Bloom and Bust: Toxic Algae's Impact on Nearby Property Values

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Abstract

Over the past decade harmful algal blooms (HABs) have become a nationwide environmental concern. HABs are likely to increase in frequency and intensity due to rising summer temperatures caused by climate change and higher nutrient enrichment from increased urbanization. Policymakers need information on the economic costs of HABs to design optimal management policies in the face of limited budgets. Using a detailed, multi-lake hedonic analysis across 6 Ohio counties between 2009 and 2015 we show capitalization losses associated with near lake homes between 12% and 17% rising to over 30% for lake adjacent homes. In the case of Grand Lake Saint Marys, we find capitalization losses exceeding $48 million for near lake homes which dwarfs the State of Ohio's cleanup expenditure of $26 million.

Keywords: harmful algal bloom; hedonic; blue green algae; cyanobacteria; capitalization; inland lake

JEL Codes: Q25, Q51, Q53, Q57

1. Introduction

On August 2nd, 2014 the city of Toledo, Ohio issued a warning to its 500,000 metro residents advising them not to drink, bathe in, or boil their tap water. Later that same day approximately 60 people were hospitalized with abdominal pain, the governor of Ohio, John Kasich, declared a state of emergency and the National Guard was called in to distribute thousands of gallons of bottled water to residents. What was at the heart of this commotion? Massive blue green algae(cyanobacteria) blooms which formed near the public water intake pipe. Although not all algae is dangerous, the blooms near Toledo produced a freshwater toxin called *microcystin* which can be harmful to humans and animals if ingested (Carmichael 1992). Symptoms of cyanobacteria poisoning include skin irritation, vomiting, diarrhea, acute liver toxicosis, gastrointestinal disturbances, fever, pneumonia, and even death.

In addition to being a public health concern, cyanobacteria blooms are becoming increasingly expensive for water treatment facilities to manage. After an algal bloom spread 650 miles across the Ohio River in early fall of 2015, the Greater Cincinnati Water Works was reportedly spending $7,500 a day to remove the harmful toxins (Arenschield 2015, Oct). The Celina water treatment plant, which pumps its untreated water from Grand Lake Saint Marys (GLSM) in Ohio, recently upgraded its facility to address worsening water conditions found at the lake. Initial construction and installation costs for the new plant were $7.2 million while the annual operating costs have remained steady around $500,000 over the past seven years (Raymond 2012). The city of Celina has passed along some of these costs to consumers by charging an additional $7.50 fee on utility bills (Miller 2015).

As a result of both health warnings and aesthetic concerns, the general public has taken notice of deteriorating water conditions associated with harmful algal blooms (HABs). Lakeshore residents across multiple states have reported anecdotal evidence of significant declines in their property values with some even suggesting a 30-50% drop due to the presence of HABs (Arenschield 2015, Oct; Rathke 2015). Highlighting the increase in public awareness of blue green algae, a nationwide LexisNexis search for the keyword “blue green algae” found 304 popular press articles relating to the topic published between 2009 and 2010. This number has steadily risen since 2009, reaching 347 in 2011 and 2012 and 438 in the 2013-2014 period. Public concern over HABs is also reflected in Google Trends data which is displayed in Figure 1.[1] Google searches for the term “algal bloom” have been rising across time, with interest in the topic appearing to be cyclical corresponding to months when algal blooms are most prevalent. Across all 50 states, Ohio residents appear to be the most attuned to this topic, garnering a relative search value of 100 as shown in Figure 2.

Building on the anecdotal evidence of negative property price impacts and the relatively high level of public awareness of blue green algae in Ohio, this paper is the first to use revealed preference housing market data to obtain direct estimates of the potential housing price capitalization losses associated with blue green algae. To accomplish this we use a number of inland lake housing markets scattered across Ohio combined with time-varying *microcystin* levels obtained from in-lake monitoring stations to estimate hedonic models of blue green algae’s impact on nearby housing prices. Given the large sums of ongoing public expenditure allocated to mitigate algal blooms, it is imperative that policymakers have actual damage (cost) estimates associated with harmful algal blooms (HABs) as an input into cost-benefit decision making when confronting this public health and amenity threat.

Using data on *microcystin* concentrations associated with HABs for four inland lakes in Ohio between 2009 and 2014 we estimate a series of first-stage hedonic models to examine the impact of HABs on surrounding property prices. Our primary findings show that housing values decline between 12% and 17% when *microcystin* concentration levels surpass the no-drinking threshold set by the World Health Organization. This finding is robust to numerous spatial and temporal constraints and the manner in which *microcystin* values are assigned to housing units.

[1] Google Trends data were collected between July 1st, 2009 and May 1st, 2015. This time frame corresponds with the sample time period.

However, we find little evidence that housing values respond to marginal changes in *microcystin* after reaching this threshold. This suggests that policies designed to eliminate, rather than constrain, *microcystin* levels are likely to have greater benefits to surrounding residents in terms of property price impacts. However, this result could also suggest a disconnect between potentially increasing public health concerns as *microcystin* levels increase and nearby residents perceptions of these risks.

The remainder of the paper is structured as follows. The next section briefly reviews the literature on water quality as it relates to property values. Section 3 describes the housing and HAB data used in our analysis. Section 4 introduces our hedonic specification and is followed in section 5 by our estimation results. Finally, section 6 concludes.

2. Linking property price impacts to water quality

There exists a significant volume of empirical literature devoted to valuing changes in water quality, with eutrophication cited as one of the primary catalysts causing a shift in water conditions (Boyle, Poor and Taylor 1999; Bejranonda, Hitzhusen and Hite 1999; Hill, Pugh and Mullen 2007; Smeltzer and Heiskary 1990). Eutrophication occurs in lakes when there is an excessive amount of nutrients present. Although nutrient levels rise naturally as lakes age, eutrophication can also be a direct consequence of human behavior. Agricultural run-off, poorly managed septic systems and increased housing development can lead to increased algal growth. When algal densities reach extreme levels a thick mat of algae will often envelop the surface of the water, preventing sunlight from reaching the bottom of the lake. Aquatic species that are dependent on this sunlight will begin to die off which in turn can shift the fundamental structure of the ecosystem (Smith, Tilman and Nekola 1999).

