}{p} = \beta \cdot 3.28 \cdot \frac{WQ_m}{p} \tag{3}$$

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

Krysel et al. (2003)

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

The lin-log specification can generally be expressed as:

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

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

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

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

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

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

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

Leggett and Bockstael (2000)

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

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

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

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,

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

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

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

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

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

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

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 study examined sediment loads, dissolved oxygen, nitrogen and phosphorous levels, and Secchi disk depth in the Hoover Reservoir, as well as nitrogen and phosphorous in rivers, focusing on the Upper Big Walnut Creek watershed in Ohio. The study estimated a single hedonic regression model, that included interaction terms for each specific water quality measure and waterbody combination listed above, yielding seven observations corresponding to waterfront homes and seven corresponding to non-waterfront homes. Therefore, the study contributed a total of 14 observations to the meta-dataset. Only eight of these observations, however, can be included in any subsequent meta-analysis. Standard errors for all the relevant coefficient estimates in the other six cases lacked the necessary number of significant digits and were essentially listed as zero. This prevented us from simulating the corresponding standard errors associated with our standardized elasticity and semi-elasticity estimates.[3]

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

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

[3] 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 undergoing revisions.

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:

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

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

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

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

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

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

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

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Netusil et al. (2014)

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

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

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

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

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

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

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

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

Olden and Tamayo (2014)

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

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

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

Taking the partial derivative with respect to WQ yields:

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

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

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

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

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

Poor et al. (2001)

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

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

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

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:

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

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

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

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:

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

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

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:

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

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

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.

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

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

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

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

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

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

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

And with some rearranging and simplification yields:

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

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

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

Walsh and Milon (2016)

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

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

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

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

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

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

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

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

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

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

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

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

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.

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

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

which can be simplified to:

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

In this case, WQ is expressed in terms of Secchi disk depth in feet, which we re-express as Secchi depth in meters using the following conversion factor: $WQ_{ft} = WQ_m \cdot \frac{3.28\, ft}{1\, m}$. Plugging the conversion factor into the hedonic price function and re-arranging so that *p* is on the on the left-hand side yields:

$$p = \mathrm{e}^{\gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ_m \cdot 3.28)} \qquad (1)$$

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

$$\frac{\partial p}{\partial WQ_m} = \mathrm{e}^{\gamma X + [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \ln(WQ_m \cdot 3.28)} \cdot [\beta_1 + \beta_2 dist_{WF} + \beta_3 \ln(dist) + \beta_4 \ln(area)] \frac{1}{WQ_m \cdot 3.28} \cdot 3.28$$

Notice that the re-scaling factor of 3.28 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.

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

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

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

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:

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

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

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

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

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

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

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

Walsh et al. (2017)

This study examined water clarity (light attenuation coefficient) in the Chesapeake Bay tidal waters for 14 adjacent counties in Maryland. The study estimated 56 separate hedonic regression models; four for each county, where the functional form (double-log versus semi-log) and period for which the water quality measure is averaged over (one versus three years) varied. Each model in turn yields a waterfront and non-waterfront estimate, implying 112 observations. Furthermore, an additional 112 observations are derived from the same regression results by converting the estimates to correspond to Secchi disk depth (instead of the light attenuation coefficient). Therefore, the study contributed a total of 224 observations to the meta-dataset.

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

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

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

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

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

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

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

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

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

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

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

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

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

Williamson et al. (2008)

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

Consider a simplified representation of Table 3 as an example.

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

Rearranging for *p*,

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

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:

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

$$p_1 = \exp\left(\gamma X + D_1\right)$$

Plugging in the above equations yields:

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

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 microcystin 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: $WQ_{\frac{tons}{acre}} = WQ_{\frac{kg}{sqm}} \cdot 4.46$.

Plugging this into the hedonic regression yields:

$$\ln(p) = \gamma X + \beta_1 WQ_{\frac{kg}{sqm}} \cdot 4.46 + \beta_2 WQ_{\frac{kg}{sqm}} \cdot 4.46 \cdot Time + \beta_3 WQ_{\frac{kg}{sqm}} \cdot 4.46 \cdot Time^2$$

which is rewritten as:

$$\mathrm{p} = \exp\left(\gamma X + \beta_1 WQ_{\frac{kg}{sqm}} \cdot 4.46 + \beta_2 WQ_{\frac{kg}{sqm}} \cdot 4.46 \cdot Time + \beta_3 WQ_{\frac{kg}{sqm}} \cdot 4.46 \cdot Time^2\right) \quad (1)$$

Now, the derivative with respect to WQ is:

$$\frac{dp}{dWQ} = p \cdot (\beta_1 \cdot 4.46 + \beta_2 \cdot 4.46 \cdot Time + \beta_3 \cdot 4.46 \cdot Time^2)$$

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

$$\frac{dp}{dWQ}\frac{1}{p} = 4.46(\beta_1 + \beta_2 \cdot Time + \beta_3 \cdot Time^2) \quad (2)$$

$$\frac{dp}{dWQ}\frac{WQ}{p} = WQ_{\frac{kg}{sqm}} \cdot 4.46(\beta_1 + \beta_2 \cdot Time + \beta_3 \cdot Time^2) \quad (3)$$

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*,

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

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

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

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

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

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

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:

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

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

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

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

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.

