A Tale of Water and Fish: Housing Market Capitalization of Freshwater Fisheries *

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Abstract

Economic valuation of freshwater attributes is crucial for lake management, yet most existing studies overlook the complex interaction between water quality and fishery populations. In some lake systems, a decrease in water quality, which typically harms recreational opportunities and amenity values, may benefit fish populations by stimulating phytoplankton growth, enhancing recreational fishing opportunities. Using a hedonic property value model and 30 years of monitoring data from Oneida Lake, the largest inland freshwater lake in New York, we undertake a first analysis of the effects of water quality and fish abundance on nearby property values. Our analysis reveals significant capitalization effects for key game fish species, notably walleye, with a one-standard-deviation population increase generating $70 million in aggregated property value. We find that omitting fish abundance leads to biased estimates for water quality valuations, particularly for lakefront properties. In contrast, models including fish abundance are robust to the exclusion of water quality variables, indicating that fisheries play a dominant role in driving housing price premiums in this mesotrophic lake system.

Key Words: Non-market Valuation; Hedonic Model; Water Quality; Recreational Fishery; Lake Ecology

JEL Codes: Q51; Q26; Q25;

Commented [WW1]: Fishery abundance should be fish abundance

TP and fish connection is important but has a lot of unexplained variability. There are several general paper on the topic. I added some for that part of the text.

I have little to add to the economic sections - just that I find it really interesting and important that fish - an ecosystem service both through food production and recreation value - make a difference for property values. I have not seen that before - only about water clarity.

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1. Introduction

Freshwater ecosystems provide multiple societal benefits through ecosystem services, including aesthetic value, recreational boating, swimming, angling, and food production (Keeler et al., 2012; Guerry et al. 2015). Evaluating the economic value of such freshwater attributes is essential for evidence-based regulatory analyses and lake management decision making (Moore et al. 2023; Irwin et al., 2018). Yet, existing studies on the economic value of water quality improvements often overlook the complex interactions among the environmental services provided by freshwater ecosystems, such as the relationship between water quality and fisheries, which is a critical consideration for the benefit-cost analyses of water quality policies (Keiser et al., 2018).

The relationships between water quality and fisheries illustrate the complex interactions. Low levels of nutrients (nitrogen and phosphorus) are associated with higher levels of water quality but can limit the growth of fish populations. In contrast, excess nutrients degrade water quality by stimulating phytoplankton growth and reducing water clarity, which may initially benefit fish populations but, beyond a certain point, degrade habitat quality and create dead zones (Ogelsby 1977, Nixon 1982, Scavia et al., 2024; Abbott et al. 2022). These opposing ecological relationships translate into economic trade-offs: changes in nutrient levels simultaneously affect amenity and recreational values for nearby communities (water quality effect) and fish abundance, which influences recreational value for anglers (fishery effect).

In the literature, the hedonic property price model (hereinafter, the hedonic model) has been used to quantify the economic value of surface water quality, often measured by water clarity and chlorophyll a concentration in lakes (Mamun et al. 2023). Prior studies have established linkages between housing market capitalization and a series of water quality indicators, e.g., water clarity, nutrient loadings, and dissolved oxygens (Boyle et al., 1999; Weng et al., 2020; Keiser and Shapiro, 2019; Wolf et al., 2021). However, none of these studies include a measure of fishing quality (Melstrom et al. 2022). Within non-market valuation of recreational fishery, recreational demand models have been used to value angling (Timmons and Murdock, 2007). Although there are joint estimations of hedonic and recreational demand models that focus on a single water quality attribute valued by both homeowners and recreational users, this framework has not accounted for fishing quality (Phaneuf et al., 2008; Kuwayama et al. 2022).

Commented [KB3]: Timmins, C. and Murdock, J., 2007. A revealed preference approach to the measurement of congestion in travel cost models. *Journal of Environmental Economics and management*, *53*(2), pp.230-249.

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Building on insights from the literature on the hedonic model and the recreational demand framework, we take a different approach by incorporating both lake water quality and fish abundance, a proxy for fishing quality, into the hedonic model. This approach is based on the fact that property owners near freshwater resources value both the aesthetics of clear water for swimming and the opportunity for fishing. Excluding fish populations can lead to omitted variable bias due to the correlation between water quality and fish growth. The exclusion of fishing quality also omits an important consideration for resource managers.

Our study utilizes a unique dataset on water and fishing quality to disentangle their joint effects on property values. We use Oneida Lake New York State, U.S. for our empirical analysis. Oneida Lake is a mesotrophic lake that nurtures a diverse fish community and has a long history of recreational fishery activities.[1] By leveraging a rich dataset of housing transactions in the four counties surrounding Oneida, spatially explicit water quality monitoring data, and annual fish population data, we are able to capture spatial and temporal changes spanning nearly three decades (1990-2018). We identify capitalization effects using a repeat-sales approach (Kuwayama et al., 2022) and explore spatial variation at different distances from the lake.

Our empirical results reveal four important findings. First, we demonstrate that excluding fishing quality leads to substantial omitted variable bias in estimating the water-quality capitalization effect. When fishing quality is not controlled for, water quality indicators—measured by Secchi depth and total phosphorus concentrations—yield statistically insignificant and counterintuitive results: Secchi depth is insignificant, and higher total phosphorus levels are associated with increased property values. However, after controlling for fishing quality, water clarity becomes positive and statistically significant, while total phosphorus shows no statistically significant effect. Second, our analysis demonstrates that fishery populations, particularly the most sought-after species in the region—walleye—are capitalized into property values. Third, we document significant capitalization effects for the walleye population, Oneida Lake's primary angling attraction according to the New York State Angler Survey (2019); a one-standard-deviation increase in the walleye population raises lakefront property-value premiums

[1] Mesotrophic lakes are those with medium biological productivity. The counterparts are eutrophic lake, which has high biological productivity, and oligotrophic lake, which has low biological productivity.

by 16%. Fourth, the capitalization effect of walleye is concentrated on lakefront properties and diminishes with distance from the lake. Overall, the total capitalized value of a one-standard-deviation increase in the walleye population is $70 million, with $64.8 million attributed to lakefront properties.

2. Study Area and Data

2.1 Study Area

We use Oneida Lake in New York State (Figure 1) for exploring the relationships between fish abundance, lake water quality and property values. The extensive information on fish abundance, spatial differences in lake water quality and rich real estate data make Oneida Lake a great location to explore the relationships between water quality and fisheries on property values.

Oneida Lake is the largest lake entirely within the borders of the state of New York, with a surface area of 207 km^2, average depth of 6.8 meter, and 54.7 miles (88 km) of shorelines (Rudstam et al. 2016a). Covering four counties in New York (Madison, Onondaga, Oswego, and Oneida), Oneida Lake real estate ranks in the top ten lake home and lake lot markets in the state.

Oneida Lake has a diverse fish community and a long history of recreational fishing (VanDeValk et al. 2016). Walleye is the most sought-after species by anglers, during the open water season, anglers typically targeted Walleyes on 60% to 70% of their trips with largemouth and smallmouth bass other important targeted species (VanDeValk et al. 2016).[2] The lake and its fish are the concern of an active lake and angler organization, the Oneida Lake Association (OLA), with between 2 and 3 thousand members and strong ties with the local community as well as connected politically. The OLA provides multiple opportunities for information dissemination, such as updates on water quality and fishery conditions at their annual meeting presented by scientist from the Cornell Biological Field Station and through newsletters, a web page, and a Facebook page. This communication channel effectively makes the public aware of the changes in the fish populations of Oneida Lake. The OLA is highly effective as evidenced

[2] Source: https://dec.ny.gov/things-to-do/freshwater-fishing/places-to-fish/statewide-opportunities/walleye

by receiving the American Fisheries Society's highest award given to an organization involved in fish conservation in North America (in 2024).

Assessing the economic benefits of water quality and recreational fisheries is challenging due to its multi-dimensional nature, which introduces variability in defining the environmental commodity (Griffiths et al., 2020; Moore et al., 2023). The crossover effect between water quality and recreational fisheries adds further complexity to the problem, particularly when some intermediary factors contribute to multiple final ecosystem goods and services through interlinked ecological processes (Keeler et al., 2012). For example, nutrients in water, an intermediary water quality factor, contribute to the growth of phytoplankton and zooplankton, the latter fish species prey on. This leaves nutrients to be correlated with two final ecosystem services: the abundance of algae, which provides (negative) amenity value; and the abundance of fish species, which provides (positive) recreational value.[3] It is thus ambiguous to the modeler as to which effect dominates, especially when the level of one of the final products is omitted from the model.

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2.2 Water Quality and Fisheries Data

Considering temporal and spatial changes in water quality is crucial to the hedonic model and the valuation of freshwater attributes (Gibbs et al., 2002; Kuwayama et al., 2022; Michael et al., 2000; Weng et al., 2020; Wolf et al., 2021). Our analysis utilizes water quality data from Cornell Biological Field Station (CBFS), which provides long-time monitoring information for limnology and ecology conditions in Oneida Lake (Rudstam et al., 2016b). During our study period, water quality was monitored weekly during the summer months (May to October) at four sampling sites (Panel A of Figure 2). These data are presented in annual reports (VanDeValk et al. 2024) and in an on-line data repository (Rudstam and Almeida 2023).

