Spatial Heterogeneity in Hedonic Price Effects for Lake Water Quality

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ABSTRACT *This study uses Zillow's Transaction and Assessment Database to investigate variation in hedonic price effects of water clarity on single-family houses throughout the United States. We consider five spatial scales and estimate models using different sample selection criteria and model specifications. The results indicate considerable spatial heterogeneity within and across the four U.S. census regions. However, we also find heterogeneity resulting from different types of investigator decisions, including sample selection and modeling choices. Thus, it is necessary to use practical knowledge to consider the limits of market areas and to investigate the robustness of estimation results to investigator choices.* (JEL Q51)

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1. Introduction

Lakes are enticing environmental features that provide myriad benefits, including recreational opportunities, aesthetic appeal, and ecosystem services. People who own properties near lakes are primary beneficiaries, and their enjoyment depends on the level of perceived lake water quality. To monetize potential water quality benefits to homeowners, economists frequently use hedonic property models that examine how lake water quality is capitalized in housing markets. Over time, these models have revealed price premiums for improved water clarity and reductions in nutrient levels and algal content (Gibbs et al. 2002; Walsh, Milon, and Scrogin 2011; Walsh and Milon 2016; Wolf and Klaiber 2017; Weng et al. 2020; Wolf and Kemp 2021).

The extant literature focuses on small areas, such as metropolitan statistical areas (MSAs) (Boyle, Poor, and Taylor 1999), counties (Walsh, Milon, and Scrogin 2011), or individual lakes (Weng et al. 2020) where

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socioeconomic and ecological conditions that impact the implicit value of water quality may be fixed in each individual study. Although these studies provide strong evidence that people value lake water quality, a key limitation arises from the effects of fixed factors on implicit price estimates that cannot be identified. This limits the ability to draw insights across study areas or to unstudied areas where the fixed factors might vary. Thus, the spatial scope of the available literature limits the ability to assess the benefits of national policies to improve water quality that are often implemented at the state level.

Recent studies aim to broaden the geographic scope of lake hedonic studies, incorporating property sales from multiple states or regions into a single model. For example, Zhang, Phaneuf, and Schaeffer (2022) consider seven regional lake housing markets made up of two to eight states each. Swedberg et al. (2022) estimate models for six states in the Northeast and Upper Midwest at the state and substate levels. Mamun et al. (2023) and Moore et al. (2020) consider a larger spatial scale using a "nationwide housing market" comprising lakes from 43 and 32 states, respectively. These studies help policy makers understand the effects of lake water quality regionally and nationally.

Local land-use regulations at the community and county levels play a key role in lake water quality, and surrounding ecological conditions determine how well a lake can respond to upstream actions to reduce activities that degrade water quality. There are tensions between local actions and policies set at large geographic scales and hedonic modeling that may not be consistent with either of these to inform the costs and benefits of lake water quality degradation and improvements. Studies conducted at the local level demonstrate differences in implicit values for water quality, which are confirmed by the Guignet et al. (2022) meta-analysis that reports significant differences in elasticity estimates across broad regions of the country (see also Heberling, Guignet, and Papenfus 2022). Further, Zhang, Phaneuf, and Schaeffer (2022) and Swedberg et al. (2022) observe heterogeneity in value estimates at the regional and state levels. In a national housing market framework, Mamun et al. (2023) observe spatial heterogeneity by state and ecoregion, whereas Moore et al. (2020) do not find evidence for heterogeneity at the state level. Given the small number of studies considering large spatial scales for hedonic models of lake water quality, we can see that this issue deserves further investigation. The open questions are whether housing markets defined on small spatial scales can be rescaled to support policy analyses at the state and national levels and if models at broad spatial scales account for important differences between lake ecosystems and the surrounding housing markets at smaller spatial scales.

A key reason many hedonic studies have examined limited spatial areas is limited property sale data and or environmental data. Because rich data across large spatial areas can be difficult or costly to obtain, researchers' spatial scale choices are often determined by cost-effective data availability. Further, while data scraping is an alternative, it can be time consuming and is limited by publicly available records and differences in reporting across states, which ultimately require a choice between geographic coverage and data richness. Hedonic studies for water quality also face the challenge of suitable and consistently measured water quality across states with different water quality standards and sampling priorities.

We exploit the broad spatial coverage of Zillow's Transaction and Assessment Database (ZTRAX) to investigate how different spatial scales of hedonic estimation affect water quality elasticity estimates for residential properties (i.e., single-family houses) (Zillow Group 2021). Models are estimated using data ranging from a local, substate scale to a single national model. Our primary goal is to evaluate spatial heterogeneity in hedonic price effects for lake water quality. Further, because such an investigation can be influenced/confounded by investigator analysis choices, such as measurement of the policy variable, inclusion/exclusion of model covariates, and functional form of the hedonic (e.g., Guignet et al. 2022; Heberling, Guignet, and Papenfus 2022), we also evaluate the sensitivity of hedonic estimates at different spatial scales to common investigator decisions.

We estimate hedonic models at five different spatial scales and evaluate spatial heterogeneity defined by differences in water quality elasticity estimates across the four census regions and U.S. Environmental Protection Agency (EPA) ecoregions. We consider the most frequently available metric of water quality, Secchi depth, that relates to environmental quality changes due to nutrient loading to lakes and eutrophication. We divide elasticity estimates by four U.S. Census regions and compare the distributions for models estimated at each spatial scale. We systematically repeat model estimation for different sample selection criteria and modeling choices to assess the sensitivity of estimates to investigator choices. In doing so, we form the largest set of spatially explicit hedonic elasticity estimates for water quality present in the literature, which includes previously understudied areas of the country. These results in aggregate can advance future research around the underlying sources of spatial heterogeneity and the impact of methodological decisions in hedonic analysis.

Our results indicate considerable spatial heterogeneity in hedonic estimates with the largest, on average, in the Northeast and most variable estimates across the West. Elasticity estimates from lake-dense states in the Northeast and Upper Midwest are more stable than those in the South or West to investigator analysis decisions. Further, elasticity estimates in substate models are highly sensitive to investigator decisions in all regions. These results highlight the importance of accounting for spatial heterogeneity when evaluating capitalized benefits of lake water quality in housing markets; small-spatial-scale models may not reflect effects at larger spatial scales and vice versa. The effects of investigator choices highlight the importance of robustness checks.