Increased algal growth has also been known to negatively affect lakeshore communities by decreasing the recreational and aesthetic benefits gained from interacting with a nutrient-rich body of water (Bejranonda, Hitzhusen, and Hite 1999). Large algal blooms will often cause the color of the water to turn green and can produce offensive odors when they start to decay. Determining the appropriate variable to model the eutrophication process and to use as a proxy for water quality, however, has not been rigorously established in the literature (Holly, Boyle and Bouchard 2000; Poor et al. 2001; Egan, et al. 2009).

Although a wide spectrum of variables have been used as a proxy for water quality, Secchi depth is perhaps the most frequently used and accepted. Studies using Secchi depth typically conclude the following two results. First, homeowners/lake-users are willing to pay (WTP) more to live near/use a lake if it is less turbid, ceteris paribus (Gibbs et al. 2002; Egan et al. 2009). The relationship between Secchi depth and WTP appears to be nonlinear, however, since WTP estimates increase at a decreasing rate as Secchi depth increases (Ge, Kling and Herriges 2013). Intuitively this suggests homeowners and lake-users are WTP more to improve the water quality of a dirty lake than a clean lake (Tait et al. 2012). Policies aimed at improving water quality are therefore considered less valuable than similar interventions that aim to prevent water quality degradation of a similar magnitude from occurring.

Second, researchers have discovered the gains from improved water quality are spatially limited and vary depending on the size of and distance from the water body in question (Jørgensen et al. 2013). Capitalization estimates derived from a one foot increase in Secchi depth, for example, were found to be almost 8 times larger for lakefront properties than for non-lakefront properties. These estimates also declined monotonically as distance from the affected water body increased and converged to 0 at distances greater than 1,000 meters (Walsh, Milon and Scrogin 2011). The size of the lake is also an important factor to consider when determining the size of the gains produced from an increase in water quality. Lakefront property values have been found to be more susceptible to changes in water conditions when they are located near larger lakes, holding all else equal (Boyle, Poor and Taylor 1999; Gibbs et al. 2002; Walsh, Milon and Scrogin 2011).

Recently a number of other measures, besides Secchi depth, have emerged in the hedonic literature to capture water quality. Poor et al. (2007) used measures of suspended solids and dissolved nitrogen as a proxy for ambient water quality in Maryland, while others have used lake depth (Bejranonda, Hitzhusen and Hite 1999), fecal coliform (Leggett and Bockstael 2000), pH (Tuttle and Heintzelman 2015) or a water index constructed from a number of physical and chemical measures (Ge, Kling and Herriges 2013). Most of these studies find a robust negative relationship between housing/land values and worsening water conditions. This suggests that although Secchi depth is an important indicator of a water body's health, it is not the only variable that can be used as a proxy for water quality.

Despite the significant amount of research dedicated to valuing changes in water quality, very few studies have directly valued the impact of toxic algae on economic behavior. No studies, to our knowledge, have obtained housing capitalization estimates for blue green algae using revealed preference data. The need for such valuation estimates is increasing due to the rise of blue green algae and other HABs globally (Anderson 1994; Hallegraeff 1993). HABs are becoming increasingly problematic for communities worldwide due to excessive nutrient loadings coupled with more favorable growth conditions resulting from climate change (Robson and Hamilton 2003; Mooij et al. 2005).

Climate change and rising average summer temperatures have promoted HAB growth via three channels. First cyanobacteria grow at a much faster rate than other phytoplankton when temperatures rise above the 23 degrees Celsius mark, making it difficult for non-toxic algae to compete (Joehnk et al. 2008). Water columns also become more stratified when temperatures rise. This in turn favors more buoyant algae (i.e. cyanobacteria) since these algae will rise to the surface of the water and prevent sunlight from reaching less buoyant algae below (Huisman et al. 2004). Last climate change has altered weather patterns around the world. Areas that are less cloudy and have lower wind speeds will tend to have greater water column stratification which, as previously mentioned, gives an advantage to cyanobacteria (Joehnk et al. 2008).

Cyanobacteria are well adapted to survive in a variety of climates but the value they remove from communities is not well understood. The few studies that have attempted to value changes in cyanobacteria levels have implemented contingent valuation (CV) methods, travel cost models or choice experiments. Hunter et al. (2012) elicit WTP estimates for a reduction in morbidity risk due to a reduction in cyanobacteria using survey data collected from residents of two towns located near Loch Leven in Scotland. The results from this study suggest that each household is willing to pay approximately £10 a year to reduce the annual number of risky days by half. However approximately 20% of the respondents had a WTP value of 0 and indicated that the "polluter should pay" (Hunter et al. 2012). Kosenius (2010) set up a choice experiment where respondents were asked to choose between four different policies that would either improve water clarity, reduce the occurrence of cyanobacteria blooms, reduce the quantity of coarse fish or improve local aquatic vegetation in the Gulf of Finland. On average improvements in water clarity were considered the most important followed by a reduction in the occurrence of cyanobacteria blooms.

Excessive amounts of cyanobacteria can also disrupt recreational activities. Using a rich set of survey data, which included responses from 8,000 Iowa households spanning 129 lakes, Egan et al. (2009) find that cyanobacteria and phytoplankton levels are the most important pair of water quality measures to supplement with Secchi depth to determine a recreators' optimal location choice. Their results also suggest that higher concentrations of cyanobacteria, while holding all other water quality measures constant, will reduce the likelihood of a person visiting a lake.

