Staying afloat: The effect of algae contamination on Lake Erie housing prices

WOLF, MICHAEL David

Gopalakrishnan, Sathya

Klaiber, H. Allen

Staying afloat: The effect of algae contamination on Lake Erie housing prices

David Wolf[*], Sathya Gopalakrishnan[**], and H. Allen Klaiber[**]

Abstract

Lake Erie has experienced unprecedented harmful algal blooms since the early 2000s, prompting the 2012 Great Lakes Water Quality Agreement between the United States and Canada, which aims to reduce lake-wide phosphorous loadings by 40%. Little is known about the economic benefits from this agreement, especially to near lake homeowners. We provide key information on the benefits of harmful algal bloom cleanup by linking housing transactions in 2003 to 2015 from seven Ohio counties bordering Lake Erie with measures of water quality using remote-sensing images. We further control for endogenous algae production using instrumental variables derived from hydrological processes that link Maumee River runoff to nutrient concentrations in Lake Erie. Using a semiparametric approach, we find the impact of harmful algal blooms on housing prices is spatially limited to properties within 1.2 kilometers of Lake Erie. For the average near lake homeowner, a 1 µg/L increase in algae concentrations is expected to decrease property values by 1.7% ($2,205). In aggregate, fulfilling the Great Lakes Water Quality Agreement will provide a yearly benefit of up to $42.9 million, fully covering the current annual expenditure on water quality improvement.

Keywords: Harmful algal blooms; hedonic analysis; instrumental variables; Lake Erie; nonmarket valuation

JEL Codes: Q51, Q53, Q57

[*]Corresponding author: Assistant Professor at Kobe University, Graduate School of Economics
Address: Frontier Hall for Social Sciences, Room 812, Kobe University, Kobe, Japan 657-0013
Telephone: 078-803-7245
E-mail address: wolf@econ.kobe-u.ac.jp
[**]The authors are, respectively, Associate Professor (Gopalakrishnan.27@osu.edu) and Professor (Klaiber.16@osu.edu) at The Ohio State University, Department of Agricultural, Environmental, and Development Economics.

Freshwater lakes contribute significantly to the health and well-being of humans and sustainable ecosystems. Lake Erie (Figure 1) is one of the largest and most influential lakes in the United States as it is the primary source of drinking water for over 11 million people, provides essential ecosystem services to humans through recreation and tourism, and is a habitat for hundreds of aquatic flora and fauna. Lake Erie also supports a housing market with over 15,000 lake adjacent properties (Wang et al. 2019) and a multibillion-dollar recreation industry that employs 128,000 people, generates $15 billion in tourism revenue, and contributes $1.9 billion in taxes annually to the State of Ohio (Markey 2018).

These essential economic and ecosystem services are in jeopardy, however, due to the emergence and spread of harmful algal blooms (HABs) in Lake Erie's western basin. HABs have been a growing concern for scientists, policy makers, and lake communities since the early 2000s when toxin-producing cyanobacteria covered 170 square kilometers of the lake. Since then, water conditions have worsened with a record-breaking bloom in 2011 covering over 3000 square kilometers (Stumpf et al. 2012). This expansion has weakened the lake ecosystem by disrupting food web dynamics (Davis et al. 2012), creating hypoxic zones (Scavia et al. 2014), and destroying freshwater habitat (Griffith and Gobler 2020). The extent and gravity of this problem led to the development of a HAB advisory system that alerts residents of toxic outbreaks at public beaches, access points, and within public water systems as ingestion of HAB toxins can lead to a myriad of health problems (Trevino-Garrison et al. 2015; Carmichael and Boyer 2016).

HABs have also had a significant impact on recreation and tourism in lake-dependent communities. Persistent HABs have decreased the number of Ohio fishing licenses sold by up to 3,600 per year (Wolf, Georgic, and Klaiber 2017), with a complete closure of the western basin

costing anglers $62.8 million[i] annually (Wolf et al. 2019). Anglers are willing to pay $9.20 more per trip to avoid boating through HABs (Zhang and Sohngen 2018), while waterfront restaurants and lodging establishments have experienced a 29% to 35% decline in revenue during months with persistent HABs (Larkin and Adams 2007). Local communities have responded by investing over $1 billion in municipal water treatment plants since 2014 (Arenschield 2015) and have allocated $30 million per year in federal aid towards lake restoration projects (Sohngen 2018).

The environmental, economic, and health impacts of HABs are exacerbated by climate change as hotter summers and wetter springs create more favorable HAB growing conditions (Wells et al. 2015; Paerl et al. 2016). To mitigate future risk, the United States and Canada signed the 2012 Great Lakes Water Quality Agreement (GLWQA) to reduce spring phosphorous loadings by 40% by the year 2025 (GLWQA 2016). However, there is little consensus on how this goal should be met, with proposed management solutions ranging from installation of riparian buffer zones in ecologically sensitive areas (Scavia et al. 2016) to a tax on fertilizer use (Sohngen et al. 2015; Liu et al. 2020). Assessing the cost-effectiveness and distributional consequences of alternative policies is also challenging. A fertilizer tax on phosphorus for example could be effective in reducing nutrient runoff (Sohngen et al. 2015; Liu et al. 2020) but is politically challenging as most of the burden is placed on farmers living in the Lake Erie watershed.

Recovering reliable water quality benefit estimates is a necessary input to evaluate alternative HAB management policies. The value of water quality can be partially recovered from housing transactions where improvements in water quality are capitalized in higher home values (Poor, Pessagno, and Paul 2007; Walsh et al. 2017; Wolf and Klaiber 2017). Secchi depth is a

commonly used water quality measure (Gibbs et al. 2002; Walsh, Milon, and Scrogin 2011; Liu et al. 2019) because of the scale and accessibility of *in situ* monitoring data across the United States (Wolf and Kemp 2021), with property values increasing between $498 (Walsh, Milon, and Scrogin 2011) and $11,330 (Moore et al. 2020) for a one-foot improvement in water transparency. This effect is spatially limited to homes near a waterbody (Walsh, Milon, and Scrogin 2011; Walsh et al. 2017; Wolf and Klaiber 2017) and will vary with ambient water conditions, with greater gains from water quality improvement observed at lower ambient conditions (Smeltzer and Heiskary 1990; Boyle, Poor, and Taylor 1999; Zhang, Boyle, and Kuminoff 2015).

Abrupt water quality changes, caused by a HAB or a combined sewer overflow event for example, will influence not only water transparency but also affect water odor and toxicity. In these cases, alternative water quality measures to Secchi depth are useful to capture homeowner perceptions. In a study of four Ohio inland lakes, *microcystin*, a freshwater toxin linked to HAB formation, was used to recover marginal willingness to pay (MWTP) measures for near lake homeowners (Wolf and Klaiber 2017) and applied within a Lake Erie policy report to estimate waterfront property value losses (Wang et al. 2019). In a study of the Chesapeake Bay where nitrogen is the limiting nutrient in algal formation, dissolved inorganic nitrogen was linked to housing prices to recover homeowner MWTP (Poor, Pessagno, and Paul 2007). In this paper, we adopt Chlorophyll *a* (CHLA) as our water quality measure as CHLA is a biomarker for HABs.

A longstanding challenge with conventional hedonic analyses is the ability to causally identify housing market impacts using imperfect measures of environmental quality (Chay and Greenstone 2005; Gopalakrishnan et al. 2011; Gamper-Rabindran and Timmins 2011). Measurement error is a potential source of bias for water quality (Moore et al. 2020) as

conventional valuation measures can be up to one order of magnitude larger when instrumental variables are employed (Keiser 2019). The lack of a consensus on how water quality should be aggregated across space and time is also a potential source of error and can result in contradictory conclusions with some finding homeowners more responsive to local measures (Walsh et al. 2017; Wolf and Klaiber 2017), while others finding the opposite (Liu, Opaluch, and Uchida 2017).

Omitted variable bias is also a concern, especially for larger waterbodies where a wide range of factors influence water quality. In Lake Erie, for example, spatial and temporal heterogeneity in water quality is driven by weather (Michalak et al. 2013), shoreline morphology (Moses et al. 2011), hydrodynamics (Manning et al. 2019), tributary loads (Wynne and Stumpf 2015), ice coverage from the preceding winter (Watson et al. 2015), water depth and temperature (Watson et al. 2015) and, amongst other things, the spread of invasive mussels (Vanderploeg et al. 2001; Jiang et al. 2015). The latter two are perhaps the most problematic as invasive mussels (Johnson and Meder 2013) and local water temperature/depth (Bejranonda et al. 1999; Netusil, Kincaid, and Chang 2014; Klemick et al. 2018) are directly capitalized in home values. Ice-coverage could also be a confounding factor as it influences the length of the HAB season (Watson et al. 2015) and is a housing price determinant for households that engage in winter recreational activities, though no study has attempted to value this amenity.[ii]

We make three contributions to the literature on water quality valuation. First, we apply a semiparametric approach (Linden and Rockoff 2008; Currie et al. 2015; Muehlenbachs, Spiller, and Timmins 2015; Haninger, Ma, and Timmins 2017) to determine the spatial extent of water quality impacts on nearby homeowners. We are the first to apply this methodology to value water quality in freshwater lakes, and our results indicate that HAB impacts are limited to

properties within 1.2 kilometers of Lake Erie. Second, we address omitted variable and measurement error concerns by instrumenting for HAB conditions using asynchronous measures of upstream phosphorus loadings, similar to the methodology employed by Keiser (2019). Using this approach, we find property values for near lake homes decrease 1.7% ($2,205) when HAB concentrations increase by 1 μg/L. Finally, we estimate the potential benefits from water quality improvements associated with the GLWQA as well as potential losses from a laissez-faire approach in which HABs continue to worsen due to climate change. Meeting the 40% reduction in phosphorus under the GLWQA could increase aggregate property values by as much as $670 million. In contrast, under a business-as-usual scenario without intervention property values are expected to decrease by at least $394.5 million.