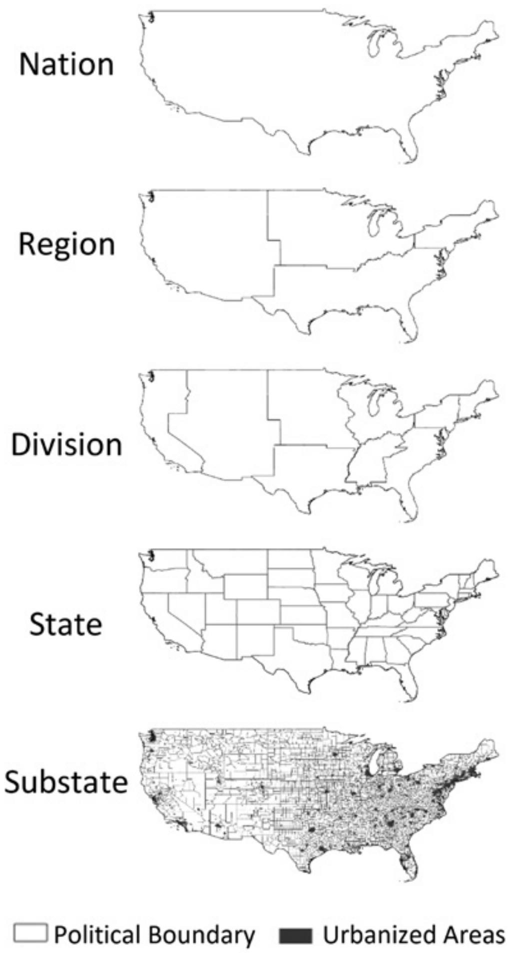
2. Exploring Spatial Heterogeneity

We investigate spatial heterogeneity in hedonic price effects of lake water quality at the substate (county and urbanized areas), state, census divisions and regions, and national scales. In estimating a hedonic model, researchers inherently define market boundaries by the geographic area(s) they choose to study. However, housing markets are a nebulous concept related to local property amenities, integrated labor markets, physical characteristics of the area, and geopolitical considerations, but rarely formally defined. Real estate multiple-listing areas traditionally were a practical guide (Michaels and Smith 1990; Michael, Boyle, and Bouchard 2000), but with the advent of online listing of properties and working from home options, the usefulness of this guidance has become less clear. From an economic perspective, one might define market boundaries where arbitrage leads to equal prices for equivalent properties at the margins (Phaneuf and Requate 2016). More commonly, when estimating hedonic models, researchers make tacit assumptions about market boundaries determined by data availability or simply a practical choice of policy reach.

Bishop et al. (2020) note that much of the focus of the broad hedonic literature is on large, data-rich metropolitan areas. County boundaries have also been used to define housing markets in hedonic studies (White and Leefers 2007; Phaneuf et al. 2008; Walsh and Milon 2016). Counties and MSAs might be loosely considered "markets." However, for lake water quality studies, these definitions may not work. For example, people in Boston looking for a second home on a lake may look over properties in Maine, New Hampshire, and Vermont. Given these challenges, we do not make the hard decision of what a real estate market is. Instead, we investigate hedonic estimation at differing spatial scales where significant differences may be indicative of different markets and lack of significance may indicate a common market, and such insights can inform future market analysis studies.

We ask if there are differences in outcomes of hedonic studies estimated at different spatial scales, which can be considered potential advantages or limitations in scaling hedonic model results to fit different policy goals. The five different spatial scales are shown in Figure 1: nation, region, division, state, and substate. Nation corresponds to the contiguous United States; region and division are U.S.

Figure 1
Market Boundary Definition by Spatial Scale



Note: The nation, region, division, and state boundaries are defined by a single census product. Substate boundaries are defined first by census urbanized areas then by census counties.

Census geographic delineations.[1] For the substate boundaries, we first use the 2010 census urbanized areas to divide sales within a state.[2] Then sales in the remaining area are divided by county boundaries.

Spatial heterogeneity can be investigated with the hedonic model by including interaction terms between water quality and dummy variables for the spatial boundary of interest. Moore et al. (2020) and Mamun et al. (2023) consider national models with state interaction terms. In addition to administrative boundaries, other characteristics may also be important to consider when determining spatial boundaries. Surrounding ecological conditions might include a unifying set of amenities that draw people to consider buying properties near lakes. To test heterogeneity related to environmental amenities, Mamun et al. (2023) specify a model using ecoregion interaction terms with water quality. To capture potential effects of geopolitical and environmental characteristics, we include both state and ecoregion interaction terms with water quality.

3. Controlling for Investigator Decisions

When comparing estimated effects across studies, investigator decisions can confound comparisons, making it difficult to identify which differences result from spatial heterogeneity versus investigator modeling decisions. Variation in investigator choices arises because the measure of water quality considered by buyers and sellers is unknown. Similarly, the appropriate mix of other property characteristics and the best functional form are not known or may simply be driven by data availability. These types of investigator decisions result in different hedonic specifications and can result in different samples due to data availability.

A crucial first step is determining how property sales are matched to water quality measures. Homebuyers may observe the lake at different points prior to the sale (e.g., over the year before the sale, at the time of purchase decision), and their bid function may be influenced by different summary measures.

[1] Census regions and divisions are grouping of states. There are four census regions that are subdivided by two or more census divisions; see https://www.census.gov/programs-surveys/economic-census/guidance-geographies/levels.html.

[2] According to the 2010 census, urbanized areas are collections of census tracts or blocks with a “densely settled core” of more than 50,000 people along with adjacent nonresidential or low-density areas that link other high-density areas to the core; see https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html.

Table 1
Sample Selection Criteria and Modeling Choices

Category	Criterion Type	Subcategory	Baseline Choice	Alternative
Water quality	Measurement	Water quality statistic	Summer mean	Summer minimum, summer maximum
Water quality	Measurement	Water quality timing	Closest within ± 5 years	Year of sale, year prior to sale, closest within previous 5 years
Water quality	Minimum threshold	Coefficient of variation for Secchi depth	0.25	N/A
Property	Measurement	Property attributes	Lot size; building size; building age	None, bedrooms and bathrooms[a]
Property	Maximum threshold	Lakefront property buffer	150 m	300 m
Property	Minimum threshold	Sales in buffer	1	0, 25
Property	Maximum threshold	Property distance to lake	1,000 m	2,500 m
Modeling Choices				
Functional form		Sale price, water quality	Log, log	Log, linear
Functional form		Covariates[b]	Log	N/A
Fixed effects		Spatial unit	Census tract	Block group
Fixed effects		Interactions	Spatial unit × sale year	Spatial unit + sale year

[a] All combinations of property attributes are considered (e.g., individual attributes, two at a time, three at a time, and all attributes). Bedrooms and bathrooms are always included together.
[b] In addition to the selected property attributes, model covariates include distance to lake, lake area, median income of block group, and slope and elevation of the parcel.

Some may make their decisions based on typical water quality conditions (e.g., average water quality over the summer months), whereas others may be most concerned about the poorest water quality conditions during the summer months. Note that with nutrient loading and eutrophication, which is the environmental quality investigated here, water quality declines over the summer months. Frequently, studies match a sale to a water quality sample in the year of sale or the year before sale (Walsh, Milon, and Scrogin 2011; Weng et al. 2020). However, given limited water quality and sale data and slow changes in water quality year to year, researchers may match sales in a specific window of time. Moore et al. (2020) match sales from 2010–2013 to 2007 water quality data, and Mamun et al. (2023) use a plus or minus five-year window from the sale date to match water quality observations. Michael, Boyle, and Bouchard (2000) test different measures of Secchi depth (water clarity) averaged over different time scales and find an effect on implicit price estimates but do not draw a conclusion about which measures are most appropriate. Wolf and Kemp (2021) find similar impacts when comparing minimum and mean Secchi depth and satellite water clarity measures.

The investigator decisions considered in the current analysis include the measurement of the water quality variable, choice of property characteristics, specification of the hedonic, and treatment of fixed effects in the hedonic (Table 1). Water quality measures considered include the summer mean, minimum, and maximum Secchi measurements of water clarity for the summer months. In addition, the Secchi measurement could be the closest in time within five years of the property sale, year of sale, year prior to sale, or closest in the time from the previous five years. We define year of sale as the most recent summer, meaning that for a year of sales data, sales in January through May will correspond to the previous year of water quality data, and sales in June through December will correspond to the same year of water quality data. The selection of the water quality measure can have a direct impact on the hedonic coefficient estimate for water quality, where the timing of the measurement more likely affects the sample size. The current or previous year measures likely result in the smallest sample while the

± five-year window likely maximizes the sample size.

