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ABSTRACT: This study provides step-by-step guidance for practitioners and local stakeholders on how to use existing study results to conduct benefit transfer, and ultimately make informed predictions of how improvements in lake water clarity may benefit surrounding communities. The procedures are demonstrated using a publicly available meta-dataset developed by the U.S. Environmental Protection Agency, and a subsequent meta-analysis that synthesizes the literature of how improvements in water clarity impacts home values. The benefit transfer procedures are demonstrated using a case study of 14 large lakes in Kosciusko County, Indiana. Lake-specific average increases in home values, as well as the value of the housing stock in aggregate, are calculated for illustrative improvements in lake water clarity. This analysis provides a critical bridge to better connect high-quality, academic research with real-world policy analysis, and ultimately serves to better equip local governments and stakeholders to make more informed policy and land use decisions.

Keywords: benefit transfer; hedonic; meta-analysis; property value; lake; water clarity

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INTRODUCTION

When making decisions regarding land use, local infrastructure investments, and environmental policy, decision-makers are constrained by limited resources and competing needs. As such, tools like benefit-cost analysis and economic impact analysis can help inform these decisions (see US EPA 2014). Such analyses can also inform the general public, which can be useful for outreach and in encouraging voluntary actions. At the same time, original studies on the environmental and economic benefits can be expensive, time-consuming, limited by data, and require technical expertise that may not be regularly accessible by all stakeholders.

In lieu of original studies, benefit transfer can be used as a cost-effective way to inform benefit-cost and economic impact analyses. Benefit transfer (BT) is when one takes the results of an existing economic benefits study for a specific location (i.e., the study site), and applies the results to estimate the benefits of a similar policy and location (i.e., the policy site). BT can be based on the results of one or several primary studies. Ideally, the study site and policy site would be as similar as possible. If no single study fits the policy site well, then practitioners may use meta-analysis to synthesize and apply results across several studies (e.g., Stapler and Johnston, 2009; Schütt, 2022). A meta-analysis can use a variety of statistical approaches in order to draw conclusions, such as generating predicted values or estimating relevant effects, from the body of literature (Nelson and Kennedy, 2009; Stanley and Doucouliagos, 2012; Boyle and Wooldridge, 2018). A meta-regression model is estimated using primary study observations and independent variables based on the study site characteristics, study design, and methodological choices to help explain variation in the values or relevant effects (Nelson and Kennedy, 2009; Stanley and Doucouliagos, 2012; Boyle and Wooldridge, 2018). Compiling results across numerous primary studies, formatting a meta-dataset, and estimating a defensible meta-analysis in and of itself can require a significant amount of technical expertise that may not always be available to agencies, advocacy groups, and other stakeholders. Nevertheless, meta-analyses are often conducted with the explicit goal of providing a tool that practitioners can directly apply to policies and locations of interest.

In this applied case study, we provide an example and step-by-step guide of how practitioners can apply the results of a recent meta-analysis of studies examining how increases in water clarity impact home values (Guignet et al., 2022).[1] Although the meta-analysis has already been conducted, the current study focuses on the technical elements for applying the results to policy. Changes in home values are often used to infer the social benefits from improvements in nonmarket goods, like local water quality, and impacts on housing stock values are sometimes of direct interest to decision-makers.

Our illustrative example focuses on 14 large lakes in Kosciusko County, Indiana, which is in the Midwest region of the United States (see Figure 1). This case study is undertaken in collaboration with the Lilly Center for Lakes and Streams, which works with the local communities on lake and

[1] The underlying meta-data developed by Guignet et al. (2022) is publicly available and can be downloaded at US EPA's Environmental Dataset Gateway: "Data for property values and water quality", https://doi.org/10.23719/1518489.

stream restoration and management issues. The Lilly Center expressed interest in carrying out a BT exercise in order to better inform residents of how private and public actions that lead to improvements in lake water clarity may impact local home values.

BACKGROUND

Kosciusko County is in north central Indiana and is currently home to over 80,000 residents and thousands more visit the county each year for recreational activities. The county's original 558 square miles (1445 sq. km) were heavily forested in the southern portion and the northern sections consisted of large prairies - some tracts up to 10,000 acres (4046 hectares). Additionally, in both the northern and southern sections, there were many lowland areas that the early settlers labeled "wet prairies" (Royse 1919). Much of the prairie area has since been converted to agricultural use. In 2017, the USDA (2017) reported that there are 261,647 acres (approximately 106,000 hectares) committed to agriculture - or approximately 73% of the county's land area.

Glaciation of the area led to the formation many natural lakes in the county. Many of these lakes are kettle lakes. One hundred and four lakes in the county are greater than five acres (Bosch et al. 2019). The lakes are used for swimming, fishing, water sports as well as drinking water (Bosch et al. 2019). The largest lake, Lake Wawasee, measures 3,006 acres (1216.5 hectares). Kosciusko County lakes comprise over 10,700 acres (about 4330 hectares) of surface water.

As displayed in Figure 1, 14 larger lakes (>75 acres or 30.35 hectares) were selected for this case study – Beaver Dam, Big Barbee, Big Chapman, Center, Dewart, James, Oswego, Pike, Syracuse, Tippecanoe, Wawasee, Webster, Winona, and Yellow Creek. Twelve of the lakes are all-sport lakes that allow for wakeboarding, water skiing, and tubing. Consequently, they are some of the more popular lakes in the county for recreation and are desirable for residential and vacation homes. These lakes are the focus of research conducted by the Lilly Center at Grace College (Lilly Center, 2021). Water quality parameters and microcystin (blue-green algae toxin) have been monitored weekly at each of these 14 lakes during the summer season since 2015.

The water quality of Kosciusko's lakes and streams is influenced by the surrounding agricultural practices and other land use activities. Approximately 77% of Kosciusko County's land area is designated as farmland (USDA 2021), with over 88% of that farmland allocated to a variety of crops (USDA 2017). Kosciusko County also has a large livestock operation and ranks fifth in the state for livestock cash receipts (USDA, 2021). A preliminary analysis by Daeger and Bosch suggests that most of the phosphorous loads contributing to many of the lakes in our analysis come from inflowing streams (Unpublished manuscript by A. Daeger and N. Bosch. 2021. Estimated 2020 nutrient budgets for Winona Lake, the Tippecanoe Lake chain, and the Wawasee lake chain in Kosciusko County, IN. Lilly Center for Lakes and Streams). Although all the instream loading cannot be attributed to agriculture, it is likely a major contributor. Lawn runoff is also a large contributor of phosphorous into some of the lakes (Unpublished manuscript by A. Daeger and N. Bosch. 2021).