Identifying Harmful Algal Blooms' Impact on Property Values

Estimation of the hedonic price function requires assumptions regarding the spatial extent of water quality capitalization. The existing literature explores a number of approaches to identify this extent including splitting the sample into increasing distance "donuts" (Walsh, Milon, and Scrogin 2011), including interaction terms between water quality and proximity (Walsh et al. 2017; Wolf and Klaiber 2017), and focusing only on lake adjacent homes (Boyle, Poor, and Taylor 1999; Gibbs et al. 2002; Zhang, Boyle, and Kuminoff 2015). As an alternative solution, we control for water quality attributes and structural, locational, seasonal, and yearly features of a housing sale parametrically before establishing a nonparametric relationship between lake proximity and housing price (Linden and Rockoff 2008; Currie et al. 2015; Muehlenbachs, Spiller, and Timmins 2015; Haninger, Ma, and Timmins 2017).

Housing price residuals are estimated from the following regression:

$$(1) \ln P_{ilt} = \lambda_0 + \lambda_1 S_{it} + \lambda_2 M_t + \lambda_3 Y_t + \xi_{ilt}$$

The natural log of housing price i sold in location l during period t, given by $\ln P_{ilt}$, is regressed

on a vector of housing attributes S_{it},[iii] and month and year fixed effects M_t and Y_t, while λ is a

coefficient vector and ξ_{ilt} is an independent and randomly distributed error term.

A nonparametric relationship is then established between housing price and Lake Erie

proximity using the residuals from equation (1) and a local linear estimator (Fan and Gijbels

1992).

$$(2) \hat{\xi}_{ilt} = m(DistancetoLake_i) + \zeta_{ilt}$$

$DistancetoLake_i$ is a measure of how far house i is from Lake Erie, ζ_{ilt} is an independent and

randomly distributed error term, while $m(.)$ is a nonparametric function. One approach to

estimating $m(.)$ is to fit the data locally by solving the following least squares problem:

$$(3) \min_{\lambda_j} \sum_{i=1}^{N} \{ \hat{\xi}_{ilt} - \sum_{j=0}^{p} \lambda_j (DistancetoLake_i - $$

$$DistancetoLake_0)^j \}^2 w(DistancetoLake_i - DistancetoLake_0 | h)$$

Equation (3) defines a pth order polynomial regression estimated at the smoothing point

$DistancetoLake_0$. Observations closer to the smoothing point are given greater weight by the

kernel function $w(.)$, while no weight is given to observations outside the kernel's bandwidth

window defined by the parameter h. An estimate for $m(.)$ in equation (2) is recovered by

estimating equation (3) multiple times over different smoothing points.

The estimated constant term from each of these regressions $\hat{\lambda}_0$ defines the position of the

local regression at the smoothing point and is the parameter of interest as $\hat{\lambda}_0 =$

$\hat{m}(DistancetoLake_0)$.[iv] The spatial extent of water quality impacts on housing prices can be

determined by observing how the distance gradient evolves across space and finding where housing prices no longer respond to lake proximity.

Having established the spatial extent of water quality capitalization, we estimate a first-stage hedonic price function (Rosen 1974; Bishop et al. 2020) to recover the implicit price for HABs. Interactions between home buyers and home sellers define a price schedule that relates the price of a house to its attributes:

$$(4) \ln P_{ilt} = \beta_0 + \beta_1 \ln Algae_{ilt} + \beta_2 X_{it} + \delta_l + M_t + Y_t + \epsilon_{ilt}$$

$ln\, P_{ilt}$, M_t, Y_t are as defined as before, X_{it} includes property and locational attributes along with a measure of lake proximity (see Table A1 of the Supplementary Appendix), δ_l is a vector of census block group fixed effects, β is a vector of parameters describing the shape of the hedonic price function, while ϵ_{ilt} is an idiosyncratic and independently distributed error term. Spatial and temporal fixed effects are included to control for unobservable shifters, limiting identification to variation across time but within the extent of the spatial fixed effects.

Proximity measures to the lake and nearest boat ramp, highway, and city are included in X_{it} with log transformation to capture nonlinear proximity effects to local amenities as observed in other housing markets (Walsh, Milon, and Scrogin 2011; Wolf and Klaiber 2017). We do not have any prior expectations on the relationship between housing price and boat ramp proximity as boat ramps provide access to recreational opportunities but can also be a source of congestion (Timmins and Murdock 2007), while we expect housing prices to increase with highway distance. Two continuous measures of water quality are included in equation (4) with log transformation: $ln\, Algae_{ilt}$ and $ln\, Ecoli_{ilt}$. $ln\, Algae_{ilt}$ is our variable of interest and is a measure of HABs derived from remote-sensing data, while $ln\, Ecoli_{ilt}$ is a measure of E. Coli computed from *in situ* water samples and is included within X_{it} to control for other sources of

water contamination that affect near Lake Erie homeowners. We discuss in detail how E. Coli and HAB data are merged to housing transactions in the following section.

To address omitted variable and measurement error concerns, equation (4) is estimated using two-stage least squares (2SLS):

$$(5) \ln Algae_{ilt} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 \ln TP_t + \alpha_3 \ln TP_t * \ln DistancetoMaumee_l + \delta_l +$$
$$M_t + Y_t + \upsilon_{ilt}$$

$$(6) \ln P_{ilt} = \beta_0 + \beta_1 \ln \widehat{Algae}_{ilt} + \beta_2 X_{it} + \delta_l + M_t + Y_t + \epsilon_{ilt}$$

where υ_{ilt} is an idiosyncratic and independently distributed error term, $\ln TP_t$ and $\ln TP_t * \ln DistancetoMaumee_l$ instrument for $\ln Algae_{ilt}$ in equation (5), and the prediction from equation (5) is added as a regressor in equation (6). By instrumenting for $\ln Algae_{ilt}$, we are able to correct for time-varying sources of bias as well as measurement error that would otherwise be unaccounted for in the standard fixed effects model. It is difficult to determine which source of bias is more problematic, however, as we cannot disentangle one source of bias from the other. Following the causal estimation of β_1, the relationship between housing price and HABs can be recovered by taking the derivative of the hedonic price equilibrium with respect to $Algae_{ilt}$. We drop the subscripts i, l, and t from here on for brevity.

Valid instruments for HABs are variables that are correlated with HAB production but uncorrelated with property values. Measures of total phosphorus (TP) from the Maumee River meet these two requirements. Regarding the first requirement (relevance), TP from the Maumee River is expected to be positively correlated with HABs. The Maumee watershed is primarily used for agricultural purposes as approximately 80% of the land is used for farming (Richards, Calhoun, and Matisoff 2002). As heavy rain hits this watershed, some of the phosphorus and nitrogen applied to the land is leached out and transported to Lake Erie via the Maumee River

9

(see Figure 1). Larger and more frequent loads in turn create more favorable HAB conditions by increasing a limiting nutrient needed for algal production (Stumpf et al. 2012; Michalak et al. 2013; Zhou et al. 2013). It is unlikely that TP from the Maumee River is directly correlated with housing price as the majority of homes near Lake Erie are far from the river,[v] TP measurements are not contemporaneous with the timing of sales and HAB measures, and while home buyers are concerned about water quality, the amount of TP discharged into the lake is unlikely to impact decisions other than through their impact on HAB growth.

It is important to note that an instrumental variables approach could replace one biased coefficient with another if measurement error in the instrument is correlated with measurement error in the HAB measure. We do not suspect this to be the case, however, as the HAB and TP data come from two completely different sources. HAB data is derived from blue and green light reflected in satellite images, while concentrations of TP are recorded from water samples taken directly from the Maumee River. Both the HAB and TP data are likely measured with some error but for inherently different reasons (Abbott and Letelier 1999; Kovar and Pierzynski 2009; Moore, Campbell, and Dowell 2009; Dierssen 2010), while the process to identify and remove errant observations follows a different set of guidelines for each measure (Abbott and Letelier 1999; National Center for Water Quality Research 2021). Finally, we note that our results are robust to various data aggregation strategies which would likely induce large changes in the coefficient of interest if measurement error correlation were strong. We discuss where both data sources come from in the following section, while sensitivity to data aggregation methodology is reported in the results section.

Lake Erie Water Quality and Housing Transactions Data

Transaction data from single family residences are combined with remote-sensing water quality data to estimate the capitalized effect of HABs on near-lake homes. We collect housing transactions data from county auditor and tax offices covering the 7 counties highlighted in Figure 1 and augment it with detailed structural data purchased from the private data vendor CoreLogic. Records from this dataset include historic sales information, a geolocation, and structural characteristics for each property sold between 2003 and 2015. Potential house flippers, houses with outlier structural characteristics[vi], and homes labeled as vacant, or delinquent are removed to limit sources of bias.

Additional spatial characteristics are added to each housing transaction using its geolocation obtained from parcel shapefiles. Block group IDs are attached to each property using census shapefiles, while a continuous measure of Lake Erie proximity is calculated using shapefiles from the United States Geological Survey (USGS)'s National Hydrography Dataset. Lake adjacent homes are assigned the same distance value of 20 meters. We also compute proximity measures to the nearest boat ramp, highway, and major city (Cleveland or Toledo) using GIS and shapefiles from the Ohio Department of Natural Resources (ODNR) and the census. Housing summary statistics for near lake homes are provided in Table 1, while a description of the variables and their data sources are given in Table A1 of the Supplementary Appendix.