The above studies consistently show that high levels of cyanobacteria impact lake-users' decision-making process. However all of the aforementioned work depends on CV or travel-cost models to elicit WTP estimates for recreation behavior or use proxies that are more general measures of lake quality rather than specific HAB indicators. We fill this gap in the literature by providing the first set of hedonic-based valuation estimates for blue-green algae.

3. Data

Our study area consists of 6 counties surrounding 4 inland Ohio lakes highlighted in Figure 3.[2] These lakes were specifically chosen due to an extensive set of time-varying water quality monitoring data as well as the availability of detailed housing transactions data available from county auditors. Given the large number of inland lakes across the country that are facing *microcystin* contamination, these lakes provide a platform to estimate potential capitalization losses that could be experienced across other inland lakes as climate change combined with increased nutrient runoff exacerbates the frequency of HABs moving forward.

Housing transactions data were collected from six different county auditor websites across Ohio including Auglaize, Fairfield, Licking, Logan, Mercer and Shelby counties. This data includes historic sales information and select structural characteristics for each property sold between July 2009 and April 2015. Depending on county, additional housing characteristics were obtained from CDs provided by county auditors. We restricted our analysis to homes identified as single family, omitting potential multi-family dwellings as is standard in much of the hedonic literature.

In addition to focusing on single family homes, houses that were sold more than once during the same year were removed to eliminate potential house flippers. Delinquent and vacant properties were also eliminated in an attempt to remove unobservable characteristics that are likely associated with these properties. Houses with extreme physical characteristics (i.e. any observation with a covariate value in the 1st or 99th percentile) were labeled as outliers and excluded from our final sample. Finally, single family residences that were sold for less than \$50,000 or had a price per square foot value less than \$40/foot were removed to eliminate potential non-arms-length transactions

[2]We omitted Perry County, which is adjacent to Buckeye lake due to limited GIS and housing data..

Summary statistics for our cleaned sample of 16,589 housing transactions are shown in Table 1 for both the whole sample as well as subsamples of lakes used in our subsequent analysis. The average house sold in our sample was valued at approximately $148,589, had 1752 square feet, one and a half stories, a garage, a fireplace, and was 32 years old. The characteristics of houses vary significantly across inland lake housing markets as shown in additional columns of Table 1. Houses near Buckeye Lake were on average worth $23,000 more than the homes sold in Ohio's west market. Houses near GLSM, Indian Lake and Lake Loramie were more likely to have a garage, were older, and had smaller lot sizes than homes located near Buckeye Lake.

Having assembled housing transactions data, we georeferenced each transaction to a spatial location using parcel shapefiles collected from either county GIS maps or engineering departments. Importantly, the use of micro-level GIS data to identify the locations of homes sold allows us to form spatially explicit measures of lake proximity which have been shown in the prior literature to play an important role in determining highly localized capitalization effects of lake quality. Figure 4 provides an example of parcel proximity to lakes and highlights parcels located within 500 meters of GLSM

To identify lake proximity measures, we obtained lake shapefiles from the USGS's National Hydrography Dataset, along with census tract shapefiles which were overlaid onto the parcel shapefiles using ArcGIS. This process enabled us to attach additional spatial characteristics to each house including distance to lake as well as census tract identifiers. We assigned homes into discrete distance bands surrounding lakes. Lakefront properties were defined based on parcels located within 20 meters of a lake. We defined additional bands at the 250 and 500 meter cutoffs with properties outside these bands in a remaining non-lake category.[3] Summary statistics for these measures are shown in the second panel of Table 1.

[3]Adding a continuous measure of distance/inverse distance to our model specification did not qualitatively change any of the study's findings.

In the first panel of Table 1 we present information on the number of housing transactions near each lake. Approximately 5% of the sample consists of homes that were sold within 500 meters of a lake: 1.2% of the properties were sold within 20 meters of a lake, 2.1% were located between 20 and 250 meters of a lake, and 2.3% were located between 250 and 500 meters of a lake. The relatively small increases between each distance band does not come as a surprise since all of the lakes used in this study come from rural areas of Ohio. In the right panel of Table 1 we separate housing transactions by lake. There are more lakefront and l near lake homes sold near GLSM, Indian Lake and Lake Loramie than near Buckeye Lake. This likely reflects the size of the lakes with the surface area for Buckeye Lake only 3,136 acres whereas the combined surface area for the three aforementioned lakes is 18,647 acres.

Cyanobacteria data were collected from the HAB division of the Ohio EPA, Ohio's Public Water Systems, the Citizen Lake Awareness and Monitoring (CLAM) database and from the Ohio Department of Natural Resources. All of these institutions measured the density of harmful algae by recording *microcystin*, *cylindrospermopsin* and/or *saxitoxin* concentration levels. Since *microcystin* are the most commonly produced freshwater toxin/by-product of cyanobacteria, it was used as a proxy for blue-green algae (Chorus and Bartarm, 1999). Of the four lakes used in this study, Buckeye and GLSM were the most frequently sampled. GLSM contained 792 readings while Buckeye Lake had 334. Indian Lake and Lake Loramie were less frequently tested only having 41 and 16 *microcystin* samples taken, respectively. Most of the sample locations within each lake did not have data for all years (2009 – 2014), but for the years that were available multiple samples were usually taken during each of the summer and fall months (June-November). Table 2 displays *microcystin* summary statistics for each lake.