Our analysis considers three important water quality measurements: Secchi depth readings (hereafter referred to as "Secchi"), total phosphorus (hereafter referred to as "TP"), and water temperature. Secchi measures water clarity, while TP indicates the nutrient levels in the lake. Water temperature is included to account for its impact on biomass growth and recreational

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[3] Nutrient levels have a domed relationship with many fish population, including walleye in Oneida: too little nutrients limit the biological productivity of zooplankton and thus fish population; too much nutrient stimulates harmful algae blooms and depletes dissolved oxygen in water bodies, causing fish population to shrink.

activities. Studies have shown that an increase in Secchi is associated with higher lakefront housing values, as lake homeowners are willing to pay more for improved water clarity (Walsh & Milon, 2016). While nutrient levels contribute to the growth of phytoplankton, they also contribute to the growth of fish populations including walleye.

Commented [LR6]: What averages are used for water quality data? Average weekly data that are averaged over May - October? That makes sense to me. So no spatial consideration for water quality? Anyway, clarify.

Commented [WW7R6]: @James, add one-or two sentences to align with the summary statistics table?

Commented [WW8R6]: We can perhaps written in a similar way as the fish abundance variable.

Commented [KB9]: Like for species, just report what is used and do not open the door for the reviewers to ask for more modeling with different water quality variables. Chl-a is not used, and nothing said about TP and temperature in this paragraph.

Commented [WW10R9]: Done. Just include secchi, tp and water temperature.

Here we use gill net catch data as an index of fish abundance and trends over time. Every year, gill nets were set following a fixed route during summer months, from the first Monday in June through mid-September. These standard gill net surveys have been conducted each year since 1957, and are highly correlated with mark-recapture estimates for walleye and yellow perch (Rudstam et al. 2016c). These data are used to index different fish species each year and analyzed in multiple studies of fish population and ecosystem dynamics (e.g. Rudstam et al. 2004, 2016c, Irwin et al. 2008, 2016, Brooking et al. 2022). Details of fishing methods are in these publications and in the online database (Rudstam and Almeida 2023). For each year, we aggregated weekly sampling data from summer months across space and time into a single metric of average gillnet catches for each species. While there are sizeable spatial variations across sampling locations (see Vidal et al. 2017), we only keep the annual trends in gillnet catches for two reasons.[4] First, these spatial variations are driven by either microhabitats within Oneida Lake, or by the temporal pattern within summer months since each site is sampled roughly the same time each year. Secondly, unlike water quality amenities, anglers can move their boats to different locations on the lake to catch their target species. We consider four fish species that are important to anglers in Oneida Lake: walleye, smallmouth bass (*Micropterus dolomieu*), yellow perch (*Perca flavescens*), and white perch (*Morone americana*). To facilitate comparison across different fish species, we standardize species abundance by creating z-scores (with a mean of zero and a variance of one) for gill-net catches of each species over time.

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Table 1 presents summary statistics of water quality and fishery attributes for years 1990 to 2022. Across these years, the average Secchi depth was 3.6 meters (standard deviation (SD)=0.5 meter), average TP concentrations was 21.9 ug/L (SD=4.8 ug/L), and average water temperature was 19.78 Celsius degree (SD=0.72 °C). For fish abundance, average gillnet catches were: walleye 19.1 (SD = 6.9), smallmouth bass 2.7 (SD = 1.0), yellow perch 42.4 (SD = 11.8),

Commented [LR12]: Is that the range of years used - need to state that somewhere.

Commented [WW13R12]: @James

[4] For example, Lewis Point, on the Southeast side of the lake, sees an average gill net catch of 40.5 walleyes and 11.1 white perches. Darkin Shoal, on the North side, averages 7.6 walleyes and 72.6 white perches.

and white perch 25.5 (SD = 12.9). Time series changes of water quality indicators, fish abundance, and their correlations are presented in Appendix Figures 2 through 3.

Commented [LR14]: What are the unit for fish numbers. Number of fish per net night? Andover what time frame?

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2.3 Property Data

We obtained property data from Estated, which contained information on the structure, deeds, parcels, transaction history, as well as the geographical location of each property.[5] We extracted arms-length real estate transactions for single-family homes from 1990 to 2018 within the four counties (Madison, Onondaga, Oswego, and Oneida) of the Oneida Lake catchment area.[6] We dropped properties with extremely high or low sales sales prices, yielding a final dataset containing 181,916 sales records.[7]

The impact of fish abundance and water quality was expected to differ between lakefront and non-lakefront properties since lakefront homeowners likely pay premiums for both water quality and recreational fishing opportunities while non-lakefront properties do not have these adjacency premiums (Zhang, 2022). We visually identified lakefront and adjacent lakefront (second row) properties using Google Map and satellite imageries from Google Earth. We identified lakefront property as property that has direct access to the lake, and second row properties as those that need to cross an additional property to access the lake.[8] We also calculated the distance of each property to Oneida shoreline based on its location.

Neighborhood attributes could also impact housing prices. In our analysis, we take into account several community factors and neighborhood characteristics, including age, race and education level at the census tract level, school districts, distance to nearest Walmart, and distance to nearest post office. Data on age, race, and education are obtained from the U.S. Census at the census tract level and capture differences in neighborhood sociodemographic characteristics. School district boundaries are obtained from the New York State GIS

[5] Estated now becomes a part of ATTOM Data.
[6] An arm's length transaction refers to the property transactions in which buyers and sellers act independently without one party influencing the other.
[7] We windsorized the top and bottom 1% of all sales records, or any sales records below $28,732 or above $475,174 (in 2012 dollars). The median sales price for our samples is $113,333.
[8] Some second-row properties may have owned or deeded access to the lake but we do not have data to identify such rights. Second-row properties belong to the non-lakefront properties categories.

Clearinghouse.[9] Distance to nearest Walmart and nearest post office are calculated using Google Maps, and reflect the convenience of property locations to daily homeowner activities.

Table 2 provides summary statistics for the housing transaction data. Comparing lakefront and non-lakefront properties, the latter are less expensive, older, with more bedrooms and they are closer to shopping areas. Compared with lakefront communities, people living in non-lakefront properties are relatively younger, with a higher percentage of non-white residents who have higher education levels.

Linking limnology data (fish abundance and water quality) with property sales data is essential to the estimation of hedonic model, but it is hard to know what limnology information home buyers used in contemplating property purchase decisions. Following Weng et al. (2020), we merged fish abundance and water quality data with property sales data based on sale year. If a sale happened between January 1st to June 30th, we used the prior sale year's fish abundance and water quality data since most recreational activities occur in summer. Similarly, if the sale happened between July 1st to December 31rd, we used the sale year fish abundance and water quality data. Since water quality data varies both spatially and temporally, we merged water quality data to property sales of that given year.

Commented [WW17]: @ James. I forgot this, did we do anything to spatially match water quality to properties. Or it is the same as fisheries.

3. Empirical Strategy

To investigate the interaction effects between water quality and fishery abundance, we empirically estimate three variations of the hedonic models: (1) the impact of water quality on lakefront property values; (2) the impact of fishery abundance on lakefront property values; and (3) the joint impact of water quality and fishery abundance on lakefront property values. The first model aligns with the approach taken in the majority of existing hedonic studies, wherein estimated coefficients for water quality variables capture both the direct amenity value of water quality improvements and potentially any correlated benefits related to recreational fishing. The second model leverages our extensive fishery species data to evaluate the impact of fishery abundance, a direct indicator of final ecosystem services within the study area. The last model assesses the potential for omitted variable bias in the valuation of water quality by examining its

[9] Available at: https://gis.ny.gov/gisdata/inventories/details.cfm?DSID=1326. Retrieved 5/3/2021.

joint relationship with fishery abundance. Overall, our hedonic estimate elicits the change in such lakefront proxy premiums, i.e., the difference in housing prices between lakefront and other properties, as a result of changes in lake ecological attributes (i.e., lake water quality, lake fishery abundance).

3.1 Repeated Sales Model

Our rich real estate transaction dataset allows us to estimate a repeated-sales specification following the best practices outlined by Bishop et al. (2020). The repeated sales model reduces omitted variable bias arising from correlations between unobserved drivers of property prices and water pollution, underscoring the necessity of differencing out property-level unobservable factors (Kuwayama et al., 2022). A potential concern is that restricting the sample to repeated sales could introduce selection bias, as noted by Freeman et al. (2024). To address this, we report the sample mean differences between repeatedly sold properties and the full sample in Table 3 and map the locations of repeatedly sold properties in our sample (Appendix Figure 1). Overall, repeatedly sold properties tend to be slightly more expensive, smaller, and relatively newer. However, these differences are not substantial, and a visual comparison of Figure 1 (entire sample) and Appendix Figure 1 (repeated sales subset) shows no significant differences in geographic distribution between the two samples. Therefore, the repeated sales model serves as a representative proxy for the entire sample and can be considered an effective method by addressing time-constant omitted variable biases (Bishop et al., 2020).