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

Appendix B.1: Random Effect Size (RES) and Random Effect Size Cluster-Adjusted (RESCA) Meta-analytic Weights.

Weights based on the inverse variance of the primary estimates are often applied in meta-analyses in order to give more weight to more precise estimates (Nelson, 2015; Borenstein et al., 2010; Nelson and Kennedy, 2009). We re-distribute the weight given to each observation within and across clusters based on the Random Effect Size (RES) weights commonly used in the meta-analysis literature (Nelson and Kennedy, 2009; Borenstein et al., 2010; and Nelson, 2015).

Before presenting our RES cluster-adjusted (RESCA) weights, we review the two conventional precision-based weighting schemes commonly used in meta-analyses. The first is the Fixed Effect Size (FES) model.[5] Under the FES framework each meta-observation is considered a draw from the same underlying population distribution (even if from different studies examining different housing markets and waterbodies), and the estimated weighted mean is interpreted as an estimate of the average from that single true distribution. In other words, under the FES framework sampling error is the only driver of differences in the observed estimates across studies. The FES weight for elasticity estimate *i*, at distance *d*, in cluster *j* $\left(\hat{\varepsilon}_{idj}\right)$ is:

$$w_{idj}^{\text{FES}} = \frac{1}{v_{idj}} \quad \text{(B1)}$$

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

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

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

The conventional RES weights are calculated as:

$$w_{idj}^{\text{RES}} = \frac{1}{v_{idj}+T^2} \tag{B2}$$

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

$$T^2 = \frac{Q-(n-1)}{\sum_{i=1}^{n} w_{idj}^{\text{FES}} - \left(\frac{\sum_{i=1}^{n}\left(w_{idj}^{\text{FES}}\right)^2}{\sum_{i=1}^{n} w_{idj}^{\text{FES}}}\right)} \tag{B3}$$

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:

$$Q = \sum_{i=1}^{n} \frac{\left(\hat{\varepsilon}_{idj} - \bar{\varepsilon}_{d}^{\text{FES}}\right)^2}{v_{idj}} \tag{B4}$$

The conventional RES weighted means are thus calculated as

$$\bar{\varepsilon}_d^{\text{RES}} = \sum_{i=1}^{n} \frac{w_{idj}^{\text{RES}}}{\sum_{i=1}^{n} w_{idj}^{\text{RES}}} \hat{\varepsilon}_{idj} \tag{B5}$$

where *n* is the number of observed estimates in the meta-dataset for distance bin *d* and the water quality measure of interest. The between-study variance is estimated via the DerSimonian and Laird (1986) method using the inverse variance weights $\left(w_{ij}^{\text{FES}}\right)$ and the FES weighted 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.[6]

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

$$\omega_{idj} = \frac{\frac{w_{idj}^{\text{RES}}}{k_{dj}}}{\sum_{j=1}^{K_d} \sum_{i=1}^{k_{dj}} \left(\frac{w_{idj}^{\text{RES}}}{k_{dj}}\right)} \tag{B6}$$

These weights take the conventional RES weights $\left(w_{idj}^{\text{RES}}\right)$, which discount the weight given to elasticities estimated with relatively less precision within *and* across clusters (i.e., unique study and housing market combinations), and then further discount the weight given to observations where multiple estimates are provided for a given cluster.

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

Appendix B.2: Mean Elasticities.

Table B1. Mean Elasticity Estimates for All Water Quality Measures Examined in the Hedonic Literature.