CHLA data are obtained from 8-day composite raster images spanning 2003 to 2014 for Lake Erie. This year-round data is derived from remote-sensing images captured on board NASA's MODIS-Aqua satellite and is uniformly gridded into 4 km by 4 km raster cells by the NASA Ocean Color program.[vii] Raster images are not available for every 8-day period due to ice coverage, cloud interference, and mixed pixels. A snapshot of the time-varying CHLA data (average conditions in 2006 and 2011) is shown in Figure 2 and highlights the heterogeneity in

water quality across space and time. There are 1,136 unique raster cells west of Ohio's eastern border (80°31'10.9"W) where CHLA data are available, with the average raster cell having 1.22 CHLA measurements available per month.

CHLA is used as the primary indicator of HABs in Lake Erie as hydrologists define occurrences of blooms using CHLA (Rinta-Kanto et al. 2005; Becker et al. 2009; Davis et al. 2012), while the Ohio EPA (2016), the US EPA (EPA 2019), and the WHO (WHO 2003) issue HAB health advisories based on CHLA concentrations. The WHO and EPA categorize the chances of having acute health effects during recreational activities as "mild" when CHLA levels are below 10 µg/L, "moderate" when CHLA levels are between 10 µg/L and 50 µg/L, and "high" when CHLA levels are greater than 50 µg/L (EPA 2020). We therefore use the terms CHLA and HABs interchangeably throughout the text, though we acknowledge that CHLA may be an imperfect measure of HABs.

CHLA measures are aggregated to the block group by year by month level by first finding the three closest satellite raster cells to each block group.[viii] CHLA readings taken over the past 6 months from these locations are then averaged and assigned to each housing transaction using the year, month, and block group in which the house sold.[ix] CHLA conditions observed 6 months preceding the sale of a home and close to the home's block group are expected to influence housing price. We define CHLA at the block group level so it will match the spatial scale of the fixed effect. This ensures the coefficient of interest β_1 is identified only from variation across time when spatial fixed effects are employed, removing spatially-varying sources of omitted variable bias. Summary statistics of the continuous HAB measure are provided in Table 1.

E. Coli data from 139 public access locations are collected from the Ohio Department of Health (ODH) and the EPA. Water samples are typically collected at least once a week during

the summer months of May – September and are available from 2003 - 2015. We follow the same practice of attaching E. Coli data to housing transactions as we did with CHLA, though a 6-month median is derived from the three closest sampling locations as opposed to a 6-month mean as it provided a better statistical fit. Unlike CHLA, E. Coli data are not available year-round. For housing transactions with no E. Coli samples taken 6 months prior to their sale date, we attach E. Coli data from the closest available month before the sale date instead (Wolf and Klaiber 2017).

TP levels from Lake Erie's largest tributary in Ohio (the Maumee River) are used as an instrument for HAB concentrations. We collect TP data from the USGS 04193500 monitoring station located in Waterville, Ohio (Figure 1). Monthly TP loads are calculated from daily readings using the flow-weighting procedure outlined in Richards et al. (2010). Using the monthly data, we create a 6-month mean TP measure. The natural log of TP is assigned to each housing transaction based on the year and month in which the property sold, though we offset TP 6 months from when the CHLA measures are taken to reflect the delayed relationship between the Maumee River and HABs (Stumpf et al. 2012; Wynne and Stumpf 2015; Sayers et al. 2019).[x] We form a second instrument by interacting the 6-month rolling TP measure with $ln\ DistancetoMaumee_l$, a measure of how far each block group centroid is to the end of Maumee River. This allows the effect of TP on HABs to vary with proximity to the Maumee River.

Results

Figure 3 shows the estimated price gradient (equation (2)) used to determine the spatial extent of water quality impacts, with the solid line representing the hedonic price gradient associated with

proximity to Lake Erie. 95% confidence intervals are also depicted in Figure 3 by the dashed black lines. Housing values decrease as one moves further from Lake Erie, reflecting the premium homeowners are willing to pay to live near and have quick access to Lake Erie. Eventually home values stabilize and are unresponsive to small changes in distance. This occurs around 1,200 meters when the 95% confidence interval crosses zero. Based on this result, we determine the spatial extent of water quality on property values to be 1.2 kilometers from the lake.

Similar housing price patterns are observed on other large waterbodies. For the Chesapeake Bay, price differentials extend up to 2 kilometers (Walsh et al. 2017), while in the Narragansett Bay property values respond to water quality change up to 1.5 kilometers away (Liu, Opaluch, and Uchida 2017). The size of the water body appears to influence this spatial threshold, with smaller waterbodies tending to have more localized effects. The spatial extent of water quality capitalization for the largest inland lake in Ohio – Grand Lake Saint Marys which has a surface area of 55 km^2 – is only 0.6 kilometers (Wolf and Klaiber 2017), while the hedonic gradient extends up to 1 kilometer away from freshwater lakes in Florida (Walsh, Milon, and Scrogin 2011).

We use the spatial patterns observed in Figure 3 to specify the hedonic market as consisting of homes within 1.2 kilometers of Lake Erie. Table 2 displays hedonic price coefficients for four separate models using this sample of 34,915 housing transactions. In the first column (Model 1) a hedonic price function is estimated using OLS with census block group fixed effects. In Model 2 – the baseline specification for equations (5) and (6) – HABs are instrumented using TP and TP interacted with distance to the Maumee River, while in Models 3 and 4 we instrument for HABs using 12-month and 18-month lagged TP.[xi]

Starting with the bold coefficient in Model 1, we find no relationship between HABs and housing price using a naïve OLS estimator. Our HAB elasticity coefficient becomes negative and statistically significant at the 1% level using instrumental variables in Model 2, with a 1% increase in HABs corresponding to a 0.11% decrease in housing price. Evaluated at the sample average housing value and HAB measure, this indicates a 1 µg/L (15.6%) increase in HABs will decrease housing price by $2,205. This estimate should be interpreted as a local average treatment effect as we identify the relationship between housing price and HABs using water quality change induced by TP runoff from the Maumee River.

As one would expect, inclusion of longer lagged instruments (Models 3 and 4) decreases the power of the instruments and attenuates the HAB elasticity towards the OLS estimate. A Durbin-Wu-Hausman (Wu 1973; Hausman 1978) test reveals the difference between the OLS and 2SLS estimate is statistically different in Models 2 and 3, while the null hypothesis is not rejected in Model 4. The first-stage Kleibergen-Paap F score (Bazzi and Clemens 2013) in the baseline model also indicates the instruments are relevant and not likely to produce coefficients more biased than OLS (Bound, Jaeger, and Baker 1995). We cluster standard errors at the block group level in all models, which is the level of spatial variation in the second instrument (Abadie et al. 2017). The sign and significance of the TP measures in the first-stage also match expectations (Table A3 of the Supplementary Appendix) with higher TP increasing HAB levels, though the relationship weakens with greater distance to the Maumee River.

The relationship between housing values and structural attributes also conforms to expectations. Housing values increase with square footage, parcel lot acreage, the number of bathrooms, but decrease with age. Adding features like a garage, fireplace, or central air conditioning will also increase the value of a home. From our spatial characteristics we also see

property values increase as a house moves closer to Lake Erie shoreline, with lake adjacent homes experiencing the largest premium. Proximity to a highway is also observed to decrease a home's value.

We consider Model 2 to be our preferred specification as the statistical tests in Table 2 suggest a 6-month lag between HABs and TP produces the strongest correlation in the first-stage. We therefore use Model 2 as our baseline going forward. It is important to note that we cannot definitively attribute our coefficient of interest to the effect of HABs alone as runoff from the Maumee River could induce change in other water quality attributes. We cannot directly test this as a full set of water quality controls (i.e. dissolved oxygen, suspended sediment, fecal coliform, etc.) is unavailable at the spatial and temporal scale of our analysis.

Temporal and Spatial Heterogeneity

In this section we test the sensitivity of our baseline estimates to alternative specifications and examine potential sources of heterogeneity. The collapse of the nationwide housing market and subsequent recession (2008 - 2010) likely changed the Lake Erie housing market. The capitalization of HABs could have changed over that time due to an unstable hedonic price equilibrium (Kuminoff and Pope 2014). To test this, we create three dummies indicating whether the property was sold during the housing boom (before December 2007), bust (December 2007 – June 2009), or recovery period (after June 2009) and allow the instruments, $ln\ Algae$, and the property characteristics to vary across these periods. We include all of the interaction terms in our model while excluding the level term ($ln\ Algae$) to prevent perfect collinearity and report the results under Model 5 in Table 3. Property damages from HABs peaked during the housing bust period, with a 1% increase in HAB concentrations corresponding to a 0.26% devaluation.

Negative capitalization is also observed during the boom and the bust period (-0.08 to -0.13), though the elasticity terms are smaller in magnitude.

Houses closer to the lakeshore may experience greater losses from water quality degradation (Walsh, Milon, and Scrogin 2011; Wolf and Klaiber 2017). We allow for this possibility by creating four spatial dummies indicating if the property is within 300 meters of Lake Erie (*Lake300*), between 300 meters and 600 meters (*Lake600*) between 600 meters and 900 meters (*Lake900*), and beyond 900 meters (*Lake1200*), and include interactions between the spatial dummies and $ln\ Algae$ in the updated model. The results from this spatially heterogenous model are reported under Model 6 of Table 3. Overall, we find the impact of HABs on property values attenuates as properties are farther from Lake Erie. Properties within 300 meters lose 0.13% of their value for every 1% increase in HABs, for instance, while properties in the farthest group experience very little to no HAB-related losses as indicated by the statistically insignificant coefficient.

Property Fixed Effects

Property fixed effects are one of the strongest hedges against time-constant omitted variable bias as they control for characteristics that are difficult to measure, like curb-appeal or the overall flow and design of a house (Palmquist 2005; Bishop et al. 2020). We swap census block group fixed effects for property fixed effects in Model 7 and Model 8 and limit the sample to repeat sale homes as inclusion of singleton observations leads to biased standard errors (Correia 2015). We report OLS and 2SLS coefficients from this auxiliary specification in Table 4 in the first and second column respectively. A statistical relationship between HABs and property values is not observed until $ln\ Algae$ is instrumented, where estimates from Model 8 indicate property values

will decrease by 0.16% for every 1% increase in HABs. This valuation is similar to our baseline elasticity as the two estimates are 0.64 standard errors apart when using Model 8 as the reference point. We continue to use Model 2 as the baseline given the similarity in estimates, concerns of selection bias in property fixed effect models (Palmquist 2005; Zabel 2008), and the ability to control for unobservables at a finer spatial scale without losing information that is useful when identifying heterogeneous treatment effects (Ortega and Taspinar 2018).