Lake communities in Kosciusko County are often densely populated with residential dwellings being located close to lakes. Private septic systems are the common wastewater treatment method used in these rural areas. While private septic systems can function for decades without issue, problems can arise due to the age of the system, quality of construction, size of the leach field, depth of the water table, and the type of soil. Groundwater in these areas often feed local lakes and failure of septic systems could be detrimental to water quality. Studies conducted on the Barbee and Chapman Lake chains in the county revealed that the soils in these areas are not appropriate for septic systems (Richardson and Jones 2000; Giolitto and Jones 2001). As described by Giolitto and Jones (2001), Grant (1999) finds that this is typical of Indiana soils and suggested that 80% of the state's soils are not suitable for a septic leach field. Grant (1999) also detected the presence of septic effluent on nearly all seven of the lakes on the Barbee chain (including Big Barbee Lake, which we analyze in this study). The infiltration of nutrients from septic tank effluent into waterways can promote excess growth of algae and macrophytes (Richardson and Jones 2000). Although most lakes in Kosciusko County have residences with aging private septic systems, public sewer systems have or are being installed at 11 of the 14 lakes included in this study. The installation of public sewer systems could lessen the potential impacts from failing septic systems.

Plant and algae growth in many lakes is limited by nitrogen and phosphorus concentrations (Horne and Goldman 1994) and excessive amounts of these nutrients can lead to an overabundance of macrophyte or algae production. In summarizing other studies, Horne and Goldman (1994) indicated that in many lakes, the growth-limited nutrient was directly related to the maximum crop of phytoplankton. Phosphorus was statistically related to the maximum phytoplankton abundance in many temperate zone lakes. Although less common in temperate lakes, this relationship also applies to nitrogen and silica in lakes where these elements limit algal growth (Horne and Goldman 1994). Consequently, limiting these nutrients would reduce algal blooms and increase water clarity. For instance, Painter et al. (1990) and Huser et al. (2016) demonstrated increases in water clarity using different treatments to reduce phosphorus loading into water bodies. Horne and Goldman (1994) reviewed studies that also showed marked improvements in water clarity after phosphorus reduction in sewage wastewater.

METHODS

To estimate changes in local home values due to improvement in lake water quality, and to provide others with the necessary information to perform their own analyses, we discuss the step-by-step procedures needed to conduct BT based on two approaches: unit value and function transfer. A unit value approach transfers a point estimate or summary statistic. In contrast, a function transfer uses an estimated equation to quantitatively adjust the transferred value based on characteristics of a policy site, its population, etc. (e.g., see Rosenberger and Loomis, 2017; Johnston et al. 2017). The unit value approach is generally less onerous to implement, and so the decision of whether to use unit value or function transfer is often driven by the available data. That said, factors such as transfer accuracy and site-specific differences should be considered (see Results section for details).

As shown in Figure 2, the process for both unit value and function transfers is generally the same, except that a function transfer requires an initial step to predict the transfer estimate for the relevant outcome (additional details can be found in Rosenberger and Loomis, 2017). In this analysis, the transferred estimate is the price elasticity with respect to water clarity, where the elasticity represents the percentage change in home value due to a one-percent change in Secchi disk depth.[2]

Step 1: Choose or predict relevant elasticity estimate from literature or meta-analysis.

Benefit transfer based on unit values first requires one to select an appropriate estimate from a primary study that closely matches the policy site and context (e.g., similar type of lake, uses, surrounding population, etc.), and/or based on the results of a comparable meta-analysis. In our context, we are using the results from a meta-analysis by Guignet et al. (2022). Guignet et al. present two separate sets of unit value estimates – one for waterfront homes, and the other for non-waterfront homes within 500 meters (~0.31 miles) of a waterbody (henceforth referred to as non-waterfront homes).

Let $\hat{\varepsilon}_d$ denote the elasticity estimate for a home in distance bin d, where the distance bin corresponds to either waterfront or non-waterfront homes (*d=1* and *d=2*, respectively). For our unit value estimates, we choose the Random Effect Size Cluster-Adjusted (RESCA) weighted mean estimates from Guignet et al. (2022). These estimates are chosen because the calculations give more weight to more precise estimates, while also maintaining consideration of the clustered nature of the dataset (i.e., that there are multiple estimates for a single housing market (or cluster), and that dependence should be accounted for).[3] As shown in Table 1, for waterfront homes the elasticity estimate is $\hat{\varepsilon}_1 = 0.109$. This implies that a one-percent increase in Secchi disk depth leads to an average increase of 0.109% in the value of a waterfront home. Similarly, the $\hat{\varepsilon}_2 = 0.026$ for non-waterfront homes suggests a 0.026% increase in value for non-waterfront homes when a one-percent increase in Secchi disk depth is experienced.[4]

Step 1 is slightly more complex when considering a function transfer approach. This is because one can adjust the applied elasticity estimate to the policy site by plugging in values for the independent variables in a parameterized meta-regression model. Guignet et al. (2022) estimate a series of meta-regression models of the form:

[2] The basic elasticity formula is $\varepsilon = (\partial p/\partial wq)(wq/p)$, where p is the home price and wq is a measure of water quality. More information on the elasticity derivations can be found in the supplementary material from Guignet et al. (2022).

[3] See Guignet et al. (2022) for details.

[4] We demonstrate this unit value transfer approach based on aggregated estimates from the literature of how water clarity impacts home values, but note that Guignet et al. (2022) provide unit value estimates pertaining to the property value impacts associated with various other water quality measures, including chlorophyll a, fecal coliform counts, nutrient concentrations, etc. The same steps apply when conducting unit value transfers based on these other measures.

$$\hat{\varepsilon}_d = \beta_0 + \boldsymbol{\beta_1 x_d} + \boldsymbol{\beta_2 z_d} + e_d \tag{1}$$

where $\hat{\varepsilon}_d$ is estimated as a function of characteristics of the study area and waterbody ($\boldsymbol{x_d}$) and methodological variables characterizing the primary study and model assumptions ($\boldsymbol{z_d}$). The error term e_{idj} is assumed to be normally distributed. The parameters β_0, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are unknown and are estimated by Guignet et al. (2022).

Using the predicted parameter estimates $\hat{\beta}_0$, $\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}$ and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{2}}$, one then plugs in "policy" site characteristics for $\boldsymbol{x_d}$ and methodological attributes for $\boldsymbol{z_d}$ in the meta-regression function. This allows one to predict elasticity estimates that are specific to the policy site. This is the main appeal of a function-based transfer approach over unit value transfer.

For this function-transfer exercise, we apply the meta-regression results from the RESCA WLS Model 6 in Guignet et al. (2022). This is one of the most comprehensive meta-regression models in their paper, and they found this model to perform the best in terms of minimizing out-of-sample transfer errors. The meta-regression results are presented in Table 2. The positive and significant coefficient corresponding to *waterfront* suggests that the price elasticity with respect to an improvement in water clarity is higher among waterfront homes, which is in agreement when comparing the earlier waterfront and non-waterfront unit value elasticity estimates. The negative and significant coefficients corresponding to the three regional dummies (*midwest*, *south*, and *west*) suggest that an increase in water clarity is associated with smaller increases in the value of homes in these regions, compared to the northeast region.[5] The positive 0.0601 coefficient corresponding to *mean clarity* suggests that a one-meter (3.3 ft) increase in baseline average Secchi disk depth corresponds to a 0.0601 increase in elasticity. Put plainly, premiums for water clarity seem to be higher among waterbodies where the baseline average water clarity levels are higher.

