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 hedonic studies of property values focus on water quality and overlook the contributions of fish populations. People can enjoy both the amenity values of lake water quality and sport fishing opportunities. However, a decrease in water quality, which has been shown to reduce property values, may benefit fish populations by stimulating phytoplankton growth and thereby enhancing recreational fishing opportunities and increasing property values. Given this relationship, where water quality and fish populations may be correlated, omitting fish data in hedonic models may result in biased estimates of the effects of water quality. Using 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. We find that omitting fish abundance leads to biased estimates for water quality, particularly for lakefront properties. In contrast, models including fish abundance are robust to the exclusion of water quality variables. 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.

Key Words: Non-market Valuation; Hedonic Model; Water Quality; Fish Populations; Omitted-variable Bias

JEL Codes: Q51; Q26; Q25

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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 surface waters often focus on one dimension (e.g., water quality in hedonic models and fishing in recreation demand models). In hedonic models focused on water quality, overlooking fisheries may be a critical consideration for benefit-cost analyses of water quality policies (Keiser et al., 2019).

The relationships between water quality and fisheries illustrate 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 biological relationships translate into economic trade-offs: changes in nutrient levels simultaneously affect amenity and recreational value of water quality and fish abundance, which influences recreational value for anglers.

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 concentrations 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). Alternatively, 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; Melstrom et al. 2022). Building on insights from the literature on hedonic and the recreational demand modeling, we incorporate both lake water quality and fish abundance, a proxy for fishing quality, into a hedonic model.

Our study utilizes a unique dataset on water and fishing quality to disentangle their effects on property values. We use Oneida Lake in 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 increase property values. After controlling for fishing quality, water clarity becomes positive and statistically significant, as expected, while total phosphorus shows no statistically significant effect. This result is plausible because people can observe water clarity, but not total phosphorous, and water clarity is influenced by total phosphorous. Second, our analysis demonstrates that fishery populations, particularly the most sought-after species in the region — walleye — are capitalized into property values. Third, a one-standard-deviation increase in the walleye population raises lakefront property-value premiums 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.

[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.

2. Study Area and Data

2.1 Study Area

We study Oneida Lake in the State of New York, USA (Figure 1) to explore 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.[2] 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 and other important targeted species (VanDeValk et al. 2016).[3] The lake and its fish are the concern of an active lake and angler organization, the Oneida Lake Association (OLA), with between 2,000-3,000 members and strong ties with the local community as well as political connections. 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.[4] The OLA is highly effective as evidenced by receiving the American Fisheries Society's highest award given to an organization involved in fish conservation in North America in 2024.[5]

[2] Source: https://www.lakehomes.com/new-york/oneida-lake. Retrieved 3/3/2025.
[3] Source: https://dec.ny.gov/things-to-do/freshwater-fishing/places-to-fish/statewide-opportunities/walleye
[4] OLA newsletters and bulletins can be found on the OLS website, dating back to Spring 1991: https://www.oneidalakeassociation.org.
[5] See American Fisheries Society's announcement: https://fisheries.org/about/awards-recognition/call-for-award-nominations/presidentsfisheryconservationaward/

2.2 Water Quality and Fisheries Data

We follow a long literature valuing the effects of ecosystem attributes on nearby housing markets for freshwater lakes (e.g., Gibbs et al., 2002; Kuwayama et al., 2022; Michael et al., 2000; Weng et al., 2020; Wolf et al., 2021). Our analysis utilizes observational data from Cornell Biological Field Station (CBFS), which provides long-time monitoring for limnological and ecological conditions in Oneida Lake (Rudstam et al., 2016b). During our study period, water quality was monitored weekly at four sampling sites from May to October. Panel A of Figure 2 shows water quality sampling locations. and fish abundance was monitored weekly with rotational sampling at over a dozen sampling locations (Panel B of Figure 2). Both data are presented in annual reports (Van De Valk et al. 2024) and published in an on-line data repository (Rudstam and Almeida 2023).

Our analysis considers three water quality indicators: 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 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 (e.g., Walsh & Milon, 2016). While nutrient levels contribute to the growth of phytoplankton, they also contribute to the growth of fish populations, including walleye. We aggregate water quality indicators' average values across summer months annually, and by sampling site.

To measure fish abundance, 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). 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.[6] 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.

Table 1 presents summary statistics of water quality and fishery attributes for years 1990-2022, our sample period. Across these years, the average Secchi depth was 3.6 meters (standard deviation (SD=0.5 meter), average TP concentrations were 21.9 ug/L (SD=4.8 ug/L), and average water temperature was 19.78 degrees Celsius (SD=0.72 °C). For fish abundance, average gillnet catches (number of fish per net) were: walleye 19.1 (SD = 6.9), smallmouth bass 2.7 (SD = 1.0), yellow perch 42.4 (SD = 11.8), 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 and 3.

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.[7] 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.[8] We dropped properties with extremely high or low sales prices, yielding a final dataset containing 181,916 sales records.[9]

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[6] 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.

[7] Estated now becomes a part of ATTOM Data Inc..

[8] An arm's length transaction refers to the property transactions in which buyers and sellers act independent without one party influencing the other.

[9] 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.

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 et al. 2022). We visually identified lakefront and adjacent lakefront (second row) properties using Google Map and satellite imageries from Google Earth. Lakefront properties are those that have direct access to the lake, and second row properties are those that need to cross an additional property and/or road to access the lake (Figure 1).[10] We also calculated the distance of each property to the Oneida shoreline based on its location.

Neighborhood attributes could also impact housing prices. In our analysis, we include 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 the 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 Clearinghouse.[11] Distance to nearest Walmart and nearest post office and serves as a proxy for the convenience of property locations to daily homeowner activities.[12]

Table 2 provides summary statistics for the housing transaction data. Compared to non-lakefront properties, lakefront homes are more expensive, newer, have fewer bedrooms, and are located further from shopping areas. Additionally, residents in lakefront communities are relatively older, with a lower percentage of non-white residents and lower education levels. There is no statistically significant difference in square footage between lakefront and non-lakefront properties.