Exclusion of Near Maumee Observations

Although most of the housing observations are far from the Maumee River (recall the average distance to the drainage point is 129 kilometers), there are some houses that are located on or near the Maumee River. TP may be directly capitalized into housing prices for this subsample of homes, and therefore invalidate the instruments as greater tributary loadings may result in localized flooding and/or increased drowning risk. Houses located in Lucas County, where the Maumee River runs through the study area (see Figure 1), are excluded to determine the severity of this concern. The exclusion of these observations has little influence on the coefficient of interest (Table A2 in the Supplementary Appendix, Model 9), indicating that localized flooding is not biasing the capitalization estimates.

Robustness to Water Quality Aggregation

In the baseline model, we aggregate HABs to the block group level by finding the average CHLA measurement from the three closest satellite raster cells. Three alternative aggregation methods are reported in Table A2 of the Supplementary Appendix. A local median is used in Model 10, while greater weight is given to more proximate CHLA measures using an inverse

distance-weighted mean in Model 11 (see Leggett and Bockstael 2000 for more details). Finally in Model 12 we form a more spatially aggregated HAB measure by averaging across the five closest raster cells.

The estimates from models 10 – 12 are nearly identical to the baseline measure, indicating that measurement error correlation between the instruments and HAB measure is unlikely a concern. In particular, changes in how HAB data is aggregated to the block group level would add measurement error, though the source and degree of error will vary across models. If measurement error in the instruments were correlated with measurement error in the HAB measure, then the strength of this correlation would likely change across models 10 – 12 and produce different results. We do not find this to be the case, however.

Robustness to Functional Form

Incorrect specification of the hedonic price function can lead to omitted variable bias (Cropper, Deck, and McConnell 1988; Kuminoff, Parmeter, and Pope 2010). Simpler functional forms perform better with parsimonious models (Cropper, Deck, and McConnell 1988), while more complex functional forms are preferred when spatial fixed effects are included (Kuminoff, Parmeter, and Pope 2010). We test the baseline log-log specification by estimating a left hand-side Box-Cox model. First-stage predictions of HABs are included along with the other covariates in Model 2 as independent variables. The theta coefficient from this test (0.19) is close to zero suggesting that the dependent variable should be log transformed. We continue to use a log transformed dependent variable but test a simpler specification with all the independent variables included linearly. The results from this alternative specification are reported in Table A4 in the Supplementary Appendix, with the HAB coefficient statistically significant at the 1%

level. The average house is also predicted to lose nearly $1,800 in value for every 1 μg/L increase in HABs, which is similar to the baseline measure.

Finally, in Table A5 in the Supplementary Appendix we allow TP's effect on HAB concentrations to be linearly (Model 14) and inversely (Model 15) related to distance to the Maumee River within the first-stage regression. Additional heterogeneity is allowed in Model 16 (Table A6 in the Supplementary Appendix) by interacting *ln Algae* with an indicator of whether the house is located along the eastern or western Ohio shoreline. Properties in Lucas, Ottawa, Erie, and Lorain County are defined as being in the west, while all other properties are in the east. Results from these specifications largely mirror our primary findings and provide additional robustness to our results.

Policy Implications, Phosphorous Reduction Targets, and Climate Stressors

Using the coefficients from Model 2, we examine the economic implications of two policy scenarios: (1) a 40% reduction in lake-wide phosphorous loadings as suggested by the GLWQA, and (2) a laissez-faire scenario in which no policy intervention occurs, and water quality continues to degrade due to wetter springs and warmer summers in the Midwest (Portmann, Solomon, and Hegerl 2009). Predictions generated from Stumpf et al. (2016)'s HAB forecasting model are used to facilitate the analysis of both scenarios. Specifically, Stumpf et al. (2016) use spring TP from the Maumee River as the sole input into one of their HAB forecasting models. For the first scenario we apply a 40% reduction to current spring loadings,[xii] while in the second scenario we rely on phosphorous predictions generated from Johnson et al. (2015)'s SWAT (Soil Water Assessment Tool) model for the Maumee River.

A 40% reduction in June phosphorous loadings is expected to improve lake-wide water quality by approximately 54%. For the average homeowner in our sample this would translate into a 6% price appreciation or $7,589. We note that since this represents a non-marginal change in water quality conditions, our capitalization measures can be interpreted as an upper bound estimate of water quality capitalization as the hedonic price function approximates the consumer's bid function well only near ambient conditions (Rosen 1974; Wolf and Klaiber 2021). Conversely when there is a non-marginal degradation in water quality, our capitalization measures provide a lower bound estimate.

Applying the $7,589 price increase to all homes within the sample (N=34,915) indicates the value of the housing stock will increase by $265 million. This estimate does not consider the benefits accrued to homeowners excluded from the sample though. If we assume all homes within 1.2 kilometers of Lake Erie experience the same water quality benefit, regardless of if they were sold between 2003 – 2015, then the GLWQA would produce a total benefit of $670 million to 88,924 single-family residences.[xiii] The state government would also benefit from a one-time tax revenue increase of $10.5 million assuming a tax rate of 1.57%.[xiv]

The GLWQA benchmark may not be fully met by 2025, though there are likely benefits from partially meeting the GLWQA. We examine the extent of these benefits in Table 5 where a 10%, 20%, and 30% reduction in phosphorous loadings are applied to current conditions. We also include a state where the GLWQA is met in full (the last row) as a reference point. Benefits for the average homeowner in terms of water quality and property price are reported in columns two and three respectively, while the fourth (fifth) column shows the aggregate price (tax) increase for all single-family residences, sold or unsold, within 1.2 kilometers of Lake Erie. It is clear

from Table 5 that the value of the housing stock will significantly increase even if the GLWQA is not met completely.

As a point of comparison, the federal government currently spends $30 million per year in the Lake Erie watershed to limit phosphorous loading (Sohngen 2018). If we annualize our benefit estimate by the user cost of housing, which is 6.4% of the total house value for the Cleveland area (Himmelberg, Mayer, and Sinai 2005), we find the benefits from fully meeting the GLWQA are $42.9 million per year.[xv] This back-of-the-envelope calculation suggests the current annual expenditure on lake restoration would be covered in full by the expected housing price appreciation from the GLWQA.

We also calculate aggregate benefit estimates from models that allow for temporal (Model 5) and spatial (Model 6) heterogeneity in the HAB coefficient and report these measures in Table 5. Columns 6 – 9 report benefit estimates from the most recent HAB capitalization estimate which is representative of HAB valuation after the housing bust ($ln\ Algae * Recovery$). Meanwhile, HAB valuations are allowed to vary across space in columns 10 – 12, with property gains set to 0 for homes in the farthest distance band (>900 meters) due to the statistically insignificant estimate reported in Model 6 of Table 3. When calculating the aggregate measures in column 11, we find the average benefit for each house type (i.e. 0 – 300 meters, 300 meters – 600 meters, etc.) and then multiply that by the number of houses in that spatial band. The total benefits reported in Table 5 are the summed value across these four groups.[xvi]

Water quality in Lake Erie is expected to degrade without any policy-intervention and result in substantial losses for near lake homeowners. As part of a nationwide analysis, Johnson et al. (2015) model the impacts of climate change and urban development on indicators of water quality and streamflow. One region highlighted in this study is the Maumee River, which is

predicted to face a 14.3% to 17.5% increase in June phosphorous loadings by the year 2070.[xvii] This increase in sediment runoff would correspond to a 31.5% and 39.8% increase in HAB concentrations and lower property values in aggregate by $394.5 million and $498.6 million respectively under the baseline model. Translated into annualized terms, this would be equivalent to a $25.2 million and $31.9 million reduction in property values.

When interpreting the property value gains (losses) attributed to HAB reduction (growth), it is important to consider whether current water quality trends are an accurate depiction of the future. Under the traditional hedonic framework housing price differentials are a reflection of current and expected amenity levels. If future amenity levels deviate from observed trends and expectations are wrong as a result, then the hedonic estimates derived under a static framework are biased (Bishop and Murphy 2019). We do not believe this to be the case for our study, however. We analyze HABs and their relationship with housing price over a long time period (2003 – 2015), making the data more representative of standard conditions on Lake Erie. In addition, the increasingly poor water quality conditions observed between 2003 and 2015 continue to be observed in the 2020s (NOAA 2021), mitigating concerns that a mean reversion or diversion has occurred. Popular media outlets have also portrayed HABs as a Lake Erie mainstay (Briscoe 2019) that is not likely to dissipate, and may increase, due to climate change (Hauser 2018) unless substantial policy steps are taken (House and Michigan 2021). This coverage may have primed homeowners to view HABs as a quasi-irreversible water quality problem (Horsch and Lewis 2009), similar to the introduction of milfoil or zebra mussels into Lake Erie. Based on this evidence, we suspect the HAB growth observed between 2003 and 2015 was perceived by near lake homeowners as a permanent, long-run shift in water quality rather than a transient problem. Our valuations should therefore be considered consistent with

long-run expectations, even though they were derived within a static framework (Bishop and Murphy 2019).