Our estimation model can be written as:

$$\begin{cases} \log(\text{SalePrice})_{it} = \alpha + \beta\text{LakeFront}_i + \sum_k \gamma_k(\text{LakeFront}_i \times \text{WQ}_{ikt}) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (1a) \\ \log(\text{SalePrice})_{it} = \alpha + \beta\text{LakeFront}_i + \sum_j \theta_j\left(\text{LakeFront}_i \times \text{Species}_{jt}\right) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (1b) \\ \log(\text{SalePrice})_{it} = \alpha + \beta\text{LakeFront}_i + \sum_k \gamma_k(\text{LakeFront}_i \times \text{WQ}_{ikt}) + \sum_j \theta_j\left(\text{LakeFront}_i \times \text{Species}_{jt}\right) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (1c) \end{cases}$$

where *log(SalePrice)* denotes the logarithm of the sales price (inflation-adjusted) for property *i* sold in year *t*; $LakeFront_i$ is a dummy variable indicating whether the property is lakefront; WQ_{ikt} represents the average of water quality variable *k* in year *t* for property *i*, which includes three water quality variables: Secchi disk depth, total phosphorus concentration, and water temperature. These three variables have been extensively used in the previous literature and are recognized as critical determinants of aquatic ecosystem health and fishery productivity (Keiser, 2019, Griffiths et al. 2012; Walsh and Milon, 2016). $Species_{jt}$ represents the abundance of fish

Commented [KB18]: Left unclear what properties are the zeros. And if this is the same set of properties as the proximity model below?

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species j in year t, where j={walleye, smallmouth bass, yellow perch and white perch}. Our analysis incorporates a variety of control variables, including property characteristics (number of bedrooms, bathrooms, total square footage, age of the property), neighborhood demographics (median income, education level, and demographics at the census block group level), neighborhood environment (distances to the nearest Walmart, nearest post office, Lake Ontario, Onondaga Lake, and Skaneateles Lake), and fixed effects at the individual house level (λ_i). $f(t)$ is a flexible control for time-trends. [10] The term ϵ_{it} is an idiosyncratic error term by property and year.

Our main parameters of interest are the coefficients γ_k and θ_j, which are interpreted as the marginal effects of ecological attributes (i.e., water quality or fishery abundance) on lakefront property prices. Specifically, these coefficients quantify the percentage change in the property price differential between the otherwise-similar lakefront and non-lakefront properties resulting from a corresponding change in water quality or fishery abundance. For γ_k, the coefficients of water quality metrics, we expect the impacts on lakefront property premiums to vary depending on the specific water quality measurement: The coefficient for Secchi is expected to be positive, reflecting a premium for higher water clarity; Total phosphorus (TP) presents a more complex relationship. In eutrophic systems, the coefficient on TP is typically negative due to its role in promoting phytoplankton growth and harmful algal blooms (HABs), which diminish water clarity and quality. However, in mesotrophic systems like Oneida Lake, TP serves as a limiting factor for both fish populations and phytoplankton growth. Consequently, the capitalization effect of TP should reflect the concurrent influences of algal growth and fish abundance, which operate in opposing directions. This dual role suggests an ambiguous net effect on lakefront property values. We expect the coefficient of mean water temperature to be positive as warmer waters improve water-based recreational activities. Regarding the coefficients of fishery abundance variable (θ_j), we anticipate positive capitalization effects, with the magnitude varying by species. The most significant effects are expected for regionally prominent game fish, particularly walleye. The impact of other species likely depends on their recreational value to residents of the region.

Commented [KB21]: Someone will read this as the dollar change, but since the dependent variable is logged, this is the proportionate increase, percentage when multiplied by 100.

Commented [WW22R21]: Kevin, could you double check my writing here?

[10] We interpret our main result using 5-degree polynomial time trend. We also test for 3-degree polynomial time trends, and the estimated effects are similar.

3.2 The spatial extent of capitalization effects

After estimating the baseline capitalization effect of species abundance on lakefront properties, we investigate to what extent these effects vary spatially, extending beyond lakefront properties. Previous studies have demonstrated spatial gradients in the capitalization impacts of water quality, such as harmful algal blooms (Wolf et al., 2021) and dissolved oxygen (Kuwayama et al., 2022). To examine this, we categorize properties according to their proximity to the lake using a series of dummy variables. These categories include lakefront properties (properties directly facing the lake), second-row properties (properties one row away from the lake), and properties excluding lakefront or second row properties that are within 250 meters, 500 meters, one kilometer, and four kilometers from Oneida Lake.[11] These categories are exclusive of one another, i.e. the 500 meter category includes homes farther than 250 meters from the lake but less than or equal to 500 meters. We then estimate models that interact species abundance with these proximity indicators, according to the equation[12]:

$$\begin{cases} \log(\text{SalePrice})_{it} = \alpha + \beta Proximity_{is} + \sum_{sk} \gamma_{sk} (Proximity_{is} \times \text{WQ}_{ikt}) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (2a) \\ \log(\text{SalePrice})_{it} = \alpha + \beta Proximity_{is} + \sum_{sj} \theta_{sj} \left(Proximity_{is} \times \text{Species}_{jt}\right) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (2b) \\ \log(\text{SalePrice})_{it} = \alpha + \beta Proximity_{is} + \sum_{sk} \gamma_{sk} (Proximity_{is} \times \text{WQ}_{ikt}) + \sum_{sj} \theta_{sj} \left(Proximity_{is} \times \text{Species}_{jt}\right) + \text{Controls}_{it} + \lambda_i + f(t) + \epsilon_{it} & (2c) \end{cases}$$

where $Proximity_{is}$ is a set of seven mutually exclusive binary indicators denoting the distance band *s* into which property *i* falls in, from lake-front property to properties more than 4 kilometers away. These proximity measures are interacted with both water quality metrics and fish species abundance to examine the spatial extent of ecological capitalization effects beyond the immediate lakefront properties. The model incorporates the same vector of controls, fixed effects, and time trends as specified in equation (1). The estimated coefficients of interest, γ_{sk} and θ_{sj}, capture the spatial decay of the capitalization effects of ecological attributes with increasing distance from the lake.

4. Results

We first present our baseline estimates of the impact of water quality on lakefront house premiums in Table 4. Specifications (1) and (2) in Table 4 report estimated coefficients on the impact of water quality measurements on lakefront property values without controlling for fish

Commented [KB23]: I would refer to these as columns rather than specifications.

[11] All lakefront and second-row properties are within 250 meters of Lake Oneida.
[12] All lakefront and second-row properties are within 250 meters of Lake Oneida.

abundance. We added the fish abundance controls in specifications (3) and (4). Column (1) and (3) include property and community-level covariates and school district and county fixed-effects, while column (2) and (4) include property-level fixed effects, i.e., the repeated sales model. We include results using Conley (1999) standard errors as a robustness check in Appendix Table 2.

Commented [KB24]: Ok, here is where I learn about the repeat sales versus the hedonic, but it is too late in the manuscript.

4.1 Capitalization Effects of Water Quality with and ~~with and~~ without Controlling for Fishery Abundance

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Commented [WW26]: We have two parts in this section.

To explore the relationship between fishery abundance and water quality, we conduct a parallel analysis examining the impact of fish abundance on lakefront house premiums, both with and without controlling for water quality. The estimation results are represented in Table 5. We consider four specifications: specifications (1) and (2) exclude water quality controls, while specifications (3) and (4) include them. Specifications (1) and (3) incorporate property- and community-level covariates, along with school district and county fixed-effects, while specifications (2) and (4) employ the repeated sales models. We focus on interpreting the repeated sales estimators for the same reasons discussed in Section 4.1.

Overall, we find a statistically significant positive relationship between walleye abundance and lakefront premiums: a one-standard-deviation increase in walleye population increases the lakefront premium by 16.5% in the repeated sales specification with water quality controls. This result aligns with expectations, as walleye is the most sought-after species by anglers at Oneida Lake. We also find a positive and statistically significant effect of white perch abundance on the lakefront premium at 10.9%. The effects of smallmouth bass and yellow perch are statistically significant, but negative. The estimated negative capitalization effect could be because of angler preferences and/or ecosystem dynamics. Despite its abundance in the Lake, yellow perch is not particularly favored by most anglers compared to walleye.[13] At the same time, age-0 yellow perch is a major prey of walleye in Oneida Lake. Studies have found that walleye catchability in Oneida Lake is inversely related to walleye growth, which is in itself strongly correlated with prey density (VanDeValk et al., 2005).[14] This means that higher yellow

[13] According to New York Angler's Survey, only 4% of the anglers fish primarily for yellow perch in Oswego and Oneida counties, the two counties covering the water body of Oneida Lake (NYSDEC, 2019). In contrast, 23-30% of anglers primary fish for walleye in those two counties, topping the angler's preference list.

[14] Interestingly, this is not the pattern in other walleye fisheries, for example in Escanaba Lake, WI (Newby et al., 2000) or Lake Erie (Isbell & Rawson, 1989). Part of the reason could be that (VanDeValk et al., 2005) draw statistical inferences on aggregated catch rates from six surveys separated by over 50 years.

perch density could lead to lower catchability of walleye, thus decreasing the desirability of the fishery. For smallmouth bass, the negative coefficients could result from sampling bias, as gillnet sampling methods used in data collection are designed to target walleye and yellow perch.