Linking limnology data (fish abundance and water quality) with property sales data is essential to the estimation of hedonic model, but it is difficult to know *a priori* 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

[10] 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.
[11] Available at: https://gis.ny.gov/gisdata/inventories/details.cfm?DSID=1326. Retrieved 5/3/2021.
[12] Location of Walmart stores are available at https://walmart-open-data-walmarttech.opendata.arcgis.com/. Post office locations are obtained from the USPS at https://postalpro.usps.com/gis/po-location-icd.

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. For water quality variables, each transaction is assigned to the observation at the nearest of the four water quality sampling sites in a given year. For fish abundance variables, each transaction is assigned to the same annual-aggregate.

3. Empirical Strategy

To investigate the interaction effects between water quality and fish abundance, we empirically estimate three variations of the hedonic models: (1) the impact of water quality on lakefront property values; (2) the impact of fish abundance on lakefront property values; and (3) the joint impact of water quality and fish 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 fish species data to evaluate the impact of fish 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 joint relationship with fish 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 fish 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. (2014). 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 main estimation model can be written as:

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

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 that equals 1 if the property is lakefront, and 0 otherwise; 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. $Species_{jt}$ represents the abundance of fish species j in year t, where j={walleye, smallmouth bass, yellow perch, white perch}. We include fixed effects at the individual house level, λ_i, and flexible controls for time-trends $f(t)$ to control for individual unobserved heterogeneity and time trends.[13] 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 fish 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 fish 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

[13] 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.

promoting phytoplankton growth and harmful algal blooms (HABs), which diminish water clarity and quality (e.g., Weng et al. 2020; Wolf et al. 2021). 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 has opposite effects on property values. 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 fish abundance variable (θ_j), we anticipate positive capitalization effects for species targeted by anglers, 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.

3.2 The spatial extent of capitalization effects

After estimating the baseline capitalization effect of species abundance on lakefront properties, we extend our analysis to estimate the extent to which these effects vary spatially 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 with direct access to 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.[14] 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:

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

where $Proximity_{is}$ is whether property i falls into one of the seven mutually exclusive binary indicators denoting distance band s = {lakefront, second row, <250m, 250-500m, 500-1,000m,

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

1,000-4,000m, or >4,000m}. The >4,000m group serves as the control group and is omitted from the regression. 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

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

We first present our baseline estimates of the impact of water quality on lakefront house premiums in Table 4. Columns (2) in Table 4 report estimated coefficients on the impact of water quality measurements on lakefront property values without controlling for fish abundance. We added the fish abundance controls in Column (3). We include results using alternative fixed effects and control variables in Appendix Table 1, and results using Conley (1999) standard errors as a robustness check in Appendix Table 3.

When fish abundance is not controlled for, we find a counterintuitively negative, but statistically insignificant, correlation between water clarity (Secchi) and lakefront property premiums. This is likely due to water clarity being negatively correlated with walleye abundance.[15] Consequently, the estimated water clarity premium without controlling for walleye abundance captures both the positive amenity value of water clarity and the negative effect of walleye abundance. After controlling for fish abundance (Column 3 in Table 4), the counterintuitive negative correlation between water clarity and housing price reverses. For total phosphorus (TP), the specification without fish controls (Column 2) shows a positive and statistically significant effect. This is likely because without including fish population variables

[15] Secchi disk reading is also positively correlated with smallmouth bass and negatively correlated with the abundance of white perch. Though walleye has the strongest correlation with Secchi disk reading amongst all species. The readers are referred to Figure A5 for a full correlation matrix between fish population and water quality indicators.

in the regression, the estimated effect on TP is dominated by its contribution to the ecological production of fish growth, especially the effect on the walleye population.[16] The estimated effect for TP becomes much smaller in magnitude and statistically insignificant once fish abundance variables are included.

For average temperature, we again find that estimates with and without controlling for fish populations diverge. Focusing on the repeated sales specifications, we find a positive and statistically significant correlation between average water temperature and the lakefront premium without including the fish population variables in the regression (Column 2 in Table 4). The effect is much smaller and statistically insignificant when we control for the fish populations (Column 3). When we fail to control for fish population variables, the effect on average temperature includes both a recreational effect, namely that residents prefer to recreate/swim in warmer water, and the positive effect of warmer water on fish productivity. Once we explicitly control for fish population, the remaining amenity is estimated to be positive but smaller in magnitude.

In addition to estimating the lakefront premium, we analyze the spatial spillover effects of water quality indicators on housing prices, both with and without controlling for fish population. The results are presented in Figure 3.[17] For Secchi, in the specification with fish population controls (our preferred model specification), we find the largest capitalization effects for lakefront and second-row properties, with the effect gradually decaying over distance. Water clarity capitalizes into property values up to 4 km away from the lake. For TP, we find a positive capitalization for properties further away (500-4,000m), but not for properties within 500 meters of Oneida Lake.[18] For average temperature, we find a positive capitalization effect for second-row properties but not at other distances.

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[16] Readers are again referred to Appendix Figure A5 for the full correlation matrix.

[17] Appendix Figure 4 presents results using alternative specifications that include property and neighborhood characteristics and school district fixed effect instead of property fixed effect.

[18] It could be that properties located farther away have higher values and contribute more to phosphorus loading due to their fertilized lawns and agricultural lands, whereas nearby properties may adopt management practices that limit phosphorus runoff.

The divergences between specifications with and without fish controls are the largest for lakefront properties: for all three water quality indicators, we find large, statistically significant differences in estimated effects on lakefront properties. By contrast, differences across other distance bands are small and statistically insignificant. These findings align with insights from the literature, highlighting that lakefront housing premiums largely drive the capitalization of water quality changes into property values (Mamun et al. 2023).