Lake water quality changes slowly year to year, and spatial variation in water quality is necessary to identify effects of water quality on property values.[3] Therefore, we set a minimum coefficient of variation (CV) for lake water quality in the sample to improve the likelihood that the coefficient estimates are meaningful. If water quality is similar across lakes in specific regions, it would be challenging to identify significant water quality effects. The minimum CV is based on estimation results from previous hedonic studies. CVs for Secchi range from as low as 0.21 for a substate area in New Hampshire (Gibbs et al. 2002) and as high as 0.90 at the national level (Moore et al. 2020). While 0.21 is the minimum CV, the next three smallest CVs are 0.31, 0.32, and 0.34 from Michael, Boyle, and Bouchard (2000), Gibbs et al. (2002), and Swedberg et al. (2022), respectively. We choose 0.25 as the minimum CV as it falls in between 0.21 and 0.31. No alternative CV is considered in the analyses.

In selecting property attributes, researchers must balance the potential for omitted variable bias against limiting the number of sales. Excluding variables with many missing observations could result in an omitted bias if the omitted variables are correlated with the policy variable (water quality here). On the other hand, including the variables can compromise sample representativeness if observations are not missing at random. Although some researchers may include all property attributes available in the data as controls, this approach often becomes untenable across broad spatial areas, because comparable property attributes are not consistently available across all regions of the country. Therefore, researchers use discretion in selecting the most commonly available property attributes that relate to the size and quality of the property. For example, Moore et al. (2020) choose bedrooms, bathrooms, house size, and building age. In contrast Zhang, Phaneuf, and Schaeffer (2022) do not use any property attributes, instead using census block group fixed effects to control for neighborhood and structural attributes of homes that remain fixed through time. We estimate models with lot size, building size, and building age for the baseline.

The maximum distance from the lake determines which properties are included in the sample, and controlling distance can influence the functional form of the hedonic. Although much of the early literature focused on lakefront properties (e.g., Michael, Boyle, and Bouchard 1996), more recent studies consider broader distances from lakes (1,000–3,000 m) (Walsh, Milon, and Scrogin 2011; Walsh and Milon 2016; Wolf and Klaiber 2017). However, recent studies consistently find that the largest effects of water quality occur for lakefront properties, and the effects decay rapidly with distance from lakes. Wolf and Klaiber (2017) find insignificant estimates beyond 250 m, while Walsh et al. (2017) find a significant effect up to 1,000 m from the waterfront. Three lake proximity characteristics are considered to address lake proximity. The first is an indicator of whether the property has lake frontage, and two buffer distances were considered: within 150 m and within 300 m of the lake. The second is distance to the lake measured in meters with two alternatives: properties within 1,000 m and 2,500 m of the lake. The third is the minimum number of sales within the lakefront buffers with the levels of 0, 1, and 25.

In the selection of minimum sample sizes, we consider prior lake hedonic studies conducted at the substate level. While studies in the late 1990s and early 2000s had sample sizes of only a few hundred and sometimes less than a hundred (Boyle, Poor, and Taylor 1999; Michael, Boyle, and Bouchard 2000; Poor et al. 2001; Boyle and Taylor 2001), recent studies, due to the advent of large spatial scale data on property sales and environmental characteristics, may include 10,000–50,000 observations (Walsh, Milon, and Scrogin 2011; Liu, Opaluch, and Uchida 2017; Weng et al. 2020). The smallest sample size we

[3] Weng et al. (2020) simulate summertime Secchi and chlorophyll a from 2008 to 2013 for Lake Mendota, Wisconsin, and find more larger seasonal variation in water quality than inter-annual variation. Kung, Guignet, and Walsh (2017) perform a scoping analysis and found that variation in *Enterococcus* levels is more spatial than temporal.

found in the recent literature comprises 1,020 observations in two counties in Wisconsin (Wolf and Kemp 2021). Thus, we set the minimum sample size for our study at 1,000 transactions, and no alternative is considered.

In addition, we consider alternative functional specifications for the hedonic and fixed effects. The alternative log-linear functional form provides a complementary interpretation of the effects, as the estimated parameter measures the average percent response in prices given a linear change (instead of a percent change) in the water quality metric. Although we vary the functional form of water quality, all continuous covariates enter the model in log form, as in Walsh and Milon (2016). Spatial fixed effects control for time-invariant characteristics in the delimited spatial unit and time interval that are not specifically addressed by property characteristics in the hedonic and that may be correlated with the water quality measurement. Two spatial controls are included census tract and block group. Interacting spatial fixed effects with sale year fixed effects allows the characteristics in the spatial unit to vary year to year to control for omitted variables that may change over time but can further restrict the identifying variation for the model. For the baseline, we consider a log-log functional form with census tract × year fixed effects.

For parsimony in reporting, our primary results feature elasticity estimates for models specified using the investigator decisions indicated in baseline choice column (Table 1). We then run models for each combination of baseline and alternative sample selection and modeling choices. We present summaries of these results in a sensitivity analysis.

4. Data

To provide an extensive analysis of lake properties throughout the contiguous United States, we draw on a wide range of several large-scale data repositories. We discuss environmental and geospatial data sources and present property sale data. The base data that we work with contains water quality measurements from over 6,000 lakes across all 48 of the contiguous United States (Table 2).

Environmental and Geospatial Data

Water quality is measured by Secchi, an indicator of water clarity.[4] Secchi is commonly used in hedonic studies for lake water quality as clearer water has repeatedly been shown to be valued by homeowners (Michael, Boyle, and Bouchard 2000; Calderón-Arrieta, Caudill, and Mixon 2019; Wolf and Kemp 2021; Guignet et al. 2022; Mamun et al. 2023) and is one of the most available measures throughout the United States. We consider water quality samples from June through September, when most people enjoy lake activities, and use average, minimum, and maximum values for each lake for each year.

We access water quality data from two large-scale data repositories: LAGOS-NE and EPA's water quality portal (WQP).[5] LAGOS-NE provides extensive water quality data in LAGOS-NE LIMNO, inspected for data quality for 17 northeastern and midwestern states, made accessible through the LAGOS-NE R package (Soranno et al. 2015, 2017; Soranno and Cheruvelil 2017a, 2017b; Stachelek, Oliver, and Masrour 2019). WQP provides water quality data for additional states, with sampling locations given as geographic coordinates that are spatially joined to the National Hydrography Database (NHD).[6] When combining the two datasets, LAGOS-NE values supersede WQP when the data sources overlap, as the LAGOS platform provides additional quality controls not documented in the WQP data assemblage.