Water quality measure	Unweighted Mean (1)	Cluster Weighted Mean (2)	Variance-Adjusted Cluster (VAC) Weighted Mean (3)	RES Cluster-Adjusted (RESCA) Weighted Mean (4)	n	Studies	Clusters (K_d)
Chlorophyll a							
waterfront	0.737*	0.324*	-0.023***	-0.026***	18	3	3
	[-0.044, 1.517]	[-0.036, 0.684]	[-0.028, -0.019]	[-0.031, -0.021]			
non-waterfront w/in 500 m	0.005	0.01	0.008***	0.009***	18	3	3
	[-0.201, 0.211]	[-0.085, 0.105]	[0.005, 0.010]	[0.006, 0.012]			
Dissolved oxygen							
waterfront	0.088	-0.014	-0.042	-0.011	10	2	3
	[-0.208, 0.384]	[-0.263, 2.34]	[-0.288, 0.205]	[-0.257, 0.236]			
non-waterfront w/in 500 m	1.064***	0.667***	0.650***	0.643	6	1	2
	[0.708, 1.419]	[0.396, 0.937]	[0.383, 0.918]	[0.375, 0.912]			
E-coli							
waterfront	-0.073***	-0.073***	-0.094***	-0.081***	5	1	1
	[-0.125, -0.022]	[-0.125, -0.022]	[-0.140, -0.048]	[-0.129, -0.033]			
non-waterfront w/in 500 m	-0.073***	-0.073***	-0.094***	-0.081***	5	1	1
	[-0.125, -0.022]	[-0.125, -0.022]	[-0.140, -0.048]	[-0.129, -0.033]			
Fecal coliform							
waterfront	-0.018***	-0.037	-0.028	-1.3E-4***	36	4	4
	[-0.026, -0.011]	[-0.088, 0.014]	[-0.079, 0.023]	[-1.8E-4, -0.7E-4]			
non-waterfront w/in 500 m	-0.020***	-0.058*	-0.061*	-0.052**	20	3	3
	[-0.034, -0.006]	[-0.127, 0.010]	[-0.129, 0.008]	[-0.096, -0.008]			
Lake trophic state index							
waterfront	-0.918***	-0.918***	-0.794***	-0.794***	2	1	1
	[-1.543, -0.293]	[-1.543, -0.293]	[-1.327, -0.262]	[-1.327, -0.262]			
non-waterfront w/in 500 m	-0.682**	-0.682**	-0.682**	-0.682**	1	1	1
	[-1.296, -0.068]	[-1.296, -0.068]	[-1.296, -0.068]	[-1.296, -0.068]			
Light attenuation							
waterfront	-0.086***	-0.086***	-0.072***	-0.082***	57	2	15
	[-0.099, -0.073]	[-0.099, -0.074]	[-0.082, -0.062]	[-0.093, -0.070]			
non-waterfront w/in 500 m	-0.014***	-0.014***	-0.012***	-0.013***	57	2	15

	[-0.022, -0.006]	[-0.021, -0.006]	[-0.019, -0.006]	[-0.020, -0.006]			
Nitrogen	-0.292***	-0.247***	-0.249***	-0.224***	10	5	5
waterfront	[-0.326, -0.257]	[-0.273, -0.221]	[-0.275, -0.223]	[-0.247, -0.201]			
	-0.221***	-0.194***	-0.195***	-0.151***	10	5	5
non-waterfront w/in 500 m	[-0.254, -0.187]	[-0.219, -0.168]	[-0.220, -0.170]	[-0.171, -0.131]			
Percent Water Visibility							
waterfront	-1.655***	-1.655***	-1.658***	-1.658***	2	1	1
	[-1.896, -1.414]	[-1.896, -1.414]	[-1.899, -1.417]	[-1.899, -1.417]			
non-waterfront w/in 500 m	-	-	-	-	0	0	0
Phosphorous							
waterfront	-0.115***	-0.107***	-0.109***	-0.106***	6	3	3
	[-0.130, -0.100]	[-0.128, -0.086]	[-0.129, -0.088]	[-0.126, -0.087]			
non-waterfront w/in 500 m	-0.016**	-0.033***	-0.033***	-0.012**	6	3	3
	[-0.029, -0.003]	[-0.053, -0.013]	[-0.053, -0.014]	[-0.022, -0.002]			
Salinity							
waterfront	0.533***	0.533***	0.551***	0.551***	2	1	1
	[0.281, 0.826]	[0.281, 0.826]	[0.279, 0.824]	[0.279, 0.824]			
non-waterfront w/in 500 m	-	-	-	-	0	0	0
Sediment							
waterfront	-0.018	-0.012	-0.011	-0.003	4	2	2
	[-0.088, 0.052]	[-0.059, 0.035]	[-0.028, 0.005]	[-0.008, 0.001]			
non-waterfront w/in 500 m	-0.018	-0.012	-0.011	-0.005	4	2	2
	[-0.088, 0.052]	[-0.059, 0.035]	[-0.028, 0.005]	[-0.014, 0.003]			
Sedimentation Rate							
waterfront	-0.132***	-0.132***	-0.112***	-0.112***	2	1	1
	[-0.183, -0.082]	[-0.183, -0.082]	[-0.134, -0.091]	[-0.134, -0.091]			
non-waterfront w/in 500 m	-0.132***	-0.132***	-0.112***	-0.112***	2	1	1
	[-0.183, -0.082]	[-0.183, -0.082]	[-0.134, -0.091]	[-0.134, -0.091]			
Temperature							
waterfront	0.138	-0.177	-0.186	-0.163	6	1	2
	[-0.241, 0.516]	[-0.720, 0.366]	[-0.726, 0.354]	[-0.688, 0.361]			
non-waterfront w/in 500 m	0.138	-0.177	-0.186	-0.164	6	1	2
	[-0.240, 0.515]	[-0.719, 0.365]	[-0.725, 0.353]	[-0.687, 0.360]			
Total Suspended Solids							
waterfront	0.002	-0.026	-0.033**	-0.032**	7	2	3
	[-0.031, 0.036]	[-0.057, 0.005]	[-0.063, -0.002]	[-0.064, -0.000]			