The remaining variables in Table 2 mainly reflect methodological choices of the primary studies, such as the statistical precision of the primary estimates (*elasticity variance*) and assumed functional forms (*linear*, *linear-log*, and *log-linear*; a *double log* specification is the omitted category). One variable we see is largely influential later is the *time trend*. This assumed linear trend was meant to capture changes in empirical methods, data, and households' tastes and preferences, and/or awareness of water quality over time (Rosenberger and Johnston, 2009). The positive and significant 0.0158 coefficient corresponding to the time trend suggests that the elasticities increase on average by 0.0158 percentage points every year. This positive trend could reflect any of the aforementioned factors, including advancements in methodological procedures and data practices, as well as changes in the environmental and housing market conditions.

Let us expand the vectors in equation (1) and plug in the coefficient estimates from Table 2. The parameterized transfer function is:

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[5] Guignet et al. (2022) base their regions of the US on the US Census Bureau's "Census Regions" (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf, accessed 7 July 2023; see also Figure 1 in Guignet et al., 2022).

$$\hat{\varepsilon}_d = 0.0034 + 0.0829(waterfront) - 0.1476(midwest) - 0.2495(south)$$
$$-0.4216(west) + 0.0601(mean\ clarity) - 0.0317(waterfront\ \times mean\ clarity)$$
$$+1.86 \times 10^{-5}(elasticity\ variance) + 0.0158(time\ trend)$$
$$-0.0953(linearlog) + 0.0493(linear) + -0.0001(loglinear) \qquad (2)$$

For the policy site and lake characteristics in the first two rows of equation (2), practitioners must simply plug in the relevant variables. Our benefit transfer application to lakes in Kosciusko County, Indiana, for example, imply that we will set *midwest* to one, but plug in a zero for the other region indicators (*south* and *west*). The mean clarity variables will be based on each one of our 14 lakes, as described in the Data section and presented in Table 3. We plug in a value of one for *waterfront* when predicting elasticities for waterfront homes ($\hat{\varepsilon}_1$), and zero for non-waterfront homes ($\hat{\varepsilon}_2$).

What values to plug in for the methodological variables in the last two rows of equation (2) can be a little trickier. For the methodological variables, practitioners should plug in values denoting "best practices" (Boyle and Wooldridge, 2018). Economic theory and simulation evidence suggest that assuming a linear hedonic price function is generally inappropriate (Bishop et al., 2020; Bockstael and McConnell, 2007). Hence, following this guidance, we set the *linear* specification indicator to zero. 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 non-linear clarity elasticity observations in the meta-data, we recommend plugging in 32.0% and 23.2% for the *linear-log* and *log-linear* variables in equation (2).

Finally, in order to infer an elasticity that is based on the most recent methods and data possible, the value for the *time trend* variable is set to 20 (which corresponds to 2014, the most recent year observed in the meta-dataset).

The lake-specific elasticities are estimated for waterfront and non-waterfront homes around each of the 14 different Kosciusko County lakes analyzed. We present those results and further illustrate this estimation procedure in the Results section.

Step 2: Calculate the dollar change in individual house prices.

Whether the predicted elasticities for benefit-transfer are based on unit value or meta-regression estimates, the remaining steps are the same. After obtaining the estimated elasticities, the next step converts those elasticities to changes in the value of a property, measured in dollars. 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 by plugging the elasticity estimates ($\hat{\varepsilon}_d$) into the following equation:

$$\Delta p_d = \hat{\varepsilon}_d \times p_d^0 \times \frac{\Delta wq}{wq^0} \tag{3}$$

To compute the change in price, the site-specific waterfront or non-waterfront elasticity ($\hat{\varepsilon}_d$) is multiplied by the baseline house price for the waterfront and non-waterfront homes (p_d^0). This could be house-specific values based on available property assessment data or could be a corresponding average house price. This is then multiplied by the posited change in water clarity (Δwq), over the baseline water clarity levels (wq^0). Lake-specific values for average p_d^0 and wq^0 are displayed in Table 3, and discussed further in the Data and Results sections.

Step 3: Extrapolate the results to all impacted houses.

To calculate the total projected change in housing stock value, one must multiply the waterfront and non-waterfront price changes calculated in equation (3) by the number of impacted homes, and then sum the increase in value across waterfront and non-waterfront homes. More formally, the total change in housing stock value (ΔHSV):

$$\Delta HSV = (\Delta p_1 \times number\ waterfront\ homes) + (\Delta p_2 \times number\ nonwaterfront\ homes) \tag{4}$$

Details on the number of waterfront and non-waterfront homes for each of the 14 Kosciusko County lakes analyzed are included in Table 3 and discussed next in the Data section.

DATA

Spatially explicit data on residential parcels were provided by the Kosciusko County Geographic Information Systems (GIS) Department. These data included baseline assessed home values and geographic coordinates. Distance to the nearest lake was then calculated. This BT analysis is of the 9,520 single-family and multi-family homes within 500 meters (~0.31 miles) of one of the 14 lakes in our study.[6] The majority of these homes (97%) are noted as single-family dwellings, which matches the common focus in the hedonic property value literature on single-family homes

[6] Residential properties classified as condos or mobile homes are excluded. We also excluded 61 properties where the property class description is not noted as a dwelling (i.e., is listed as “other residential structures” or “cash grain/general farm”). Nine additional properties were dropped because the total assessed value was listed as zero, leading to our final sample size of 9,520 residential parcels.

(Guignet et al., 2022). As described in the county data, 47% of these homes are located on the lakefront.

The water quality variable examined in this case study is water clarity as measured by Secchi disk depth. A Secchi disk is a 20-cm weighted disk with alternating black and white quadrants that is lowered into the water. Depth is recorded at the point where the disk is no longer visible from the water's surface. These data are collected by the Lilly Center and the Indiana Division of Fish & Wildlife. Time frames vary by lake, but water clarity data are available at most of the 14 lakes from 1989-2021 or 1994-2021. Secchi depths are primarily measured in June, July, and August. There are a few samples from May and September. There is a substantial amount of variability in the Secchi depths for each lake across the years. Interquartile ranges averaged 3.0 ft and were spread from 0.6 ft at Pike Lake to 4.5 ft at Wawasee.

As shown in Table 3, there is noticeable variation across the lakes in terms of the number of homes, average assessed value of the homes, and baseline water clarity. Yellow Creek Lake has the smallest number of homes, with only 144 residences located within 500 meters (~0.31 miles). In contrast, Lake Wawasee has over 2,250 homes around it. Assessed values of waterfront homes near these 14 lakes range from about $117k to $673k, on average. Non-waterfront home values are notably less, ranging from an average of $61,800 to just over $262k. Water clarity ranges from as little as just 32 inches (0.813 meters) in Pike Lake, to over 109 inches (2.77 meters) in Center Lake (see Table 3, as well as the map in Figure 1). These baseline water clarity levels were calculated as the average Secchi disk depth readings that the Lilly Center recorded for each lake from 2018 through 2021.[7]

RESULTS

The results of the unit value and function transfer estimates are for an illustrative, sustained 1-inch (2.54 centimeters) increase in average water clarity across all lakes. We then present an illustrative policy scenario that posits a 12-inch (0.3048 meter) sustained increase in average water clarity.

Unit value transfer results.