Algal condition across the four lakes in our sample exhibit substantial heterogeneity. GLSM and Buckeye Lake tend to be the "dirtiest". Their average *microcystin* concentration levels are well above the 1 ug/ L, no drinking threshold set by the World Health Organization (WHO), with GLSM's average exceeding the WHO's 20 ug/L no contact threshold (World Health

Organization 2003)[4]. The other two lakes are relatively clean with both having some samples where no *microcystin* was detected in the water. A significant amount of within lake variation exists as well which is central to our hedonic identification. GLSM and Buckeye Lake both have at least 4 months of algal readings below the 1 ug/L threshold despite having individual algal readings near 200 ug/L in other months. Indian Lake, on the other hand, is the opposite of GLSM and Buckeye Lake. Most of the monthly algal values are well below the WHO's 1 ug/L threshold, while there are only a few months with algal blooms. Finally, Lake Loramie did not exhibit a significant amount of within variation in water quality with all of its monthly algal readings below the 1 ug/L threshold.

To attach *microcystin* levels to housing transactions we examined a number of temporal aggregates of recent *microcystin* observations. Since the sale price of a home is typically determined 30-60 days before the actual sale date occurs, we used the mean of all *microcystin* samples taken two months preceding the month of the sale as the primary proxy for algal conditions on each lake.[5] If there were no *microcystin* readings taken within 2 months of the sale, the temporal lag used would extend an additional month until a *microcystin* reading was available up to 6 months prior to the sale[6]. If there were no readings taken within 6 months of the sale month, however, the transaction was excluded from the sample due to missing data.[7] Summary statistics for algae levels associated with transactions are shown in Table 2 and reflect the overall heterogeneity in lake conditions discussed previously. A time trend, depicting how *microcystin* values varied across seasons is provided in Figure 5.

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[4] The Ohio EPA implemented a similar set of guidelines in 2014 (Raymond, 2014).

[5] *Microcystin* readings taken during the month of the sale were removed from consideration to eliminate any possibility that future algal conditions were used to predict the market value of a home

[6] For robustness we also examined using a 6 month average. While we see some attenuation of results likely due to measurement error arising from algae aggregation, results are qualitatively similar to our primary results presented below.

[7] Results are robust when the sample is restricted to using only transactions with a *microcystin* reading taken within 2 months of the sale month.

4. Identification of Algae's Impact on Housing Prices

Econometric identification of the capitalization impacts of *microcystin* on nearby housing prices follows the familiar first-stage hedonic logic (Rosen 1974). We assume that utility maximizing residents bid on houses with the highest bid accepted by sellers resulting in housing transactions. Modeling the equilibrium price that arises from this process produces the familiar first-stage hedonic regression given by:

$$(1)\ \ln P_{ijt} = \alpha_0 + \boldsymbol{\alpha_1 X_i} + \boldsymbol{\alpha_2 Z_j} + \boldsymbol{\alpha_3 Y_t} + \boldsymbol{\alpha_4 M_t} + \boldsymbol{\alpha_5 Lake_{it}} + \epsilon_{ijt}$$

where we have specified the first stage regression as a semi-log specification with the price of house i sold in location j during time period t given by P_{ijt}. House specific structural attributes are given by $\boldsymbol{X_i}$, dummy variables controlling for neighborhood-specific, time-invariant characteristics are given by $\boldsymbol{Z_j}$, time specific dummy variables are represented by $\boldsymbol{Y_t}$ and $\boldsymbol{M_t}$ where $\boldsymbol{Y_t}$ are year-specific dummy variables and $\boldsymbol{M_t}$ are month-specific dummy variables, $\boldsymbol{\alpha}$ are vectors of parameters to be estimated and ϵ_{ijt} is an idiosyncratic error term. Our key variables of interest are spatially and temporally varying measures of lake quality represented by $\boldsymbol{Lake_{it}}$ where the subscripts highlight that this variable varies by house and time.

Our use of distinct lakes raises several challenging issues in our estimation of the hedonic equation in (1). The first of these concerns the source of algal variation needed for identification. One approach is to assume that changes in algal conditions have the same impact on all lake adjacent and lake community properties. This can be modeled using (2):

$$(2)\ \ln P_{ijt} = \alpha_0 + \boldsymbol{\alpha_1 X_i} + \boldsymbol{\alpha_2 Z_j} + \boldsymbol{\alpha_3 Y_t} + \boldsymbol{\alpha_4 M_t} + \alpha_5 LakeAdj_i + \alpha_6 NearLake_i + \alpha_7 Algae_{it} * (LakeAdj_i + NearLake_i) + \epsilon_{ijt}.$$

Equation (2) differs from equation (1) by decomposing the $\boldsymbol{Lake_{it}}$ term into three different components. The first two terms—$LakeAdj_i$ and $NearLake_i$—control for any benefits that are derived from being located next to or near a lake. We specify two, mutually-exclusive proximity variables here to separate the adjacency effect from the lake community effect. Any capitalization that accrues from being adjacent to a lake will be captured by the α_5 coefficient, while α_6 captures the remaining lake proximity effect that may be present for non-adjacent homes located within 500 meters of a lake but non-adjacent. The final term in equation (2) is our primary variable of interest. It is an interaction between a time-varying indicator variable for *microcystin* ($Algae_{it}$) and an indicator for any home located within 500 meters of a lake formed as the union of the indicator variables $LakeAdj_i$ and $NearLake_i$. This term represents a single average effect of worsening algae conditions on lake adjacent and near lake property values.

Although equation (2) is useful in capturing *microcystin's* overall effect, it does not allow us to examine spatial heterogeneity that algae is likely to have on near lake and lake adjacent prices. To further investigate this issue we modify equation (2) to allow for this possibility:

$$(3)\quad \ln P_{ijt} = \alpha_0 + \boldsymbol{\alpha_1 X_i} + \boldsymbol{\alpha_2 Z_j} + \boldsymbol{\alpha_3 Y_t} + \boldsymbol{\alpha_4 M_t} + \alpha_5 LakeAdj_i + \alpha_6 Lake250_i + \alpha_7 Lake500_i + \alpha_8 LakeAdj_i * Algae_{it} + \alpha_9 Lake250_i * Algae_{it} + \alpha_{10} Lake500_i * Algae_{it} + \epsilon_{ijt}$$

There are once again several terms in equation (3) that account for the impact various measures of proximity to a lake have on property values. $LakeAdj_i$ is an indicator variable indicating whether or not a property is located on the shoreline while $Lake250_i$ and $Lake500_i$ are mutually exclusive distance bands each representing different distance "donuts", in meters, away from the lake. The key variables of interest are the interaction terms between the time varying $Algae_{it}$ variable and the various lake proximity measures.