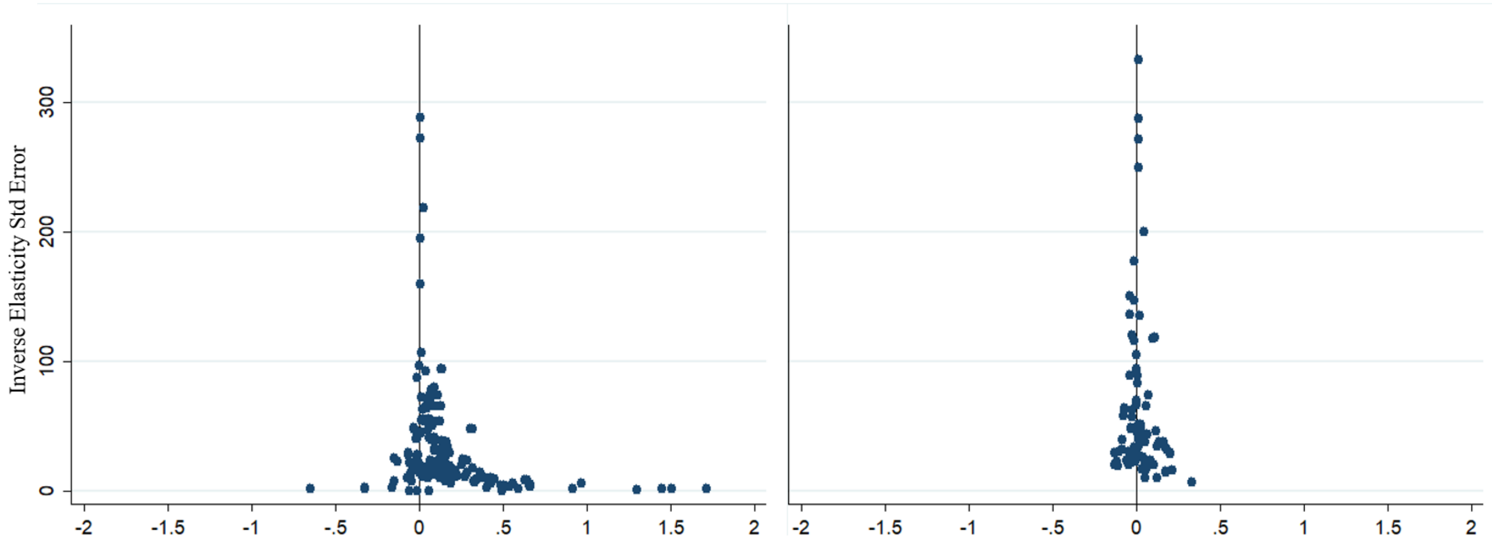
non-waterfront w/in 500 m	0.002	0.002	-0.033**	-0.032**	7	2	3
	[-0.031, 0.036]	[-0.031, 0.036]	[-0.063, -0.002]	[-0.063, -0.000]			
Turbidity							
waterfront	-0.036***	-0.036***	-0.037***	-0.037***	2	1	1
	[-0.057, -0.016]	[-0.057, -0.016]	[-0.057, -0.016]	[-0.057, -0.016]			
non-waterfront w/in 500 m	-	-	-	-	0	0	0
pH							
waterfront	2.175***	1.989***	1.418***	0.782**	13	3	4
	[1.017, 3.33]	[0.843, 3.136]	[0.347, 2.488]	[0.022, 1.542]			
non-waterfront w/in 500 m	-0.333	0.011	0.042	-0.186	6	1	2
	[-1.125, 0.458]	[-1.402, 1.425]	[-1.365, 1.449]	[-1.085, 0.712]			
Trophic state index							
waterfront	-0.181***	-0.160***	-0.160***	-0.158***	4	2	2
	[-0.209, -0.154]	[-0.183, -0.137]	[-0.183, -0.138]	[-0.181, -0.136]			
non-waterfront w/in 500 m	0.029***	0.018**	0.018**	0.015**	4	2	2
	[0.007, 0.050]	[0.003, 0.034]	[0.003, 0.034]	[0.001, 0.029]			
Water clarity							
waterfront	0.158	0.206	0.191	0.109***	177	18	66
	[-6.099, 6.416]	[-16.575, 16.987]	[-16.590, 16.972]	[0.099, 0.118]			
non-waterfront w/in 500 m	0.028***	0.042***	0.041***	0.026***	83	6	19
	[0.020, 0.036]	[0.025, 0.059]	[0.024, 0.058]	[0.017, 0.034]			

