

Essays in Surface Water Quality Valuation

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ABSTRACT

This dissertation is comprised of three essays examining methods for surface water quality valuation. The first essay uses Zillow's ZTRAX property transaction database to investigate variation in hedonic price effects of water clarity on single-family houses throughout the United States. I consider five spatial scales and estimate models using different sample selection criteria and model specifications. The results indicate considerable spatial heterogeneity both within and across the four U.S. Census regions. However, I also find heterogeneity resulting from different types of investigator decisions, including sample selection and modelling 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.

In the second essay, I integrate a coastal recreation demand model for Southern New England with property sales in Massachusetts and Rhode Island to estimate the impacts of water quality improvements for freshwater and saltwater resources throughout the region. While traditional hedonic studies for water quality reveal the direct effects of local water quality on housing prices, the spatial extent of the models is limited to 2 km from the waterfront. Integrating recreation demand models with hedonic models allows identification of additional indirect effects of water quality at recreation sites that are capitalized in housing markets through a recreational index (i.e., the potential recreational benefits for a neighborhood). However, the spatial extent of these models is currently untested. I compare the spatial extent of indirect and direct effects of water quality for multiple water quality inputs isolating spatial and temporal sources of variation. The results indicate heterogeneity in the direct effects of freshwater and saltwater clarity depending on

whether the source of variation is spatial or temporal. Conflating spatial and temporal water quality variation can lead to anomalous conclusions on the impacts of coastal recreation on housing markets.

In the third essay, I evaluate meta-regression models (MRMs) that are used by policy makers in calculating the potential benefits of improvements in environmental quality resulting from proposed regulatory actions. MRMs lay the foundation for benefit transfers applied by EPA to recent rulemakings under the Clean Water Act (CWA) in addition to other environmental contexts (e.g., health benefits under the Clean Air Act). While recent literature has emphasized the necessity that MRMs satisfy key theoretical conditions, including scope sensitivity and the adding up condition, existing MRMs that fulfil these properties require imposing structural model restrictions or removing relevant explanatory variables from the MRM at the expense of model fit and predictive performance. This study presents a method for defining MRMs that draws on characteristics of the given benefits transfer scenario and its relationship to the metadata while satisfying the adding up condition. This modelling framework outperforms the model used by EPA in model fit and predictive performance. Applying the results to a recent CWA rule, I find the model used by EPA substantially underestimates the potential benefits.

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GENERAL AUDIENCE ABSTRACT

This dissertation is comprised of three essays examining methods for surface water quality valuation. The first essay uses property sale models to evaluate spatial differences in the impacts of lake water quality on housing markets throughout the United States. I evaluate how investigator decisions related to spatial scale of the model, sample selection criteria, and model specification effects the observed results. I find variation in the impacts of water on property sale prices across the nation. However, the results in some regions are highly sensitive to investigator decisions, implying limitations to using a single model to represent the impacts. The second essay integrates a property sale model for water quality with a model that examines willingness to pay for coastal recreation in Southern New England. I evaluate the impacts of water quality at coastal recreation sites on property sales in Massachusetts and Rhode Island and compare the results to the impacts of local water quality. I find the effects of local water quality is largest on the coast but only capitalized into property sales up to 2 km from the waterfront. I do not find expected results for coastal recreation. The third essay evaluates the models used by policy makers to calculate the potential benefits of improvements in water quality resulting from regulatory action. Previous models prioritized theoretical properties of models, such as the adding up condition, at the expense of model fit and predictive performance. I develop a hybrid model approach that can be used model water quality benefits while satisfying the adding up condition with improved model performance. I apply the model to a recently proposed rulemaking and find the benefits potential benefits greatly exceed those presented in the rule making.

Dedication

For my parents, sister, and cats.

Acknowledgements

First, I would like to thank my advisor Dr. Kevin Boyle for his invaluable guidance and support for the past six years. Thank you for all the time and effort you have spent helping me realize my passion for environmental economics, encouraging me to pursue my interdisciplinary interests, and strengthening my research and communication skills. I would not be where I am in my career without you. I would also like to thank my committee members Elinor Benami, Darrell Bosch, Kelly Cobourn, and Christoph Nolte for your time, patience, and guidance as my research has developed throughout the years. I am so lucky to have such an incredible group of scientists supporting me. Last, I would like to thank my family for the years of love and encouragement. You have taken care of me through all the ups and downs, and I am truly grateful to have you in my life.

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Preface & Attribution

The U.S. landscape features different types of waterbodies that provide a wide range of benefits to humans related to recreation, aesthetics, and ecosystem services. However, human activity throughout the country has led to surface water quality impairments that impact these benefits. Excess nutrients can lead to high levels of algal content and harmful algal blooms, while wastewater and stormwater loading can lead to pathogen outbreaks and beach closures. Although there is wide agreement in the need to protect water quality in the United States, policies intended to improve water quality can be costly, and regulators must consider whether the monetary value of proposed improvements outweighs the costs.

Economists have many tools for assessing the monetary value of different environmental resources. Yet, surface water quality valuation poses several key challenges that still need to be addressed. Heterogeneity in the types, sizes, and uses of surface water across the country leads to wide differences in associated benefits and willingness to pay for improvements. Moreover, because much of the water in the United States is treated prior to consumption, there are fewer human health benefits associated with surface water protection, and economists often need to consider benefits associated with the housing market and recreation or elicited from stated preference studies. While all valuation methods provide some insight into the value of water quality, they each face different methodological limitations. The research described in this prospectus explores issues in water quality valuation related to the heterogeneity of benefits and addresses limitations in existing valuation methods in the literature.

This dissertation is comprised of three essays. The first essay titled “Spatial Heterogeneity in Hedonic Price Effects for Lake Water Quality” was co-authored by Kristen Swedberg, Diego

S. Cardoso, Adriana Castillo-Castillo, Saleh Mamun, Kevin J. Boyle, Christoph Nolte, Michael Papenfus, and Stephen Polasky. This essay was published in *Land Economics* vol. 100 no. 1 (2024): 89-108. © 2024 by the Board of Regents of the University of Wisconsin System. It is reprinted courtesy of the University of Wisconsin Press. The authors use national property sales and water quality data to evaluate geographic and methodological sources of heterogeneity in elasticities for lake water quality. This research reveals how investigator decisions, relating to spatial scale and sample selection of the hedonic model, influence estimated results, and the resulting meta-dataset can be used to further study the impacts of common methodological decisions. As the lead author, I was responsible for completing all the data analysis, modelling, and drafting of the manuscript. Diego S. Cardoso, Adriana Castillo-Castillo, and Saleh Mamun provided technical assistance in developing models, helped interpret and visualize results, and revising the manuscript. Diego S. Cardoso played a crucial role in developing ways to simplify the model results into simplified figures. Saleh Mamun helped develop the merging procedure used to match properties to water quality samples from the Water Quality Portal. Christoph Nolte developed the PLACES dataset that allowed us to match national property sales data to nearby lakes throughout the US and provided strong technical assistance in processing the property sales data. Kevin J. Boyle, Michael Papenfus, and Stephen Polasky provided high level guidance in developing modelling approach, helped simplify and interpret the results, and revised the manuscript.

The second essay titled “Evaluating the Spatial Extent of Direct and Indirect Coastal Water Quality Capitalization in Hedonic Property Sales Models” continues advancements hedonic literature related to water quality. It is co-authored by Kristen Swedberg, Nathaniel H. Merrill, Joel Corona, and Matthew T. Heberling. This study applies an emerging theoretical model that

links property sales models to recreation demand, allowing identification of the effects of water quality directly from nearby water features and indirectly from coastal water features homeowners may travel to for recreation. By considering a larger study area than previous studies, this research can evaluate the appropriate spatial extent of integrated recreation and hedonic models and inform future studies. As the lead author, I was responsible for performing all property data analysis, conceptualizing and applying the hedonic approach, and drafting the manuscript. Nathaniel H. Merrill processed the water quality data and recreation demand model that served as inputs into the hedonic model and assisted in drafting select sections of the manuscript relevant to his analysis. Joel Corona and Matthew T. Heberling provided high level guidance model development, helped interpret results, and revised the manuscript.

The final essay titled “Locally Satisfying Adding Up Condition in Meta-Regression Models: A Simple Solution to a Persistent Regulatory Challenge” diverges from the above hedonic analyses to address another method of water quality valuation commonly used by policy makers in benefits-costs analyses. This study is solo authored and presents a new meta-regression model that can be used by policy makers to predict willingness-to-pay for water quality improvements, which resolves challenges to existing methods.

Spatial Heterogeneity in Hedonic Price Effects for Lake Water Quality

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1. Introduction

Lakes are charismatic environmental features that are spread across the United States providing a myriad of benefits that include recreational opportunities, aesthetic appeal, and ecosystem services. People who own properties near lakes are primary beneficiaries, and their enjoyment of lakes 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 (Boyle, Poor, and Taylor 1999), counties (Walsh, Milon, and Scrogin 2011), or individual lakes (Weng et al. 2020) where socio-economic and ecological conditions that impact the implicit value of water quality may be fixed within each individual study. While 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 in 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) both consider a larger spatial scale using a “nationwide housing market” comprised of 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 also 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. Thus, 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) studies observe heterogeneity in value estimates at the Regional and State levels. Within a national housing market framework, Mamun et al. (2023) observe spatial heterogeneity by state and ecoregion, while 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, this is an issue that 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, limited by publicly available records, and differences in reporting across states, which ultimately requires 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.

In this study, we exploit the broad spatial coverage of Zillow's ZTRAX property transaction database to investigate how different spatial scales of hedonic estimation affect water quality elasticity estimates for residential properties (i.e. single-family houses) (Zillow 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, since such an investigation can be influenced/confounded by investigator analysis choices, such as measurement of the policy variable, inclusion/exclusion of model covariates, functional form of the hedonic, and other considerations (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 EPA ecoregions. We consider the most frequently available metric of water quality, Secchi depth (Secchi), 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. In conducting this analysis, 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 concerning the underlying sources of spatial heterogeneity and the impacts 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 be reflective of effects at larger spatial scales and vice versa. The effects of investigator choices highlight the importance of robustness checks.

2. Exploring Spatial Heterogeneity

For this study 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 geo-political 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 on-line listing of properties and work-from-home, 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). But, 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, Palmquist, and Pope 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. Rather, 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.

In this paper 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 aims. The five different spatial scales are delineated in Figure 1: Nation, Region, Division, State, and Substate. Nation corresponds to the contiguous United States, Region, and Division are U.S. Census geographic delineations, and Substate boundaries.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.

¹ Census regions and Divisions are grouping of states. There are four Census regions that are subdivided by two or more Census Divisions. <https://www.census.gov/programs-surveys/economic-census/guidance-geographies/levels.html>

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

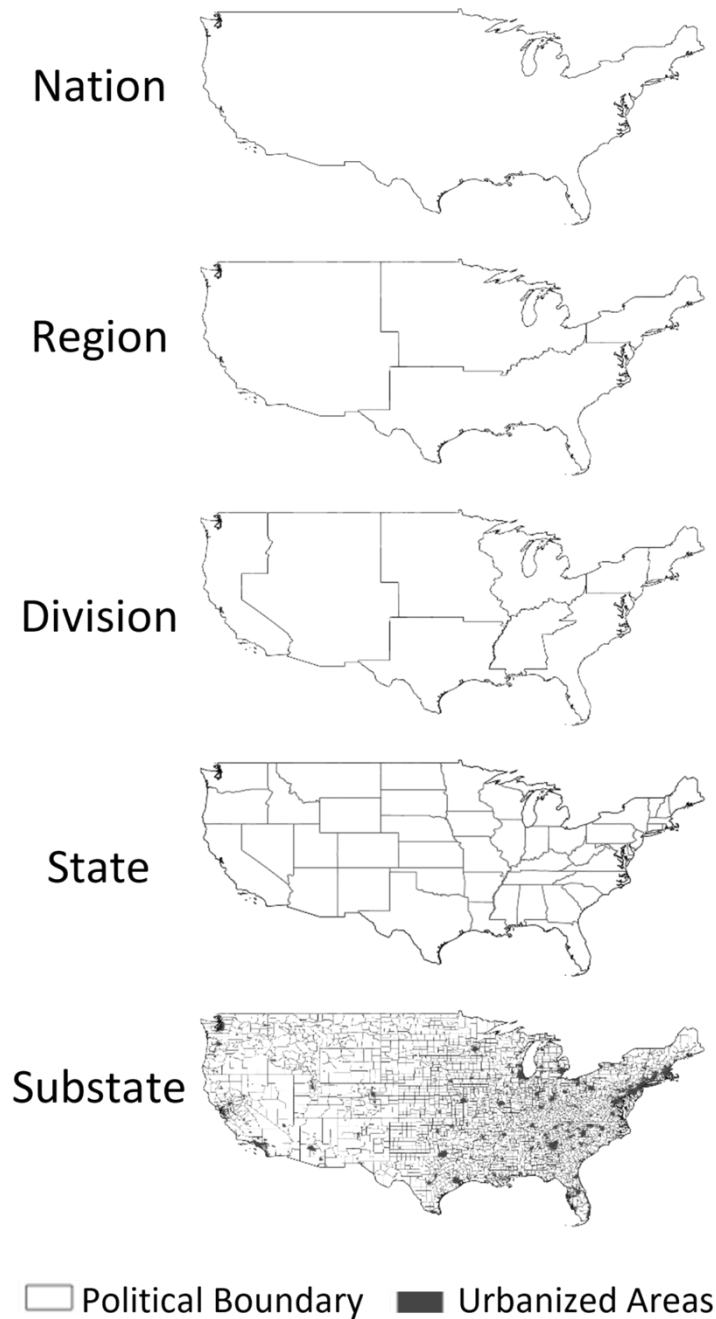


Figure 1 Market Boundary Definition by Spatial Scale

Notes: Nation, Region, Division, and State boundaries defined by single Census product. Substate boundaries defined first by Census Urbanized Areas, then by Census counties.

Spatial heterogeneity can also be investigated with the hedonic model by the inclusion of interaction terms between water quality and dummy variables the spatial boundary of interest.

Moore et al. (2020) and Mamun et al. (2023) both consider national models with state interaction terms. In addition to administrative boundaries, other characteristics may also be important to consider when determining spatial boundaries. For example, surrounding ecological conditions might include a unifying set of amenities that draw people to consider buying properties near lakes. To test for heterogeneity related to environmental amenities, Mamun et al. (2023) also 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 what differences result from spatial heterogeneity versus investigator modeling decisions. Variation in investigator choices arises because the measure of water quality buyers and sellers consider 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 prior to the sale, at the time of purchase decision, etc.), and their bid function may be influenced by different summary measures. Some may make their decisions based on typical water quality conditions (e.g., average water quality over the summer months), while others may be most concerned about the poorest water quality conditions during the summer months. Note, with

nutrient loading and eutrophication, which is the environmental quality investigated in this paper, 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 prior to 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 within a specific window of time. For example, Moore et al. (2020) match sales from 2010-2013 to 2007 water quality data, whereas 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 month. In addition, the Secchi measurement could be the closest in time within five 5 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 for a given 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 ± 5 year window likely maximizes the sample size.

Table 1 Sample Selection Criteria and Modelling Choices

<i>Sample Selection Criteria</i>				
Category	Criterion type	Sub-category	Baseline choice	Alternatives
Water Quality	Measurement	Water quality statistic	Summer mean	Summer minimum, Summer maximum
	Measurement	Water quality timing	Closest within ± 5 years	Year of sale, Year prior to sale, Closest within previous 5 years
	Threshold, minimum	Coefficient of variation for Secchi depth	0.25	NA
Property	Measurement	Property attributes	Lot size, Building size, Building age	None, Bedrooms & Bathrooms ⁱ
	Threshold, maximum	Lakefront property buffer,	150 m	300 m
	Threshold, minimum	Sales in buffer	1	0, 25
	Threshold, maximum	Property distance to lake	1,000 m	2,500 m
<i>Modelling Choices</i>				
Category	Sub-category		Baseline choice	Alternatives
Functional form	Sale price, water quality		Log, log	Log, linear
	Covariates ⁱⁱ		Log	NA
Fixed effects	Spatial unit		Census tract	Block group
	Interactions		Spatial unit x sale year	Spatial unit + sale year

ⁱ All combinations of property attributes considered, e.g. individual attributes, two at a time, three at a time, and all attributes. Bedrooms and bathrooms are always included together.

ⁱⁱ 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.

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 within the sample to improve the likelihood the coefficient estimates are meaningful. If water quality is similar across lakes within 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. While 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,

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

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 what properties are included in the sample and controlling distance can influence the functional form of the hedonic. While much of the early literature focused on lakefront properties (e.g., Michael, Boyle, and Bouchard 1996), more recent studies consider broader distances from lakes between 1,000 to 3,000 m (meters) from the lake. (Walsh, Milon, and Scrogin. 2011; Walsh and Milon 2016; Wolf and Klaiber 2017). However, recent studies consistently find the largest effects of water quality occur for lakefront properties, and the effects decay rapidly with distance from lakes. For example, 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 and within 300 meters of the lake. The second is distance to the lake measured in meters with two alternatives, properties within 1,000 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 1990's and early 2000's had sample sizes of only a few hundred and at times 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 to 50,000 observations (Walsh, Milon, and Scrogin 2011; Liu, Opaluch, and Uchida 2017;

Weng et al. 2020). The smallest sample size we 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. While 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 within 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 within 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 x 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 modelling 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, this study draws on a wide range of several large-scale data repositories. In sections 4.1,

we discuss environmental and geospatial data sources. In section 4.2, we 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 within LAGOS-NE LIMNO, inspected for data quality for 17 Northeastern and Midwestern states, that is made accessible through the LAGOSNE R package (Soranno et al. 2015, 2017; Soranno and Cheruvilil 2017a, b; 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

⁴ We also ran the models using Chlorophyll-a (Chl-a) and 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 <https://lagoslakes.org/the-lagos-database/>. More information about the Water Quality Portal is available at <https://www.epa.gov/waterdata/water-quality-data-download>.

⁶ USGS National Hydrography Dataset <https://www.usgs.gov/national-hydrography/national-hydrography-dataset>

values supersede WQP when the two 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 a combination of ecosystem characteristics specific to a given location (Figure 2a). These regions divide the country into areas that share similar environmental resources to help develop resource management goals, including water-quality standards (USEPA 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 hectares (ha) are obtained from LAGOS-NE GIS (Soranno and Cheruvilil 2017b) (Figure 2b).⁸

⁷ TIGER/Line Shapefiles 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 due 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 <https://www.dnr.state.mn.us/faq/mnfacts/water.html>.

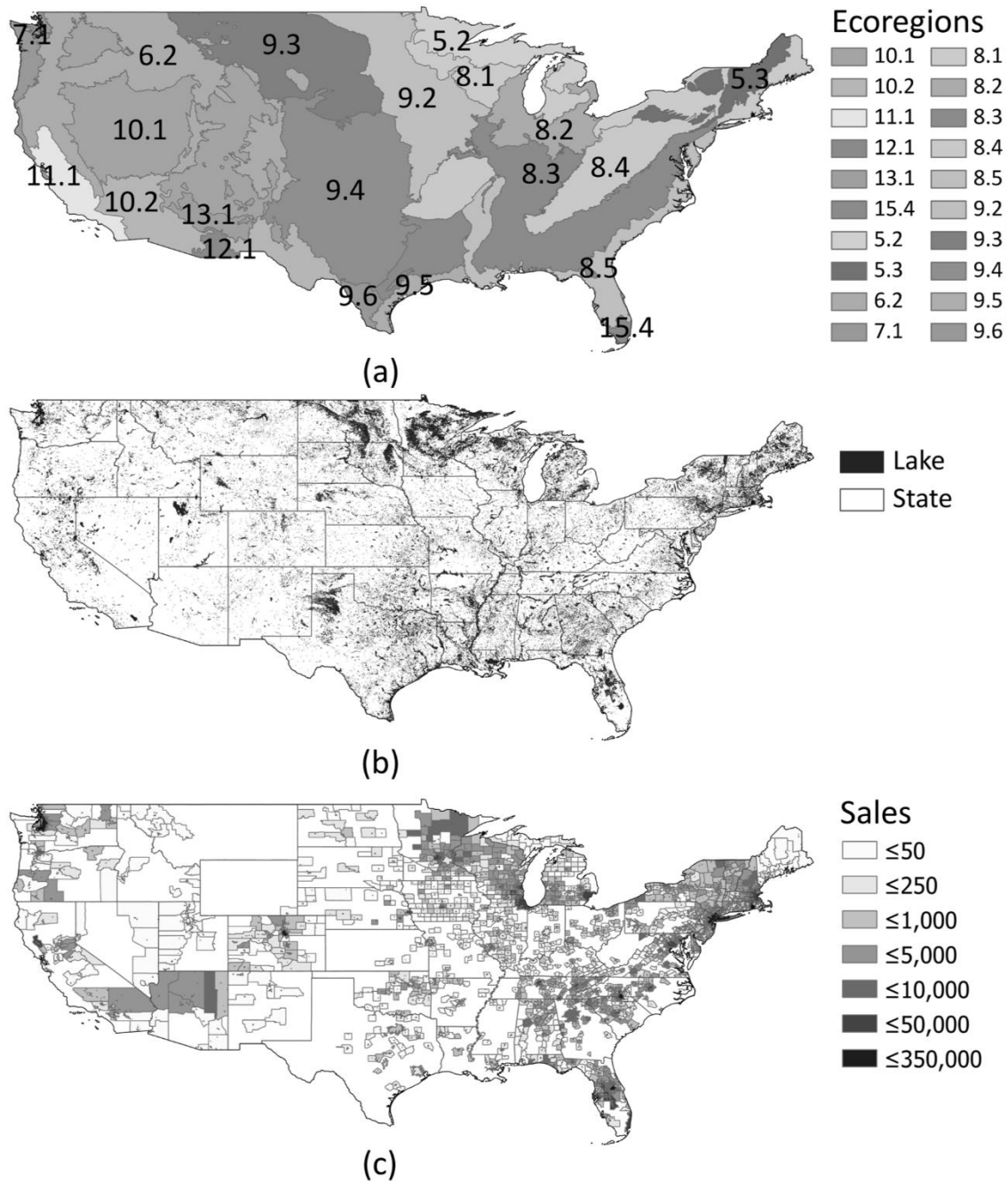


Figure 2 Spatial Distribution of Ecoregions (a), Lakes (b), and Property Sales (c)

Notes: Panel (a) depicts 20 EPA ecoregions with labels referencing level II ecoregion codes. Panel (b) depicts NHD lakes larger than 4ha in dark gray with State boundaries. Panel (c) depicts the number of sales within 2,500 m of lakes that have Secchi depth samples within 5 years of sale for individual counties and urbanized areas.

Lake density and properties of lakes, such as size and hydrological characteristics, vary across the contiguous United States. Lakes are highly concentrated in the Northeast, Upper Midwest and Florida compared to 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). Absent 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 to 1,000 ha in the Midwest.

Table 2 Descriptive Statistics by Region

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

Means reported with standard deviations in parentheses.

Property Data

Property sale data for the hedonic analysis come from Zillow's ZTRAX database that is made available through the PLACES lab at Boston University (Zillow 2021). PLACES merged ZTRAX parcel-level data with spatially explicit datasets, including the National Historical Geographic Information System (NHGIS)⁹, the 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 \$'s using the Federal Housing Finance Agencies' seasonally adjusted housing price index.¹¹ We further use a filter within PLACES to identify sales that are considered arms-length transactions with high and medium confidence (Nolte et al. 2023).¹² We exclude sale prices less than \$10,000 (Gindelsky, Moutlton, and Wentland 2022) and remove the top 1% of sale prices in each State (Chun et al. 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 meters contains 3,371,394 transactions. Imposing investigator decisions, such as the inclusion of 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,

⁹ National Historical Geographic Information System <https://www.nhgis.org/>

¹⁰ USGS National Elevation Dataset <https://www.sciencebase.gov/catalog/item/4f4e48b1e4b07f02db530759>

¹¹ FRED Data <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 Discussion of ZTRAX data processing is also discussed in Appendix E.

we also 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 2c shows the spatial distribution of the full sample, which follows the distribution of lakes (Figure 2b) except in non-disclosure 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 to 0.60 in the Northeast. At least 20% of properties in the Northeast, Midwest, and South are within 300 m from the lakefront, whereas only 9% of sales in the West are within this lakefront buffer.

When considering summary statistics for property attributes available in the ZTRAX data there are numerous missing observations that vary by characteristic (Zillow 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. 2023). 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%.

¹⁴ Wentland et al. (2020) and Nolte et al. (2023) note non-disclosure 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 non-disclosure states where available in the sample to maximize potential geographic coverage.

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 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 spatial 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. Then, in section 5.2, 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. In section 5.3 we 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

¹⁵ Other hedonic studies (e.g. Walsh and Milon, 2016) make use of a waterfront indicator present in the assessment data. However, a similar variable is not available nationally in the ZTRAX data. Therefore, we choose a unifying GIS measurement, i.e. distance to lake < 150 m, to define lakefront by. Given 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 .

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), while others are included in all models. These variables include median income in block group, and slope and elevation of the parcel. Lastly, 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 x 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: $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_E$, 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). However, 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

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.

water quality in the combination of all omitted categories. For simplicity, in the results and discussion, we will refer to all coefficients by variable name as opposed to the corresponding β .

Computing Elasticities

While the coefficients of interest allow us to examine heterogeneity within a given sample, they provide less insight when comparing across samples that are modeled with different specifications. Additionally, interpreting the results of models with many spatial interaction terms can be challenging. Thus, we compute individual elasticities for observations in each sample using the corresponding model coefficients. For the log-log model specified 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.

$$\widehat{elast}_i = \hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 [\ln(Area_i) - \overline{\ln(Area)}] + \hat{\beta}_5 U_i + \hat{\beta}_E E_i + \hat{\beta}_S S_i \quad [2]$$

After computing elasticities for each observation within 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 distance 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.^{18,19}

¹⁷ Derivations for elasticity formulas are 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.

¹⁹ We investigate variation in lake area and distance to lake within 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.

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 within a single region and differences in the central tendencies of distributions between different regions implies spatial heterogeneity. We also compare the distributions of elasticities with regard to 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 again 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, then the regional medians will differ.

6. Results

First, in section 6.1, we discuss the National model specified in equation [1] for the baseline conditions defined in Table 1. Section 6.2 presents the distributions of elasticities for all spatial

scales and regions. Section 6.3 addresses the sensitivity of the elasticities to the spatial scale in each region.²⁰

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 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 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.²¹ Overall, Secchi elasticities for lakefront properties in the excluded category on lakes with area at the sample mean is 0.256. However, this effect decays rapidly to 0.061 for properties 150 m away from the lakefront and to 0.000 for properties 900 m away.

²⁰ A complete set of model results and associated descriptive statistics are available at <https://zenodo.org/records/7844473>.

²¹ We investigate this further using county level fixed effects in Appendix B finding a positive significant effect.

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 ^{i,ii,iii}	0.231***	(0.034)	Secchi * ME	2.428***	(0.077)
Secchi * Lake Area Demeaned ³	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 ^{iv}	-0.0150	(0.014)	Secchi * NC	-0.1830	(0.123)
Secchi * Ecoregion 5.2 ^{iv}	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 ^{iv}	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 ^v	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)

Notes: N = 485,860 Standard Errors Clustered at Tract Level. *p<.05 **p<.01 ***p<.001

ⁱInteraction terms for MN and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

ⁱⁱDuring estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

ⁱⁱⁱThe 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.

^{iv}Because this model is estimated with census tract by year fixed effects, it is not necessary to include Urban, Ecoregion, and State constituents in the model as control variables.

^vLake area when not interacted with Secchi is not demeaned, as it only serves as a control variable in the model rather than a coefficient of interest.

We find some evidence for spatial heterogeneity, as indicated by significant coefficient estimates for interactions terms with some ecoregions and states. We find more significant coefficients for states than ecoregions, indicating political boundaries may play a stronger role in capitalization rates for water quality than 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.²² From Figure 2c, we can see these regions contain a small portion of the overall sample.²³

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,

²² In Appendix B, we implement additional controls for the hedonic price gradient by interacting state dummies with all control variables, and find the coefficient estimates for the outliers are still large and significant.

²³ We consider dropping interactions 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.

differences in lake size throughout the country can make it difficult to understand the total effect. Thus, we provide maps summarizing the elasticities for all observations in the baseline sample in Appendix A.

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 show the distributions of elasticity values.

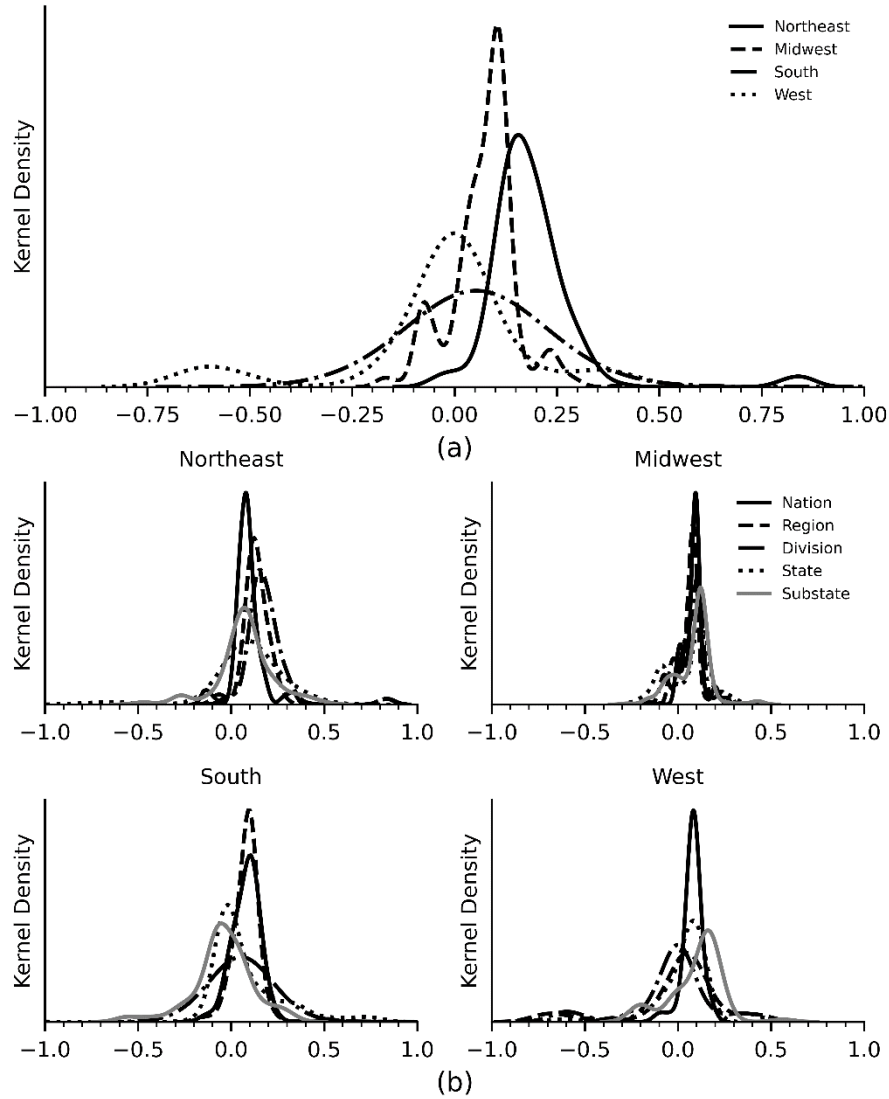


Figure 3 Distribution of Baseline Elasticity Estimates by Region (a) and Spatial Scale (b)
Notes: Kernel density plots of elasticities of property value with respect to water quality by region and spatial scale. Median elasticity estimates at census tract level for properties within 150m from lakefront along x axis. Kernel density along y axis rescaled to 1 for each plot. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure. Panel (a) presents the Division results in a single plot broken out by region. Panel (b) presents the results for each Region in separate plots broken out by spatial scale.

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, as 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 spatial heterogeneity in the effect of water quality is present both broadly across the different regions and within regions.

We next 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 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, while the State and Substate elasticities are centered around -0.05. Lastly, in the West, there is wide variation in elasticities except at the National scale. Some 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 scale, sample selection criteria, and modelling choices for the models sorted by region and spatial scale.²⁴ Each

²⁴ While the points are also sorted by respective data selection criteria and modeling techniques, these categories are not presented in this plot but are explored more in Appendix B.

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 observed in the baseline results, estimates in Midwest are the least sensitive to spatial scale, and are also the most stable across different sample selection criteria and model choices. Results in the Northeast, while 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 within each spatial scale, indicating elasticity estimates are highly sensitive to sample selection and modelling choices as well as spatial scale. Across all regions, we note hedonic results are most sensitive at the Substate spatial scale.

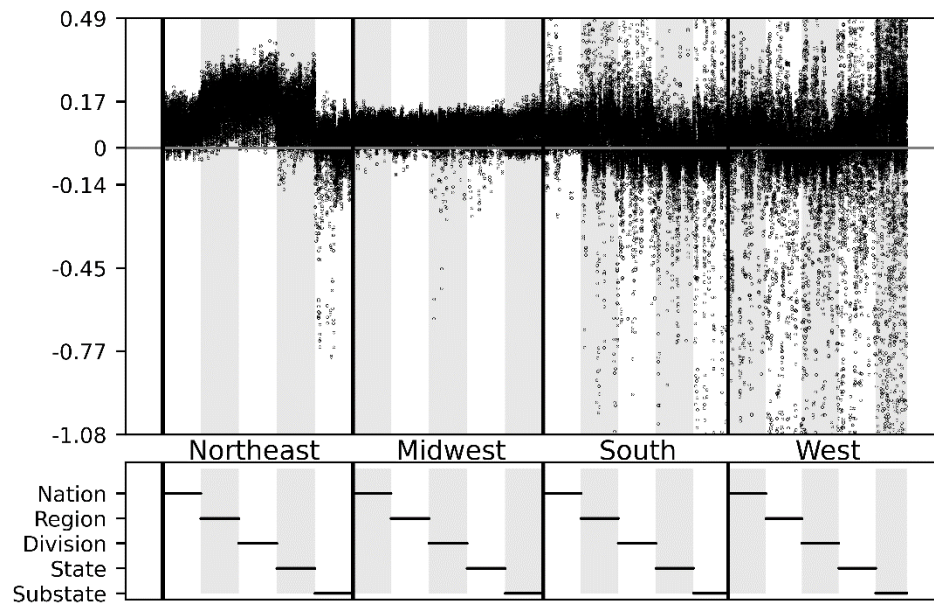


Figure 4 Regional Median Elasticity Estimates for All Models

Notes: Census tract median estimates for properties within 150m from 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. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

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 aligns 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 is indicative of 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 reflect a national average and a national model can obscure unique local or regional effects. In sum, 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 heterogeneity within spatial scales, represented by differences in regional medians, is indicative of the influence of investigator choices when estimating hedonic equations. Thus, our study also demonstrates an important insight: differences in investigator decisions observed within 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 interocular differences in hedonic estimates across highly restricted spatial scales in the literature are real or just 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.²⁵ Such reporting will allow richer meta-analysis to clarify if results observed are real spatial differences or simply due to differences in investigator choices across studies.²⁶

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 counter intuitive 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. However, one

²⁵ In Appendix B, we evaluate the sensitivity of our results to water quality sample parameters, property location parameters, and fixed effects, and find that water quality sample selection parameters have a larger effect on regional medians.

²⁶ Some of this work is already underway, with Heberling et al. (2022) finding methodological choices play a larger role in estimated relationships than variables related to market and commodity.

must be careful when taking anomalous outcomes as prima facia evidence that some do not value water quality or there is no effect. One must keep in mind many considerations. No hedonic sample is a representative sample of homeowners, just those that 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 what, specifically, people consider when they buy a property. These issues are compounded by property and water quality data limitations. Non-disclosure states scattered throughout much of the West and in select 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 or not. Thus, there are necessary caveats when attempting to interpret results from a single hedonic model. Rather, we maintain insights should only be made after repeated hedonic modeling in the locations where results are found to be highly robust.

Lastly, when choosing a hedonic modeling framework, our study was fortunate to have access to ZTRAX data that 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 2021). In the absence of nationwide freely available property sales data, researchers may not be able to conduct similar tests. We hope the results from this study 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 sunseting of ZTRAX, it is critical that new large-scale open access or low-cost property sale databases become

available, allowing more researchers to study the broad range of environmental and other pertinent policy topics at scale.

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Appendix A Additional Secchi Baseline Results

Class II Models

In models presented in the paper (which we will now refer to as Class I), we consider only administrative boundaries. However, other characteristics may also be important to consider when determining spatial boundaries. For example, surrounding ecological conditions might include a unifying set of amenities that draw people to consider buying properties near lakes. Therefore, we consider an additional class of market boundaries (Class II) to better account for local environmental conditions: ecoregions and urban location. At each Class I spatial scale, we also collect sales that fall within 2010 Census Urbanized Areas into a single group for estimation, as urban locations are densely populated by humans and feature distinct land use patterns that may obscure the unique characteristics of the ecoregions. Then we divide sales throughout the remaining landscape by ecoregions within each Class I spatial designation into distinct groups for estimation. These overlays are shown at each spatial scale in the second column in Figure 1. As urbanized areas and counties are nested within ecoregion boundaries, the Substate spatial scale boundaries defined for Class I models also meet the criteria for Class II models.

For the Class II market boundaries, we estimate the following hedonic model:

$$\begin{aligned} \ln(P_{it}) = & \beta_0 + \beta_1 \ln(WQ_{it}) + \beta_2 \ln(WQ_{it}) * LF_i + \beta_3 \ln(WQ_{it}) * \ln(Dist_i) \\ & + \beta_4 \ln(WQ_{it}) * [\ln(Area_i) - \overline{\ln(Area)}] + \beta_6 LF_i + \beta_7 Dist_i + \beta_8 Area_i + \beta_{Prop} Prop_i \\ & + \gamma_q + \tau_{it} + \epsilon_{it} \end{aligned} \quad [A1]$$

The key difference between equation [A1] and equation [1] in the manuscript is the exclusion of State interaction terms at the Nation, Region, and Division spatial scales. By omitting these terms, we capture how increasing spatial scale impacts estimated effects of water quality

without controlling for State level spatial heterogeneity. The elasticities for the Class II market boundaries are thereby calculated by:

$$\widehat{elast}_i = \hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 [\ln(Area_i) - \overline{\ln(Area)}] \quad [A2]$$

In Figure A2, we present the baseline results for Class II models analogous to Figure 3 in the manuscript. In panel a, we hold the spatial scale of the model constant at the Division level, we compare the distributions of elasticities for the Northeast, Midwest, South, and West. We find much more within region spatial heterogeneity than the Class I models, with distributions for the Northeast, Midwest, and West all characterized by multiple nodes. The Northeast elasticities are still largest overall. Moving to panel b, we compare differences in distribution across the five spatial scales. Here we see more overlap in distributions in the Northeast and the West (except at the Substate level) compared to the Class I models, while in the Midwest, there is slightly less overlap. In the South, we still find larger elasticity estimates for Nation II and Region II compared to the smaller spatial scales.

In Figure A3, we assess the sensitivity of the Class II regional medians to spatial scale analogous to Figure 4 in the manuscript. Overall, the results are similar to the Class I models. We find the results in the Midwest are least sensitive to spatial scale or different sample select and model choices. In the Northeast and the West, we find slightly less sensitivity to spatial scale in line with our findings from Figure A2. The results in the South and the West are again the most sensitive to sample selection and model choice. Notably, Nation II results in all regions are considerably more stable relative to other spatial scales and the Nation I results. We surmise this tightness might be related to pooling of hedonic estimates. As many ecoregions span multiple regions, information from sample rich areas could be driving the results in others. Direct comparison between Figure 4 and Figure A3 also reveals potential systematic differences in the

magnitude of the medians between model classes in the Northeast and the West. Medians in the Northeast are larger for Region I, Division I, and State I, when compared to their Class II counterparts, whereas medians in the West are smaller for Region I and Division I than Region II and Division II.

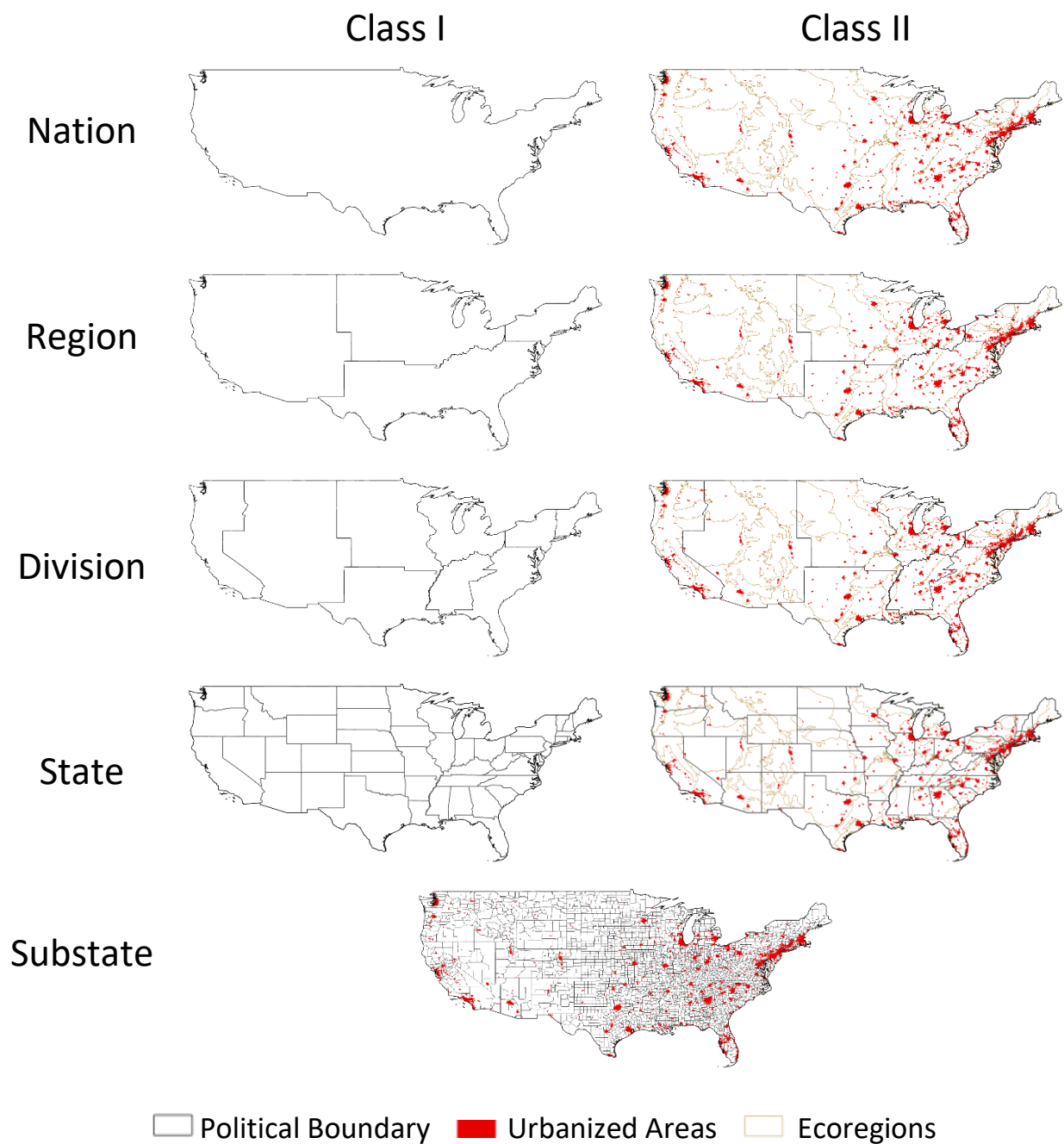


Figure A1 Market Boundary Definition by Spatial Scale and Boundary and Boundary Class

Notes: Nation I represents a single housing market for all sales across the United States. For Nation II, Region, Division, and State level spatial scales, property sales are first divided by political boundaries. Next sales with urbanized areas are grouped together to form an urban market. Then remaining sales are divided by level II ecoregion boundaries to form rural markets. At the Substate level, urbanized areas and county boundaries that do not fall within an urbanized area form individual market boundaries.

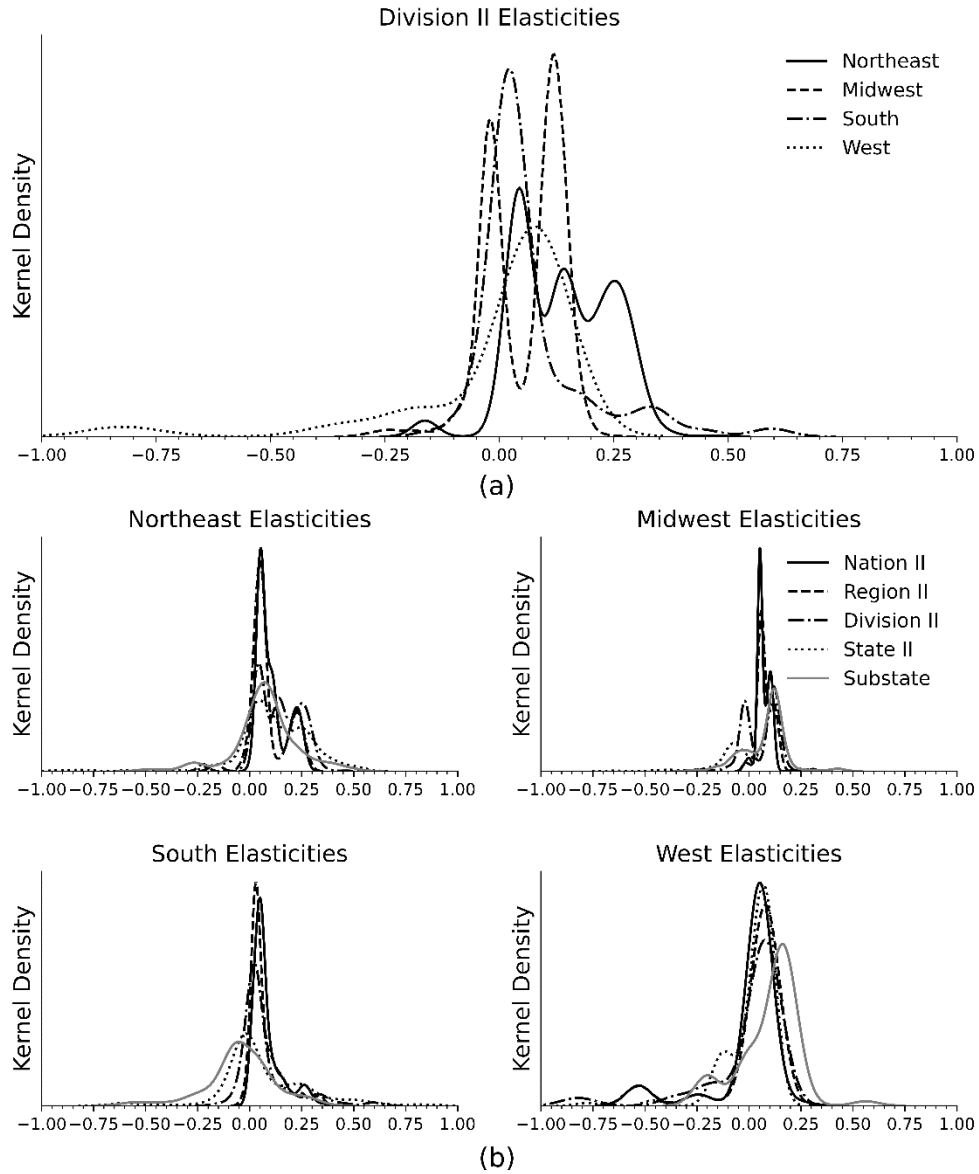


Figure A2 Distribution of Baseline Elasticity Estimates for Secchi Class II Models

Notes: Kernel density plots of elasticities of property value with respect to water quality by Region and market boundary definition. Median elasticity estimates at census tract level for properties within 150m from lakefront along x axis. Kernel density along y axis rescaled to 1 for each plot. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure. Panel (a) presents the Division II results in a single plot broken out by Region. Panel (b) presents the results for each Region in separate plots broken out by spatial scale for Class II models.