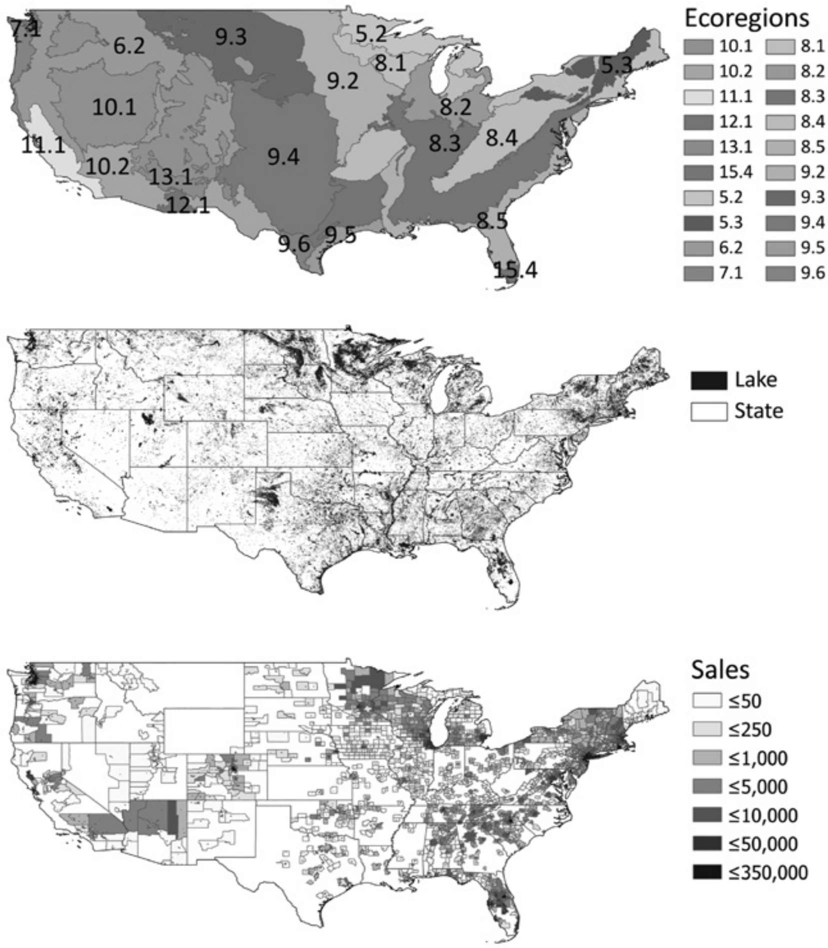
Throughout the contiguous United States, there are 20 level II ecoregions that capture

[4] We also ran the models using chlorophyll a (chl-a); those results are presented in Appendix C. Both Secchi measurements of clarity and chlorophyll a are measures of the effects of nutrient loading on water quality.

[5] LAGOS data products are available at https://lagoslakes.org/the-lagos-database. More information about the WQP is available at https://www.epa.gov/waterdata/water-quality-data-download.

[6] The USGS National Hydrography Dataset is available at https://www.usgs.gov/national-hydrography/national-hydrography-dataset.

Figure 2
Spatial Distribution of Ecoregions, Lakes, and Property Sales



Note: The top map depicts 20 EPA ecoregions with labels referencing level II ecoregion codes. The middle map depicts NHD lakes larger than 4 ha in dark gray with state boundaries. The bottom map depicts the number of sales within 2,500 m of lakes that have Secchi depth samples within five years of sale for individual counties and urbanized areas.

a combination of ecosystem characteristics specific to a given location (Figure 2, top). These regions divide the country into areas that share similar environmental resources to help develop resource management goals, including water quality standards (U.S. EPA 2021). We overlay these data with political boundaries from TIGER/Line for U.S. counties, urbanized areas, and states, which are then aggregated into respective census regions and divisions.[7] Lake shapefiles for all U.S. lakes greater than 4 ha are obtained from LAGOS-NE GIS (Soranno and Cheruvelil 2017b) (Figure 2, middle).[8]

Lake density and properties of lakes, such as size and hydrological characteristics, vary across the United States. Lakes are highly concentrated in the Northeast, Upper Midwest,

[7] TIGER/Line Shapefiles are available yearly for all census boundary definitions at https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

[8] LAGOS sets 4 ha as the threshold for lakes in its data owing to errors in digitization of lakes between 1 and 4 ha (Soranno et al. 2015). This threshold corresponds with the minimum size threshold for lakes in Minnesota; see https://www.dnr.state.mn.us/faq/mnfacts/water.html.

Table 2

Descriptive Statistics by Region

	Northeast	Midwest	South	West
Full Sample				
Sale price (2020 $)	450,060	344,023	356,748	642,456
	(426,614)	(250,921)	(282,424)	(377,061)
Secchi depth (m)	2.49	1.67	1.49	2.93
	(1.61)	(1.22)	(0.87)	(1.85)
Lake distance (m)	1,016	924	1,016	1,325
	(734)	(687)	(708)	(695)
Lake distance < 150 m (1/0)	0.13	0.14	0.11	0.04
	(0.34)	(0.34)	(0.32)	(0.19)
Lake distance 150–300 m (1/0)	0.09	0.10	0.09	0.05
	(0.29)	(0.30)	(0.28)	(0.21)
Lake area (ha)	8,944	967	5,334	2,451
	(28,427)	(5,083)	(17,441)	(7,227)
Urbanized area (1/0)	0.60	0.67	0.67	0.76
	(0.49)	(0.47)	(0.47)	(0.43)
Median income (2016 $)	83,769	78,565	66,228	82,623
	(35,013)	(32,392)	(30,839)	(37,863)
Slope (degrees)	3.89	2.69	3.41	3.93
	(3.27)	(2.22)	(3.41)	(3.88)
Elevation (m)	148.95	291.20	136.82	885.74
	(130.50)	(59.09)	(142.42)	(791.58)
N	396,988	1,241,194	1,388,818	344,394
Lakes	1,112	4,012	830	308
States	9	12	16	10
Ecoregions	5	10	7	8
Samples Restricted by Property Attribute Availability				
Lot size (sq. ft.)	43,190	30,916	31,008	17,659
	(78,291)	(64,055)	(55,912)	(40,489)
	n = 380,289	*n* = 1,057,113	*n* = 1,291,411	*n* = 323,733
Building age (years)	48.60	43.19	27.23	32.70
	(29.12)	(30.09)	(21.85)	(27.29)
	n = 318,287	*n* = 870,459	*n* = 1,069,065	*n* = 286,611
Building size (sq. ft.)	1,924	1,820	2,057	1,969
	(871)	(972)	(1,024)	(846)
	n = 345,396	*n* = 860,124	*n* = 684,586	*n* = 271,974
Bathrooms	2.07	2.39	2.71	2.24
	(0.92)	(1.33)	(1.30)	(0.84)
	n = 258,968	*n* = 725,467	*n* = 473,398	*n* = 170,154
Bedrooms	3.20	3.59	3.61	3.27
	(0.98)	(1.46)	(1.36)	(0.97)
	n = 258,968	*n* = 725,467	*n* = 473,398	*n* = 170,154

Note: The means are reported with standard deviations in parentheses.

and Florida compared with the West, which may partially explain the concentration of hedonic studies conducted in those areas. The South has the lowest water clarity on average (1.49 m), whereas the West has the clearest water on average (2.93 m) (Table 2). With the exception of the Great Lakes, states throughout the Midwest are characterized by many small lakes, whereas the Northeast has much larger lakes—9,000 ha on average compared with 1,000 ha in the Midwest.

Property Data

Property sale data for the hedonic analysis come from the ZTRAX database that is made available through the PLACES lab at Boston University (Zillow Group 2021).

PLACES merged ZTRAX parcel-level data with spatially explicit datasets, including the National Historical Geographic Information System (NHGIS),[9] the U.S. Geological Survey (USGS) National Elevation Database (NED),[10] and the USGS NHD. From NHGIS we include historical median income data for each census block group, and from NED we use elevation and slope data for each parcel. PLACES further uses the NHD data to calculate distances between individual residential land parcels and the nearest lake larger than 4 ha. Thus, the analysis only includes lakes larger than 4 ha.