Commented [MOU27]: Is it sampling bias or measurement error?

We also examine how the capitalization effects of fish abundance vary spatially, with results displayed in Figure 4. Our findings indicate that the impact of fish abundance is most pronounced for lakefront properties and diminishes rapidly with distance from the lake. The spatial decay pattern is consistent across multiple fish species and categories. Focusing on the repeated sales specification with water quality controls, we find that walleye abundance has a statistically significant marginal effect of 17.3% on lakefront housing premiums, consistent with the baseline model in Table 4. However, the effect declines sharply with distance: the marginal effect drops to 2.6% for second-row properties, 0.6% for properties within 250 meters (but neither lakefront nor second-row), 2.1% for properties 250–500 meters away, and -1.0% for properties 500–1,000 meters away. All other estimated coefficients are statistically insignificant at the 5% level. White perch shows a similar spatial pattern. The capitalization effect on lakefront properties is significant, with a premium of 11.3%, consistent with baseline estimates. For properties farther from the lake, the effects are smaller and generally statistically insignificant, with the exception of properties 1–4 km away, where the estimated premium is 1.4%, much smaller than that for lakefront properties.

Unlike the divergences observed in the water quality specifications, the results for fishery abundance are nearly identical across models. Formal t-tests (Table 4) show no significant differences in the capitalization effects of fish abundance across specifications for all fish species. This consistency suggests that fishery abundance is a primary driver of recreational value in our study area. These findings underscore the importance of incorporating key ecosystem services in valuation studies.

Commented [MOU28]: I think this is the result you refer to in the abstract. You may want to revisit the abstract to include this explanation, which is clearer.

4.2 Capitalization Effects of Fishery Abundance with and ~~with and~~ without Controlling for Water Quality

Commented [KB29]: Make with both section 4.3 to follow logic established earlier in the paper.

To explore the relationship between fishery abundance and water quality, we conduct a parallel analysis examining the impact of fish abundance on lakefront house premiums, both with and without controlling for water quality. The estimation results are represented in Table 5. We consider four specifications: specifications (1) and (2) exclude water quality controls, while specification (3) and (4) include them. Specifications (1) and (3) incorporate property- and community-level covariates, along with school district and county fixed-effects, while specification (2) and (4) employ repeated sales models. We focus on interpreting the repeated sales estimators for the same reasons discussed in Section 4.1.

Overall, we find a statistically significant positive relationship between walleye abundance and lakefront premiums: a one-standard-deviation increase in walleye population increases the lakefront premium by 16.5% in the repeated sales specification with water quality controls. This result aligns with expectations, as walleye is the most sought-after species by anglers at Oneida Lake, and its abundance significantly capitalizes into lakefront housing prices. We also find positive and statistically significant effect of white perch abundance on lakefront premium at 10.9% in the repeated sales specification. The effects of smallmouth bass and yellow perch are statistically significant, but negative. The estimated negative capitalization effect could be because of angler preferences and/or ecosystem dynamics. Despite its abundance in the Lake, yellow perch is not particularly favored by most anglers compared to walleye.[15] At the same time, age-0 yellow perch is a major prey of walleye in Oneida Lake. Studies have found that walleye catchability in Oneida Lake is inversely related to walleye growth, which is in itself strongly correlated with prey density (VanDeValk et al., 2005).[16] This means that higher yellow perch density could lead to lower catchability of walleye, thus decreasing the desirability of the fishery. For smallmouth bass, the negative coefficients could result from sampling bias, as gillnet sampling methods used in data collection are designed to target walleye and yellow perch.

We also examine how the capitalization effects of fish abundance vary spatially, with results displayed in Figure 4. Our findings indicate that the impact of fish abundance is most pronounced for lakefront properties and diminishes rapidly with distance from the lake. The spatial decay pattern is consistent across multiple fish species and categories. Focusing on the repeated sales specification with water quality controls, we find that walleye abundance has a statistically significant marginal effect of 17.3% on lakefront housing premiums, consistent with

[15] According to New York Angler's Survey, only 4% of the anglers fish primarily for yellow perch in Oswego and Oneida counties, the two counties covering the water body of Oneida Lake (NYSDEC, 2019). In contrast, 23-30% of anglers primary fish for walleye in those two counties, topping the angler's preference list.

[16] Interestingly, this is not the pattern in other walleye fisheries, for example in Escanaba Lake, WI (Newby et al., 2000) or Lake Erie (Isbell & Rawson, 1989). Part of the reason could be that (VanDeValk et al., 2005) draw statistical inferences on aggregated catch rates from six surveys separated by over 50 years.

the baseline model in Table 4. However, the effect declines sharply with distance: the marginal effect drops to 2.6% for second-row properties, 0.6% for properties within 250 meters (but neither lakefront nor second-row), 2.1% for properties 250–500 meters away, and -1.0% for properties 500–1,000 meters away. All other estimated coefficients are statistically insignificant at the 5% level. White perch shows a similar spatial pattern. The capitalization effect on lakefront properties is significant, with a premium of 11.3%, consistent with baseline estimates. For properties farther from the lake, the effects are smaller and generally statistically insignificant, with the exception of properties 1–4 km away, where the estimated premium is 1.4%, much smaller than that for lakefront properties.

Unlike the divergences observed in the water quality specifications, the results for fishery abundance are nearly identical across models. Formal t-tests (Table 4) show no significant differences in the capitalization effects of fish abundance across specifications for all fish species. This consistency suggests that fishery abundance is a primary driver of recreational value in our study area. These findings underscore the importance of incorporating key ecosystem services in valuation studies.

4.3 Capitalized value of fish abundance and its economic impacts

To put our estimated effects into context, we calculate the effect of an increase in species abundance of one standard deviation on lakefront and total real estate property value and local property tax revenue, following Weng et al. (2020). The total capitalization value (CV) for a species *j* is given by:

$$CV_j = \sum_{\mathrm{k}} \beta_{jk} \times \mathrm{NP}_k \qquad (3)$$

where β_{jk} is the marginal effect of species abundance on property value for each distance band *k* and NP_k represents the number of properties within that distance band, which we acquire from assessor records. We sum the capitalization effects for different distance bands to calculate the total capitalized value of the fish species considered for Oneida Lake.

We present the values calculated using the estimated results from equation (3), shown in column (4) in Table 5. We find economically sizeable capitalization effects, particularly for lakefront properties: the capitalized value of a one-standard-deviation increase in walleye abundance amounts to \$70.0 million, of which \$64.8 million is for lakefront properties.[17]

We then predict the annual property tax revenue (TR_j) as a result of changes in species abundance:

$$TR_j = CV_j \times t \tag{4}$$

where CV_j is defined in equation (3) and the average effective tax rate, *t,* is calculated by dividing the average amount of property tax by the assessed property value, both of which we acquired from assessor records. We find that a one-standard-deviation increase in walleye abundance increases local property tax revenue by \$2.38 million per year, of which \$2.20 million can be attributed to increased property values for lakefront homes. For each individual homeowner, our estimates suggest that the annual rent premium for a one-standard-deviation increase in the walleye population is around \$872 under a 3% interest rate.

To benchmark the relative magnitude of our estimated effects, in Panel B of Table 6, we compare our estimated property tax implications with tax revenues associated with recreational fisheries in the four counties adjacent to Oneida Lake, estimated in the New York Angler's Survey (NYSDEC, 2019). While the angler's survey is the closest estimate we could find, the numbers are overstated for Oneida Lake because it reports tax revenues for all recreational fishery activities within each county, which include other lakes. For example, Oswego County has prominent alternative fishing sites on the Oswego River (feeding from Oneida Lake through the Oneida River) and Lake Ontario, and so has much higher tax revenues and mean angler travel distances. In the three other nearby counties, we find that the magnitude of the property tax effects is a sizeable portion of the total tax revenue: in Oswego County, increases in property taxes are comparable to 33% of the total fishing-related tax revenue; in Onondaga County, 36%; in Madison County, 131%. Our exercise highlights the public finance implications of recreational fisheries, not only through direct consumption (for example, dining, lodging, and fishing gear) but also through property market linkages.

[17] All monetized values are in 2012 dollars.

5. Conclusion and Discussion

Accurate monetary valuation of freshwater attributes is crucial for informed regulatory analysis (Moore et al., 2023). Yet, valuation is challenging due to complex interactions among environmental commodities, which lead to substantial variability in the estimated values of water quality indicators across studies (Griffiths et al., 2012; Moore et al., 2023). The interaction between water quality and fisheries adds further complexity to the problem, particularly when some intermediary factors (such as nutrients) contribute to multiple final ecosystem goods and services through linked ecological processes (Keeler et al., 2012).

Using 30 years of Oneida Lake monitoring data, we examine how water quality and fish populations affect housing premiums. Our findings indicate that fish abundance, which is often omitted in the hedonic property price model, is a key driver of lakefront housing premium, particular on a lake that is highly valued for its recreational fishery, such as walleye. Our results indicate exclusion of fish populations in the hedonic model results in significant discrepancies in capitalization effects, introducing biases and altering both the sign and significance of water quality coefficients.