Table 4presents the results for all 14 lakes in our policy area (Kosciusko County), but we will focus on Lake Wawasee for purposes of discussion. Lake Wawasee is the largest natural lake in Indiana and one of the most popular lakes in Kosciusko County. Of the 14 lakes studied, it also has the greatest number of homes around it. To carry out the unit value transfer, we first follow Step 1 and take the estimated unit value elasticities from Table 1, which is $\hat{\varepsilon}_1 = 0.109$ and $\hat{\varepsilon}_2 = 0.026$ for waterfront and non-waterfront homes, respectively. As can be seen by Table 4, the unit

[7] The Lilly Center provided the annual average for all readings for each lake, and we then averaged this across all four years. We judged four years as a sufficient time period to reflect baseline clarity levels. It captures more recent trends, while also trying to minimize the effect of any year-to-year fluctuations due to abnormal weather conditions or other natural processes.

value estimates of the elasticity ($\hat{\varepsilon}_d$) are applied equally to each of the 14 lakes, regardless of differences in baseline water clarity levels.

As per equation (3), we next take Step 2 and calculate the average change in home value by multiplying the estimated elasticities by the baseline home prices, and the percent change in water clarity. The latter values are all displayed in Table 3. Using Lake Wawasee as an example; the average waterfront home value is $652,447, and the baseline water clarity is a Secchi disk depth of 2.20 meters (86.5 inches). Converting our 1-inch increase in clarity to meters implies $\Delta wq = 0.0254$. Following equation (3), the average change in value for a waterfront home is:

$$\begin{aligned}\Delta p_1 &= 0.109 \times 652{,}447 \times \tfrac{0.0254}{2.197} \\ &= \$822.20\end{aligned} \tag{5}$$

Note that to ease presentation we round some intermediate values in some equations. However, when displaying the final values for these illustrative calculations, we use the values derived directly from the programming code and that are presented in the results tables. Intermediate values are not rounded in the underlying calculations, even though some of the presented intermediate values in the example are rounded.

Now turning to non-waterfront homes around Lake Wawasee, the baseline water clarity and change in water clarity values are the same, but the estimated unit value elasticity and baseline average home value differ; more specifically $\hat{\varepsilon}_2 = 0.026$ and $p_2^0 = \$148{,}502$. The average change in price for non-waterfront homes around Lake Wawasee is calculated as:

$$\begin{aligned}\Delta p_2 &= 0.026 \times 148{,}502 \times \tfrac{0.0254}{2.197} \\ &= \$44.60\end{aligned} \tag{6}$$

This estimate is substantially less due to the smaller elasticity (i.e., improvements to lake clarity impact homes farther from the waterfront less), as well as the lower baseline home values. It is well established that waterfront properties are generally valued at a premium (e.g., Walsh et al. 2011, Guignet et al. 2017, Wolf and Klaiber 2017), and that is reflected in our data as well.

The estimated average change in home values for waterfront and non-waterfront homes around each of the 14 Kosciusko County lakes are presented in Table 4. The 95% confidence intervals presented in Table 4 are based on the same formulas, but use the corresponding upper and lower bounds of the elasticity estimates in Table 1.

We next follow Step 3 and calculate the total change in housing stock value (ΔHSV) for each lake by applying the average change in value to all waterfront and non-waterfront homes, and then summing across the two groups. Following equation (4), we can calculate ΔHSV for Lake Wawasee, for example, as follows:

$$\Delta HSV = (822.20 \times 1500) + (44.60 \times 757) \quad (7)$$
$$= \$1{,}267{,}085$$

where $\Delta p_1 = \$822.20$ and $\Delta p_1 = \$44.60$ come from equations (5) and (6), respectively, and the number of waterfront and non-waterfront homes around Lake Wawasee are from Table 3, and as discussed in the Data section, are based on GIS data from the Kosciusko County GIS Department. Overall, the unit value transfer projects that a sustained 1-inch increase in water clarity in Lake Wawasee would yield a total increase in housing stock value of $1.267 million. The results for the other lakes are presented in Table 4, and range anywhere from $22,728 at Center Lake to the $1.267 million in Lake Wawasee. These differences in projected increases in home values are largely driven by differences in the number of residential properties around these lakes, but variation in house prices and the composition of waterfront versus non-waterfront homes also play a role.

Function transfer results.

As before, we present the results for all 14 lakes in Kosciusko County but focus on Lake Wawasee for purposes of discussion. As per Step 1, we first use the parameterized transfer function estimated by Guignet et al. (2022) and presented as equation (2) here, and then plug in policy site or lake-specific values. As described in the methods section, we set $midwest = 1$, and set the *south* and *west* regional indicators to zero. For Lake Wawasee, the mean baseline water clarity is $mean\,clarity$ = 86.5 inches (2.197 meters), as displayed in Table 3. Following Boyle and Wooldridge's (2018) guidance for methodological variables, we set *linear* equal to zero, and plug in the corresponding proportions for the other functional forms in the literature based on Guignet et al.'s (2022) meta-dataset, more specifically $linearlog = 0.320$ and $loglinear = 0.232$. For this function transfer, we also set $elasticity\ variance$ to zero (Stanley and Doucouliagos, 2012). In order to infer an elasticity that is based on the most recent methods and data possible, the value for the *time trend* variable is set to 20, which is the most recent year observed in the meta-dataset (2014). Plugging these values into equation (2), and for waterfront homes setting $waterfront = 1$ yields:

$$\hat{\varepsilon}_1 = 0.0034 + 0.0829(1) - 0.1476(1) - 0.2495(0)$$
$$-0.4216(0) + 0.0601(2.197) - 0.0317(1 \times 2.197)$$
$$+1.86 \times 10^{-5}(0) + 0.0158(20)$$

$$-0.0953(0.320) + 0.0493(0) + -0.0001(0.232) \quad (8)$$
$$= 0.2867$$

The elasticity calculation for non-waterfront homes around Lake Wawasee is similar, but now $waterfront = 0$ is plugged in. Otherwise, the calculation is the same, as shown:

$$\hat{\varepsilon}_2 = 0.0034 + 0.0829(0) - 0.1476(1) - 0.2495(0)$$
$$-0.4216(0) + 0.0601(2.197) - 0.0317(0 \times 2.197)$$
$$+1.86 \times 10^{-5}(0) + 0.0158(20)$$
$$-0.0953(0.320) + 0.0493(0) + -0.0001(0.232) \quad (9)$$
$$= 0.2734$$

Here we calculate the corresponding confidence intervals in Table 5 using the delta method (Greene, 2003, page 70),[8] but one can also use Monte Carlo simulations (Hansen, 2022). The full variance-covariance matrix that is needed to derive a statistical confidence interval in either case is provided in the Appendix (Table A1).