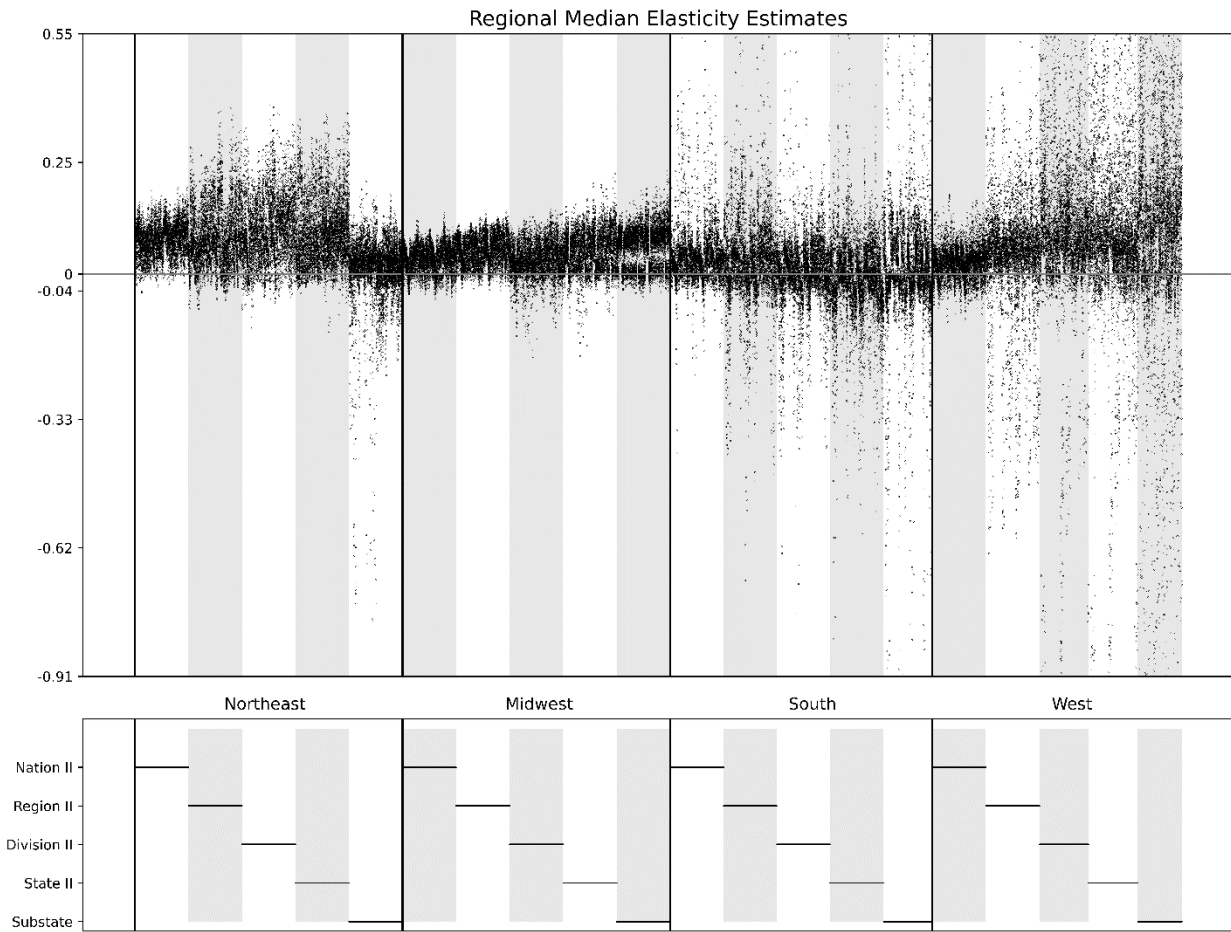


Figure A3 Regional Median Elasticity Estimates for All Secchi Class II Models

Notes: Census tract median estimates for properties within 150m from lakefront for Class II models 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. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

Spatial Distribution of Results

Figure A4 depicts the spatial distribution of baseline Secchi elasticity estimates for properties within 150 m from the lakefront aggregated at the county level. For each market boundary condition, we find evidence of spatial heterogeneity given by the range of elasticity estimates. Counties in the Northeast predominantly have more positive elasticity estimates as shown in the deeper shades of green. Counties on the West Coast have a wide range of both positive and negative elasticities shown in shades of green and red respectively. We further note differences in estimates across spatial scales and model classes. For example, in Michigan counties that are positive in Nation I and Nation II are negative for State I and State II. In New York, we see the Class II model elasticities are larger in magnitude than the Class II elasticities. Lastly, we can observe how the spatial distribution of the sample changes as we define market boundaries more narrowly. At the substate level, many states are excluded from the model results when compared to the national scale.

We note that the spatial distribution of implicit prices may not be the same as elasticities, due to large differences in average housing prices. Using the Nation I results, for a 1% improvement in water clarity, we find the median implicit price for properties within 150 m in our sample in the West is largest at \$63,139 compared to \$23,789 in the South. However, this result is more reflective of sale prices, as the median elasticity in the West at 0.082 is smaller than that in the South at 0.096.

Table A4 depicts how the baseline elasticity estimates for each market boundary compare across the three buffer groups: <150 m, 150-300 m, and >300 m. We find the median for properties within 150 m ranges from 0.06 to 0.10 compared to a range of 0.01 to 0.03 in the 150-300 m group.

Beyond 300 m from the lakefront the medians are mostly negative or very close to zero. Negative values may reflect a large distance decay rate.

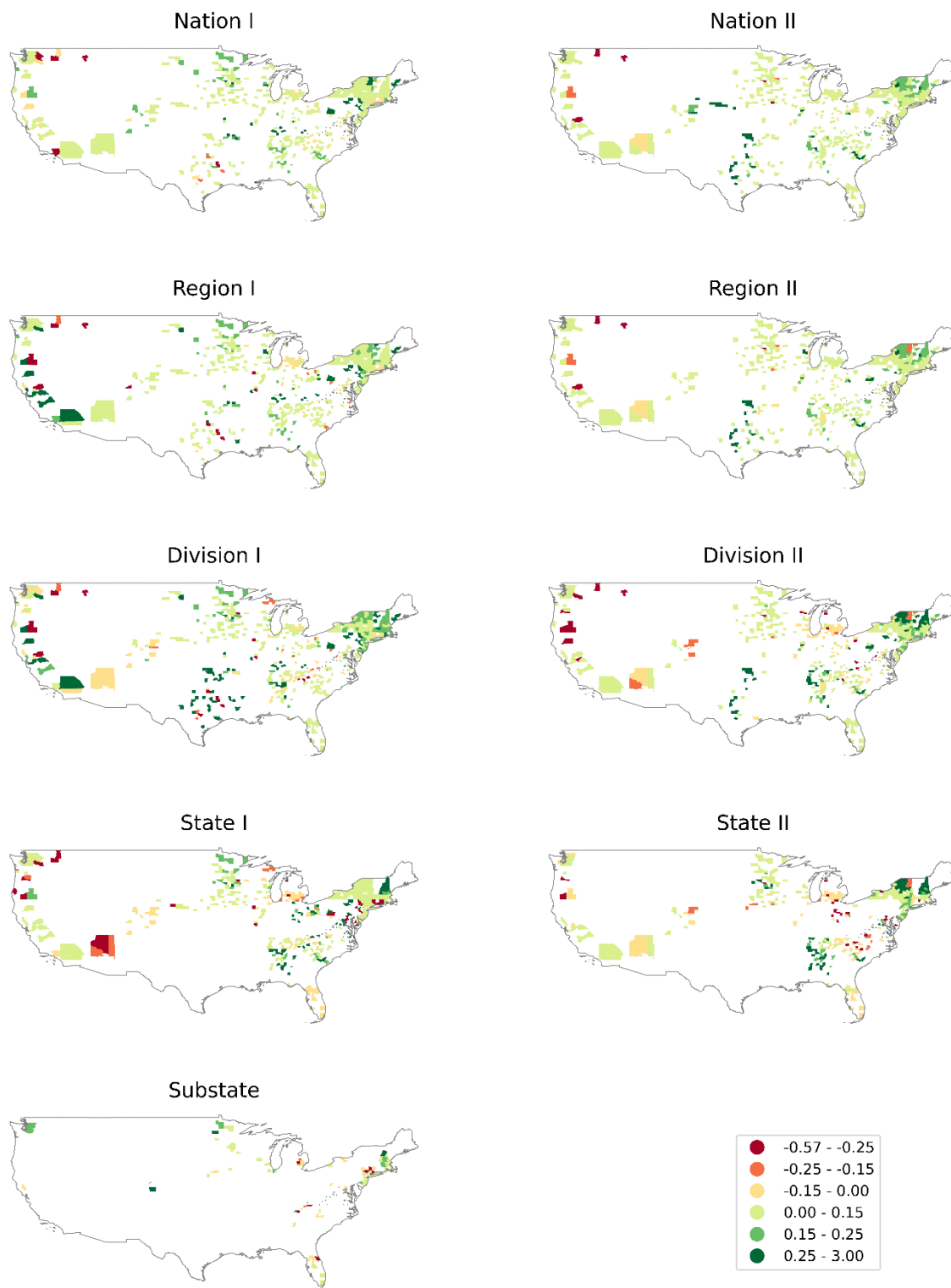


Figure A4 Spatial Distribution of Baseline Elasticity Estimates for Secchi

Notes: Census tract median estimates for properties within 150m from lakefront are aggregated by county and

Table A1

	Nation I	Nation II	Region I	Region II	Division I	Division II	State I	State II	Substate
<i><=150 m</i>									
min	-1.28	-0.54	-1.37	-0.54	-2.47	-1.28	-44.78	-34.07	-1.47
25%	0.05	0.05	0.06	0.04	0.03	0.02	-0.01	-0.02	-0.01
50%	0.09	0.06	0.09	0.06	0.10	0.06	0.08	0.09	0.08
75%	0.11	0.11	0.13	0.11	0.16	0.14	0.13	0.14	0.13
max	2.59	16.28	2.39	16.28	2.56	16.28	3.02	1.52	2.72
N	2,412	2,409	2,416	2,372	2,406	2,323	2,249	1,991	1,061
<i>150-300 m</i>									
min	-1.42	-0.58	-1.41	-0.58	-9.24	-1.30	-45.13	-34.32	-1.52
25%	-0.01	0.02	-0.02	0.01	-0.03	-0.01	-0.04	-0.04	-0.02
50%	0.03	0.02	0.03	0.03	0.03	0.03	0.01	0.03	0.03
75%	0.05	0.03	0.05	0.04	0.05	0.05	0.04	0.05	0.07
max	2.52	1.27	2.23	1.27	7.32	2.89	2.59	1.06	2.66
N	2,649	2,658	2,644	2,627	2,639	2,572	2,467	2,206	1,225
<i>>300 m</i>									
min	-1.49	-0.60	-1.43	-0.61	-9.24	-1.37	-68.54	-34.44	-0.80
25%	-0.05	-0.03	-0.08	-0.03	-0.09	-0.03	-0.10	-0.07	-0.04
50%	-0.01	0.00	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01	-0.01
75%	0.01	0.01	0.02	0.02	0.01	0.03	0.02	0.04	0.03
max	2.51	1.27	2.20	2.44	10.57	3.49	2.93	0.97	2.74
N	4,297	4,284	4,292	4,192	4,277	4,102	3,909	3,425	1,902

N represents number of census tracts. Estimates from baseline models.

Appendix B Additional Robustness Analysis and Sensitivity Tests

Robustness of Nation I Model to Varying Model Specifications

In Table B1, we investigate the effect of using broader scale fixed effects on the baseline Nation I results. The effect of Secchi in the excluded category is similar with broader fixed effects as the baseline with a few key differences. The coefficient for Secchi is smaller with county spatial units but still significant. The interaction term between Secchi and < 150 m, while similar in size, is not significant without spatial fixed effects. We find a positive effect for the interaction of the Secchi and Urban variable that was not previously identifiable using census tract level spatial units. However, we also find the coefficient estimates for many of the interaction terms change in magnitude, direction, and significance relative to the baseline. Namely, an increasing amount of interaction terms are significant at the county level, and even more significant when we remove spatial fixed effects all together. We are concerned that these differences result from omitted variable bias at the neighborhood level, as we have relatively few neighborhood spatial control variables.

In Table B2, we implement additional controls on the hedonic price gradient. This approach entails interacting all of the control variables by state dummies. However, given issues with violation of the rank condition, we could only add interaction terms for states with more than four times the number of observations as control variables. This threshold was determined by iteratively increasing the multiplier until the rank condition was met. The biggest difference is that the Secchi interaction terms with <150 m and Lake Area Demeaned are much smaller and no longer significant. It is unclear whether these differences result from potential omitted variable bias in the baseline estimations or identification issues, due to the effects of these variables being absorbed by the new state interaction terms or the reduced sample that may inadvertently omit important

variation in water quality across lakes. Considering the estimated coefficients for the state and ecoregion interaction terms with water quality, we find relative agreement between the two models. Some of the coefficients are smaller in magnitude with the additional controls and are no longer significant. We further see that the outlier interaction terms noted in the baseline (e.g., Secchi * KY; Secchi * ME; and Secchi * MT) are still outliers with the addition of the control variables.

In Table B3, using the Nation I model, we evaluate the effect of varying property attributes for a single sample that contains all property attributes considered: lot size, building age, building size, bedrooms, and bathrooms. The new sample contains 35% less observation and spans fewer states and ecoregions. For example, Maryland, Arizona, and Indiana are excluded. Notably, in the new sample with the same baseline specification, Secchi * <150 m is smaller and no longer significant. There are further differences in the magnitude, direction, and significance of ecoregion and state interaction terms with Secchi, indicating the availability of property attributes influences the overall results, likely due to changing the spatial distribution of the sample. We then compare the robustness of the baseline model results of the new sample to which attributes are included in the model. We find large differences in effects for Secchi when no property attributes are included in the model, with the effect of Secchi 0.08 smaller without property attributes than with all attributes included. Thus, even with the inclusion of fine scale fixed effects property attributes play a role in identification of water quality. This provides context for studies that may forego property attributes entirely. Future analysis can provide insight into which property attributes are most important for identification of the water quality on housing prices.

In Table B4, we consider broader aggregations for state and ecoregion interactions to simplify the Nation I model results. We aggregate state interactions by division and region using level 2 and level 1 ecoregions. We also consider a restricted model with no ecoregion, state, division, or region

interaction terms. We find little differences in estimates for our excluded category across models. One exception is the interaction between Secchi and Lake Area Demeaned variables, which is smaller in the restricted model and in the model with the broadest aggregations. We also find the aggregate categories tend to smooth over heterogeneity in the effect of Secchi, especially related to state boundaries. We conduct likelihood ratio tests on all models relative to the restricted models and find that the spatial heterogeneity interaction terms are jointly significant for all specifications. We further find, while our baseline has the largest loglikelihood, the specification comprised of level 1 ecoregions and states has a slightly smaller AIC to our baseline (55,293 compared to 55,297), indicating a potential better fit for the data.

Table B1 Nation I Results for Broader Spatial Fixed Effects Compared to Baseline

Parameter	tract x year ¹	county x year ²	county + year ³	year
const	7.123***	5.388***	5.313***	2.625***
Secchi ^{4,5}	0.231***	0.162**	0.155**	0.277***
Secchi * <150 m	0.025**	0.03*	0.029*	0.0280
Secchi * Lake Distance	-0.034***	-0.023**	-0.022**	-0.029*
Secchi * Urban	-0.0150	0.027*	0.032*	0.079**
Secchi * Lake Area Demeaned ⁵	0.009*	0.014**	0.013**	0.047***
Secchi * Ecoregion 5.2	0.075*	-0.0220	-0.0640	-0.171***
Secchi * Ecoregion 5.3	0.0430	0.0180	0.0430	0.0110
Secchi * Ecoregion 6.2	0.5940	0.581*	0.242*	1.162***
Secchi * Ecoregion 7.1	0.9910	0.912*	0.523***	1.368***
Secchi * Ecoregion 8.2	0.0570	-0.0740	-0.0770	0.0060
Secchi * Ecoregion 8.3	0.0550	0.0440	0.0350	0.1550
Secchi * Ecoregion 8.4	-0.0170	0.0490	0.0150	0.421***
Secchi * Ecoregion 8.5	0.0260	0.0280	0.076*	0.1340
Secchi * Ecoregion 9.2	0.150	0.0270	0.0350	0.110
Secchi * Ecoregion 9.3	0.2230	0.1660	0.0890	0.4430
Secchi * Ecoregion 9.4	0.2030	0.330	0.1190	0.332*
Secchi * Ecoregion 10.1		0.3350	0.243*	1.105***
Secchi * Ecoregion 10.2	0.3060	-0.2450	-0.4090	1.169***
Secchi * Ecoregion 11.1	0.6620	0.2390	-0.1320	0.941***
Secchi * Ecoregion 12.1				0.668*
Secchi * Ecoregion 13.1	0.3660	-0.0610	-0.0530	1.094***
Secchi * Ecoregion 15.4	0.0320	-0.146***	0.0040	0.422***
Secchi * AL	0.0030	0.684***	0.45*	-0.769***
Secchi * AR	0.1210	-0.250	-0.0560	-0.759***
Secchi * AZ	-0.3960	0.0530	0.0360	-0.97***
Secchi * CA	-0.7280	-0.3310	0.2260	-0.776**
Secchi * CO	-0.4980	-0.4920	-0.1570	-0.761***
Secchi * CT	-0.266*	-0.291**	-0.20	-0.1430
Secchi * DE	-0.0860	-0.549***	-0.591***	0.1690
Secchi * FL	-0.0190	-0.084*	-0.136***	-0.314***
Secchi * GA	0.0330	0.0730	-0.1370	-0.446*
Secchi * IA	-0.221*	0.0260	-0.030	0.0270
Secchi * IL	-0.1070	-0.0020	-0.0060	-0.326*
Secchi * IN	0.20	0.312*	0.249*	0.0460
Secchi * KS			-0.3140	0.1390
Secchi * KY	-1.956***	-0.886***	-0.758**	-0.821*
Secchi * LA	0.0840	0.080	0.473***	0.4260
Secchi * MA	-0.0270	-0.0130	-0.053*	0.0380
Secchi * MD	-0.259**	-0.0960	-0.0630	-0.00
Secchi * ME	2.428***	0.595***	1.308***	-0.398**
Secchi * MI	-0.0680	0.1480	0.1090	-0.301***
Secchi * MO	0.6730	-0.394***	-0.681**	-1.399***
Secchi * MT	-2.021***	-1.012*	-0.514***	-1.309***
Secchi * NC	-0.1830	-0.1660	-0.0640	-0.20
Secchi * ND	-0.2230	-0.1890	-0.2590	-1.016*
Secchi * NE	-0.1790	-0.087*	-0.082*	-0.0670
Secchi * NH	-0.0650	-0.0060	-0.0250	-0.136**
Secchi * NJ	-0.0030	-0.0460	-0.09*	-0.236***
Secchi * NM				-0.953**
Secchi * NY	-0.0740	0.0410	0.0350	-0.307***

Table B1 (2/2)

Parameter	tract x year ¹	county x year ²	county + year ³	year
Secchi * OH	-0.1980	-0.39***	-0.254***	-0.1030
Secchi * OK	-0.1240	-0.2990	-0.0170	-0.1130
Secchi * OR	-0.8670	-0.707*	-0.316*	-1.145***
Secchi * PA	0.154***	0.4580	0.1010	-0.548***
Secchi * RI	0.102*	-0.0480	-0.072*	-0.158***
Secchi * SC	-0.0530	-0.0910	0.0110	-0.582***
Secchi * SD	-0.1270	-0.0450	0.0290	-0.461**
Secchi * TN	-0.1130	-0.157*	-0.1360	-0.664***
Secchi * TX	-0.3930	-0.2590	-0.2230	-0.3070
Secchi * UT		-0.8**	-0.529***	-1.313***
Secchi * VA	-0.1340	-0.0420	-0.040	-0.1020
Secchi * VT	-0.0780	-0.1620	-0.244**	0.0270
Secchi * WA	-0.9890	-1.036*	-0.642***	-1.159***
Secchi * WI	-0.0330	0.1440	0.152*	-0.00
Secchi * WV				-0.703***
<150 m	0.124***	0.13***	0.13***	0.132***
Lake Distance	-0.095***	-0.068***	-0.067***	-0.042**
Lake Area	0.013*	-0.010	-0.010	-0.055***
Median Income	0.131***	0.305***	0.312***	0.516***
Slope	0.019***	0.021***	0.022***	0.035**
Elevation	-0.0230	-0.15***	-0.154***	0.0170
Lot Size	0.101***	0.064***	0.064***	0.0110
Building Age	-0.125***	-0.091***	-0.091***	-0.061***
Building Size	0.547***	0.63***	0.634***	0.633***
Quarter 2	0.044***	0.046***	0.049***	0.054***
Quarter 3	0.05***	0.05***	0.053***	0.061***
Quarter 4	0.015***	0.014***	0.015***	0.017***

Notes: N = 485,860 Standard Errors Clustered at Tract Level. *p<.05 **p<.01 ***p<.001

¹Baseline model includes tract x year fixed effects. During estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

²During estimation, interaction terms for KS, NM, WV, 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.

³During estimation, interaction terms for NM, WV, 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 NM and WV can be explained by the corresponding ecoregion interactions.

⁴Interaction terms for MN and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

⁵ 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.

Table B2 Nation I Results State Interactions with Controls Compared to Baseline

Parameter	Baseline		State Interactions with Controls	
	Estimate	Std. Error	Estimate ¹	Std. Error
const	7.123***	(0.207)	6.139***	(0.432)
Secchi ^{2,3,4}	0.231***	(0.034)	0.232***	(0.034)
Secchi * <150 m	0.025**	(0.009)	0.0120	(0.009)
Secchi * Lake Distance	-0.034***	(0.005)	-0.034***	(0.005)
Secchi * Urban	-0.0150	(0.014)	-0.0130	(0.013)
Secchi * Lake Area Demeaned ⁴	0.009*	(0.004)	0.0060	(0.004)
Secchi * Ecoregion 5.2	0.075*	(0.036)	0.08*	(0.034)
Secchi * Ecoregion 5.3	0.0430	(0.033)	0.0220	(0.039)
Secchi * Ecoregion 6.2	0.5940	(0.462)	0.3890	(0.286)
Secchi * Ecoregion 7.1	0.9910	(0.596)	0.944*	(0.459)
Secchi * Ecoregion 8.2	0.0570	(0.077)	0.070	(0.072)
Secchi * Ecoregion 8.3	0.0550	(0.048)	0.0170	(0.045)
Secchi * Ecoregion 8.4	-0.0170	(0.069)	-0.0270	(0.067)
Secchi * Ecoregion 8.5	0.0260	(0.031)	0.0190	(0.028)
Secchi * Ecoregion 9.2	0.150	(0.1)	0.1360	(0.111)
Secchi * Ecoregion 9.3	0.2230	(0.201)	0.1950	(0.201)
Secchi * Ecoregion 9.4	0.2030	(0.149)	0.1830	(0.144)
Secchi * Ecoregion 10.2	0.3060	(0.462)	0.0630	(0.288)
Secchi * Ecoregion 11.1	0.6620	(0.462)	0.3590	(0.287)
Secchi * Ecoregion 13.1	0.3660	(0.475)	0.090	(0.307)
Secchi * Ecoregion 15.4	0.0320	(0.048)	0.0120	(0.045)
Secchi * AL	0.0030	(0.202)	0.0820	(0.179)
Secchi * AR	0.1210	(0.15)	0.1720	(0.219)
Secchi * AZ	-0.3960	(0.475)	-0.1250	(0.307)
Secchi * CA	-0.7280	(0.465)	-0.4120	(0.29)
Secchi * CO	-0.4980	(0.461)	-0.3670	(0.28)
Secchi * CT	-0.266*	(0.12)	-0.273*	(0.12)
Secchi * DE	-0.0860	(0.402)	-0.2930	(0.447)
Secchi * FL	-0.0190	(0.037)	-0.0090	(0.033)
Secchi * GA	0.0330	(0.128)	0.0760	(0.143)
Secchi * IA	-0.221*	(0.11)	-0.1630	(0.115)
Secchi * IL	-0.1070	(0.08)	-0.1160	(0.074)
Secchi * IN	0.20	(0.515)	-0.6590	(0.39)
Secchi * KY	-1.956***	(0.058)	-3.282***	(0.724)
Secchi * LA	0.0840	(0.211)	-0.2410	(0.177)
Secchi * MA	-0.0270	(0.024)	-0.0230	(0.022)
Secchi * MD	-0.259**	(0.085)	-0.22**	(0.085)
Secchi * ME	2.428***	(0.077)	2.533***	(0.092)
Secchi * MI	-0.0680	(0.048)	-0.0850	(0.045)
Secchi * MO	0.6730	(0.739)	-1.1660	(1.699)
Secchi * MT	-2.021***	(0.465)	-5.222***	(0.288)
Secchi * NC	-0.1830	(0.123)	-0.0680	(0.117)
Secchi * ND	-0.2230	(0.292)	0.3390	(0.272)
Secchi * NE	-0.1790	(0.101)	-0.1670	(0.112)
Secchi * NH	-0.0650	(0.047)	-0.0970	(0.053)
Secchi * NJ	-0.0030	(0.052)	0.0140	(0.052)
Secchi * NY	-0.0740	(0.04)	-0.0730	(0.054)
Secchi * OH	-0.1980	(0.16)	-0.1710	(0.143)

Table B2 (2/2)

Parameter	Estimate	Baseline	State Interactions with Controls	
		Std. Error	Estimate ¹	Std. Error
Secchi * OK	-0.1240	(0.266)	-0.1830	(0.267)
Secchi * OR	-0.8670	(0.525)	-0.95*	(0.41)
Secchi * PA	0.154***	(0.036)	0.0830	(0.084)
Secchi * RI	0.102*	(0.047)	0.061*	(0.029)
Secchi * SC	-0.0530	(0.084)	-0.0020	(0.078)
Secchi * SD	-0.1270	(0.287)	-0.0020	(0.228)
Secchi * TN	-0.1130	(0.078)	-0.0860	(0.077)
Secchi * TX	-0.3930	(0.233)	-0.40	(0.216)
Secchi * VA	-0.1340	(0.083)	-0.0930	(0.079)
Secchi * VT	-0.0780	(0.129)	-0.10	(0.143)
Secchi * WA	-0.9890	(0.597)	-0.926*	(0.46)
Secchi * WI	-0.0330	(0.08)	-0.0480	(0.073)
<150 m	0.124***	(0.009)	0.138***	(0.012)
Lake Distance	-0.095***	(0.005)	-0.074***	(0.008)
Lake Area	0.013*	(0.005)	0.011*	(0.005)
Median Income	0.131***	(0.014)	0.097***	(0.015)
Slope	0.019***	(0.002)	0.018***	(0.003)
Elevation	-0.0230	(0.023)	0.310	(0.167)
Lot Size	0.101***	(0.004)	0.11***	(0.007)
Building Age	-0.125***	(0.003)	-0.138***	(0.005)
Building Size	0.547***	(0.01)	0.435***	(0.013)
Quarter 2	0.044***	(0.002)	0.053***	(0.003)
Quarter 3	0.05***	(0.002)	0.059***	(0.003)
Quarter 4	0.015***	(0.002)	0.021***	(0.004)

Notes: N = 485,860 Standard Errors Clustered at Tract Level. *p<.05 **p<.01 ***p<.001

¹Control variables are interacted with dummy variables for each state, excluding Minnesota which is chosen as the excluded category. Given rank violations a further restriction on these interactions terms is imposed requiring a state to have a sample count larger than 4 times the number of control variables. Lower count thresholds were attempted but results in rank violations of the data matrix. During estimation the following terms were fully absorbed by fixed effects and dropped from the model: lake_area * CA, lake_area * MD, lake_area * NE, lake_area * GA, lake_area * PA, lake_area * OK, lake_area * KY, lake_area * MO, lake_area * MT, hh_inc_med_bg_2012-2016 * ND. Coefficient estimates for these interactions are available from the authors upon request.

²Interaction terms for MN and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

³During estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

⁴The 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.

Table B3 Nation I Results for Sample with All Property Attributes

Parameter	baseline	sample with all attributes ²						
	sample ¹	baseline	none	all	lot size	age	bld size	bld rooms
const	7.123***	7.67***	10.535**	8.14***	9.068***	11.838**	6.901***	10.535**
Secchi ^{3,4}	0.231***	0.259***	0.174**	0.258***	0.216***	0.213***	0.22***	0.174**
Secchi * <150 m	0.025**	0.0190	0.0010	0.0180	0.0150	0.00	0.0150	0.0010
Secchi * Lake Distance	-0.034***	-0.037***	-0.017*	-0.036***	-0.031***	-0.023**	-0.027***	-0.017*
Secchi * Urban	-0.0150	-0.020	-0.0620	-0.0210	-0.0170	-0.050	-0.049*	-0.0620
Secchi * Lake Area		0.012**	0.0090	0.012**	0.0110	0.012*	0.009*	0.0090
demeaned ⁴	0.009*							
Secchi * Ecoregion 5.2	0.075*	0.173*	0.178*	0.167*	0.175*	0.182*	0.17*	0.178*
Secchi * Ecoregion 5.3	0.0430	0.050	0.0410	0.0490	0.0530	0.0290	0.0530	0.0410
Secchi * Ecoregion 6.2	0.5940	0.2110	3.052***	0.1060	2.312*	1.86*	0.9520	3.052***
Secchi * Ecoregion 7.1	0.9910	4.417***	8.12***	4.568***	6.541***	5.779***	6.436***	8.12***
Secchi * Ecoregion 8.2	0.0570	0.0670	0.0510	0.0690	0.0780	0.0120	0.0830	0.0510
Secchi * Ecoregion 8.3	0.0550	0.186*	0.1940	0.16*	0.192*	0.201*	0.181*	0.1940
Secchi * Ecoregion 8.4	-0.0170	-0.1110	0.0530	-0.1170	-0.020	-0.0210	-0.0430	0.0530
Secchi * Ecoregion 8.5	0.0260	0.0090	0.0070	0.0060	0.020	-0.020	0.0230	0.0070
Secchi * Ecoregion 9.2	0.150	0.2760	0.458*	0.2640	0.387*	0.2950	0.409*	0.458*
Secchi * Ecoregion 9.3	0.2230							
Secchi * Ecoregion 9.4	0.2030	1.439*	1.8150	1.1710	1.7730	2.117*	1.13*	1.8150
Secchi * Ecoregion 10.2	0.3060							
Secchi * Ecoregion 11.1	0.6620	0.2610	3.26***	0.1530	2.32*	2.101*	1.0730	3.26***
Secchi * Ecoregion 13.1	0.3660							
Secchi * Ecoregion 15.4	0.0320	0.0510	0.0760	0.050	0.0850	0.0260	0.0790	0.0760
Secchi * AL	0.0030	-0.1730	-0.1230	-0.2050	-0.1240	-0.1630	-0.1530	-0.1230
Secchi * AR	0.1210	-0.1480	-0.385*	-0.1840	-0.367*	-0.1760	-0.269*	-0.385*
Secchi * AZ	-0.3960							
Secchi * CA	-0.7280	-0.3470	-3.349***	-0.2440	-2.385*	-2.209*	-1.16*	-3.349***
Secchi * CO	-0.4980	-0.4160	-2.971**	-0.3470	-2.394*	-1.997*	-0.9420	-2.971**
Secchi * CT	-0.266*	-0.282*	-0.291*	-0.28*	-0.2620	-0.317*	-0.278*	-0.291*
Secchi * DE	-0.0860	0.0090	-0.2580	0.0030	-0.190	-0.1350	-0.0690	-0.2580
Secchi * FL	-0.0190	-0.0420	-0.0460	-0.0390	-0.0520	-0.0120	-0.0630	-0.0460
Secchi * GA	0.0330	-0.1120	-0.2140	-0.0880	-0.2040	-0.1770	-0.1230	-0.2140
Secchi * IA	-0.221*	-0.3180	-0.519**	-0.306*	-0.424*	-0.362*	-0.457**	-0.519**
Secchi * IL	-0.1070	-0.110	-0.0340	-0.1080	-0.0720	-0.0330	-0.1040	-0.0340
Secchi * IN	0.20							
Secchi * KY	-1.956***							
Secchi * LA	0.0840	-0.1870	-0.140	-0.20	-0.2150	-0.0890	-0.1880	-0.140
Secchi * MA	-0.0270	-0.0150	0.0470	-0.0130	0.0260	0.0260	0.0010	0.0470
Secchi * MD	-0.259**							
Secchi * ME	2.428***	2.346***	1.766***	2.197***	1.887***	1.883***	2.315***	1.766***
Secchi * MI	-0.0680	-0.111*	-0.122*	-0.107*	-0.121*	-0.149**	-0.087*	-0.122*
Secchi * MO	0.6730	0.5090	0.2060	0.5610	-0.1910	0.310	0.7740	0.2060
Secchi * MT	-2.021***	-1.673*	-5.141***	-1.626*	-4.029***	-4.059***	-2.421***	-5.141***
Secchi * NC	-0.1830	-0.282*	-0.2070	-0.2470	-0.2240	-0.2090	-0.288*	-0.2070
Secchi * ND	-0.2230	-0.156***	-0.361***	-0.146***	-0.193***	-0.167***	-0.375***	-0.361***
Secchi * NE	-0.1790	-0.2740	-0.445*	-0.260	-0.3640	-0.3010	-0.402*	-0.445*
Secchi * NH	-0.0650	-0.0730	-0.1030	-0.070	-0.0910	-0.0740	-0.0970	-0.1030

Table B3 (2/2)

Parameter	baseline	sample with all attributes ²						
	sample ¹	baseline	none	all	lot size	age	bld size	bld rooms
Secchi * NJ	-0.0030	0.130	0.2010	0.1580	0.1940	0.1630	0.1480	0.2010
Secchi * NY	-0.0740	-0.099*	-0.1290	-0.097*	-0.1040	-0.1260	-0.111*	-0.1290
Secchi * OH	-0.1980	-0.2290	-0.1680	-0.2350	-0.2230	-0.1540	-0.2190	-0.1680
Secchi * OK	-0.1240	-0.2380	-0.8290	0.0470	-0.0860	-1.1340	-0.3520	-0.8290
Secchi * OR	-0.8670	-4.601***	-8.37***	-4.752***	-6.766***	-6.076***	-6.582***	-8.37***
Secchi * PA	0.154***	0.14***	0.1070	0.22***	0.111*	0.245***	0.0350	0.1070
Secchi * RI	0.102*	0.105*	0.020	0.105*	0.142**	0.0140	0.0480	0.020
Secchi * SC	-0.0530	-0.2070	-0.1470	-0.1730	-0.1530	-0.2110	-0.1670	-0.1470
Secchi * SD	-0.1270	-0.0780	0.0650	-0.0380	0.1370	0.0940	-0.1860	0.0650
Secchi * TN	-0.1130	0.1670	-0.0090	0.1920	-0.0450	-0.0220	0.2460	-0.0090
Secchi * TX	-0.3930	-0.3450	-0.5970	-0.1970	-0.4370	-1.0180	-0.0540	-0.5970
Secchi * VA	-0.1340	-0.291**	-0.419***	-0.282**	-0.429**	-0.415***	-0.255*	-0.419***
Secchi * VT	-0.0780	-0.0790	-0.0040	-0.0660	0.0020	-0.0710	-0.0480	-0.0040
Secchi * WA	-0.9890	-4.466***	-8.051***	-4.598***	-6.52***	-5.754***	-6.447***	-8.051***
Secchi * WI	-0.0330	-0.0490	0.0260	-0.0470	-0.020	0.0350	-0.0430	0.0260
<150 m	0.124***	0.128***	0.143***	0.125***	0.134***	0.159***	0.118***	0.143***
Lake Distance	-0.095***	-0.093***	-0.092***	-0.092***	-0.102***	-0.107***	-0.075***	-0.092***
Lake Area	0.013*	0.0070	0.0050	0.0070	0.010	0.0050	0.0040	0.0050
Median Income	0.131***	0.125***	0.265***	0.122***	0.226***	0.219***	0.152***	0.265***
Slope	0.019***	0.016***	0.047***	0.014***	0.033***	0.036***	0.026***	0.047***
Elevation	-0.0230	-0.0340	-0.065*	-0.0360	-0.0520	-0.074*	-0.0270	-0.065*
Lot Size	0.101***	0.108***		0.108***	0.198***			
Building Age	-0.125***	-0.124***		-0.115***		-0.193***		
Building Size	0.547***	0.498***		0.43***			0.625***	
Quarter 2	0.044***	0.045***	0.04***	0.045***	0.04***	0.048***	0.04***	0.04***
Quarter 3	0.05***	0.052***	0.04***	0.051***	0.04***	0.056***	0.043***	0.04***
Quarter 4	0.015***	0.017***	0.0030	0.017***	0.0020	0.022***	0.007*	0.0030
Bathrooms				0.143***				
Bedrooms				-0.054***				
N	485,860	311,938	311,938	311,938	311,938	311,938	311,938	311,938

Notes: Standard Errors Clustered at Tract Level. *p<.05 **p<.01 ***p<.001

¹During estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

²During estimation, interactions terms for Ecoregion 10.1, Ecoregion 10.2, WV, KS, and KY are fully absorbed by fixed effects and dropped from the model. Estimates for Ecoregion 9.3, Ecoregion 13.1, AZ, IN, and MD are not included because there are not enough observations in these states that have all the required property attributes.

³Interaction terms for MN and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

⁴The 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.

Table B4 Nation I Results for Broad Interaction Categories and Restricted Model

Parameter	Ecoregion Level 2			Ecoregions Level 1			restricted
	state ¹	division ²	region ³	state ⁴	division ⁵	region ⁶	
const	7.123***	7.117***	7.112***	7.122***	7.109***	7.099***	7.093***
Secchi ⁷	0.231***	0.228***	0.226***	0.231***	0.228***	0.215***	0.22***
Secchi * <150 m	0.025**	0.025**	0.025**	0.025**	0.025**	0.025**	0.025**
Secchi * Lake Distance	-0.034***	-0.034***	-0.033***	-0.034***	-0.033***	-0.033***	-0.034***
Secchi * Urban	-0.0150	-0.0140	-0.0140	-0.0150	-0.0130	-0.010	-0.0140
Secchi * Lake Area Demeaned ⁷	0.009*	0.0080	0.0080	0.009*	0.0080	0.0050	0.00
Secchi * Ecoregion 5.2	0.075*	0.078*	0.08*				
Secchi * Ecoregion 5.3	0.0430	0.0410	0.0410				
Secchi * Ecoregion 6.2	0.5940	0.3520	0.3460				
Secchi * Ecoregion 7.1	0.9910	0.5360	0.3070				
Secchi * Ecoregion 8.2	0.0570	0.0410	-0.0280				
Secchi * Ecoregion 8.3	0.0550	0.0250	0.0210				
Secchi * Ecoregion 8.4	-0.0170	-0.0540	-0.0710				
Secchi * Ecoregion 8.5	0.0260	0.0540	0.0510				
Secchi * Ecoregion 9.2	0.150	-0.0320	-0.0310				
Secchi * Ecoregion 9.3	0.2230	-0.0020	0.0170				
Secchi * Ecoregion 9.4	0.2030	-0.0360	0.0110				
Secchi * Ecoregion 10.1	0.3060	0.1610	0.1650				
Secchi * Ecoregion 10.2	0.6620	0.4680	0.2550				
Secchi * Ecoregion 11.1	0.3660	0.2280	0.2740				
Secchi * Ecoregion 13.1	0.0320	0.0610	0.0580				
Secchi * Ecoregion 15.4				0.0490	0.0410	0.0440	
Secchi * Ecoregion 5				0.1520	-0.0310	-0.020	
Secchi * Ecoregion 6				0.2560	0.1650	0.1390	
Secchi * Ecoregion 7				0.0060	0.0080	0.0180	
Secchi * Ecoregion 9				0.5440	0.3560	0.3110	
Secchi * Ecoregion 10				0.3160	0.2310	0.2360	
Secchi * Ecoregion 11				0.6120	0.4720	0.2320	
Secchi * Ecoregion 13				0.9410	0.5370	0.2670	
Secchi * Ecoregion 15	0.0030			0.0050			
Secchi * AL	0.1210			0.1040			
Secchi * AR	-0.3960			-0.3470			
Secchi * AZ	-0.7280			-0.6790			
Secchi * CA	-0.4980			-0.4480			
Secchi * CO	-0.266*			-0.269*			
Secchi * CT	-0.0860			-0.060			
Secchi * DE	-0.0190			0.0070			
Secchi * FL	0.0330			0.0870			
Secchi * GA	7.123***	7.117***	7.112***	7.122***	7.109***	7.099***	7.093***

Table B4 (2/3)

Parameter	Ecoregion Level 2			Ecoregions Level 1			restricted
	state ¹	division ²	region ³	state ⁴	division ⁵	region ⁶	
Secchi * IA	-0.221*			-0.224*			
Secchi * IL	-0.1070			-0.05*			
Secchi * IN	0.20			0.2410			
Secchi * KY	-1.956***			-1.902***			
Secchi * LA	0.0840			0.1220			
Secchi * MA	-0.0270			-0.0080			
Secchi * MD	-0.259**			-0.271***			
Secchi * ME	2.428***			2.422***			
Secchi * MI	-0.0680			-0.0550			
Secchi * MO	0.6730			0.6710			
Secchi * MT	-2.021***			-1.971***			
Secchi * NC	-0.1830			-0.140			
Secchi * ND	-0.2230			-0.1530			
Secchi * NE	-0.1790			-0.1770			
Secchi * NH	-0.0650			-0.0690			
Secchi * NJ	-0.0030			-0.0020			
Secchi * NY	-0.0740			-0.0690			
Secchi * OH	-0.1980			-0.1540			
Secchi * OK	-0.1240			-0.0810			
Secchi * OR	-0.8670			-0.8180			
Secchi * PA	0.154***			0.148***			
Secchi * RI	0.102*			0.102*			
Secchi * SC	-0.0530			0.0010			
Secchi * SD	-0.1270			-0.130			
Secchi * TN	-0.1130			-0.123**			
Secchi * TX	-0.3930			-0.3430			
Secchi * VA	-0.1340			-0.0820			
Secchi * VT	-0.0780			-0.0790			
Secchi * WA	-0.9890			-0.940			
Secchi * WI	-0.0330			0.0230			
Secchi * New England		-0.0520			-0.0280		
Secchi * Middle Atlantic		-0.0710			-0.0330		
Secchi * East North Central		-0.0430			-0.0370		
Secchi * East South Central		0.060			0.0530		
Secchi * West South Central		-0.2570			-0.2610		
Secchi * South Atlantic		-0.0680			-0.111*		
Secchi * Mountain		-0.0460			0.0050		
Secchi * Pacific		-0.5320			-0.5340		
Secchi * Northeast			-0.0470			-0.0240	
Secchi * South			-0.0420			0.0030	

Table B4 (3/3)

Parameter	Ecoregion Level 2			Ecoregions Level 1			restricted
	state ¹	division ²	region ³	state ⁴	division ⁵	region ⁶	
Secchi * West			-0.3020			-0.2590	
<150 m	0.124***	0.124***	0.124***	0.124***	0.124***	0.124***	0.124***
Lake Distance	-0.095***	-0.095***	-0.095***	-0.095***	-0.095***	-0.095***	-0.095***
Lake Area	0.013*	0.014*	0.014*	0.013*	0.013*	0.015**	0.017***
Median Income	0.131***	0.132***	0.131***	0.131***	0.132***	0.131***	0.131***
Slope	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
Elevation	-0.0230	-0.0230	-0.0230	-0.0230	-0.0220	-0.0220	-0.0230
Lot Size	0.101***	0.101***	0.101***	0.101***	0.101***	0.101***	0.1***
Building Age	-0.125***	-0.125***	-0.125***	-0.125***	-0.125***	-0.125***	-0.125***
Building Size	0.547***	0.547***	0.547***	0.547***	0.547***	0.547***	0.547***
Quarter 2	0.044***	0.044***	0.044***	0.044***	0.044***	0.044***	0.044***
Quarter 3	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
Quarter 4	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
Loglikelihood	-230,106	-230,150	-230,157	-230,111	-230,160	-230,190	-230,201
AIC	533,297	533,321	533,327	533,293	533,328	533,378	533,379

Notes: N = 485,860 Standard Errors Clustered at Tract Level. *p<.05 **p<.01 ***p<.001

¹State interaction terms is the baseline. Interaction terms for MN and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample. During estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

²Interaction terms for West North Central and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

³Interaction terms for Midwest and Ecoregion 8.1 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample.

⁴Interaction terms for MN and Ecoregion 8 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample. During estimation, interaction terms for KS, NM, WV, Ecoregion 10.1, 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.

⁵Interaction terms for West North Central and Ecoregion 8 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample. During estimation, the interaction term for Ecoregion 12 was fully absorbed by fixed effects and dropped from model. Observations for Ecoregion 12 all fall within Mountain.

⁶Interaction terms for Midwest and Ecoregion 8 were pre-selected as the excluded categories, because the area intersection contains the most observations in the sample. During estimation, the interaction term for Ecoregion 12 was fully absorbed by fixed effects and dropped from model. Observations for Ecoregion 12 all fall within West.

⁷The 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.

Sensitivity of Regional Median to Sample Parameters and Methods

In Figure B1 we consider the sensitivity of the regional medians to two sample selection parameters related to water quality: water quality summary measure and sample matching method. Note that we used minimum, mean, and maximum water quality measures. We find that estimates in the Midwest and South appear to be slightly sensitive to the summary measure, with the elasticities for minimum lower than those for mean or maximum. We also find the regions medians are very sensitive to the water quality sample and property sale matching method. In all regions except the Midwest, sales that were matched to samples only in the past—those matched for only the year prior to sale or to a sale in the past 5 years—tend to have higher elasticity estimates. However, there also appears to be much wider variation in elasticity estimates in the years, with more negative and positive outliers found. Matching using plus or minus five years or the most recent summer appear to have the most stable medians across all regions.

In Figure B2 we consider the sensitivity of the regional medians to three sample selection parameters related to property location: maximum distance to lake, lakefront buffer distance, and minimum sales in lakefront buffer. We see medians are slightly higher when using the maximum distance of 2,500 m over 1,000 m. In the Midwest, we also see slightly larger estimates when using the 150 m buffer over 300 m. We do not observe any sensitivity to the minimum requirement in the buffer.

In Figure B3 we consider the sensitivity of the regional medians to the functional forms of the model and the type of spatial fixed effect. We do not observe sensitivity in relation to the specification of Secchi in the model. We also do not observe sensitivity to the spatial unit of the fixed effect, likely because census tract and block groups are both fine scales. However, we do

find wider dispersion of medians in all regions when we interact sale year with the spatial fixed effect.