The second issue we face is the longstanding concern in the hedonic literature over the appropriate extent of market (Michaels and Smith 1990; Goodman and Thibodeau 2002). Given that our data are associated with spatially noncontiguous lakes, there are a variety of potential approaches to examining this issue. The simplest approach is to simply estimate a version of equation (2) with pooled data accounting for shifts in the hedonic price function across space and time through fixed effects. This approach ensures that identification for algae covariates arises due to both within lake and between lake variation while exploiting a large reservoir of housing transactions to help identify additional covariates in the hedonic specification.

An alternative extent of market arises if one focuses only on specific subsets of lakes. When dividing the housing market by more specific localities a natural breakpoint is to consider the lakes of GLSM, Loramie and Indian as one market and Buckeye as another. For markets containing lakes with algal readings both above and below key toxicity thresholds identification is still achieved through within and between lake variation in algal readings. Finally, a third alternative is to focus exclusively on individual lakes that have both experienced algal fluctuations and contain significant nearby housing transactions needed for identification. In our sample, this restricts our analysis to Buckeye and GLSM.

Buckeye Lake and GLSM fulfill the stringent data requirements needed to test this third alternative because of the consistent water quality sampling that has occurred at both lakes, with each lake having over 300 samples taken during our study's time period. One limitation in running this analysis, however, is the ability to estimate spatially heterogeneous proximity effects associated with algae. Due to GLSM's consistently poor water conditions, there were only two lakefront properties sold when algae conditions were below the 1 ug/L threshold. These two observations are not sufficient to separately identify the effect of being close to a lake with the loss in value due to higher algal concentrations. Subsequently we provide estimates only using equation (2) for each individual lake. We present results for all three extent of market definitions in the following section.

5. Results

Estimation results for two base specification using a pooled dataset of all lakes based on equations (2) and (3) are shown in Table 3. The first specification reports estimation results based on equation (2), while the second specification allows the algal coefficient to vary across space using the functional form describe in equation (3). Both specifications include census tract, year, and monthly fixed effects.[8] Census tract effects control for baseline differences across space such as school quality or proximity to urban areas. Year fixed effects control for shifts in the hedonic equilibrium due to appreciation or other time-varying but spatially uniform impacts. Finally, month fixed effects control for potential seasonality in housing prices. Given that our primary focus centers on lake quality impacted by algae, the inclusion of month fixed effects helps to absorb differences in lake home sales between colder winter months and warmer summers.

Examining results for each specification, housing covariates have the expected signs and significance suggesting that the hedonic is reliably capturing baseline housing features. Housing values increase at a decreasing rate as square footage and lot size increase. Adding an additional bathroom to a house adds considerably more value to a property than if the space were used instead for an additional room. Adding an additional story to a house, while holding the square footage constant, slightly reduces the value of a home. This could be capturing some of the higher annual heating and cooling costs that are associated with multi-story homes.

Examining lake covariates in more detail, the first column of results reveals that lake adjacent homes located within 20 meters of a lake are approximately 86%[9] higher valued than non-adjacent homes. As expected, homes further away, yet within 500 meters, maintain a capitalization premium although this premium decreases to approximately 22%. Turning attention to our key algae variable, we find a negative and significant capitalization effect of algae contamination of 12.52%.

[8] Additional model specifications using census blockgroup, census blockgroup by year and census tract by year fixed effects to examine the role of spatially and temporally varying unobservables on our primary algae estimates (Abbott and Klaiber 2010). We show these results in appendix Table A1.
[9] Dummy variable estimates presented in the text have been corrected using the technique suggested by (Halvorsen and Palmquist 1980).

Column 2 shows results where algae impacts are allowed to vary by lake proximity. It is clear from these results that crossing the 1 ug/L microcystin threshold significantly reduces the value of lakefront and near lake properties. Lakefront properties appears to be the most affected by changes in algae concentrations, losing approximately 32% of their value. Houses located between 20 and 250 meters are also negatively impacted by increased algal density, but to a lesser extent, losing around 11% of their value. However, when examining homes between 250 and 500 meters we no longer find a significant impact of algae contamination. This suggests that the impact of poor water quality driven by algae contamination is spatially limited to near lake properties.

Extent of market

To examine the role of market extent we split the sample into two groups as described in section 4. Houses located in Auglaize, Mercer, Logan and Shelby County are grouped together and form the "West" market, while observations from Fairfield and Licking County form the "Buckeye" market. Hedonic results from each market estimated independently are displayed in Table 4. Results indicate there is a significant amount of heterogeneity present across housing markets. The premium associated with living near Buckeye Lake is much larger, regardless of which distance band a home is located in compared to the premium associated with homes in the West market. This divergence likely reflects the heterogeneous quality of the lakes and the surrounding amenities that they support.

In addition to different lake proximity impacts we also see evidence that the capitalized value of structural housing attributes is slightly different across markets. While generally the same significance and sign, magnitudes vary slightly. This difference is much more pronounced when examining lake and algae specific covariates. Lakefront homes in the west market lose an additional 24.5% in value as compared to their counterparts on Buckeye when algae is above 1 ug/L. This large drop in property values in the West market removes nearly half of the premium that is typically associated with lakefront homes. However, the effect of algae on housing values appears to extend further in the Buckeye market than in the western market. Homes within 250 meters of Buckeye Lake lose 19.1% of their value when water conditions worsen. This is almost 4% more than their counterparts in the western market.