Our study yields both methodological and policy contributions. Methodologically, we demonstrate that omitting key ecosystem services can bias water quality valuations, especially in mesotrophic environments where fish growth effects may outweigh water quality concerns. To our knowledge, this study is the first to concurrently model the effects of both fish stocks and water quality on property prices. For policy applications, our study highlights the importance of considering multiple, interrelated environmental outputs that may differ across lakes. The strong link between fishery abundance and property values—affecting municipal tax revenues—emphasizes the economic value of maintaining healthy fish populations, even if doing so comes at the expense of small declines in water quality. Given the non-linear relationship between nutrient levels and fisheries, uniform water quality standards may not optimize ecosystem benefits across both eutrophic and mesotrophic lakes, suggesting that efficient management strategies should consider lake-specific conditions.

We acknowledge three primary limitations of our current study and propose directions for future research.

First, while our application of hedonic modeling to value fisheries is new to the literature, further research is needed to compare these results with those from travel cost methods. This is crucial as homeowners and recreational anglers may differ significantly in their preferences, socio-demographic profiles, and information sources. Future studies should also explore linking hedonic models with recreational demand models to assess the joint impacts.

Second, the scalability of our results to other water bodies remains uncertain, as our analysis may not be directly applicable beyond lakes with significant recreational fisheries. Effective valuation of water quality and fisheries depends on high-quality environmental and ecological data. Creel surveys, traditionally used to measure fishing effort and fish abundance, provide valuable fisheries information across multiple lakes. Concurrently, long-term water quality monitoring efforts, including citizen science initiatives, offer extensive data on water quality conditions. Integrating these data sources can yield a robust, interdisciplinary dataset for examining water quality–fishery interactions in diverse settings, although potential spatial and temporal mismatches warrant caution.

Lastly, although our study initiates a comparison of valued commodities, more rigorous analysis is required to fully capture the endpoints impacting human welfare. Future research could employ bioeconomic models to explicitly examine the trade-offs between water quality and fishing, acknowledging that improvements in fish quality may translate into benefits for water quality. Collaborative efforts among limnologists, fisheries biologists, and economists are needed to assess lake users' exposure to and interactions with various ecosystem services, ultimately informing more effective management strategies for both water quality and fishery resources.

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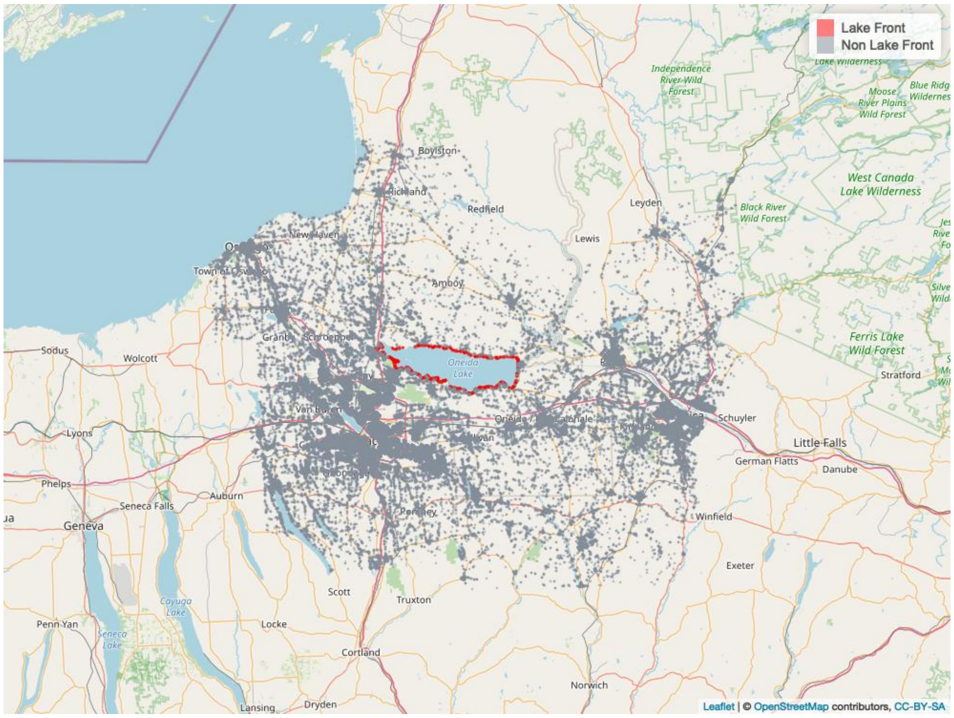

Figure 1: Property Sales Near Oneida Lake. Note: Each dot denotes the location of one property. Red dots denote properties with frontage of the Oneida Lake (lakefront). Grey dots denote non-lakefront properties.

Panel (A): Water quality sampling locations

Panel (B): Gill net sampling locations

Figure 2: Gill net and water quality sampling locations. Panel (A) displays water quality sampling locations. Panel (B) displays gill net sampling locations. Each blot dot denotes a sampling location, with its respective names denoted alongside.

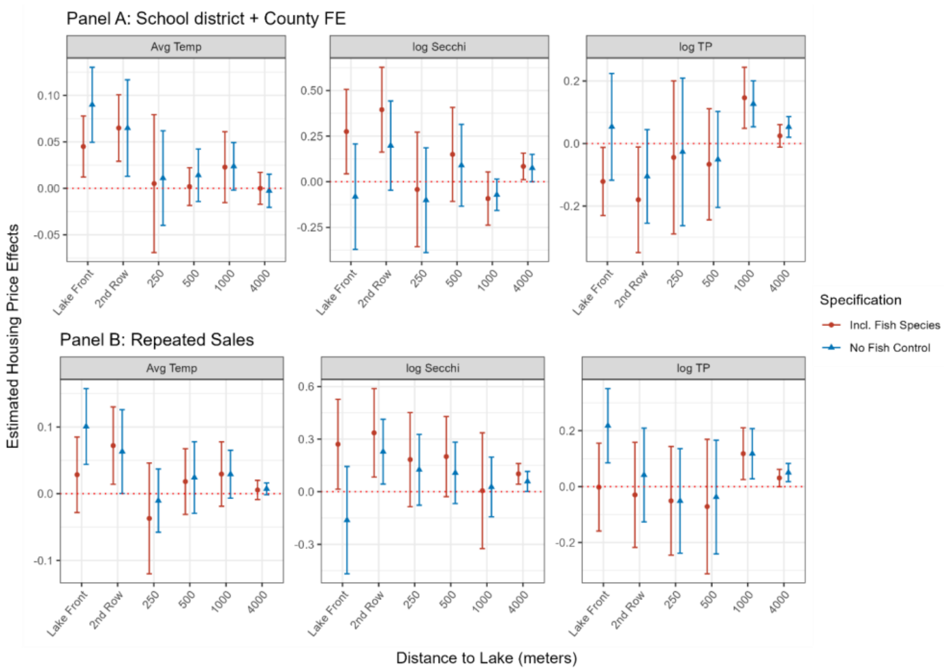

Figure 3: Spatial Spillover for Water Quality Capitalization, with or without fishery controls. Note: Panel A (top) shows model estimates using school district and county fixed effects plus controls. Panel B (bottom) shows model estimates using property fixed effects (repeated sales model). Each panel estimated the capitalization effects of average water temperature (left), the logarithm of Secchi disk reading (middle), and the logarithm of total phosphorus (right), across different proximities to Lake Oneida. Error bars denote 95% confidence intervals. Red dots and error bars denote estimated impacts of water quality by including interaction terms between property proximity bands and the four fish species: walleye, smallmouth bass, white perch, and yellow perch; Blue triangles and error bars denote estimated impacts of water quality without controlling for fish abundance.