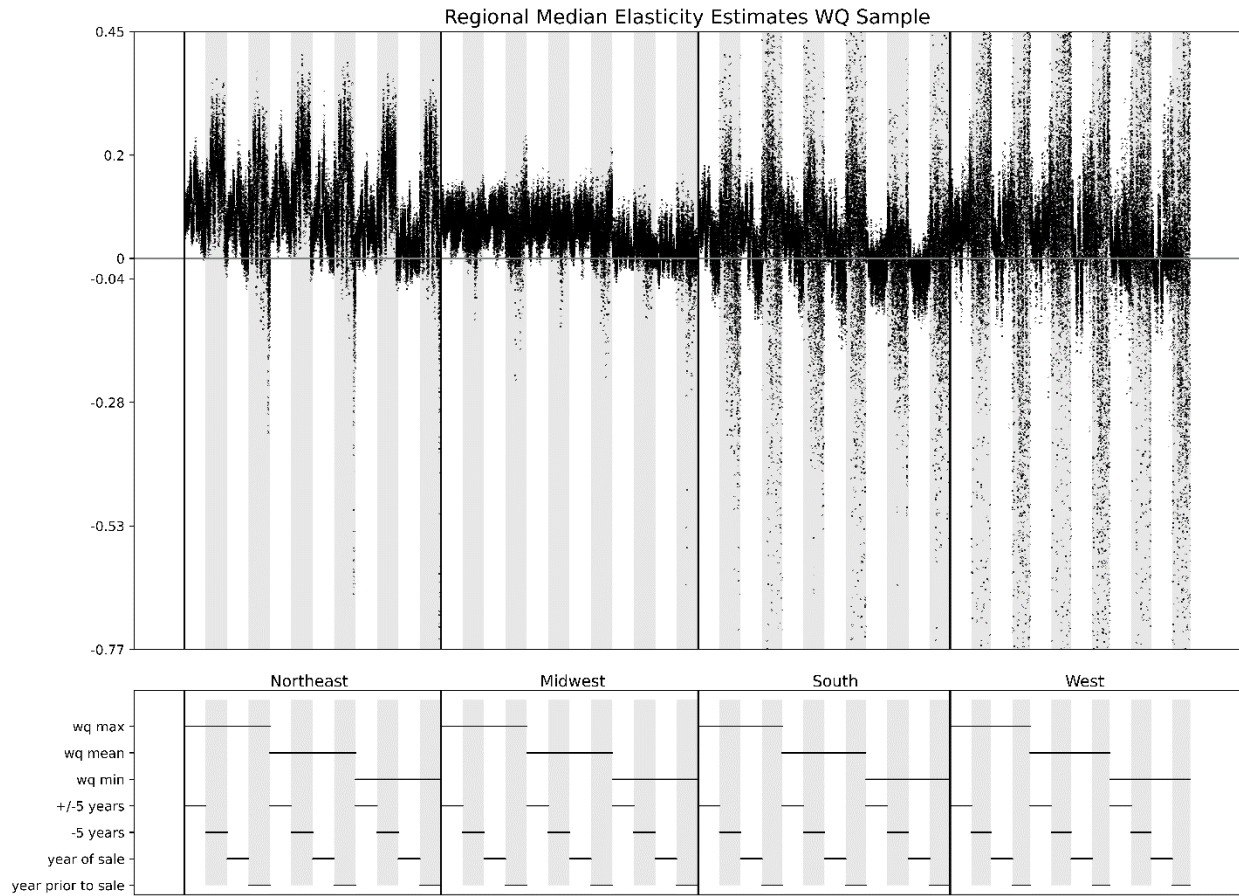


Figure B1 Regional Median Secchi Elasticity Estimates Sorted by Water Quality Sample Parameters

Notes: Census tract median estimates for properties within 150m from lakefront for all models are divided by region for unique combinations of spatial scale, sample selection, and model choice before computing regional median. Medians are sorted by region and water quality sample selection criteria. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

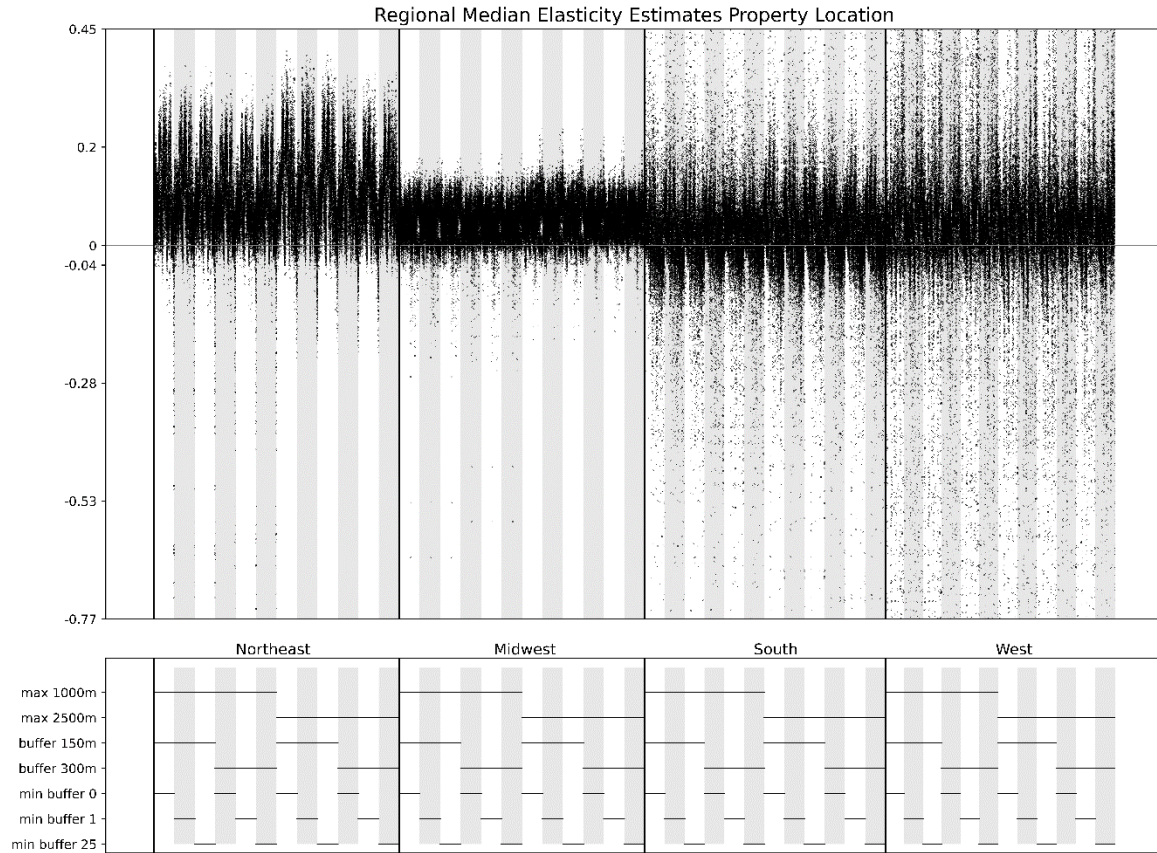


Figure B2 Regional Median Secchi Elasticity Estimates Sorted by Property Location Sample Parameters
Notes: Census tract median estimates for properties within 150m from lakefront for all models are divided by region for unique combinations of spatial scale, sample selection, and model choice before computing regional median. Medians are sorted by region and property location sample selection criteria. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

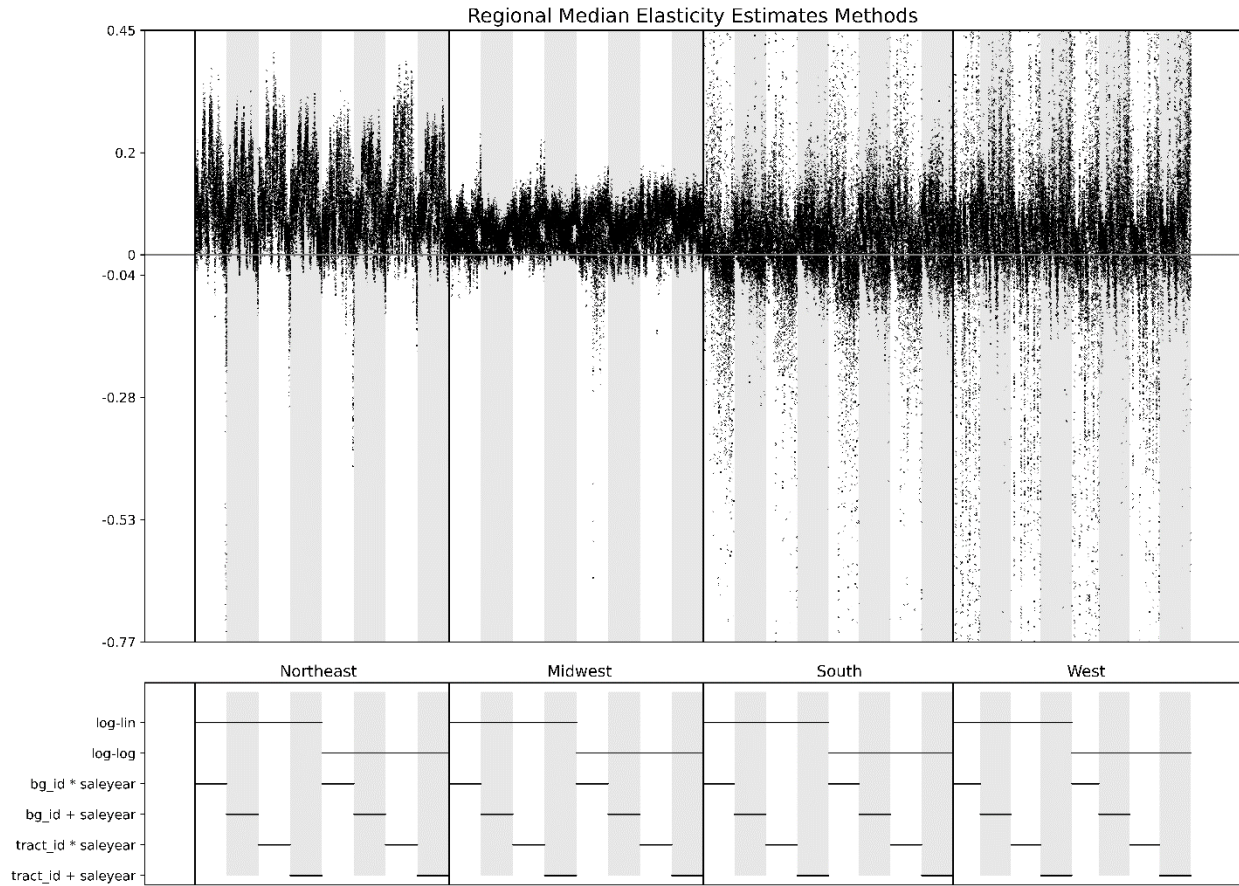


Figure B3 Regional Median Secchi Elasticity Estimates Sorted by Methods

Notes: Census tract median estimates for properties within 150m from lakefront for all models are divided by region for unique combinations of spatial scale, sample selection, and model choice before computing regional median. Medians are sorted by region and methodological choices. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

Appendix C Chl-a Results

We consider the effects of Chl-a as a secondary measure of water quality, related to the amount of algae present in a lake, which serves as a disamenity through unpleasant sights and smells. A high concentration of Chl-a can be attributed to excess nutrients in the lake and has been found to have a negative effect on property sale prices (Walsh and Milon 2016; Weng et al. 2020). However, there are fewer samples and less spatial coverage available for Chl-a.

In prior studies, CVs for Chl-a range from 0.66 to 1.23 for Substate areas in Florida and Minnesota, respectively (Walsh and Milon 2016; Swedberg et al. 2022). However, there were very few Substate markets in the baseline sample that met the minimum 1,000 sample size, so we selected a lower CV requirement of 0.50 for Chl-a.

Figure C1 summarizes the effects of the baseline models for chl-a using kernel density plots analogous to Figure 3 in the manuscript and Figure A2. As high levels of Chl-a are considered a disamenity, negative elasticity estimates are expected. In Figure C1a, we can see elasticities in the Northeast are larger in magnitude than those in the Midwest or the South for the Division I models. Even after dropping the 1st and 99th percentile, the distribution in the West is relatively flat. In Figure C1b, we find the distributions of elasticities in all regions are sensitive to spatial scale. We note there are no Substate estimates available in the West. Moving to the Class II models, in Figure C1c, we observe more heterogeneity within individual region for the Division II models with some positive effects in all regions except the Northeast. Figure C1d reveals more overlap in distributions across spatial scales compared to the Class I models.

Figure C2 provides more context to the distributions in C1. As with Secchi, we find differences across regions, spatial scales, and model classes. While the Northeast has consistently

negative elasticities, elasticities in the Midwest are both positive and negative. In Florida, counties with negative elasticities at Nation, Region, and Division spatial scales, have positive elasticities at State and Substate scales. In Washington Region I and Division I elasticities are positive for select counties. However, these counties are negative for all Class II models.

Figures C3 and C4, we assess the sensitivity of the Class I and Class II regional medians to spatial scale analogous to Figure 4 in the manuscript and Figure A3. Once again, we note wide variability in the regional medians in the West across all spatial scales. The size of the outliers is so large, especially for the Class I models, that it increased the range of the y-axis in Figure C3 to -1.71 to 0.59. For comparison, the range of C4 is -0.3 to 0.8. We surmise it is related to the interaction terms in Class I models and small sample sizes throughout the West. In Class II, areas with small sample sizes or too little variation are not modelled, and areas with enough samples and variation are pooled for a single estimate (i.e., no spatial heterogeneity interaction terms). In Class I, interaction terms may be overfitting the data leading to extreme outliers.

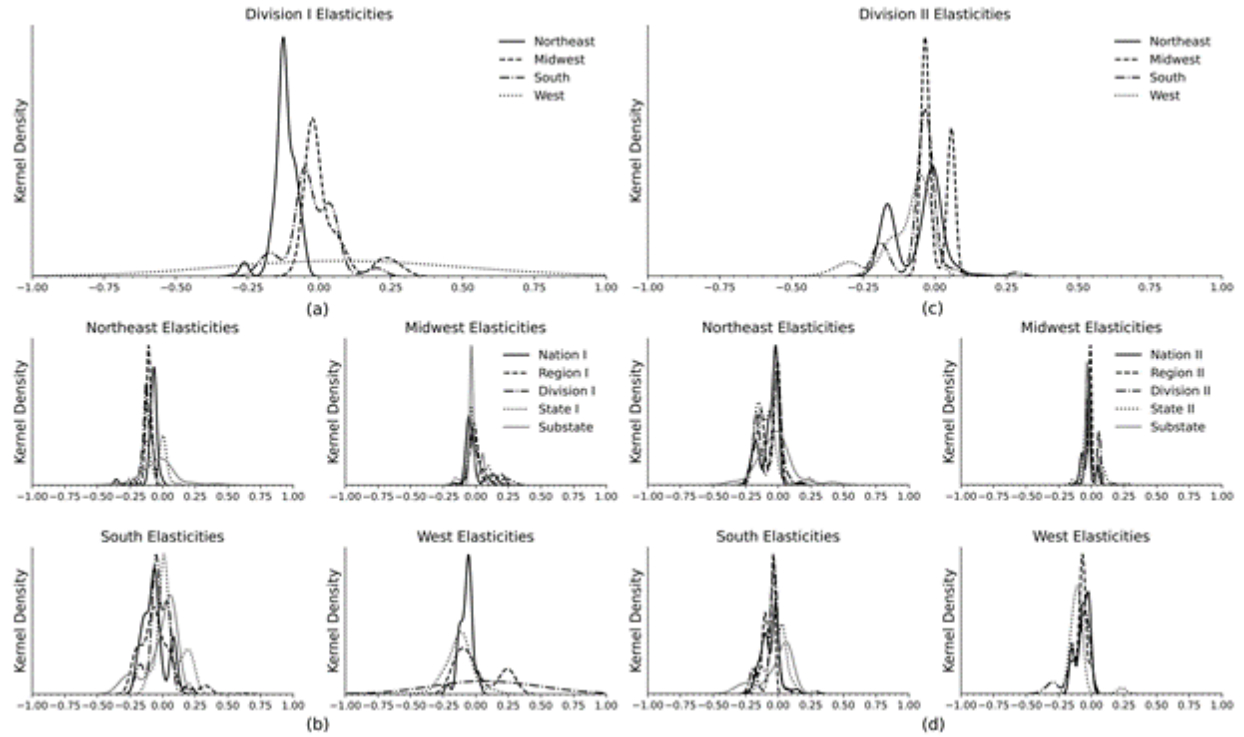


Figure C1 Distribution of Baseline Elasticity Estimates for Chl-a

Notes: Kernel density plots of elasticities of property value with respect to water quality by Region and market boundary definition. Median elasticity estimates at census tract level for properties within 150m from lakefront along x axis. Kernel density along y axis rescaled to 1 for each plot. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure. Panel (a) presents the Division I results in a single plot broken out by Region. Panel (b) presents the results for each Region in separate plots broken out by spatial scale for Class I models. Panel (c) presents the Division II results in a single plot broken out by Region. Panel (b) presents the results for each Region in separate plots broken out by spatial scale for Class II models.

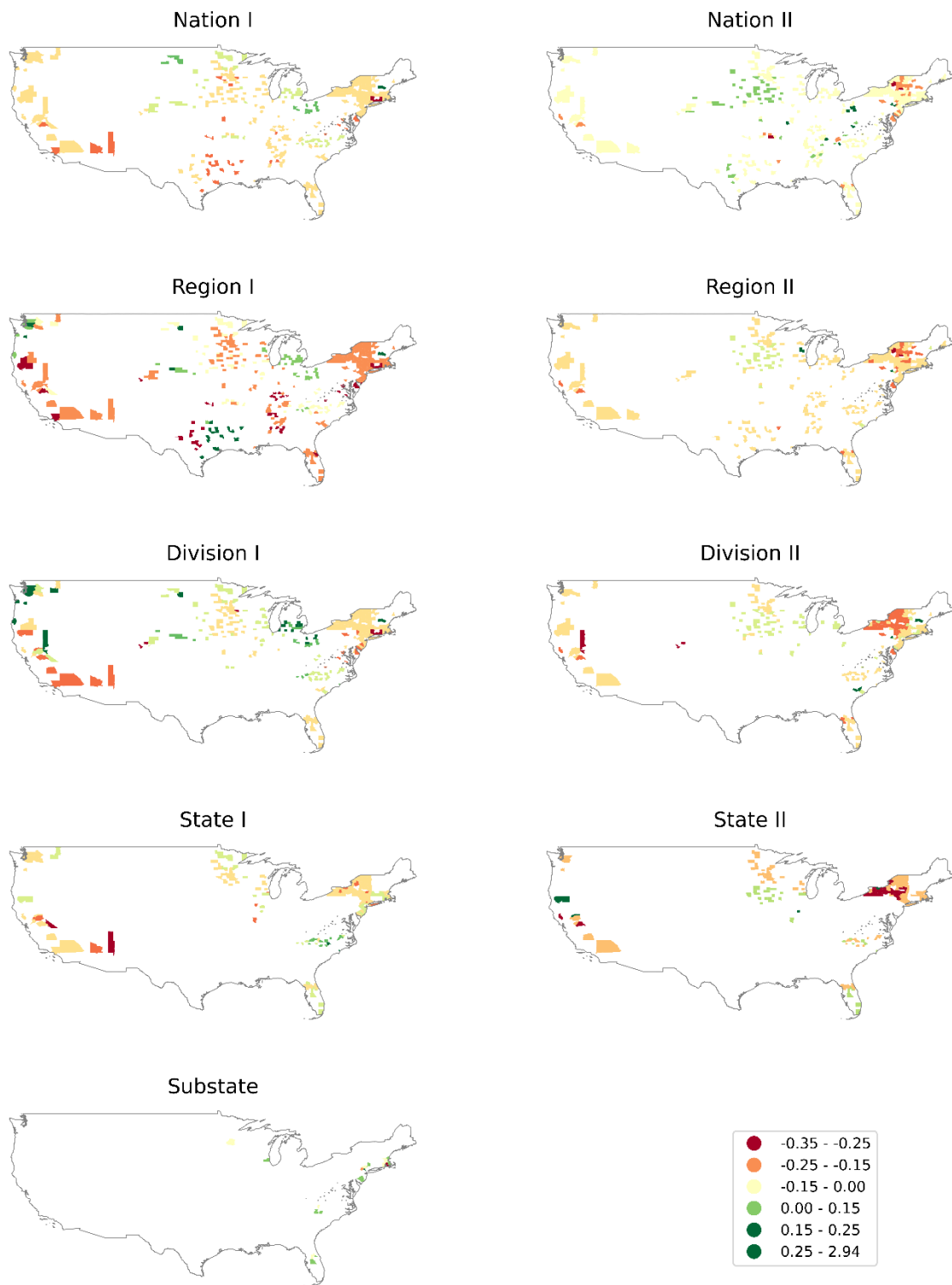


Figure C2 Spatial Distribution of Baseline Elasticity Estimates for Chl-a
Notes: Census tract median estimates for properties within 150m from lakefront are aggregated by county

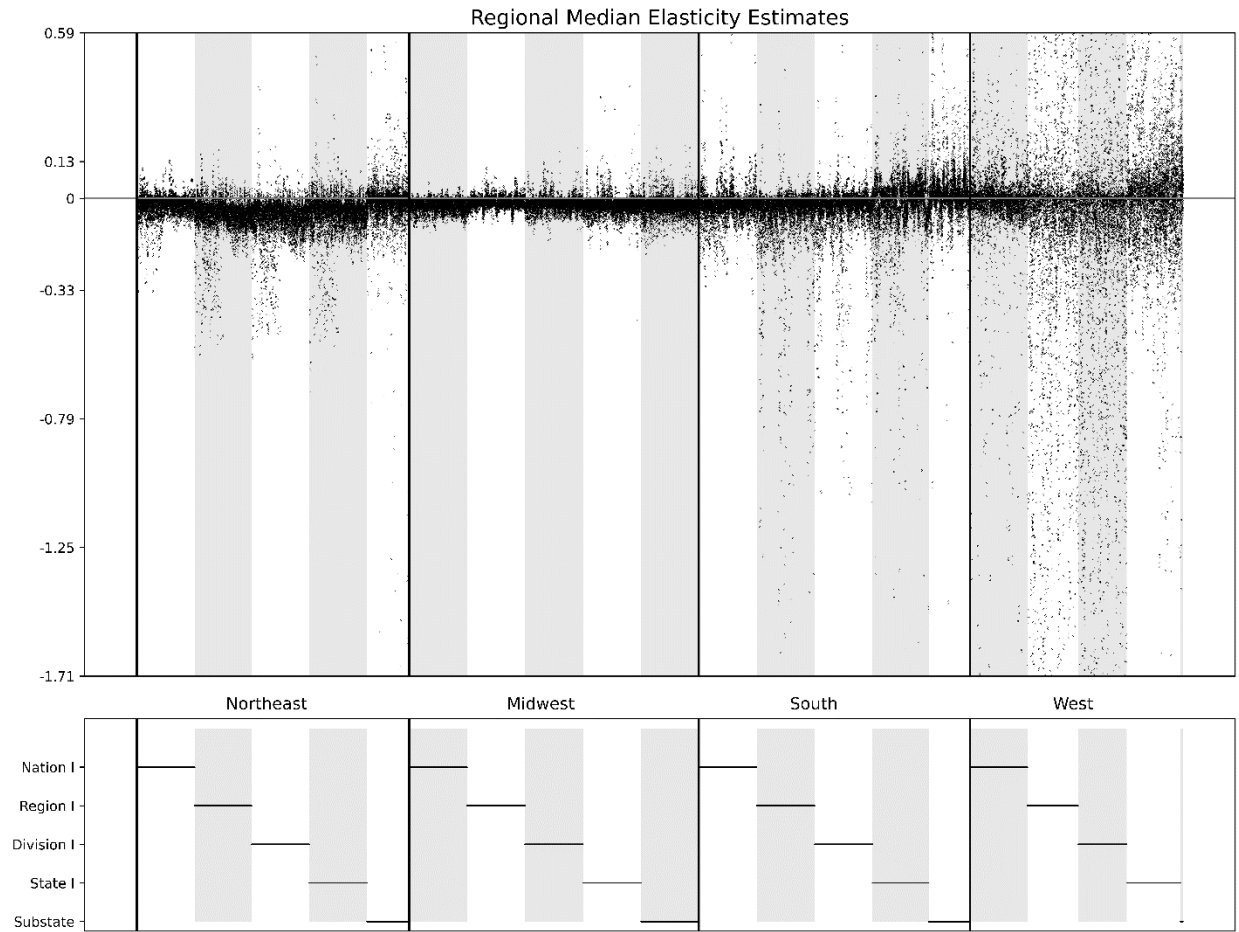


Figure C3 Regional Median Elasticity Estimates for All Chl-a Class I Models

Notes: Census tract median estimates for properties within 150m from lakefront for Class I models 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. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

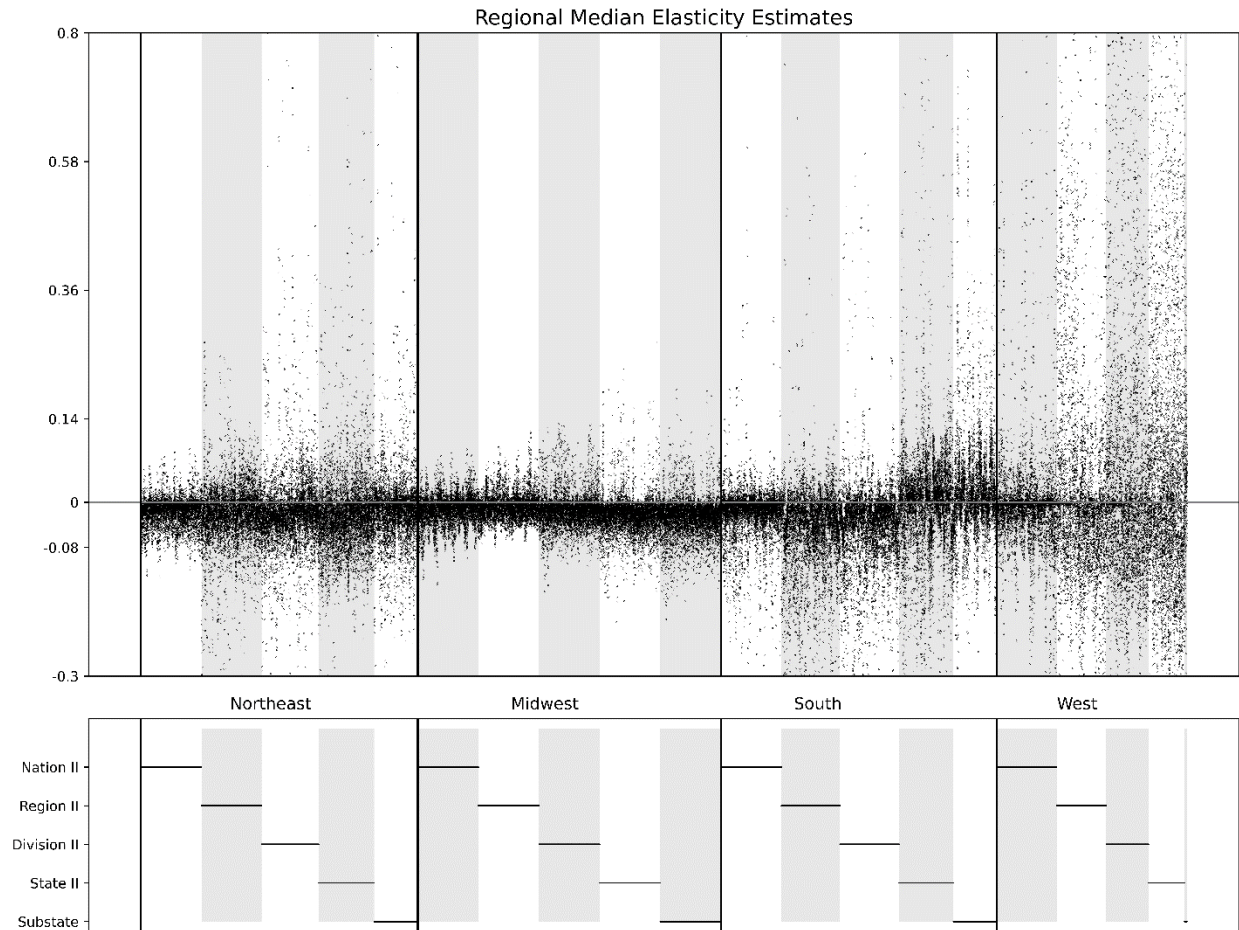


Figure C4 Regional Median Elasticity Estimates for All Chl-a Class II Models

Notes: Census tract median estimates for properties within 150m from lakefront for Class II models 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. Due to the relative magnitude of outliers, 1st and 99th percentiles are dropped from figure.

Appendix D Elasticity Formula Derivations

Elasticity Equation

$$\widehat{elast}_i = \frac{\partial P_{it}}{\partial WQ_{it}} \frac{WQ_{it}}{P_{it}} \quad [D1]$$

Log-log Model Specification

$$\begin{aligned} \ln(P_{it}) = & \beta_0 + \beta_1 \ln(WQ_{it}) + \beta_2 \ln(WQ_{it}) * LF_i + \beta_3 \ln(WQ_{it}) * \ln(Dist_i) \\ & + \beta_4 \ln(WQ_{it}) * \ln(Area_i - \overline{Area}) + \beta_5 \ln(WQ_{it}) * U_i + \beta_E \ln(WQ_{it}) * E_i \\ & + \beta_S \ln(WQ_{it}) * S_i + \beta_{Prop} Prop_i + \beta_{Control} Control_i + \gamma_{it} + \tau_{it} + \epsilon_{it} \end{aligned} \quad [D2]$$

Talking partial derivative

$$\begin{aligned} \frac{\partial P_{it}}{\partial WQ_{it}} = \\ \frac{P_{it}}{WQ_{it}} * (\hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 \ln(Area_i - \overline{Area}) + \hat{\beta}_5 U_i + \hat{\beta}_E E_i + \hat{\beta}_S S_i) \end{aligned} \quad [D3]$$

Rearranging

$$\begin{aligned} \hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 \ln(Area_i - \overline{Area}) + \hat{\beta}_5 U_i + \hat{\beta}_E E_i + \hat{\beta}_S S_i = \\ \frac{\partial P_{it}}{\partial WQ_{it}} \frac{WQ_{it}}{P_{it}} \end{aligned} \quad [D4]$$

Thus

$$\frac{\partial \ln(P_{it})}{\partial \ln(WQ_{it})} = elast_i \quad [D5]$$

Log-linear Model Specification

$$\begin{aligned}
 \ln(P_{it}) = & \beta_0 + \beta_1 WQ_{it} + \beta_2 WQ_{it} * LF_i + \beta_3 WQ_{it} * \ln(Dist_i) \\
 & + \beta_4 WQ_{it} * \ln(Area_i - \overline{Area}) + \beta_{Prop} \mathbf{Prop}_i + \beta_{Control} \mathbf{Control}_i \\
 & + \gamma_t + \tau_{it} + \epsilon_{it}
 \end{aligned} \tag{D6}$$

Taking partial derivative

$$\begin{aligned}
 \frac{\partial P_{it}}{\partial WQ_{it}} = \\
 P * (\hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 \ln(Area_i - \overline{Area}) + \hat{\beta}_5 U_i + \hat{\beta}_E E_i + \hat{\beta}_S S_i)
 \end{aligned} \tag{D7}$$

Rearranging and multiplying by WQ_{it}

$$\begin{aligned}
 WQ_{it} * (\hat{\beta}_1 + \hat{\beta}_2 * LF_i + \hat{\beta}_3 \ln(Dist_i) + \hat{\beta}_4 \ln(Area_i - \overline{Area}) + \hat{\beta}_5 U_i + \hat{\beta}_E E_i + \hat{\beta}_S S_i) = \\
 \frac{\partial P_{it}}{\partial WQ_{it}} \frac{WQ_{it}}{P_{it}}
 \end{aligned} \tag{D8}$$

Thus

$$\frac{\partial \ln(P_{it})}{\partial WQ_{it}} * WQ_{it} = elast_i \tag{D9}$$

Appendix E ZTRAX Cleaning Decisions

As described in the manuscript, Zillow's ZTRAX database was made available through PLACES lab at Boston University (Zillow 2021). First, property sales were linked to property boundary polygons by PLACES, and those proximate to NHD lakes larger than 4 ha and met the medium-confidence transaction sale filter described in (Nolte et al. 2023) were selected. This filter varies by state and includes a range of different filter categories, such as document type, sale code, and intra-family transfers. This data was further filtered by state, such that if more than 67% of sales in a state met the high-confidence filter, only high-confidence sales were included. For the remaining states, medium and high confidence sales were selected.

We then merge the sales with the water quality data, keeping only those observations with a Secchi of chl-a sample on a lake within 2,500 m from the property within 5 years from the closest summer to the year of sale. After adjusting sales prices to 2021 \$, we further exclude sale prices less than \$10,000 (Gindelsky, Moutlton, and Wentland 2022) and remove the top 1% of sale prices in each State (Chun et al. 2021). To handle the missing property attributes problem, we consider a range of different sample selection criteria documented in Table 1 in the manuscript. For one sample, we do not include any property attributes and only perform additional data refinement related to water quality, (e.g. must meet a minimum number of sales within the lakefront property buffer). Samples that did not meet these criteria were dropped.

For samples with property attributes included, we cleaned the sample based on the selected attribute first removing all nonsensical values, such as negatives and zero values. We then identify outlier values in the 99th percentile. For continuous property attributes, we also define the 1st percentile as outliers. Then all outliers are removed from the sample. Finally, we keep only properties classified as residential, single-family houses (RR000, RR101, RR102, RR999).

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Evaluating the Spatial Extent of Direct and Indirect Coastal Water Quality Capitalization in Hedonic Property Sales Models

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1. Introduction

While coastal counties make up less than 10% of total land in the contiguous United States, they are home to almost 40% of the U.S. population (National Oceanic and Atmospheric Administration, 2023). Households living near the coast value coastal water quality for recreational activities like swimming, boating, and fishing. However, this preference for proximity to coastal waters results in dense coastal development and urbanization that can lead to water quality impairments. For example, in New England, wastewater discharges, failed septic systems, and stormwater runoff all carry pollutants, such as bacteria and nutrients, to coastal waters. High concentrations of these pollutants in the water result in beach closures, shellfish contamination, algal blooms, and fish kills (Cape Cod Commission, 2015; Narragansett Bay Estuary Program, 2017). For those visiting or living near the coast, water quality impairments have a demonstrated impact on their enjoyment of recreational opportunities (Merrill et al., 2024), health outcomes (Richards, 2016) and property values (Liu et al., 2017). State governments in New England have spent billions of dollars in the last fifty years, with more planned, to upgrade wastewater and stormwater infrastructure in the region resulting in considerable improvements to coastal water

quality (Massachusetts Water Resources Authority, 2014; Narragansett Bay Commission, 2018). Measuring the potential economic benefits to recreation and the housing market from intended environmental improvements permits comparison to the more salient fiscal cost of large public infrastructure investments.

Economic studies typically evaluate the benefits of improved water quality to recreation and the housing market separately. Recreation demand models relate travel costs of site visitation to environmental conditions and site characteristics (Lupi et al., 2020). For decades researchers have applied these models to freshwater and saltwater resources (Bockstael et al., 1987; Parsons et al., 2009; Phaneuf, 2002). Recently, Merrill et al. (2024) used a travel cost model to evaluate the recreational benefits of improvements in bacterial and water clarity conditions at a set of coastal sites in Southern New England. While this study showed recreators' willingness to pay for improvements in both water quality measures were significant, it did not evaluate how housing markets proximal to the sites capitalize the benefits of the improved water quality.

Property sale models help to understand the capitalization of benefits into housing markets. There is extensive literature on property sale models that relate the local aquatic resource ambient water quality measures to the property sale price. Much of this literature focuses on water clarity in freshwater lakes with fewer studies considering rivers or estuaries (Guignet et al., 2022; Nicholls & Crompton, 2018). In addition to clarity, researchers have estimated property elasticities for a range of other ambient measures, including chlorophyll-a and pathogens (Kung et al., 2022; Liu et al., 2017).²⁷ A key limitation of the existing hedonic literature for water quality is in understanding the spatial extent of benefits. In a meta-analysis of hedonic water quality studies,

²⁷ Other hedonic studies evaluate events, such as harmful algal blooms (HABs), rather than ambient water quality (Zhang et al., 2022).

Guignet et al. (2022) report more than half of water clarity elasticity observations are for waterfront properties, and the remaining observations are within 0.5 km of the waterfront. Prior hedonic studies that considered benefits for properties beyond 0.5 km from the waterfront found estimated effects diminish rapidly beyond the waterfront (Mamun et al., 2022; P. J. Walsh et al., 2011) and are insignificant beyond 1 km (Klemick et al., 2018). However, homeowners may drive long distances, more than 150 km, for a recreational day trip (English et al., 2018; Mazzotta et al., 2022). This suggests hedonic models for ambient water quality do not capture attributes of recreation, as it is reasonable housing markets would capitalize the availability and quality of recreational resources near properties into the value of homes much further from the waterfront.

There is emerging empirical evidence that demonstrates property sales prices reflect the quality of resources at surrounding recreation sites. Phaneuf et al. (2008) introduced a theoretical framework combining a recreational index estimated from a recreation demand model for lake recreation with a hedonic property price model.²⁸ The results of their integrated model showed housing markets in Wake County, NC, capitalize lake water quality in sale prices indirectly through the recreational index. The use of this model also expanded the beneficiaries of water quality improvements beyond households immediately adjacent to lakes to households throughout the entire county. Wan (2021) builds on this approach by combining multiple ambient water quality parameters directly in the hedonic model with the recreational index for lakes in Iowa. Kuwayama et al. (2022) further expand on this work by integrating a coastal recreation demand model for fishing trips with the hedonic model to estimate benefits from improvements in dissolved oxygen conditions in three counties near Tampa Bay, FL. Focused on a single metro

²⁸ Phaneuf et al. (2008) suggest that the index represents water recreation opportunities from a given neighborhood and measured as the expected benefits from the given neighborhood.

area, they find indirect capitalized benefits of coastal recreation on the bay consistently larger than the ambient water quality directly included in the hedonics model.

Given the number of homeowners that live on the coast, it is important to understand how housing markets capitalize coastal recreation. Yet, as recreators potentially drive far distances to reach coastal sites, a natural extension is to explore the appropriate spatial extent of the integrated models more explicitly. This research can inform future studies on the impacts of coastal water quality on housing markets. More broadly, this work presents a model for identifying the housing market capitalization of a wide range of environmental amenities at recreation sites, which can be specified to include other local amenities.

In this study, we estimate direct effects of freshwater and coastal water quality on property sales in Southern New England as well as the indirect effects of water quality through coastal recreation. We capture the indirect effects by integrating a recreation index into the hedonic model using a travel demand model fit to a 2018 regional household survey on coastal recreation throughout Southern New England (Merrill et al., 2024). The survey data are paired with remotely sensed water clarity data from Landsat 8, *in situ* bacterial conditions along the coast from the Water Quality Portal, and shoreline boundaries from NOAA. We specify the direct effects in our hedonic model by averaging local water quality across buffers ranging from 500 m to 8,000 m from the parcel centroids. We evaluate three separate types of local water quality: freshwater clarity, saltwater clarity, and bacteria levels on the shoreline. Property sales and parcels data for Massachusetts and Rhode Island are provided by MassGIS and LightBox respectively.

Our results show heterogeneous effects of freshwater and saltwater clarity on housing market. Saltwater estimates are consistently larger than freshwater, and the spatial extent of saltwater exceeds that of freshwater. Property prices are also impacted by coastal water quality

through bacteria samples on nearby shorelines up to 2 km away. We do not find significant effects of year-to-year variation in water quality at coastal recreational sites on home prices, and we demonstrate how these results conflating spatial and temporal variation in the hedonic model confound integrated model results.

2. Theoretical Model

The theoretical model developed by Phaneuf et al. (2008) and adapted by Kuwayama et al. (2022) includes both long-run and short-run household decision-making. Long-run, homebuyers consider property characteristics and amenities near the property, including local water quality and recreational amenities. Short-run, after buying a home, a household allocates its remaining budget to a wide range of goods and services. These include visits to recreational sites where the optimal number of household trips depends on water quality at each site and the associated travel costs. The long-run choice of property location impacts the distance to recreational amenities and therefore the short-run decision about the number of recreational trips to make. The result is that the expected recreational benefits of the nearby amenities factor into the home buying decision.

Starting with the short-run decision, the household maximizes utility (U) for recreation (x) and other goods (z) conditional on household income after housing expenditures (m):

$$\max_{x,z} U(x(\mathbf{Q}), z | h(\mathbf{a}, \mathbf{q})) \quad s.t. \quad m = p_x x(\mathbf{Q}) + z \quad (1)$$

where $x(\mathbf{Q})$ is the number of trips to a recreation site with water quality represented as a vector of attributes $\mathbf{Q}$, z is a numeraire good with a price of one, $h(\mathbf{a}, \mathbf{q})$ is the quasi-fixed value of housing services from vectors of property attributes $\mathbf{a}$ and nearby water quality attributes $\mathbf{q}$, and

p_x is the price of each trip. Solving this maximization problem leads to the following indirect utility function:

$$V = V(p_x, m, \mathbf{Q}, \mathbf{q}, \epsilon) \quad (2)$$

where ϵ reflects household-level heterogeneity.

If water quality improves at recreation sites from $\mathbf{Q}_0$ to $\mathbf{Q}_1$, compensating surplus (CS), or the income a household would trade for the water quality improvement, would be represented by:

$$V(p_x, m, \mathbf{Q}_0, \mathbf{q}) = V(p_x, m - CS(m), \mathbf{Q}_1, \mathbf{q}) \quad (3)$$

We can estimate the expected value of $CS(\mathbf{Q}, \epsilon)$ from a recreation demand model, specific to each home's location as it relates to the recreational sites. Following Phaneuf et al. (2008) and Kuwayama et al. (2022), we call this expected compensating surplus ECS or the recreational index for that home location.

Moving to the long-run household maximization problem, households choose from a range of property locations where the recreational index ($ECS(\mathbf{Q})$) is now capitalized into home prices given the property's location and water quality at the recreational sites.

$$\max_{\mathbf{a}, \mathbf{q}} U(ECS(\mathbf{Q}), h(\mathbf{a}, \mathbf{q}), z) \quad s. t. \quad m = p_h(\mathbf{a}, \mathbf{q}, ECS(\mathbf{Q})) + p_x \tilde{x} + z \quad (4)$$

where p_h is the price of the property and $\tilde{x}$ is the optimal number of recreational trips. Essentially, we are seeking to estimate a function for p_h empirically in the hedonic model using our sample of home transactions. This specification allows us to test whether housing prices capitalize water quality indirectly through ECS or directly through ambient measures. In the following section, we detail the recreation demand model and the derivation of the recreational index term. Then we

describe the hedonic methods and the empirical model we use to evaluate the spatial extent for both direct and indirect water quality effects.

3. Recreation Demand Model

The recreation demand model we use for this study was first presented in a forthcoming paper by Merrill et al. (2024). In the following sections, we summarize the data and preferred model from the working paper and explain how we derived the recreational index from the results.

3.1 RUM Data and Specification

Merrill et al. (2024) defined a random utility model (RUM) for coastal recreation day trips in New England using a 2018 mail survey of New England households described in Mazzotta et al. (2022).²⁹ The choice set included over 7,000 coastal shoreline segments using NOAA's Ecosystem Sensitivity Index shoreline data combined with locations for swimming beaches from EPA's BEACON program.^{30,31} Each site was matched with ambient water clarity and bacteria data for the summer months (June-September) averaged over five years (2014-2019). We applied a quasi-analytic algorithm (Lee et al., 2016) to Landsat 8 data within a 0.4 km buffer of each shoreline segment to derive clarity values. We assigned bacteria values using enterococci measurements in water segments along the shoreline from the Water Quality Portal (WQP).³²

The Merrill et al. (2024) preferred RUM is specified with the following logit discrete choice model:

²⁹ Details about RUM inputs are provided in Appendix A.

³⁰ NOAA Ecosystem Sensitivity Index data available at <https://response.restoration.noaa.gov/resources/environmental-sensitivity-index-esi-maps>.

³¹ EPA's BEACON data available at <https://www.epa.gov/waterdata/beacon-20-beach-advisory-and-closing-online-notification>.

³² WQP data available at <https://www.waterqualitydata.us/>.

$$\text{logit}(pr_{nk}) = \alpha T_{nk} + A_k \zeta \quad (5)$$

where $\text{logit}(pr_{nk})$ is the log-odds of respondent n choosing site k , α is the travel cost coefficient, interpreted as the marginal utility of travel cost T_{nk} , ζ is a vector of coefficients for site attributes A_k .³³

3.2 Predicting ECS

A fundamental assumption for this analysis is that spatial variation in water quality between sites in the RUM can be equated to temporal variation in water quality at an individual site. This assumption is necessary because the 2018 survey data are cross-sectional (Merrill et al., 2022; Mazzotta et al., 2022) which differs from more narrowly designed surveys that are repeated over multiple years, like NOAA Fisheries' Marine Recreational Information Program. Under this assumption, we recreate the Merrill et al. (2024) choice set and input new temporally varying water quality data into the estimated RUM to predict a recreational index for each census tract and corresponding year of property sales.

Annual water clarity for the recreational sites was derived from estimates of Secchi depth from Landsat 8 and a quasi-analytical algorithm (Lee et al., 2016) for each summer from 2014 to 2019 using Google Earth Engine (Gorelick et al., 2017). This resulted in a 30-m resolution clarity raster across the study area for each year. Shoreline segments were assigned clarity values by averaging the Secchi depth raster data within a 0.4 km buffer of the segment. Bacterial conditions were created for each shoreline segment based on averaging summer enterococci numbers of colony-forming units (CFUs) from the WQP for each year within the nearby coastal water segments. Each shoreline segment abutting a water segment was assigned the same bacteria value.

³³ Model outputs are available in Appendix A.

We calculated travel times and distances from the centroid of each census tract j from the 2020 Census in the study area to each site in the RUM choice set, through a road network using the Open-Source Routing Machine (Luxen & Vetter, 2011). We then calculated the associated travel costs using the following equation:

$$T_{jk} = 2 * \left[\frac{(g * km_{jk})}{adults} + \left(\frac{1}{3} * \frac{income_j}{2080} * hours_{jk} \right) \right] \quad (6)$$

where T_{jk} is the round-trip travel cost of choosing site k for census tract j ; g is the fuel cost and depreciation, approximated at 17¢ per km; km_{jk} is the one-way travel distance in km; $hours_{jk}$ is the one-way travel time in hours; $income_j$ is the mean annual household income from the 2015 ACS in USD, which we divide by 2,080 (the standard number of work hours in a year); and $adults$ is number of adults on trip, which we set at the average from the survey sample of 2.4.³⁴

Using these new data inputs and RUM regression coefficients, we predict temporally varying indirect utilities for each site k , census tract j , and year t :

$$\hat{V}_{jkt} = \hat{\alpha} T_{jk} + \mathbf{A}_{kt} \hat{\boldsymbol{\zeta}} \quad (7)$$

where $\hat{V}_{jkt}$ represents the observable element of utility and $\mathbf{A}_{kt}$ now includes temporally varying water quality. The expected per trip utility for census tract j and year t is then:

$$EV_{jt} = \ln \left[\sum_{k=1}^K e^{\hat{V}_{jkt}} \right] + C \quad (8)$$

³⁴We calculated the per mile costs as a combination of gas costs, depreciation and maintenance, following English (2018). Gas and maintenance costs per mile came from AAA (2018). We took the difference between the total annual depreciation cost reported at 5,000 miles above and below a baseline of 15,000 mile average annual miles driven. We divided this difference by 10,000 miles to generate a marginal depreciation expense per mile driven.

where C is a constant unobserved element of utility. We then divide the expected per trip utility by the marginal utility of the cost of the trip to calculate the average per trip consumer surplus:

$$\mathbb{E}(CS)_{jt} = \frac{EV_{jt}}{-\alpha} \quad (9)$$

When differencing across census tracts or years, C from equation 8 drops out and $\Delta\mathbb{E}(CS)_{jt}$ can be expressed in monetary units. Because we define $\mathbb{E}(CS)_{jt}$ at the census tract level rather than the individual household level, it serves as an aggregate index representative of potential recreational benefits in the tract. In the remainder of the text, we refer to $\mathbb{E}(CS)_{jt}$ as ECS or the recreational index.³⁵ We can interpret ECS as a neighborhood amenity that varies spatially by proximity to coastal recreation and other attributes of recreation sites. ECS will be larger for properties nearest to the coast and decay with distance. Within a census tract, ECS varies temporally due to changes in water quality over time, with the water quality at proximate recreation sites having more influence than those further away.

4. Property Sales Analysis

In the following sections, we describe the additional data used in the hedonic property sale models and how we identified spatial extents for direct and indirect measure of water quality. We further discuss how we calculate the total capitalization effects for different water quality improvement scenarios.

³⁵ In Phaneuf et al. (2008) theoretical model, $\mathbb{E}(CS)$ is derived for an individual household. ECS is calculated in the subsequent step by averaging the $\mathbb{E}(CS)$ across all person trips in the market area of interest.

4.1 Property Data

We obtained property data from two different sources. The Massachusetts Bureau of Geographic Information (MassGIS) provided historical parcel data for the relevant study years that included most recent sales and assessment data.³⁶ Further parcel, sales, and assessment data for Rhode Island were purchased from LightBox Holdings, L.P. We first cleaned the property data at the state level, identifying single-family residential sales and removing property sales with prices less than \$10,000 and more than the 99th percentile as in Swedberg et al. (2023). Then we adjusted the sales price to 2022 using state level quarterly not seasonally adjusted House Price Index (HPI) from the Federal Reserve Economic Data (FRED).³⁷ We further removed sales with lot sizes below 5,000 sq ft, building areas less than 120 sq ft, and less than 1 room.^{38,39} We also removed observations with property attributes that exceed the 99th percentile.

For each sale, we identified the parcel centroid and calculated distances to relevant features. To calculate distance to freshwater, we used the USGS National Hydrography Database (NHD) Waterbody layer and selected all lakes and rivers with area greater than 1 ha.⁴⁰ We obtained airport and town hall locations from MassGIS for Massachusetts and RIGIS for Rhode Island.⁴¹ We use

³⁶ Bureau of Geographic Information (MassGIS), Commonwealth of Massachusetts, Executive Office of Technology and Security Services. For property sales, we used the 'Assess' and 'Taxpar' layers for all towns and tax years within 'AllParcelData_FGDB_20220810.zip'. For capitalization, we used the most recent tax parcels in 'L3_TAXPAR_POLY_ASSESS_EAST.shp' and 'L3_TAXPAR_POLY_ASSESS_WEST.shp' (August, 2022).

³⁷ Federal Reserve Economic Data (FRED), Economic Research Division, Federal Reserve Bank of St. Louis. <https://fred.stlouisfed.org>

³⁸ The largest frequency of sales comes from Worcester, MA, which zoning requirements list a minimum 5,000 sqft lot size for RG-5 <https://www.worcesterma.gov/uploads/9e/b6/9eb6a548500c0ae454906c4220d2e04f/zoning-ord.pdf>. Similarly, Providence, RI also requires minimum of 5,000 sqft for R1 properties <https://www.providenceri.gov/wp-content/uploads/2023/01/22.12.21-Zoning-Ordinance.pdf>.

³⁹ The minimum building area threshold was selected using International Property Maintenance Code section 404.4 available at <https://codes.iccsafe.org/content/IPMC2021P1>.

⁴⁰ USGS National Hydrography Database <https://www.usgs.gov/national-hydrography/national-hydrography-dataset>

⁴¹ RIGIS data obtained from <https://www.rigis.org>

TIGER/Line primary roads data and US rails data from 2014 to represent highways and railroads.⁴² We further include American Community Survey (ACS) block group level estimates for each year of sale to represent different neighborhood attributes.⁴³ Proportions are calculated by dividing the ACS count estimates by the total population estimate. Nonseasonal vacancies are calculated by subtracting the estimates for seasonal vacancies from the estimates of total vacancies.

Table 1 presents descriptive statistics for all property variables used in the hedonic analysis. The average sale price for the sample is \$597,964. Some properties in Boston and Nantucket have very high sale prices with the maximum over \$3 million. Most of the urban centers throughout the study area are in Rhode Island and Eastern Massachusetts with relatively few properties in the western part of the state. Accordingly, the mean distance to saltwater is 24 km with the furthest property 158 km from the coast. Many properties are also located near freshwater with the mean distance less than 1 km.