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

Appendix B.3: Examination of Publication Bias

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

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



(a) Elasticity: Waterfront homes

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

We next implement the more formal funnel-asymmetry test (FAT) and precision-effect test (PET) following Stanley and Doucouliagos (2012). We estimate the following FAT-PET weighted least squares regression:

$$\hat{\varepsilon}_{idj} = \theta_0 + \theta_1 SE_{idj} + u_{idj} \quad \text{(B7)}$$

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

The null hypothesis under the FAT is $H_0\colon \theta_1 = 0$, which would suggest no evidence of publication bias. The intuition behind this null hypothesis ties back to the funnel plots. If $\theta_1 = 0$, then the magnitude of an observed elasticity estimate is independent of its statistical precision. In other words, the funnel plot is symmetrical – estimates will be randomly and symmetrically distributed around the true mean population parameter (Stanley and Doucouliagos, 2012). As can be seen in column 1 of Table B2, we reject the null hypothesis due to the statistically significant coefficient on the standard error term, suggesting that publication bias is a concern with the meta-data collected from this literature. The fact that $\hat{\theta}_1 > 0$ suggests that the higher elasticity estimates provided by the literature systematically tend to be less precise.

Nonetheless, the statistically significant constant implies that we reject the PET null hypothesis, $H_0\colon \theta_0 = 0$. Therefore, even after adjusting for publication bias, we find evidence of a statistically significant true effect of water clarity on home values. The intuition here again ties back to the funnel plots. The parameter θ_0 is the true mean population parameter of interest, elasticity in our case (Stanley and Doucouliagos, 2012, 2014). The true value has a standard error of zero, and plugging $SE_{idj} = 0$ into equation (B7) leaves just θ_0 (plus random noise).

Simulation studies have suggested that including the elasticity variances v_{idj} on the righthand side of equation (B7) instead of SE_{idj} provides a better estimate of the true empirical effect of interest (Stanley and Doucouliagos, 2012, 2014). Referred to as the precision-effect estimate with standard error (PEESE), $\hat{\theta}_0$ can be interpreted as the true elasticity estimate purged of any selection bias. As shown in column 2 of Table B2, the significant constant term or PEESE estimate reveals a significant and positive elasticity of 0.0237.

With such tests it is important to control for sources of high heterogeneity (Stanley and Doucouliagos, 2019). The model in column 3 includes a *waterfront* dummy denoting meta-observations corresponding to homes in the closest waterfront distance bin, as opposed to non-waterfront homes within 500 meters. The constant term suggests a statistically significant and positive 0.0131 elasticity for non-waterfront homes, and the sum of the constant term and waterfront coefficient suggest a positive and significant elasticity of 0.0386 for waterfront homes. Even after adjusting for publication bias, these tests reveal that the literature suggests that a one-percent increase in Secchi disk depth (an average increase of 2.34 centimeters, or a little less than one inch) leads to an average increase in waterfront home values of 0.04%, and an increase of 0.01% in the value of non-waterfront homes within 500 meters. Caution is warranted in interpreting these PEESE estimates because here we do not account for the clustered nature of the dataset and other potential sources of heterogeneity, as we do in the main meta-regression analysis (see sections 3 and 4 in the manuscript).

Table B2. Simple Meta-regression Models Testing for Publication Bias.

VARIABLES	(1)	(2)	(3)
Elasticity std error	1.5738***		
	(0.249)		
Elasticity variance		0.0001	0.0001
		(0.006)	(0.006)
Waterfront			0.0256***
			(0.006)
Constant	0.0088**	0.0237***	0.0131***
	(0.004)	(0.003)	(0.004)
Observations	260	260	260
Adjusted R-squared	0.135	0.000	0.064

Dependent variable: home price elasticity with respect to water clarity (Secchi disk depth). *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Weighted least squares estimated using the "regress" routine in Stata 16 and defining analytical weights equal to the inverse variance of each of the corresponding elasticity estimates.

Appendix C: Supplemental meta-regression results.

Table C1. Variance-Adjusted Cluster (VAC) Weighted Random Effects (RE) Panel Meta-regression Results.