To examine a more restrictive extent of market we report results for individual lake markets in Table 5. We estimate Buckeye Lake and GLSM individually as described in section 4. The results in Table 5 match well with what has already been discussed. Surpassing the 1 ug/L threshold reduces property values between 17% and 13%, respectively. The effect is heterogeneous across lakes, with Buckeye residents being more adversely impacted by water quality changes than GLSM residents. The distance band coefficients once again show that quality of the lakes are heterogeneous, with Buckeye Lake being more expensive to live near. The larger algal coefficients associated with transactions located near Buckeye Lake could be a consequence of people's perception of both lakes. GLSM has often been in the news over the past several years due to poor water conditions (Arenschield 2015, Oct; Devito 2015; Henry 2011; Egan 2014). Buckeye Lake, on the other hand, has only recently started to experience water quality issues.

6. Discussion

State and local governments across the United States are paying closer attention to cyanobacteria blooms. According to a survey sent out to all 50 states in 2014 by the Resource Media and National Wildlife Federation, 71% of responding states said harmful algal blooms (HAB) were either a "somewhat serious" or "very serious" problem. Almost half of the respondents also said they were actively monitoring cyanobacteria levels at lakes that experienced problems with HABs in the past (Resource Media 2014). Findings from the EPA`s 2007 National Lakes Assessment survey support this widespread level of concern. 378 of the 1,156 lakes sampled nationwide had detectable levels of *microcystin*. This suggests approximately one out of every three lakes nationwide have *microcystin* present (EPA 2009).

Several states have taken action in response to this spread of HABs by funding lake restoration projects. These projects have attempted to curb further toxic algal growth by dredging sediment from the lake bottom (Barbosa 2013), creating new wetlands to filter out toxins (Devito 2015) and implementation of more stringent fertilizer restrictions to reduce the amount of runoff that occurs (Miller 2012). Lake restoration projects can be very costly and do not ensure the underlying problem will be eliminated. The Ohio EPA, for example, spent over $26 million chemically treating and dredging Grand Lake Saint Marys. Despite these significant efforts many still consider GLSM to be the poster child for HABs (Arenschield 2015, Oct).

To combat the environmental and health damages from *microcystin* local policymakers face budgetary constraints given limited funding and competing demands on scarce resources. To aid policymakers, it is important that they are aware of real costs and benefits of potential environmental cleanup and mitigation. This paper adds key revealed preference data on the potential impacts of cyanobacteria blooms which will aid in making budgetary tradeoffs. Our results show a large impact of algal contamination on housing values, which are likely a lower bound estimate of algal damages given additional health and recreation damages.

Using estimates from Table 5 we compute the total capitalization for GLSM due to algal conditions surpassing the 1 ug/L WHO threshold. Using the average value of a house located within 500 meters of Grand Lake Saint Marys of $132,327, we estimate the loss per house to be $17,619. Multiplying this value by the total number of single-family residences within 500 meters (2,775) of GLSM provides an overall capitalization loss of nearly $49 million. These large losses to local communities help justify the considerable time and effort that has been allocated by the State and Ohio EPA in attempt to curb worsening water conditions. Despite already spending $26 million to help cleanup GLSM, this simple back-of-the-envelope calculation suggests these funds are well spent and additional funds would likely pass a cost-benefit analysis based on housing damages alone. Nationally, the likely magnitude of substantial algal related property value losses suggest a need for large public expenditure and policy intervention that would address this growing challenge to local communities.

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Table 1. Housing summary statistics

	All Lakes (N=16589)				Buckeye Lake (N=12169)				West Market (N=4420)			
Variable Name	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Purchase Price	148,589	69,050	50,000	522,500	154,791	71,049	50,000	522,500	131,513	60,002	50,000	510,000
Price Per Square Foot	85.00	26.10	40	276.1	85.25	24.98	40	276.1	84.33	28.94	40	276.1
Total Number of Rooms	6.380	1.328	3	12	6.501	1.299	3	12	6.045	1.350	3	12
Total Number of Bathrooms	1.982	0.681	1	4.500	2.087	0.683	1	4.500	1.693	0.588	1	3.500
Total Square Feet	1752	603	580	4054	1820	624	580	4054	1564	495	580	3671
Parcel Lot Acreage	0.661	0.875	0.0523	5	0.687	0.899	0.0523	5	0.589	0.800	0.0523	5
Age	31.80	22.25	1	100	28.06	20.77	1	100	42.09	22.94	1	100
Sale Year	2012	1.768	2009	2015	2012	1.768	2009	2015	2012	1.807	2009	2015
Fireplace (0/1)	0.473	0.499	-	-	0.547	0.498	-	-	0.270	0.444	-	-
Garage Dummy (0/1)	0.744	0.436	-	-	0.707	0.455	-	-	0.845	0.361	-	-
Stories	1.384	0.473	-	-	1.470	0.488	-	-	1.148	0.329	-	-
LakeAdj (0/1)	0.0123	0.110	-	-	0.00362	0.0600	-	-	0.0362	0.187	-	-
Lake250 (0/1)	0.0212	0.144	-	-	0.0107	0.103	-	-	0.0502	0.218	-	-
Lake500 (0/1)	0.0229	0.150	-	-	0.00912	0.0951	-	-	0.0609	0.239	-	-

Table 2. Lake and algal summary statistics

Lake Name	Area (acres)	Depth (feet)	Algal Reading (ug/L)				# Months with Algal Readings	
			Mean	Std Dev	Min	Max	< 1 ug/L	> 1 ug/ L
Buckeye	3136	14	10.08	10.54	0.33	38.76	9	47
Grand Lake St Marys	12700	16	35.70	34.02	0.33	225.2	4	66
Indian	5104	15	1.59	4.57	0	19.15	35	2
Loramie	843	12	0.06	0.07	0	0.15	21	0
Total Sample	--	--	14.49	20.60	0.00	225.20	--	--