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

To explore the relationship between fish 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 4. We consider two specifications: column (1) excludes water quality controls, while column (3) include them. We include results using alternative fixed effects and control variables in Appendix Table 2 and Appendix Figure 4, and results using Conley (1999) standard errors as a robustness check in Appendix Table 3.

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% with water quality controls. 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.[19] 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

[19] 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.

strongly correlated with prey density (VanDeValk et al., 2005).[20] 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.[21] 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 fish 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 fish 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.

[20] 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.

[21] Appendix Figure 5 presents results using alternative specifications that include property and neighborhood characteristics and school district fixed effect instead of property fixed effect.

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:

$$CV_j = \sum_k \beta_{jk} \times NP_k \tag{3}$$

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 values calculated using the estimated results from equation (1c), with both water quality and fish abundance variables included. 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.[22] 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 5, 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

[22] All monetized values are in 2012 dollars.

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.

5. Conclusion and Discussion

Our study yields both methodological and policy contributions. Methodologically, we demonstrate that omitting an important ecosystem service can bias water quality valuations, especially in mesotrophic environments where fish growth is an important factor, and both water clarity and sport-fish abundance affect water quality. To our knowledge, this is the first study to concurrently model the effects of fish stocks and water quality on property prices. Our findings suggest that studies of lake water quality that do not account for fish populations, which is an indicator of fishing quality, may produce biased estimates of improvements in water quality. Further, failure to account for fish stocks in hedonics analysis omits an important category of benefits. Our study highlights the importance of considering multiple, interrelated, ecosystem services and suggests that future analyses might consider other attributes that affect the ecosystem services of lakes.

The strong capitalization of fish populations, with a one-standard-deviation increase in the walleye population resulting in a $70 million increase in the capitalization of property values, has important local, state and national policy implications. The link between fish abundance and property values is particularly important at the local level, as communities depend heavily on property values that influence municipal tax revenues. In New York, property taxes are used to support local governments and schools.[23] At the state level, the New York State Department of Environmental Conservation has responsibility for lake water quality and managing recreational fishing, and biased or missing estimates of benefits can lead to suboptimal management decisions. The undesirable outcome can also translate nationally, influencing U.S. EPA promulgation of policies to protect and enhance freshwater ecosystems. The joint benefits of water quality and fish populations also emphasizes the economic importance of balancing the healthy fish populations while considering potential tradeoffs with water quality.

We propose three extensions of our study and directions for future research. First, this is a single case study that needs to be replicated to other water bodies to understand the scalability of outcomes and how the results vary for other types of lakes. The availability of long term, spatially explicit creel survey data, traditionally collected by fish biologists used to measure fishing effort and fish abundance and water quality monitoring data, often provided by citizen science initiatives, offer the potential to accomplish this effort. Second, jointly modeling recreational demand for fishing and other uses of lakes can expand that analysis to include those who enjoy the ecosystem services of lakes but do not own property near lakes. Lastly, future research could link the outcomes of hedonic and recreation demand models to bioeconomic models to explicitly examine the trade-offs between water quality and fishing. Collaborative efforts among limnologists, fishery biologists, and economists are needed.

[23] Retrieved from https://www.tax.ny.gov/pit/property/learn/proptax.htm on March 14, 2025.

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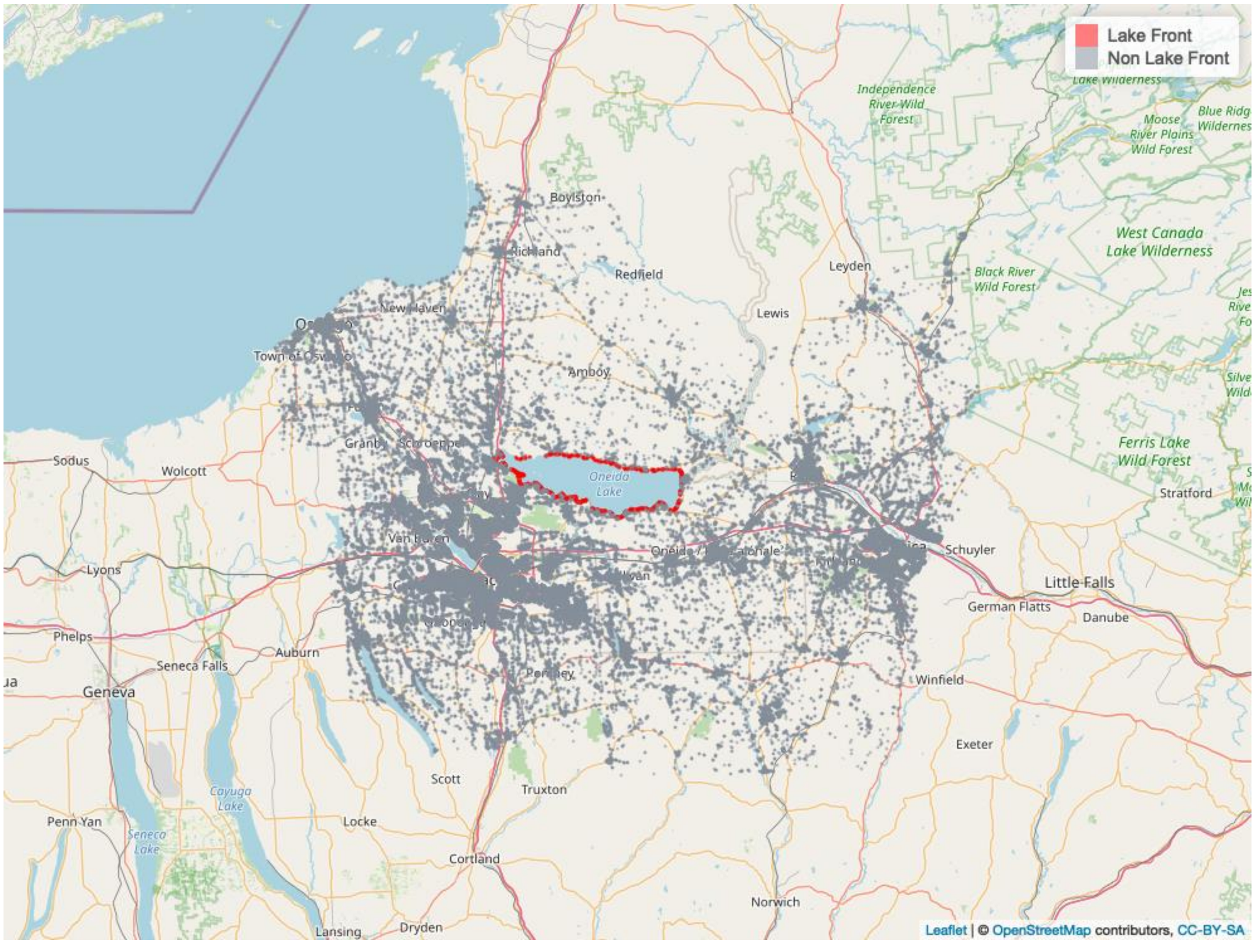