VARIABLES[a]	(1)	(2)	(3)	(4)	(5)	(6)
Waterfront[a]	0.1457***	0.0170	-0.0677	0.1010***	-0.1126	0.1251***
	(0.046)	(0.023)	(0.051)	(0.038)	(0.084)	(0.041)
Midwest[a]		-0.1056	-0.1488*	-0.2059	-0.2561***	-0.3156***
		(0.086)	(0.081)	(0.130)	(0.094)	(0.114)
South[a]		-0.2248***	-0.2797***	-0.3209*	-0.2889***	-0.3945***
		(0.075)	(0.083)	(0.169)	(0.105)	(0.128)
West[a]		-0.1803	-0.1803	-0.1747	-0.3745**	-0.3772**
		(0.119)	(0.119)	(0.145)	(0.176)	(0.170)
Estuary[a]			-0.0401**		-0.1223***	
			(0.016)		(0.038)	
Waterfront × estuary			0.1274**		0.1721**	
			(0.054)		(0.086)	
Mean clarity				0.0375		0.0799**
				(0.030)		(0.034)
Waterfront × mean clarity				-0.0684**		-0.1061**
				(0.029)		(0.049)
Elasticity variance	0.0000***	0.0000**	0.0000**	0.0000	0.0000**	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time trend					0.0183***	0.0223***
					(0.006)	(0.006)
Linear-log[a]					0.1973	0.1987
					(0.158)	(0.156)
Linear[a]					0.2198***	0.1159
					(0.084)	(0.081)
Log-linear[a]					-0.0020	-0.0059
					(0.008)	(0.008)
Constant	0.0414**	0.2474***	0.3320***	0.3092*	0.1681	0.0493
	(0.021)	(0.076)	(0.089)	(0.179)	(0.119)	(0.176)
Observations	260	260	260	260	260	260
ll	-0.1001	-0.0118	-0.0035	0.0053	0.0390	0.0461

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 16, where the cluster specific effects are defined according to the K=66 unique study-housing market clusters. Observations weighted following the VAC weights (see equation 3 in section 2). (a) Denotes independent variables that are dummy variables.

Appendix D: Cluster-weighted Descriptive Statistics and Benefit-Transfer Illustration.

The cluster-weighted averages used in the illustrative function transfer calculations in section 4 of the manuscript are shown in Table D1 below. A similar hypothetical policy illustration is then discussed, where we provide step-by-step guidance for practitioners on how to use the meta-regression results for function-based benefit transfers.

Appendix D.1: Cluster-weighted Descriptive Statistics.

Table D1. Cluster-weighted Descriptive Statistics of Observations Pertaining to Water Clarity.

Variable	Mean	Std. Dev.	Min	Max
Dependent variable:				
Elasticity	0.1241	0.2737	-0.6478	1.7198
Study area/commodity variables:				
Waterfront[a]	0.5000	0.5010	0	1
Mean clarity (Secchi disk depth, meters)	2.19	1.93	0.38	6.45
Lake or Reservoir[a]	0.4916	0.5009	0	1
Estuary[a]	0.5084	0.5009	0	1
Median income (thousands, 2017$)	61.208	14.573	37.865	91.174
College degree (% population)	0.1452	0.0403	0.0768	0.2734
Population density (households /sq. km.)	54.06	63.31	1.41	227.96
Mean house price (thousands, nominal $)	219.320	121.359	31.287	675.364
Northeast[a]	0.2879	0.4536	0	1
Midwest[a]	0.1547	0.3623	0	1
South[a]	0.5423	0.4992	0	1
West[a]	0.0152	0.1224	0	1
Methodological variables:				
Elasticity variance	2419.083	26195.880	0.000	301448.500
Unpublished[a]	0.0905	0.2875	0	1
Assessed values[a]	0.0680	0.2522	0	1
Time Trend (0=1994 to 20=2014)	9.46	6.08	0	20
No spatial methods[a]	0.3321	0.4719	0	1
Double-log[a]	0.3541	0.4792	0	1
Linear-log[a]	0.3258	0.4696	0	1
Linear[a]	0.0490	0.2164	0	1
Log-linear[a]	0.2711	0.4454	0	1

Cluster weighted descriptive statistics for n=260 unique elasticity estimates in meta-dataset pertaining to water clarity. Weighted by study-housing market clusters (K=66). (a) Denotes independent variables that are dummy variables.

Appendix D.2: A Hypothetical Benefit-Transfer Illustration.

Consider a hypothetical policy that is expected to increase water clarity in a small lake in the Midwest from a Secchi disk depth of 2.00 meters to 2.05 meters – an increase of five centimeters (almost two inches). Further suppose that there are 15 waterfront homes around this lake, and 20 non-waterfront homes within 500 meters of the lake. If available, one could carry out this exercise with home-specific baseline home values, based on recent transactions or assessed values. However, such data are not always available, and therefore practitioners may have to rely on average or median housing value estimates. Due to such cases, and for ease of communication, we illustrate the latter situation here. Suppose the average waterfront and non-waterfront homes around this lake are estimated to be valued at $300,000 and $250,000, respectively. We illustrate how to conduct a function-transfer using the results of RESCA WLS model 6 (from Table IV in the manuscript). Similar procedures apply when using other meta-regressions for function transfers, including models that researchers may estimate on their own using our meta-dataset.