Discussion and Conclusion

Investments in reducing the effects of harmful algal blooms in Lake Erie are a crucial step towards securing long-term economic and ecological stability in the area. Many shoreline communities depend on the revenue from visitors and residents drawn to Lake Erie and the wildlife it supports. Agricultural runoff and climate change have disrupted the economic balance of the area through the promotion of toxin-producing HABs. Public officials have responded by implementing relatively small-scale lake restoration projects, though larger investments are likely to follow. Reliable estimates of the impact of changes in water quality on nearby housing values are needed to better understand tradeoffs between land use patterns and maintaining healthy ecosystems. The capitalization estimates from this study provide policy insight for reliably weighing the cost of alternative lake restoration policies with their potential benefits.

Determining the appropriate extent of an environmental impact is challenging and is often a judgement made by the econometrician. Our study contributes to the water quality valuation literature by applying semiparametric methods (Linden and Rockoff 2008; Muehlenbachs, Spiller, and Timmins 2015; Haninger, Ma, and Timmins 2017) to determine the extent of water quality impacts on nearby homeowners. We find the impact of HABs on housing prices is spatially limited to properties within 1.2 kilometers of Lake Erie.

Second, we address omitted variable and measurement error concerns by developing instrumental variables from hydrological processes that link Maumee River runoff to nutrient concentrations in Lake Erie. We demonstrate that controlling for omitted variables and

24

measurement error offers economically and econometrically significant improvements over naïve OLS estimation. For the average near Lake Erie homeowner, a 1 μg/L reduction in HABs would result in capitalized gains of $2,205, which is statistically larger than the naïve OLS estimate. This difference highlights the need to mitigate potential sources of attenuation and omitted variable bias that are prevalent when studying large waterbodies. We note that sellers may be more likely to list their properties when water quality is better, responding to price expectations. This decision of when and how long to list could have additional welfare implications that are not captured by our housing price analysis and is left as an avenue for future research.

Finally, we use our econometric model to estimate the potential benefits from meeting the water quality goals outlined in the GLWQA as well as potential losses in a scenario where no intervention occurs. Estimates from Stumpf et al. (2016)'s HAB forecasting model indicate a 40% reduction in spring total phosphorous loadings, as called for by the GLWQA, would correspond to approximately a 54% reduction in HABs. In aggregate, this policy would produce a yearly benefit of up to $42.9 million which exceeds the current annual expenditure on water quality improvement. Homeowners are also found to benefit significantly from water quality improvement even if the GLWQA guidelines are not met in full.

If no policy intervention were to occur, near lake homeowners would lose at least $394.5 million due to additional, climate-driven water quality degradation. These potential losses highlight the importance of water quality management policies already implemented by the United States and Canadian government. Further research that integrates HAB valuations from this study within a coupled land-use and hydrology model under projected climate scenarios would likely be a promising avenue for future research.

Works Cited

[1]Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. 2017. "When should you adjust standard errors for clustering?" National Bureau of Economic Research (NBER) Working Paper Series.

[2]Abbott, Mark R., and Ricardo M. Letelier. "Algorithm theoretical basis document chlorophyll fluorescence (MODIS product number 20)." *NASA (http://www. modis. gsfc. nasa. gov/data/atbd)* (1999).

[3]Arenschield, Laura. "Toxic algae bloom now stretches 650 miles along ohio river." *The Columbus Dispatch* (2015).

[4]Bazzi, Samuel, and Michael A. Clemens. 2013. "Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth." *American Economic Journal: Macroeconomics* 5(2): 152-86.

[5]Becker, Richard H., Mohamed I. Sultan, Gregory L. Boyer, Michael R. Twiss, and Elizabeth Konopko. 2009. "Mapping cyanobacterial blooms in the Great Lakes using MODIS." *Journal of Great Lakes Research* 35(3): 447-453.

[6]Bejranonda, Somskaow, Fred J. Hitzhusen, and Diane Hite. 1999. "Agricultural sedimentation impacts on lakeside property values." *Agricultural and Resource Economics Review* 28(2): 208-218.

[7]Bishop, Kelly C., and Alvin D. Murphy. 2019. "Valuing time-varying attributes using the hedonic model: when is a dynamic approach necessary?" *Review of Economics and Statistics* 101(1): 134-145.

[8]Bishop, Kelly C., Nicolai V. Kuminoff, H. Spencer Banzhaf, Kevin J. Boyle, Kathrine von Gravenitz, Jaren C. Pope, V. Kerry Smith, and Christopher D. Timmins. 2020. "Best practices for using hedonic property value models to measure willingness to pay for environmental quality." *Review of Environmental Economics and Policy* 14(2): 260-281.

[9]Bound, J., Jaeger, D. A., & Baker, R. M. 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association*, *90*(430), 443-450.

[10]Boyle, K. J., Poor, P. J., & Taylor, L. O. 1999. Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics*, *81*(5), 1118-1122.

[11]Briscoe, T. "In the Great Lakes' most productive fishing grounds, algae-fueled dead zones are eroding livelihoods." *Chicago Tribune* (2019).

[12] Carmichael, Wayne W., and Gregory L. Boyer. 2016. "Health impacts from cyanobacteria harmful algae blooms: Implications for the North American Great Lakes." *Harmful Algae* 54: 194-212.

[13] Chay, Kenneth Y., and Michael Greenstone. 2005. "Does air quality matter? Evidence from the housing market." *Journal of Political Economy* 113(2): 376-424.

[14] Correia, Sergio. "Singletons, cluster-robust standard errors and fixed effects: A bad mix." *Technical Note, Duke University* 7 (2015).

[15] Cropper, Maureen L., Leland B. Deck, and Kenenth E. McConnell. 1988. "On the choice of funtional form for hedonic price functions." *The Review of Economics and Statistics*: 668-675.

[16] Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings." *American Economic Review* 105(2): 678-709.

[17] Davis, Timothy W., Florian Koch, Maria Alejandra Marcoval, Steven W. Wilhelm, and Christopher J. Gobler. 2012. "Mesozooplankton and microzooplankton grazing during cyanobacterial blooms in the western basin of Lake Erie." *Harmful Algae* 15: 26-35.

[18] Dierssen, Heidi M. 2010. "Perspectives on empirical approaches for ocean color remote sensing of chlorophyll in a changing climate." *Proceedings of the National Academy of Sciences* 107(40): 17073-17078.

[19] EPA. "Recommended human health recreational ambient water quality criteria or swimming advisories for microcystins and cylindrospermopsin (EPA 822-R-19-001)." (2019).

[20] EPA. "Recreational Water Quality Criteria and Methods." *Environmental Protection Agency* (2020). Retrieved August 25, 2020, from https://www.epa.gov/wqc/recreational-water-quality-criteria-and-methods#rec3

[21] Fan, Jianqing, and Irene Gijbels. 1992. "Variable bandwidth and local linear regression smoothers." *The Annals of Statistics*: 2008-2036.

[22] Gamper-Rabindran, Shanti, and Christopher Timmins. 2011. "Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data." *American Economic Review* 101(3): 620-24.

[23] Giardino, Claudia, Mariano Bresciani, Ilaria Cazzaniga, Karin Schenk, Patrizia Rieger, Federica Braga, Erica Matta, and Vittorio E. Brando. 2014. "Evaluation of multi-resolution satellite sensors for assessing water quality and bottom depth of Lake Garda." *Sensors* 14(12): 24116-24131.

[24]Gibbs, Julie P., John M. Halstead, Kevin J. Boyle, and Ju-Chin Huang. 2002. "An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties." *Agricultural and Resource Economics Review* 31(1): 39-46.

[25]Gopalakrishnan, Sathya, Martin D. Smith, Jordan M. Slott, and A. Brad Murray. 2011. "The value of disappearing beaches: a hedonic pricing model with endogenous beach width." *Journal of Environmental Economics and Management* 61(3): 297-310.

[26]GLWQA (Great Lakes Water Quality Agreement). "The United States and Canada adopt phosphorus load reduction targets to combat Lake Erie algal blooms." (2016). Available at: https://www.epa.gov/glwqa/recommended-binational-phosphorus-targets.

[27]Griffith, Andrew W., and Christopher J. Gobler. 2020. "Harmful algal blooms: a climate change co-stressor in marine and freshwater ecosystems." *Harmful Algae* 91: 101590.

[28]Haninger, Kevin, Lala Ma, and Christopher Timmins. 2017. "The value of brownfield remediation." *Journal of the Association of Environmental and Resource Economists* 4(1): 197-241.

[29]Hauser, C. "Algae Bloom in Lake Superior Raises Worries on Climate Change and Tourism." *New York Times* (2018).

[30]Hausman, Jerry A. 1978. "Specification tests in econometrics." *Econometrica: Journal of the Econometric Society*: 1251-1271.

[31]Himmelberg, Charles, Christopher Mayer, and Todd Sinai. 2005. "Assessing high house prices: Bubbles, fundamentals and misperceptions." *Journal of Economic Perspectives* 19(4): 67-92.

[32]Horsch, Eric J., and David J. Lewis. 2009. "The effects of aquatic invasive species on property values: evidence from a quasi-experiment." *Land Economics* 85(3): 391-409.

[33]House, Kelly., & Bridge Michigan. "Too few farmers are curbing pollution in Lake Erie. Should they be forced?" *Radio Broadcast, Michigan Public Radio* (2021).

[34]Jiang, Long, Meng Xia, Stuart A. Ludsin, Edward S. Rutherford, Doran M. Mason, Jose Marin Jarrin, and Kevin L. Pangle. 2015. "Biophysical modeling assessment of the drivers for plankton dynamics in dreissenid-colonized western Lake Erie." *Ecological Modelling* 308: 18-33.

[35]Johnson, Marianne, and Martin Meder. 2013. "Effects of aquatic invasive species on home prices: Evidence from Wisconsin." Social Science Research Network (SSRN) Working Paper Series.