Figure 1: Property Sales Near Oneida Lake. Note: Each dot denotes the location of one property. Red dots denote properties with frontage of the Oneida Lake (lakefront). Grey dots denote non-lakefront properties.

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.

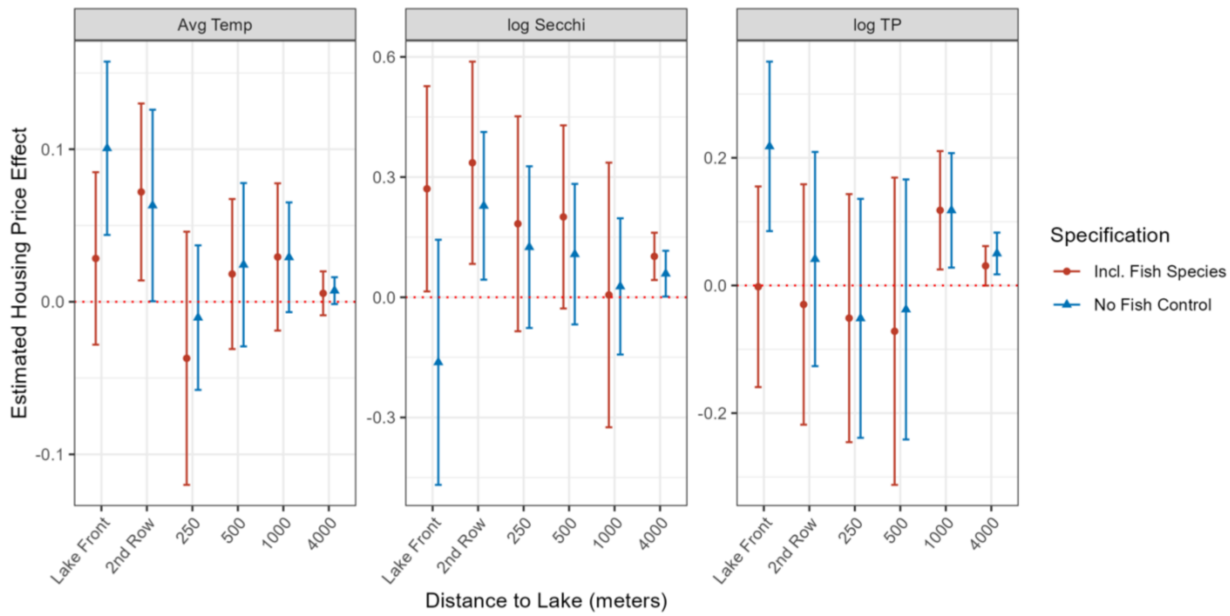


Figure 3: Spatial Spillover for Water Quality Capitalization with or without fishery controls. Note: Panels show coefficient estimates for the capitalization effects of average water temperature (left), the logarithm of Secchi disk reading (middle), and the logarithm of total phosphorus (right), over different proximities to Lake Oneida. Property fixed effects are included in all regressions. Distance intervals include properties that are lakefront, on the second row, within 250 meters of Oneida (but not lakefront or second row), 250-500m, 500-1000m, and 1000-4000m. 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 the estimated impacts of water quality without controlling for fish abundance.