Table 3. Pooled hedonic estimates (semi-log)

Variable	(1) Average Affect	(2) Spatially Hetereogeneous
LakeAdj*Algae	-	-0.278**
	-	(0.114)
Lake250*Algae	-	-0.105*
	-	(0.0605)
Lake500*Algae	-	0.0262
	-	(0.0635)
Algae*(LakeAdj + NearLake)	-0.118**	-
	(0.0527)	-
Stories	-0.0551***	-0.0560***
	(0.0117)	(0.0116)
totalrooms	0.00839***	0.00866***
	(0.00304)	(0.00297)
totalbaths	0.0940***	0.0937***
	(0.00693)	(0.00690)
Sqft (100s)	0.0534***	0.0536***
	(0.00343)	(0.00343)
acres	0.145***	0.146***
	(0.0187)	(0.0187)
age	-0.00984***	-0.00985***
	(0.000786)	(0.000783)
fireplace(0/1)	0.0609***	0.0599***
	(0.00606)	(0.00599)
garage(0/1)	0.0232**	0.0234**
	(0.0116)	(0.0117)
LakeAdj	0.623***	0.748***
	(0.111)	(0.0829)
Lake250	-	0.249***
	-	(0.0897)
Lake500	-	-0.0216
	-	(0.0669)
NearLake	0.195***	-
	(0.0717)	-
Sqft Squared (10000s)	-0.000533***	-0.000537***
	(8.21e-05)	(8.21e-05)
Acres Squared	-0.0208***	-0.0210***
	(0.00359)	(0.00359)
Age Squared	5.73e-05***	5.72e-05***
	(8.96e-06)	(8.93e-06)
Constant	10.62***	10.61***
	(0.0506)	(0.0506)
Tract FE	104	104
Year FE	6	6
Monthly FE	11	11
Observations	16589	16589
R-squared	0.715	0.717

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the tract level.

Table 4. Hedonic results for Buckeye and Western Ohio market (semi-log)

Variable	(1) Buckeye	(2) West
LakeAdj*Algae	-0.224***	-0.403***
	(0.0569)	(0.116)
Lake250*Algae	-0.175***	-0.143*
	(0.0303)	(0.0790)
Lake500*Algae	-0.0377	0.0604
	(0.0677)	(0.106)
Stories	-0.0636***	0.0228
	(0.0127)	(0.0190)
totalrooms	0.00784*	0.0128***
	(0.00397)	(0.00346)
totalbaths	0.0885***	0.106***
	(0.00753)	(0.0136)
Sqft (100s)	0.0456***	0.0700***
	(0.00316)	(0.00686)
acres	0.152***	0.127***
	(0.0228)	(0.0248)
age	-0.0102***	-0.0106***
	(0.00106)	(0.00104)
fireplace(0/1)	0.0644***	0.0499***
	(0.00647)	(0.0118)
garage(0/1)	0.0224*	0.0331
	(0.0133)	(0.0208)
LakeAdj	0.900***	0.736***
	(0.0767)	(0.0792)
Lake250	0.431***	0.115
	(0.0378)	(0.0995)
Lake500	0.0686	-0.131
	(0.0591)	(0.0857)
Sqft Squared (10000s)	-0.000362***	-0.000948***
	(7.82e-05)	(0.000155)
Acres Squared	-0.0217***	-0.0189***
	(0.00436)	(0.00486)
Age Squared	6.45e-05***	5.99e-05***
	(1.25e-05)	(1.16e-05)
Constant	10.94***	10.39***
	(0.0544)	(0.0749)
Tract FE	63	41
Year FE	6	6
Monthly FE	11	11
Observations	12169	4420
R-squared	0.712	0.718

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the tract level.

Table 5. Individual lake hedonic (semi-log)

Variable	(1) Buckeye	(2) GLSM
Algae*(LakeAdj + NearLake)	-0.155***	-0.125**
	(0.0205)	(0.0476)
Stories	-0.0630***	0.00524
	(0.0127)	(0.0201)
totalrooms	0.00760*	0.0108**
	(0.00406)	(0.00438)
totalbaths	0.0888***	0.0893***
	(0.00758)	(0.0142)
Sqft (100s)	0.0457***	0.0790***
	(0.00316)	(0.00797)
acres	0.151***	0.122***
	(0.0228)	(0.0317)
age	-0.0102***	-0.0112***
	(0.00107)	(0.000901)
fireplace(0/1)	0.0654***	0.0294***
	(0.00644)	(0.0100)
garage(0/1)	0.0219	0.00785
	(0.0133)	(0.0229)
LakeAdj	0.868***	0.295***
	(0.0441)	(0.0386)
NearLake	0.326***	0.0258
	(0.0183)	(0.0480)
Sqft Squared (10000s)	-0.000362***	-0.00110***
	(7.83e-05)	(0.000183)
Acres Squared	-0.0215***	-0.0199***
	(0.00435)	(0.00656)
Age Squared	6.48e-05***	6.13e-05***
	(1.27e-05)	(1.09e-05)
Constant	10.94***	10.39***
	(0.0546)	(0.0954)
Tract	63	20
Year FE	6	6
Monthly FE	11	11
Observations	12169	3247
R-squared	0.711	0.734

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the tract level.