As depicted in Figure 2, the remaining function transfer steps are similar to that of a unit value transfer. In Step 2, we again follow equation (3) and calculate the average change in the value of a home by multiplying the estimated elasticities by the baseline home prices, and the percent change in water clarity. Again, applying the illustrative 1-inch increase in water clarity (i.e., setting $\Delta wq = 0.0254$ meters), and plugging in the baseline Secchi disk depth and of 2.20 meters (86.5 inches) and average waterfront home value of \$652,447, and \$148,502 average non-waterfront home value, for Lake Wawasee yields the following waterfront and non-waterfront average changes in home value, respectively:

$$\Delta p_1 = 0.2867 \times 652{,}447 \times \frac{0.0254}{2.197} \quad (10)$$
$$= \$2{,}162.94$$

$$\Delta p_2 = 0.026 \times 148{,}502 \times \frac{0.0254}{2.197} \quad (11)$$

[8] More specifically, we use the "nlcom" command in Stata 17.

$$= \$469.43$$

Finally, as per Step 3 we calculate the total change in housing stock value (ΔHSV) for each lake. Applying equation (4) to the case of Lake Wawasee, and plugging the corresponding parcel counts from Table 3, as well as the estimates from equations (10) and (11), the final calculation of the function transfer is:

$$\Delta HSV = (2{,}162.94 \times 1500) + (469.43 \times 757) \tag{12}$$
$$= \$3{,}599{,}774$$

And so, the total projected increase in home values around Lake Wawasee due to a one-inch increase in water clarity is almost \$3.6 million. The results for the other lakes are presented in Table 4, and range anywhere from \$109,773 at Yellow Creek Lake to the almost \$3.6 million at Lake Wawasee.

Comparison of unit value versus function transfer results.

In general, comparison of Tables 3 and 4 demonstrate that estimated increases in home values based on the unit value transfers are substantially smaller. For example, comparison of the average increase in the value of a waterfront home at Lake Wawasee is \$822 based on the unit value transfer, but \$2,163 based on the function transfer. The total increase in housing stock value due to a 1-inch increase in water clarity is \$1.267 million versus \$3.600 million – a 184% difference.

The literature is mixed as to whether unit value or function transfers provide more accurate transfer estimates. The general motivation for function transfers is that they allow researchers to adjust the predicted estimates to a particular policy context, and therefore provide more accurate estimates (Johnston and Rosenberger, 2010; Rosenberger and Loomis, 2017). Several empirical studies have found, however, that simpler unit value predictions perform better in practice (Barton 2002; Lindhjem and Navrud 2008; Johnston and Duke 2010; Bateman et al. 2011; Klemick et al. 2018). Guignet et al. (2022) found that the out-of-sample transfer performance was similar across the unit value estimates and the function transfer model used in the current study.

One must be careful not to confuse similar out-of-sample prediction performance with yielding similar transferred estimates in practice. In this study we find that the estimated increases in home values are substantially less from the unit value transfer versus the function transfer. The much larger function transfer estimates are driven primarily by the time trend variable in the meta-regression (see Table 2). Recall that this linear trend variable was included to capture changes in empirical methods, data, and households' tastes and preferences, and/or awareness of water quality over time (Rosenberger and Johnston, 2009).

In our benefit transfer exercise, we plug in a value of 20 to reflect the most recent year observed in the meta-dataset (2014), which is meant to ensure that the transferred values reflect the most recent study results. This trend may account for improved estimates due to better methodological and data practices, higher quality and more abundant data, as well as the more current situation in terms of preferences, income, market and environmental conditions, etc. In contrast, the weights used in the unit value estimates do not distinguish between time periods, essentially treating old and new studies evenly. For this reason, we generally favor the function transfer approach.

This exercise highlights that one must consider the implications of predicted benefit transfer results across different methods, and not just consider out-of-sample performance. Although both approaches developed by Guignet et al. (2022) suggested similar out-of-sample performance, we find that they can yield very different results when carrying out an actual benefit transfer exercise.

An illustrative policy scenario: a 12-inch increase in water clarity.

Studies of several different management options implemented at various lakes across the US have shown that an increase in Secchi depth in the range of 12 inches is plausible and could be accomplished in various ways. For example, in Shagawa Lake, Minnesota, phosphorus present in treated domestic wastewater entering the lake was reduced by 80%. This resulted in a 1-meter (3.3 ft) improvement in water clarity three years post-treatment (Horne and Goldman 1994). Lake Washington in Seattle experienced a 2 to 3 meters (6.6 to 9.8 ft) improvement in water clarity after 50% of the sewage entering the lake was diverted (Horne and Goldman 1994). After removing common carp from Pickerel Lake, Minnesota, Huser et al. (2022) found a 600% increase in clarity from 0.2 to 1.2 meters (3.3 ft).

The Lilly Center and other stakeholders in Kosciusko County are interested in illustrating the potential property value gains for a similar, sustained average increase of 12-inches in water clarity at the 14 lakes. We do so here using a function transfer approach. The BT steps are the same. As can be seen in equation (3), one must simply set $\Delta wq = 0.3048$ meters (12 inches), instead of 0.0245 meters (1 inch). We also divide ΔHSV by the total number of waterfront and non-waterfront homes within 500 meters (~0.31 miles) of each lake (see Table 3) to calculate an average per home increase in value for residences around each lake. Estimates of ΔHSV are displayed in Panel (A) of Figure 3 for each of the 14 lakes. Lake Wawasee clearly would experience the largest increase in total housing stock value under this scenario, suggesting home values would increase over $43 million. This result is largely driven by the greater number of homes around Lake Wawasee. Panel (B) of Figure 3 shows that the average increase per home is similar across several of the lakes. For example, the average increase projected for homes around James Lake in this scenario is about $18,000 per home, which is just slightly below the average increase of about $19,140 projected for homes around Lake Wawasee. At the same time, James Lake has significantly less homes around it, and so the projected increase in total housing stock value is projected to be much less ($3.1 million, compared to the $43.2 million projected for Lake Wawasee). Summing the ΔHSV estimates across all 14 lakes suggests that *if an average sustained increase of 12 inches is achieved* across all lakes, then Kosciusko County is projected to experience a total increase in housing values of almost $122 million. This implies an average of $8.7 million per lake.

CONCLUSION

There are substantial uncertainties when projecting future scenarios. One can never perfectly forecast the future, and the same is true when performing benefit transfer (BT) like the unit value and function transfer approaches outlined. Nonetheless, BT and the approaches illustrated in our case study provide a useful benchmark to inform local policy, land use and management decisions; as well as inform residents, businesses, and other stakeholders. This study is meant as a step-by-step guide to help local governments, advocacy groups, etc. to conduct their own BT exercises using a readily accessible public meta-dataset developed by the US EPA, and a subsequent meta-analysis by Guignet et al. (2022). Our hope is that making this tool more accessible to resource constrained communities and groups will help empower local stakeholders to make more optimal decisions. The results of such BT exercises may reveal economic incentives to encourage lake residents to be better stewards of their property. Being able to demonstrate that increased water clarity can lead to higher property values may encourage lake homeowners to implement best management practices to improve water quality. If residents understand that protecting their shoreline from erosion, testing soil to minimize lawn fertilizer applications, and composting yard waste could result in increased property values, they may be more likely to participate in activities that improve lake health.

A broader lesson that came out of our case study of Kosciusko County was that similar predictive performance across meta-analysis models and BT approaches does not necessarily imply similar projected benefits. Although the unit value and function transfer approaches applied here were found to perform similarly in terms of out-of-sample prediction by Guignet et al. (2022), we see that the projected increases in home values are quite different. Perhaps practitioners should not rely solely on predictive performance when choosing an appropriate approach and model for BT. Sound and transparent rationale, and ideally economic theory, are also important when conducting BT. When in doubt, sensitivity analysis using multiple approaches and models is recommended.