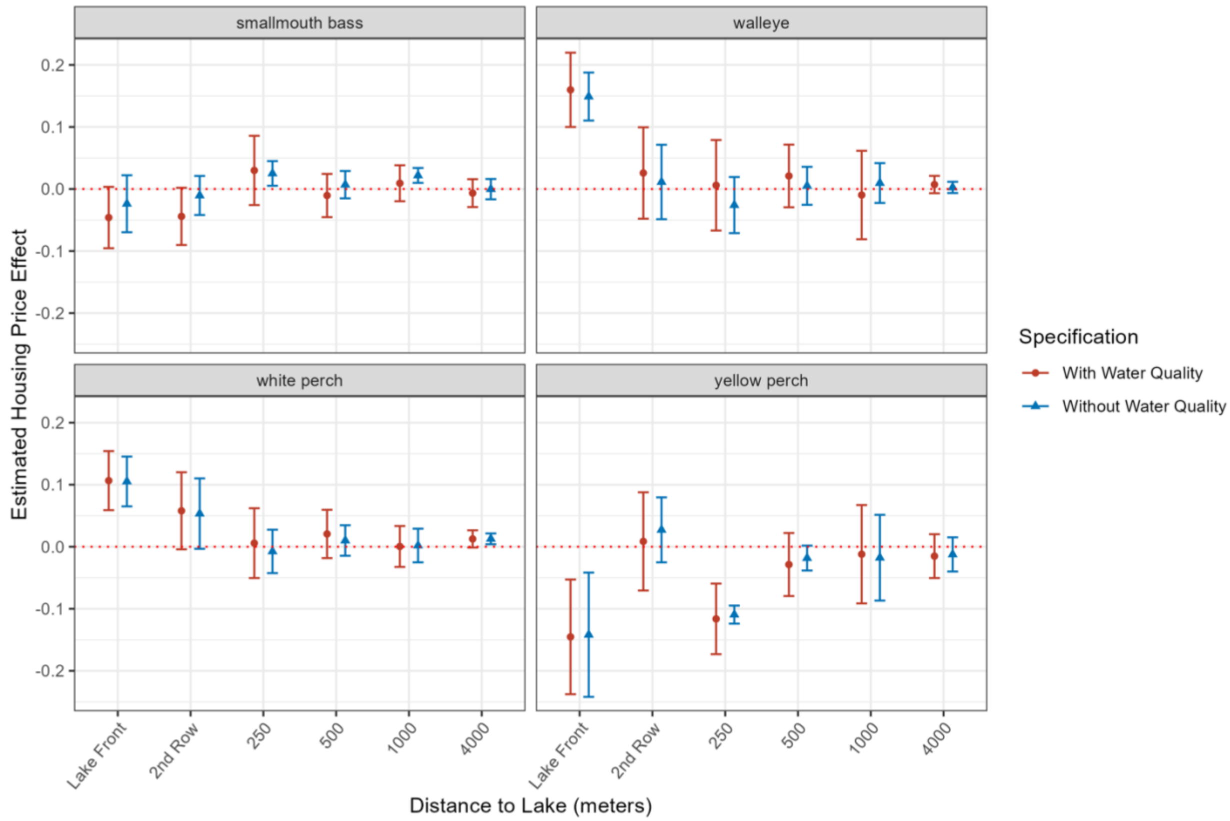


Figure 4: Spatial Spillover for Capitalization of fisheries, with and without water quality controls. Panels plot point estimates of individual species abundance interacted with proximity dummy variables, corresponding to equation (2). Property fixed effects are included in all regressions. Distance intervals include properties that are lakefront, on the second row, within 250 meters of Oneida (but not lakefront or second row), 250-500m, 500-1000m, and 1000-4000m. Control group are properties beyond 4km of the Oneida shoreline and are omitted. 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 that exclude 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	1,447		180,469			

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	115,170		181,916		
# Property	45,585		112,331		

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 Fish Abundance and Water Quality Indicators

	Dependent Variable: log(sale price)			Difference: (1) - (2)	Difference: (2) - (3)
	(1)	(2)	(3)		
LakeFront x walleye	0.154*** (0.024)		0.165*** (0.033)	-0.011	
LakeFront x smallmouth bass	-0.024 (0.028)		-0.045* (0.026)	0.021	
LakeFront x yellow perch	-0.147** (0.060)		-0.150*** (0.051)	0.003	
LakeFront x white perch	0.104*** (0.025)		0.109*** (0.026)	-0.005	
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**
Property Characteristics	--	--	--		
Neighborhood Characteristics	--	--	--		
School District Fixed Effect	--	--	--		
County Fixed Effect	--	--	--		
Property Fixed Effect	Yes	Yes	Yes		
Time Trend	5-degree Polynomial	5-degree Polynomial	5-degree Polynomial		
Observations	184,744	184,744	184,744		
R2	0.89	0.89	0.89		
Within R2	0.05	0.05	0.05		

Note: This table shows the coefficient estimates of fish abundance and water quality indicators on lakefront premiums. Column (1) presents the specification with only fish abundance x lakefront dummy in the model. Column (2) presents the specification with only water quality indicators x lakefront dummy in the model. Column (3) presents the specification with both fish abundance x lakefront dummy and water quality indicators x lakefront dummy included in the model. 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 and Local Tax Revenue from Oneida Lake Fishery

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

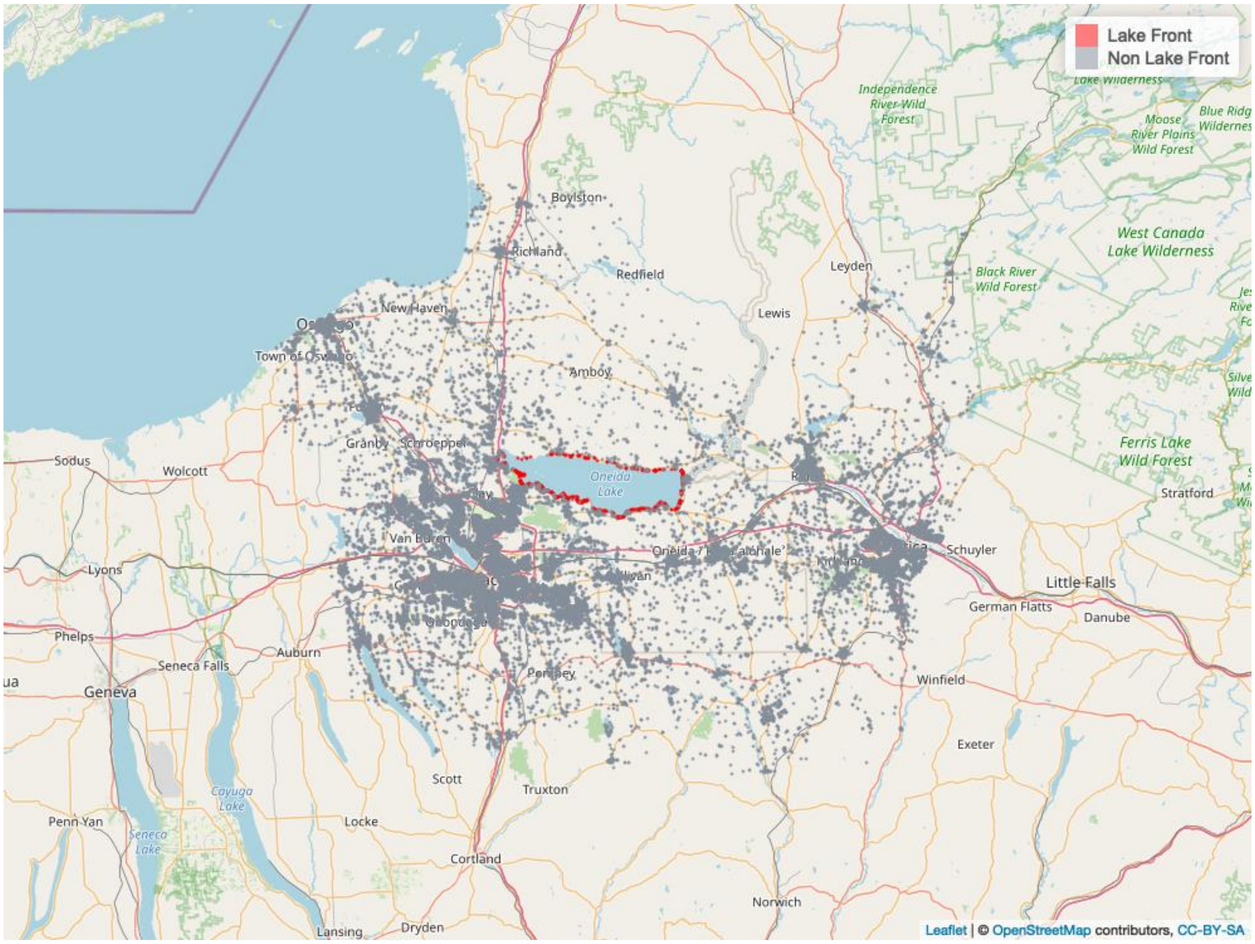
Species	Total Value of Capitalization (Million $)		Property Tax Revenue (Million $)		Annualized Rent Premium ($)	Per Trip Premium ($)
	Lake Front Property	All Property within 4km	Lake Front Property	All Property within 4km		
Smallmouth Bass	-18.47	-10.50	-0.63	-0.36	-49.4	-1.7
Walleye	64.84	70.02	2.20	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