We adjust sale prices to 2020 dollars using the Federal Housing Finance Agencies' seasonally adjusted housing price index.[11] We use a filter in PLACES to identify sales that are considered arm's-length transactions with high and medium confidence (Nolte et al. 2024 [this issue]).[12] We exclude sale prices less than $10,000 (Gindelsky, Moulton, and Wentland 2022) and remove the top 1% of sale prices in each state (Chun, Pierce, and Van Leuven 2021). Finally, we keep only properties classified as residential, single-family houses (RR000, RR101, RR102, RR999).[13] The full sample of property sales within 2,500 m contains 3,371,394 transactions. Imposing investigator decisions, such as including property attributes, reduces the available data for estimation due to missing data and data exclusions. For example, data cleaning removed observations with negative or zero bedrooms or are in the top 1% for each state. For continuous property attributes, we drop observations in the bottom 1% of observations. The property characteristic summary statistics (Table 2) show how sample sizes are reduced by region as these restrictions are placed on the data.

Figure 2 (bottom) shows the spatial distribution of the full sample, which follows the distribution of lakes (Figure 2, middle) except in nondisclosure states where property sales are not required to be publicly reported and other states, like Maine, that have limited transaction data available.[14] We find average sale prices are the largest in the West at $642,456 and smallest in the Midwest at $344,023 (Table 2). The West, at 0.76, also has the highest proportion of urbanized areas, compared with 0.60 in the Northeast. At least 20% of properties in the Northeast, Midwest, and South are within 300 m of the lakefront, whereas only 9% of sales in the West are within this buffer.

When it comes to summary statistics for property attributes available in the ZTRAX data, there are numerous missing observations that vary by characteristic (Zillow Group 2021). These missing values are not missing at random; rather, select attributes are often missing for entire counties and sometimes for most of a state (Nolte et al. 2024 [this issue]). Lot size is the most widely available property attribute, and we find properties in the Northeast are characterized by larger parcels (1.29 acres on average), whereas parcels in the West are approximately half that size. The next most available property attribute is building age, although the overall sample shrinks considerably by about 25%.

5. Econometric Analysis

Examining spatial heterogeneity across the different spatial scales requires multiple model specifications. For a national-scale hedonic model, heterogeneity can be modeled using interaction terms between water quality and dummy variables for the

[9] See https://www.nhgis.org.

[10] The USGS National Elevation Dataset is available at https://www.sciencebase.gov/catalog/item/4f4e48b1e4b07f02db530759.

[11] FRED Data available at https://fred.stlouisfed.org/tags/series?t=hpi.

[12] For states where medium-confidence sales account for more than 33% of the combined high- and medium-confidence sales, we consider both confidence levels. For states where medium-confidence sales account for less than 33% of the combined high- and medium-confidence sales, we only consider high-confidence sales.

[13] ZTRAX data processing is discussed in Appendix E.

[14] Wentland et al. (2020) and Nolte et al. (2024 [this issue]) note that nondisclosure states include Alaska, Idaho, Indiana, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, South Dakota, Texas, Utah, and Wyoming, and states with markedly lower available sales data throughout the country include Maine and Missouri. We choose to include data from nondisclosure states where available in the sample to maximize potential geographic coverage.

spatial boundaries of interest (e.g., states), as in Moore et al. (2020) or Mamun et al. (2023). At finer spatial scales or with more restrictive boundaries, spatial heterogeneity is controlled through sample selection (e.g., a state model). Thus, we first define the national model, and models for smaller spatial scales are adjustments with the relevant dummy variable interaction terms removed. We describe how we compute elasticities for each observation to compare the effects between the different spatial scale models and with different investigator choices imposed and then discuss the sensitivity analysis.

Model Specification

We specify the national hedonic model as

$$\begin{aligned} ln(P_{it}) = {} & \beta_0 + \beta_1 ln(WQ_{it}) + \beta_2 ln(WQ_{it})^* LF_{ig} \\ & + \beta_3 ln(WQ_{it})^* ln(Dist_i) + \beta_4 ln(WQ_{it}) \\ & ^*[\ln(Area_i) - \overline{\ln(Area)}] + \beta_5 ln(WQ_{it}) \\ & ^*U_i + \beta_E ln(WQ_{it})^* E_i + \beta_S ln(WQ_{it})^* S_i \\ & + \beta_6 LF_i + \beta_7 Dist_i + \beta_8 Area_i \\ & + \beta_{Prop} Prop_i + \gamma_q + \tau_{it} + \epsilon_{it}, \end{aligned} \quad [1]$$

where P_{it} is sales price of a property i at the time t and WQ_{it} is the associated water quality. LF_i is a dummy variable for properties within the selected lakefront distance buffer as described in Table 1 (150 m in the baseline).[15] $Dist_i$ is distance of the property to the lake, and $Area_i$ is the corresponding lake surface area, with $\overline{\ln(Area)}$ equal to its sample log mean. U is a dummy variable for properties in urbanized areas, and E and S are vectors of dummy variables for ecoregions and states, respectively. We exclude one ecoregion and one state from each model to preserve full rank of the data matrix. $Prop_i$ is a vector of other property attributes. Some of these attributes vary based on selected sample selection parameters (e.g., lot size, building size, and building age for the baseline), whereas others are included in all models. These variables include median income in block group and slope and elevation of the parcel. Last, γ_q are sale quarter fixed effects and τ_{it} are spatial-temporal fixed effects that vary according to Table 1. For the baseline, τ_{it} represents census tract × year fixed effects. For models, where year fixed effects are added to (as opposed to interacted with) spatial fixed effects, τ_{it} implicitly includes the spatial fixed effects and year fixed effects.

The coefficients of interest are the water quality coefficient and its associated interaction terms: β_1, β_2, β_3, β_4, β_5, β_E, and β_S. The first three interaction terms (β_2, β_3, and β_4) capture local heterogeneity related to proximity to lake and lake area using variable specifications that are common in the literature (Walsh and Milon 2016). We further interact water quality with demeaned lake area $[ln(Area_i) - \overline{\ln(Area)}]$, which improves interpretability of regression coefficients (Wooldridge 2010). Using this specification, β_1 represents the effect of Secchi on a lake with area at the sample log mean, and β_4 remains the effect of Secchi for an increase in lake area.[16] β_5, β_E, and β_S are spatial interaction terms that capture potential heterogeneity in the effect of water quality relative to the omitted categories. At the state level, β_S drops out of the model, and at the substate level, β_5, β_E, and β_S drop out of the model. β_1 collects the baseline effect of water quality in the combination of all omitted categories. For simplicity, in the results and discussion, we refer to all coefficients by variable name as opposed to the corresponding β.

Computing Elasticities

Although the coefficients of interest allow us to examine heterogeneity in a sample, they provide less insight when comparing across samples that are modeled with different specifications. In addition, interpreting the results of models with many spatial interaction terms

[15] Other hedonic studies (e.g., Walsh and Milon 2016) make use of a waterfront indicator in the assessment data. However, a similar variable is not available nationally in the ZTRAX data. We choose a unifying GIS measurement (i.e., distance to lake < 150 m) to define lakefront. Given that this measurement may be imprecise, especially as the average distance to lake may vary across rural and urban areas, there may be more variance in our estimate of β_2.