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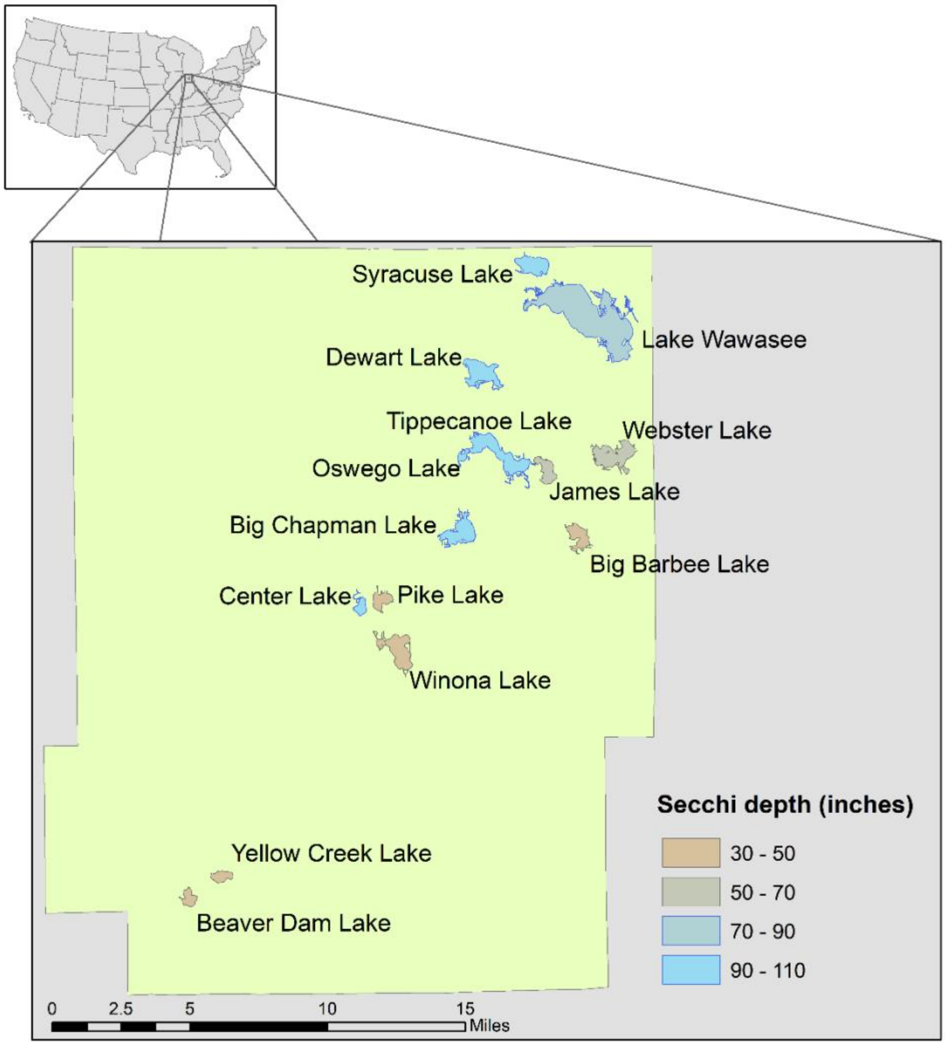
FIGURES AND TABLES

Figure 1. Kosciusko County and Average Baseline Water Clarity across 14 Larger Lakes.



Note: Kosciusko County is depicted by the larger green polygon. Baseline Secchi disk depth is based on the average of the annual mean summertime measures from 2018 to 2021.

Figure 2. Benefit Transfer (BT) Steps for Unit Value versus Function-transfer Approaches.

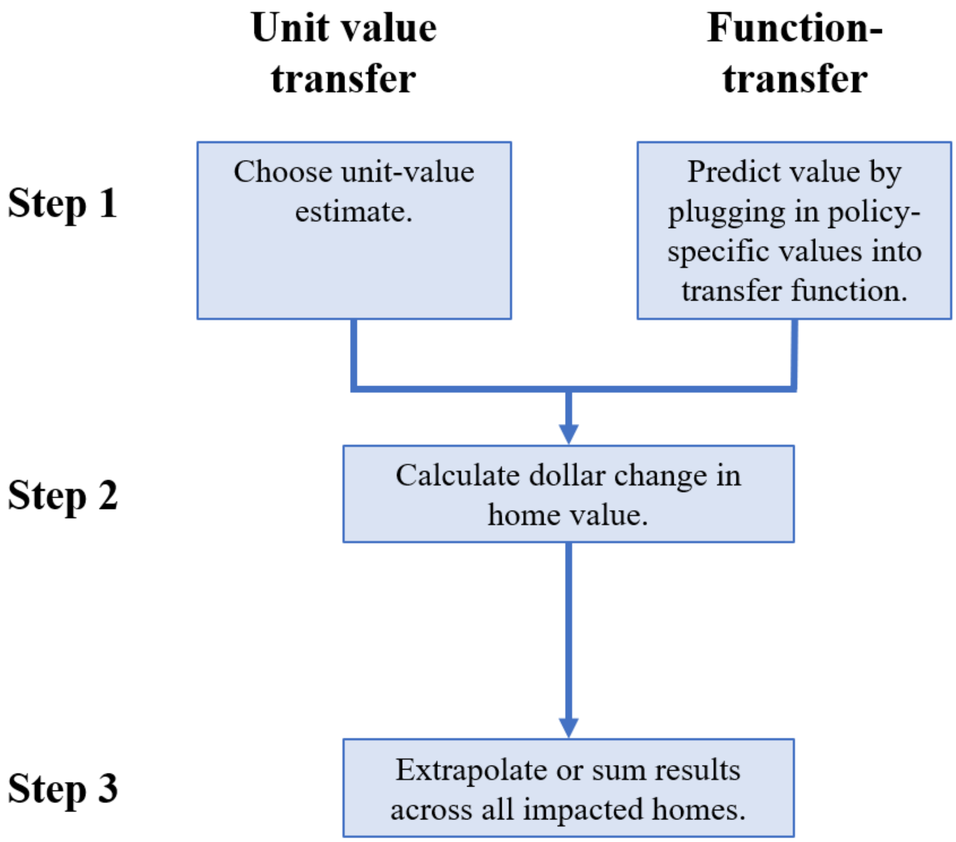
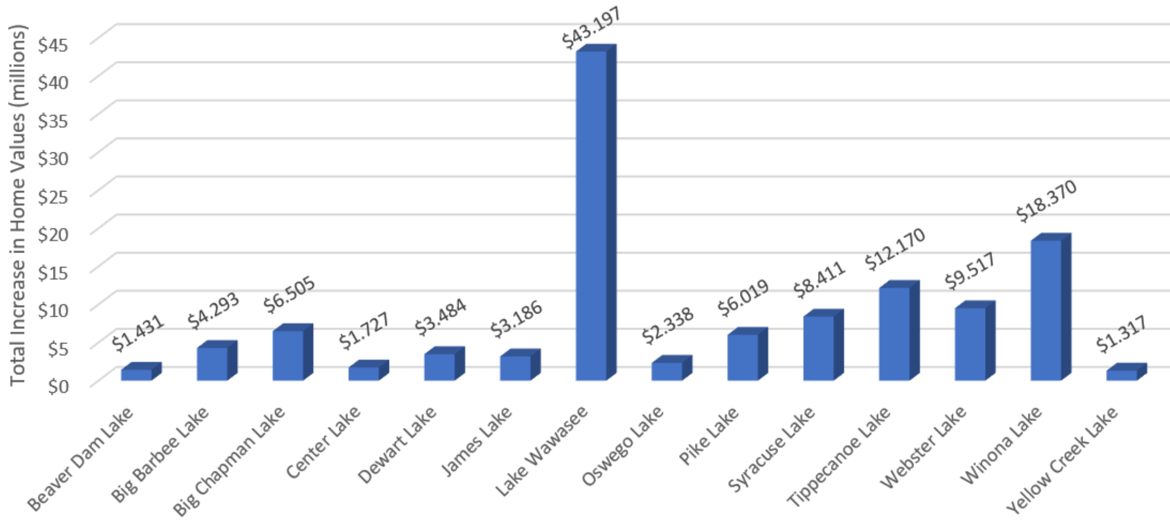