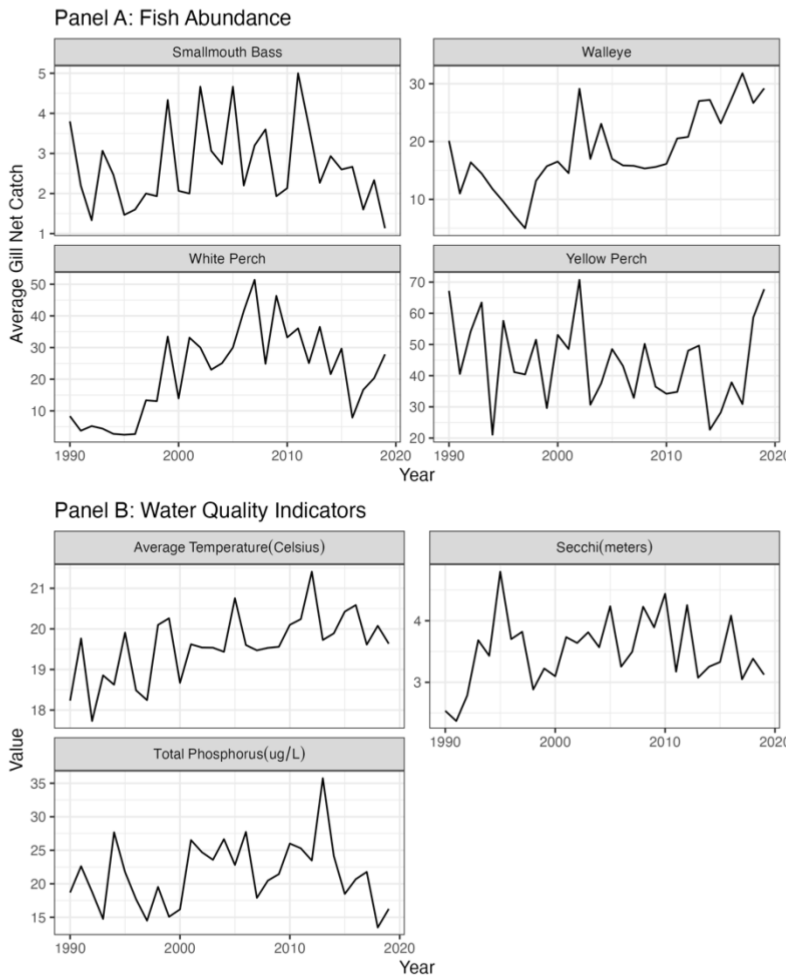
County	Oneida Lake Only			All Recreational Fishery within County		
	Number of Properties		Property Tax Revenue, +1SD Walleye (Million $)	Mean Angler Travel Distance (Miles)	State and Local Tax Revenue (Million $)	
	Lakefront	Within 4km			Angling Activity, Local Residents	Angling Activity, All Anglers
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.

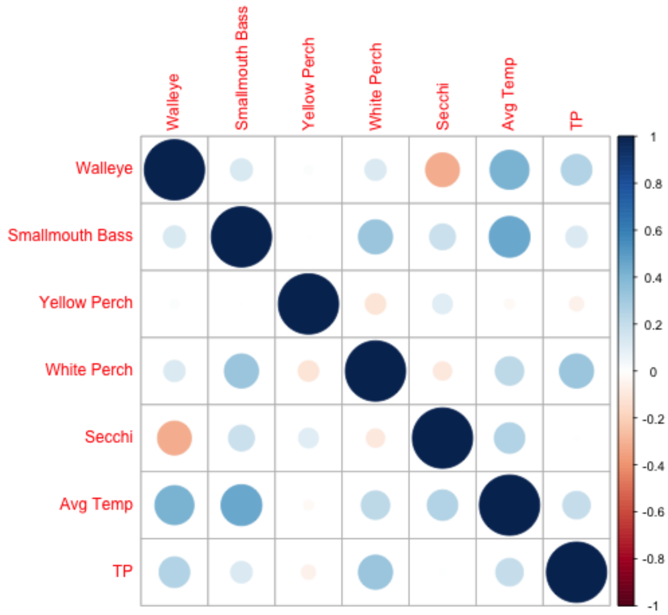
Appendix A.Additional Figures and Tables