⁴² TIGER/Line shapefiles available at <https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html>

⁴³ An API was used to extract block group level features for study area and year. More information on ACS and direct data downloads available at <https://www.census.gov/programs-surveys/acs/data.html>

Table 1 Descriptive Statistics

Variable	count	mean	std	min	max
Property Attributes					
Sale Price (2022\$)	264679	597964	389086	13368	3314333
Lot Size (acres)	264679	0.7	0.89	0.11	7.93
Building Area (sq ft)	264679	2573	1406	144	8491
Building Age (years)	264679	56.94	35.56	1	220
Rooms	264679	6.8	2.53	1	50
Distance to Saltwater (m)	264679	23687	29944	0	157815
Distance to Freshwater (m)	264679	892	652	0	7910
Distance to Airport (m)	264679	8263	4197	31.33	28889
Distance to Highway (m)	264679	8547	11080	18.22	83412
Distance to Railroad (m)	264679	2497	3239	0.31	50728
Distance to Townhall (m)	264679	2884	1670	31.74	13422
Total Population	264679	1668	747	31	6270
Median Income (ACS \$)	264679	96278	39105	2499	250001
Proportion Black	264679	0.04	0.06	0	0.92
Proportion Bachelor's Deg	264679	0.18	0.07	0	0.61
Median Age (years)	264679	44.49	7.5	13.7	86.2
Seasonal Vacancies	264679	43.94	158	0	2255
Nonseasonal Vacancies	264679	30.14	36.44	0	314
Water Quality					
Bacteria 500 (cfu/mpn)	6660	24.97	42.52	0.00	435
Bacteria 1000 (cfu/mpn)	15529	26.44	41.06	0.00	435
Bacteria 2000 (cfu/mpn)	30183	30.49	45.25	0.00	437
Bacteria 4000 (cfu/mpn)	52733	36.32	50.88	0.00	437
Bacteria 8000 (cfu/mpn)	79455	40.21	50.89	0.00	440
Fresh 500 (m)	66355	1.26	0.56	0.00	3.2
Fresh 1000 (m)	142206	1.25	0.54	0.01	3.2
Fresh 2000 (m)	231149	1.27	0.51	0.00	3.2
Fresh 4000 (m)	262208	1.34	0.45	0.01	3.2
Fresh 8000 (m)	264007	1.4	0.39	0.22	3.2
Salt 500 (m)	24996	1.17	0.41	0.23	2.57
Salt 1000 (m)	42565	1.15	0.41	0.19	2.57
Salt 2000 (m)	63368	1.15	0.4	0.23	2.57
Salt 4000 (m)	85327	1.17	0.39	0.24	2.57
Salt 8000 (m)	116992	1.2	0.37	0.24	2.57

4.2 Water Quality Data

The hedonic model includes water quality attributes in multiple ways to assess both the direct effects of water quality improvements near a home and the indirect effects of water quality improvements through coastal recreation (Figure 1). We represent the freshwater clarity, saltwater clarity, and saltwater bacteria directly in the model using the average measurement within a circular buffer around each parcel centroid for a given year. The distance buffers range from 0.5 km to 8 km. Considering freshwater and saltwater clarity separately allows homebuyers to have heterogenous preferences relating to the type of waterbody.⁴⁴ Saltwater clarity and bacteria also enter the model indirectly through ECS.

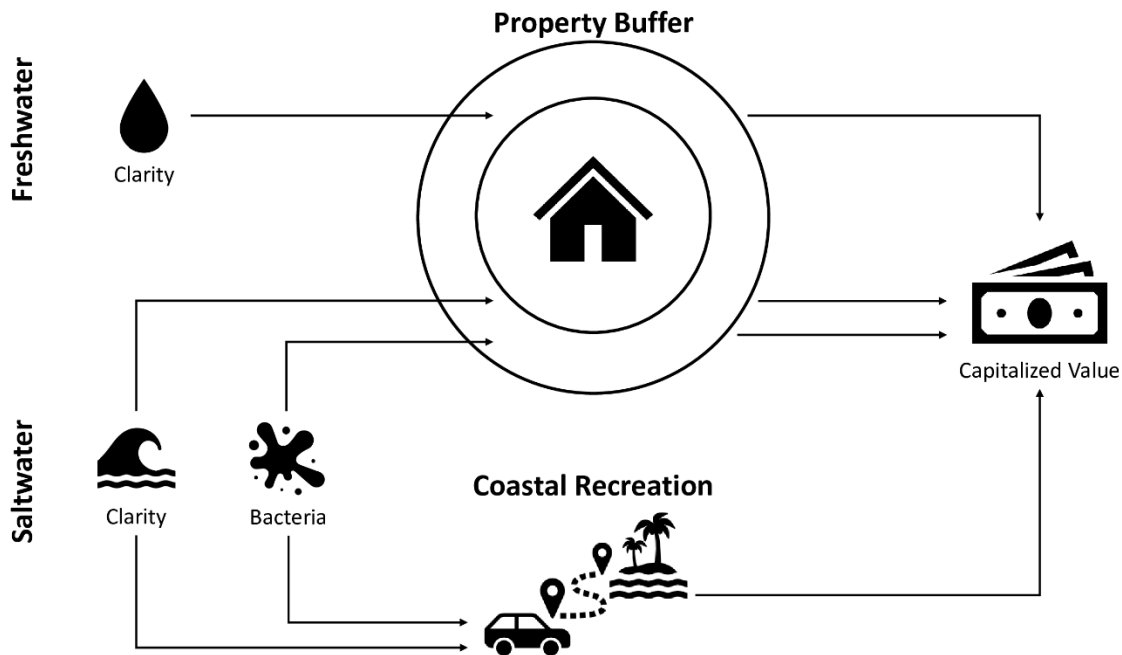


Figure 1 Water Quality Data Pathways

⁴⁴ In the Guignet et al. (2022) meta-analysis, the researchers find differences between the impacts of freshwater and estuarine waters on housing prices.

Direct freshwater and saltwater clarity measurements are derived from Landsat 8 data following the procedure described in section 3.⁴⁵ For saltwater clarity, we used the same 0.4 km wide shoreline segment averaged clarity raster as we used for the RUM. For freshwater clarity, we clipped the clarity raster to NHD Plus V2 waterbodies defined as either lakes and ponds (“LakePonds”), or rivers and streams (“RiverStreams”). We excluded any waterbody under 1 ha in size and clipped out areas that overlapped with coastal water segments.⁴⁶ Then we averaged clarity throughout each waterbody by year, resulting in a raster layer with uniform cell values for each cell within a given waterbody.^{47,48} Separately for freshwater and saltwater, we averaged all clarity cells that fall within each distance buffer around a parcel centroid for each year in the analysis. If a property buffer contained multiple shoreline segments or multiple waterbodies, the resulting average was weighted by the area of the shoreline segments or waterbodies in the buffer.⁴⁹ If the buffer contained fewer than five pixels of total clarity data across all shoreline segments or buffers, we dropped the water quality observation. Direct saltwater bacteria data comes from the same WQP derived summer enterococci samples used in the RUM. We average samples from all monitoring stations that fall within each distance buffer around a parcel centroid. Because there

⁴⁵ Quasi-analytic algorithms used to represent clarity in coastal waters have also successfully been applied in freshwater contexts (Qing et al., 2021). However, it is important to note that this research has focused on lakes, and there are additional challenges in resolving satellite for smaller freshwater waterbodies.

⁴⁶ The NHD waterbodies layer only includes polygons for wide rivers and stream. Narrower features are only represented as lines NHD, which we do not include in the analysis. See <https://www.usgs.gov/national-hydrography/national-hydrography-dataset> for more information on NHD.

⁴⁷ Images of this freshwater clarity raster along with all code documentation is provided in Appendix D.

⁴⁸ The uniform water quality measurements in the buffer prevents variation in water clarity related to water depth. Thus, properties adjacent to the same waterbody or shoreline have the same level of clarity regardless of their distance from the water.

⁴⁹ See https://code.earthengine.google.com/?accept_repo=users/nateme16/recHedonics for code package showing the water quality metric creation.

are zeros in the bacteria counts, we add one to all the counts before taking the log in the hedonic specification.⁵⁰

We match sales in individual years to water quality using the year corresponding to the previous summer. Thus, properties sold January through June of a given year are assigned the previous year of water quality, and properties sold July through December are assigned the current year of water quality. This process results in water quality measurements that vary both spatially and temporally. Typically, hedonic models featuring ambient water quality measures rely primarily on spatial variation between properties to identify an affect, as year-to-year variation may be limited. Spatial variation also fits the narrative of homebuyers comparing observed water quality across different properties when making their bid. To account for potential differences in price effects related to different sources of variation, we decompose our water clarity estimates spatially and temporally. To isolate spatial variation, we average quality within each buffer for a property across all years in the analysis before assigning to individual sales.⁵¹ To isolate temporal variation, for each year of the analysis we average the water quality within each buffer across all properties in the Census tract that sold within any year of the analysis.⁵² We then match the water quality to sales using the sale year of the previous summer.

Overall, we see the most ambient water quality observations for freshwater clarity (Table 1). For the 0.5 km buffer, 25% of sales have a freshwater clarity observation, compared to 9% and 2% for saltwater clarity and bacteria respectively. The average clarity in freshwater was about 0.2

⁵⁰ Zero count data typically represent observations below the detection limit and not necessarily values of zero.

⁵¹ Often spatial variation is isolated in the hedonic model by interacting spatial fixed effects by individual years (e.g., Census tract x Year fixed effects). However, as ECS is defined at the Census tract level, including such fixed effects would cause ECS to drop out of the model.

⁵² Temporal variation is typically isolated in repeat sales models that identify the effect by differencing the sales price for a single property relative to the change or introducing property level fixed effects. We apply these methods in Appendix C.

m greater than in saltwater and had a wider range with some observations near zero potentially related to small shallow water features. The mean bacteria measurements are low and steadily increase from 25 with the 0.5 km buffer and 40 with the 8 km buffer. This distribution likely results from many monitoring locations with observations below the detectable limits with few locations featuring outbreaks at the time of sampling. Thus, as the buffer increases it is more likely that one of the locations with extreme counts will fall within the buffer.

4.3 Hedonic Model Specifications

We use the following double-log specification for the hedonic model:

$$\ln(p_{it}) = \beta_0 + \beta_1 \ln(Fresh_{it}) + \beta_2 \ln(Salt_{it}) + \beta_3 \ln(Bact_{it}) + \beta_4 ECS_{jt} + \beta_{D^{WQ}} D_i^{WQ} + \beta_{Prop} Prop_{it} + \beta_{Dist} Dist_i + \beta_{ACS} ACS_{kt} + \omega_j + \lambda_t + \gamma_t + \varepsilon_{it} \quad (10)$$

where p_{it} is the adjusted sale price for property i in water quality year t , $Fresh_{it}$ is freshwater clarity, $Salt_{it}$ is saltwater clarity, and $Bact_{it}$ is saltwater bacteria. ECS_{jt} is the predicted ECS for census tract j in water quality year t . D_i^{WQ} is a vector of water quality measurement dummy variables indicating whether a property has an observation for $Fresh_{it}$, $Salt_{it}$, or $Bact_{it}$ within the buffer. These dummies are necessary as not all properties have observations for all the water quality measurements. $Prop_{it}$ is a vector of attributes specific to the property that includes lot size, building area, building age, and number of rooms.⁵³ Lot size and building size are both specified using the natural log. $Dist_i$ is a vector of the natural logs of distance measurements from the property to the nearest saltwater, freshwater, airport, highway, railroad, and townhall. ACS_{kt} is a vector of time varying ACS characteristics specified at the block group level k . These

⁵³ For Massachusetts, we have access to historical assessment data, so property characteristics can vary over time. For Rhode Island, we only have access to the most recent assessment, so these attributes are fixed.

characteristics include total population, median income, proportion black, proportion bachelor's degree, median age, seasonal vacancies, and nonseasonal vacancies. All characteristics except proportions and age are specified using the natural log. The model also includes three types of fixed effects: census tract (ω_j), water quality year (λ_t), and sale month (γ_t).⁵⁴ We choose census tract fixed effects, as they are the largest spatial unit over which ECS remains constant.⁵⁵ Using this specification allows us to isolate temporal variation in ECS that is solely driven by year-to-year changes in water clarity and bacteria at the recreational sites.

$Fresh_{it}$, $Salt_{it}$, and $Bact_{it}$ are first specified using the spatiotemporal varying water quality measurements. Then we estimate separate models using the spatially varying measurements and the temporally varying measurements.⁵⁶ Each model is first estimated with measurements for the 0.5 km buffer distance from the parcel centroid. This distance is similar to using a hedonic specification that consider only waterfront properties as common in the literature. Then, to test for the spatial extent of each ambient water quality measure, we respecify the model with four other distance buffers: 1, 2, 4, and 8 km.

$Fresh_{it}$ and $Salt_{it}$ are both expected to have positive coefficients reflecting homebuyers' preferences for clear water. As $Bact_{it}$ is related to poorer health outcomes, β_3 is expected to have a negative effect on sale price. Given the double-log specification, β_1 , β_2 , and β_3 are interpreted as elasticities. As the buffer size increases, we expect the magnitudes of β_1 , β_2 , and β_3 to decrease. For buffer sizes that exceed the spatial extent for a specific water quality measure, we expect the

⁵⁴ We use water quality year rather than sale year to constrain variation in ECS. We also consider half year fixed effects in Appendix B.

⁵⁵ We also consider finer levels of spatial fixed effects at the block group level in Appendix B.

⁵⁶ The temporally varying water quality measurements are similar to ECS in that they must be paired with Census tract of finer levels of spatial fixed effects to isolate temporal variation.

coefficient will be insignificant. We expect β_4 to be positive indicating increases in ECS related to improved water quality have a positive effect on sales price. However, this effect will only be significant if there is a strong relationship between sales prices and the temporally varying measurements of $Bact_{it}$ and $Salt_{it}$. Because of the collinearity between ECS and these terms, we estimate the model with and without the ECS term.

To test for spatial differences in the effect of ECS, we introduce two variations of equation 10 where ECS is interacted with different spatial dummy variables. In equation 11, we consider five different spatial extents for ECS defined by distance to coast:

$$\ln(p_{it}) = \beta_0 + \beta_1 \ln(Fresh_{it}) + \beta_2 \ln(Salt_{it}) + \beta_3 \ln(Bact_{it}) + \beta_{ECS^r} ECS_{jt} * D_i^r + \beta_{Dr} D_i^r + \beta_{D^{WQ}} D_i^{WQ} + \beta_{Prop} Prop_{it} + \beta_{Dist} Dist_i + \beta_{ACS} ACS_{kt} + \omega_j + \lambda_t + \gamma_t + \varepsilon_{it} \quad (11)$$

where D_i^r is a vector of dummy variables indicating the distance of the property to the coast in km falls within the specified range r . The five ranges are: 0-8, 8-16, 16-40, 40-80, and 80-161 km. D_i^r enters the model both as an interaction term with ECS and linearly as a vector of control variables.⁵⁷ We expect the coefficients to be positive and more significant near the coast, where it is more likely that the quality of nearby coastal amenities impacts the prices homebuyers are willing to pay. Insignificant coefficients at further distances from the coast indicate coastal recreation is not capitalized in property sales or there is not enough variation in ECS at that distance to detect an effect. Significant differences between estimates of β_4 through β_8 indicate spatial variation in the effect of ECS, resulting from differences in homeowner preferences for coastal recreation.

Next, we consider variation by state:

⁵⁷ To prevent collinearity in the linear controls, the distance range 80-161 is dropped from the model.

$$\ln(p_{it}) = \beta_0 + \beta_1 \ln(Fresh_{it}) + \beta_2 \ln(Salt_{it}) + \beta_3 \ln(Bact_{it}) + \beta_{ECS^r} ECS_{jt} * D_i^s + \beta_{D^wq} D_i^{wq} + \beta_{Prop} Prop_{it} + \beta_{Dist} Dist_i + \beta_{ACS} ACS_{kt} + \omega_j + \lambda_t + \gamma_t + \varepsilon_{it} \quad (12)$$

where D_i^s is a vector of dummy variables indicating the property is in Massachusetts or Rhode Island.⁵⁸ Significant differences in the effect of ECS between states indicate capitalization of coastal recreation relates to geopolitical boundaries.

4.4 Capitalization Scenarios

To compare the total potential benefits of ambient water quality and ECS, which have varying spatial coverage and extents, we calculate capitalized values for improvements in each type of water quality throughout the study area. For the first three scenarios, we consider the direct capitalized values of 10% improvements in nearby freshwater clarity, saltwater clarity, and saltwater bacteria individually. As the estimated coefficients for ambient water quality are elasticities, each coefficient can be interpreted as the percent increase in price for a 1% improvement in quality. Thus, the capitalized value (CV) for a 10% improvement in mean ambient water quality (q) for all single-family residential properties (N) within buffer distance ($dist$) is:

$$CV_{q,dist} = 10 * \sum_i^{N_{q,dist}} \hat{\beta}_q * p_i / 100 \quad (13)$$

We identify all single-family residential properties using the MassGIS and RIGIS parcel data and measure distances to fresh waterbodies and the coast. For freshwater clarity, we select only those properties with distance to freshwater measurements that fall within each buffer distance. Analogously for saltwater clarity and bacteria, we select properties with distance to coast

⁵⁸ Linear controls for state dummy variables are not necessary, as state variation is controlled by the spatial fixed effects.

measurements that fall within each buffer distance. As not all properties in the study area were sold during the time period, we use the most recent assessed value for each p_i .

In the fourth scenario, we first evaluate the effect of 10% improvements in saltwater clarity and bacteria at recreational sites from the 2020 data and then pass these improved water quality measurements into the RUM results to calculate the corresponding improvements in ECS. Then we take the difference in the improved ECS and the 2020 ECS (ΔECS) for all census tracts and calculate the capitalized values as follows:

$$CV_{ECS} = \sum_i^{N_{ECS}} \hat{\beta}_{ECS} * p_i * \Delta ECS_j \quad (14)$$

Here $\hat{\beta}_{ECS}$ refers to any of the estimated coefficients for ECS from equations 10-12 where a significant effect is found and N_{ECS} is the number of properties that correspond to the coefficient.

5. Results

In the following sections, we first summarize ECS predictions across the study area, before discussing the results of the property sale models. Then we compare the results from the different capitalizations scenarios.

5.1 ECS Predictions

Figure 2 summarizes ECS predictions from the RUM after matching to individual the property sales. In Panel A we consider the average ECS in each census tract. Throughout the study area we see clear distance decay, with ECS predictions largest in census tracts near the coast and decreasing at census tracts further inland. These results make sense, as travel distance is the primary driver of travel cost, with some census tract level heterogeneity driven by differences in median income. Overall, census tracts on the coast have approximately \$100 more expected

consumer surplus for coastal recreation relative to those in northwest Massachusetts. In panel B we map the standard deviation of ECS for each census tract to isolate the temporal variation exploited in the hedonic model. We can see ECS is most variable outside of Boston with standard deviations around \$2. Tracts in Northeast Massachusetts, Southern Rhode Island, and the island of Martha's Vineyard also have standard deviations between \$1 to \$2. In contrast, there is very little variation in ECS in Western Massachusetts or Cape Cod. Because the RUM held travel distance and site characteristics constant, year-to-year differences in saltwater clarity and bacteria levels drive the observed temporal variation in ECS.

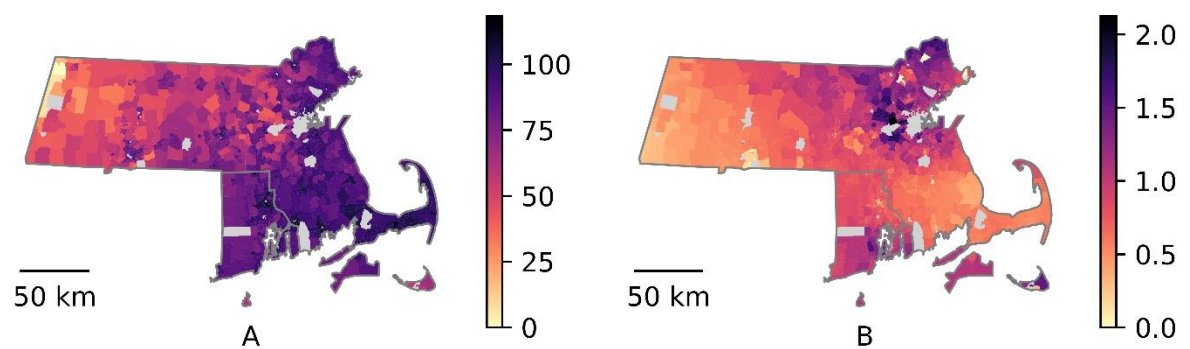


Figure 2 ECS Results by Census Tract

Notes: Grey areas represent Census tracts without property sales data. Panel A depicts mean ECS for property sales by Census tract. Panel B depicts the standard deviations of ECS (2022 \$) for each Census tract over time.

5.2 Hedonic Results

First, we consider the results for ambient water quality alone for the different sources of water quality variation (Table 2 – model 1). With the 0.5 km buffer, we see elasticity estimates for freshwater clarity and saltwater clarity are positive, as expected, and significant for the spatiotemporal and spatial variation measurements. However, with temporal variation the freshwater clarity estimate is not significant, while saltwater clarity is negative and significant. For

saltwater bacteria, the results are negative and significant for all sources of variation, but the magnitude of the temporal variation results are much smaller. As the buffers increase in size, different patterns emerge between spatial and temporal variation. With spatial variation, the results for freshwater are not significant for all buffers except the 2 km, where the effect is negative. For saltwater clarity and bacteria, the magnitudes of the estimates steadily decrease and are not significant at 4 and 8 km. However, with temporal variation, the clarity estimates are increasingly positive for freshwater and negative for saltwater with temporal variations. The effect of bacteria is only significant for the 8 km buffer. The spatiotemporal results reflect the combination of the patterns observed in the spatial and temporal results. Overall, the spatial variation models fit the property sales data the best with respect to the Akaike Information Criterion (AIC), except for the 8 km buffer where the spatiotemporal results perform best. The spatial variation model with the 1 km buffer outperforms the other models with respect to AIC.⁵⁹

⁵⁹ With block group level fixed effects, the 0.5 km buffer outperforms the 1 km buffer (see Appendix B).

Table 2 Selected Regression Results by Water Quality Buffer Distance

	0.5 km		1 km		2 km		4 km		8 km	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
<i>Spatiotemporal Variation</i>										
Log Fresh	0.0161** (0.0054)	0.0161** (0.0054)	0.0083* (0.004)	0.0082* (0.004)	-0.0003 (0.0036)	-0.0004 (0.0036)	0.0005 (0.0063)	0.0002 (0.0063)	0.0131 (0.0099)	0.0129 (0.0099)
Log Salt	0.1082*** (0.0201)	0.1104*** (0.0201)	0.0656*** (0.0163)	0.0685*** (0.0164)	0.0282* (0.0139)	0.0315* (0.0142)	-0.0054 (0.0128)	-0.002 (0.0133)	-0.0318** (0.0101)	-0.0304** (0.0107)
Log Bacteria	-0.0343*** (0.0074)	-0.0344*** (0.0073)	-0.0298*** (0.005)	-0.03*** (0.005)	-0.0185*** (0.004)	-0.0186*** (0.004)	-0.0031 (0.0025)	-0.0033 (0.0025)	-0.0034* (0.0017)	-0.0035* (0.0017)
ECS		-0.0042** (0.0013)		-0.0043** (0.0013)		-0.004** (0.0014)		-0.003* (0.0015)		-0.001 (0.0015)
Log-likelihood	-56526.22	-56518.04	-56508.31	-56499.53	-56750.34	-56743.0	-56959.27	-56955.2	-57065.57	-57065.14
AIC	59598.22	59592.04	59580.31	59573.53	59822.34	59817.0	60031.27	60029.2	60137.57	60139.14
<i>Spatial Variation</i>										
Log Fresh	0.0204** (0.0066)	0.0204** (0.0066)	0.0062 (0.0058)	0.0062 (0.0058)	-0.0123* (0.0062)	-0.0122* (0.0062)	-0.0155 (0.0136)	-0.0155 (0.0136)	0.0034 (0.0282)	0.0034 (0.0282)
Log Salt	0.1692*** (0.0302)	0.1692*** (0.0302)	0.1124*** (0.0275)	0.1124*** (0.0275)	0.087** (0.0301)	0.0871** (0.0301)	0.0557 (0.0328)	0.0557 (0.0328)	-0.0071 (0.0302)	-0.0072 (0.0302)
Log Bacteria	-0.0525*** (0.0153)	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0381*** (0.0111)	-0.0168* (0.0081)	-0.0168* (0.0081)	0.0007 (0.0063)	0.0007 (0.0063)	-0.0026 (0.0061)	-0.0026 (0.0062)
ECS		-0.0027* (0.0013)		-0.0026 (0.0013)		-0.0025 (0.0013)		-0.0026 (0.0013)		-0.0027* (0.0013)
Log-likelihood	-56388.9	-56385.44	-56379.03	-56375.9	-56677.82	-56674.94	-56932.31	-56929.15	-57089.9	-57086.6
AIC	59460.9	59459.44	59451.03	59449.9	59749.82	59748.94	60004.31	60003.15	60159.9	60158.6
<i>Temporal Variation</i>										
Log Fresh	0.0059 (0.0038)	0.0059 (0.0038)	0.0092* (0.0039)	0.0092* (0.0039)	0.0118** (0.0044)	0.0117** (0.0044)	0.0154** (0.0056)	0.0152** (0.0056)	0.0186* (0.0074)	0.0183* (0.0075)
Log Salt	-0.0214* (0.01)	-0.0176 (0.0103)	-0.0218* (0.0095)	-0.018 (0.0098)	-0.0282*** (0.0081)	-0.0254** (0.0085)	-0.039*** (0.0081)	-0.0374*** (0.0087)	-0.0376*** (0.0076)	-0.0366*** (0.0082)
Log Bacteria	-0.0055* (0.0028)	-0.0056* (0.0028)	-0.0032 (0.0025)	-0.0033 (0.0025)	-0.0027 (0.002)	-0.0028 (0.002)	-0.0014 (0.0016)	-0.0015 (0.0016)	-0.003* (0.0015)	-0.0031* (0.0015)
ECS		-0.0021 (0.0014)		-0.0021 (0.0014)		-0.0015 (0.0014)		-0.0008 (0.0014)		-0.0005 (0.0014)
Log-likelihood	-57094.62	-57092.68	-57092.35	-57090.47	-57088.38	-57087.36	-57076.61	-57076.32	-57079.25	-57079.14
AIC	60166.62	60166.68	60164.35	60164.47	60160.38	60161.36	60148.61	60150.32	60151.25	60153.14

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Next, we evaluate the effect of introducing ECS (Table 2 – model 2). For the spatiotemporal models, the ambient water quality estimates are similar to those in model 1. The effect of ECS is negative and significant up to 4 km. For the spatial variation models, the effects of ambient water quality are the exact same as in model 1. The effect of ECS is also negative and significant but smaller in magnitude. For temporal variation, the freshwater clarity and saltwater bacteria results remain similar to model 1. There appears to be strong collinearity between saltwater clarity and ECS, with the effect of saltwater smaller in magnitude and no longer significant with 0.5 and 1 km buffers. As the buffer size increases, the effect of ECS decreases to zero, while the effect of saltwater clarity negative and significant. These results demonstrate the negative effect of ECS is driven primarily by the negative relationship between temporal variation in saltwater clarity and sale prices. The effect of ECS is largest with the spatiotemporal variation where spatial variation is dominant, because the collinearity between temporal element of saltwater variation and ECS persists confounding the effect of ECS.

To demonstrate potential spatial variation in the effect of ECS, we present the results for distance and state interactions with ECS using the 0.5 km buffer (Table 3).⁶⁰ The results for the distance dummy interactions (model 3) do not demonstrate a clear distance gradient. Instead, we see the results are approximately twice as large for properties in the furthest distance category as the remaining categories. We also find differences related to state with ECS estimate for Massachusetts approximately half the size of the Rhode Island estimate (model 4). Using Wald tests, we do not find significant differences between any of the interaction terms at a 5% confidence level.⁶¹

⁶⁰ Model results for the additional buffers are included in Appendix B.

⁶¹ Wald test statistics available in Appendix B.

Table 3 Selected Regression Results by ECS Specification

	<i>Spatiotemporal Variation</i>		<i>Spatial Variation</i>		<i>Temporal Variation</i>	
	(3)	(4)	(3)	(4)	(3)	(4)
Log Fresh	0.0162** (0.0054)	0.016** (0.0054)	0.0205** (0.0066)	0.0204** (0.0066)	0.0062 (0.0038)	0.0059 (0.0038)
Log Salt	0.1109*** (0.0201)	0.1107*** (0.0201)	0.1693*** (0.0302)	0.1692*** (0.0302)	-0.0168 (0.0103)	-0.0169 (0.0102)
Log Bacteria	-0.0345*** (0.0073)	-0.0344*** (0.0073)	-0.0525*** (0.0153)	-0.0525*** (0.0153)	-0.0056* (0.0028)	-0.0056* (0.0028)
ECS x 0-8 km	-0.0047*** (0.0014)		-0.0031* (0.0014)		-0.0025 (0.0014)	
ECS x 8-16 km	-0.0034* (0.0015)		-0.0019 (0.0015)		-0.0014 (0.0015)	
ECS x 16-40 km	-0.0041* (0.0016)		-0.0028 (0.0016)		-0.0023 (0.0016)	
ECS x 40-80 km	-0.0035 (0.0025)		-0.0025 (0.0025)		-0.0019 (0.0026)	
ECS x 80-161 km	-0.0075* (0.0034)		-0.0063 (0.0034)		-0.0059 (0.0034)	
ECS x MA		-0.0039** (0.0014)		-0.0024 (0.0014)		-0.0019 (0.0014)
ECS x RI		-0.007* (0.0028)		-0.0052 (0.0028)		-0.0044 (0.0028)
Log-likelihood	-56493.8	-56516.59	-56362.66	-56384.34	-57068.02	-57091.8
AIC	59583.8	59592.59	59452.66	59460.34	60158.02	60167.8

Notes: N = 264679. Ambient water quality specified using 0.5 km buffer. All models specified Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level. *p<.05, **p<.01, ***p<.001

5.3 Capitalized Values

In Figure 3, we map capitalization effects for 10% improvements in each ambient water quality variable and ECS by census tract using the results for model 1 with spatial variation and a 0.5 km buffer.⁶² We do not consider the effects of ECS, because they are linked to the anomalous relationship between temporal variation in saltwater clarity and property sale prices. Starting with

⁶² In Appendix B, we evaluate capitalization values using this model with a 1 km buffer for ambient water quality and find similar results for total values with the counts of properties approximately doubling.

freshwater clarity (Panel A), we see small effects throughout most census tracts in the study area for a total of \$561 million distributed across 506,734 properties throughout most census tracts in the two states. The effects for saltwater clarity (Panel B) are much larger with many individual census tracts contributing more than \$15 million. In total, the direct capitalized value of a 10% improvement in saltwater clarity is \$2.9 billion. However, these effects are concentrated in 198,043 properties. The effects of saltwater bacteria (Panel C) across the sample of properties are smaller than clarity with a total capitalization value of \$864 million.

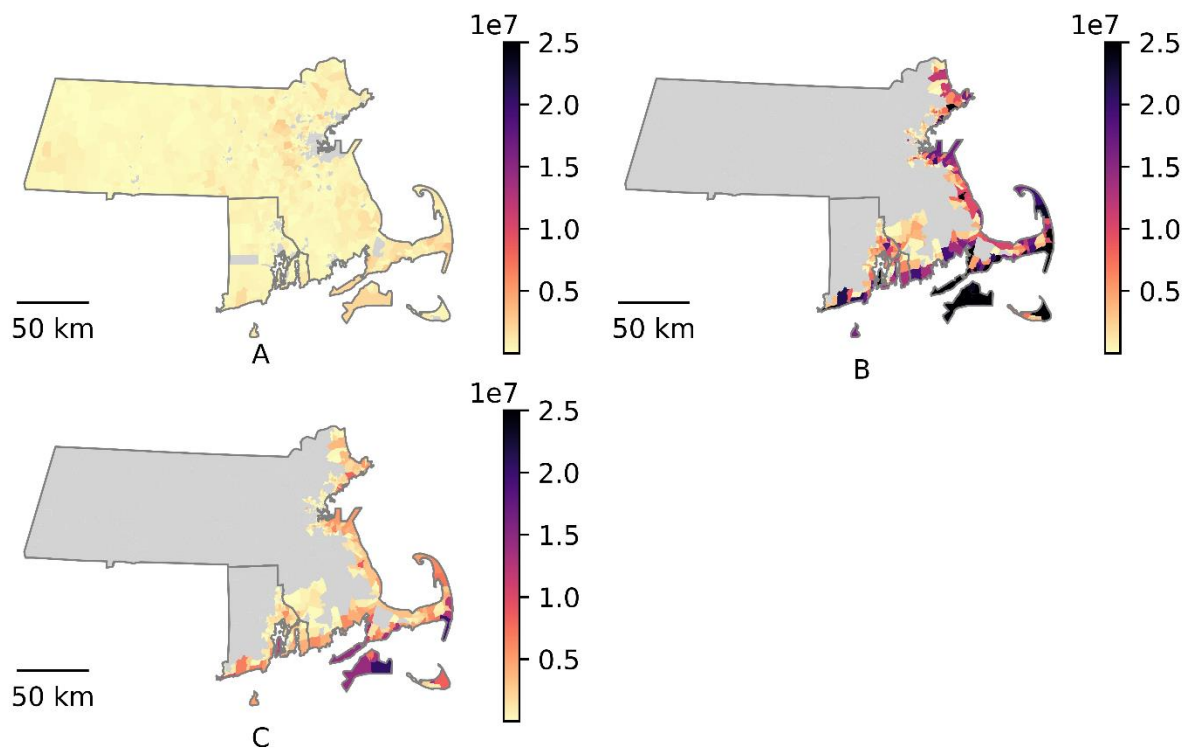


Figure 3 Total Capitalization Effects for Water Quality Improvement Scenarios by Census Tract
 Notes: Grey areas represent Census tracts that fall outside the spatial extent of the water quality improvement or do not have any single-family homes. Total number of single-family homes throughout both states is 1,652,070. Panel A depicts total capitalization effects for a 10% increase in mean freshwater clarity within a 0.5 km distance buffer from property (Properties = 506,734, Total = \$561 Million). Panel B depicts total capitalization effects for a 10% increase in mean saltwater clarity within a 0.5 km distance buffer from property (Properties = 198,043, Total = \$2,783 Million). Panel C depicts total capitalization effects for a 10% decrease in mean saltwater bacteria within a 0.5 km distance buffer from property (Properties = 198,043, Total = \$864 Million).

6. Discussion and Conclusion

The primary goal of this analysis was to better understand the spatial extent of the indirect effects of water quality from coastal recreation on housing markets. While we expected the effect of ECS to be positive and decay with distance, we instead found the opposite relationship. The effect of year-to-year variation of ECS on property sales appears to be negative and larger furthest from the coast. Decomposing the effects of ambient water quality reveals the key driver for these results is the anomalous relationship between temporal variation in saltwater clarity and property sale price. While it is unclear why we observe this relationship, we believe it is related to fundamental differences between the sources of variation and the related assumption we needed to make to integrate the cross-sectional RUM model to create a time varying ECS.

Spatial variation in water clarity is driven by long-term differences in water quality associated with the location of the property, whereas temporal variation in the short-term is likely more related to yearly changes in weather and precipitation. Prior coastal hedonic studies have also found counterintuitive relationships between water quality and property sales. Walsh et al. (2017) report counterintuitive results for water clarity beyond 0.5 km in select counties on the Chesapeake Bay. For Narragansett Bay, which falls within our study area, Liu et al. (2017) report counterintuitive estimates for chlorophyll-a concentration (a measure of algal levels and related to nutrient pollution) at distances beyond 1.5 km. Interestingly, these studies also find the expected signs near the waterfront before changing signs, similar to the behavior we observed in the spatiotemporal variation models. The underlying models in these studies do not explicitly isolate spatial variation, meaning the large effects of spatial variation for waterfront properties may be masking anomalous temporal relationships. Thus, future hedonic studies should avoid conflating spatial and temporal variation in ambient water quality valuation.

When we isolate spatial variation, our results demonstrate expected behavior that is consistent with the literature. Both water clarity elasticity estimates for the 0.5 km buffer fall within the range of the Guignet et al. (2022) metadata that had an RES cluster weighted mean of 0.109 on the waterfront and 0.026 off the waterfront within 0.5 km. While Guignet et al. (2022) do not include enterococci elasticity estimates, they report RES cluster weighted means for fecal coliforms of -0.00013 on the waterfront and -0.052 off the waterfront within 0.5 km. The spatial extents of the ambient water quality measures also conform with results in prior studies. For freshwater lakes, Mamun et al. (2022) find elasticities for clarity are not significant beyond 0.3 km from the lakefront. On the Chesapeake Bay, Klemick et al. (2018) do not find significant negative effects of light attenuation (inverse of clarity) beyond 1 km of the waterfront. For coastal enterococcus on Long Island Sound, Kung et al. (2022) do not find significant negative effects beyond 2 km from the property.

Unlike prior hedonic studies for ambient water quality that have traditionally relied on monitoring data, we incorporate remotely sensed water clarity data in our analysis. This data allows us to examine the potential homeowner benefits of water quality improvements to a much wider range of aquatic resources. While researchers tend to trust monitoring data in large lakes and well-known estuaries, like the Chesapeake Bay, these resources may also be valued more highly in real estate markets. To evaluate potential evaluate the validity of using remotely sensed clarity data in hedonic valuation, Wolf and Kemp (2021) compared hedonic estimates for water clarity on lakes using remotely sensed data and Secchi disk samples. They find the remotely sensed estimates were larger in some model specification but not significantly different. We posit this occurred because Wolf and Kemp (2021) focused on a consistent set of lakes where clarity was regularly monitored with Secchi disks to make their comparisons. In contrast, our estimates for

freshwater of 0.020 are somewhat smaller than those reported that relied solely on monitoring data. For example, Mamun et al. (2022) report nationwide elasticities for lake water clarity of 0.175 within 0.1 km of the lake and 0.048 from 0.1-0.3 km the lakefront. Therefore, we argue prior hedonic results that were driven by the availability of monitoring data may suffer from sampling bias toward larger and more valuable aquatic resources. While remotely sensed data product restrictions (e.g., resolution, tree cover absence) may bias certain water features, utilizing these products will allow policymakers to have a more holistic view of the potential benefits of surface water quality improvements on property sales.

While the remotely sensed data provides a more wholistic set of water quality values, our modelling approach allowed us to represent meaningful heterogeneity in clarity estimates. We find elasticities for saltwater are more than eight times larger than freshwater. The Guignet et al. (2022) meta-analysis also find heterogenous effects of freshwater and saltwater clarity, reporting consistently larger elasticities for estuaries on the waterfront relative to lakes.⁶³ Some of this heterogeneity may result from preferences for coastal waters where there are different recreational activities, such as swimming, and thus saltwater and freshwater clarity quality measurements may represent meaningfully different economic goods. While some freshwater locations, like large lakes, may afford swimming, the freshwater data we used also includes smaller ponds and rivers, that may provide different services to homeowners. Thus, future studies may further examine heterogeneity in the effects of freshwater clarity across waterbody types or sizes to account for meaningful differences ecological processes and ecosystem services. However, there are challenges in applying algorithms for remotely sensed data to smaller ponds and streams that may

⁶³ Beyond the waterfront their results also indicate smaller elasticities for estuaries, which we do not observe in our results.

result in measurement error and lead to attenuation bias in resulting estimates. Researchers will need to choose an identification strategy that allows controls for potential measurement errors while evaluating the heterogeneity of different features.

However, one obstacle in utilizing remotely sensed clarity data is with regularly improving sensor technology and new satellites, the available time series at present does not provide opportunity to observe meaningful changes in water quality over time. Thus, economists face a choice between relying on spatial variation or temporal variation to evaluate potential benefits of proposed policies that may result in long term improvements in water quality. Temporal variation may be appropriate for some types of water quality measurements, where there are sufficient information pathways to inform potential homebuyers. For example, we find yearly variation in bacteria levels that homebuyers can readily observe through beach closures does impact property sale prices. In contrast, it is unlikely that homebuyers can observe yearly differences in water clarity, especially for waters that are not proximate to the property they are visiting. Even for bacteria, when recent information can inform sales prices, we see larger effects resulting from spatial variation, implying long-term differences in bacterial levels may be more salient to homebuyers. Given the impacts of short-term temporal variation in water quality do not represent the same impacts as those in the long run, researchers must decide whether to wait twenty or fifty years for policy relevant water quality changes to manifest or whether spatial variation driven by long-term differences in water quality is sufficient to approximate the potential benefits of water quality improvements. Leveraging spatial variation, we find 10% improvements in saltwater clarity and bacteria could yield more than \$3.6 billion in potential benefits long term. Thus, while the costs of infrastructure upgrades required to improve coastal water quality by 10% are large, they may be partially offset by housing market capitalization.

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Appendix A RUM Inputs and Outputs

The recreation behavior data came from a mail survey of households in New England, as explained in Mazzotta et al. (2022). The survey asked for information about general coastal recreation behavior, including participation in activities and the number of trips taken. It also elicited a last-trip profile for day and overnight trips for recreation on the coast of New England for water quality perceptions. Using only the day-trip responses, Merrill et al. (2024) defined a random utility model (RUM) for coastal recreation trips in New England as a function of water quality including bacteria and water clarity along different coastal segments. The coast of New England was broken up into segments using NOAA's Ecosystem Sensitivity Index shoreline data, combined with EPA's BEACON program locations for swimming beaches. This resulted in just over 7,000 segments in the choice set for the RUM. Each shoreline segment was attributed with a type (sandy, rocky, armored, vegetated), wave exposure, length, and measurements of water quality.

The water quality inputs to the RUM were derived from 5-year average summer conditions (June-September). As discussed in the paper, water clarity was derived from estimates of Secchi depth using remote sensing from Landsat 8 and a quasi-analytical algorithm (Lee et al., 2016) for the years 2014-2019 using Google Earth Engine (Gorelick et al., 2017). Each shoreline segment was assigned a clarity value based on averaging the Secchi depth raster data within a 0.4 km buffer of the segment across all years. Bacterial conditions were created for each shoreline segment based on averaging enterococci numbers of colony forming units (CFUs) from the National Water Quality Portal (WQP) for 2014-2019 that were within the nearby coastal water segments. Each shoreline segment abutting a water segment was assigned the same bacteria value. The water segments were created using state 303d coastal water segments and shellfish closure zones. Most

of the bacteria measurements in the WQP came from swimming beach water quality monitoring programs covered by EPA's BEACHES program. See Merrill et al. (2024) for a detailed description of the shoreline attributes, water quality measurements and RUM.

Table A1 includes the Merrill et al. (2024) coefficients and WTP estimates. The effects of Secchi depth and bacteria (CFU or MPN) are both significant and in the expected direction, positive for Secchi and negative for bacteria.

Table A1 RUM Results used for ECS Derivation		
Variable	Description	Estimate
Travel Cost (\$)	Round trip cost of travel	-0.051*** (0.001)
Beach	Site includes a beach	1.297*** (0.096)
Size (1000m)	Straight line length of shoreline	0.625*** (0.033)
% Sheltered	% of shoreline segment that is sheltered	-0.470*** (0.154)
% Sandy	% of shoreline segment that is sandy	-6.494*** (0.193)
% Rocky	% of shoreline segment that is rocky	-7.967*** (0.338)
% Vegetated	% of shoreline segment that is vegetated	-7.557*** (0.238)
% Armored	% of shoreline segment that is armored	-6.322*** (0.250)
% Impervious	% of nearby area that is impervious cover	-0.091*** (0.012)
Secchi depth (m)	Remote sensing estimate of Secchi depth	0.227*** (0.064)
Impaired	1/0 existence of 303(d) impairment in adjacent water	0.117 (0.090)
CFU or MPN	Bacteria measure by colony forming units or most probable number	-0.004*** (0.001)
CFU or MPN data available	1/0 to indicate sites with bacteria data	0.287** (0.117)
N of respondents		706
Note: * p < .1, ** p < .05, *** p < .01		

Appendix B Additional Regression Results

In this appendix, we present regression outputs for coefficients not presented in the manuscript and discuss additional model results that highlight the robustness of the primary analysis. Tables B1-B6 contain the full set of coefficient estimates for models 1-4 with all five buffers using each type of ambient water quality variation component with Census tract spatial fixed effects. Table B7 includes Wald Test results discussed in the manuscript for models 3 and 4 with the 0.5 km buffer and Census tract fixed effects.

Tables B8 and B9 present analogous results to tables 2 and 3 in the manuscript using Census block group spatial fixed effects. For ambient water quality, we see the effects with spatial variation are somewhat smaller in magnitude with block group fixed effects, and for temporal variation the negative effect of saltwater clarity is slightly larger. We find little difference in the ECS estimates or their interactions. Table B10 and B11 similarly present results analogous to tables 2 and 3 using Census tract spatial fixed effects with half year temporal fixed effects. These results are almost identical to those in the manuscript.

Table B12 presents the total capitalization and number of households for the 1 km buffer in addition to the 0.5 km buffer presented in the manuscript. While the number of households approximately doubles for each ambient water quality measure, the total capitalization is smaller for freshwater clarity, and approximately the same for saltwater clarity and bacteria. Figure B1 displays the number of single-family properties and the median assessed prices used to derive the capitalization estimates. The number of properties within a tract varies throughout the study area, while the largest assessed values are concentrated outside of Boston, Martha's Vineyard, and Nantucket.