Figure 3. Projected Increase in Home Values for a 12-inch Sustained Increase in Water Clarity.

Panel A. Total Increase in Home Values (12-inch increase).



Panel B. Average Increase in Home Values (12-inch increase)

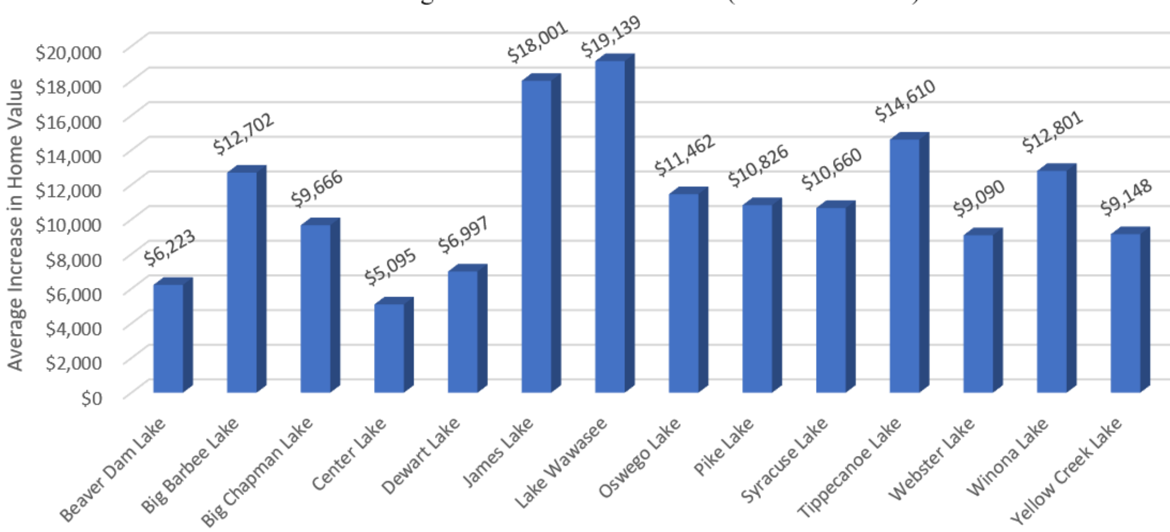


Table 1. Unit value estimates of the price elasticity with respect to water clarity.

	Weighted Mean Elasticity
Waterfront	0.109***
	[0.099, 0.118]
Non-waterfront w/in 500 m	0.026***
	[0.017, 0.034]

Notes: *** p<0.01, ** p<0.05, * p<0.1. Random Effect Size Cluster-Adjusted (RESCA) weighted mean estimates of the price elasticity with respect to water clarity (i.e., Secchi disk depth). Taken from column (4) in Table 1 of Guignet et al. (2022). 95% confidence interval in brackets. 95% confidence interval in brackets.

Table 2. Meta-regression model of price elasticity with respect to water clarity.

VARIABLES[a]	Meta-regression Model 6
Waterfront[a]	0.0829**
	(0.031)
Midwest[a]	-0.1476***
	(0.039)
South[a]	-0.2495***
	(0.044)
West[a]	-0.4216***
	(0.077)
Mean clarity	0.0601***
	(0.022)
Waterfront × mean clarity	-0.0317
	(0.024)
Elasticity variance	1.86E-05
	(1.89E-05)
Time trend	0.0158***
	(0.002)
Linear-log[a]	-0.0953*
	(0.049)
Linear[a]	0.0493
	(0.052)
Log-linear[a]	-0.0001
	(0.005)
Constant	0.0034
	(0.063)
Observations	260
Adjusted R-squared	0.222

Notes: *** p<0.01, ** p<0.05, * p<0.1. Random Effect Size Cluster-Adjusted (RESCA) Weighted Least Squares meta-regression model. Taken from column (6) in Table 4 of Guignet et al. (2022). Clustered-robust standard errors in parentheses.

(a) Independent variables that are dummy variables.

Table 3. Descriptive statistics by lake.

Lake	Number of homes within 500 meters (~0.31 miles)			Average Home Value (p_d^0)		Baseline Water Clarity (wq^0)	
	Waterfront	Non-waterfront	Total	Waterfront ($)	Non-waterfront ($)	Inches	Meters
Beaver Dam Lake	112	118	230	117,274	61,805	40.3	1.024
Big Barbee Lake	188	150	338	262,241	139,245	48.3	1.226
Big Chapman Lake	384	289	673	308,728	194,029	93.1	2.364
Center Lake	60	279	339	231,400	134,049	109.4	2.778
Dewart Lake	254	244	498	276,695	129,394	105.7	2.684
James Lake	69	108	177	599,913	263,552	69.3	1.759
Lake Wawasee	1,500	757	2,257	652,447	148,502	86.5	2.197
Oswego Lake	111	93	204	453,747	145,009	95.7	2.432
Pike Lake	128	428	556	219,998	110,809	31.9	0.809
Syracuse Lake	263	526	789	673,022	130,194	105.4	2.677
Tippecanoe Lake	529	304	833	511,746	192,296	94.6	2.402
Webster Lake	501	546	1,047	264,211	126,551	66.7	1.693
Winona Lake	291	1,144	1,435	435,478	155,433	45.9	1.165
Yellow Creek Lake	84	60	144	127,776	99,837	35.0	0.890

Table 4. Unit value transfer results for 1-inch (2.54 centimeters) increase in water clarity.