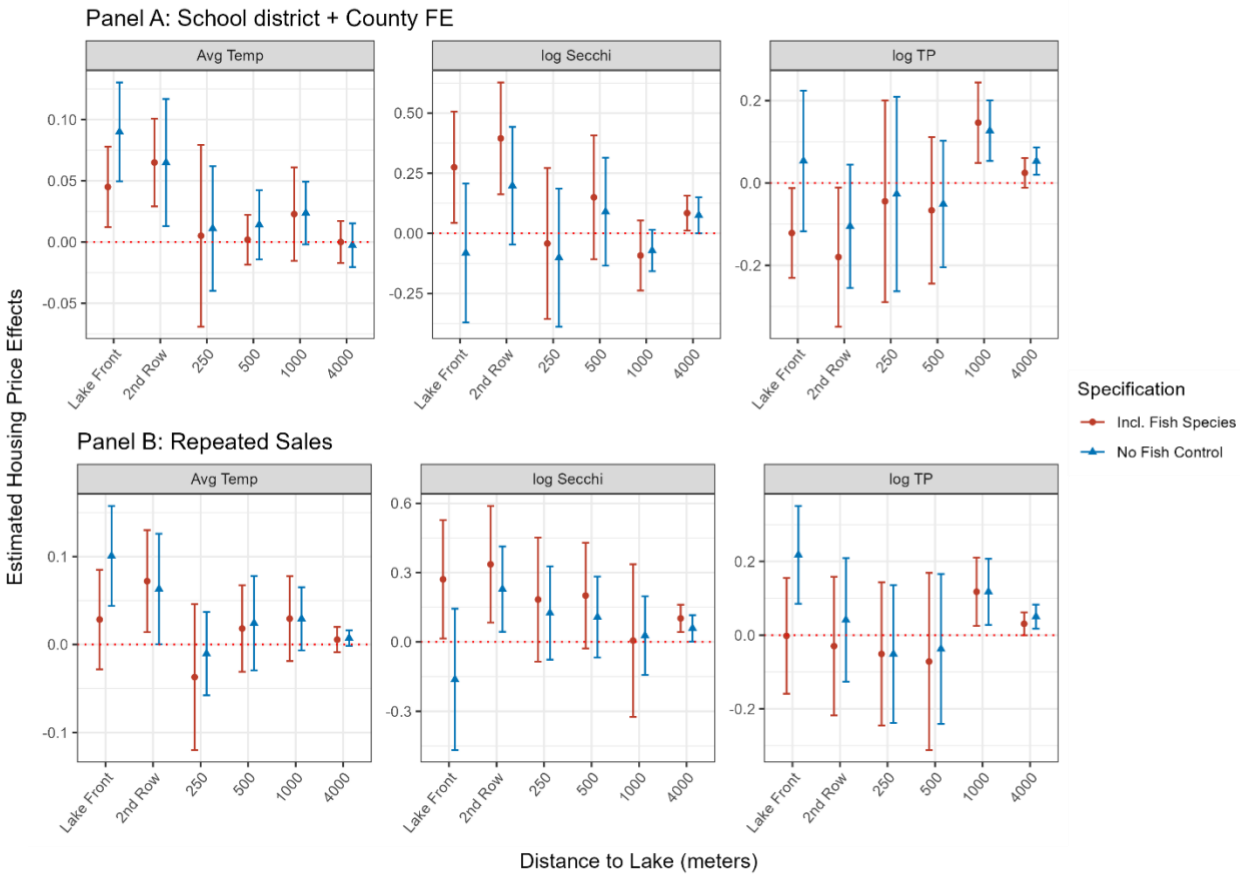
Appendix Figure 1: Map of Repeatedly Sold Properties. Note: Each dot denotes the location of one property that has been sold at least twice during our sample period. Red dots denote properties in front of Oneida Lake (lakefront). Grey dots denote non-lakefront properties.