[36]Johnson, T., J. Butcher, D. Deb, M. Faizullabhoy, P. Hummel, J. Kittle, S. McGinnis, L.O. Mearns, D. Nover, A. Parker, S. Sarkar, R. Srinivasan, P. Tuppad, M. Warren, C. Weaver,

and J. Witt. 2015. "Modeling streamflow and water quality sensitivity to climate change and urban development in 20 US watersheds." *JAWRA Journal of the American Water Resources Association* 51(5): 1321-1341.

[37] Keiser, David A. 2019. "The missing benefits of clean water and the role of mismeasured pollution." *Journal of the Association of Environmental and Resource Economists* 6(4): 669-707.

[38] Klemick, Heather, Charles Griffiths, Dennis Guignet, and Patrick Walsh. 2018. "Improving water quality in an iconic estuary: an internal meta-analysis of property value impacts around the Chesapeake Bay." *Environmental and Resource Economics* 69(2): 265-292.

[39] Kovar, John L., and Gary M. Pierzynski. 2009. "Methods of phosphorus analysis for soils, sediments, residuals, and waters second edition." *Southern Cooperative Series Bulletin* 408.

[40] Kuminoff, Nicolai V., Christopher F. Parmeter, and Jaren C. Pope. 2010. "Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities?." *Journal of Environmental Economics and Management* 60(3): 145-160.

[41] Kuminoff, Nicolai V., and Jaren C. Pope. 2014. "Do "capitalization effects" for public goods reveal the public's willingness to pay?." *International Economic Review* 55(4): 1227-1250.

[42] Larkin, Sherry L., and Charles M. Adams. 2007. "Harmful algal blooms and coastal business: economic consequences in Florida." *Society and Natural Resources* 20(9): 849-859.

[43] Leggett, Christopher G., and Nancy E. Bockstael. 2000. "Evidence of the effects of water quality on residential land prices." *Journal of Environmental Economics and Management* 39(2): 121-144.

[44] Linden, Leigh, and Jonah E. Rockoff. 2008. "Estimates of the impact of crime risk on property values from Megan's laws." *American Economic Review* 98(3): 1103-1127.

[45] Liu, Tingting, James J. Opaluch, and Emi Uchida. 2017. "The impact of water quality in Narragansett Bay on housing prices." *Water Resources Research* 53(8): 6454-6471.

[46] Liu, Hongxing, Sathya Gopalakrishnan, Drew Browning, and Gajan Sivandran. 2019. "Valuing water quality change using a coupled economic-hydrological model." *Ecological Economics* 161: 32-40.

[47] Liu, Hongxing, Wendong Zhang, Elena Irwin, Jeffrey Kast, Noel Aloysius, Jay Martin, and Margaret Kalcic. 2020. "Best management practices and nutrient reduction: an integrated economic-hydrologic model of the Western Lake Erie basin." *Land Economics* 96(4): 510-530.

[48]Markey, Matt. "Lake Erie's economic impact highlighted by officials." *The Toledo Blade* (2018).

[49]Manning, Nathan F., Yu-Chen Wang, Colleen M. Long, Isabella Bertani, Michael J. Sayers, Karl R. Bosse, Robert A. Shuchman, and Donald Scavia. 2019. "Extending the forecast model: Predicting Western Lake Erie harmful algal blooms at multiple spatial scales." *Journal of Great Lakes Research* 45(3): 587-595.

[50]McCluskey, Jill J., and Gordon C. Rausser. 2003. "Hazardous waste sites and housing appreciation rates." *Journal of Environmental Economics and Management* 45(2): 166-176.

[51]Michalak, Anna M., Eric J. Anderson, Dmitry Beletsky, Steven Boland, Nathan S. Bosch, Thomas B. Bridgeman, Justin D. Chaffin et al. 2013. "Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions." *Proceedings of the National Academy of Sciences* 110(6): 6448-6452.

[52]Moore, Michael R., Jonathan P. Doubek, Hui Xu, and Bradley J. Cardinale. 2020. "Hedonic price estimates of lake water quality: valued attribute, instrumental variables, and ecological-economic benefits." *Ecological Economics* 176: 106692.

[53]Moore, Timothy S., Janet W. Campbell, and Mark D. Dowell. 2009. "A class-based approach to characterizing and mapping the uncertainty of the MODIS ocean chlorophyll product." *Remote Sensing of Environment* 113(11): 2424-2430.

[54]Moses, Sheela A., Letha Janaki, Sabu Joseph, J. Justus, and Sheeja Ramakrishnan Vimala. 2011."Influence of lake morphology on water quality." *Environmental Monitoring and Assessment* 182(1): 443-454.

[55]Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins. 2015. "The housing market impacts of shale gas development." *American Economic Review* 105(12): 3633-3659.

[56]National Center for Water Quality Research. "The Heidelberg Tributary Loading Program." *National Center for Water Quality Research* (2021). Available at: https://ncwqr.org/monitoring/.

[57]Netusil, Noelwah R., Michael Kincaid, and Heejun Chang. 2014. "Valuing water quality in urban watersheds: A comparative analysis of Johnson Creek, Oregon, and Burnt Bridge Creek, Washington." *Water Resources Research* 50(5): 4254-4268.

[58]NOAA. "Annual Maximum Ice Cover - Lake Erie." *National Oceanic and Atmospheric Administration* (2020a). Retrieved from https://www.glerl.noaa.gov/data/ice/#historical

[59]NOAA. "Lake Erie Average GLSEA Surface Water Temperature (1995 - 2020)." *National Oceanic and Atmospheric Administration* (2020b). Retrieved from https://coastwatch.glerl.noaa.gov/statistic/

[60]NOAA. "NOAA Great Lakes Environmental Research Lab." *National Oceanic and Atmospheric Administration* (2020c). Retrieved from https://www.glerl.noaa.gov/data/dashboard/info/opLevels.html

[61]NOAA. "NOAA Lake Erie Harmful Algal Bloom Bulletin." *National Oceanic and Atmospheric Administration* (2021). Retrieved from https://www.glerl.noaa.gov/res/HABs_and_Hypoxia/lakeErieHABArchive/

[62]Ohio EPA. "Public Water System Harmful Algal Bloom Response Strategy." *Ohio Environmental Protection Agency, Division of Drinking and Ground Waters* (2016). Retrieved June, 2019, from https://epa.ohio.gov/Portals/28/documents/habs/PWS_HAB_Response_Strategy.pdf

[63]Ortega, Francesc, and Süleyman Taşpınar. 2018. "Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market." *Journal of Urban Economics* 106: 81-100.

[64]Paerl, Hans W., Wayne S. Gardner, Karl E. Havens, Alan R. Joyner, Mark J. McCarthy, Silvia E. Newell, Boqiang Qin, and J. Thad Scott. 2016. "Mitigating cyanobacterial harmful algal blooms in aquatic ecosystems impacted by climate change and anthropogenic nutrients." *Harmful Algae* 54: 213-222.

[65]Palm-Forster, Leah H., Frank Lupi, and Min Chen. 2016. "Valuing Lake Erie beaches using value and function transfers." *Agricultural and Resource Economics Review* 45(2): 270-292.

[66]Palmquist, Raymond B. "Property value models." *Handbook of Environmental Economics* 2 (2005): 763-819.

[67]Phaneuf, Daniel J., V. Kerry Smith, Raymond B. Palmquist, and Jaren C. Pope. 2008. "Integrating property value and local recreation models to value ecosystem services in urban watersheds." *Land Economics* 84(3): 361-381.

[68]Poor, P. Joan, Keri L. Pessagno, and Robert W. Paul. 2007. "Exploring the hedonic value of ambient water quality: a local watershed-based study." *Ecological Economics* 60(4): 797-806.

[69]Portmann, Robert W., Susan Solomon, and Gabriele C. Hegerl. 2009. "Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States." *Proceedings of the National Academy of Sciences* 106(18): 7324-7329.

[70]Richards, R. Peter, Frank G. Calhoun, and Gerald Matisoff. 2002."The Lake Erie agricultural systems for environmental quality project: An introduction." *Journal of Environmental Quality* 31(1): 6-16.

[71]Richards, R. P., D. B. Baker, J. P. Crumrine, and A. M. Stearns. 2010. "Unusually large loads in 2007 from the Maumee and Sandusky Rivers, tributaries to Lake Erie." *Journal of Soil and Water Conservation* 65(6): 450-462.

[72]Rinta-Kanto, J. M., A. J. A. Ouellette, G. L. Boyer, M. R. Twiss, T. B. Bridgeman, and S. W. Wilhelm. 2005. "Quantification of toxic Microcystis spp. during the 2003 and 2004 blooms in western Lake Erie using quantitative real-time PCR." *Environmental science & technology* 39(11): 4198-4205.

[73]Rosen, Sherwin. 1974. "Hedonic prices and implicit markets: product differentiation in pure competition." *Journal of Political Economy* 82(1): 34-55.

[74]Sayers, Michael J., Amanda G. Grimm, Robert A. Shuchman, Karl R. Bosse, Gary L. Fahnenstiel, Steven A. Ruberg, and George A. Leshkevich. 2019. "Satellite monitoring of harmful algal blooms in the Western Basin of Lake Erie: A 20-year time-series." *Journal of Great Lakes Research* 45(3): 508-521.

[75]Scavia, Donald, J. David Allan, Kristin K. Arend, Steven Bartell, Dmitry Beletsky, Nate S. Bosch, Stephen B. Brandt, Ruth D. Briland, Irem Daloğlu, Joseph V. DePinto, David M. Dolan, Mary Anne Evans, Troy M. Farmer, Daisuke Goto, Haejin Han, Tomas O. Höök, Roger Knight, Stuart A. Ludsin, Doran Mason, Anna M. Michalak, R. Peter Richards, James J. Roberts, Daniel K. Rucinski, Edward Rutherford, David J. Schwab, Timothy M. Sesterhenn, Hongyan Zhang, and Yuntao Zhou. 2014. "Assessing and addressing the re-eutrophication of Lake Erie: Central basin hypoxia." *Journal of Great Lakes Research* 40(2): 226-246.