[16] Without demeaning lake area, the interpretation of β_1 is the effect of water quality for a lake of size 0, which is not a meaningful value.

can be challenging. Thus, we compute individual elasticities for observations in each sample using the corresponding model coefficients. For the log-log model in equation [1], the formula for elasticities is just the first derivative of the model equation with respect to $ln(WQ_{it})$.[17] Then we input the relevant coefficient estimates and sample data for each observation.

$$\begin{aligned}\widehat{elast_i} &= \hat{\beta}_1 + \hat{\beta}_2{*}LF_i + \hat{\beta}_3 ln(Dist_i) \\ &\quad + \hat{\beta}_4[\ln(Area_i) - \overline{\ln(Area)}] + \hat{\beta}_5 U_i \\ &\quad + \hat{\beta}_E E_i + \hat{\beta}_S S_i. \qquad [2]\end{aligned}$$

After computing elasticities for each observation in a sample, we divide them into three groups based on distance to lake: less than 150 m, between 150 m and 300 m, and greater than 300 m. We select the first two categories based on our baseline and alternative definitions for lakefront properties, which allow us to investigate the effect of water quality in properties adjacent to the lake and slightly farther away. The remaining category contains the distances where we expect smaller effects and less variation related to distance. After splitting into groups, we take the median of the estimates in each group by census tract.[18]

Comparing elasticities across census tract allows us to observe spatial heterogeneity in our results. To examine this heterogeneity more broadly, we divide elasticities by region and examine their distributions. Wide variation in elasticities in a single region and differences in the central tendencies of distributions between different regions implies spatial heterogeneity. We also compare the distributions of elasticities regarding spatial scale. Differences in elasticity distributions across spatial scales indicate potential heterogeneity related to the scale of the model, model misspecification, or sample selection bias.

Sensitivity Analysis

To assess the sensitivity of estimated elasticities to spatial scale and investigator decisions, we consider elasticity estimates from all combinations of the investigator choices and sample criteria outlined in Table 1. For each combination, we divide the median census tract elasticities by buffer group, spatial scale, and region and then compute the regional median. Because medians are less sensitive to extreme outliers than the mean, regional medians should be constant across all investigator decisions under ideal conditions. However, if the model estimates are sensitive to spatial scale, sample selection criteria, or model selection, the regional medians will differ.

6. Results

First we discuss the national model specified in equation [1] for the baseline conditions defined in Table 1. We present the distributions of elasticities for all spatial scales and regions and address the sensitivity of the elasticities to the spatial scale in each region.[19]

National Results

The estimation results indicate a positive significant effect of Secchi depth of 0.262 for lakes in the excluded category, defined by Minnesota in ecoregion 8.1, with lake area equal to the sample mean (Table 3). The interaction term between Secchi and lake area demeaned is also positive, indicating that the effect of Secchi increases with the size of the lake. As expected, we observe the largest effect of Secchi within 150 m of the lakefront, which decays at further distances from the

[17] Derivations for elasticity formulas are found in Appendix D.

[18] As we are focused on spatial heterogeneity, we aggregate elasticity estimates from the property level to census tracts thereby controlling for the larger number of observations in urbanized areas. We investigate variation in lake area and distance to lake in the census tract to test whether aggregation is appropriate. We find no variation in lake area in more than 75% of census tracts in our baseline sample. Only in 6% of census tracts is the standard deviation in lake area larger than 100 ha. For distance, we find a median standard deviation across census tracts of 200 m and maximum standard deviation of 643 m. After we divide the observations by buffer groups, the median standard deviation is 115 m and the maximum is 565 m.

[19] A complete set of model results and associated descriptive statistics is available at https://zenodo.org/records/7844473.

Table 3
National Regression Results

Parameter	Estimate	Std. Error	Parameter	Estimate	Std. Error
Const	7.123***	(0.207)	Secchi * MD	−0.259**	(0.085)
Secchi[a, b, c]	0.231***	(0.034)	Secchi* ME	2.428***	(0.077)
Secchi * lake area demeaned[c]	0.009*	(0.004)	Secchi * MI	−0.0680	(0.048)
Secchi * < 150 m	0.025**	(0.009)	Secchi * MO	0.6730	(0.739)
Secchi * lake distance	−0.034***	(0.005)	Secchi * MT	−2.021***	(0.465)
Secchi * urban[d]	−0.0150	(0.014)	Secchi * NC	−0.1830	(0.123)
Secchi * ecoregion 5.2[d]	0.075*	(0.036)	Secchi * ND	−0.2230	(0.292)
Secchi * ecoregion 5.3	0.0430	(0.033)	Secchi * NE	−0.1790	(0.101)
Secchi * ecoregion 6.2	0.5940	(0.462)	Secchi * NH	−0.0650	(0.047)
Secchi * ecoregion 7.1	0.9910	(0.596)	Secchi * NJ	−0.0030	(0.052)
Secchi * ecoregion 8.2	0.0570	(0.077)	Secchi * NY	−0.0740	(0.04)
Secchi * ecoregion 8.3	0.0550	(0.048)	Secchi * OH	−0.1980	(0.16)
Secchi * ecoregion 8.4	−0.0170	(0.069)	Secchi * OK	−0.1240	(0.266)
Secchi * ecoregion 8.5	0.0260	(0.031)	Secchi * OR	−0.8670	(0.525)
Secchi * ecoregion 9.2	0.150	(0.1)	Secchi * PA	0.154***	(0.036)
Secchi * ecoregion 9.3	0.2230	(0.201)	Secchi * RI	0.102*	(0.047)
Secchi * ecoregion 9.4	0.2030	(0.149)	Secchi * SC	−0.0530	(0.084)
Secchi * ecoregion 10.2	0.3060	(0.462)	Secchi * SD	−0.1270	(0.287)
Secchi * ecoregion 11.1	0.6620	(0.462)	Secchi * TN	−0.1130	(0.078)
Secchi * ecoregion 13.1	0.3660	(0.475)	Secchi * TX	−0.3930	(0.233)
Secchi * ecoregion 15.4	0.0320	(0.048)	Secchi * VA	−0.1340	(0.083)
Secchi * AL[d]	0.0030	(0.202)	Secchi * VT	−0.0780	(0.129)
Secchi * AR	0.1210	(0.15)	Secchi * WA	−0.9890	(0.597)
Secchi * AZ	−0.3960	(0.475)	Secchi * WI	−0.0330	(0.08)
Secchi * CA	−0.7280	(0.465)	< 150 m	0.124***	(0.009)
Secchi * CO	−0.4980	(0.461)	Lake distance	−0.095***	(0.005)
Secchi * CT	−0.266*	(0.12)	Lake area[e]	0.013*	(0.005)
Secchi * DE	−0.0860	(0.402)	Median income	0.131***	(0.014)
Secchi * FL	−0.0190	(0.037)	Slope	0.019***	(0.002)
Secchi * GA	0.0330	(0.128)	Elevation	−0.0230	(0.023)
Secchi * IA	−0.221*	(0.11)	Lot size	0.101***	(0.004)
Secchi * IL	−0.1070	(0.08)	Building age	−0.125***	(0.003)
Secchi * IN	0.20	(0.515)	Building size	0.547***	(0.01)
Secchi * KY	−1.956***	(0.058)	Quarter 2	0.044***	(0.002)
Secchi * LA	0.0840	(0.211)	Quarter 3	0.05***	(0.002)
Secchi * MA	−0.0270	(0.024)	Quarter 4	0.015***	(0.002)

Note: $N = 485{,}860$, standard errors clustered at tract level.
[a] Interaction terms for MN and ecoregion 8.1 were preselected as the excluded categories, because the area intersection contains the most observations in the sample.
[b] During estimation, interaction terms for KS, NM, WV, ecoregion 10.1, and ecoregion 12.1 were fully absorbed by fixed effects and dropped from model. Observations for ecoregion 12.1 all fall within AZ. Variation in estimates for KS, NM, and WV can be explained by the corresponding ecoregion interactions.
[c] The log of lake area is demeaned in the interaction term with Secchi. Thus, the Secchi coefficient alone can be interpreted as the effect of water quality for a lake with the mean log-lake area. Secchi * Lake area demeaned can be interpreted as the effect of an increase in lake size over the sample mean.
[d] Because this model is estimated with census tract by year fixed effects, it is not necessary to include urban, ecoregion, and state constituents as control variables.
[e] The lake area when not interacted with Secchi is not demeaned, as it only serves as a control variable in the model not a coefficient of interest.
$^{*}p < 0.005$ $^{**}p < 0.01$ $^{***}p < 0.001$.

lake, as evidenced by the negative and significant interaction between Secchi and lake distance. The interaction term for urban is negative but not significant, resulting from census tract by year fixed effects in the model specification with urbanized areas defined as collections of census tracts.[20] Overall, Secchi

[20] We investigate this further using county-level fixed effects in Appendix B, finding a positive significant effect.

elasticities for lakefront properties in the excluded category on lakes with area at the sample mean is 0.256. his effect decays rapidly to 0.061 for properties 150 m from the lakefront and to 0.000 for properties 900 m away.