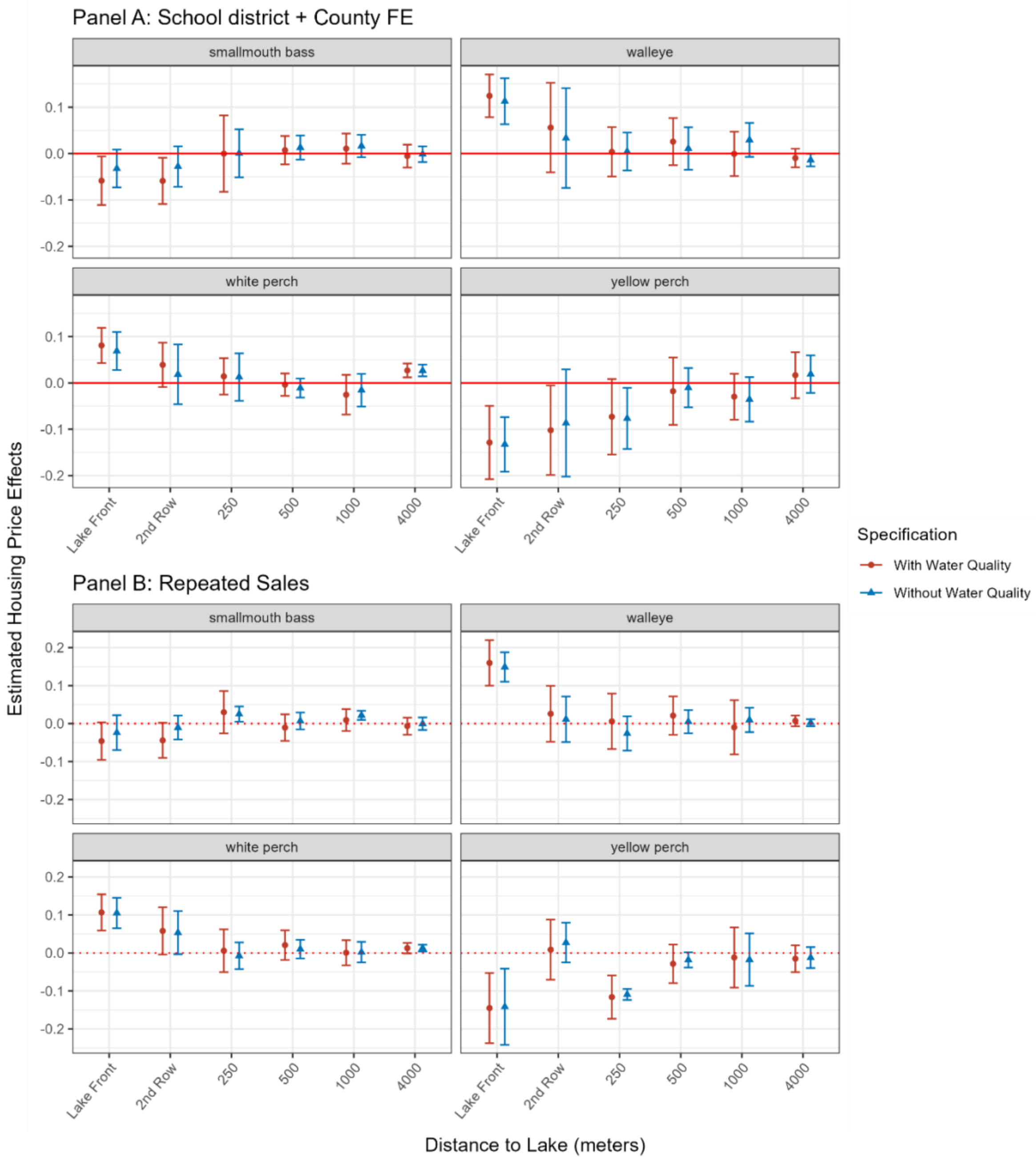
Appendix Figure 2: Time series of fish abundance and water quality indicators. Note: Panel A shows the average gill net catches per sample each year during summer months for four species: smallmouth bass, walleye, white perch, and yellow perch, 1990-2020. Panel B shows the annual average value of water quality indicators, averaged over summer months and across sampling locations. Units: Average Temperature: degree Celsius; Secchi: meters; TP: µg/L.



Appendix Figure 3: Correlation Matrix Between Fish Population and Water Quality Indicators. Note: 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 Figure 4: 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.



Appendix Figure 5: Spatial Spillover for Capitalization of fisheries with and without Water Quality Controls. Note: 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.

Appendix Table 1: 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**
LakeFront x walleye			0.154*** (0.024)	0.165*** (0.033)	
LakeFront x smallmouth bass			-0.024 (0.028)	-0.045* (0.026)	
LakeFront x yellow perch			-0.147** (0.060)	-0.150*** (0.051)	
LakeFront x white perch			0.104*** (0.025)	0.109*** (0.026)	
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	0.58465	0.89266	0.58458	0.89264	
Within R2	0.47388	0.04843	0.47378	0.04821	

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.

Appendix Table 2: 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
LakeFront x log(Secchi)			0.293* (0.111)	0.283 (0.155)	
LakeFront x Ave Temp			0.021* (0.011)	0.025 (0.030)	
LakeFront x log(TP)			-0.150*** (0.038)	-0.008 (0.086)	
Property Characteristics	Yes	Yes	--	--	
Neighborhood Characteristics	Yes	Yes	--	--	
School District Fixed Effect	Yes	Yes	--	--	
County Fixed Effect	Yes	Yes	--	--	
Property Fixed Effect	No	No	Yes	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.

Appendix Table 3: Estimates with Conley (1999) Standard Errors.

	(1)	(2)	(3)	(4)	(5)	(6)
			Fish Variables			
LakeFront x walleye	0.130***	0.130***	0.130***	0.165***	0.165***	0.165***
	(0.016)	(0.026)	(0.009)	(0.033)	(0.026)	(0.014)
LakeFront x smallmouth bass	-0.053**	-0.053***	-0.053***	-0.045*	-0.045**	-0.045***
	(0.020)	(0.020)	(0.011)	(0.026)	(0.022)	(0.007)
LakeFront x yellow perch	-0.130***	-0.130***	-0.130***	-0.150***	-0.150***	-0.150**
	(0.018)	(0.042)	(0.019)	(0.051)	(0.049)	(0.066)
LakeFront x white perch	0.081***	0.081***	0.081***	0.109***	0.109***	0.109***
	(0.014)	(0.015)	(0.015)	(0.026)	(0.024)	(0.024)
			Water Quality Variables			
LakeFront x log(Secchi)	0.277**	0.277**	0.277***	0.283*	0.283***	0.283***
	(0.104)	(0.110)	(0.053)	(0.155)	(0.109)	(0.085)
LakeFront x Avg Temp	0.038**	0.038*	0.038*	0.025	0.025	0.025
	(0.017)	(0.022)	(0.021)	(0.030)	(0.021)	(0.033)
LakeFront x log(TP)	-0.130***	-0.130***	-0.130***	-0.008	-0.008	-0.008
	(0.044)	(0.047)	(0.028)	(0.086)	(0.100)	(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	184,744	184,744	184,744	184,744	184,744	184,744

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) present robust standard errors in the main specification, clustered at the school district and year levels. Specifications (2) and (5) present Conley (1999)'s standard error, assuming error correlation within a 3 km distance. Specifications (3) and (6) present Conley standard errors with error correlation up to a 10 km distance All other control variables remain the same from Table 3. Standard errors are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.