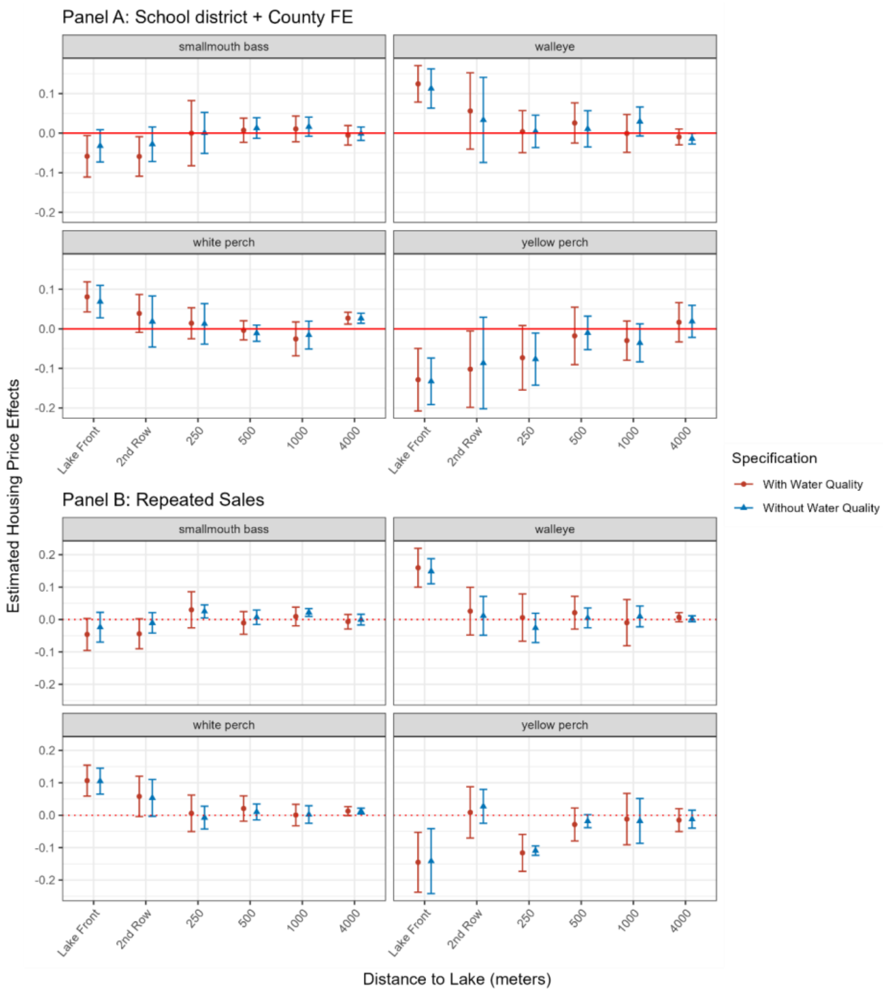

Figure 4: Spatial Spillover for Capitalization of fisheries, with and without Water Quality Controls. Both panels plot point estimates of individual species abundance interacted with proximity dummy variables. Panel A displays estimates of equation (2) with school district and county fixed effects and neighborhood-level controls. Panel B displays estimates equation (2) with property fixed effects. Red dots and error bars depict point estimates and 95% confidence intervals from the specification that include water quality variables interacted with proximity dummy variables as controls. Blue triangles and error bars depict point estimates and 95% confidence intervals from the specification excluding water quality variables as controls.

Table 1: Summary Statistics of Ecological Variables

	Mean	SD	Min	Max
	Water Quality Indicators			
Secchi Disk Reading (m)	3.614	0.484	2.371	4.796
Total Phosphorus (µg/L)	21.922	4.822	13.475	35.748
Avg Temp (degree C)	19.777	0.715	17.73	21.41
	Average Gillnet Catches			
Walleye	19.046	6.93	5	31.8
Smallmouth Bass	2.73	1.032	1.133	5
Yellow Perch	42.41	11.784	21.067	70.733
White Perch	25.419	12.896	2.467	51.4

Note: Average gillnet catches are calculated as the average summer gillnet sampling catches for each species within a given year.

Table 2: Summary Statistics of Properties

	Lakefront Properties		Non-lakefront Properties		Difference	Significance
	Mean	SD	Mean	SD		
Real Sales Price ($1,000, in 2012 dollars)	168.476	79.232	129.581	68.453	38.895	***
Distance to Oneida Lake (km)	0.045	0.029	20.863	11.692	-20.818	***
No. Bedrooms	2.787	0.843	3.179	0.736	-0.392	***
No. Bathrooms	1.544	0.664	1.467	0.6	0.077	***
Square Footage	1593.487	650.84	1599.896	585.566	-6.409	
Lot Size (acres)	0.541	0.857	1.824	53.001	-1.283	
Property Age	46.753	31.045	51.301	36.521	-4.548	***
% Senior (age>60)	0.268	0.081	0.254	0.092	0.014	***
% White	0.971	0.027	0.894	0.136	0.077	***
% College and Above	0.528	0.134	0.657	0.144	-0.129	***
Distance to Nearest Walmart (km)	12.449	4.299	7.408	6.158	5.041	***
Distance to Nearest Post Office (km)	3.904	2.418	2.268	1.579	1.636	***
N	1447		180469			

Note: Pairwise mean difference test reported between lakefront and non-lakefront properties in column 6, and statistical significance code reported in column 7. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Summary Statistics of Repeatedly Sold Properties.

	Repeatedly Sold Properties		Full Sample		Difference
	Mean	SD	Mean	SD	
Real Sales Price ($1,000)	131.625	68.434	129.89	68.632	1.735***
Distance to Oneida Lake (km)	20.153	11.615	20.697	11.791	-0.544***
No. Bedrooms	3.183	0.724	3.176	0.737	0.007***
No. Bathrooms	1.474	0.598	1.467	0.6	0.007***
Square Footage	1588.41	573.708	1599.85	586.11	-11.433***
Lot Size (acres)	1.386	2.958	1.806	52.614	-0.42
Property Age	50.68	35.795	51.265	36.482	-0.585***
% Senior (age>60)	0.252	0.091	0.254	0.092	-0.002***
% White	0.895	0.13	0.895	0.136	0
% College and Above	0.664	0.142	0.656	0.144	0.008***
Distance to Nearest Walmart (km)	7.192	5.896	7.448	6.162	-0.256***
Distance to Nearest Post Office (km)	2.252	1.555	2.281	1.594	-0.029***
# Sales	115170		181916		
# Property	45585		112331		

Note: Pairwise mean difference test reported between lakefront and non-lakefront properties. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Capitalization Effects of Water Quality with and without Controlling for Species Abundance

	Dependent Variable: log(sale price)				
	(1)	(2)	(3)	(4)	Difference: (2) - (4)
LakeFront x log(Secchi)	-0.156 (0.174)	-0.166 (0.185)	0.293** (0.111)	0.283* (0.155)	-0.449***
LakeFront x Ave Temp	0.029 (0.022)	0.100*** (0.029)	0.021** (0.011)	0.025 (0.030)	0.075***
LakeFront x log(TP)	-0.004 (0.097)	0.216*** (0.075)	-0.150*** (0.038)	-0.008 (0.086)	0.224***
Fish Controls	No Fish Controls	No Fish Controls	LakeFront x Species	LakeFront x Species	
Property Characteristics	Yes	--	Yes	--	
Neighborhood Characteristics	Yes	--	Yes	--	
School District Fixed Effect	Yes	--	Yes	--	
County Fixed Effect	Yes	--	Yes	--	
Property Fixed Effect	No	Yes	No	Yes	
Time Trend	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	
Observations	184,744	184,744	184,744	184,744	
R^2	0.58	0.89	0.58	0.89	
Within R^2	0.47	0.05	0.47	0.05	

Note: This table shows the coefficient estimates of water quality indicators on lakefront premiums. Models (1) and (2) do not have fish species x lakefront dummy as controls. Columns (3) and (4) include the interaction term between the lakefront dummy and standardized abundance of walleye, smallmouth bass, yellow perch, and white perch. Property characteristics include the number of bedrooms, bathrooms, square footage, and the age of the property. Neighborhood characteristics include census-tract-level demographic information on race, age, income, education level, and median income, distances to the nearest Walmart and the nearest post office, and dummy variables for whether the property is within 100 meters of Lake Ontario, Onondaga Lake, and Skaneateles Lake. Robust standard errors are clustered at the school district and year levels (two-way clustering). Standard errors are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Commented [WW30]: Combine table 4 and 5.

Commented [KB31]: I would want to see these coefficients in this table.

Table 4: Capitalization Effects of Water Quality with and without Controlling for Species Abundance

	Dependent Variable: log(sale price)		
	(1)	(2)	Difference: (1) - (2)
LakeFront x log(Secchi)	-0.166 (0.185)	0.283* (0.155)	-0.449***
LakeFront x Ave Temp	0.100*** (0.029)	0.025 (0.030)	0.075***
LakeFront x log(TP)	0.216*** (0.075)	-0.008 (0.086)	0.224***
Fish Controls	No Fish Controls	LakeFront x Species	
Property Characteristics	--	--	
Neighborhood Characteristics	--	--	
School District Fixed Effect	--	--	
County Fixed Effect	--	--	
Property Fixed Effect	Yes	Yes	
Time Trend	5-degree Polynomial	5-degree Polynomial	
Observations	184,744	184,744	
R^2	0.89	0.89	
Within R^2	0.05	0.05	

Note: This table shows the coefficient estimates of water quality indicators on lakefront premiums. Models (1) and (2) do not have fish species x lakefront dummy as controls. Columns (3) and (4) include the interaction term between the lakefront dummy and standardized abundance of walleye, smallmouth bass, yellow perch, and white perch. Property characteristics include the number of bedrooms, bathrooms, square footage, and the age of the property. Neighborhood characteristics include census-tract-level demographic information on race, age, income, education level, and median income, distances to the nearest Walmart and the nearest post office, and dummy variables for whether the property is within 100 meters of Lake Ontario, Onondaga Lake, and Skaneateles Lake. Robust standard errors are clustered at the school district and year levels (two-way clustering). Standard errors are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Commented [WW32]: Combine Table 4 and 5

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Table 5: Capitalization Effects of Species Abundance