Step 1: Plug the "policy" site variables into the estimated meta-regression function in order to calculate site-specific elasticity values.

This step allows practitioners to develop an elasticity estimate that is catered to their specific context, which is the main appeal of a function-based transfer. To more clearly present this step, let us expand the vectors in the meta-regression model described by equation (6) in the manuscript, and plug in the estimates from the RESCA WLS model 6 (from Table IV) for β_0, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$. This yields the following equation:

$$\hat{\varepsilon}_d = 0.0034 + 0.0829(waterfront) + -0.1476(midwest) + -0.2495(south)$$
$$+ - 0.4216(west) + 0.0601(mean\ clarity) + -0.0317(waterfront\ \times mean\ clarity)$$
$$+1.86E - 05(elasticity\ variance) + 0.0158(time\ trend)$$
$$+ - 0.0953(linearlog) + 0.0493(linear) + -0.0001(loglinear)$$

where the first two rows include the variables corresponding to the study area and waterbody, and the last two rows include methodological variables. We next show the calculations separately for waterfront and non-waterfront homes.

First consider a waterfront home around our hypothetical lake. We can plug in the relevant market and waterbody characteristics, as described above, but in practice researchers should plug in variable values that pertain to the housing market and waterbody for which they want to transfer the estimates to.

As described in section 4 of the manuscript, for the methodological variables, practitioners should plug in values denoting "best practices" (Boyle and Wooldridge, 2018). Following this guidance, we set the *linear* specification indicator to zero. Economic theory and simulation evidence suggest that assuming a linear hedonic price function is generally inappropriate (Bishop et al., 2020; Bockstael and McConnell, 2006). A similar motivation lends itself to setting the *elasticity variance* to zero (Stanley and Doucouliagos, 2012). When a "best practice" is not clear, Boyle and Wooldridge (2018) suggest using the average value across the literature. Therefore, based on the unweighted means among the remaining clarity elasticity observations in our meta-data, we recommend plugging in 32.0% and 23.2% for the linear-log and log-linear variables above (similar to the illustrative benefit transfer example in section 4 of the manuscript). Lastly, in order to infer an elasticity that is based on the most recent methods and data possible, the value for the time trend index is set to 20 (which corresponds to 2014, the most recent year observed in the meta-data).

The elasticity for a waterfront home in this hypothetical case would be calculated as:

$$\begin{aligned}\hat{\varepsilon}_{wf} &= 0.0034 + 0.0829(1) + -0.1476(1) + -0.2495(0)\\ &+ - 0.4216(0) + 0.0601(2.00) + -0.0317(1\ \times 2.00)\\ &+1.86E - 05(0) + 0.0158(20)\\ &+ - 0.0953(0.320) + 0.0493(0) + -0.0001(0.232)\\ &=\ 0.2810\end{aligned}$$

A similar calculation can be carried for a non-waterfront home, where a zero is plugged in for the waterfront indicator variable and its corresponding interaction with baseline mean water clarity.

$$\begin{aligned}\hat{\varepsilon}_{nonwf} &= 0.0034 + 0.0829(0) + -0.1476(1) + -0.2495(0)\\ &+ - 0.4216(0) + 0.0601(2.00) + -0.0317(0\ \times 2.00)\\ &+1.86E - 05(0) + 0.0158(20)\\ &+ - 0.0953(0.320) + 0.0493(0) + -0.0001(0.232)\\ &=\ 0.2615\end{aligned}$$

<u>Step 2:</u> Calculate the dollar change in individual house prices.

The estimated elasticities describe the percentage change in home price due to a one-percent change in Secchi disk depth. This can be re-arranged to show how the estimated change in price (Δp) can be calculated from our elasticity estimates and the available information. More specifically:

$$\Delta p_d = \hat{\varepsilon}_d p_{d0} \frac{\Delta wq}{wq_0}$$

where $\hat{\varepsilon}_d$ is the site-specific waterfront or non-waterfront elasticities calculated above, p_{d0} is the corresponding baseline house price for waterfront or non-waterfront homes, and Δwq and wq_0 are the change in water quality and baseline water quality values, respectively. Plugging in the respective values yields the following price change estimates for the average waterfront and non-waterfront home:

$$\begin{aligned}\Delta p_{wf} &= \hat{\varepsilon}_{wf} p_{wf0} \frac{\Delta wq}{wq_0} \\ &= 0.2810(300{,}000)\frac{(2.05 - 2.00)}{2.00} \\ &= \$2{,}107.36\end{aligned}$$

$$\begin{aligned}\Delta p_{nonwf} &= \hat{\varepsilon}_{nonwf} p_{nonwf0} \frac{\Delta wq}{wq_0} \\ &= 0.2615(250{,}000)\frac{(2.05 - 2.00)}{2.00} \\ &= \$1{,}634.25\end{aligned}$$

Step 3: Extrapolate the results to all impacted houses to get the projected change in total housing stock value.