[76]Scavia, Donald, Margaret Kalcic, Rebecca Logsdon Muenich, Noel Aloysius, Jeffrey Arnold, Chelsie Boles, R. Confessor, J. O. S. E. P. H. De Pinto, Marie Gildow, and Jay Martin. "Informing Lake Erie agriculture nutrient management via scenario evaluation." *University of Michigan: Ann Arbor, MI, USA* (2016).

[77]Smeltzer, Eric, and Steven A. Heiskary. 1990. "Analysis and applications of lake user survey data." *Lake and Reservoir Management* 6(1): 109-118.

[78]Sohngen, Brent, Kevin W. King, Gregory Howard, John Newton, and D. Lynn Forster. 2015. "Nutrient prices and concentrations in Midwestern agricultural watersheds." *Ecological Economics* 112: 141-149.

[79]Sohngen, Brent. "Reducing Phosphorus Could Require New Regulations." *The Columbus Dispatch* (2018).

[80]Stumpf, Richard P., Timothy T. Wynne, David B. Baker, and Gary L. Fahnenstiel. 2012. "Interannual variability of cyanobacterial blooms in Lake Erie." *Plos One* 7: e42444.

[81]Stumpf, Richard P., Laura T. Johnson, Timothy T. Wynne, and David B. Baker. 2016. "Forecasting annual cyanobacterial bloom biomass to inform management decisions in Lake Erie." *Journal of Great Lakes Research* 42(6): 1174-1183.

[82]Timmins, Christopher, and Jennifer Murdock. 2007. "A revealed preference approach to the measurement of congestion in travel cost models." *Journal of Environmental Economics and Management* 53(2): 230-249.

[83]Trevino-Garrison, Ingrid, Jamie DeMent, Farah S. Ahmed, Patricia Haines-Lieber, Thomas Langer, Henri Ménager, Janet Neff, Deon Van der Merwe, and Edward Carney. 2015. "Human illnesses and animal deaths associated with freshwater harmful algal blooms— Kansas." *Toxins* 7(2): 353-366.

[84]Vanderploeg, Henry A., James R. Liebig, Wayne W. Carmichael, Megan A. Agy, Thomas H. Johengen, Gary L. Fahnenstiel, and Thomas F. Nalepa. 2001. "Zebra mussel (Dreissena polymorpha) selective filtration promoted toxic Microcystis blooms in Saginaw Bay (Lake Huron) and Lake Erie." *Canadian Journal of Fisheries and Aquatic Sciences* 58(6): 1208-1221.

[85]Walsh, Patrick J., J. Walter Milon, and David O. Scrogin. 2011. "The spatial extent of water quality benefits in urban housing markets." *Land Economics* 87(4): 628-644.

[86]Walsh, Patrick, Charles Griffiths, Dennis Guignet, and Heather Klemick. 2017. "Modeling the property price impact of water quality in 14 Chesapeake Bay Counties." *Ecological Economics* 135: 103-113.

[87]Wang, Sonia, Carolyn Alkire, Anna Perry, and Spencer Phillips. 2019. "Lake Erie Ecosystem Services Assessment: Economic Benefits from Phosphorous Reductions" *Report, Key-Log Economics*.

[88]Watson, Sue B., Brian A. Whitton, Scott N. Higgins, Hans W. Paerl, Bryan W. Brooks, and John D. Wehr. "Harmful algal blooms." In *Freshwater Algae of North America*, pp. 873-920. Academic Press, 2015.

[89]Wells, Mark L., Vera L. Trainer, Theodore J. Smayda, Bengt SO Karlson, Charles G. Trick, Raphael M. Kudela, Akira Ishikawa, Stewart Bernard, Angela Wulff, Donald Anderson, and William Cochlan. 2015."Harmful algal blooms and climate change: Learning from the past and present to forecast the future." *Harmful Algae* 49: 68-93.

[90]WHO. "Guidelines for Safe Recreational Water Environments: Volume 1: Coastal and Fresh Waters." *World Health Organization* (2003). Available at: http://www.who.int/water_sanitation_health/publications/srwe1/en/. Last Accessed: 11/27/2019

[91]Wolf, David, Will Georgic, and H. Allen Klaiber. 2017. "Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry." *Journal of Environmental Management* 199: 148-157.

[92]Wolf, David, and H. Allen Klaiber. 2017. "Bloom and bust: Toxic algae's impact on nearby property values." *Ecological Economics* 135: 209-221.

[93]Wolf, David, Wei Chen, Sathya Gopalakrishnan, Timothy Haab, and H. Allen Klaiber. 2019. "The impacts of harmful algal blooms and E. coli on recreational behavior in lake erie." *Land Economics* 95(4): 455-472.

[94]Wolf, David, and Thomas Kemp. 2021. "Convergent Validity of Satellite and Secchi Disk Measures of Water Clarity in Hedonic Models." *Land Economics*, *97*(1): 39-58.

[95]Wolf, David, and H. Allen Klaiber. 2021. "Willingness to Pay in Hedonic Pricing Models." In *Oxford Research Encyclopedia of Economics and Finance*.

[96]Wu, De-Min. 1973. "Alternative tests of independence between stochastic regressors and disturbances." *Econometrica: Journal of the Econometric Society* (1973): 733-750.

[97]Wynne, Timothy T., and Richard P. Stumpf. 2015. "Spatial and temporal patterns in the seasonal distribution of toxic cyanobacteria in western Lake Erie from 2002–2014." *Toxins* 7(5): 1649-1663.

[98]Zabel, Jeffrey E. "Using hedonic models to measure racial discrimination and prejudice in the US housing market." In *Hedonic methods in housing markets*, pp. 177-201. Springer, New York, NY, 2008.

[99]Zhang, Congwen, Kevin J. Boyle, and Nicolai V. Kuminoff. 2015. "Partial identification of amenity demand functions." *Journal of Environmental Economics and Management* 71:180-197.

[100]Zhang, Wendong, and Brent Sohngen. 2018. "Do US anglers care about harmful algal blooms? A discrete choice experiment of Lake Erie recreational anglers." *American Journal of Agricultural Economics* 100(3): 868-888.

[101]Zhou, Yuntao, Daniel R. Obenour, Donald Scavia, Thomas H. Johengen, and Anna M. Michalak. 2013. "Spatial and temporal trends in Lake Erie hypoxia, 1987–2007." *Environmental Science & Technology* 47(2): 899-905.

Figure 1 – Lake Erie and the Maumee River watershed
Figure notes: our study area includes Lucas, Ottawa, Erie, Lorain, Cuyahoga, Lake, and Ashtabula County, which are cross-hatched in the figure above. Phosphorous loadings from the Maumee River watershed (light grey) are transported to Lake Erie's western basin via the Maumee River.

Figure 2 – Housing transactions and water quality in 2006 (top) and 2011 (bottom)
Figure Notes: Chlorophyll *a* measures in 2006 and 2011 are displayed in the top and bottom panel respectively, with darker grid cells corresponding to higher concentration levels. Housing transactions within 1.2km of Lake Erie are also depicted by circles.

Figure 3 – Housing price and Lake Erie proximity
Figure Notes: Results from local linear regressions (bandwidth = 100 meters) relating housing price residuals to Lake Erie distance.

Table 1 – Housing Summary Statistics of Near Lake Erie Homes

Variable Name	(N=34,915)			
	Mean	Std. Dev.	Min	Max
Purchase Price (2010 dollars)	126,696	84,112	17,057	752,081
Price Per Square Foot (2010 dollars)	82.76	36.60	25.00	331.20
Square Feet (100s)	14.97	5.58	5.76	48.15
Total Baths	1.54	0.63	1.00	4.50
Total Rooms	6.24	1.38	3.00	11.00
Acres	0.22	0.24	0.04	4.95
Age	56.79	26.84	1.00	115.00
Stories	1.42	0.45	1.00	3.00
Sale Year	2008	3.60	2003	2015
Sale Month	6.82	3.16	1.00	12.00
Garage (0/1)	0.72	0.45	-	-
Basement (0/1)	0.66	0.47	-	-
Fireplace (0/1)	0.39	0.49	-	-
AC (0/1)	0.59	0.49	-	-
Ecoli (CFU/mL)	0.76	0.92	0.01	18.00
Algae (μg/L)	6.43	2.12	2.39	21.77
TP (metric tons)	157.92	110.42	7.58	528.52
Distance to Lake (100s of Meters)	5.86	3.21	0.20	12.00
Distance to Ramp (100s of Meters)	27.97	19.81	0.45	137.04
Distance to Highway (100s of Meters)	6.71	8.70	0.06	59.05
Distance to City (100s of Meters)	373.48	242.19	18.68	1,079.85
Distance to Maumee (100s of Meters)	1,291.87	534.50	16.05	2,434.52