	Dependent Variable: log(sale price)		
	(1)	(2)	Difference: (1)-(2)
LakeFront x walleye	0.142*** (0.018)	0.165*** (0.033)	-0.011
LakeFront x smallmouth bass	-0.049** (0.016)	-0.045* (0.026)	0.021
LakeFront x yellow perch	-0.130*** (0.021)	-0.150*** (0.051)	0.003
LakeFront x white perch	0.084*** (0.016)	0.109*** (0.026)	-0.005
Water Quality Controls	No	Yes	
LakeFront x Water Quality Controls	No	Yes	
Property Characteristics	--	--	
Neighborhood Characteristics	--	--	
School District Fixed Effect	--	--	
County Fixed Effect	--	--	
Property Fixed Effect	Yes	Yes	
Time Trend	5-degree Polynomial	5-degree Polynomial	
Observations	184,744	184,744	
R2	0.89	0.89	
Within R2	0.05	0.05	

Note: This table shows coefficient estimates of fish abundance indicators on lakefront premiums. Models (1) and (2) do not have water quality variables (logarithm of Secchi disk reading, average water temperature, and total phosphorus) as controls. Columns (3) and (4) include the interaction term between the lakefront dummy and standardized abundance of walleye, smallmouth bass, yellow perch, and white perch. Property characteristics include the number of bedrooms, bathrooms, square footage, and the age of the property. Neighborhood characteristics include census-tract-level demographic information on race, age,

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income, education level, and median income, distances to the nearest Walmart and the nearest post office, and dummy variables for whether the property is within 100 meters of Lake Ontario, Onondaga Lake, and Skaneateles Lake. Robust standard errors are clustered at the school district and year levels (two-way clustering). Standard errors are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Capitalization Effects of Species Abundance

	Dependent Variable: log(sale price)				
	(1)	(2)	(3)	(4)	Difference: (2)-(4)
LakeFront x walleye	0.047 (0.028)	0.142*** (0.018)	0.154*** (0.024)	0.165*** (0.033)	-0.011
LakeFront x smallmouth bass	0.023 (0.029)	-0.049** (0.016)	-0.024 (0.028)	-0.045* (0.026)	0.021
LakeFront x yellow perch	-0.380*** (0.036)	-0.130*** (0.021)	-0.147** (0.060)	-0.150*** (0.051)	0.003
LakeFront x white perch	0.057* (0.025)	0.084*** (0.016)	0.104*** (0.025)	0.109*** (0.026)	-0.005
Water Quality Controls	No	No	Yes	Yes	
LakeFront x Water Quality Controls	No	No	Yes	Yes	
Property Characteristics	Yes	--	Yes	--	
Neighborhood Characteristics	Yes	--	Yes	--	
School District Fixed Effect	Yes	--	Yes	--	
County Fixed Effect	Yes	--	Yes	--	
Property Fixed Effect	No	Yes	No	Yes	
Time Trend	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	
Observations	184,744	184,744	184,744	184,744	
R2	0.58	0.89	0.58	0.89	
Within R2	0.47	0.05	0.47	0.05	

Note: This table shows coefficient estimates of fish abundance indicators on lakefront premiums. Models (1) and (2) do not have water quality variables (logarithm of Secchi disk reading, average water temperature, and total phosphorus) as controls. Columns (3) and (4) include the interaction term between the lakefront dummy and standardized abundance of walleye, smallmouth bass, yellow perch, and white perch. Property characteristics include the number of bedrooms, bathrooms, square footage, and the age of the property. Neighborhood characteristics include census-tract-level demographic information on race, age, income, education level, and median income, distances to the nearest Walmart and the nearest post office, and dummy variables for whether the property is within 100 meters of Lake Ontario, Onondaga Lake, and Skaneateles Lake. Robust standard errors are clustered at the school district and year levels (two-way clustering). Standard errors are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.

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Table 6: Capitalization and Local Tax Revenue from Oneida Lake Fishery

Panel A: Capitalization Effect of One-SD Increase in Species Abundance

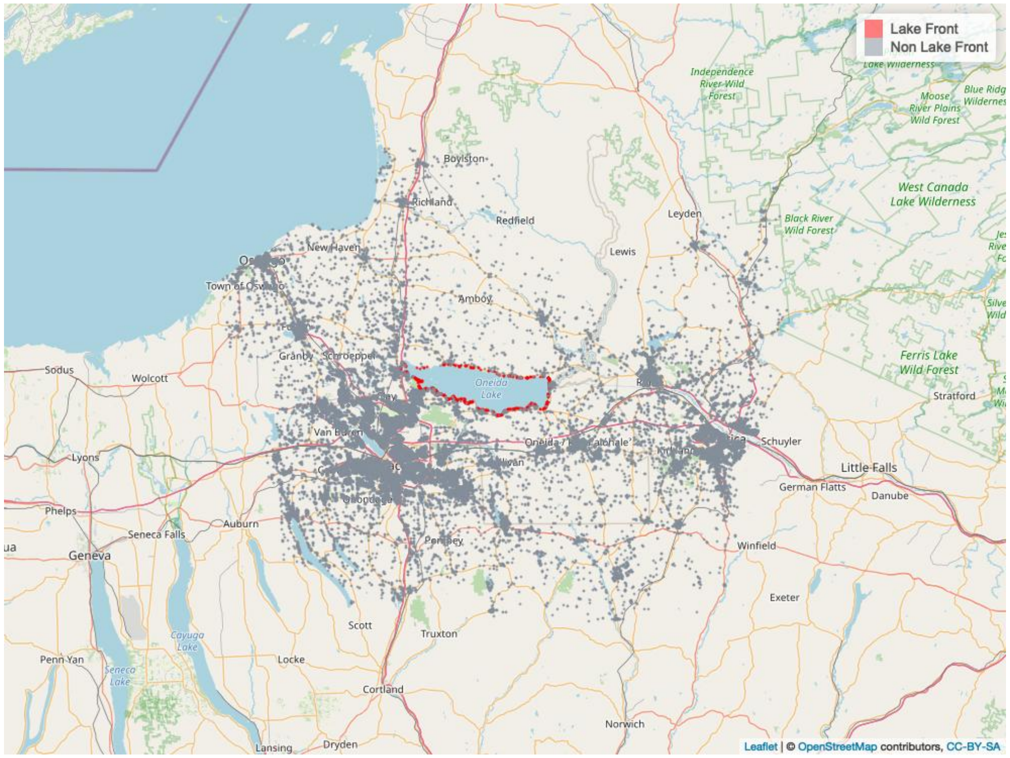
Species	Total Value of Capitalization (Million $)		Property Tax Revenue (Million $)		Annualized Rent Premium ($)	Per Trip Premium ($)
	Lake Front Property	All Property within 4km	Lake Front Property	All Property within 4km		
Smallmouth Bass	-18.47	-10.50	-0.63	-0.36	-49.4	-1.7
Walleye	64.84	70.02	2.20	2.38	872.0	29.1
White Perch	43.26	62.94	1.47	2.14	821.0	27.4
Yellow Perch	-58.90	-86.80	-2.00	-2.95	-1250.0	-41.7

Panel B: Capitalization Effect of Walleye Abundance, by County

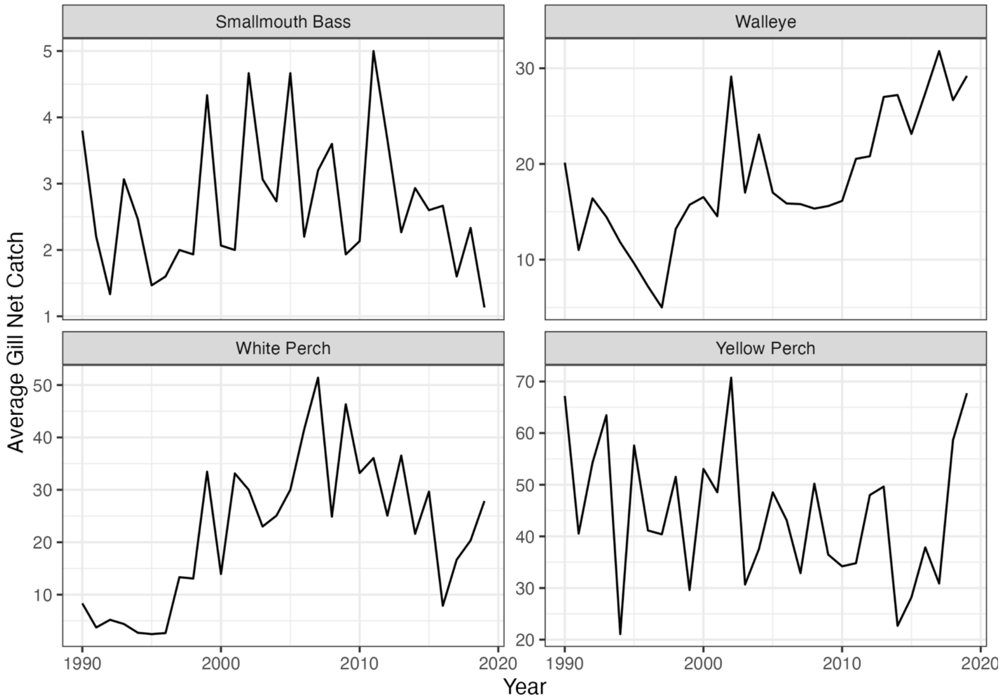
County	Oneida Lake Only			All Recreational Fishery within County		
	Number of Properties		Property Tax Revenue, +1SD Walleye (Million $)	Mean Angler Travel Distance (Miles)	State and Local Tax Revenue (Million $)	
	Lakefront	Within 4km			Angling Activity, Local Residents	Angling Activity, All Anglers
Madison	727	2,432	0.64	25.2	0.49	1.33
Oneida	454	1,620	0.43	43.7	2.79	8.44
Onondaga	638	7,134	0.82	36.1	2.28	4.47
Oswego	512	2,412	0.45	132.5	1.34	33.72