To get the total projected change in housing stock value, one must multiply the waterfront and non-waterfront average price changes by the number of impacted homes, and sum the increase in value across waterfront and non-waterfront homes. At the beginning of this hypothetical exercise, we posited that there are 15 waterfront homes and 20 non-waterfront homes within 500 meters of the lake. Therefore, the total estimated increase in housing stock value is:

$$Total\ change\ in\ housing\ value = \left(\Delta p_{wf} \times number\ of\ waterfront\ homes\right)$$

$$+(\Delta p_{nonwf} \times number\ of\ nonwaterfront\ homes)$$
$$= (2{,}107.36 \times 15) + (1{,}634.25 \times 20)$$
$$= 31{,}610.34 + 32{,}685.10$$
$$= \$64{,}295.44$$

The variance-covariance matrix in Appendix E can be used to derive the corresponding standard errors and statistical confidence intervals using the delta method (Greene, 2003, page 70) or Monte Carlo simulations. We used the delta method based on the "nlcom" command in Stata 16, which yields the results below. Note that there are slight differences compared to the illustrative calculations due to rounding errors in the above formulas.

Table D2. Hypothetical Policy Estimates from RESCA WLS Model 6.

	Estimate	95% Confidence Interval
$\hat{\varepsilon}_{wf}$	0.2812***	[0.2398, 0.3225]
	(0.0211)	
$\hat{\varepsilon}_{nonwf}$	0.2616***	[0.1884, 0.3348]
	(0.0373)	
Δp_{wf}	2,108.6422***	[1,798.34, 2,418.94]
	(158.3187)	
Δp_{nonwf}	1,634.9863***	[1,177.76, 2,092.21]
	(233.2809)	
Total Δp waterfront homes	31,629.6331***	[26,975.15, 36,284.12]
	(2,374.7805)	
Total Δp non-waterfront homes	32,699.7262***	[23,555.28, 41,844.17]
	(4,665.6173)	
Total change in housing value	64,329.3593***	[51,768.55, 76,890.17]
	(6,408.6941)	

*** p<0.01, ** p<0.05, * p<0.1. Estimates calculated using the RESCA WLS Model 6 coefficient estimates (see Table IV in manuscript). Standard errors and 95% confidence intervals are calculated via the delta method, using the 'nlcom' command in Stata 16.

Appendix E: Variance-Covariance Matrix for Select Meta-regressions.

Table E1. Variance-Covariance Matrix for RESCA WLS model 1.

	Waterfront	Elasticity variance	Constant
Waterfront	3.246E-04		
Elasticity variance	1.247E-08	4.764E-10	
Constant	-1.896E-04	1.092E-08	2.427E-04

Table E2. Variance-Covariance Matrix for RESCA WLS model 6.

	Waterfront	Mean clarity	Waterfront × mean clarity	Midwest	South	West
Waterfront	9.92E-04					
Mean clarity	4.62E-04	4.87E-04				
Waterfront × mean clarity	-6.22E-04	-4.04E-04	5.91E-04			
Midwest	-4.36E-04	-1.33E-04	4.48E-04	1.54E-03		
South	-2.43E-04	9.45E-05	3.03E-04	1.56E-03	1.90E-03	
West	8.42E-05	-4.39E-04	-3.54E-04	3.15E-04	7.71E-05	5.91E-03
Elasticity variance	-2.58E-09	-8.66E-09	6.56E-09	-3.78E-08	-4.70E-08	-3.84E-08
Time trend	3.48E-05	4.14E-05	-3.20E-05	-1.22E-05	9.13E-06	-5.49E-05
Linear-log	4.58E-04	1.30E-04	-7.40E-04	-3.23E-04	-2.95E-04	2.39E-03
Linear	-3.32E-04	-8.91E-05	2.34E-04	1.78E-04	1.15E-04	-1.78E-03
Log-linear	2.95E-05	1.72E-05	-3.23E-06	1.98E-05	8.55E-05	-2.63E-05
Constant	-6.79E-04	-1.03E-03	4.54E-04	-1.31E-03	-1.97E-03	9.71E-04

	Elasticity variance	Time trend	Linear-log	Linear	Log-linear	Constant
Waterfront						
Mean clarity						
Waterfront × mean clarity						
Midwest						
South						
West						
Elasticity variance	3.57E-10					
Time trend	-1.27E-09	4.20E-06				
Linear-log	-2.52E-08	1.01E-05	2.44E-03			
Linear	-4.37E-09	3.69E-06	-3.32E-04	2.67E-03		
Log-linear	1.97E-10	1.07E-06	-2.38E-05	-1.59E-05	2.25E-05	
Constant	7.35E-08	-9.36E-05	1.20E-04	-4.34E-05	-8.10E-05	4.02E-03

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