Table B1 Full Regression Results for Models (1) and (2) with Spatiotemporal Variation and Census Tract Spatial Fixed Effects

	(1)					(2)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0161** (0.0054)	0.0083* (0.004)	-0.0003 (0.0036)	0.0005 (0.0063)	0.0131 (0.0099)	0.0161** (0.0054)	0.0082* (0.004)	-0.0004 (0.0036)	0.0002 (0.0063)	0.0129 (0.0099)
Log Salt	0.1082*** (0.0201)	0.0656*** (0.0163)	0.0282* (0.0139)	-0.0054 (0.0128)	-0.0318** (0.0101)	0.1104*** (0.0201)	0.0685*** (0.0164)	0.0315* (0.0142)	-0.002 (0.0133)	-0.0304** (0.0107)
Log Bacteria	-0.0343*** (0.0074)	-0.0298*** (0.005)	-0.0185*** (0.004)	-0.0031 (0.0025)	-0.0034* (0.0017)	-0.0344*** (0.0073)	-0.03*** (0.005)	-0.0186*** (0.004)	-0.0033 (0.0025)	-0.0035* (0.0017)
ECS						-0.0042** (0.0013)	-0.0043** (0.0013)	-0.004** (0.0014)	-0.003* (0.0015)	-0.001 (0.0015)
Dummy Fresh	-0.015*** (0.004)	-0.0089** (0.0033)	-0.0112* (0.0047)	-0.0187 (0.0137)	0.0143 (0.0284)	-0.015*** (0.004)	-0.0089** (0.0033)	-0.0113* (0.0047)	-0.0199 (0.0136)	0.0136 (0.0283)
Dummy Salt	-0.0137 (0.0095)	-0.0521*** (0.01)	-0.0799*** (0.0093)	-0.0611*** (0.0091)	-0.0223* (0.0089)	-0.0139 (0.0095)	-0.0522*** (0.01)	-0.0798*** (0.0093)	-0.061*** (0.0091)	-0.0222* (0.0089)
Dummy Bacteria	0.2044*** (0.0288)	0.1775*** (0.0202)	0.0994*** (0.0166)	-0.0148 (0.0133)	-0.0002 (0.0151)	0.2045*** (0.0287)	0.1774*** (0.0201)	0.0992*** (0.0165)	-0.0147 (0.0133)	-0.0001 (0.0151)
Constant	9.5535*** (0.1266)	9.6106*** (0.1231)	9.6531*** (0.1221)	9.6544*** (0.1272)	9.538*** (0.1323)	9.548*** (0.1263)	9.6048*** (0.1229)	9.6474*** (0.1218)	9.6509*** (0.1269)	9.5372*** (0.1322)
Log Distance to Freshwater	-0.0076* (0.0034)	-0.0054 (0.0031)	-0.0038 (0.0027)	-0.0029 (0.0027)	-0.0029 (0.0027)	-0.0076* (0.0034)	-0.0054 (0.0031)	-0.0038 (0.0027)	-0.0029 (0.0027)	-0.0029 (0.0027)
Log Distance to Saltwater	-0.0949*** (0.0073)	-0.1014*** (0.0067)	-0.1058*** (0.0067)	-0.1064*** (0.0071)	-0.1015*** (0.0071)	-0.0949*** (0.0073)	-0.1015*** (0.0067)	-0.1058*** (0.0067)	-0.1064*** (0.0071)	-0.1015*** (0.0071)
Log Distance to Airport	0.0165* (0.0073)	0.0155* (0.0072)	0.0151* (0.0073)	0.0162* (0.0077)	0.017* (0.0079)	0.0165* (0.0073)	0.0156* (0.0072)	0.0152* (0.0073)	0.0162* (0.0077)	0.017* (0.0079)
Log Distance to Highway	0.0168*** (0.0031)	0.0169*** (0.003)	0.0178*** (0.0031)	0.0178*** (0.0032)	0.0183*** (0.0033)	0.0168*** (0.0031)	0.0168*** (0.003)	0.0178*** (0.0031)	0.0177*** (0.0032)	0.0183*** (0.0033)
	0.0181***	0.0181***	0.0184***	0.0196***	0.0194***	0.0181***	0.0181***	0.0183***	0.0196***	0.0194***

Log Distance to Railroad	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Log Distance to Townhall	-0.0081*	-0.0087*	-0.0087*	-0.0078	-0.0064	-0.0081*	-0.0087*	-0.0087*	-0.0078	-0.0063
	(0.0041)	(0.004)	(0.004)	(0.0041)	(0.0041)	(0.0041)	(0.004)	(0.004)	(0.0041)	(0.0041)
Building Age	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log Lot Size	0.0506***	0.0505***	0.0496***	0.049***	0.0488***	0.0506***	0.0505***	0.0496***	0.049***	0.0488***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Log Building Area	0.4946***	0.4948***	0.4947***	0.4955***	0.4957***	0.4947***	0.4948***	0.4947***	0.4955***	0.4957***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Rooms	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Log Population	-0.0027	-0.0026	-0.0033	-0.0046	-0.005	-0.0027	-0.0026	-0.0033	-0.0046	-0.005
	(0.0049)	(0.0048)	(0.0049)	(0.005)	(0.005)	(0.0049)	(0.0048)	(0.0049)	(0.005)	(0.005)
Log Income	0.0295***	0.0296***	0.0296***	0.0289***	0.0295***	0.0295***	0.0296***	0.0295***	0.0289***	0.0295***
	(0.0051)	(0.005)	(0.005)	(0.0051)	(0.0051)	(0.0051)	(0.005)	(0.005)	(0.0051)	(0.0051)
Proportion Black	-0.0185	-0.0119	-0.0147	-0.0212	-0.0213	-0.018	-0.0114	-0.0144	-0.0209	-0.0213
	(0.0261)	(0.0258)	(0.0268)	(0.0271)	(0.0271)	(0.026)	(0.0258)	(0.0268)	(0.0271)	(0.0271)
Proportion Bachelors	0.1492***	0.1503***	0.1597***	0.1634***	0.1628***	0.1496***	0.1507***	0.16***	0.1638***	0.1629***
	(0.0264)	(0.0262)	(0.0267)	(0.0272)	(0.0273)	(0.0264)	(0.0262)	(0.0268)	(0.0273)	(0.0273)
Median Age	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Seasonal Vacancies	0.005***	0.0048***	0.0053***	0.0059***	0.006***	0.005***	0.0048***	0.0053***	0.0059***	0.006***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)
Log Nonseasonal Vacancies	-0.0003	-0.0002	-0.0003	-0.0002	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002	-0.0002
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Log-likelihood	-56526.22	-56508.31	-56750.34	-56959.27	-57065.57	-56526.22	-56508.31	-56750.34	-56959.27	-57065.57
AIC	59598.22	59580.31	59822.34	60031.27	60137.57	59598.22	59580.31	59822.34	60031.27	60137.57

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B2 Full Regression Results for Models (1) and (2) with Spatial Variation and Census Tract Spatial Fixed Effects

	(1)					(2)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0204** (0.0066)	0.0062 (0.0058)	-0.0123* (0.0062)	-0.0155 (0.0136)	0.0034 (0.0282)	0.0204** (0.0066)	0.0062 (0.0058)	-0.0122* (0.0062)	-0.0155 (0.0136)	0.0034 (0.0282)
Log Salt	0.1692*** (0.0302)	0.1124*** (0.0275)	0.087** (0.0301)	0.0557 (0.0328)	-0.0071 (0.0302)	0.1692*** (0.0302)	0.1124*** (0.0275)	0.0871** (0.0301)	0.0557 (0.0328)	-0.0072 (0.0302)
Log Bacteria	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0168* (0.0081)	0.0007 (0.0063)	-0.0026 (0.0061)	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0168* (0.0081)	0.0007 (0.0063)	-0.0026 (0.0062)
ECS						-0.0027* (0.0013)	-0.0026 (0.0013)	-0.0025 (0.0013)	-0.0026 (0.0013)	-0.0027* (0.0013)
Dummy Fresh	-0.0211*** (0.0044)	-0.0127*** (0.0037)	-0.0223*** (0.0058)	-0.044 (0.0338)	9.5578*** (0.1288)	-0.0211*** (0.0044)	-0.0127*** (0.0037)	-0.0223*** (0.0058)	-0.044 (0.0339)	9.5541*** (0.1286)
Dummy Salt	-0.0201* (0.0102)	-0.056*** (0.0104)	-0.0807*** (0.0107)	-0.0565*** (0.0102)	-0.0188 (0.0102)	-0.0201* (0.0102)	-0.056*** (0.0104)	-0.0806*** (0.0107)	-0.0565*** (0.0102)	-0.0188 (0.0102)
Dummy Bacteria	0.2581*** (0.0512)	0.2076*** (0.0376)	0.0842** (0.0281)	-0.0408 (0.0242)	-0.0106 (0.023)	0.2581*** (0.0512)	0.2076*** (0.0376)	0.0841** (0.0281)	-0.0408 (0.0242)	-0.0106 (0.023)
Constant	9.5737*** (0.1276)	9.6134*** (0.1236)	9.6551*** (0.1215)	9.6802*** (0.1282)		9.5698*** (0.1274)	9.6097*** (0.1234)	9.6515*** (0.1213)	9.6764*** (0.128)	
Log Distance to Freshwater	-0.0102** (0.0037)	-0.0071* (0.0032)	-0.0049 (0.0028)	-0.003 (0.0027)	-0.003 (0.0027)	-0.0102** (0.0037)	-0.0071* (0.0032)	-0.0049 (0.0028)	-0.003 (0.0027)	-0.003 (0.0027)
Log Distance to Saltwater	-0.0944*** (0.0073)	-0.0998*** (0.0067)	-0.1048*** (0.0066)	-0.1062*** (0.0071)	-0.1013*** (0.0071)	-0.0944*** (0.0073)	-0.0998*** (0.0067)	-0.1048*** (0.0066)	-0.1062*** (0.0071)	-0.1013*** (0.0071)
Log Distance to Airport	0.0165* (0.0072)	0.0157* (0.007)	0.0158* (0.0071)	0.0161* (0.0074)	0.0166* (0.0079)	0.0165* (0.0072)	0.0157* (0.007)	0.0158* (0.0071)	0.0161* (0.0074)	0.0166* (0.0079)
Log Distance to Highway	0.0167*** (0.0031)	0.0168*** (0.003)	0.0178*** (0.003)	0.0178*** (0.0031)	0.018*** (0.0032)	0.0167*** (0.0031)	0.0168*** (0.003)	0.0178*** (0.003)	0.0178*** (0.0031)	0.018*** (0.0032)
Log Distance to Railroad	0.0179*** (0.0022)	0.0179*** (0.0022)	0.0182*** (0.0022)	0.0198*** (0.0023)	0.0195*** (0.0023)	0.0179*** (0.0022)	0.0179*** (0.0022)	0.0182*** (0.0022)	0.0198*** (0.0023)	0.0195*** (0.0023)

Log Distance to Townhall	-0.0083* (0.0042)	-0.0088* (0.004)	-0.009* (0.004)	-0.008 (0.0041)	-0.0062 (0.0041)	-0.0083* (0.0042)	-0.0087* (0.004)	-0.009* (0.004)	-0.008 (0.0041)	-0.0062 (0.0041)
Building Age	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)
Log Lot Size	0.0508*** (0.0024)	0.0508*** (0.0024)	0.0497*** (0.0024)	0.0492*** (0.0024)	0.0488*** (0.0024)	0.0508*** (0.0024)	0.0508*** (0.0024)	0.0497*** (0.0024)	0.0492*** (0.0024)	0.0488*** (0.0024)
Log Building Area	0.4943*** (0.0071)	0.4945*** (0.0071)	0.4946*** (0.0071)	0.4954*** (0.0071)	0.4957*** (0.0071)	0.4943*** (0.0071)	0.4945*** (0.0071)	0.4947*** (0.0071)	0.4955*** (0.0071)	0.4958*** (0.0071)
Rooms	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)
Log Population	-0.0022 (0.0049)	-0.002 (0.0047)	-0.0027 (0.0048)	-0.0042 (0.005)	-0.0049 (0.0051)	-0.0022 (0.0049)	-0.002 (0.0047)	-0.0027 (0.0048)	-0.0042 (0.005)	-0.0049 (0.0051)
Log Income	0.0293*** (0.0051)	0.0293*** (0.005)	0.0297*** (0.0051)	0.0289*** (0.0051)	0.0294*** (0.0052)	0.0293*** (0.0051)	0.0293*** (0.005)	0.0297*** (0.0051)	0.0289*** (0.0051)	0.0294*** (0.0052)
Proportion Black	-0.0164 (0.026)	-0.0108 (0.0258)	-0.0163 (0.0269)	-0.0197 (0.0271)	-0.0212 (0.027)	-0.0161 (0.026)	-0.0106 (0.0258)	-0.016 (0.0269)	-0.0194 (0.027)	-0.0209 (0.027)
Proportion Bachelors	0.145*** (0.0266)	0.145*** (0.0262)	0.1591*** (0.0269)	0.1635*** (0.0271)	0.1631*** (0.0273)	0.1452*** (0.0266)	0.1453*** (0.0262)	0.1593*** (0.0269)	0.1638*** (0.0272)	0.1634*** (0.0273)
Median Age	0.001*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.001*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Log Seasonal Vacancies	0.0049*** (0.0015)	0.0046*** (0.0015)	0.0051*** (0.0015)	0.0058*** (0.0015)	0.006*** (0.0015)	0.0049*** (0.0015)	0.0046*** (0.0015)	0.0051*** (0.0015)	0.0058*** (0.0015)	0.006*** (0.0015)
Log Nonseasonal Vacancies	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0002 (0.0007)
Log-likelihood	-56388.9	-56379.03	-56677.82	-56932.31	-57089.9	-56385.44	-56375.9	-56674.94	-56929.15	-57086.6
AIC	59460.9	59451.03	59749.82	60004.31	60159.9	59459.44	59449.9	59748.94	60003.15	60158.6

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B3 Full Regression Results for Models (1) and (2) with Temporal Variation and Census Tract Spatial Fixed Effects

	(1)					(2)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0059 (0.0038)	0.0092* (0.0039)	0.0118** (0.0044)	0.0154** (0.0056)	0.0186* (0.0074)	0.0059 (0.0038)	0.0092* (0.0039)	0.0117** (0.0044)	0.0152** (0.0056)	0.0183* (0.0075)
Log Salt	-0.0214* (0.01)	-0.0218* (0.0095)	-0.0282*** (0.0081)	-0.039*** (0.0081)	-0.0376*** (0.0076)	-0.0176 (0.0103)	-0.018 (0.0098)	-0.0254** (0.0085)	-0.0374*** (0.0087)	-0.0366*** (0.0082)
Log Bacteria	-0.0055* (0.0028)	-0.0032 (0.0025)	-0.0027 (0.002)	-0.0014 (0.0016)	-0.003* (0.0015)	-0.0056* (0.0028)	-0.0033 (0.0025)	-0.0028 (0.002)	-0.0015 (0.0016)	-0.0031* (0.0015)
ECS						-0.0021 (0.0014)	-0.0021 (0.0014)	-0.0015 (0.0014)	-0.0008 (0.0014)	-0.0005 (0.0014)
Dummy Fresh	0.0013 (0.0084)	0.004 (0.01)	-0.0026 (0.0158)	-0.0366** (0.0113)	0.0149 (0.0096)	0.0011 (0.0084)	0.0041 (0.01)	-0.0026 (0.0158)	-0.0373*** (0.0113)	0.0146 (0.0096)
Dummy Salt	0.0909*** (0.0262)	0.0753*** (0.0221)	0.0867*** (0.0261)	-0.0604 (0.0417)	0.0442 (0.0522)	0.087** (0.0265)	0.0716** (0.0225)	0.0839** (0.0264)	-0.0619 (0.0418)	0.0434 (0.0523)
Dummy Bacteria	0.011 (0.0115)	-0.0067 (0.0118)	0.0026 (0.0109)	0.0018 (0.0103)	-0.007 (0.0124)	0.0104 (0.0115)	-0.0075 (0.0118)	0.0021 (0.011)	0.0016 (0.0103)	-0.0069 (0.0124)
Constant	9.5044*** (0.1287)	9.5051*** (0.1289)	9.5013*** (0.1308)	9.586*** (0.1301)	9.4933*** (0.131)	9.5025*** (0.1286)	9.5032*** (0.1287)	9.5001*** (0.1306)	9.5861*** (0.1302)	9.4934*** (0.131)
Log Distance to Freshwater	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)
Log Distance to Saltwater	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)
Log Distance to Airport	0.0173* (0.0078)	0.0173* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)	0.0173* (0.0078)	0.0173* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)
Log Distance to Highway	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)
Log Distance to Railroad	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)
Log Distance to Townhall	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)

Building Age	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)
Log Lot Size	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)
Log Building Area	0.4957*** (0.0071)	0.4957*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4957*** (0.0071)	0.4957*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)
Rooms	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)
Log Population	-0.0048 (0.005)	-0.0049 (0.005)	-0.0049 (0.0051)	-0.0049 (0.0051)	-0.0049 (0.005)	-0.0049 (0.0051)	-0.0049 (0.005)	-0.0049 (0.0051)	-0.0049 (0.0051)	-0.0049 (0.005)
Log Income	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0294*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0294*** (0.0052)	0.0293*** (0.0052)
Proportion Black	-0.0217 (0.027)	-0.0217 (0.027)	-0.0217 (0.0269)	-0.0216 (0.0269)	-0.0213 (0.027)	-0.0215 (0.027)	-0.0216 (0.027)	-0.0216 (0.0269)	-0.0215 (0.0269)	-0.0213 (0.027)
Proportion Bachelors	0.1633*** (0.0273)	0.1634*** (0.0273)	0.1631*** (0.0273)	0.1633*** (0.0273)	0.1627*** (0.0273)	0.1635*** (0.0273)	0.1636*** (0.0273)	0.1633*** (0.0273)	0.1634*** (0.0273)	0.1627*** (0.0273)
Median Age	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Log Seasonal Vacancies	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)
Log Nonseasonal Vacancies	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)
Log-likelihood	-57094.62	-57092.35	-57088.38	-57076.61	-57079.25	-57094.62	-57092.35	-57088.38	-57076.61	-57079.25
AIC	60166.62	60164.35	60160.38	60148.61	60151.25	60166.62	60164.35	60160.38	60148.61	60151.25

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B4 Full Regression Results for Models (3) and (4) with Spatiotemporal Variation and Census Tract Spatial Fixed Effects

	(3)					(4)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0162** (0.0054)	0.0085* (0.004)	0.0001 (0.0036)	0.0009 (0.0063)	0.0147 (0.0099)	0.016** (0.0054)	0.0082* (0.004)	-0.0004 (0.0036)	0.0002 (0.0063)	0.013 (0.0099)
Log Salt	0.1109*** (0.0201)	0.069*** (0.0164)	0.032* (0.0142)	-0.0017 (0.0134)	-0.0323** (0.0108)	0.1107*** (0.0201)	0.0689*** (0.0164)	0.0321* (0.0142)	-0.0015 (0.0133)	-0.0299** (0.0107)
Log Bacteria	-0.0345*** (0.0073)	-0.03*** (0.005)	-0.0187*** (0.004)	-0.0033 (0.0025)	-0.0036* (0.0017)	-0.0344*** (0.0073)	-0.03*** (0.005)	-0.0187*** (0.004)	-0.0034 (0.0025)	-0.0036* (0.0017)
ECS x 0-8 km	-0.0047*** (0.0014)	-0.0049*** (0.0014)	-0.0046** (0.0015)	-0.0035* (0.0016)	-0.0012 (0.0016)					
ECS x 8-16 km	-0.0034* (0.0015)	-0.0036* (0.0015)	-0.0033* (0.0016)	-0.0023 (0.0016)	-0.0001 (0.0016)					
ECS x 16-40 km	-0.0041* (0.0016)	-0.0042** (0.0016)	-0.004* (0.0016)	-0.0032 (0.0017)	-0.0012 (0.0017)					
ECS x 40-80 km	-0.0035 (0.0025)	-0.0036 (0.0025)	-0.0033 (0.0026)	-0.0027 (0.0026)	-0.0008 (0.0026)					
ECS x 80-161 km	-0.0075* (0.0034)	-0.0075* (0.0034)	-0.007* (0.0034)	-0.0066 (0.0034)	-0.0051 (0.0034)					
ECS x MA						-0.0039** (0.0014)	-0.0041** (0.0014)	-0.0037** (0.0014)	-0.0028 (0.0015)	-0.0009 (0.0015)
ECS x RI						-0.007* (0.0028)	-0.0072** (0.0028)	-0.0069* (0.0028)	-0.0057* (0.0029)	-0.0026 (0.0029)
Dummy Fresh	-0.015*** (0.0039)	-0.0088** (0.0033)	-0.0111* (0.0047)	-0.02 (0.0135)	0.0105 (0.0287)	-0.015*** (0.004)	-0.0089** (0.0033)	-0.0113* (0.0047)	-0.0198 (0.0136)	0.0137 (0.0283)
Dummy Salt	-0.0153 (0.0095)	-0.0531*** (0.01)	-0.0803*** (0.0093)	-0.0609*** (0.0091)	-0.0064 (0.0142)	-0.0139 (0.0095)	-0.0522*** (0.01)	-0.0798*** (0.0093)	-0.061*** (0.0091)	-0.0221* (0.0089)
Dummy Bacteria	0.2044*** (0.0287)	0.1771*** (0.0201)	0.0989*** (0.0165)	-0.0149 (0.0133)	0.0007 (0.0151)	0.2044*** (0.0288)	0.1773*** (0.0201)	0.099*** (0.0166)	-0.0146 (0.0133)	0.0002 (0.0151)
Dummy x 0-8 km	0.0566 (0.0859)	0.0488 (0.0862)	0.043 (0.0867)	0.0517 (0.0865)	0.0729 (0.0867)					

Dummy x 8-16 km	0.0748	0.0689	0.0644	0.0722	0.0896					
	(0.0849)	(0.0853)	(0.0858)	(0.0856)	(0.085)					
Dummy x 16-40 km	0.0652	0.061	0.057	0.0637	0.0778					
	(0.0849)	(0.0853)	(0.0859)	(0.0856)	(0.085)					
Dummy x 40-80 km	0.1163	0.1147	0.1104	0.1141	0.1262*					
	(0.0616)	(0.0617)	(0.0622)	(0.0619)	(0.0611)					
Constant	9.4918***	9.5547***	9.6014***	9.5944***	9.4495***	9.5523***	9.6091***	9.6518***	9.6546***	9.5393***
	(0.1517)	(0.1484)	(0.1466)	(0.1512)	(0.155)	(0.1266)	(0.1231)	(0.122)	(0.1271)	(0.1324)
Log Distance to Freshwater	-0.0077*	-0.0054	-0.0039	-0.003	-0.003	-0.0076*	-0.0054	-0.0038	-0.0029	-0.0029
	(0.0034)	(0.003)	(0.0027)	(0.0027)	(0.0027)	(0.0034)	(0.0031)	(0.0027)	(0.0027)	(0.0027)
Log Distance to Saltwater	-0.0958***	-0.1023***	-0.1065***	-0.107***	-0.1017***	-0.0949***	-0.1015***	-0.1058***	-0.1064***	-0.1015***
	(0.0074)	(0.0068)	(0.0067)	(0.0071)	(0.0071)	(0.0073)	(0.0067)	(0.0067)	(0.0071)	(0.0071)
Log Distance to Airport	0.0161*	0.0151*	0.0146*	0.0158*	0.0169*	0.0165*	0.0156*	0.0152*	0.0162*	0.017*
	(0.0073)	(0.0072)	(0.0073)	(0.0077)	(0.0079)	(0.0073)	(0.0072)	(0.0073)	(0.0077)	(0.0079)
Log Distance to Highway	0.0168***	0.0168***	0.0178***	0.0177***	0.0183***	0.0168***	0.0168***	0.0178***	0.0177***	0.0183***
	(0.0031)	(0.003)	(0.003)	(0.0032)	(0.0032)	(0.0031)	(0.003)	(0.0031)	(0.0032)	(0.0033)
Log Distance to Railroad	0.0181***	0.0181***	0.0183***	0.0197***	0.0195***	0.0181***	0.0181***	0.0183***	0.0196***	0.0194***
	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Log Distance to Townhall	-0.0078	-0.0084*	-0.0085*	-0.0076	-0.0061	-0.0081*	-0.0087*	-0.0087*	-0.0078	-0.0063
	(0.0041)	(0.004)	(0.004)	(0.0041)	(0.0041)	(0.0041)	(0.004)	(0.004)	(0.0041)	(0.0041)
Building Age	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***	-0.0024***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log Lot Size	0.0505***	0.0504***	0.0495***	0.0489***	0.0488***	0.0506***	0.0505***	0.0496***	0.049***	0.0488***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Log Building Area	0.4947***	0.4949***	0.4947***	0.4955***	0.4957***	0.4947***	0.4948***	0.4947***	0.4955***	0.4957***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Rooms	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Log Population	-0.0028	-0.0027	-0.0034	-0.0046	-0.0051	-0.0027	-0.0026	-0.0033	-0.0046	-0.005
	(0.0049)	(0.0048)	(0.0049)	(0.005)	(0.0051)	(0.0049)	(0.0048)	(0.0049)	(0.0051)	(0.005)

Log Income	0.0293*** (0.0051)	0.0294*** (0.005)	0.0294*** (0.005)	0.0287*** (0.0051)	0.0294*** (0.0051)	0.0295*** (0.0051)	0.0296*** (0.005)	0.0296*** (0.0051)	0.0289*** (0.0051)	0.0295*** (0.0051)
Proportion Black	-0.0177 (0.0259)	-0.011 (0.0257)	-0.014 (0.0267)	-0.0206 (0.027)	-0.0212 (0.027)	-0.018 (0.026)	-0.0113 (0.0258)	-0.0143 (0.0268)	-0.0208 (0.0271)	-0.0212 (0.0271)
Proportion Bachelors	0.1486*** (0.0263)	0.1497*** (0.0261)	0.1591*** (0.0266)	0.1628*** (0.0271)	0.1622*** (0.0272)	0.1495*** (0.0264)	0.1505*** (0.0262)	0.1599*** (0.0268)	0.1636*** (0.0273)	0.1629*** (0.0273)
Median Age	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Log Seasonal Vacancies	0.0049*** (0.0014)	0.0047*** (0.0014)	0.0052*** (0.0014)	0.0059*** (0.0015)	0.006*** (0.0015)	0.005*** (0.0015)	0.0048*** (0.0015)	0.0052*** (0.0015)	0.0059*** (0.0015)	0.006*** (0.0016)
Log Nonseasonal Vacancies	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0001 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0002 (0.0007)
Log-likelihood	-56493.8	-56473.25	-56716.6	-56930.18	-57047.96	-56516.59	-56498.05	-56741.48	-56953.96	-57064.69
AIC	59583.8	59563.25	59806.6	60020.18	60137.96	59592.59	59574.05	59817.48	60029.96	60140.69

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B5 Full Regression Results for Models (3) and (4) with Spatial Variation and Census Tract Spatial Fixed Effects

	(3)					(4)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0205** (0.0066)	0.0065 (0.0058)	-0.0116 (0.0062)	-0.0145 (0.0136)	0.0054 (0.0285)	0.0204** (0.0066)	0.0062 (0.0058)	-0.0123* (0.0062)	-0.0155 (0.0136)	0.0035 (0.0283)
Log Salt	0.1693*** (0.0302)	0.1124*** (0.0275)	0.0869** (0.0301)	0.0554 (0.0328)	-0.0112 (0.0296)	0.1692*** (0.0302)	0.1125*** (0.0275)	0.0871** (0.0301)	0.0558 (0.0328)	-0.0071 (0.0302)
Log Bacteria	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0167* (0.0081)	0.0007 (0.0063)	-0.0028 (0.0061)	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0168* (0.0081)	0.0007 (0.0063)	-0.0026 (0.0062)
ECS x 0-8 km	-0.0031* (0.0014)	-0.003* (0.0014)	-0.0028* (0.0014)	-0.0029* (0.0014)	-0.0031* (0.0014)					
ECS x 8-16 km	-0.0019 (0.0015)	-0.0018 (0.0015)	-0.0018 (0.0015)	-0.0019 (0.0015)	-0.0019 (0.0015)					
ECS x 16-40 km	-0.0028 (0.0016)	-0.0027 (0.0016)	-0.0027 (0.0016)	-0.0028 (0.0016)	-0.0028 (0.0016)					
ECS x 40-80 km	-0.0025 (0.0025)	-0.0022 (0.0026)	-0.0021 (0.0026)	-0.0023 (0.0026)	-0.0023 (0.0026)					
ECS x 80-161 km	-0.0063 (0.0034)	-0.006 (0.0034)	-0.0058 (0.0034)	-0.0061 (0.0034)	-0.0062 (0.0034)					
ECS x MA						-0.0024 (0.0014)	-0.0023 (0.0013)	-0.0022 (0.0014)	-0.0024 (0.0014)	-0.0024 (0.0014)
ECS x RI						-0.0052 (0.0028)	-0.0051 (0.0028)	-0.005 (0.0028)	-0.0049 (0.0028)	-0.0049 (0.0028)
Dummy Fresh	-0.021*** (0.0043)	-0.0125*** (0.0036)	-0.0223*** (0.0058)	-0.0442 (0.0337)	9.4776*** (0.1512)	-0.0211*** (0.0044)	-0.0127*** (0.0037)	-0.0223*** (0.0058)	-0.044 (0.0339)	9.5574*** (0.1287)
Dummy Salt	-0.0214* (0.0102)	-0.057*** (0.0104)	-0.0812*** (0.0107)	-0.0564*** (0.0102)	0.0033 (0.0127)	-0.0201* (0.0102)	-0.056*** (0.0104)	-0.0806*** (0.0107)	-0.0564*** (0.0102)	-0.0188 (0.0102)
Dummy Bacteria	0.2578*** (0.0513)	0.2071*** (0.0377)	0.0835** (0.0281)	-0.0411 (0.0242)	-0.0092 (0.0228)	0.2581*** (0.0513)	0.2076*** (0.0376)	0.0841** (0.0281)	-0.0409 (0.0242)	-0.0106 (0.023)

Dummy x 0-8 km	0.0578 (0.0864)	0.0513 (0.087)	0.0475 (0.087)	0.0507 (0.0865)	0.0521 (0.0873)					
Dummy x 8-16 km	0.0757 (0.0854)	0.0711 (0.086)	0.0692 (0.0861)	0.0715 (0.0856)	0.0749 (0.0859)					
Dummy x 16-40 km	0.0646 (0.0854)	0.0616 (0.086)	0.0601 (0.0862)	0.0623 (0.0857)	0.0645 (0.086)					
Dummy x 40-80 km	0.1119 (0.0619)	0.1114 (0.0619)	0.1098 (0.062)	0.1127 (0.0617)	0.1146 (0.0622)					
Constant	9.5112*** (0.1533)	9.5558*** (0.1494)	9.5999*** (0.146)	9.6206*** (0.1507)		9.5734*** (0.1276)	9.6134*** (0.1236)	9.6552*** (0.1215)	9.6797*** (0.1281)	
Log Distance to Freshwater	-0.0102** (0.0037)	-0.0071* (0.0031)	-0.005 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.0102** (0.0037)	-0.0071* (0.0032)	-0.0049 (0.0028)	-0.003 (0.0027)	-0.003 (0.0027)
Log Distance to Saltwater	-0.0953*** (0.0074)	-0.1006*** (0.0067)	-0.1055*** (0.0067)	-0.1068*** (0.0071)	-0.1014*** (0.0071)	-0.0944*** (0.0074)	-0.0998*** (0.0067)	-0.1048*** (0.0066)	-0.1062*** (0.0071)	-0.1013*** (0.0071)
Log Distance to Airport	0.0161* (0.0072)	0.0152* (0.007)	0.0153* (0.0071)	0.0157* (0.0074)	0.0165* (0.0079)	0.0165* (0.0072)	0.0157* (0.007)	0.0158* (0.0071)	0.0161* (0.0074)	0.0166* (0.0079)
Log Distance to Highway	0.0167*** (0.003)	0.0168*** (0.003)	0.0178*** (0.003)	0.0178*** (0.0031)	0.018*** (0.0032)	0.0167*** (0.0031)	0.0168*** (0.003)	0.0178*** (0.003)	0.0178*** (0.0031)	0.018*** (0.0032)
Log Distance to Railroad	0.0179*** (0.0022)	0.0179*** (0.0022)	0.0182*** (0.0022)	0.0198*** (0.0023)	0.0196*** (0.0023)	0.0179*** (0.0022)	0.0179*** (0.0022)	0.0182*** (0.0022)	0.0198*** (0.0023)	0.0195*** (0.0023)
Log Distance to Townhall	-0.008 (0.0041)	-0.0085* (0.004)	-0.0088* (0.0039)	-0.0078 (0.0041)	-0.006 (0.0041)	-0.0083* (0.0042)	-0.0087* (0.004)	-0.009* (0.004)	-0.008 (0.0041)	-0.0062 (0.0041)
Building Age	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)
Log Lot Size	0.0507*** (0.0024)	0.0507*** (0.0024)	0.0496*** (0.0024)	0.0492*** (0.0024)	0.0488*** (0.0024)	0.0508*** (0.0024)	0.0508*** (0.0024)	0.0497*** (0.0024)	0.0492*** (0.0024)	0.0488*** (0.0024)
Log Building Area	0.4943*** (0.0071)	0.4945*** (0.0071)	0.4947*** (0.0071)	0.4955*** (0.0071)	0.4958*** (0.0071)	0.4943*** (0.0071)	0.4945*** (0.0071)	0.4947*** (0.0071)	0.4955*** (0.0071)	0.4958*** (0.0071)
Rooms	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)

Log Population	-0.0022 (0.0049)	-0.002 (0.0047)	-0.0028 (0.0048)	-0.0043 (0.005)	-0.005 (0.0051)	-0.0022 (0.0049)	-0.002 (0.0047)	-0.0027 (0.0048)	-0.0042 (0.005)	-0.0049 (0.0051)
Log Income	0.0292*** (0.0051)	0.0291*** (0.005)	0.0295*** (0.0051)	0.0287*** (0.0051)	0.0293*** (0.0052)	0.0293*** (0.0051)	0.0293*** (0.005)	0.0297*** (0.0051)	0.0289*** (0.0051)	0.0294*** (0.0052)
Proportion Black	-0.0158 (0.0259)	-0.0102 (0.0257)	-0.0156 (0.0268)	-0.0191 (0.027)	-0.0209 (0.0269)	-0.0161 (0.026)	-0.0105 (0.0258)	-0.0159 (0.0269)	-0.0193 (0.0271)	-0.0209 (0.027)
Proportion Bachelors	0.1444*** (0.0265)	0.1444*** (0.0261)	0.1584*** (0.0268)	0.1628*** (0.027)	0.1627*** (0.0272)	0.1451*** (0.0267)	0.1452*** (0.0262)	0.1592*** (0.0269)	0.1637*** (0.0272)	0.1633*** (0.0273)
Median Age	0.001*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.001*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Log Seasonal Vacancies	0.0049*** (0.0015)	0.0045** (0.0015)	0.0051*** (0.0014)	0.0057*** (0.0015)	0.0059*** (0.0015)	0.0049*** (0.0015)	0.0046** (0.0015)	0.0051*** (0.0015)	0.0058*** (0.0015)	0.0059*** (0.0015)
Log Nonseasonal Vacancies	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0001 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0003 (0.0007)	-0.0002 (0.0007)	-0.0002 (0.0007)
Log-likelihood	-56362.66	-56351.77	-56650.7	-56904.93	-57069.85	-56384.34	-56374.77	-56673.76	-56928.18	-57085.66
AIC	59452.66	59441.77	59740.7	59994.93	60157.85	59460.34	59450.77	59749.76	60004.18	60159.66

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B6 Full Regression Results for Models (3) and (4) with Temporal Variation and Census Tract Spatial Fixed Effects

	(3)					(4)				
	0.5 km	1 km	2 km	4 km	8 km	0.5 km	1 km	2 km	4 km	8 km
Log Fresh	0.0062 (0.0038)	0.0096* (0.0039)	0.0122** (0.0044)	0.016** (0.0056)	0.0199** (0.0074)	0.0059 (0.0038)	0.0092* (0.0039)	0.0117** (0.0044)	0.0152** (0.0056)	0.0183* (0.0075)
Log Salt	-0.0168 (0.0103)	-0.0172 (0.0098)	-0.0248** (0.0085)	-0.0371*** (0.0087)	-0.0366*** (0.0083)	-0.0169 (0.0102)	-0.0172 (0.0097)	-0.0247** (0.0084)	-0.0368*** (0.0085)	-0.0358*** (0.008)
Log Bacteria	-0.0056* (0.0028)	-0.0033 (0.0025)	-0.0028 (0.0021)	-0.0015 (0.0016)	-0.0031* (0.0015)	-0.0056* (0.0028)	-0.0033 (0.0025)	-0.0029 (0.0021)	-0.0016 (0.0016)	-0.0032* (0.0015)
ECS x 0-8 km	-0.0025 (0.0014)	-0.0025 (0.0014)	-0.0019 (0.0015)	-0.0011 (0.0015)	-0.0007 (0.0015)					
ECS x 8-16 km	-0.0014 (0.0015)	-0.0014 (0.0015)	-0.0008 (0.0015)	-0.0001 (0.0016)	0.0002 (0.0016)					
ECS x 16-40 km	-0.0023 (0.0016)	-0.0023 (0.0016)	-0.0019 (0.0016)	-0.0012 (0.0016)	-0.001 (0.0017)					
ECS x 40-80 km	-0.0019 (0.0026)	-0.0019 (0.0026)	-0.0014 (0.0026)	-0.0009 (0.0026)	-0.0006 (0.0026)					
ECS x 80-161 km	-0.0059 (0.0034)	-0.006 (0.0034)	-0.0056 (0.0034)	-0.0052 (0.0034)	-0.0051 (0.0034)					
ECS x MA						-0.0019 (0.0014)	-0.0019 (0.0014)	-0.0014 (0.0014)	-0.0007 (0.0014)	-0.0004 (0.0015)
ECS x RI						-0.0044 (0.0028)	-0.0045 (0.0028)	-0.0037 (0.0028)	-0.0025 (0.0028)	-0.002 (0.0028)
Dummy Fresh	0.0012 (0.0084)	0.0041 (0.01)	-0.0027 (0.0159)	-0.0379*** (0.011)	0.0122 (0.0095)	0.001 (0.0084)	0.004 (0.01)	-0.0026 (0.0158)	-0.0371*** (0.0112)	0.0146 (0.0096)
Dummy Salt	0.0862** (0.0266)	0.0707** (0.0226)	0.0833** (0.0265)	-0.0621 (0.0418)	0.0437 (0.0524)	0.0855** (0.0267)	0.0694** (0.023)	0.0822** (0.0267)	-0.0626 (0.0415)	0.0432 (0.0523)
Dummy Bacteria	0.0104 (0.0115)	-0.0076 (0.0118)	0.0021 (0.011)	0.0017 (0.0102)	-0.0072 (0.0124)	0.0089 (0.0115)	-0.0089 (0.0119)	0.0017 (0.0111)	0.0014 (0.0103)	-0.0067 (0.0124)

Dummy x 0-8 km	0.0579 (0.0866)	0.0604 (0.0864)	0.0623 (0.0863)	0.069 (0.0862)	0.0744 (0.0859)					
Dummy x 8-16 km	0.0779 (0.0857)	0.0804 (0.0855)	0.0825 (0.0854)	0.0892 (0.0852)	0.0946 (0.085)					
Dummy x 16-40 km	0.0675 (0.0857)	0.07 (0.0856)	0.0716 (0.0854)	0.0777 (0.0853)	0.0827 (0.085)					
Dummy x 40-80 km	0.1173 (0.0618)	0.1196 (0.0615)	0.1213* (0.0614)	0.1256* (0.0611)	0.1295* (0.0605)					
Constant	9.4397*** (0.1523)	9.4378*** (0.1522)	9.4324*** (0.1539)	9.5113*** (0.1533)	9.4146*** (0.154)	9.5065*** (0.1288)	9.5076*** (0.129)	9.5039*** (0.1309)	9.5887*** (0.1303)	9.4955*** (0.1312)
Log Distance to Freshwater	-0.0031 (0.0027)	-0.0031 (0.0027)	-0.0031 (0.0027)	-0.0031 (0.0027)	-0.0031 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)	-0.003 (0.0027)
Log Distance to Saltwater	-0.1007*** (0.0071)	-0.1007*** (0.0071)	-0.1007*** (0.0071)	-0.1007*** (0.0071)	-0.1007*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)	-0.1002*** (0.0071)
Log Distance to Airport	0.0168* (0.0078)	0.0168* (0.0078)	0.0168* (0.0078)	0.0168* (0.0078)	0.0168* (0.0078)	0.0173* (0.0078)	0.0173* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)	0.0172* (0.0078)
Log Distance to Highway	0.0178*** (0.0032)	0.0178*** (0.0032)	0.0178*** (0.0032)	0.0178*** (0.0032)	0.0178*** (0.0032)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)	0.0178*** (0.0033)
Log Distance to Railroad	0.0197*** (0.0023)	0.0196*** (0.0023)	0.0197*** (0.0023)	0.0197*** (0.0023)	0.0197*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)	0.0196*** (0.0023)
Log Distance to Townhall	-0.0057 (0.0041)	-0.0057 (0.0041)	-0.0057 (0.0041)	-0.0058 (0.0041)	-0.0058 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)	-0.006 (0.0041)
Building Age	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)
Log Lot Size	0.0488*** (0.0024)	0.0488*** (0.0024)	0.0488*** (0.0024)	0.0488*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)	0.0489*** (0.0024)
Log Building Area	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)	0.4958*** (0.0071)
Rooms	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)	0.008*** (0.0016)

Log Population	-0.0049 (0.005)	-0.0049 (0.005)	-0.0049 (0.0051)	-0.005 (0.0051)	-0.005 (0.005)	-0.0048 (0.0051)	-0.0048 (0.0051)	-0.0049 (0.0051)	-0.0049 (0.0051)	-0.0049 (0.0051)
Log Income	0.0291*** (0.0052)	0.0291*** (0.0052)	0.0291*** (0.0052)	0.0292*** (0.0052)	0.0291*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0293*** (0.0052)	0.0294*** (0.0052)	0.0293*** (0.0052)
Proportion Black	-0.0212 (0.0269)	-0.0212 (0.0268)	-0.0213 (0.0268)	-0.0213 (0.0268)	-0.021 (0.0269)	-0.0215 (0.027)	-0.0215 (0.027)	-0.0215 (0.0269)	-0.0215 (0.0269)	-0.0213 (0.027)
Proportion Bachelors	0.1626*** (0.0272)	0.1627*** (0.0272)	0.1624*** (0.0272)	0.1625*** (0.0272)	0.1618*** (0.0272)	0.1634*** (0.0273)	0.1636*** (0.0273)	0.1633*** (0.0273)	0.1634*** (0.0274)	0.1627*** (0.0274)
Median Age	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)	0.0011*** (0.0002)
Log Seasonal Vacancies	0.0059*** (0.0015)	0.0059*** (0.0015)	0.0059*** (0.0015)	0.0059*** (0.0015)	0.0059*** (0.0015)	0.0059*** (0.0016)	0.0059*** (0.0016)	0.0059*** (0.0016)	0.006*** (0.0016)	0.006*** (0.0016)
Log Nonseasonal Vacancies	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0002 (0.0007)	-0.0001 (0.0007)	-0.0002 (0.0007)	-0.0001 (0.0007)
Log-likelihood	-57068.02	-57065.71	-57062.6	-57051.61	-57054.14	-57091.8	-57089.45	-57086.54	-57075.82	-57078.77
AIC	60158.02	60155.71	60152.6	60141.61	60144.14	60167.8	60165.45	60162.54	60151.82	60154.77

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B7 Selected Wald Test Results

Model	WQ Variation	Test Variables	$F_{1,n-k-1}$	n-k-1
2	Spatiotemporal	ECS x 0-8 km, ECS x 8-16 km	1.582783	264634
2	Spatiotemporal	ECS x 0-8 km, ECS x 16-40 km	0.23971	264634
2	Spatiotemporal	ECS x 0-8 km, ECS x 40-80 km	0.249045	264634
3	Spatiotemporal	ECS x 0-8 km, ECS x 80-161 km	0.74461	264634
3	Spatiotemporal	ECS x 8-16 km, ECS x 16-40 km	0.589227	264634
3	Spatiotemporal	ECS x 8-16 km, ECS x 40-80 km	0.004126	264634
3	Spatiotemporal	ECS x 8-16 km, ECS x 80-161 km	1.710731	264634
3	Spatiotemporal	ECS x 16-40 km, ECS x 40-80 km	0.064903	264634
3	Spatiotemporal	ECS x 16-40 km, ECS x 80-161 km	1.209452	264634
3	Spatiotemporal	ECS x 40-80 km, ECS x 80-161 km	2.585624	264634
3	Spatiotemporal	ECS x MA, ECS x RI	1.318272	264641
2	Spatial	ECS x 0-8 km, ECS x 8-16 km	1.166666	264634
2	Spatial	ECS x 0-8 km, ECS x 16-40 km	0.045509	264634
2	Spatial	ECS x 0-8 km, ECS x 40-80 km	0.072743	264634
3	Spatial	ECS x 0-8 km, ECS x 80-161 km	0.961328	264634
3	Spatial	ECS x 8-16 km, ECS x 16-40 km	0.980265	264634
3	Spatial	ECS x 8-16 km, ECS x 40-80 km	0.054091	264634
3	Spatial	ECS x 8-16 km, ECS x 80-161 km	1.891877	264634
3	Spatial	ECS x 16-40 km, ECS x 40-80 km	0.028269	264634
3	Spatial	ECS x 16-40 km, ECS x 80-161 km	1.222737	264634
3	Spatial	ECS x 40-80 km, ECS x 80-161 km	2.38013	264634
3	Spatial	ECS x MA, ECS x RI	1.004085	1.004085
2	Temporal	ECS x 0-8 km, ECS x 8-16 km	1.098975	264634
2	Temporal	ECS x 0-8 km, ECS x 16-40 km	0.018455	264634
2	Temporal	ECS x 0-8 km, ECS x 40-80 km	0.067497	264634
3	Temporal	ECS x 0-8 km, ECS x 80-161 km	1.050073	264634
3	Temporal	ECS x 8-16 km, ECS x 16-40 km	1.078181	264634
3	Temporal	ECS x 8-16 km, ECS x 40-80 km	0.043563	264634
3	Temporal	ECS x 8-16 km, ECS x 80-161 km	1.954653	264634
3	Temporal	ECS x 16-40 km, ECS x 40-80 km	0.041708	264634
3	Temporal	ECS x 16-40 km, ECS x 80-161 km	1.248147	264634
3	Temporal	ECS x 40-80 km, ECS x 80-161 km	2.55388	264634
3	Temporal	ECS x MA, ECS x RI	0.826	264641

Notes: Ambient water quality specified using 0.5 km buffer, Census tract spatial fixed effects, and year and month fixed effects. Values are significant if greater than $F_{1,inf,05} = 3.84$.