	Waterfront		Non-waterfront within 500 meters (~0.31 miles)		Total
	Elasticity ($\hat{\varepsilon}_1$)	Avg Increase in Value ($) ($\Delta p_1$)	Elasticity ($\hat{\varepsilon}_2$)	Avg Increase in Value ($) ($\Delta p_2$)	Increase in Value ($) ($\Delta HSV$)
Beaver Dam Lake	0.109	317.08	0.026	39.86	40,216
	[0.099 -0.118]	[287.99 - 343.26]	[0.017 - 0.034]	[26.06 - 52.12]	[35,330 - 55,595]
Big Barbee Lake	0.109	592.20	0.026	75.01	122,585
	[0.099 -0.118]	[537.87 - 641.10]	[0.017 - 0.034]	[49.04 - 98.09]	[108,476 - 135,240]
Big Chapman Lake	0.109	361.57	0.026	54.20	154,506
	[0.099 -0.118]	[328.40 - 391.42]	[0.017 - 0.034]	[35.44 - 70.88]	[136,346 - 170,790]
Center Lake	0.109	230.62	0.026	31.87	22,728
	[0.099 -0.118]	[209.46 - 249.66]	[0.017 - 0.034]	[20.84 - 41.67]	[18,381 - 26,606]
Dewart Lake	0.109	285.42	0.026	31.84	80,264
	[0.099 -0.118]	[259.23 - 308.98]	[0.017 - 0.034]	[20.82 - 41.63]	[70,924 - 88,640]
James Lake	0.109	944.24	0.026	98.95	75,839
	[0.099 -0.118]	[857.61 - 1,022.21]	[0.017 - 0.034]	[64.70 - 129.39]	[66,163 - 84,507]
Lake Wawasee	0.109	822.20	0.026	44.64	1,267,085
	[0.099 -0.118]	[746.76 - 890.08]	[0.017 - 0.034]	[29.19 - 58.37]	[1,142,241 - 1,379,314]
Oswego Lake	0.109	516.55	0.026	39.38	60,999
	[0.099 -0.118]	[469.16 - 559.20]	[0.017 - 0.034]	[25.75 - 51.49]	[54,471 - 66,860]
Pike Lake	0.109	752.89	0.026	90.46	135,084
	[0.099 -0.118]	[683.81 - 815.05]	[0.017 - 0.034]	[59.14 - 118.29]	[112,842 - 154,954]
Syracuse Lake	0.109	696.05	0.026	32.12	199,956
	[0.099 -0.118]	[632.19 - 753.52]	[0.017 - 0.034]	[21.00 - 42.00]	[177,313 - 220,269]
Tippecanoe Lake	0.109	589.85	0.026	52.87	328,103
	[0.099 -0.118]	[535.74 - 638.55]	[0.017 - 0.034]	[34.57 - 69.14]	[293,913 - 358,813]
Webster Lake	0.109	432.07	0.026	49.36	243,420
	[0.099 -0.118]	[392.43 - 467.75]	[0.017 - 0.034]	[32.28 - 64.55]	[214,231 - 269,587]
Winona Lake	0.109	1,034.91	0.026	88.11	401,955
	[0.099 -0.118]	[939.96 - 1,120.36]	[0.017 - 0.034]	[57.61 - 115.22]	[339,434 - 457,836]
Yellow Creek Lake	0.109	397.48	0.026	74.08	37,834
	[0.099 -0.118]	[361.02 - 430.30]	[0.017 - 0.034]	[48.44 - 96.88]	[33,232 - 41,958]

Note: All estimates are statistically significant at conventional levels ($p \leq 0.01$). 95% confidence intervals displayed in brackets.

Table 5. Function transfer results for 1-inch (2.54 centimeters) increase in water clarity.

	Waterfront		Non-waterfront within 500 meters (~0.31 miles)		Total
	Elasticity ($\hat{\varepsilon}_1$)	Avg Increase in Value ($) ($\Delta p_1$)	Elasticity ($\hat{\varepsilon}_2$)	Avg Increase in Value ($) ($\Delta p_2$)	Increase in Value ($) ($\Delta HSV$)
Beaver Dam Lake	0.2534 [0.2104 - 0.2965]	737.14 [611.92 - 862.37]	0.2029 [0.1580 - 0.2479]	311.12 [242.21 - 380.02]	119,272 [98,907 - 139,637]
Big Barbee Lake	0.2591 [0.2184 - 0.2999]	1407.96 [1186.45 - 1629.47]	0.2151 [0.1659 - 0.2642]	620.47 [478.63 - 762.30]	357,766 [299,559 - 415,973]
Big Chapman Lake	0.2915 [0.2450 - 0.3380]	966.92 [812.64 - 1,121.19]	0.2835 [0.1968 - 0.3701]	590.94 [410.31 - 771.56]	542,077 [443,751 - 640,403]
Center Lake	0.3033 [0.2484 - 0.3581]	641.62 [525.55 - 757.69]	0.3083 [0.2056 - 0.4111]	377.91 [251.96 - 503.86]	143,934 [104,909 - 182,959]
Dewart Lake	0.3006 [0.2478 - 0.3534]	787.09 [648.87 - 925.30]	0.3027 [0.2036 - 0.4017]	370.65 [249.36 - 491.93]	290,358 [234,194 - 346,521]
James Lake	0.2743 [0.2348 - 0.3138]	2,376.16 [2,033.62 - 2,718.71]	0.2471 [0.1823 - 0.3119]	940.40 [693.83 - 1,186.98]	265,519 [219,833 - 311,205]
Lake Wawasee	0.2867 [0.2429 - 0.3306]	2,162.94 [1,832.25 - 2,493.64]	0.2734 [0.1931 - 0.3538]	469.43 [331.48 - 607.39]	3,599,774 [3,036,347 - 4,163,202]
Oswego Lake	0.2934 [0.2457 - 0.3412]	1,390.53 [1,164.35 - 1,616.71]	0.2875 [0.1983 - 0.3768]	435.48 [300.32 - 570.64]	194,848 [161,213 - 228,484]
Pike Lake	0.2473 [0.2009 - 0.2937]	1,708.12 [1,387.92 - 2,028.32]	0.1900 [0.1480 - 0.2320]	661.09 [514.92 - 807.26]	501,585 [407,425 - 595,745]
Syracuse Lake	0.3001 [0.2477 - 0.3525]	1,923.59 [1,587.59 - 2,259.58]	0.3017 [0.2033 - 0.4000]	374.05 [252.06 - 496.03]	702,652 [569,749 - 835,555]
Tippecanoe Lake	0.2926 [0.2454 - 0.3398]	1,583.24 [1,327.93 - 1,838.56]	0.2857 [0.1976 - 0.3738]	581.04 [401.91 - 760.17]	1,014,172 [843,063 - 1,185,281]
Webster Lake	0.2724 [0.2331 - 0.3117]	1,079.86 [924.10 - 1,235.62]	0.2431 [0.1805 - 0.3057]	461.63 [342.76 - 580.50]	793,062 [662,791 - 923,333]
Winona Lake	0.2574 [0.2160 - 0.2988]	2.444.02 [2,051.28 - 2,837]	0.2114 [0.1636 - 0.2592]	716.44 [554.58 - 878.30]	1,530,817 [1,255,233 - 1,806,401]
Yellow Creek Lake	0.2496 [0.2046 - 0.2946]	910.19 [746.04 - 1,074.35]	0.1949 [0.1520 - 0.2378]	555.29 [433.03 - 677.54]	109,773 [90,394 - 129,153]

Note: All estimates are statistically significant at conventional levels ($p \leq 0.01$). 95% confidence intervals displayed in brackets.

ONLINE APPENDIX

Table A1. Variance-Covariance Matrix for Meta-regression in Table 2 (Taken from Table E2 in Online Appendix of Guignet et al., 2022).

	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