We find some evidence for spatial heterogeneity, as indicated by significant coefficient estimates for interaction terms with some ecoregions and states. We find more significant coefficients for states than ecoregions, indicating that political boundaries may play a stronger role in capitalization rates for water quality than do ecological conditions. Coefficient estimates for ecoregions and states indicate both positive and negative effects relative to the excluded category. In many areas, the sum of the corresponding ecoregion and state interaction is needed to assess the magnitude of the effect. In other areas, where there are relatively few observations, variation in water quality is fully absorbed by the census tract by year fixed effects, and the effect of Secchi relative to the excluded category can be explained by a single ecoregion or state interaction term. Some of the coefficients are surprisingly large, such as KY, ME, and MT, indicating potential outliers in the sample or factors that might not be captured by the spatial fixed effects.[21] From Figure 2 (bottom), we can see that these regions contain a small portion of the overall sample.[22]

The coefficient estimates provide information on the relative differences in the effect of Secchi across spatial boundaries and the statistical significance of the estimated effects. However, differences in lake size throughout the country can make it difficult to understand the total effect. We provide maps summarizing the elasticities for all observations in the baseline sample in Appendix A.

[21] In Appendix B, we implement additional controls for the hedonic price gradient by interacting state dummies with all control variables, and we find that the coefficient estimates for the outliers are still large and significant.

[22] We consider dropping interaction terms in state and ecoregions with few observations. However, setting an appropriate observation threshold can be problematic, as dropping the interaction term would result in the elasticity for the excluded category being misattributed to observations in these locations, whereas keeping the interaction terms allows us to identify locations where further investigation is warranted.

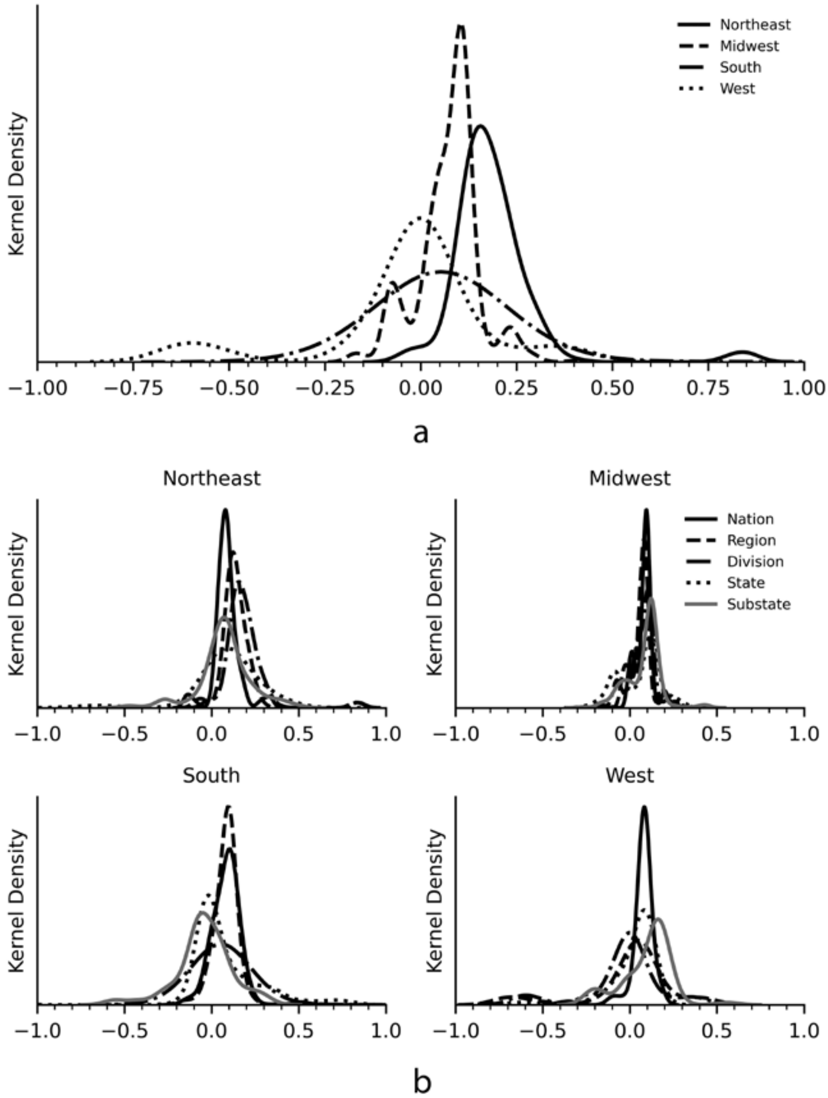
Baseline Results

For the remaining baseline models, we consider only elasticity estimates for properties within 150 m from the lake. We use kernel density plots to present the different distributions of elasticities for each region across spatial designations to help understand spatial heterogeneity and the effect of spatial scale on elasticity estimates (Figure 3). Kernel density plots depict distribution as continuous curves, similar to histograms, allowing us to observe broad dispersion patterns in our results. Rather than simply considering means and standard deviations, the plot shows the distributions of elasticity values.

First, holding the spatial scale of the model constant at the division level, we compare the distributions of elasticities for the Northeast, Midwest, South, and West (Figure 3a). We chose the division level because it is the smallest spatial scale that preserves the spatial distribution of the national sample. We find the largest elasticities in the Northeast, with a peak centered around 0.15. The distribution in the Midwest exhibits the least variance and is characterized by multiple distinct peaks. The tallest is centered 0.10, while the smaller peaks are centered around –0.10 and 0.25. In the South and the West, we find the widest distributions centered around 0 and –0.05, respectively. Overall, these results indicate that spatial heterogeneity in the effect of water quality is present broadly across the different regions and within regions.