Table B8 Selected Regression Results by Water Quality Buffer Distance with Block Group Spatial Fixed Effects

	0.5 km		1 km		2 km		4 km		8 km	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
<i>Spatial-Temporal Variation</i>										
Log Fresh	0.0115*	0.0115*	0.0085*	0.0084*	0.0028	0.0028	0.0036	0.0033	0.015*	0.0149*
	(0.0048)	(0.0048)	(0.0035)	(0.0035)	(0.0031)	(0.0031)	(0.0052)	(0.0052)	(0.0074)	(0.0075)
Log Salt	0.0799***	0.0821***	0.0444***	0.0474***	-0.0009	0.0019	-0.0267**	-0.0242**	-0.0414***	-0.0408***
	(0.0146)	(0.0146)	(0.0122)	(0.0123)	(0.0099)	(0.01)	(0.0082)	(0.0086)	(0.0077)	(0.0082)
Log Bacteria	-0.0203***	-0.0204***	-0.0187***	-0.0188***	-0.0092**	-0.0094**	-0.0031	-0.0032	-0.0036*	-0.0036*
	(0.006)	(0.006)	(0.0047)	(0.0047)	(0.0031)	(0.0031)	(0.002)	(0.002)	(0.0015)	(0.0015)
ECS		-0.0036**		-0.0037**		-0.0028*		-0.0019		-0.0004
		(0.0013)		(0.0013)		(0.0013)		(0.0014)		(0.0014)
Log-likelihood	-50269.06	-50262.65	-50306.8	-50300.14	-50416.27	-50412.57	-50462.73	-50461.07	59756.95	-50532.9
AIC	59493.06	59488.65	59530.8	59526.14	59640.27	59638.57	59686.73	59687.07	59756.95	59758.9
<i>Spatial Variation</i>										
Log Fresh	0.0139*	0.0139*	0.0058	0.0058	-0.0078	-0.0077	-0.015	-0.015	0.0022	0.0023
	(0.0062)	(0.0062)	(0.0054)	(0.0054)	(0.0059)	(0.0059)	(0.0144)	(0.0144)	(0.0289)	(0.0289)
Log Salt	0.148***	0.148***	0.0953***	0.0953***	0.0398	0.0398	0.012	0.0121	-0.0335	-0.0336
	(0.0222)	(0.0222)	(0.0242)	(0.0242)	(0.0257)	(0.0256)	(0.0266)	(0.0266)	(0.0285)	(0.0285)
Log Bacteria	-0.0405***	-0.0405***	-0.026**	-0.026**	-0.0063	-0.0063	0.0016	0.0016	-0.0035	-0.0034
	(0.0104)	(0.0104)	(0.008)	(0.008)	(0.0074)	(0.0074)	(0.0055)	(0.0055)	(0.0062)	(0.0062)
ECS		-0.0025		-0.0024		-0.0023		-0.0024		-0.0025
		(0.0013)		(0.0013)		(0.0013)		(0.0013)		(0.0013)
Log-likelihood	-50161.93	-50158.78	-50240.82	-50237.92	-50390.78	-50388.1	-50450.12	-50447.33	-50561.62	-50558.62
AIC	59385.93	59384.78	59464.82	59463.92	59614.78	59614.1	59674.12	59673.33	59783.62	59782.62
<i>Temporal Variation</i>										
Log Fresh	0.0056	0.0056	0.0089*	0.0089*	0.0116**	0.0116**	0.014*	0.0138*	0.0182*	0.0181*
	(0.0037)	(0.0037)	(0.0039)	(0.0039)	(0.0043)	(0.0043)	(0.0055)	(0.0055)	(0.0072)	(0.0073)
Log Salt	-0.0235*	-0.0201*	-0.0241**	-0.0209*	-0.0317***	-0.0296***	-0.0421***	-0.0411***	-0.0406***	-0.0403***
	(0.0094)	(0.0097)	(0.009)	(0.0093)	(0.0077)	(0.0081)	(0.0076)	(0.0082)	(0.0073)	(0.0078)
Log Bacteria	-0.0053*	-0.0054*	-0.0029	-0.0029	-0.0026	-0.0026	-0.0018	-0.0018	-0.0035*	-0.0035*
	(0.0026)	(0.0026)	(0.0024)	(0.0024)	(0.002)	(0.002)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
ECS		-0.0019		-0.0018		-0.0012		-0.0005		-0.0002
		(0.0013)		(0.0013)		(0.0014)		(0.0014)		(0.0014)
Log-likelihood	-50564.53	-50562.93	-50562.78	-50561.34	-50556.81	-50556.21	-50544.77	-50544.67	-50545.53	-50545.52
AIC	59788.53	59788.93	59786.78	59787.34	59780.81	59782.21	59768.77	59770.67	59769.53	59771.52

Notes: N = 264679. Models specified with Census block group, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B9 Selected Regression Results by ECS Specification with Block Group Spatial Fixed Effects

	<i>Spatiotemporal Variation</i>		<i>Spatial Variation</i>		<i>Temporal Variation</i>	
	(3)	(4)	(3)	(4)	(3)	(4)
Log Fresh	0.0117* (0.0048)	0.0114* (0.0048)	0.0141* (0.0061)	0.0139* (0.0062)	0.0058 (0.0037)	0.0056 (0.0037)
Log Salt	0.0824*** (0.0146)	0.0826*** (0.0145)	0.148*** (0.0222)	0.1481*** (0.0222)	-0.0199* (0.0097)	-0.019* (0.0096)
Log Bacteria	-0.0205*** (0.006)	-0.0204*** (0.006)	-0.0405*** (0.0104)	-0.0405*** (0.0104)	-0.0053* (0.0026)	-0.0054* (0.0026)
ECS x 0-8 km	-0.0041** (0.0014)		-0.0028* (0.0014)		-0.0021 (0.0014)	
ECS x 8-16 km	-0.0036* (0.0014)		-0.0026 (0.0014)		-0.0019 (0.0014)	
ECS x 16-40 km	-0.0028 (0.0016)		-0.002 (0.0016)		-0.0014 (0.0016)	
ECS x 40-80 km	-0.005 (0.0026)		-0.0044 (0.0026)		-0.0037 (0.0027)	
ECS x 80-161 km	-0.007* (0.0035)		-0.0061 (0.0036)		-0.0057 (0.0036)	
ECS x MA		-0.0033* (0.0013)		-0.0022 (0.0013)		-0.0016 (0.0014)
ECS x RI		-0.0073** (0.0027)		-0.0059* (0.0028)		-0.0052 (0.0027)
Log-likelihood	-50247.95	-50260.12	-50144.75	-50156.64	-50548.76	-50560.95
AIC	59489.95	59488.12	59386.75	59384.64	59790.76	59788.95

Notes: N = 264679. Ambient water quality specified using 0.5 km buffer. All models specified Census block group, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level. *p<.05, **p<.01, ***p<.001

Table B10 Selected Regression Results by Water Quality Buffer Distance with Yeah Half Effects

	0.5 km		1 km		2 km		4 km		8 km	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
<i>Spatial-Temporal Variation</i>										
Log Fresh	0.0161** (0.0054)	0.016** (0.0054)	0.0083* (0.004)	0.0082* (0.004)	-0.0003 (0.0036)	-0.0004 (0.0036)	0.0004 (0.0063)	0.0002 (0.0063)	0.0131 (0.0099)	0.0129 (0.0099)
Log Salt	0.1083*** (0.0201)	0.1105*** (0.0201)	0.0656*** (0.0163)	0.0684*** (0.0164)	0.0282* (0.0139)	0.0315* (0.0142)	-0.0053 (0.0128)	-0.002 (0.0133)	-0.0318** (0.0101)	-0.0305** (0.0107)
Log Bacteria	-0.0343*** (0.0074)	-0.0344*** (0.0073)	-0.0298*** (0.005)	-0.0299*** (0.005)	-0.0185*** (0.004)	-0.0186*** (0.004)	-0.0031 (0.0025)	-0.0033 (0.0025)	-0.0034* (0.0017)	-0.0035* (0.0017)
ECS		-0.0041** (0.0013)		-0.0043** (0.0013)		-0.0039** (0.0014)		-0.003* (0.0015)		-0.0009 (0.0015)
Log-likelihood	-56518.08	-56510.17	-56500.43	-56491.93	-56742.46	-56735.38	-56951.64	-56947.75	-57057.87	-57057.5
AIC	59600.08	59594.17	59582.43	59575.93	59824.46	59819.38	60033.64	60031.75	60139.87	60141.5
<i>Spatial Variation</i>										
Log Fresh	0.0204** (0.0066)	0.0204** (0.0066)	0.0062 (0.0058)	0.0062 (0.0058)	-0.0123* (0.0062)	-0.0122* (0.0062)	-0.0155 (0.0136)	-0.0155 (0.0136)	0.0033 (0.0282)	0.0033 (0.0283)
Log Salt	0.1692*** (0.0302)	0.1693*** (0.0302)	0.1124*** (0.0275)	0.1124*** (0.0275)	0.087** (0.0301)	0.087** (0.0301)	0.0557 (0.0328)	0.0557 (0.0328)	-0.0073 (0.0302)	-0.0074 (0.0302)
Log Bacteria	-0.0525*** (0.0153)	-0.0525*** (0.0153)	-0.0381*** (0.0111)	-0.0381*** (0.0111)	-0.0168* (0.0081)	-0.0168* (0.0081)	0.0006 (0.0063)	0.0007 (0.0063)	-0.0027 (0.0062)	-0.0026 (0.0062)
ECS		-0.0026* (0.0013)		-0.0025 (0.0013)		-0.0024 (0.0013)		-0.0025 (0.0013)		-0.0026 (0.0013)
Log-likelihood	-56380.79	-56377.51	-56371.05	-56368.09	-56670.01	-56667.29	-56924.72	-56921.72	-57082.12	-57078.99
AIC	59462.79	59461.51	59453.05	59452.09	59752.01	59751.29	60006.72	60005.72	60162.12	60160.99
<i>Temporal Variation</i>										
Log Fresh	0.0058 (0.0038)	0.0058 (0.0038)	0.0091* (0.0039)	0.0091* (0.0039)	0.0118** (0.0044)	0.0116** (0.0044)	0.0153** (0.0056)	0.0151** (0.0056)	0.0185* (0.0074)	0.0183* (0.0075)
Log Salt	-0.0213* (0.01)	-0.0177 (0.0103)	-0.0216* (0.0095)	-0.018 (0.0098)	-0.0281*** (0.0081)	-0.0254** (0.0085)	-0.0389*** (0.0081)	-0.0375*** (0.0087)	-0.0374*** (0.0076)	-0.0366*** (0.0082)
Log Bacteria	-0.0055* (0.0028)	-0.0055* (0.0028)	-0.0032 (0.0025)	-0.0032 (0.0025)	-0.0027 (0.002)	-0.0027 (0.002)	-0.0014 (0.0016)	-0.0015 (0.0016)	-0.003* (0.0015)	-0.0031* (0.0015)
ECS		-0.002 (0.0013)		-0.002 (0.0014)		-0.0015 (0.0014)		-0.0008 (0.0014)		-0.0004 (0.0014)
Log-likelihood	-57086.98	-57085.17	-57084.77	-57083.01	-57080.78	-57079.85	-57068.93	-57068.69	-57071.64	-57071.56
AIC	60168.98	60169.17	60166.77	60167.01	60162.78	60163.85	60150.93	60152.69	60153.64	60155.56

Notes: N = 264679. Models specified with Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level.

*p<.05, **p<.01, ***p<.001

Table B11 Selected Regression Results by ECS Specification with Year Half Effects

	<i>Spatiotemporal Variation</i>		<i>Spatial Variation</i>		<i>Temporal Variation</i>	
	(3)	(4)	(3)	(4)	(3)	(4)
Log Fresh	0.0162** (0.0054)	0.016** (0.0054)	0.0205** (0.0066)	0.0204** (0.0066)	0.0062 (0.0038)	0.0058 (0.0038)
Log Salt	0.111*** (0.0202)	0.1108*** (0.0201)	0.1694*** (0.0302)	0.1693*** (0.0302)	-0.0169 (0.0103)	-0.0169 (0.0102)
Log Bacteria	-0.0345*** (0.0073)	-0.0344*** (0.0073)	-0.0525*** (0.0154)	-0.0525*** (0.0154)	-0.0056* (0.0028)	-0.0056* (0.0028)
ECS x 0-8 km	-0.0047*** (0.0014)		-0.003* (0.0014)		-0.0024 (0.0014)	
ECS x 8-16 km	-0.0033* (0.0015)		-0.0019 (0.0015)		-0.0013 (0.0015)	
ECS x 16-40 km	-0.004* (0.0016)		-0.0028 (0.0016)		-0.0023 (0.0016)	
ECS x 40-80 km	-0.0035 (0.0025)		-0.0024 (0.0025)		-0.0018 (0.0026)	
ECS x 80-161 km	-0.0074* (0.0034)		-0.0062 (0.0034)		-0.0058 (0.0034)	
ECS x MA		-0.0038** (0.0014)		-0.0024 (0.0014)		-0.0018 (0.0014)
ECS x RI		-0.007* (0.0028)		-0.0051 (0.0028)		-0.0043 (0.0028)
Log-likelihood	-56486.08	-56508.67	-56354.88	-56376.37	-57060.67	-57084.26
AIC	59586.08	59594.67	59454.88	59462.37	60160.67	60170.26

Notes: N = 264679. Ambient water quality specified using 0.5 km buffer. All models specified Census tract, year, and month fixed effects. Standard errors in parentheses clustered at Census tract level. *p<.05, **p<.01, ***p<.001

Table B12 Capitalization Totals and Counts

	Total Capitalization (\$1,000,000s)		Number of Households (1,000s)	
Freshwater Clarity	561	359	507	1,034
Saltwater Clarity	2,783	2,716	198	320
Saltwater Bacteria	864	920	198	320
Water Quality Buffer	0.5 km	1 km	0.5 km	1 km

Notes: Capitalization calculated using most recent assessed values adjusted to 2022 \$.

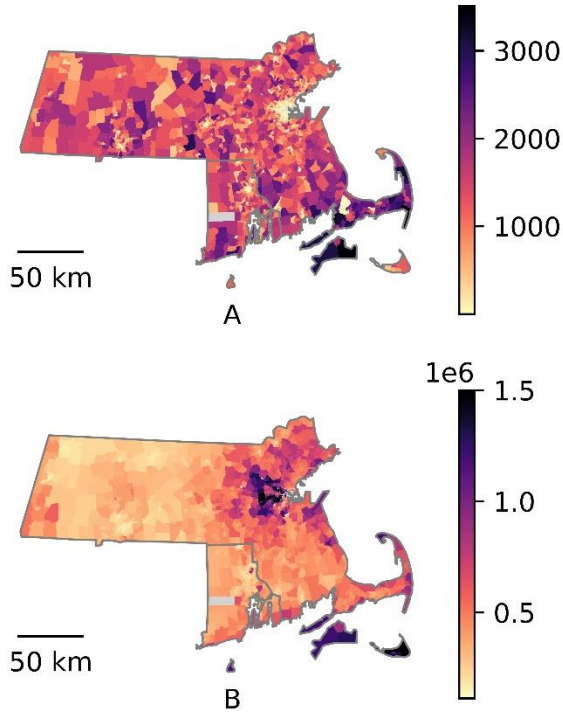


Figure B1 Residential Single-Family Property Counts and Assessed Values

Notes: Panel A depicts the number of single-family residential properties. (N = 1,652,070) Panel B depicts the median assessed price. Legend capped \$1.5 million.

Appendix C Isolating Temporal Variation

A preferred way economists isolate temporal variation in hedonic models is through repeat sales analysis. This differs from the approach used in the manuscript as the observations are more locally specific rather than aggregated over a large unit. However, using repeat sales greatly limits the sample size and amount of identifying variation. For a short time period as in this study, there may also be concerns with sample selection bias for properties that have been sold frequently. In Figure C1, we map our sales count and proportion of sales by census tract. Overall looking at sale counts, we see only 33,585 repeat sales compared to 264,679 sales in the baseline sample. The sample distributions throughout the study area look similar across the two samples. The only exception is one census tract in southwest Massachusetts that makes up 1% of the repeat sales sample and only 0.4% of the baseline sample.

Table C1 shows the estimates for model 2 for each buffer with Census tract, block group, and property fixed effects. All models are estimated using spatiotemporal variation, which at the property fixed effect level will reflect on temporal variation. With the repeat sales sample, we see the effect of freshwater clarity with Census tract fixed effects is much larger than before. The effects of saltwater clarity and bacteria are slightly smaller, and the bacteria estimate is not significant for the 0.5 km buffer. The effect of ECS is larger in magnitude but not significant. With property fixed effects, the freshwater clarity estimates are similar in direction and magnitude, while the saltwater clarity and bacteria switch signs. ECS remains negative and smaller in magnitude. None of the results are significant.

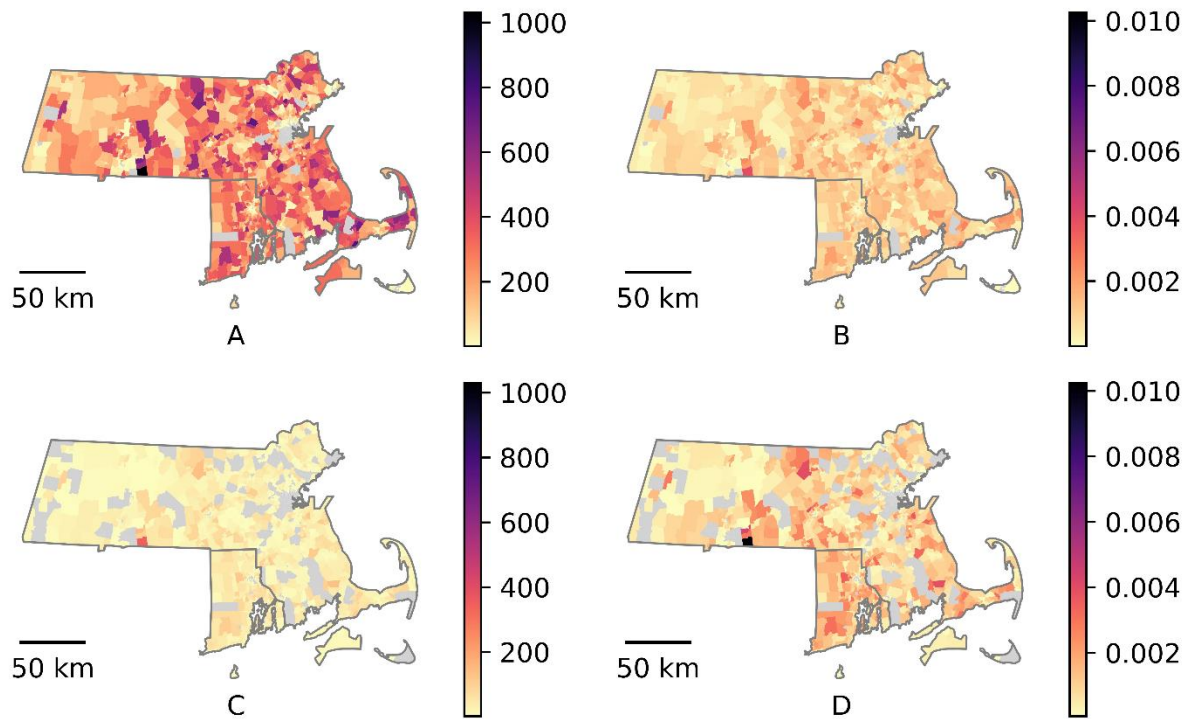


Figure C1 Baseline and Repeat Sale Counts by Census Tract

Notes: Panel A depicts the baseline sample sale count ($N = 264679$, Median = 144.5) by Census Tract. Panel B depicts the proportion of baseline sales in each census tract. Panel C depicts the repeat sales sample ($N = 33585$, Median = 24.0) by Census Tract. Panel D depicts the proportion of repeat sales in each census tract.

Table C1 Selected Results from Repeat Sales Sample by Water Quality Buffer Distance

	0.5 km	1 km	2 km	4 km	8 km
<i>Census Tract Fixed Effects</i>					
Log Fresh	0.0315** (0.0114)	0.0283** (0.0088)	0.0072 (0.0077)	0.0165 (0.0131)	0.0245 (0.0193)
Log Salt	0.0914*** (0.0275)	0.0587* (0.0228)	0.0194 (0.0219)	-0.0118 (0.0201)	-0.0157 (0.0176)
Log Bacteria	-0.0261 (0.0137)	-0.0331*** (0.0094)	-0.0181* (0.0083)	0.0028 (0.0047)	0.0029 (0.0036)
ECS	-0.0058 (0.0036)	-0.0064 (0.0036)	-0.0058 (0.0036)	-0.0045 (0.0037)	-0.0038 (0.0037)
Log-Likelihood	-7722.41	-7709.08	-7746.57	-7768.79	-7778.1
AIC	10092.41	10079.08	10116.57	10138.79	10148.1
<i>Block Group Fixed Effects</i>					
Log Fresh	0.0252* (0.0118)	0.0287** (0.0096)	0.0068 (0.0084)	0.0121 (0.0132)	0.0267 (0.0195)
Log Salt	0.0703* (0.0284)	0.0354 (0.0209)	0.0017 (0.021)	-0.0226 (0.0199)	-0.0362* (0.0181)
Log Bacteria	-0.0008 (0.0153)	-0.0194* (0.0094)	-0.0056 (0.0071)	0.0026 (0.0048)	0.0006 (0.0038)
ECS	-0.0053 (0.0036)	-0.0055 (0.0037)	-0.0047 (0.0037)	-0.0038 (0.0038)	-0.0024 (0.0038)
Log-Likelihood	-5943.77	-5947.04	-5969.35	-5966.43	-5974.71
AIC	12121.77	12125.04	12147.35	12144.43	12152.71
<i>Property Fixed Effects</i>					
Log Fresh	0.0296 (0.0209)	0.0221 (0.0153)	0.0169 (0.0129)	0.022 (0.0206)	0.0324 (0.0298)
Log Salt	-0.0174 (0.0422)	0.0048 (0.0338)	-0.0216 (0.0309)	-0.0304 (0.033)	-0.0424 (0.0309)
Log Bacteria	0.0156 (0.0121)	0.0126 (0.011)	0.0011 (0.01)	-0.0007 (0.0071)	0.0022 (0.0052)
ECS	-0.0024 (0.006)	-0.0026 (0.006)	-0.0019 (0.0061)	-0.0013 (0.0063)	-0.0002 (0.0063)
Log-Likelihood	7681.86	7685.48	7681.96	7682.26	7688.2
AIC	25702.14	25698.52	25702.04	25701.74	25695.8

Notes: N = 33585. All models specified year and month fixed effects. Ambient water quality specified with spatiotemporal variation Standard errors in parentheses clustered at Census Tract level. *p<.05, **p<.01, ***p<.001

Appendix D Code Documentation

This section summarizes the data processing methods and software utilized in this study. This work was completed using python 3.9.13, R, and Google Earth Engine. The python code uses the following non base python packages: pandas 1.4.4 (McKinney, 2010; The pandas development team, 2022), geopandas 0.13.2 (Bossche et al., 2023), numpy 1.25.1 (Harris et al., 2020), matplotlib 3.5.2 (Caswell et al., 2022; Hunter, 2007), census 0.8.19 (Carbaugh & Gregg, 2022), pynhd 0.15.0 (Chegini et al., 2021, 2023), statsmodels 0.13.2 (Seabold & Perktold, 2010), linearmodels 4.27 (Sheppard et al., 2022), and matplotlib-scalebar 0.8.1 (Pinard et al., 2022). The R libraries used include readr (Wickham et al., 2024), here 1.0.0 (Müller, 2020), dplyr (Wickham et al., 2023), ggplot2 (Wickham, 2016), terse (FC, 2020), lubridate (Grolemund & Wickham, 2011), osrm (Giraud, 2022) plyr (Wickham, 2011) and reshape2 (Wickham, 2007). All code and readme describing code files and steps necessary for replication are available at <https://github.com/swedkm/NE-Rec-Hedonic>.

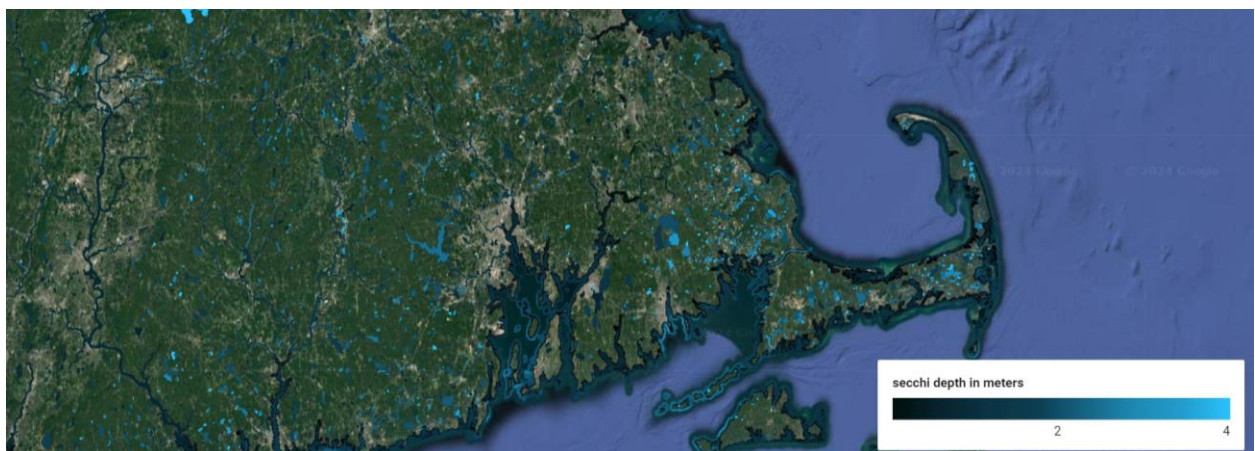
We used two different sources for property sale locations for each state. For Massachusetts, MassGIS shared geodatabases with current most recent assessment data as of 2022 for the eastern and western parts of the state and historical assessment data for each town and tax year. We used the historical data to identify the property sales used in the hedonic model and current assessment data to determine the location of a residential properties for capitalization. For Rhode Island, LightBox provided a shapefile with the most recent assessment data as of 2022 and previous three sales, which was used in the hedonic and capitalization section. Coordinates for property sales and single-family residential properties were passed into water quality processing scripts.

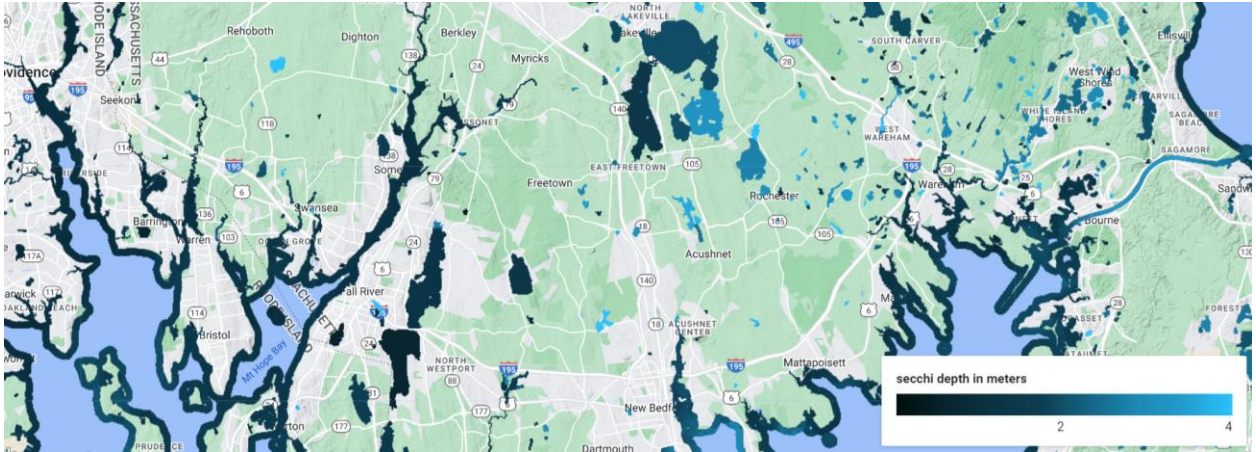
We created the remotely sensed water quality data using Google Earth Engine. The code process we used is here in this project:

https://code.earthengine.google.com/?accept_repo=users/nateme16/recHedonics . The data used in the scripts are on Google Cloud and shared for anyone to read. For freshwater body spatial boundaries, we accessed NHDPlus data via phnhd, clipped out lakes and rivers larger than 1 ha, and exported to a shapefile. To define salt water we used the states' marine water definitions, NEWQ polygons, from Merrill et al. (2024). We queried the Water Quality Portal for marine enterococci measurements for marine waters in CT, RI, MA, NH, ME for the years 2014-2022. Each of these inputs were uploaded to Google Earth Engine and are called by the scripts in the project.

Within the Earth Engine process, we create water clarity (Secchi depth in m) estimates using the Landsat 8 SR Tier 1, Collection 1 catalog hosted on EE. The water quality script takes these images, applies a cloud and land mask, and applies the algorithm. This process generates intermediate raster layers for freshwater and saltwater clarity for each year (see Figure D1). Buffers are then applied for shoreline to create inputs for ECS calculations and each property to create inputs for hedonics and capitalization.

Figure D1 2020 Saltwater and Freshwater Clarity





Using an R script, we used the bacteria data and clarity data for each year and shoreline segment to estimate ECS using the regression from Merrill et al. (2020) and travel distances calculated using OSRM from each census tract to shoreline segment. The output dataset is and ECS value for each year based on the water quality values changes for each shoreline. All other regression inputs were held constant across the timeframe.

We used the property sales and coordinates to measure distances from all waterbody boundaries and shorelines. We downloaded shapefiles with locations of airports, townhalls, roads, and rails and measured the distance from the sales. Further property data was collected through the census api and merged with property sales by block group. All sales data, including water quality and ECS, is merged and cleaned as the input to hedonic analyses and Wald tests. Results from hedonic models, cleaned property sales, and residential locations are used to generate the descriptive statistics, output tables, and capitalization results.

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Locally Satisfying Adding Up Condition in Meta-Regression Models: A Simple Solution to a Persistent Regulatory Challenge

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1. Introduction

Understanding potential health, social, and economic benefits of improvements in environmental amenities is critical to natural resource managers, environmental nonprofits, and policy makers responsible for deciding which resources to protect and to what extent. However, as the spatial scale of the analysis increases, it can become more costly and less time effective to conduct original valuation studies for the resources of interest. Instead decision makers often turn to benefits transfer from existing studies to inform benefit analyses that provide necessary context to balance costs of environmental improvements (Griffiths et al., 2012; S. Newbold et al., 2018). While there are different analytical methods that may be used for benefit transfer, function transfer through meta-regression models (MRMs) is preferred (Boyle et al., 2013; Boyle & Parmeter, 2017). This process relies on constructing a model fit on the metadata of existing valuation studies to predict willingness to pay (WTP) for potential environmental improvements. Examples of MRMs used in benefits transfer can be seen in previous EPA recent rulemakings under the Clean Water Act (CWA) (USEPA, 2023; USEPA & US Army, 2022).

Recent guidance for use of MRMs in benefits transfer advocates for structural limitations on WTP functions to satisfy key theoretical conditions, with particular emphasis on scope sensitivity and the adding up condition (Moeltner, 2019; S. C. Newbold et al., 2018). Scope

sensitivity is a property of a normal good that simply requires increasing WTP for increasing environmental improvements. There is preference for functional forms that allow scope elasticities to be freely estimable, meaning the scope elasticity for a particular improvement will vary based on the specific regression estimates and level of improvement (Kling & Phaneuf, 2018; Whitehead, 2016). The adding up condition, a core concept in welfare economics, requires WTP for a given improvement equal the sum of WTP for multiple sequential improvements of the same total magnitude while adjusting for income and substitution effects. While well-designed contingent valuation studies tend to satisfy scope sensitivity (Carson, 2012), attempts to demonstrate the adding up condition in contingent valuation and laboratory settings have been unsuccessful (Desvousges et al., 2015; Elbakidze & Nayga, 2018). In an MRM context, coupling scope sensitivity and the adding up condition can only be strictly achieved through imposing structural restrictions on the model that results in a nonlinear WTP curve for all potential levels of improvement. However, in a water quality context prior studies have shown these models are a poor fit for the existing metadata relative to simpler linear model specifications (Moeltner, 2019; S. C. Newbold et al., 2018).

Despite known challenges with its application, EPA maintains a strong preference for MRMs that satisfy adding up for benefit analyses conducted under the Clean Water Act (USEPA, 2015). The primary model used to estimate the benefits of environmental improvements in both surface water quality and wetland quantity settings, henceforth referred to as the MRM2, was chosen specifically for its adding up properties (USEPA, 2015).⁶⁴ Yet there are inherent econometric challenges in applying the MRM2. Throughout this paper, I will demonstrate the

⁶⁴ In 2015 EPA argued that MRM2 satisfied adding up by construction, but Moeltner (2019) demonstrates that this is not true. However, in empirical application the adding up bias for the MRM2 is negligible, leading to the conclusion that this model empirically satisfies adding up.

MRM2 as applied by EPA both underfits the surface water quality metadata and exhibits omitted variable bias that results in underestimates of willingness to pay. While economic theory is an important guide in the development and assessment of MRMs, neglect of omitted variable bias to maintain theoretical consistency misrepresents the metadata and obstructs the fundamental purpose evaluating the benefits of potential environmental improvements.

The open question is whether these theoretical properties need to be met globally across the entire WTP space, or could they be applied locally to fit the particular context of a benefits transfer? Recent work suggests thinking more locally about the transfer scenario and its relationship to the metadata can result in better modelling outcomes. Moeltner et al. (2023) employ a locally weighted regression approach that weights model coefficient estimates toward metadata observations most similar to the transfer scenario. While this approach helps tailor MRM estimates to specific transfer scenarios, the underlying model is still subject to bias. In this study, I evaluate how researchers can use information about a specific transfer scenario to develop an MRM that locally satisfies adding up in the benefits transfer application.

Specifically, I consider a 2023 proposed national rulemaking under the CWA that updates effluent limitation guidelines for a set of regulated point sources, henceforth referred to as Steam Electric (USEPA, 2023). I use information about this context and its relationship to the metadata to propose alternative modelling structures that locally satisfy adding up. These models all outperform the MRM2 both in model fit and prediction accuracy for out of sample prediction. In aggregate, my results show the MRM2 underestimates total annualized WTP for Steam Electric by more than \$10 million (67% of the total) with approximately \$2 million resulting from omitted variable bias. Overall, my analysis shows how returning the specific benefit transfer scenario and the associated metadata to the forefront of MRM development can improve model performance

without sacrificing theoretical consistency in the application. It also provides general guidance on selecting context appropriate MRMs that can aid decision makers using benefits transfer for a wide range of potential environmental improvements.

2. Benefits Transfer Scenario

Critical in developing a model for benefits transfer is understanding the context of the transfer scenario and the relationship to the underlying metadata. In the following subsections I discuss the water quality improvements under Steam Electric and the process EPA uses to integrate modeled environmental outcomes into economic benefits analysis. Next, I describe the metadata underlying the analysis and how it compares to the context of the rule. I close with key insights from assessing the data that are relevant to model development and evaluation.

2.1 Steam Electric Context

The 2023 Proposed Steam Electric Effluent Limitations Guidelines strengthens existing controls on the point discharges from steam electric power plants into surface waterbodies and evaluates the benefits and costs of different technology-based limitation options (USEPA, 2023). Each option will result in yearly point source load reductions for a set of pollutants over the lifetime of the technology (approximately 20 years). Because the effluent flows downstream from the point source, water quality improvements associated with the load reductions do not accumulate over time.⁶⁵ Instead, the baseline and improved levels of water quality in a stream segment are the same

⁶⁵ While water quality models have the ability to model improvements over time, the results are highly dependent on specific weather conditions. Given uncertainty in predicting future weather, water quality is modelled over a range of years with historical weather data under the baseline conditions and with proposed load reductions. Water quality is then averaged across the range of years for both sets of conditions.

in the first year of analysis (2030) as they are in final year (2049).⁶⁶ To represent these levels of water quality, EPA constructs a seven-parameter water quality index (WQI) on a 100-point scale.

To access the baseline and improved WQIs from the rule, I use an EPA tool – the Benefits Spatial Platform for Aggregation Socioeconomics and H2O Quality (BenSPLASH). BenSPLASH allows researchers to replicate a similar benefits transfer process to the approach used in EPA rule makings (Corona et al., 2020).⁶⁷ The 2023 Steam Electric sample files included with the tool present the baseline and improved WQIs for the 9,358 stream segments affected by the rule. The baseline WQIs range from 31 to 94, whereas total improvements are generally small with the median improvement only 0.0002 points (Table 1). However, there are outliers with a maximum improvement of almost 19 points. To translate improvements in water quality at the stream level to households, EPA draws a 160 km radius around small spatial units (e.g. Census block groups) used to represent households and takes a stream-weighted average for the baseline WQI and improved WQI separately. For a given year and spatial unit, the improvements in water quality are found by subtracting the average baseline WQI from the average improved WQI. Using BenSPLASH, I identified 63,766 grid cells (7,290 m) within range of improved stream segments and calculated the average WQIs.⁶⁸ Averaging across the stream does not impact the baseline WQI but does change the distribution of the improvements, with the median now 0.0008 points and the maximum at 1.34 points.

⁶⁶ Implementation occurs over a five-year period from 2025-2029 that is represented by the same constant baseline level of water quality and another improved level of water quality associated with partial annual load reductions.

⁶⁷ Embedded in the platform are valuation functions built off the different MRMs developed by EPA, a national grid with population demographics and projected growth rates, NHDPlus stream reaches, and WQI calculation functions. BenSPLASH is still under development and has not been used by EPA to calculate benefits for Steam Electric or any other proposed policy.

⁶⁸ BenSPLASH has two options for grid cell size: 7,290 m and 2,340 m. Given the spatial scale of the analysis, I choose the coarser resolution. This choice differs from the rulemaking, where EPA used Census block groups as the spatial unit of analysis.

To evaluate the potential monetized benefits of the rule, yearly per household WTP estimates are required for each spatial unit in each year of the analysis, resulting in 63,766 x 25 individual benefit transfers. Thus, for this context it is preferred to estimate a single MRM for all transfers, using predictor variables that are nationally available. WTP predictions within a spatial unit are multiplied by the projected population in that spatial unit in the year of the analysis and then multiplied by a discount rate and adjusted for the number of years in the analysis. Summing up across all spatial units and years results in the total annualized WTP that can be compared to the costs of implementing the technology. While a central estimate is useful for summary, it is also helpful to provide a range of benefits that accounts for the uncertainty in the MRM.

Table 1 Water Quality Descriptive Statistics from Benefits Transfer and Metadata

	Benefits Transfer (Stream Segments)		Benefits Transfer (Grid Cells)		Metadata (Study Observations)	
	q_0	dq	q_0	dq	q_0	dq
Min.	31	0.0000	32	0.0000	10	2.38
1st Qu.	61	0.0000	61	0.0002	45	6.7
Median	68	0.0002	67	0.0008	49	20
3rd Qu.	76	0.0012	75	0.0043	50	20
Max.	94	18.7692	89	1.3415	85	57.5
Count	9,358	9,358	63,766	63,766	189	189

Notes: Benefits Transfer Stream Segments describe the baseline water quality index (q_0) and modelled changes (dq) for an individual year at the stream segment level. Benefits Transfer Grid Cells describe the water quality inputs at the grid cell level after averaging across stream segments within a 160 km buffer. These values are inputs to the benefits transfer. Metadata describes the study observations that serve as inputs to the meta-regression model.

2.2 Metadata

The 2023 meta-data is comprised of 189 observations from 59 stated-preference studies published from 1985 through 2021 that estimate per household WTP for different water quality

changes throughout the United States.⁶⁹ A full list of primary studies is presented in EPA (2023). Many of these studies rely on a general measure of water quality to represent the baseline and improved scenario that can be represented by the water quality ladder (Mitchell & Carson, 1986) or a 100 point water quality index (WQI) (Walsh & Wheeler, 2013). Those that use the ladder are converted to the WQI for standardization. While the baseline water quality ranges from 10 to 85, more than half the observations fall between 45 and 50. Limited variation in this variable can potentially make it difficult to estimate its effect in a meta-analysis. Similarly, the changes WQI observed in the metadata range from 2.4 to 57.5, but 53 observations have 20-point changes. This grouping at 20 points is an artifact of studies anchored to the water quality ladder, where improvements were expressed in changes from “fishable to swimmable” or “boatable to fishable”. The meta-data also contains a range of other variables related to the region of the country where the original study was conducted and surveyed population, sample market, affected resource, study methodology and year the data was collected.

2.3 Insights for MRMs

Comparing the context of benefits transfer to the metadata provides key insights into MRM development. Critically, this comparison reveals the improvements found in the metadata are significantly larger than those in the benefits transfer. Therefore, the MRM results need to be extrapolated out of sample. Extrapolation relative to dq requires WTP to decrease with smaller and smaller values of dq . Because the changes in the benefits transfer are so small, the WTP curve effectively needs to be scaled to zero with dq . If this relationship is already present in the metadata, then the resulting MRM can model a simple relationship between WTP and dq . If this relationship

⁶⁹ We indicate changes here instead of improvements as 15 observations used by EPA have negative changes and thus reflect willingness to accept payments. For these observations, we use the absolute value of the change.

is not present, then the MRM must estimate an effect for the average WTP (WTP/dq) instead. Then, the resulting WTP can be calculated by multiplying estimates of WTP/dq by dq , thus imposing this relationship and forcing WTP to scale to zero. To observe whether this relationship is present in the metadata, I plot WTP and dq (Figure 1 – panel A). While there appears to be some positive correlation between WTP and dq , the relationship is very weak. Therefore, an MRM for WTP would not scale close enough to zero to extrapolate in the benefits transfer.⁷⁰

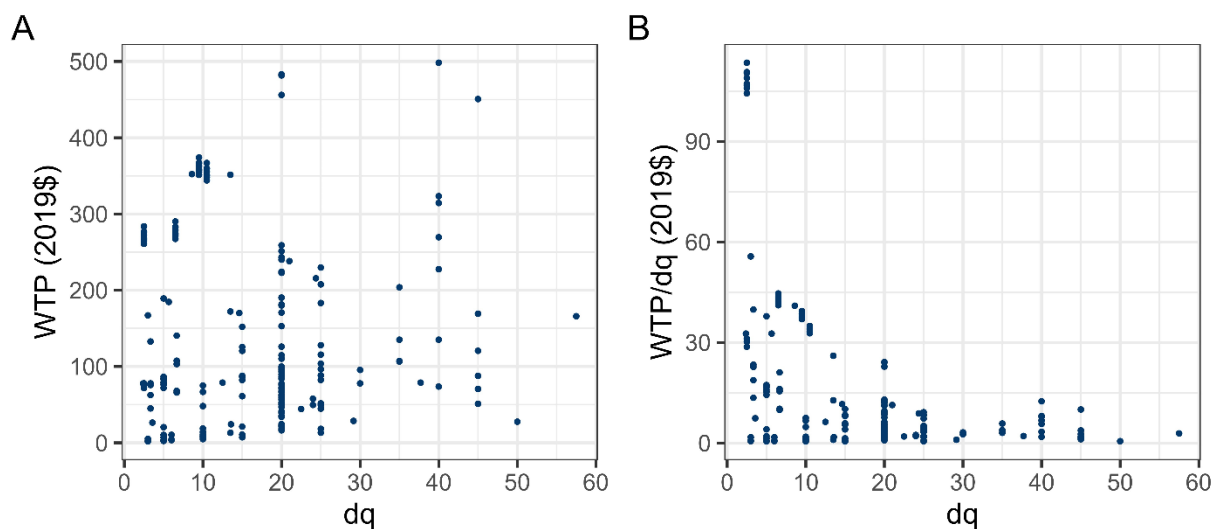


Figure 1 Relationship between Willingness to Pay (WTP) and Water Quality Changes (dq) in Metadata

Next, I consider the relationship between the average WTP and dq (Figure 1 – panel B). In this case, there appears to be a strong negative relationship between average WTP and dq . Not accounting for this relationship in MRM will underfit the data, and the resulting estimates for average WTP will be more representative of observations with larger changes near the median change of 20. As the benefits transfer context features very small improvements, the MRM results should be closer to observations in the metadata with the smallest changes. Therefore, it is

⁷⁰ An alternative is to fit a model for $\log(WTP)$ with $\log(1+dq)$ as an independent variable. But this model will be susceptible to overfitting the data with implications for extrapolation.

important to control for dq in the MRM. However, the figure also reveals a group of outlier observations at $dq = 2.5$ with average WTP more than \$100. Fitting the average WTP curve to these outliers may result in overestimates for average WTP for small changes. Thus, it may be useful to also consider fitting an MRM that represents average WTP for a wider range of potential values of dq beyond 2.5 or looking at the sensitivity of removing outliers.

3. MRM Theoretical Properties

In the following subsections I describe the theoretical properties that have guided the meta-model development for benefit transfers by EPA. First, I discuss formal definitions of scope sensitivity and the adding up condition and explore their relevance to the Steam Electric context. Next, I walk through the derivation of the MRM2 and highlight how the model's theoretical properties are at odds with econometric best practices. Last, I explore how appropriate use of the MRM2-S and a hybrid modelling framework, which I label MRM2-DSx, can resolve these issues without sacrificing theoretical consistency.

3.1 Formal Definitions

Scope sensitivity is a relatively simple constraint that requires that WTP scale with increasing improvements in the environmental good. For example, given two changes in quality, $dq_{0 \rightarrow 1}$ and $dq_{0 \rightarrow 2}$, from the baseline level q_0 , with $dq_{0 \rightarrow 1} < dq_{0 \rightarrow 2}$,

$$WTP(dq_{0 \rightarrow 1}, u_0) < WTP(dq_{0 \rightarrow 2}, u_0) \quad (1)$$

where u_0 is an arbitrary level of utility. This relationship implies:

$$\partial WTP / \partial dq|_{q_0} > 0 \quad (2)$$

Thus, scope sensitivity only requires a positive relationship between WTP and dq , but does not require the WTP curve to pass through zero, as necessary for extrapolation in the benefits transfer application.

Beyond scope sensitivity, recent attention has been paid to the scope elasticity represented by:

$$\epsilon_{WTP, \widetilde{dq}} = \left(\partial WTP / \partial dq \right) \left(\widetilde{dq} / WTP \right) \quad (3)$$

where $\widetilde{dq}$ is given improvement associated with WTP (Kling & Phaneuf, 2018; Whitehead, 2016). Essentially this value represents the percent change in WTP relative to the magnitude of the improvement. It is preferable for the scope elasticity to be vary based on WTP estimates resulting from a contingent valuation study or meta-analysis to reflect nonlinearities in WTP for different levels of improvements.

The adding up condition puts more restrictions on the WTP relationship beyond scope. Formally, the adding up test can be represented as:

$$WTP(dq_{0 \rightarrow 1}, u_0) + WTP(dq_{1 \rightarrow 2}, u_1) \leq WTP(dq_{0 \rightarrow 2}, u_0) \quad (4)$$

where u_1 is the income adjusted utility level after the first improvement (Diamond, 1996). Two key insights can be drawn from this definition. First adding up need only apply for improvements in the state of the good ($q_0 \rightarrow q_1$) that result in a new utility level u_1 . If the baseline and level of the improvement stays constant over time, adding up may not be relevant. Secondly, the test only requires that adding up be satisfied for improvements up to $dq_{0 \rightarrow 2}$. Thus, the highly restrictive models that globally enforce adding as presented in Newbold et al. (2018) and Moeltner (2019) are not necessary for applications with relatively small improvements. Instead, researchers could

find the MRM that best represents the metadata for the context of the application and restrict the resulting WTP estimates only for the portion of the curve below the total level of environmental improvements over time.

3.2 MRM2 Properties

Following Newbold et al. (2018), the MRM2 defines the Marshallian inverse demand curve for marginal WTP (MWTP) for an environmental improvement:

$$MWTP = \exp(\mathbf{D}\boldsymbol{\beta}_D + \beta_q q) \quad (5)$$

where $\mathbf{D}$ is a vector of demand shifters, including income. Critically, this equation is defined for a marginal improvement at $q = q_0$. Estimation of the MRM2 assumes that MWTP (not observed) is equal to the average estimated WTP from original empirical studies ($MWTP \sim WTP/dq$).⁷¹ To account for this substitution, q is represented using the midpoint of $q_{0 \rightarrow 1}$, the rationale being that intermediate value theorem implies MWTP will equal the average WTP at some point between q_0 and q_1 . In the 2023 Steam Electric, EPA specifies q using the log of the midpoint, with the resulting MRM2 broadly defined by:

$$\log(WTP/dq) = \mathbf{D}\boldsymbol{\beta}_D + \beta_{q_{mid}} \log(q_0 + dq/2) + \varepsilon \quad (6)$$

where ε is an idiosyncratic error term. WTP is then recovered by:

$$WTP = \exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (q_0 + dq/2)^{\hat{\beta}_{q_{mid}}} * dq \quad (7)$$

⁷¹ MWTP values are commonly observed in hedonic property sale applications as implicit prices. Yet, these models are estimated under the assumption of market equilibrium, and thus, cannot be used to recover WTP for large changes in environmental quality.

Given positive values of the baseline and change, the MRM2 is sensitive to scope with a scope elasticity represented by:

$$\epsilon_{WTP, \widetilde{dq}} = 1 + \hat{\beta}_{q_{mid}} * \left(q_0 + dq/2\right)^{-1} * \left(dq/2\right) \quad (8)$$

Had equation 6 been estimated at the baseline quality rather than the midpoint, the scope elasticity would simplify to 1.⁷²

To evaluate potential restrictions in scope elasticity, I consider the limits as the improvement approaches 0 and positive infinity, finding the respective bounds on the scope elasticity to be 1 and $1 + \hat{\beta}_{q_{mid}}$. For the Steam Electric application with marginal improvements in water quality, the scope elasticity would be approximately 1 for all spatial units. Thus, use of the midpoint does not introduce meaningful variation in the scope elasticity for this application.

Another outcome of MRM2 estimation at the midpoint is that by introducing a nonlinear relationship between WTP and q , the MRM2 cannot strictly satisfy the adding up condition. To demonstrate, let $dq_{0 \rightarrow 1} = dq$ and $dq_{0 \rightarrow 2} = 2dq$. The adding up test for MRM2 is then expressed by:

$$\begin{aligned} & \left(\exp(\mathbf{D}\widehat{\boldsymbol{\beta}}_{\mathbf{D}} + \varepsilon) * \left(q_0 + dq/2\right)^{\hat{\beta}_{q_{mid}}} * dq \right) + \left(\exp(\mathbf{D}\widehat{\boldsymbol{\beta}}_{\mathbf{D}} + \varepsilon) * \left(q_0 + dq + dq/2\right)^{\hat{\beta}_{q_{mid}}} * dq \right) \\ & \leq \exp(\mathbf{D}\widehat{\boldsymbol{\beta}}_{\mathbf{D}} + \varepsilon) * (q_0 + dq)^{\hat{\beta}_{q_{mid}}} * 2dq \end{aligned} \quad (9)$$

which simplifies to:

$$\left(q_0 + dq/2\right)^{\hat{\beta}_{q_{mid}}} + \left(q_0 + dq + dq/2\right)^{\hat{\beta}_{q_{mid}}} \leq (q_0 + dq)^{\hat{\beta}_{q_{mid}}} + (q_0 + dq)^{\hat{\beta}_{q_{mid}}} \quad (10)$$

⁷² This derivation is included in Appendix A.

Rearranging equation 10, the following must hold to satisfy adding up:

$$\left(q_0 + dq/2\right)^{\hat{\beta}_{q_{mid}}} - (q_0 + dq)^{\hat{\beta}_{q_{mid}}} \leq (q_0 + dq)^{\hat{\beta}_{q_{mid}}} - \left(q_0 + dq + dq/2\right)^{\hat{\beta}_{q_{mid}}} \quad (11)$$

Assuming $\hat{\beta}_{q_{mid}} < 0$, as consistent with decreasing marginal utility, implies the following:

$$\frac{1}{\left(q_0 + dq/2\right)^{|\hat{\beta}_{q_{mid}}|}} - \frac{1}{(q_0 + dq)^{|\hat{\beta}_{q_{mid}}|}} \leq \frac{1}{(q_0 + dq)^{|\hat{\beta}_{q_{mid}}|}} - \frac{1}{\left(q_0 + dq + dq/2\right)^{|\hat{\beta}_{q_{mid}}|}} \quad (12)$$

which simplifies to:

$$\frac{(q_0 + dq)^{|\hat{\beta}_{q_{mid}}|} - \left(q_0 + dq/2\right)^{|\hat{\beta}_{q_{mid}}|}}{\left(q_0 + dq/2\right)^{|\hat{\beta}_{q_{mid}}|}} \leq \frac{\left(q_0 + dq + dq/2\right)^{|\hat{\beta}_{q_{mid}}|} - (q_0 + dq)^{|\hat{\beta}_{q_{mid}}|}}{\left(q_0 + dq + dq/2\right)^{|\hat{\beta}_{q_{mid}}|}} \quad (13)$$

For all nonzero values of $\hat{\beta}_{q_{mid}}$, the denominator on the left-hand side of the equation is less than the denominator the right. For $0 > \hat{\beta}_{q_{mid}} \geq -1$, the numerator on the left-hand side is greater than or equal to the numerator on the right. Therefore, equation 11 does hold for $0 > \hat{\beta}_{q_{mid}} \geq -1$, and adding up is not satisfied.⁷³ However, it can be demonstrated empirically, that for small values of dq , the discrepancy is small, and the MRM2 effectively satisfies adding up.

When equation 6 is estimated at the baseline, instead of the midpoint, equation 10 simplifies to:

$$(q_0 + dq)^{\hat{\beta}_{q_0}} \leq (q_0)^{\hat{\beta}_{q_0}} \quad (14)$$

⁷³ For $\hat{\beta}_{q_{mid}} \geq -1$, the results depend on the ratio of baseline to change. We do not evaluate these scenarios as previous estimates for $\hat{\beta}_{q_{mid}}$ fall between 0 and 1.

which is always satisfied for $\hat{\beta}_{q_0} < 0$. This point demonstrates a critical flaw in attempts to apply MRMs solely on theoretical properties. If the metadata does not fit the exact curvature prescribed by the Newbold et al. 2018 or Moeltner 2019 models, then it cannot achieve both satisfaction of adding up and have a scope elasticity that varies for different levels of improvement. However, observations in the metadata are aggregated over different surveyed populations, in contrast to the theoretical models that are developed with an individual household in mind. Thus, it may be asking too much of the aggregated data to exhibit the same relationships that economists would expect at the household level, let alone fit a specific nonlinear functional form.