Note: This table shows total capitalization effects and local tax revenue. Panel A shows the capitalization effects from a one-standard-deviation increase of gillnet catches for four species using coefficients estimated from the spatial spillover model (Figure 2a). Property tax revenue is calculated using the average effective tax rate (i.e., levied property tax divided by assessed property value), 3.4%, for all properties within 10 km of Oneida Lake, averaged across all counties. The annualized price premium is calculated with a 3% discount rate, showing numbers only for lakefront properties. Per trip premium is calculated by assuming that the average lakefront property owner go on fishing trips 30 times per year. Panel B shows a breakdown of local economic impacts from fishery in the four counties adjacent to Oneida Lake. The property tax column shows the property tax impact of one-standard-deviation increase of walleye abundance, using effective property tax rates disaggregated by county, which range from 3.1% (Madison County) to 3.7% (Oneida County). The number of properties (regardless of transaction records) and effective tax rates are taken from assessor records. The angler travel distance and local tax revenue columns are taken from the New York Angler's Survey for the year 2017 (NYSDEC 2019). The three columns contains accounts for all recreational angling activities within these four counties, not just the Oneida Lake fishery. All property tax revenues and property premiums are discounted into 2012 dollar.

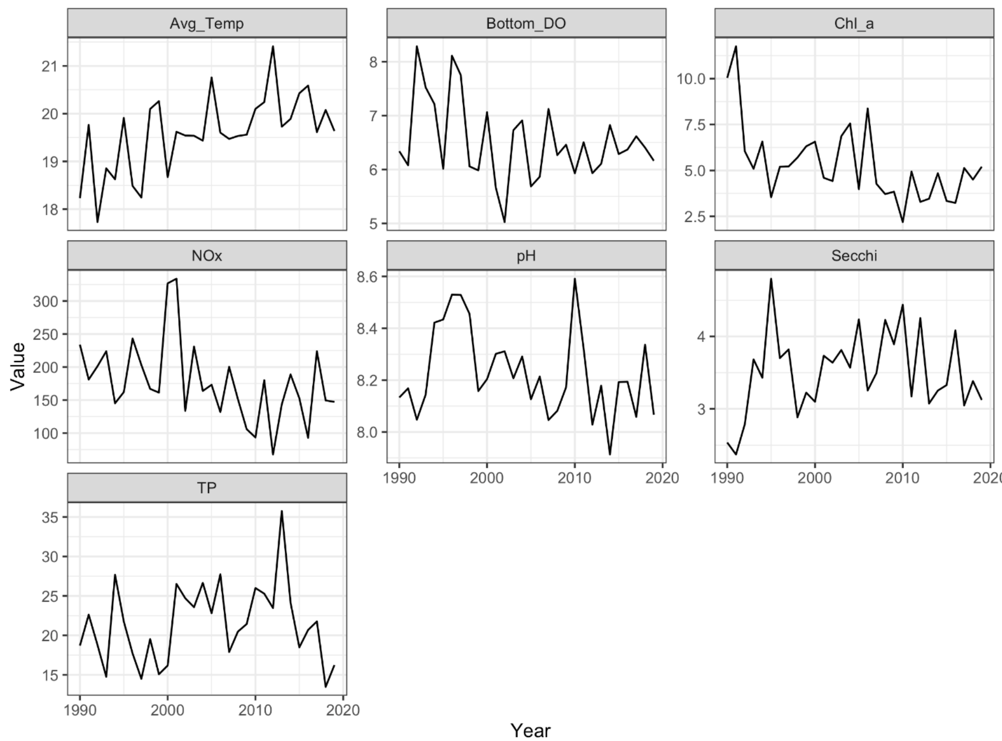
Appendix A.Additional Figures and Tables



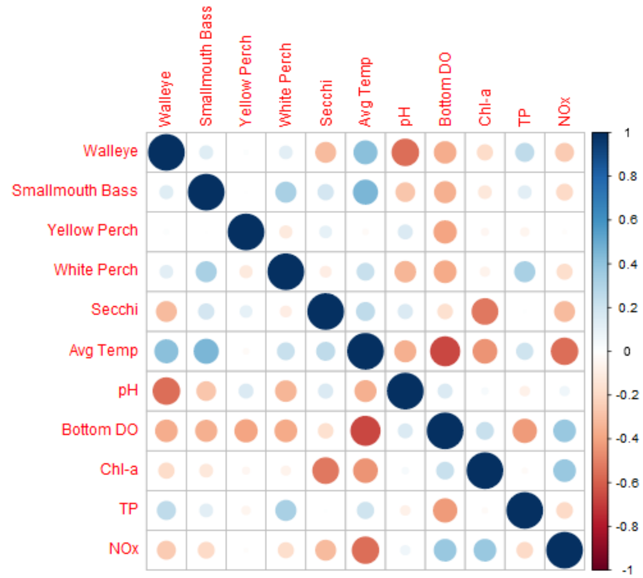
Appendix Figure 1: Map of Repeated Sale Properties. Each dot denotes the location of one property that has been sold at least twice during our sample period. Red dots denote properties in front of Oneida Lake (lakefront). Grey dots denote non-lakefront properties.



Appendix Figure 2: Average Gill Net Catch by Species and Year. Panel shows average gill net catches per sample during summer months for four species: smallmouth bass, walleye, white perch, and yellow perch.



Appendix Figure 3: Water Quality Indicators over Time. Each Panel denotes the annual average value of a water quality indicator, averaged over summer months and across sampling locations. Units: Avg Temp: degree Celsius; Bottom DO: mg/L; Chl-a: µg/L; NOx: µg/L; pH: Dimensionless; Secchi: meters; TP: µg/L.



Appendix Figure 4*: Correlation Matrix Between Fish Population and Water Quality Indicators. Each dot denotes the correlation coefficient (between -1 and 1) between a pair of indicators. Larger-sized dots indicate stronger correlations. Red dots indicate negative correlations, and blue dots indicate positive correlations.*

Appendix Table 1: Estimates with Conley (1999) Standard Errors.

Commented [WW37]: need to remove hedonic estimates, just keep repeated sales ones.

	(1)	(2)	(3)	(4)	(5)	(6)
			Fish Variables			
LakeFront x walleye	0.130*** (0.016)	0.130*** (0.026)	0.130*** (0.009)	0.165*** (0.033)	0.165*** (0.026)	0.165*** (0.014)
LakeFront x smallmouth bass	-0.053** (0.020)	-0.053*** (0.020)	-0.053*** (0.011)	-0.045* (0.026)	-0.045** (0.022)	-0.045*** (0.007)
LakeFront x yellow perch	-0.130*** (0.018)	-0.130*** (0.042)	-0.130*** (0.019)	-0.150*** (0.051)	-0.150*** (0.049)	-0.150** (0.066)
LakeFront x white perch	0.081*** (0.014)	0.081*** (0.015)	0.081*** (0.015)	0.109*** (0.026)	0.109*** (0.024)	0.109*** (0.024)
			Water Quality Variables			
LakeFront x log(Secchi)	0.277** (0.104)	0.277** (0.110)	0.277*** (0.053)	0.283* (0.155)	0.283*** (0.109)	0.283*** (0.085)
LakeFront x Avg Temp	0.038** (0.017)	0.038* (0.022)	0.038* (0.021)	0.025 (0.030)	0.025 (0.021)	0.025 (0.033)
LakeFront x log(TP)	-0.130*** (0.044)	-0.130*** (0.047)	-0.130*** (0.028)	-0.008 (0.086)	-0.008 (0.100)	-0.008 (0.075)
Water Quality Controls	Yes	Yes	Yes	Yes	Yes	Yes
LakeFront x Water Quality Controls	Yes	Yes	Yes	Yes	Yes	Yes
Property/Neighborhood Controls	Yes	Yes	Yes	--	--	--
Property Fixed Effect	No	No	No	Yes	Yes	Yes
Time Trend	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial
Standard Error	School District + Year Clustered	Conley (1999) with 1 km cutoff	Conley (1999) with 5 km cutoff	School District + Year Clustered	Conley (1999) with 1 km cutoff	Conley (1999) with 5 km cutoff
Observations	184744	184,744	184,744	184,744	184744	184744

Note: This table shows the coefficient estimates with different estimates for standard errors. Panel (A) presents models with individual fish species. Panel (B) presents models with species categories. Specifications (1) and (4) presents robust standard errors in the main specification, clustered at the school district and year levels. Specifications (2) and (5) presents Conley (1999)'s standard error, assuming error correlation within a 3 km distance. Specifications (3) and (6) presents Conley standard errors with error correlation up to a 10 km distance All other control variables remains the same from Table 3. Standard errors are shown in parenthesis. ***p<0.01, **p<0.05, *p<0.1.