Table 2 – Identifying Harmful Algae's Relationship with Housing Price

VARIABLES	Model (1) OLS	Model (2) 6 Month Stagger	Model (3) 12 Month Stagger	Model (4) 18 Month Stagger
ln Algae	**0.0045**	**-0.1119*****	**-0.0838****	**-0.0030**
	(0.0101)	**(0.0354)**	**(0.0425)**	**(0.0735)**
ln Square Feet	0.5650***	0.5656***	0.5655***	0.5651***
	(0.0158)	(0.0158)	(0.0158)	(0.0158)
ln Age	-0.0729***	-0.0727***	-0.0728***	-0.0729***
	(0.0083)	(0.0083)	(0.0083)	(0.0083)
ln Acres	0.0961***	0.0961***	0.0961***	0.0961***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Total Baths	0.0932***	0.0932***	0.0932***	0.0932***
	(0.0076)	(0.0077)	(0.0077)	(0.0076)
Total Rooms	-0.0017	-0.0017	-0.0017	-0.0017
	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Stories	0.0290***	0.0286***	0.0287***	0.0290***
	(0.0093)	(0.0093)	(0.0093)	(0.0093)
Garage (0/1)	0.0630***	0.0633***	0.0632***	0.0630***
	(0.0074)	(0.0074)	(0.0074)	(0.0074)
Basement (0/1)	0.0538***	0.0539***	0.0539***	0.0538***
	(0.0092)	(0.0091)	(0.0091)	(0.0092)
Fireplace (0/1)	0.0394***	0.0396***	0.0395***	0.0394***
	(0.0065)	(0.0065)	(0.0065)	(0.0065)
AC (0/1)	0.0577***	0.0570***	0.0572***	0.0576***
	(0.0077)	(0.0078)	(0.0078)	(0.0077)
ln Ecoli	-0.0326***	-0.0382***	-0.0369***	-0.0330***
	(0.0071)	(0.0074)	(0.0074)	(0.0080)
ln Distance to Lake	-0.1346***	-0.1341***	-0.1342***	-0.1345***
	(0.0107)	(0.0107)	(0.0107)	(0.0107)
ln Distance to Ramp	-0.0055	-0.0044	-0.0047	-0.0054
	(0.0243)	(0.0243)	(0.0243)	(0.0244)
ln Distance to Highway	0.0358***	0.0357***	0.0357***	0.0358***
	(0.0069)	(0.0069)	(0.0069)	(0.0069)
ln Distance to City	0.0936	0.0922	0.0925	0.0935
	(0.2394)	(0.2404)	(0.2402)	(0.2393)
Month FE	YES(11)	YES(11)	YES(11)	YES(11)
Year FE	YES(12)	YES(12)	YES(12)	YES(12)
Census Block Group FE	YES(332)	YES(332)	YES(332)	YES(332)
KP F-statistic[a]	-	340.6	86.86	22.06
Durbin-Wu-Hausman ($X^2(1)$ value)	-	10.38***	3.60**	0.01
Observations	34,915	34,915	34,915	34,915

Notes: [a]Kleibergan-Paap Wald F statistics are reported. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Robust standard errors are clustered at the census block group level.

Table 3 – Spatial and Temporal Heterogeneity

VARIABLES	Model (5) Boom, Bust, Recovery	Model (6) Spatial Heterogeneity
ln Algae*Boom	-0.0844***	-
	(0.0297)	-
ln Algae*Bust	-0.2568***	-
	(0.0634)	-
ln Algae*Recovery	-0.1349***	-
	(0.0444)	-
ln Algae*Lake300	-	-0.1265***
	-	(0.0471)
ln Algae*Lake600	-	-0.1237***
	-	(0.0394)
ln Algae*Lake900	-	-0.1145***
	-	(0.0402)
ln Algae*Lake1200	-	-0.0578
	-	(0.0484)
Property and Locational Controls	YES (43)[b]	YES(15)
Distance Band Indicators	NO	YES(3)
Month FE	YES(11)	YES(11)
Year FE	YES(12)	YES(12)
Census Block Group FE	YES(332)	YES(332)
KP F-statistic[a]	143.9	85.44
Durbin-Wu-Hausman (X^2 value)	17.10***	16.44***
Observations	34,915	34,915

Notes: [a]Kleibergan-Paap Wald joint F statistics are reported. [b]Property and locational controls, excluding ln Ecoli, are interacted with period dummies. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Robust standard errors are clustered at the census block group level.

Table 4 – Property Fixed Effects

VARIABLES	Model (7) OLS	Model (8) 2SLS
ln Algae	**-0.0188**	**-0.1558****
	(0.0176)	**(0.0684)**
Month FE	YES(11)	YES(11)
Year FE	YES(12)	YES(12)
Property FE[a]	YES(6,514)	YES(6,514)
KP F-statistic[b]	-	202
Durbin-Wu-Hausman (X^2 value)	-	5.15**
Observations	14,415	14,415

Notes: ln Ecoli is included as a control along with property-level fixed effects. [b]Kleibergan-Paap Wald F statistic is reported. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Robust standard errors are clustered at the census block group level.

Table 5 – Aggregate Benefits from Partially and Fully Meeting the Great Lake's Water Quality Agreement

Lake-wide Phosphorous Reduction	HAB Reduction for Average Homeowner (μg/L)	Baseline (Model 2)			Temporal Heterogeneity (Model 5)			Spatial Heterogeneity (Model 6)		
		Homeowner Benefits	Total Benefits (millions)[a]	Tax Revenue (millions)[b]	Homeowner Benefits	Total Benefits (millions)[a]	Tax Revenue (millions)[b]	Homeowner Benefits	Total Benefits (millions)[a]	Tax Revenue (millions)[b]
10%	1.12	$2,471.10	$218.18	$3.43	$2,979.01	$263.03	$4.13	$2,178.58	$196.48	$3.08
20%	2.05	$4,520.14	$399.10	$6.27	$5,449.22	$481.13	$7.55	$3,984.69	$359.37	$5.64
30%	2.81	$6,196.89	$547.15	$8.59	$7,470.60	$659.61	$10.36	$5,463.33	$492.72	$7.74
40%	3.44	$7,589.10	$670.07	$10.52	$9,148.97	$807.80	$12.68	$6,690.73	$603.42	$9.47

Notes: Homeowner benefits are measured in 2010 dollars, while aggregate benefits and tax revenue are measured in millions of 2010 dollars. [a]Aggregate benefits are calculated for all homes (sold or unsold) within 1.2 kilometers of Lake Erie. [b]Based on a 1.57% tax rate.

[i]All values cited in the text are converted into 2010 dollars using the Consumer Price Index or National Case-Shiller Home Price Index.

[ii]Lake Erie experienced significant changes in water depth, surface temperature, and ice-coverage over the last 20 years, with conditions fluctuating by 3.2 feet, 10°F, and 83.7% respectively (NOAA 2020a; NOAA 2020b; NOAA 2020c). Historical measurements for these conditions are not available at a high spatial and temporal resolution, however.

[iii]S_{it} includes all of the housing and water attributes listed in Table 1A of the Supplementary Appendix, except for Lake Erie proximity.

[iv]We estimate a local linear estimator ($p = 1$) using an Epanechnikov kernel function and a bandwidth equal to 100 meters. Our results are robust to larger and smaller bandwidths, different kernel functions, and higher and lower ordered polynomial functions.

[v]The average distance to the drainage point in our sample is 129 kilometers.

[vi]Any observation with a covariate value in the 1st or 99th percentile was removed from the sample to eliminate outliers.

[vii]4 km by 4 km is the finest level of mapped data provided by NASA Ocean Color program. Although the grid size is measured at a low spatial resolution, it is less susceptible to errant satellite readings (Giardino et al. 2014; Wolf and Kemp 2021) and is representative of water quality at the block group level, which is the level at which we allow our HAB measure to vary spatially. CHLA data are free to the public and available to download at: https://oceandata.sci.gsfc.nasa.gov/MODIS-Aqua/Mapped/8-Day/4km/chlor_a/.

[viii]The average distance between the satellite raster cell and the block group centroid is 2.9 km, with a standard deviation of 1.9 km.

[ix]For the average house in the sample, their 6-month block group measure of CHLA is derived from 22 satellite readings. Our results are robust to a number of aggregation strategies, including using a 6-month rolling median as opposed to a 6-month rolling average, aggregating across the 5 closest neighbors and giving greater weight to more proximate raster cells. Results from these alternative specifications are consistent with those in the main text. We display three of these alternative specifications in Table A2 in the Supplementary Appendix.

[x]TP 7 to 12 months prior to the sale month are used as an instrument for HAB conditions 1 to 6 months prior, in other words.

[xi]To test the robustness of this spatial threshold, we estimate a series of hedonic regressions (Model 2) where the spatial cutoff is slowly increased. In the first regression we limit the sample to properties within 500 meters of Lake Erie and increase the cutoff by 250-meter increments until 10 kilometers is reached. The *ln Algae* coefficients and their 95% confidence intervals are displayed in panel A of Figure A1 in the Supplementary Appendix, with the overall trend matching expectations that the effect of HABs attenuates towards 0 as more distant homes are added to the sample.

[xii]Specifically, we find the average March - June total phosphorous loadings collected between 2003 and 2015 and use this as a reference point for current water quality conditions. To predict future water quality conditions, we apply a 40% reduction to this reference point and input that number into Stumpf et al. (2016)'s HAB forecasting model.

[xiii]We examine how this benefit estimate changes across different sample cutoffs in panel B of Figure A1 in the Supplementary Appendix.

[xiv]We continue to include unsold and sold homes in our aggregated benefit calculations from hereon due to the rationale provided by McCluskey and Rausser (2003). H&R Block indicates the average property tax rate in Ohio is 1.57%.

[xv]The annualized benefits from a 40% reduction in phosphorous are likely larger than our scenario estimates as meeting the GLWQA will not only improve current water quality conditions but also prevent additional water degradation from occurring. Improvements in water quality will also lead to higher welfare through recreation (Wolf, Georgic, and Klaiber 2017; Zhang and Sohngen 2018; Wolf et al. 2019) and increased non-use value, though some of these benefits are already accounted for in our capitalization measures. In particular, our capitalization estimates reflect both the recreational and amenity value conferred to near Lake Erie homeowners from a reduction in HABs (Phaneuf et al. 2008). They do not, however, include benefits that extend to recreationalists living far from Lake Erie (>1.2km) or from renters and near Lake Erie residents living in multifamily homes.

xviAs a point of reference, there are 24,738, 23,776, 21,559 and 18,221 homes within the first, second, third, and fourth closest distance band respectively.

xviiWe limit our focus to only climate predictions generated from the Geophysical Fluid Dynamics Laboratory (GFDL) Model and the Third Generation Coupled Global Climate (CGCM3) Model. These are denoted as scenarios L0W3 and L0W5 respectively in Johnson et al. (2015)'s paper.