3.3 Econometric Implications

The focus on theoretical properties in deriving the MRM2 without consideration of the metadata or application poses multiple challenges in econometric estimation. The dependent variable in the MRM2, $\log(WTP/dq)$, is highly correlated with dq . As noted previously, not controlling for dq in the model underfits the data. It also increases the uncertainty with the effect of dq captured by the error term ε . If no other variables in the model are correlated with dq , then the estimates will be unbiased. However, the point estimate will reflect the dependent variable at the median dq in the metadata of 20. In applications with improvements of similar magnitude underfitting the data is not of concern, but for applications with small changes in water quality, underfitting the data will result in underestimating WTP.

Econometric issues with the MRM2 go beyond underfitting the data. Specifying water quality at the midpoint introduces omitted variable bias into the estimate of $\beta_{q_{mid}}$, because

$\log(q_0 + dq/2)$ is clearly correlated with the error term ε .⁷⁴ Given the decreasing relationship between the dependent variables and the improvement, the direction of this bias will be negative. Moreover, as there is limited identifying variation in q_0 in the metadata, the biased estimated for $\beta_{q_{mid}}$ will be more reflective of the effect of dq than q_0 . Yet in the application, dq is so small that $\beta_{q_{mid}}$ is effectively only multiplied by q_0 . Thus, the impact of the omitted variable bias in the MRM2 is even more pronounced in contexts with marginal improvements in water quality. In the following section I demonstrate two ways to introduce dq into the model to resolve these issues that locally comply with the adding up condition.

3.4 MRM2-S and MRM2-DSx Frameworks

The clearest way to resolve these issues is to add dq directly into the model, resulting in the MRM2-S:

$$\log(WTP/dq) = \mathbf{D}\boldsymbol{\beta}_D + \beta_{q_{mid}} \log(q_0 + dq/2) + \beta_{dq} \log(dq) + \varepsilon \quad (15)$$

This model can be estimated at the baseline (Johnston et al., 2017) or midpoint (Johnston et al., 2019) as represented in the above equation. To maintain the theoretical properties of the MRM2, $\log(dq)$ is used as a demand shifter in the benefits transfer application rather than a predictor variable. This can be represented as:

$$WTP = \exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (\overline{dq})^{\hat{\beta}_{dq}} * (q_0 + dq/2)^{\hat{\beta}_{q_{mid}}} * dq \quad (16)$$

⁷⁴ This omitted variable bias can also be introduced by including any demand shifters that are correlated with the improvement.

where $\overline{dq}$ is a constant value (or set of values) for all improvements. However, EPA (2023) suggests using the first and third quartile value to present a range. But this approach is problematic, as the interquartile range of the metadata may not be representative of the range of improvements in the transfer application. A better approach may be to only consider improvements from observations most similar in scope to the application.

To resolve potential issues with the MRM2-S, I consider a hybrid of the MRM2 and MRM2-S specifications that employs a shift (DS) term where:

$$\log(WTP/dq) = \mathbf{D}\boldsymbol{\beta}_D + \beta_{q_{mid}} \log(q_0 + dq/2) + \beta_{DS_x} DS_x \log(dq) + \varepsilon \quad (17)$$

where x is a threshold set by the investigator. $DS_x = 1$ when $x > dq$ and 0 otherwise. Like the MRM2-S this equation can be specified at the midpoint or baseline, depending on whether it is necessary for the scope elasticity to vary. Here there is no need to choose a level of $\overline{dq}$ in the benefits transfer. Instead, DS_x will be set to 0, simplifying the transfer applications for scope extrapolation with marginal levels of improvement. The value of x can be selected based on the metadata and fit of the model, so the resulting estimate for $\log(WTP/dq)$ represents a range of observations most similar in scope to the application. To control for correlation between dq and other variables in the model, x should be set low enough to mitigate omitted variable bias, but large enough to avoid overfitting. For improvements that accumulate over time, this value should also be set beyond the total level of improvement for a household.

4. Empirical Methods

Below I describe the empirical methods used to estimate the MRM2, MRM2-S, and MRM2-DSx models, assess model fit and predictive performance, and apply the estimates to the Steam Electric benefits-transfer application.

4.1 Bayesian Estimation

The empirical models are estimated using a Bayesian framework:

$$\begin{aligned} y_{is} &\sim \text{Student}(\beta_0 + \mathbf{S}\boldsymbol{\beta}_S + \mathbf{C}\boldsymbol{\beta}_C + u_s, \nu, \sigma_\varepsilon^2), \\ u_s &\sim \text{Normal}(0, \sigma_u^2) \end{aligned} \quad (18)$$

where y_{is} is the logged average WTP for observation i in study s .⁷⁵ $\mathbf{S}$ are variables that vary by study in the model and spatially when used as predictors in the transfer scenario. I run each model separately using either the midpoint (ln_qmid) or the baseline (ln_q0) in $\mathbf{S}$. For all models, $\mathbf{S}$ further includes the logged ratio of agriculture in the affected resource area (ln_ar_agr), the logged ratio of the study population sampled area to the affected resource area (ln_ar_ratio), the proportion of waters to those of the same Strahler order⁷⁶ in the state (sub_frac), the logged income of the population (lnincome), and three dummy variables corresponding to different census regions (census_south, census_midwest, and census_west). $\mathbf{C}$ are other controls variables related to the population and study methodology that will be held constant in the transfer application. These include a range of dummy variables related to use of the affected resource (nonusers and gamefish), the payment mechanism used in the study (volunt, tax_only, user_cost, and lump_sum), characteristics of the study (OneShotVal, RUM, thesis, and non_reviewed), and the use of IBI to

⁷⁵ While the models used by EPA for Steam Electric use frequentist estimation methods, recent work in MRM's use Bayesian methods to better account for uncertainty in WTP estimates (Moeltner, 2019; Moeltner et al, 2023).

⁷⁶ The Strahler order defines the hierarchy of streams as they merge into larger stream segments.

define water quality in the survey (IBI). $\mathbf{C}$ also includes a continuous measure for the year of the study (lnyear). For the MRM2-S, $\mathbf{C}$ further includes the natural log of the water quality improvement (ln_dq) that will be set to a constant value in the benefits transfer. For the MRM-DSx models, $\mathbf{C}$ includes DSx*ln_dq that will be set to 0 in the benefits transfer. I estimate 14 different specifications of MRM2-DSx for values of x between 3 and 20. Lastly, u_s are study random effects that are normally distributed with variance σ_u^2 , which control for heterogeneity between studies.⁷⁷ Including random effects has the benefit of minimizing the impact of outlier studies on population level results while preserving model efficiency.

The model is estimated using the Student's t distribution with degrees of freedom ν and variance σ_ε^2 , which allows for robust estimation with observation level heteroskedasticity.⁷⁸ Using error specifications that allow for study-level heterogeneity and observation-level heteroskedasticity is consistent with best practices (Johnston & Rosenberger, 2010; Moeltner, 2019; Moeltner et al., 2007). All linear coefficients, including the intercept term, have priors distributed Normal(0, 10) that are relatively uninformative. Priors for the model variances are distributed Cauchy⁺(0, 10). Half-Cauchy priors are recommended as weakly informative priors and are preferred over commonly used inverse-gamma priors that can be sensitive to the choice in scale parameter (Gelman, 2006; Polson & Scott, 2012). The prior for ν is Gamma(2, 0.1) as recommended by Juárez and Steel (2010). Estimation is performed in R using Stan through the brms package (Bürkner, 2017, 2018, 2021).⁷⁹ Stan estimation features a Hamiltonian Monte Carlo

⁷⁷ The models used by EPA for Steam Electric use inverse sample size weighting to control for study heterogeneity instead of random effects. However, as noted in Moeltner (2019), this approach may unnecessarily down weight high quality studies that have small sample sizes.

⁷⁸ This estimation approach is analogous to estimation to $y_{is} \sim \text{Normal}(\beta_0 + \mathbf{S}\boldsymbol{\beta}_S + \mathbf{C}\boldsymbol{\beta}_C + u_s, \sigma_\varepsilon^2 \omega_{is})$, where the weight ω_{is} is drawn from the inverse gamma distribution with shape and scale $\frac{\nu}{2}$ (Geweke, 1993).

⁷⁹ Stan is a statistical modelling platform for Bayesian inference. More information available at <https://mc-stan.org/>

(HMC) sampler with the default no-U-turn sampler (NUTS) that has shown to be more efficient at sampling the posterior than traditional Gibbs sampling (Hoffman & Gelman, 2011; Hoffman & Gelman, 2014). Each model is sampled with four chains each comprised of 11,000 iterations with 1,000 warmup draws. The four chains allow evaluation of sampling convergence from different starting points, and the draws from each chain are thinned by a factor of four, resulting in a total of 10,000 draws from the posterior per model.

4.2 Evaluating Model Performance

The first method used to assess model performance is Bayes factors. Pairwise Bayes factors are calculated across all estimated models. If the log10 BF for one model relative to another is larger than 0.5, then there is evidence the first model is more probable than the other given the data. If log10 Bayes factor is between -0.5 and 0.5, both models are equally as probable. If log10 Bayes factor is less than -0.5, then there is evidence the second model is more probable. I use the Bayes factors to select the most probable MRM2-DSx model for further testing against the MRM2 and MRM2-S.

Next, I test whether each model satisfies the adding up condition for a range of different baseline qualities (q_0), total improvements ($dq_{0 \rightarrow 2}$), and ratio of the first improvement to the total improvement ($dq_{0 \rightarrow 1}/dq_{0 \rightarrow 2}$). I predict the posterior WTP for each of these scenarios and choose the median of the distribution to represent WTP. The associated adding up error is calculated as:

$$\% \text{ Error} = 100 * \frac{WTP(q_0, dq_{0 \rightarrow 2}) - (WTP(q_0, dq_{0 \rightarrow 1}) + WTP(q_1, dq_{1 \rightarrow 2}))}{WTP(q_0, dq_{0 \rightarrow 2})} \quad (19)$$

with negative errors indicating the model does not strictly satisfy the adding up test presented in equation 4. It is expected the MRM2 specified with the midpoint, or the baseline, will

approximately satisfy adding up, i.e., a very small negative error. For the MRM2-S, I consider two different methods for setting $\overline{dq}$ to demonstrate the conditions under which it can be used to satisfy adding up. In the first method, $\overline{dq}$ is set to a constant value equal to $dq_{0 \rightarrow 2}$. If $dq_{0 \rightarrow 2}$ is less than the minimum of the metadata or exceeds the maximum of the metadata, $\overline{dq}$ is set to 2.38 or 57.5 respectively. In the second approach, labelled as MRM2-S1, $\overline{dq}$ equals $dq_{a \rightarrow b}$ in each WTP estimate. It is expected the results for MRM2-S will approximately satisfy adding up, whereas MRM2-S1 results will not. The MRM2-DSx should satisfy adding up only for $x < dq_{0 \rightarrow 2}$.

Last, I evaluate out of sample predictive performance for small changes in water quality. To achieve this, I split the metadata into training and testing samples. The training sample is comprised of all observations in the metadata with $dq \geq 10$ ($n=129$). The testing sample is comprised of only observations for rivers or streams with $dq \leq 5$ ($n=19$). Using the training sample, I estimate four models using the midpoint and baseline: MRM2, MRM2-DS11, MRM2-DS16, and MRM2-S. I then predict the distribution of WTP for each observation in the testing sample. Like above I consider two different cases for the MRM2-S. In the first, I set $\overline{dq}$ to the minimum of the training sample (10). In MRM2-S1, $\overline{dq}$ varies with each observation to test the impact of extrapolation outside of the training sample. For each observation, I calculate the difference between the median WTP prediction and the observed WTP and test whether observation falls within the 90% credible interval of WTP estimates. I summarize these results across the entire testing sample with the root mean square error (RMSE), the percent of underestimates, and the percent of estimates that fall within the credible interval. I then calculate the median and 90% credible interval across all predictions for each model to compare with the median and range of the testing sample.

4.3 Benefits Transfer

After model evaluation, I evaluate how differences in model estimates scale in the national benefits transfer scenario. Using BenSPLASH, I collect the spatially varying predictor variables $\mathbf{S}$ for each grid cell and year and their associated dq inputs, as well as constants for the control variables $\mathbf{C}$ and the projected population in each grid cell and year. These inputs are used to predict the distributions of per Household WTP/ dq and per Household WTP for each grid cell and year, which are summarized by the median and the 90% credible interval. Next, the per Household WTP summary variables are multiplied by the projected population (HH) in a grid cell for the respective year. Using a 3% discount rate adjusted for a 25-year period starting in 2025, I calculate the total annualized WTP median and credible interval for a given grid cell and then sum across grid cells.

$$Total\ Annualized\ WTP = \sum_{i=1}^{63,766} \sum_{j=2025}^{2049} \left(\frac{\widehat{WTP}_{ij} * HH_{ij}}{(1 + .03)^{j-2025}} \right) \left(\frac{.03 * (1 + .03)^{25}}{(1 + .03)^{25+1} - 1} \right) \quad (20)$$

The median estimate can be used to represent the primary models results for point comparisons. The credible interval represents the potential range in total WTP given uncertainty in the model.

5. Results

The results will be presented as follows. First, I evaluate all the MRM2-DSx models relative to the MRM2 and MRM2-S on probabilistic terms and select a preferred value for x given the data. Then I compare the regression output and performance in adding up tests for the MRM2, MRM2-S, and preferred MRM2-DSx model. Next, I discuss the out of sample prediction tests and close with the benefits transfer results.

5.1 Model Comparisons

To compare models on probabilistic terms, pairwise Bayes factors are calculated for all MRM2, MRM2-S, and MRM2-DSx models, which are then transformed to the log10 scale. In table 2, I select a subset of log10 Bayes factors results for models specified with the midpoint and baseline.⁸⁰ The results in the table are rounded to the nearest whole number, so any positive number indicates support for the model designated by the row label over the model designated by the column label. A negative number implies the opposite relationship, and zero implies neither model is preferred. Bold indicates the most probable models. Starting with midpoint models, all MRM2-DSx models are preferred over the MRM2 except MRM2-DS20. There is increasing support for MRM2-DSx over the MRM2 up to $x=6$, after which the log10 Bayes factors begin to decline.⁸¹ None of the MRM2-DSx models are preferred over the MRM2-S, but the MRM2-DS6 is equally as probable as the MRM2-S. Similar relationships hold for the models specified with the baseline, with the exception that the MRM2-S is now preferred over the MRM2-DS6. However, MRM2DS6 is still the most probable MRM2-DSx model specified at the baseline. The bottom panel of table 2 shows for MRM2 and MRM2-DS6, the midpoint specifications are preferred over specifications with baseline. These results reflect the explanatory power of dq in the models. They also demonstrate how the dummy shift term in the MRM2-DSx models does not control for dq less than or equal to x . Thus, while MRM2-DS6 fits the data better when estimated at the midpoint, it may still exhibit omitted variable bias. After controlling for dq in the MRM2-S, both specifications are equally probable.

⁸⁰ All log10 BF results presented in Appendix C.

⁸¹ There are no observations in the metadata with changes between 15 and 20, and thus no MRM2-DSx models with $15 < x < 20$.

Table 2 Log10 Bayes Factors for Selected Models

	MRM2	-DS4	-DS6	-DS8	-DS10	-DS15	-DS20	-S
<i>Midpoint (m)</i>								
MRM2	NA							
-DS4	17	NA						
-DS6	19	1	NA					
-DS8	11	-6	-8	NA				
-DS10	6	-11	-13	-5	NA			
-DS15	4	-13	-14	-7	-2	NA		
-DS20	-1	-19	-20	-12	-7	-6	NA	
-S	18	1	0	7	12	14	20	NA
<i>Baseline (b)</i>								
MRM2	NA							
-DS4	18	NA						
-DS6	20	1	NA					
-DS8	12	-7	-8	NA				
-DS10	6	-12	-13	-5	NA			
-DS15	5	-14	-15	-7	-2	NA		
-DS20	-1	-20	-21	-13	-7	-6	NA	
-S	20	2	1	9	14	16	21	NA
	MRM2 (<i>m</i>)	MRM2 (<i>b</i>)	-DS6 (<i>m</i>)	-DS6 (<i>b</i>)	-S (<i>m</i>)	-S (<i>b</i>)		
MRM2 (<i>m</i>)	NA							
MRM2 (<i>b</i>)	-2	NA						
-DS6 (<i>m</i>)	19	20	NA					
-DS6 (<i>b</i>)	18	20	-1	NA				
-S (<i>m</i>)	19	20	0	1	NA			
-S (<i>b</i>)	19	20	0	1	0	NA		

Notes: Bold indicates most probable models.

Table 3 summarizes model results for the MRM2, MRM2-DS6, and MRM2-S estimated at both the midpoint ($\ln_qmid$) and baseline ($\ln_q0$). Comparing the estimates for the midpoint across models reveals omitted variable bias in the MRM2 and MRM2-DS6. For the MRM2 and MRM2-DS6, the posterior means for $\ln_qmid$ are -0.85 and -0.51 respectively with both 95% credible intervals excluding 0. However, in the MRM2-S the posterior mean is -0.30 and the 95%

credible interval ranges from -0.73 to 0.12. While there is overlap between the credible intervals, the posterior distribution of the midpoint coefficients for the MRM2 shows negative bias (Figure 2). This omitted variable bias is problematic for benefit transfers with marginal improvements in water quality. Because the midpoint is approximately the same as the improvement, model estimates specified with $\ln_q0$ may be more appropriate. In the MRM2-S posterior distributions for $\ln_qmid$ and $\ln_q0$ are approximately the same; whereas, in the MRM2-DS6 the posterior mean for $\ln_q0$ is approximately half the size of $\ln_qmid$. Notably, the distributions of $\ln_q0$ in the MRM2-S and MRM2-DS6 are quite similar. However, in the MRM2, the distribution of $\ln_q0$ shifts much closer to 0 with a positive mean of 0.12. These results may occur due to the limited identifying variation of the baseline in the metadata coupled with poor efficiency of the MRM2 without dq . When dq is included as $DS6*\ln_dq$ in the MRM2-DS6 and $\ln_dq$ in the MRM2-S, its posterior distributions are narrow with very small standard deviations relative to the posterior means, allowing for efficiency spillovers in identifying the effect of the baseline. These efficiency spillovers can also be observed in the tightening of the credible intervals for other variables, such as $census_south$ and $OneShotVal$, in the MRM2-DS6 and MRM2-S models relative to the MRM2. However, the posterior means of $DS6*\ln_dq$ are smaller in magnitude than the posterior means for $\ln_dq$ and the credible intervals do not intersect. Therefore, while these models are similar probabilistically, their results imply potential differences in the effects of $\ln_dq$ in the metadata based on the size of dq .

Table 3 Regression Output for Selected Models

Variable	MRM2		MRM2		MRM2-DS6		MRM2-DS6		MRM2-S		MRM2-S	
	Mean	Std.	Mean	Mean	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Intercept	4.12	4.12	0.04	3.80	4.59	2.78	3.81	2.89	3.52	3.30	3.73	3.32
ln_qmid	-0.85	0.34*			-0.51	0.19*			-0.30	0.22		
ln_q0			0.12	0.19			-0.27	0.16			-0.27	0.18
DS6*ln_dq					-0.44	0.03*	-0.46	0.03*				
ln_dq									-0.71	0.06*	-0.76	0.06*
lnyear	-0.18	0.18	-0.12	0.18	-0.38	0.17*	-0.39	0.17*	-0.38	0.15*	-0.41	0.15*
ln_ar_agr	-0.42	0.14*	-0.42	0.14*	-0.34	0.13*	-0.35	0.13*	-0.42	0.11*	-0.42	0.12*
ln_ar_ratio	-0.09	0.05	-0.08	0.05	-0.07	0.04*	-0.07	0.04	-0.09	0.04*	-0.09	0.04*
sub_frac	0.87	0.38*	0.90	0.37*	0.59	0.32	0.62	0.33	0.60	0.31	0.60	0.32
lnincome	-0.03	0.35	-0.00	0.33	-0.03	0.23	-0.04	0.24	0.06	0.28	0.05	0.28
census_south	0.62	0.36	0.55	0.34	0.75	0.31*	0.76	0.31*	0.77	0.29*	0.80	0.30*
census_midwest	0.44	0.40	0.56	0.38	0.48	0.36	0.53	0.35	0.62	0.33	0.63	0.33
census_west	0.32	0.43	0.30	0.42	0.37	0.38	0.35	0.38	0.22	0.36	0.22	0.36
nonusers	-0.35	0.17*	-0.40	0.16*	-0.33	0.12*	-0.36	0.12*	-0.36	0.13*	-0.36	0.13*
swim_use	0.04	0.19	-0.19	0.19	0.04	0.14	-0.02	0.14	0.03	0.14	0.03	0.13
gamefish	0.46	0.40	0.30	0.38	0.16	0.21	0.11	0.21	0.21	0.24	0.19	0.25
volunt	-1.21	0.39*	-1.42	0.39*	-1.24	0.33*	-1.27	0.33*	-1.32	0.33*	-1.31	0.33*
tax_only	-0.18	0.27	-0.21	0.27	-0.29	0.23	-0.30	0.24	-0.33	0.22	-0.33	0.23
user_cost	-1.10	0.47*	-1.10	0.50	-0.89	0.35*	-0.94	0.36*	-0.77	0.36*	-0.79	0.36*
lump_sum	0.22	0.27	0.19	0.27	0.23	0.23	0.23	0.23	0.23	0.22	0.24	0.22
OneShotVal	0.36	0.28	0.40	0.27	0.52	0.24*	0.54	0.24*	0.46	0.23*	0.47	0.23*
thesis	0.58	0.50	0.37	0.51	0.62	0.44	0.62	0.45	0.48	0.42	0.53	0.42
non_reviewed	-0.41	0.35	-0.50	0.34	-0.49	0.32	-0.55	0.31	-0.40	0.29	-0.43	0.30
RUM	0.95	0.30*	0.73	0.30*	0.81	0.26*	0.77	0.27*	0.69	0.25*	0.70	0.25*
IBI	-2.03	0.55*	-2.29	0.54*	-1.74	0.52*	-1.75	0.53*	-2.04	0.47*	-1.99	0.48*
sigma	0.32	0.09	0.30	0.07	0.22	0.05	0.22	0.05	0.27	0.04	0.27	0.04
nu	5.11	6.61	3.20	3.59	3.29	2.52	3.27	2.38	5.41	3.40	5.29	3.12
sd(u)	0.77	0.11	0.75	0.10	0.71	0.09	0.71	0.09	0.65	0.09	0.66	0.09

Notes: * indicates 95% credible interval excludes 0.

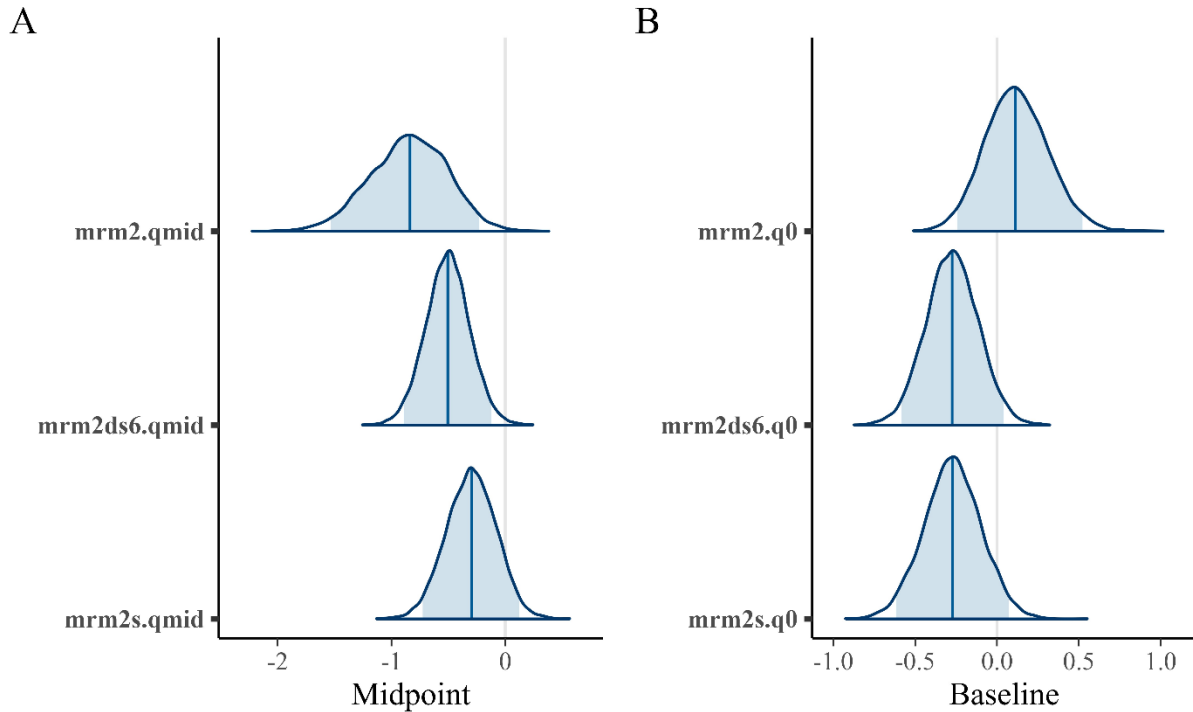


Figure 2 Posterior Distributions for Midpoint and Baseline Quality Coefficients with 95% credible intervals

While comparing distributions of coefficient estimates across models demonstrates the existence and direction of omitted variable bias in the model, it does not show the magnitude of this bias on WTP predictions. The best way to evaluate effects of the different model specification is to compare the predicted posterior distributions for WTP. As the adding up tests involve predicting WTP at different levels of baseline and change across the different models, their results can provide insight into the magnitude of effect of omitted variable bias on WTP. They will also reveal how these effects compare to the impacts of underfitting the metadata.

5.2 Adding Up Results

Table 4 presents a subset of the adding up results for total changes ($dq_{0 \rightarrow 2}$) of 1 and 10 with a constant baseline of 50 and ratio of $dq_{0 \rightarrow 1}$ to $dq_{0 \rightarrow 2}$ equal to 0.25.⁸² To examine the magnitude

⁸² The adding up errors for all changes, baselines, and ratios are presented in Appendix C.

of omitted variable bias on WTP, I compare the differences in per household WTP, represented by the median of the predicted posterior distribution, between baseline and midpoint estimates in MRM2 and MRM2-DS6. For a 1-point change, the difference is approximately \$2 for both the MRM2 and MRM2-DS6. For a 10-point change, this difference scales almost linearly for the MRM2 but not in the MRM2-DS6, due to the dummy shift term.

Table 4 Adding Up Test Results

	MRM2	MRM2-DS6	MRM2-S	MRM2-S1
<i>Midpoint</i>				
WTP($q_0=50.00$, $dq_{0 \rightarrow 2} = 1.00$)	\$7	\$16	\$23	\$42
WTP($q_0=50.00$, $dq_{0 \rightarrow 1} = 0.25$)	\$2	\$4	\$6	\$28
WTP($q_0=50.25$, $dq_{1 \rightarrow 2} = 0.75$)	\$5	\$12	\$17	\$39
Adding Up Error (%)	-0.20	0.18	0.53	-57.55
WTP($q_0=50.00$, $dq_{0 \rightarrow 2} = 10.0$)	\$62	\$57	\$80	\$81
WTP($q_0=50.00$, $dq_{0 \rightarrow 1} = 2.50$)	\$16	41	\$21	\$54
WTP($q_0=52.50$, $dq_{1 \rightarrow 2} = 7.50$)	\$46	48	\$60	\$74
Adding Up Error (%)	0.55	-54.74	-0.44	-58.37
<i>Baseline</i>				
WTP($q_0=50.00$, $dq_{0 \rightarrow 2} = 1.00$)	\$9	\$18	\$23	\$45
WTP($q_0=50.00$, $dq_{0 \rightarrow 1} = 0.25$)	\$2	\$4	\$6	\$32
WTP($q_0=50.25$, $dq_{1 \rightarrow 2} = 0.75$)	\$7	\$13	\$17	\$42
Adding Up Error (%)	0.36	-0.31	-0.40	-65.41
WTP($q_0=50.00$, $dq_{0 \rightarrow 2} = 10.0$)	\$88	\$61	\$78	\$78
WTP($q_0=50.00$, $dq_{0 \rightarrow 1} = 2.50$)	\$22	\$44	\$20	\$55
WTP($q_0=52.50$, $dq_{1 \rightarrow 2} = 7.50$)	\$67	\$51	\$58	\$72
Adding Up Error (%)	-1.27	-57.30	0.39	-64.51

Notes: Median per household willingness to pay estimates for given improvement ($dq_{a \rightarrow b}$) from baseline (q_a) in 2019\$. In MRM2-S $\overline{dq}$ is set to a constant equal to the minimum of the metadata for $dq_{0 \rightarrow 2} = 1.00$ and 10 for $dq_{0 \rightarrow 2} = 10.0$. In MRM2-S1, $\overline{dq}$ is set to the $dq_{a \rightarrow b}$ indicated. Adding up error in bold, computed as $[WTP(q_0, dq_{0 \rightarrow 2}) - [WTP(q_0, dq_{0 \rightarrow 1}) + WTP(q_1, dq_{1 \rightarrow 2})]]/WTP(q_0, dq_{0 \rightarrow 2}) * 100$.

To evaluate the effect of underfitting the metadata in the MRM2 relative to the MRM2-DS6 and MRM2-S, I compare the WTP medians across models. For a 1-point change, WTP is much smaller in the MRM2 models compared to the other models, less than half the WTP in the

MRM2-DS6 or MRM2-S. Thus, the impact of underfitting the metadata outweighs the impact of omitted variable bias for small improvements. For a 10-point change, the relative differences in WTP are smaller, and the WTP for the MRM2 estimated with the baseline is larger than the other models. This result demonstrates how the MRM2 results are more reflective of observations in the metadata with larger improvements. Comparing the MRM2-S and MRM2-S1 results highlights the sensitivity of MRM2-S results to $\overline{dq}$, especially for small improvements. When $\overline{dq}$ is set to the minimum in the metadata (2.38), per household WTP for a 1-point change is approximately \$20 less, than when $\overline{dq}$ is equal to 1.

While underfitting the metadata using the MRM2 has been justified by its satisfaction of the adding up condition, the adding up test results show the MRM2-DSx and MRM2-S models also approximately satisfy adding up under certain conditions. For a 1-point change, the adding up error is less than 1 percent for all models except the MRM2-S1 where $\overline{dq}$ varies between $dq_{a \rightarrow b}$. For a 10-point change, the MRM2-DS6 does not satisfy adding up, which is expected as 10 exceeds the threshold 6. However, the MRM2-S still satisfies adding up in this case, because $\overline{dq}$ is held constant at 10. Thus, when $\overline{dq}$ is set appropriately large, this model can be used to represent WTP. The MRM2-DSx models are preferred for smaller changes, where WTP may be more sensitive to $\overline{dq}$. Lastly, while theoretically, it was expected that the MRM2, MRM2-DS6, and MRM2-S would strictly satisfy adding up when estimated with the baseline over the midpoint, that result is not observed empirically. The small negative percent errors observed in the models may be driven by model uncertainty that results in a wider distribution of posterior predictions. This problem is especially relevant for the MRM2, where more than half of the distribution of $\ln_q0$ were positive, which was not the expected sign in the derivation.

5.3 Out of Sample Prediction

Before applying the models to the benefits transfer it important to understand how the estimated models may predict when extrapolating to smaller changes in water quality. From the prediction results in Table 5, all models perform poorly with RMSE exceeding \$250. The MRM2-S1 estimated at the midpoint has the smallest RMSE of \$255. While the MRM2 has the largest RMSE, it still outperforms multiplying the median WTP/dq from the training sample by dq for each test observation (RMSE = \$299). The large prediction errors are related to large positive outliers in the testing sample with a maximum of \$189. Large outliers may also explain why few credible intervals contain the observed WTP. The extrapolated results are mostly underestimates, with medians ranging from as low as \$12 for the MRM2 (q_0) to \$19 for the MRM2-S1 (q_0) compared to the median of the testing sample at \$72. Only the credible interval for the MRM2-S1 results contain this median, due to the extrapolation with the $\overline{dq}$ term.

Overall, the out of sample prediction results demonstrate strong heterogeneity in the metadata observations that cannot be explained by any of the models. While models may be potentially be improved by the addition of new explanatory variables, it may be that the primary valuation studies have unique features and different contexts that cannot be resolved through new variables. Thus, it is important that the benefit transfer results reflect the wide uncertainty in the metadata by presenting the credible interval. When applying these MRMs to the benefits transfer context, the results demonstrate that the central estimate will likely be an underestimate, and the upper bound of the credible interval may not represent the largest potential WTP. However, it is expected the predictions will provide an appropriate lower bound that may be suitable in many benefits transfer applications.

Table 5 Per Household WTP Out of Sample Prediction Results

	MRM2	MRM2- DS11	MRM2- DS16	MRM2-S	MRM2-S1	
<i>Midpoint</i>						
RMSE	\$282	\$279	\$271	\$273	\$258	
Underestimates	79%	74%	74%	74%	68%	
In Credible Interval	47%	47%	42%	53%	47%	
WTP Median	\$13	\$13	\$15	\$14	\$18	
Credible Interval	\$1 – \$50	\$1 – \$53	\$1 – \$56	\$1 – \$56	\$1 – \$75	
<i>Baseline</i>						
RMSE	\$289	\$284	\$274	\$275	\$255	
Underestimates	79%	74%	74%	74%	68%	
In Credible Interval	42%	42%	37%	47%	53%	
WTP Median	\$12	\$13	\$15	\$15	\$19	
Credible Interval	\$1 – \$39	\$1 – \$43	\$1 – \$50	\$1 – \$51	\$1 – \$75	
<i>Sample Descriptions</i>	<i>dq</i>		WTP		WTP/ <i>dq</i>	
	Median	Range	Median	Range	Median	Range
Training Sample (n=129)	20	10 – 57.5	\$86	\$5 – \$498	\$4	\$0 - \$35
Testing Sample (n=19)	5	2.5 – 5	\$72	\$2 - \$189	\$15	\$0 - \$56

Notes: All \$ in 2019 USD. In MRM2-S $\overline{dq}$ is set to a constant equal to the minimum of the training sample. In MRM2-S1, $\overline{dq}$ is set to the *dq* for each observation in the test sample. The training sample is comprised of all observations in the metadata with $dq \geq 10$. The testing sample is comprised of only observations for river or streams with $dq \leq 5$.

5.4 Benefits Transfer

Table 5 presents the benefit transfer results for the MRM2, MRM2-DS6, and MRM2-S models estimated at the baseline and midpoint. While the out of sample prediction results show that extrapolation may not be a concern for $\overline{dq}$ between 2.5-5, as $\overline{dq}$ approaches zero for many observations the application, MRM2-S1 results will be increasingly sensitive. Therefore, I only include estimates with the MRM2-S with $\overline{dq}$ set to the minimum observation in the metadata, meaning all the benefits transfer results presented satisfy the adding up condition. As observed in the adding up tests, the median per Household WTP/*dq* for the MRM2 models are much lower

than in the MRM2-DS6 or MRM2-S. The associated credible intervals are also lower and do not contain the median estimates of the other models. While the medians for the MRM2-DS6 and MRM2-S differ slightly, the credible intervals are similar with the upper bound for MRM2-S slightly larger than the MRM2-DS6. After multiplying by dq , the resulting per household WTP is very small, which is appropriate given the marginal nature of the changes.

Table 5 National Willingness to Pay Results

	per Household WTP/ dq	per Household WTP	Total Annualized WTP
<i>MRM2 (Midpoint)</i>			
Median	\$5	\$0.004	\$4,898,659
Credible Interval	\$1 – \$12	\$0.001 – \$0.009	\$821,614 – \$11,205,951
<i>MRM2 (Baseline)</i>			
Median	\$7	\$0.006	\$6,850,401
Credible Interval	\$1 – \$16	\$0.001 – \$0.013	\$1,155,829 – \$15,605,269
<i>MRM2-DS6 (Midpoint)</i>			
Median	\$17	\$0.012	\$13,684,798
Credible Interval	\$5 – \$33	\$0.004 – \$0.024	\$4,169,249 – \$26,786,250
<i>MRM2-DS6 (Baseline)</i>			
Median	\$18	\$0.013	\$14,969,819
Credible Interval	\$6 – \$36	\$0.004 – \$0.026	\$4,583,695 – \$29,296,585
<i>MRM2-S (Midpoint)</i>			
Median	\$19	\$0.014	\$16,793,016
Credible Interval	\$6 – \$38	\$0.004 – \$0.027	\$5,074,809 – \$32,834,978
<i>MRM2-S (Baseline)</i>			
Median	\$20	\$0.015	\$17,370,828
Credible Interval	\$6 – \$39	\$0.004 – \$0.029	\$5,316,159 – \$33,867,033

Notes: All willingness to pay (WTP) in 2021\$. Per household MWTP and WTP results are for year 2030 with median and 90% credible interval calculated first for each grid cell and benefits year. The total annualized WTP is then calculated for each grid cell and year using the median per household WTP and its credible interval bounds and then summed across all grid cells and years using an annualized discount rate of 3% from 2025-2049.

While these differences appear negligible at the household level, they compound when aggregated up to the national level for the 25-year time period. The median total annualized WTP for the MRM2 estimated at the midpoint is the smallest at approximately \$5 million, which is slightly larger than the estimate presented in the rulemaking (USEPA, 2023).⁸³ In comparison, the median WTP estimates for the MRM2-DS6 estimated at the baseline and both MRM2-S models are more than three times as large. Some of these missing benefits in the MRM2 can be attributed to the omitted variable bias from the midpoint, \$2 million, but the remaining difference is a result of underfitting the data. Once accounting for the effect of the change in the MRM2-DS6 or MRM2-S, the lower end of the credible interval increases from \$1 million to more than \$4 million. Thus, the MRM2 results presented in the rule are more likely a lower bound on potential estimates rather than a central measure. The aggregation also amplifies the differences between the MRM2-DS6 and MRM2-S results, with the MRM2-S results more than \$2 million larger than the MRM2-DS6 results. However, this gap would lessen if $\overline{dq}$ were set to a value above the metadata minimum. Therefore, while both MRM2-S models fit the data slightly better than the MRM2-DS6 estimated at the midpoint, this model is preferred as it adequately represents the potential benefits of the rule without requiring a choice of $\overline{dq}$.

6. Discussion and Conclusion

This paper demonstrates that inattention to model fit and omitted variable bias in MRMs can have a large impact on benefits estimates at a national scale. While recent guidance has stressed

⁸³ EPA (2023) reports total annualized WTP of \$4.09 million with a 3% discount rate. Given differences in model estimation and aggregation methods, it is unsurprising the results vary. In Appendix D, we present the BenSPLASH results that use the same valuation functions and find the central estimate of \$4.19 million. Therefore, much of the differences may result from using random effects to control for study heterogeneity instead of weighting by inverse sample size.

the importance in satisfying key theoretical conditions in MRM development, the results of this study show how understanding the transfer context and its relationship to the metadata can result in better modelling outcomes than those guided by theory alone. Moreover, I demonstrate that the choice between fitting the metadata or satisfying theoretical conditions is a false dichotomy. Rather, by focusing on a specific transfer context, researchers gain flexibility in how to satisfy key theoretical conditions.

For the benefit transfer context in this study, I develop a flexible class of models, the MRM2-DSx, that can be applied to different environmental contexts. There are many contexts where pollutants have built up in the environment over time, and the expected response to a reduction in pollutant loadings and associated health risks is likely to occur over time. Because the MRM2-DSx approach satisfies the adding up condition when the total improvements are small, this model can be a useful tool in approaching these applications. It is important to note that such extrapolation efforts are not a first best solution, and strong arguments can be made that the value of information for new primary valuation studies within scope of the application is worth the cost (S. C. Newbold & Johnston, 2020). Yet, it is difficult for an average person to conceptualize the effect of marginal changes for small improvements. Moreover, in the water quality context, what defines a marginal change is highly dependent on the index or parameter in use. If the measurement of quality in the primary study is a 10-point index, a marginal 1-point change will be reflected as a 10-point change on a 100-point scale. Therefore, it may be appropriate to include observations in the MRM, where scope appears to be a mismatch, if the results can be appropriately scaled down to zero.

While this analysis focused on a single benefits transfer application, the results provide general insights into how information about the transfer application and metadata can be used in

conjunction with theoretical reasoning in developing an MRM. The first step in developing an MRM for benefits transfer is to characterize the transfer application. Key attributes are the spatial scale of the application, the relevant time scale, and the range of the improvements. When identifying the time scale, it is useful to consider whether the improvements accumulate over time. If not, perhaps the model need not strictly enforce adding up. If they do accumulate, evaluating the range of total improvements provides information on how much of the WTP curve to restrict in the model. Evaluating the magnitude of the improvements and their range also provides information on whether a scope elasticity that varies with the level of improvement is necessary. If the changes are all marginal, a simpler model with a fixed scope elasticity of 1 may be more appropriate and limit introduction of omitted variable bias. If there is a wide range of improvements, then introducing nonlinearity in WTP by estimating at the midpoint will allow scope to vary for the different improvements within the transfer scenario. As demonstrated in this study, estimating at the midpoint can result in omitted variable bias, implying an MRM2-S model may be preferred.

After characterizing the transfer application, it is necessary to evaluate the metadata as it relates to the context of the benefits transfer application. For applications that require scope extrapolation, it is important to use a model that can scale to zero and minimize extrapolation error, like the MRM2-DSx. Researchers may consider out of sample prediction tests to understand the potential behavior of the model when scaled down and decide whether that behavior serves the purpose of the transfer application. It is also useful to understand the relationships between the environmental amenity baseline, level of improvement, WTP, and average WTP. If there is limited scope sensitivity in the metadata, i.e. not a strong relationship between the improvement and WTP, then excluding the improvement as a demand shifter will underfit the data, resulting in

underestimates for smaller improvements. Additionally, including any variable correlated with the improvement will introduce omitted variable bias. After preparing the metadata it is useful to identify which observations are most similar to the benefit transfer scenario, so the resulting model estimates may more strongly reflect the information provided by those studies. For small scale applications it may be useful to develop weights based on similarity. For large scale applications, it may be simpler to focus on general attributes like type of amenity and scope.

In summary, this study advocates for a nuanced approach to MRM development that is guided both by economic theory and by the relationship between the benefit transfer application and the existing metadata. Instead of developing MRMs that globally satisfy theoretical conditions for the entirety of the WTP relationship, analysts may consider developing more flexible local approaches to modelling that account for key challenges decision makers face in benefit transfer applications, such as scope extrapolation. The design of these approaches requires going beyond a simple stylized benefit transfer example, and instead building upon knowledge about the types of environmental contexts decision makers face, the scale of the applications, and how the environmental modelling is undertaken to represent associated improvements. In short, to advance the methods used in environmental policy, the underlying studies themselves should be informed by environmental policy.

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Appendix A Additional Derivations

The MRM2, estimated at the baseline instead of the midpoint can be represented by:

$$\log(WTP/dq) = \mathbf{D}\boldsymbol{\beta}_D + \beta_{q_0} \log(q_0) + \varepsilon \quad (\text{A1})$$

where ε is an idiosyncratic error term. WTP is then recovered by:

$$WTP = \exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (q_0)^{\hat{\beta}_{q_0}} * dq \quad (\text{A2})$$

Given positive values of the baseline and change, the MRM2 is sensitive to scope with a scope elasticity represented by:

$$\epsilon_{WTP, \widetilde{dq}} = 1 \quad (\text{A3})$$

To demonstrate the adding up test for this model, let $dq_{0 \rightarrow 1} = dq$ and $dq_{0 \rightarrow 2} = 2dq$:

$$\begin{aligned} & \left(\exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (q_0)^{\hat{\beta}_{q_0}} * dq \right) + \left(\exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (q_0 + dq)^{\hat{\beta}_{q_0}} * dq \right) \\ & \leq \exp(\mathbf{D}\hat{\boldsymbol{\beta}}_D + \varepsilon) * (q_0)^{\hat{\beta}_{q_{mid}}} * 2dq \end{aligned} \quad (\text{A4})$$

which simplifies to:

$$(q_0 + dq)^{\hat{\beta}_{q_0}} \leq (q_0)^{\hat{\beta}_{q_0}} \quad (\text{A5})$$

Assuming $\hat{\beta}_{q_0} < 0$, as consistent with decreasing marginal utility, implies the following:

$$(q_0)^{\hat{\beta}_{q_0}} > (q_0 + dq)^{\hat{\beta}_{q_0}} \quad (\text{A6})$$

And thus, equation A5 is always strictly satisfied for $\hat{\beta}_{q_0} < 0$.

Appendix B Metadata and Benefit Transfer Inputs

Table B1 Metadata Descriptive Statistics

	Mean	Min.	1st Qu.	Median	3rd Qu.	Max.
Q_mid	53.48	11.25	47.50	54.25	60.00	85.00
dQ	16.83	2.38	6.67	20.00	20.00	57.50
lnyear	2.63	0.00	2.20	3.00	3.40	3.61
ln_ar_agr	-1.65	-4.26	-2.05	-1.50	-1.18	-0.08
ln_ar_ratio	-0.59	-8.48	-1.42	0.00	0.59	6.65
sub_frac	0.35	0.00	0.01	0.12	0.72	1.00
lnincome1	10.95	10.65	10.84	10.93	11.06	11.48
census_south	0.35	0.00	0.00	0.00	1.00	1.00
census_midwest	0.23	0.00	0.00	0.00	0.00	1.00
census_west	0.09	0.00	0.00	0.00	0.00	1.00
nonusers	0.06	0.00	0.00	0.00	0.00	1.00
swim_use	0.22	0.00	0.00	0.00	0.00	1.00
gamefish	0.19	0.00	0.00	0.00	0.00	1.00
volunt	0.06	0.00	0.00	0.00	0.00	1.00
tax_only	0.40	0.00	0.00	0.00	1.00	1.00
user_cost	0.02	0.00	0.00	0.00	0.00	1.00
lump_sum	0.18	0.00	0.00	0.00	0.00	1.00
OneShotVal	0.53	0.00	0.00	1.00	1.00	1.00
thesis	0.08	0.00	0.00	0.00	0.00	1.00
non_reviewed	0.16	0.00	0.00	0.00	0.00	1.00
RUM	0.57	0.00	0.00	1.00	1.00	1.00
IBI	0.08	0.00	0.00	0.00	0.00	1.00

N = 189

Table B2 2023 MRM2 and MRM2-S Variable Coefficients and Default Values

	MRM2	MRM2-S			
intercept	-2.823	-10.02	1		
Thesis	0.431	0.58	0		
Lnyear	-0.135	-0.362	3.6109		
Volunt	-1.656	-1.87	0		
non_reviewed	-0.233	-0.247	0		
lump_sum	0.534	0.518	0		
south	0.693	0.99	Varies by grid cell		
nonusers_only	-0.283	-0.38	0		
lnincome	0.478	1.199	Varies by grid cell and year	10.65331	11.47961
swim_use	0.3	0.361	0		
Gamefish	0.871	0.531	0		
ln_ar_agr	-0.572	-0.654	Varies by grid cell	-4.26144	-0.08351
ln_ar_ratio	-0.157	-0.153	Varies by grid cell	-8.47949	6.651365
sub_proportion	0.993	0.65	Varies by grid cell	0.000318	1
lnQuality_ch (IndQ)	N/A	-0.683	ln(7) with a high alternative of ln(20)		
IBI	-2.355	-2.185	0		
OneShotVal	0.247	0.552	1		
RUM	0.901	0.68	1		
census_midwest	0.667	0.945	Varies by grid cell		
census_west	0.393	0.4	Varies by grid cell		
ln_Q	-0.666	-0.259	Varies by grid cell	2.420368	4.442651
tax_only	-0.177	-0.478	1		
user_cost	-0.873	-1.199	0		
eWTP	0.687	0.58918	N/A		

Source: BenSPLASH 0.16.1 Technical Documentation Table C2. Edited to remove rows from 2015 MRM not used in this analysis. Further edit indicated in red.