We compare differences in distributions across our five spatial designations, nation, region, division, state, and substate, within each census region (Figure 3b). Starting with the Northeast, we find the central peaks of the distributions at the region and division scales are larger than those at the nation, state, and substate scales. In the Midwest, we find that all the distributions overlap considerably, indicating strong agreement between model estimates at different spatial scales. In the South, the nation and region elasticities are mostly positive, whereas the state and substate elasticities are centered around –0.05. Last, in the West, there is wide variation in elasticities except at the national scale. Some

Figure 3
Distribution of Baseline Elasticity Estimates by (a) Region and (b) Spatial Scale



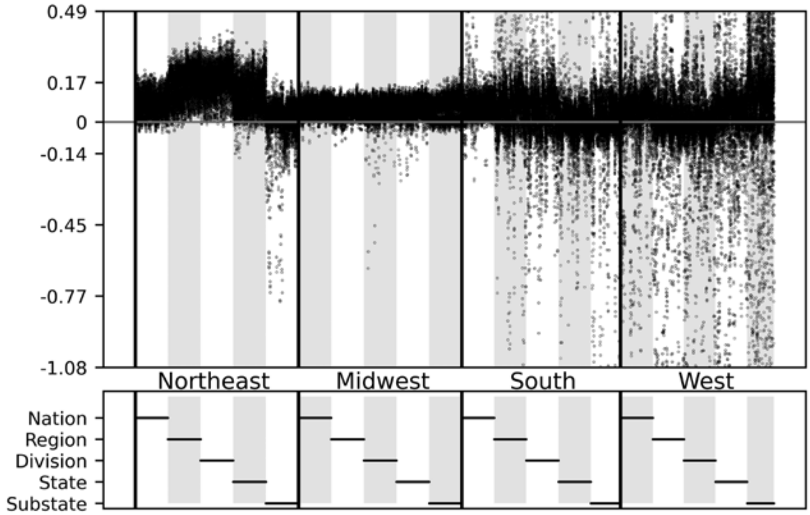
Note: The median elasticity estimates at the census tract level for properties within 150 m of the lakefront are shown on the *x*-axis. The kernel density along the *y*-axis is rescaled to one for each plot. The 1st and 99th percentiles are dropped from the figure because of the relative magnitude of outliers.

differences in distributions across spatial scale can be attributed to differences in the underlying sample at the state and substate levels. However, differences in the distributions at the larger spatial scales suggest that scale of the model can influence results and potential decision-making.

Sensitivity Analysis

We further assess the sensitivity of our elasticity estimates to spatial scale by comparing elasticities estimated across all combinations of sample selection criteria and model choices. In Figure 4, we plot the regional medians associated with each combination of spatial

Figure 4
Regional Median Elasticity Estimates for All Models



Note: Census tract median estimates for properties within 150 m of the lakefront are divided by region for unique combinations of spatial scale, sample selection, and model choice before computing regional median. Medians are sorted by region, spatial scale, sample selection criteria, and methods. For each region and market boundary, estimates vary along different sample selection criteria and methods. The 1st and 99th percentiles are dropped from the figure because of the relative magnitude of outliers.

scale, sample selection criteria, and modeling choices for the models sorted by region and spatial scale.[23] Each regional median is represented by a single dot in the top panel, and each region is separated by a solid black line with the associated label below the top panel. Lines in the bottom panel indicate the spatial scale of the model. As seen in the baseline results, estimates in the Midwest are the least sensitive to spatial scale and are the most stable across different sample selection criteria and model choices. Results in the Northeast, though sensitive to spatial scale, are also relatively stable but are more sensitive to investigator decisions. The South demonstrates more variability and the West even more variability in each spatial scale, indicating that elasticity estimates are highly sensitive to sample selection and modeling choices as well as spatial scale. Across all regions, we note that hedonic results are most sensitive at the substate spatial scale.

[23] While the points are also sorted by respective data selection criteria and modeling techniques, these categories are not presented in this plot. They are explored more in Appendix B.

7. Discussion and Conclusion

In the analyses reported here, we observe heterogeneity in terms of the central tendency of elasticity estimates across spatial scales and dispersion of elasticity estimates within spatial scales. The results reveal wide variation in estimated elasticities for lake water quality throughout the United States, and the heterogeneity varies across the Northeast, Midwest, South, and West regions with the largest heterogeneity effects occurring at the state and substate scales. Thus, contrary to Moore et al. (2020), we observe significant spatial heterogeneity along state and substate scales using a national scale model. Similarly, Zhang, Phaneuf, and Schaeffer (2022) report regional heterogeneity in the effect of harmful algal blooms on lakes when the United States is divided into seven climate regions. Our results are also in line with the Guignet et al. (2022) meta-analysis that revealed significantly larger elasticity estimates for Secchi in the Northeast.

The differences in elasticity estimates we observe at the state and substate scales align with the many small-spatial-scale models in the published literature. Our results provide suggestive evidence that this heterogeneity may be smoothed and averaged out in models estimated at larger spatial scales, thereby missing important market and ecosystem differences. We conclude that heterogeneity across spatial scales indicates market differences that may not support the rescaling of hedonic models to fit local and national policy aims in all parts of the country. That is, small-spatial-scale models may reflect locally unique effects that do not represent a national average, and a national model can obscure unique local or regional effects. We recommend caution in transferring model results across spatial boundaries to ensure the effects documented by the underlying model match that of the policy application.

We further conclude that heterogeneity within spatial scales, represented by differences in regional medians, indicates the influence of investigator choices when estimating hedonic equations. Thus, our study demonstrates an important insight: differences in investigator decisions observed in spatial scales indicate that modeling choices may have more influence on the magnitudes of elasticity estimates than changes in spatial scale. This observation brings into question whether the differences in hedonic estimates across highly restricted spatial scales in the literature are real or the outcomes of investigator choices. This observation implies that rigorous robustness analyses are needed for all hedonic studies, regardless of spatial scale, and such analyses should be reported, at least in appendix tables, so more can be learned about the necessary choices investigators make when estimating hedonic models. A rigorous robustness analysis would go beyond the usual varying of model specifications, such as testing different levels of fixed effects, and quantify the impact of alternative sample criteria and data merging procedures, including reasonable variations of water quality summary metrics and matching time frame.[24] Such reporting will allow a richer meta-analysis to clarify whether results observed are real spatial differences or simply due to differences in investigator choices across studies.[25]

Another consideration is that the distributions we report of elasticity estimates indicate that estimates can be zero or negative when the expectation that elasticity estimates will be positive and significant. There are counterintuitive hedonic estimates published in the peer-reviewed literature from time to time (e.g., Swedberg et al. 2022) but not often. Thus, our study suggests more anomalous outcomes than what a casual observation of the literature reveals. One must be careful when taking anomalous outcomes as prima facie evidence that some do not value water quality or there is no effect. One must keep many considerations in mind. No hedonic sample is representative of homeowners, just those who bought a property during a specific period. Matching sale dates with water quality is challenging because water quality measures are limited, and one does not know specifically what people consider when they buy a property. These issues are compounded by property and water quality data limitations. Nondisclosure states scattered throughout much of the West and in some states in the Midwest and South restrict which communities are incorporated in hedonic models, and the small sample sizes in these areas may lead to high variability in model results. Lake water quality samples are also not representative, as a variety of factors related to state and local government, community activism, use type, and existing water quality impairments impact whether a lake is routinely sampled. Thus, there are necessary caveats when attempting to interpret results from a single hedonic model. Instead, we maintain that insights should only be made after repeated hedonic modeling in the locations where results are found to be highly robust.

Last, when choosing a hedonic modeling framework, our study was fortunate to have

[24] In Appendix B, we evaluate the sensitivity of our results to water quality sample parameters, property location parameters, and fixed effects. We find that water quality sample selection parameters have a larger effect on regional medians.

[25] Some of this work is already under way, with Heberling, Guignet, and Papenfus (2022) finding that methodological choices play a larger role in estimated relationships than variables related to market and commodity.

access to ZTRAX data, which enabled us to run a broad set of hedonic property models and explore how different sample selection criteria and modeling techniques shape the various model coefficients (Zillow Group 2021). Without freely available nationwide property sales data, researchers may not be able to conduct similar tests. We hope the results from this work can lay the groundwork for future research concerning systematic effects of spatial scale on market boundaries and investigator decisions on hedonic estimates. Therefore, given the sunsetting of ZTRAX, it is critical that new large-scale open-access or low-cost property sale databases become available, allowing more research into the broad range of environmental and other pertinent policy topics at scale.

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