Appendix C Full Model Comparisons

Table C1 Log10 Bayes Factors (1 of 2)

	mrm2	mrm2	-ds3	-ds3	-ds4	-ds4	-ds5	-ds5	-ds6	-ds6	-ds7	-ds7	-ds8	-ds8	-ds9	-ds9	-ds10	-ds10	-ds11	-ds11	-ds12	-ds12	-ds13	-ds13	-ds14	-ds14	-ds15	-ds15	-ds20	-ds20	-s	-s
	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0
mrm2	NA																															
.qmid		NA																														
mrm2	-2	NA																														
.q0			NA																													
-ds3	17	19	NA																													
.qmid				NA																												
-ds3	17	18	-1	NA																												
.q0					NA																											
-ds4	17	19	0	1	NA																											
.qmid						NA																										
-ds4	17	18	-1	0	-1	NA																										
.q0							NA																									
-ds5	17	19	0	1	0	1	NA																									
.qmid								NA																								
-ds5	16	18	-1	0	-1	0	-1	NA																								
.q0									NA																							
-ds6	19	20	1	2	1	2	1	2	NA																							
.qmid																																
-ds6	18	20	1	1	1	1	0	1	-1	NA																						
.q0																																
-ds7	11	13	-6	-6	-6	-6	-6	-5	-8	-7	NA																					
.qmid																																
-ds7	10	12	-8	-7	-8	-7	-8	-7	-9	-8	-1	NA																				
.q0																																
-ds8	11	13	-6	-6	-6	-6	-6	-5	-8	-7	0	1	NA																			
.qmid																																
-ds8	10	12	-8	-7	-8	-7	-8	-7	-9	-8	-1	0	-1	NA																		
.q0																																
-ds9	11	13	-6	-5	-6	-5	-6	-5	-7	-7	0	2	0	2	NA																	
.qmid																																
-ds9	10	12	-7	-7	-7	-6	-7	-6	-9	-8	-1	0	-1	0	-1	NA																
.q0																																
-ds10	6	8	-11	-11	-11	-10	-11	-10	-13	-12	-5	-4	-5	-4	-5	-4	NA															
.qmid																																
-ds10	5	6	-13	-12	-13	-12	-13	-12	-14	-13	-7	-5	-7	-5	-7	-6	-2	NA														
.q0																																

Table C1 (2 of 2)

	mrm2	mrm2	-ds3	-ds3	-ds4	-ds4	-ds5	-ds5	-ds6	-ds6	-ds7	-ds7	-ds8	-ds8	-ds9	-ds9	-ds10	-ds10	-ds11	-ds11	-ds12	-ds12	-ds13	-ds13	-ds14	-ds14	-ds15	-ds15	-ds20	-ds20	-s	-s
	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0	.qmid	.q0
-ds11	5	7	-12	-12	-12	-12	-12	-11	-14	-13	-6	-5	-6	-5	-6	-5	-1	1	NA													
.qmid																																
-ds11	3	5	-14	-13	-14	-13	-14	-13	-15	-14	-8	-6	-8	-6	-8	-7	-3	-1	-2	NA												
.q0																																
-ds12	5	7	-12	-12	-12	-12	-12	-11	-14	-13	-6	-5	-6	-5	-6	-5	-1	1	0	2	NA											
.qmid																																
-ds12	3	5	-14	-13	-14	-13	-14	-13	-15	-14	-8	-6	-8	-6	-8	-7	-3	-1	-2	0	-2	NA										
.q0																																
-ds13	5	7	-12	-12	-12	-12	-12	-12	-14	-13	-6	-5	-6	-5	-6	-5	-1	0	0	2	0	1	NA									
.qmid																																
-ds13	4	5	-14	-13	-14	-13	-14	-13	-15	-14	-8	-6	-8	-6	-8	-7	-3	-1	-2	0	-2	0	-1	NA								
.q0																																
-ds14	4	6	-13	-12	-13	-12	-13	-12	-14	-14	-7	-5	-7	-5	-7	-6	-2	0	-1	1	-1	1	-1	1	NA							
.qmid																																
-ds14	3	4	-15	-14	-15	-14	-15	-14	-16	-15	-8	-7	-8	-7	-9	-7	-3	-2	-2	-1	-2	-1	-2	-1	-2	NA						
.q0																																
-ds15	4	6	-13	-12	-13	-12	-13	-12	-14	-14	-7	-5	-7	-5	-7	-6	-2	0	-1	1	-1	1	-1	1	0	2	NA					
.qmid																																
-ds15	3	5	-14	-14	-15	-14	-15	-14	-16	-15	-8	-7	-8	-7	-9	-7	-3	-2	-2	-1	-2	-1	-2	-1	-1	0	-1	NA				
.q0																																
-ds20	-1	1	-19	-18	-19	-18	-19	-18	-20	-19	-12	-11	-12	-11	-13	-11	-7	-6	-6	-5	-6	-5	-6	-5	-6	-4	-6	-4	NA			
.qmid																																
-ds20	-3	-1	-20	-20	-20	-20	-20	-19	-22	-21	-14	-13	-14	-13	-14	-13	-9	-7	-8	-6	-8	-6	-8	-6	-7	-6	-7	-6	-2	NA		
.q0																																
-s	19	20	1	2	1	2	1	2	0	1	7	9	7	9	7	8	12	14	13	15	13	15	14	15	14	16	14	16	20	21	NA	
.qmid																																
-s	19	20	1	2	1	2	1	2	0	1	7	9	8	9	7	8	12	14	13	15	14	15	14	15	14	16	14	16	20	21	0	NA
.q0																																

Notes: Bold indicates most probably models.

Table C2 Adding Up Bias (1 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.25	0.01	10	-0.81	-0.11	-0.08	-59.00	-0.77	-0.28	-0.74	-63.18
0.25	0.1	10	0.25	-1.18	-0.77	-60.14	0.25	-0.86	0.19	-63.79
0.25	0.5	10	0.28	-0.10	-0.79	-58.32	0.58	0.59	1.12	-64.11
0.25	1	10	0.19	0.28	0.91	-58.04	-0.72	1.04	0.33	-63.34
0.25	2	10	1.17	1.11	-0.13	-59.32	-0.18	1.90	0.85	-63.00
0.25	3	10	0.65	-0.12	-0.35	-62.30	-0.26	1.20	1.11	-61.59
0.25	4	10	-0.08	-0.41	0.04	-59.90	0.29	2.53	2.11	-61.34
0.25	5	10	-0.15	-0.09	-1.53	-61.22	-0.57	1.71	2.03	-63.17
0.25	6	10	-0.43	-0.53	0.47	-63.03	-1.45	2.74	2.43	-62.87
0.25	7	10	-2.26	-137.43	-0.23	-62.63	-0.71	-137.19	3.12	-60.96
0.25	8	10	-1.84	-149.03	0.10	-60.91	-2.69	-153.39	4.31	-59.11
0.25	9	10	-2.10	-55.56	-0.78	-64.01	-0.84	-49.99	4.13	-59.58
0.25	10	10	-1.56	-61.38	-0.38	-60.77	-1.93	-54.38	4.94	-60.25
0.25	11	10	-1.01	-64.87	-0.61	-63.49	-2.10	-56.67	5.01	-58.22
0.25	12	10	-2.53	-68.77	-0.95	-63.99	-2.60	-58.71	4.64	-58.11
0.25	13	10	-3.55	-73.16	-0.15	-63.22	-1.71	-61.91	5.67	-58.54
0.25	14	10	-2.42	-78.19	-1.07	-64.17	-2.39	-63.16	5.66	-56.09
0.25	15	10	-2.50	-81.26	-0.79	-65.09	-3.79	-66.94	5.99	-56.92
0.25	16	10	-2.91	-83.82	-0.72	-64.63	-2.88	-69.38	7.42	-57.23
0.25	17	10	-3.79	-88.33	-1.32	-64.03	-3.17	-69.63	7.58	-55.93
0.25	18	10	-4.69	-89.13	-0.62	-65.08	-2.53	-73.12	6.56	-56.86
0.25	19	10	-2.72	-96.01	-1.17	-64.85	-3.87	-75.54	7.57	-55.31
0.25	20	10	-5.18	-96.92	-0.91	-65.96	-3.81	-74.85	7.94	-54.76
0.25	25	10	-5.69	-41.16	-2.39	-68.46	-4.53	-22.48	8.69	-53.53
0.25	30	10	-7.56	-40.98	-1.22	-67.62	-3.36	-20.70	11.34	-50.22
0.25	35	10	-8.98	-42.35	-1.87	-69.85	-4.79	-20.78	12.95	-49.06
0.25	40	10	-9.69	-44.14	-1.72	-72.02	-8.99	-18.78	13.21	-47.66
0.25	45	10	-12.90	-44.34	-2.81	-71.62	-7.30	-18.42	13.59	-46.11
0.25	50	10	-13.02	-45.81	-3.04	-69.62	-7.82	-16.46	14.50	-45.90
0.25	60	10	-14.98	-48.82	-3.30	-73.08	-9.56	-15.46	16.54	-42.75
0.25	70	10	-15.60	-50.76	-3.73	-73.53	-10.41	-12.14	18.19	-42.20
0.25	80	10	-19.25	-50.72	-4.69	-74.57	-10.10	-11.28	19.08	-39.91
0.25	0.01	20	0.40	-0.02	0.64	-59.54	1.42	-0.67	-0.56	-63.57
0.25	0.1	20	1.21	0.27	-0.12	-58.41	-0.89	0.50	-0.16	-66.44
0.25	0.5	20	-0.29	-0.02	1.26	-58.10	1.01	-0.23	1.01	-64.65
0.25	1	20	0.65	0.00	-0.17	-59.42	-0.20	0.13	0.65	-63.80
0.25	2	20	0.78	-0.06	-0.31	-59.51	-0.14	0.72	0.46	-64.32
0.25	3	20	-1.12	0.62	-0.56	-60.11	-0.91	0.78	0.19	-63.51
0.25	4	20	-0.64	-0.62	-0.72	-61.23	0.27	0.39	0.54	-63.87
0.25	5	20	0.15	0.00	-0.50	-58.90	0.29	1.90	1.62	-63.32
0.25	6	20	-0.63	-0.21	-0.31	-60.66	-0.97	1.33	0.67	-63.90
0.25	7	20	-0.64	-136.04	-0.68	-58.47	-1.22	-144.76	2.54	-62.52
0.25	8	20	-0.30	-147.69	0.28	-60.18	0.19	-158.91	1.29	-63.73
0.25	9	20	-0.24	-53.62	-0.25	-59.62	-1.45	-53.90	1.91	-61.38
0.25	10	20	-1.52	-56.64	-1.23	-59.74	-0.69	-54.41	2.79	-60.92
0.25	11	20	-1.85	-60.27	0.29	-62.03	-1.55	-60.81	2.89	-61.96
0.25	12	20	-1.33	-63.29	-0.67	-60.47	-1.15	-61.44	2.56	-59.30
0.25	13	20	-0.84	-68.10	-0.28	-61.13	-2.02	-63.90	4.04	-59.54
0.25	14	20	-0.46	-71.11	0.15	-61.31	-0.59	-67.33	2.61	-61.78
0.25	15	20	-1.76	-74.76	0.46	-61.12	-2.05	-70.25	4.44	-60.15
0.25	16	20	-1.21	-77.70	0.37	-61.53	-2.15	-72.04	4.08	-59.49
0.25	17	20	-1.27	-79.97	-0.71	-61.73	-1.67	-73.07	3.90	-61.16
0.25	18	20	-3.45	-83.88	-0.35	-63.74	-1.96	-77.19	4.16	-59.95
0.25	19	20	-2.60	-86.09	-1.17	-64.30	-2.16	-79.11	4.02	-57.37
0.25	20	20	-1.42	-89.07	0.57	-62.12	-2.20	-81.22	4.51	-58.53

Table C2 Adding Up Bias (2 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.25	25	20	-2.59	-35.25	-0.91	-61.80	-2.23	-26.38	6.15	-58.31
0.25	30	20	-3.92	-36.69	-1.01	-64.47	-3.84	-26.13	5.89	-57.57
0.25	35	20	-4.79	-38.10	-0.83	-63.99	-3.29	-26.00	6.93	-56.77
0.25	40	20	-4.59	-38.43	-1.48	-64.82	-2.99	-24.09	7.51	-54.61
0.25	45	20	-5.86	-40.70	-1.73	-65.60	-4.73	-22.90	9.08	-53.15
0.25	50	20	-6.94	-40.61	-0.67	-66.23	-3.80	-23.86	9.34	-53.36
0.25	60	20	-8.48	-41.25	-2.32	-66.91	-4.72	-22.90	10.67	-50.03
0.25	70	20	-9.20	-42.47	-2.11	-68.03	-5.71	-19.97	11.71	-50.03
0.25	80	20	-11.75	-43.27	-2.19	-70.37	-7.06	-17.71	12.43	-48.32
0.25	0.01	50	0.90	-0.76	-0.78	-58.52	-0.44	-0.03	-0.22	-66.12
0.25	0.1	50	-0.20	0.23	0.08	-59.16	-0.16	-0.72	0.77	-63.48
0.25	0.5	50	0.31	-0.62	1.05	-60.83	-0.08	-0.26	-0.28	-62.97
0.25	1	50	-0.20	0.18	0.53	-57.55	0.36	-0.31	-0.40	-65.41
0.25	2	50	-1.12	-0.11	-0.37	-60.48	-0.04	-0.60	0.08	-65.32
0.25	3	50	-0.14	-1.16	0.67	-58.94	-0.14	1.83	1.07	-64.45
0.25	4	50	0.00	-0.84	0.43	-57.74	-1.81	1.45	-0.27	-63.47
0.25	5	50	-0.22	-0.04	0.53	-60.99	0.12	0.94	0.59	-63.90
0.25	6	50	0.14	-1.47	-0.94	-60.65	-0.79	1.46	2.03	-63.11
0.25	7	50	0.43	-133.76	0.09	-59.81	-0.79	-143.45	1.35	-63.35
0.25	8	50	0.77	-147.34	-0.14	-59.97	0.17	-160.02	0.59	-64.42
0.25	9	50	-0.87	-51.78	-0.65	-58.95	-0.49	-55.33	1.25	-62.05
0.25	10	50	-0.51	-54.64	-0.44	-58.37	-1.27	-57.30	0.39	-64.51
0.25	11	50	-0.83	-58.25	-0.93	-59.83	-0.47	-58.36	1.61	-62.85
0.25	12	50	0.35	-62.65	0.84	-58.88	-2.09	-61.66	1.07	-64.13
0.25	13	50	0.14	-65.11	-0.90	-61.53	0.65	-65.12	2.13	-64.05
0.25	14	50	0.54	-68.21	0.27	-60.54	0.53	-69.27	1.53	-63.74
0.25	15	50	-2.11	-70.03	-0.50	-59.16	-0.73	-72.48	1.75	-63.93
0.25	16	50	0.03	-72.86	-0.96	-59.49	-0.16	-74.39	1.39	-61.76
0.25	17	50	0.95	-75.40	-0.44	-60.33	-2.82	-76.74	2.70	-62.95
0.25	18	50	-0.09	-78.81	-0.41	-58.84	-0.20	-79.62	2.24	-62.62
0.25	19	50	-1.15	-80.83	-0.36	-60.62	-0.73	-82.27	2.30	-61.40
0.25	20	50	-0.38	-82.46	0.08	-59.76	-0.99	-82.19	2.78	-61.60
0.25	25	50	-0.38	-32.43	0.44	-59.72	-1.70	-30.10	2.03	-63.21
0.25	30	50	-0.92	-32.68	0.10	-61.12	-1.15	-30.43	3.56	-61.69
0.25	35	50	-0.15	-34.10	-0.42	-61.25	-0.64	-29.60	2.34	-59.82
0.25	40	50	-2.00	-34.12	-0.20	-62.29	-1.90	-28.99	3.65	-60.33
0.25	45	50	-0.86	-35.02	-0.66	-62.21	0.12	-28.69	3.49	-59.66
0.25	50	50	-1.59	-35.28	-0.59	-64.11	-2.33	-28.98	4.56	-59.78
0.25	60	50	-2.43	-35.47	-0.40	-61.59	-2.59	-27.87	4.95	-57.93
0.25	70	50	-3.92	-36.76	-1.32	-63.64	-0.98	-26.69	5.58	-57.99
0.25	80	50	-3.86	-38.08	0.21	-65.66	-2.44	-25.64	6.56	-57.23
0.25	0.01	80	-0.94	-0.11	-0.18	-59.41	-0.72	-0.32	0.07	-63.42
0.25	0.1	80	-0.85	0.68	0.04	-58.90	-0.39	0.20	1.08	-64.91
0.25	0.5	80	-1.65	-0.07	-0.68	-57.12	0.50	-0.89	0.36	-64.58
0.25	1	80	-1.47	0.04	0.29	-58.92	0.50	-0.19	-0.31	-65.25
0.25	2	80	0.42	0.38	-0.04	-59.65	0.99	-0.05	0.30	-66.02
0.25	3	80	-0.40	-0.37	-1.29	-58.10	-1.21	0.50	0.30	-64.68
0.25	4	80	-1.96	-0.47	-0.56	-59.53	0.26	0.56	1.13	-64.05
0.25	5	80	-0.03	-0.12	-0.29	-60.39	-1.18	0.66	0.85	-63.64
0.25	6	80	-0.37	0.35	-0.93	-59.19	0.35	0.11	0.40	-63.61
0.25	7	80	-0.57	-137.02	0.49	-58.33	0.15	-147.20	-0.47	-63.73
0.25	8	80	-0.25	-149.09	-1.00	-57.89	0.50	-161.40	0.74	-64.16
0.25	9	80	-0.31	-51.98	0.09	-59.53	-0.40	-53.60	1.57	-64.06
0.25	10	80	0.03	-55.13	-0.50	-58.97	0.05	-59.27	0.26	-62.72
0.25	11	80	-0.23	-58.55	-0.02	-57.63	0.24	-60.33	-0.20	-62.75

Table C2 Adding Up Bias (3 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.25	12	80	-0.14	-61.79	-0.30	-58.92	-0.11	-63.39	1.74	-62.65
0.25	13	80	-1.13	-62.87	0.47	-59.72	-0.41	-66.78	1.38	-62.75
0.25	14	80	-0.02	-66.53	-0.15	-59.44	-1.23	-69.70	0.50	-63.51
0.25	15	80	0.64	-68.23	-0.25	-59.91	0.77	-72.24	0.68	-64.61
0.25	16	80	-0.20	-72.04	0.14	-59.09	-0.79	-75.53	1.09	-63.02
0.25	17	80	0.57	-74.06	-0.43	-60.75	-0.66	-76.57	0.20	-65.13
0.25	18	80	-1.53	-76.32	0.17	-60.08	-0.29	-80.03	1.13	-63.84
0.25	19	80	0.41	-79.76	0.11	-59.13	-0.98	-84.41	1.38	-62.36
0.25	20	80	1.84	-80.24	-0.45	-60.60	-0.95	-83.12	1.59	-62.41
0.25	25	80	0.72	-31.99	-0.25	-60.32	0.50	-31.28	2.39	-61.53
0.25	30	80	-0.30	-31.33	-0.53	-60.97	-0.13	-30.62	1.35	-62.22
0.25	35	80	0.04	-32.05	-0.07	-57.74	-0.92	-30.23	1.00	-60.88
0.25	40	80	0.06	-32.24	-0.66	-60.14	-1.13	-30.60	2.59	-62.35
0.25	45	80	-1.53	-32.78	0.62	-61.66	-0.99	-29.94	3.19	-59.89
0.25	50	80	-1.12	-32.11	-1.03	-62.16	-1.76	-30.31	3.80	-61.50
0.25	60	80	-2.05	-34.19	-0.02	-61.88	-1.77	-29.57	2.44	-60.24
0.25	70	80	-2.31	-34.41	-0.46	-60.66	-2.01	-29.76	3.23	-59.82
0.25	80	80	-0.84	-34.09	-1.13	-62.09	-2.65	-28.03	5.13	-58.61
0.5	0.01	10	0.35	-0.25	0.02	-62.90	-0.87	-0.33	0.00	-67.98
0.5	0.1	10	-0.33	-0.65	-0.47	-63.98	-0.38	0.61	0.38	-68.27
0.5	0.5	10	1.39	0.13	0.73	-63.69	-0.51	0.09	0.39	-69.93
0.5	1	10	0.67	-0.12	-0.63	-65.93	-0.57	0.65	0.43	-67.77
0.5	2	10	0.82	-0.10	0.56	-64.49	-1.14	1.92	0.79	-66.49
0.5	3	10	0.36	0.00	1.20	-64.10	-0.73	1.95	1.72	-63.63
0.5	4	10	0.56	0.70	-0.33	-63.62	-1.36	2.58	2.16	-62.26
0.5	5	10	-1.70	-0.59	-0.53	-62.82	-0.71	2.89	3.13	-65.35
0.5	6	10	-3.13	-0.80	-0.58	-64.25	-1.27	2.58	2.98	-63.75
0.5	7	10	-1.37	-135.63	-0.93	-65.66	-1.00	-137.46	4.63	-61.46
0.5	8	10	-1.14	-153.22	0.46	-64.82	-2.12	-150.37	3.81	-62.78
0.5	9	10	-1.05	-165.39	-1.18	-64.52	-2.96	-165.54	4.43	-61.50
0.5	10	10	-2.28	-176.63	-0.73	-63.26	-1.87	-174.82	5.40	-59.28
0.5	11	10	-2.53	-187.97	-0.41	-67.27	-1.25	-188.36	5.62	-59.88
0.5	12	10	-2.07	-199.06	0.32	-65.28	-2.97	-197.82	6.62	-58.48
0.5	13	10	-3.71	-37.28	-0.97	-65.56	-2.28	-29.46	6.72	-57.41
0.5	14	10	-3.85	-36.52	-2.35	-65.51	-1.99	-29.02	5.94	-57.64
0.5	15	10	-4.14	-37.92	-0.29	-65.87	-3.64	-28.46	7.12	-57.29
0.5	16	10	-3.76	-37.59	-0.34	-65.89	-3.09	-29.24	8.21	-57.64
0.5	17	10	-4.27	-38.86	-1.29	-65.62	-3.28	-26.97	6.34	-56.61
0.5	18	10	-4.08	-38.56	-1.43	-64.39	-4.54	-25.92	7.76	-56.49
0.5	19	10	-5.71	-39.84	-2.01	-64.88	-4.84	-27.09	9.17	-53.73
0.5	20	10	-5.28	-40.62	-1.69	-64.55	-3.40	-26.70	9.24	-54.17
0.5	25	10	-7.07	-39.29	-1.18	-67.06	-5.78	-24.57	10.60	-52.60
0.5	30	10	-6.93	-41.07	-1.43	-68.09	-3.72	-22.65	10.59	-52.55
0.5	35	10	-9.03	-40.48	-2.63	-66.57	-7.08	-21.32	12.04	-48.15
0.5	40	10	-8.66	-40.97	-2.79	-65.52	-7.07	-19.45	14.25	-47.68
0.5	45	10	-10.70	-43.47	-1.44	-67.36	-6.83	-18.62	13.67	-45.96
0.5	50	10	-11.58	-42.32	-2.39	-66.05	-7.81	-17.86	14.19	-44.88
0.5	60	10	-11.50	-43.52	-2.76	-69.76	-8.48	-15.87	15.27	-43.14
0.5	70	10	-13.95	-44.96	-3.04	-68.65	-8.89	-14.35	16.23	-41.00
0.5	80	10	-16.67	-43.37	-4.03	-68.82	-10.00	-13.15	18.49	-38.99
0.5	0.01	20	-0.07	-0.31	0.61	-63.74	0.11	0.30	0.42	-70.07
0.5	0.1	20	-0.24	-0.04	0.11	-64.55	-1.04	-0.63	-0.23	-70.49
0.5	0.5	20	0.17	-0.24	0.24	-63.03	0.29	1.05	-1.61	-67.96
0.5	1	20	-0.79	-0.10	1.23	-64.23	-0.17	-0.20	-0.12	-68.56
0.5	2	20	-0.36	0.40	0.00	-64.12	-0.99	0.44	0.49	-66.39

Table C2 Adding Up Bias (4 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.5	3	20	-0.38	-0.60	-0.26	-65.40	1.04	1.57	0.26	-66.42
0.5	4	20	-0.01	-0.93	-1.21	-64.80	-0.15	1.00	0.36	-66.47
0.5	5	20	-1.12	-0.41	-0.09	-61.85	0.54	1.11	2.33	-66.37
0.5	6	20	-0.33	-0.41	0.02	-62.54	-0.09	2.02	0.83	-64.48
0.5	7	20	1.46	-137.26	-0.82	-64.93	-0.40	-138.76	2.12	-65.54
0.5	8	20	-1.44	-147.32	-0.50	-64.29	0.25	-155.18	2.49	-65.29
0.5	9	20	-0.59	-162.80	-1.22	-63.50	-0.31	-168.27	2.54	-63.42
0.5	10	20	-1.70	-177.96	0.66	-65.65	-2.00	-182.45	2.63	-63.25
0.5	11	20	-0.29	-189.83	-0.63	-63.62	-1.29	-195.03	3.57	-64.02
0.5	12	20	-1.44	-199.83	-0.41	-64.05	-0.55	-207.60	3.52	-64.02
0.5	13	20	0.04	-35.95	0.07	-63.76	-2.91	-31.67	3.57	-62.41
0.5	14	20	-2.07	-37.15	-0.27	-64.64	-1.64	-33.13	3.41	-64.28
0.5	15	20	-0.14	-35.60	-1.03	-64.27	-1.67	-32.74	4.67	-62.44
0.5	16	20	-1.68	-34.99	-0.93	-63.51	-1.63	-31.85	4.02	-62.76
0.5	17	20	-2.14	-35.57	0.18	-64.08	-1.20	-31.65	4.75	-60.31
0.5	18	20	-0.94	-37.68	-0.36	-65.21	-1.96	-32.21	6.08	-60.91
0.5	19	20	-1.70	-36.28	-0.66	-63.77	-2.50	-31.63	5.10	-59.51
0.5	20	20	-2.56	-38.17	-0.51	-64.86	-1.74	-31.11	4.99	-60.42
0.5	25	20	-2.63	-38.44	-1.23	-66.15	-3.24	-29.94	5.38	-58.31
0.5	30	20	-3.86	-38.63	-0.51	-64.58	-3.02	-28.50	6.92	-57.17
0.5	35	20	-4.85	-37.52	-1.48	-66.05	-4.09	-27.96	8.32	-55.19
0.5	40	20	-3.93	-39.13	-1.43	-65.66	-3.88	-25.96	9.28	-54.03
0.5	45	20	-5.98	-40.66	-2.13	-65.47	-5.19	-24.10	9.34	-53.60
0.5	50	20	-7.51	-40.78	-2.06	-67.63	-4.70	-24.51	9.82	-52.78
0.5	60	20	-9.02	-40.98	-1.93	-66.18	-6.98	-22.04	10.64	-50.20
0.5	70	20	-8.27	-40.90	-1.90	-66.75	-7.04	-21.93	12.25	-46.12
0.5	80	20	-9.04	-40.74	-2.77	-68.69	-6.37	-19.41	13.07	-47.03
0.5	0.01	50	0.61	0.14	-0.33	-65.17	-0.40	0.21	-0.63	-67.37
0.5	0.1	50	0.19	-1.29	-0.95	-64.17	0.32	0.21	0.49	-68.37
0.5	0.5	50	0.52	-0.25	-0.07	-62.73	0.28	0.89	0.11	-67.42
0.5	1	50	-0.48	-0.28	-0.15	-62.04	0.23	0.40	0.98	-69.96
0.5	2	50	0.96	0.81	0.33	-64.49	-0.74	0.21	-0.14	-67.02
0.5	3	50	0.94	-0.46	0.02	-64.05	0.17	1.40	0.90	-68.10
0.5	4	50	1.09	-0.41	-0.28	-64.23	0.01	2.31	0.37	-67.50
0.5	5	50	-0.18	-0.08	-0.43	-63.83	-0.47	1.72	0.28	-67.55
0.5	6	50	-1.35	0.37	-1.07	-64.46	0.58	0.43	0.54	-68.47
0.5	7	50	0.14	-134.70	-0.11	-62.10	-0.68	-145.33	1.53	-68.05
0.5	8	50	0.04	-149.56	0.28	-65.54	-0.53	-158.95	1.89	-67.57
0.5	9	50	0.55	-160.74	0.64	-64.34	0.40	-173.53	0.68	-66.22
0.5	10	50	-0.66	-173.08	0.19	-63.36	-1.53	-187.57	1.96	-67.31
0.5	11	50	-0.13	-187.97	-0.61	-64.55	-1.14	-198.12	1.51	-66.68
0.5	12	50	-0.01	-200.17	0.01	-63.31	-0.76	-212.21	1.13	-67.18
0.5	13	50	0.33	-34.76	-0.26	-62.38	-0.56	-35.50	1.49	-66.07
0.5	14	50	-0.65	-35.85	0.29	-65.13	-2.20	-35.58	2.51	-66.62
0.5	15	50	-1.21	-36.73	-0.45	-62.77	-0.60	-36.30	1.41	-65.85
0.5	16	50	-0.69	-36.42	-0.11	-64.55	-0.98	-35.34	1.87	-66.48
0.5	17	50	-0.71	-35.97	-0.98	-62.91	0.36	-34.22	3.04	-65.56
0.5	18	50	-1.59	-34.62	-0.08	-65.05	0.82	-35.44	2.63	-64.61
0.5	19	50	-0.22	-37.01	0.08	-64.36	-0.56	-35.56	2.99	-63.71
0.5	20	50	-0.08	-36.68	-0.25	-63.13	0.23	-34.34	3.43	-64.53
0.5	25	50	-1.33	-37.14	-1.23	-65.38	-1.72	-34.05	2.68	-62.95
0.5	30	50	-0.27	-38.36	-0.17	-64.66	-1.86	-33.00	3.36	-64.00
0.5	35	50	-1.73	-35.68	-1.15	-63.54	-1.44	-32.58	4.01	-62.66
0.5	40	50	-2.83	-34.73	-0.32	-64.93	-3.29	-31.25	4.24	-61.34
0.5	45	50	-1.80	-37.66	-1.25	-63.40	-1.54	-31.76	5.16	-61.02

Table C2 Adding Up Bias (5 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.5	50	50	-2.22	-36.52	-0.57	-65.62	-3.25	-30.68	5.36	-61.30
0.5	60	50	-3.52	-37.50	-0.32	-63.57	-1.73	-29.81	4.95	-58.63
0.5	70	50	-4.23	-38.34	-1.53	-65.07	-3.45	-29.08	5.80	-57.63
0.5	80	50	-3.55	-37.54	-1.66	-65.12	-3.88	-27.52	8.00	-55.64
0.5	0.01	80	-1.11	0.16	0.53	-64.74	0.36	0.13	0.16	-68.86
0.5	0.1	80	0.87	-1.07	0.25	-61.46	0.06	-0.24	0.25	-68.53
0.5	0.5	80	-0.85	-0.13	0.69	-63.11	-0.98	0.86	-0.34	-68.40
0.5	1	80	0.21	-0.17	0.82	-62.94	0.65	-0.29	1.74	-68.16
0.5	2	80	0.63	-0.96	0.19	-62.52	-1.15	-0.23	0.45	-69.83
0.5	3	80	-0.02	-1.19	0.19	-61.15	-1.03	0.02	1.06	-69.36
0.5	4	80	-0.89	0.27	-0.30	-65.46	0.96	0.09	0.83	-68.82
0.5	5	80	-1.02	-0.99	-0.01	-63.46	0.35	1.02	0.25	-69.63
0.5	6	80	-0.44	-0.65	-0.17	-64.55	-0.61	0.39	0.68	-67.70
0.5	7	80	0.33	-134.90	-0.20	-66.19	-0.14	-144.80	1.52	-68.60
0.5	8	80	0.27	-146.59	-0.93	-62.73	0.12	-162.79	0.39	-67.74
0.5	9	80	-0.07	-161.95	-0.39	-64.45	-0.79	-173.54	1.00	-68.89
0.5	10	80	1.01	-173.07	-0.38	-63.24	-0.44	-189.16	0.61	-67.28
0.5	11	80	-0.71	-188.25	-0.74	-63.67	-2.01	-198.26	0.53	-66.21
0.5	12	80	0.26	-194.01	-0.29	-65.38	0.60	-217.89	0.61	-66.76
0.5	13	80	0.09	-35.85	-0.23	-63.37	0.01	-35.26	1.02	-66.46
0.5	14	80	-1.77	-35.74	-1.20	-63.08	1.26	-36.24	0.84	-65.14
0.5	15	80	-0.94	-35.47	-0.02	-64.32	-1.18	-35.56	2.47	-67.00
0.5	16	80	-0.68	-35.67	0.12	-63.83	0.13	-36.09	1.13	-66.58
0.5	17	80	-0.02	-35.44	-1.22	-62.48	-0.11	-35.76	1.71	-66.14
0.5	18	80	-0.57	-37.12	0.91	-62.45	-1.35	-35.40	0.76	-64.29
0.5	19	80	-0.05	-35.74	0.12	-64.58	-1.87	-36.17	1.45	-65.45
0.5	20	80	0.45	-35.72	0.15	-64.26	-1.16	-35.54	1.41	-65.79
0.5	25	80	0.84	-35.96	0.66	-65.16	0.20	-36.28	1.64	-65.97
0.5	30	80	-1.10	-36.74	-0.07	-65.17	-0.65	-35.41	1.60	-64.51
0.5	35	80	-0.96	-35.48	-0.55	-65.05	-0.98	-33.61	2.05	-65.35
0.5	40	80	-2.03	-36.05	-0.13	-63.16	-2.04	-33.29	3.54	-64.81
0.5	45	80	-0.21	-35.62	-0.18	-62.30	-1.55	-33.52	3.60	-63.63
0.5	50	80	-0.87	-35.55	-0.96	-64.34	-1.05	-31.68	3.61	-63.30
0.5	60	80	-1.84	-36.81	-0.54	-65.56	-0.83	-32.89	4.74	-62.32
0.5	70	80	-3.57	-36.05	-0.31	-64.91	-1.28	-31.90	6.09	-59.69
0.5	80	80	-2.39	-37.10	-0.51	-64.55	-1.10	-31.80	5.01	-62.34
0.75	0.01	10	0.27	-0.01	-0.32	-58.99	0.25	-0.52	0.08	-62.30
0.75	0.1	10	-1.23	0.71	-0.10	-57.76	-0.38	-0.17	-0.40	-64.31
0.75	0.5	10	-0.95	0.44	0.22	-59.69	1.05	-0.36	-0.18	-62.49
0.75	1	10	1.15	-0.05	0.56	-59.58	0.26	-0.08	-0.29	-63.59
0.75	2	10	0.56	0.74	-0.20	-57.94	-1.79	1.72	1.42	-62.05
0.75	3	10	1.19	-0.88	0.36	-58.55	-1.54	0.59	1.47	-59.52
0.75	4	10	-0.70	-0.46	-0.01	-58.11	-0.15	1.86	2.03	-59.35
0.75	5	10	-1.55	-0.28	-0.66	-57.94	-0.53	1.53	2.21	-58.13
0.75	6	10	-0.26	-0.65	-0.32	-57.80	-1.00	1.20	3.12	-56.81
0.75	7	10	-0.69	-135.65	-0.48	-57.80	-1.43	-139.18	2.66	-56.16
0.75	8	10	-0.75	-151.32	-0.36	-58.09	-1.73	-156.51	3.09	-56.90
0.75	9	10	-1.71	-47.31	-1.27	-56.83	-0.19	-46.61	2.84	-55.23
0.75	10	10	-0.77	-50.27	0.40	-57.51	-0.84	-48.96	4.47	-54.62
0.75	11	10	-0.71	-54.20	-0.94	-57.50	-1.70	-48.62	3.69	-52.51
0.75	12	10	-2.13	-54.87	-0.74	-56.32	-2.18	-53.64	2.99	-54.01
0.75	13	10	-0.64	-57.12	-0.78	-58.20	-2.77	-54.34	3.72	-52.83
0.75	14	10	-2.65	-59.89	-1.81	-56.19	-2.76	-53.85	4.24	-52.59
0.75	15	10	0.07	-62.01	-0.65	-57.61	-2.78	-55.02	5.16	-50.95
0.75	16	10	-2.61	-62.90	-0.08	-55.86	-3.00	-58.69	5.06	-50.96

Table C2 Adding Up Bias (6 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.75	17	10	-0.84	-65.89	-1.12	-57.93	-2.83	-59.47	4.35	-51.12
0.75	18	10	-2.90	-65.87	-0.65	-56.59	-3.43	-61.90	5.43	-49.55
0.75	19	10	-1.86	-69.24	-0.60	-57.91	-2.09	-61.75	5.31	-48.92
0.75	20	10	-3.04	-70.11	-0.70	-58.27	-2.91	-64.60	6.07	-47.22
0.75	25	10	-2.75	-29.82	-1.28	-57.91	-3.73	-21.20	5.72	-45.80
0.75	30	10	-3.96	-31.14	-0.77	-56.19	-3.34	-19.72	7.33	-44.42
0.75	35	10	-4.52	-29.91	-1.59	-55.81	-3.97	-19.88	7.59	-44.31
0.75	40	10	-5.47	-30.66	-0.22	-55.78	-4.00	-17.52	7.05	-40.46
0.75	45	10	-4.76	-30.53	-0.87	-54.11	-5.03	-17.60	8.04	-40.45
0.75	50	10	-5.34	-29.95	-0.40	-56.24	-4.06	-17.18	8.36	-39.63
0.75	60	10	-7.09	-31.69	-1.10	-56.83	-6.31	-15.03	9.01	-38.22
0.75	70	10	-6.18	-30.06	-2.59	-54.95	-6.07	-14.46	9.48	-36.44
0.75	80	10	-7.98	-30.93	-1.76	-56.07	-6.44	-13.14	10.52	-35.73
0.75	0.01	20	-0.87	0.56	0.55	-58.31	0.31	-1.05	0.17	-64.05
0.75	0.1	20	-1.02	0.74	0.05	-58.23	0.59	0.75	0.65	-63.91
0.75	0.5	20	0.45	-0.78	0.54	-58.86	-0.15	-0.41	-0.42	-64.75
0.75	1	20	-0.01	0.88	0.71	-58.36	-0.81	0.84	0.16	-64.72
0.75	2	20	0.33	0.54	-0.76	-58.37	-0.80	0.54	0.34	-63.89
0.75	3	20	-1.20	-1.19	0.15	-57.88	-1.38	1.31	1.40	-62.45
0.75	4	20	0.52	0.84	-0.26	-57.55	-0.53	-0.39	0.90	-61.86
0.75	5	20	-0.08	-0.36	0.09	-58.16	-1.36	0.67	0.14	-61.64
0.75	6	20	0.71	-0.01	-0.39	-57.33	-0.06	0.86	2.37	-60.82
0.75	7	20	-0.34	-135.75	-0.04	-58.08	-0.28	-140.83	0.49	-58.93
0.75	8	20	-0.83	-148.60	-0.15	-57.64	0.15	-157.30	0.99	-59.64
0.75	9	20	-0.36	-47.34	0.09	-56.15	-0.88	-48.35	1.99	-58.11
0.75	10	20	1.06	-50.91	0.04	-58.03	-0.95	-53.01	2.38	-57.11
0.75	11	20	-0.83	-53.70	-0.87	-57.17	-0.62	-55.04	2.25	-58.10
0.75	12	20	-1.23	-56.11	-0.08	-58.31	-0.84	-56.72	2.39	-56.27
0.75	13	20	-1.59	-58.94	-0.87	-57.10	-0.25	-59.07	2.12	-56.48
0.75	14	20	-0.65	-59.98	-0.14	-56.66	-2.30	-62.68	2.60	-58.69
0.75	15	20	-1.25	-63.27	-0.06	-56.49	-1.72	-61.50	3.27	-57.99
0.75	16	20	-0.86	-66.23	-1.71	-56.85	-0.31	-65.47	2.84	-55.87
0.75	17	20	-1.04	-64.53	0.34	-56.23	-1.72	-67.92	3.11	-56.67
0.75	18	20	-2.49	-67.91	-0.60	-58.71	-0.39	-70.00	3.68	-54.96
0.75	19	20	-1.69	-69.81	0.14	-57.53	-1.58	-70.87	3.00	-54.33
0.75	20	20	-1.10	-72.70	-0.06	-57.35	-1.11	-72.19	3.08	-54.96
0.75	25	20	-2.64	-29.14	-0.54	-56.37	-3.68	-25.89	4.05	-53.13
0.75	30	20	-2.30	-30.08	-0.39	-56.20	-2.69	-24.28	4.83	-50.01
0.75	35	20	-2.15	-30.22	0.29	-56.37	-2.54	-23.98	5.53	-48.83
0.75	40	20	-2.49	-31.22	-1.03	-57.32	-3.10	-21.43	6.30	-47.98
0.75	45	20	-3.47	-30.44	-0.59	-57.10	-3.22	-21.37	6.45	-48.38
0.75	50	20	-3.73	-31.38	-1.27	-57.24	-2.61	-21.47	6.65	-45.74
0.75	60	20	-4.26	-30.75	-0.45	-56.59	-5.03	-19.11	6.89	-44.70
0.75	70	20	-4.17	-29.61	-1.01	-57.80	-3.30	-18.96	7.00	-43.43
0.75	80	20	-4.66	-31.83	-2.52	-56.69	-3.83	-18.83	8.65	-42.68
0.75	0.01	50	0.39	0.65	0.73	-60.46	0.43	0.56	0.60	-64.95
0.75	0.1	50	0.12	-0.24	0.55	-58.91	0.26	-0.22	0.36	-62.96
0.75	0.5	50	0.17	0.07	-0.56	-58.75	-0.04	0.26	-0.45	-64.56
0.75	1	50	-0.04	0.43	-0.20	-59.06	-1.08	0.70	-0.12	-62.98
0.75	2	50	0.46	-0.07	0.76	-58.83	-0.25	0.12	0.41	-64.08
0.75	3	50	0.60	0.56	-0.44	-59.96	-1.04	0.39	-0.04	-63.38
0.75	4	50	0.01	0.36	0.33	-59.21	0.51	0.46	1.40	-63.07
0.75	5	50	-0.28	0.41	0.62	-60.00	-0.65	0.28	0.21	-63.22
0.75	6	50	-0.33	-0.10	-0.22	-57.07	-1.15	0.80	0.87	-61.62
0.75	7	50	-0.85	-134.08	0.16	-57.79	-0.62	-146.25	0.51	-63.40

Table C2 Adding Up Bias (7 of 7)

ratio	dq	q0	Midpoint				Baseline			
			mrm2	mrm2ds6	mrm2s	mrm2s1	mrm2	mrm2ds6	mrm2s	mrm2s1
0.75	8	50	-0.47	-150.02	-0.38	-57.42	-1.19	-160.62	0.76	-61.41
0.75	9	50	-0.08	-49.14	0.72	-58.59	0.21	-52.92	0.36	-62.38
0.75	10	50	0.13	-53.03	-0.35	-59.63	-1.01	-56.50	1.48	-62.14
0.75	11	50	-0.85	-56.29	0.77	-58.28	-2.11	-58.65	0.51	-61.26
0.75	12	50	-0.18	-58.31	0.23	-56.04	0.28	-60.14	0.68	-63.16
0.75	13	50	0.12	-59.53	0.19	-59.63	-1.45	-64.05	1.55	-61.26
0.75	14	50	-0.92	-62.75	-0.94	-59.73	-1.09	-66.88	1.26	-62.27
0.75	15	50	-0.19	-64.33	0.78	-58.08	-0.13	-69.51	0.35	-60.42
0.75	16	50	-0.83	-66.80	-0.49	-58.36	-1.17	-72.21	1.16	-60.41
0.75	17	50	1.14	-69.31	-0.38	-57.14	-0.51	-73.80	1.43	-59.60
0.75	18	50	-0.14	-69.82	0.06	-56.80	0.24	-75.65	1.39	-62.08
0.75	19	50	-0.28	-72.92	0.16	-57.03	-1.29	-77.98	2.35	-60.62
0.75	20	50	0.36	-73.71	-0.35	-57.74	-0.10	-79.17	1.69	-59.48
0.75	25	50	-0.02	-31.21	-0.74	-58.28	0.15	-28.27	3.17	-57.94
0.75	30	50	-0.38	-30.50	-0.11	-58.13	-1.73	-28.50	2.17	-58.84
0.75	35	50	-0.53	-30.58	0.16	-57.16	-0.84	-29.03	3.82	-57.84
0.75	40	50	-1.27	-32.50	-0.83	-56.79	-0.31	-26.81	2.99	-56.57
0.75	45	50	-2.66	-31.31	0.24	-56.15	-1.86	-25.72	3.42	-56.60
0.75	50	50	-2.12	-30.75	-1.14	-55.53	-2.95	-26.23	3.95	-52.60
0.75	60	50	-2.96	-30.39	-0.46	-56.24	-3.05	-24.89	3.25	-54.11
0.75	70	50	-2.79	-31.65	-0.29	-56.72	-1.64	-25.22	4.12	-51.48
0.75	80	50	-2.70	-31.29	-0.79	-56.20	-2.43	-24.07	4.29	-50.14
0.75	0.01	80	-0.24	-0.53	-0.17	-58.58	-0.18	-0.35	-0.42	-64.43
0.75	0.1	80	1.47	-0.62	-0.75	-58.82	0.17	1.05	1.09	-65.37
0.75	0.5	80	1.19	0.68	0.28	-59.41	-0.13	0.35	-0.37	-62.89
0.75	1	80	-1.59	-0.25	0.00	-58.60	0.02	0.05	-0.22	-64.27
0.75	2	80	0.16	-0.04	0.95	-57.43	1.01	0.33	0.25	-63.39
0.75	3	80	-1.46	0.46	0.21	-58.45	0.62	0.07	1.53	-63.80
0.75	4	80	-0.16	0.52	-1.59	-59.75	-1.51	0.44	0.15	-64.98
0.75	5	80	-0.08	0.37	1.16	-60.05	0.13	-0.06	1.28	-63.58
0.75	6	80	-0.58	0.12	-0.47	-58.87	-0.13	-0.72	-0.36	-63.97
0.75	7	80	-0.87	-133.47	0.50	-59.27	-0.29	-144.90	0.05	-61.85
0.75	8	80	-0.44	-149.16	0.50	-59.01	-0.78	-159.94	0.04	-62.34
0.75	9	80	0.66	-49.06	-0.49	-59.12	0.23	-53.38	-0.37	-62.45
0.75	10	80	-0.10	-52.60	-0.23	-58.60	-0.76	-57.24	0.10	-61.46
0.75	11	80	0.87	-55.91	-0.70	-58.18	0.17	-61.29	0.30	-63.30
0.75	12	80	-1.11	-55.86	0.00	-56.95	0.84	-62.17	1.34	-62.90
0.75	13	80	0.87	-60.38	-0.39	-58.76	-1.23	-66.64	1.45	-59.97
0.75	14	80	0.33	-62.60	0.38	-58.67	-1.01	-68.73	1.01	-63.20
0.75	15	80	-0.96	-66.29	0.08	-57.70	-1.48	-71.09	2.39	-62.80
0.75	16	80	-0.03	-68.37	0.06	-60.04	-0.76	-72.75	0.14	-62.04
0.75	17	80	0.54	-69.23	-0.92	-58.18	-0.46	-75.67	0.49	-61.19
0.75	18	80	-0.40	-71.77	-0.12	-57.33	-1.07	-77.31	0.20	-60.87
0.75	19	80	-0.83	-74.08	0.65	-57.58	0.56	-79.70	1.02	-60.94
0.75	20	80	-0.25	-77.53	0.27	-58.91	-1.25	-82.33	0.69	-62.55
0.75	25	80	-1.11	-30.38	0.32	-58.88	0.58	-30.08	1.58	-59.08
0.75	30	80	0.14	-29.95	-1.16	-56.84	-1.22	-30.76	2.17	-61.64
0.75	35	80	0.11	-28.39	0.76	-58.33	-0.31	-29.18	2.90	-59.65
0.75	40	80	-0.55	-30.60	-1.39	-58.20	-1.70	-29.07	2.23	-58.62
0.75	45	80	-0.50	-31.56	-0.39	-58.78	-1.21	-30.41	1.17	-57.51
0.75	50	80	0.25	-29.38	-0.64	-58.15	-0.32	-29.38	2.99	-55.83
0.75	60	80	-0.25	-30.41	-0.56	-56.74	-2.12	-27.39	2.34	-57.46
0.75	70	80	-2.08	-30.31	-0.37	-56.41	-1.95	-26.13	2.11	-54.57
0.75	80	80	-0.60	-29.42	-0.36	-57.11	-0.94	-26.51	3.18	-54.27

Notes: Red indicates results that fail the adding up test with % Error < -1.

Appendix D BenSPLASH Benefit Transfer Results

First, I run the Steam Electric period 1 and period 2 scenarios in BenSPLASH using the MRM2_2023, MRM2-S_2023_Low, and MRM2-S_2023_High valuation functions. I set the discount year and dollar year to 2025 and 2021 respectively for both periods, which allows me to combine the outputs into a single total. I use 0.5 and 0.95 as the inputs for the uncertainty calculations. I construct a MRM2-S interval using the totals for the MRM2-S_2023_High and MRM2-S_2023_Low functions. The results from the MRM2_2023 will represent the primary estimates used in Steam Electric, while the MRM2-S interval will reflect the sensitivity analysis. The uncertainty interval is a feature of BenSPLASH that constructs a distribution of predictions using the variance-covariance matrix that can be compared to Bayesian credible intervals.

Table D1 BenSPLASH National Willingness to Pay Results

	per Household MWTP	per Household WTP	Total Annualized WTP
Median	\$5	\$0.004	\$4,189,425
Uncertainty Interval	\$2 – \$10	\$0.002 – \$0.008	\$1,576,159 – \$9,277,917
MRM2-S Interval	\$4 – \$8	\$0.003 – \$0.006	\$3,686,475 – \$7,548,798

Notes: The median estimate uses the default MRM2_2023 coefficients with an uncertainty interval of 0.05 – 0.95. The low and high interval bounds use the median from MRM2-S_High_2023 and MRM2-S_Low_2023 coefficients.