Figure 1 – Google trends relative search volume across time (United States)

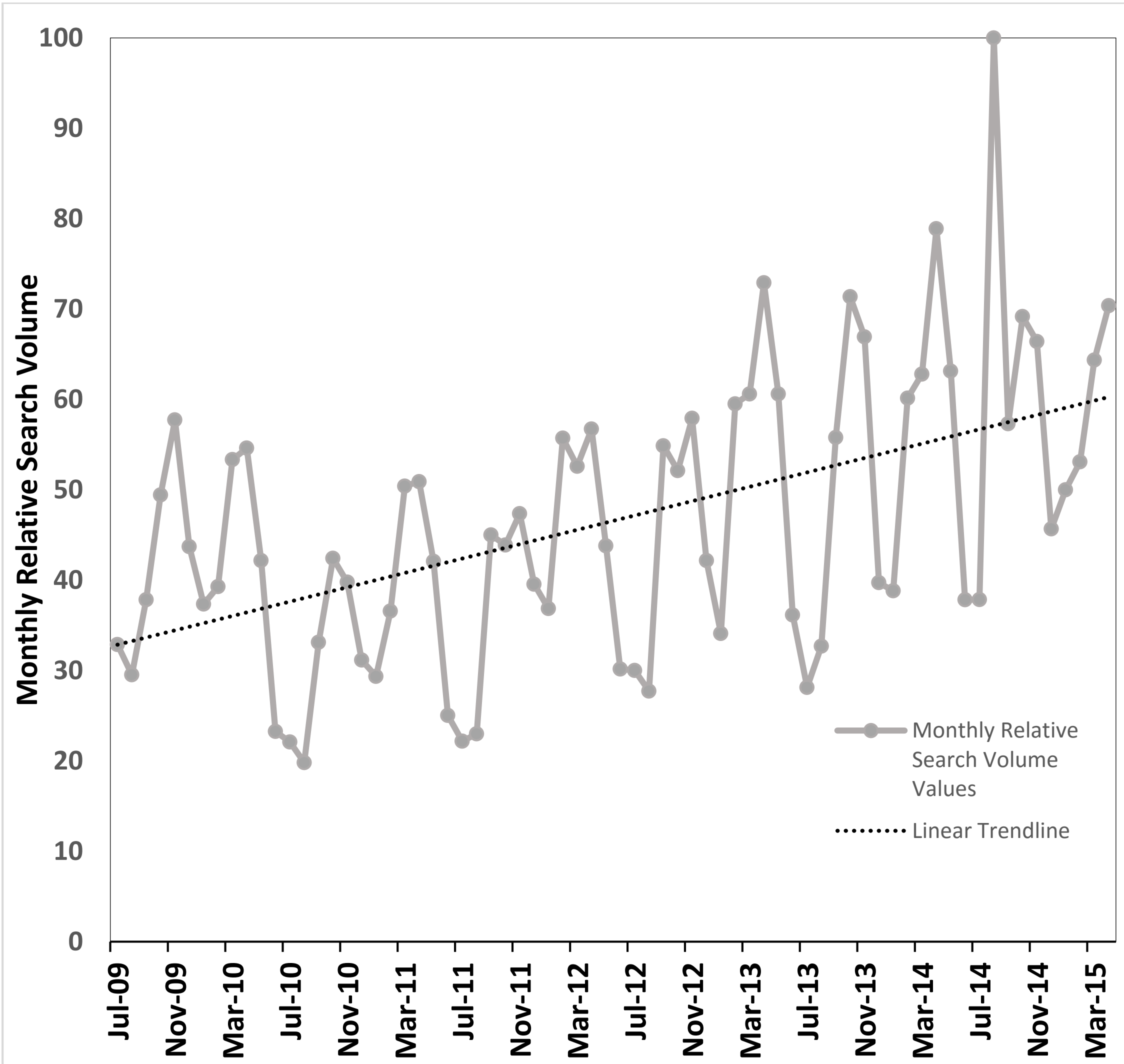


Figure 2 – Google trends relative search volume by State between July 2009 and April 2015

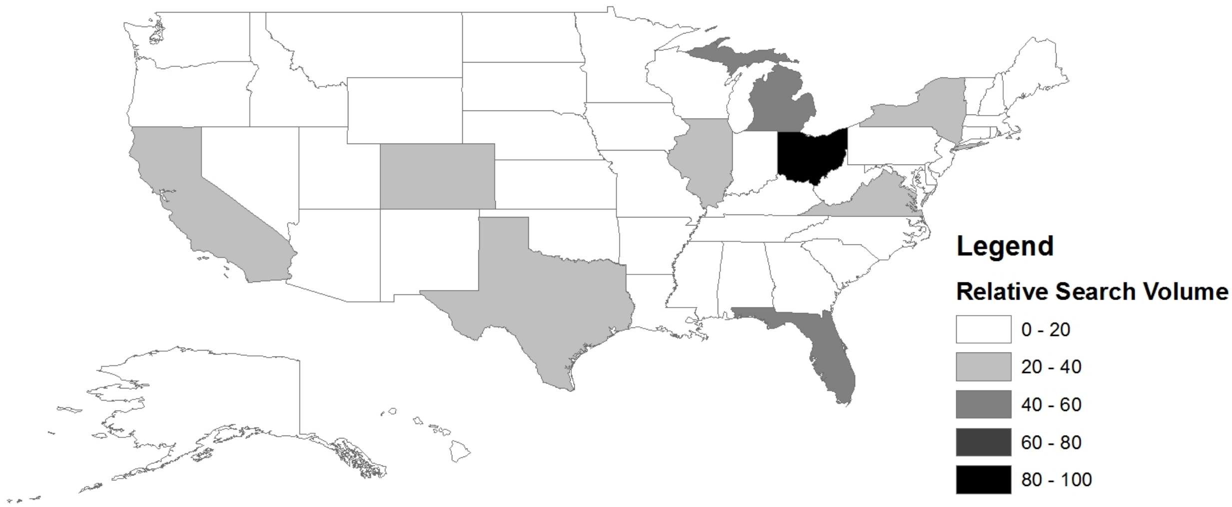


Figure 3 – Study area and housing transactions

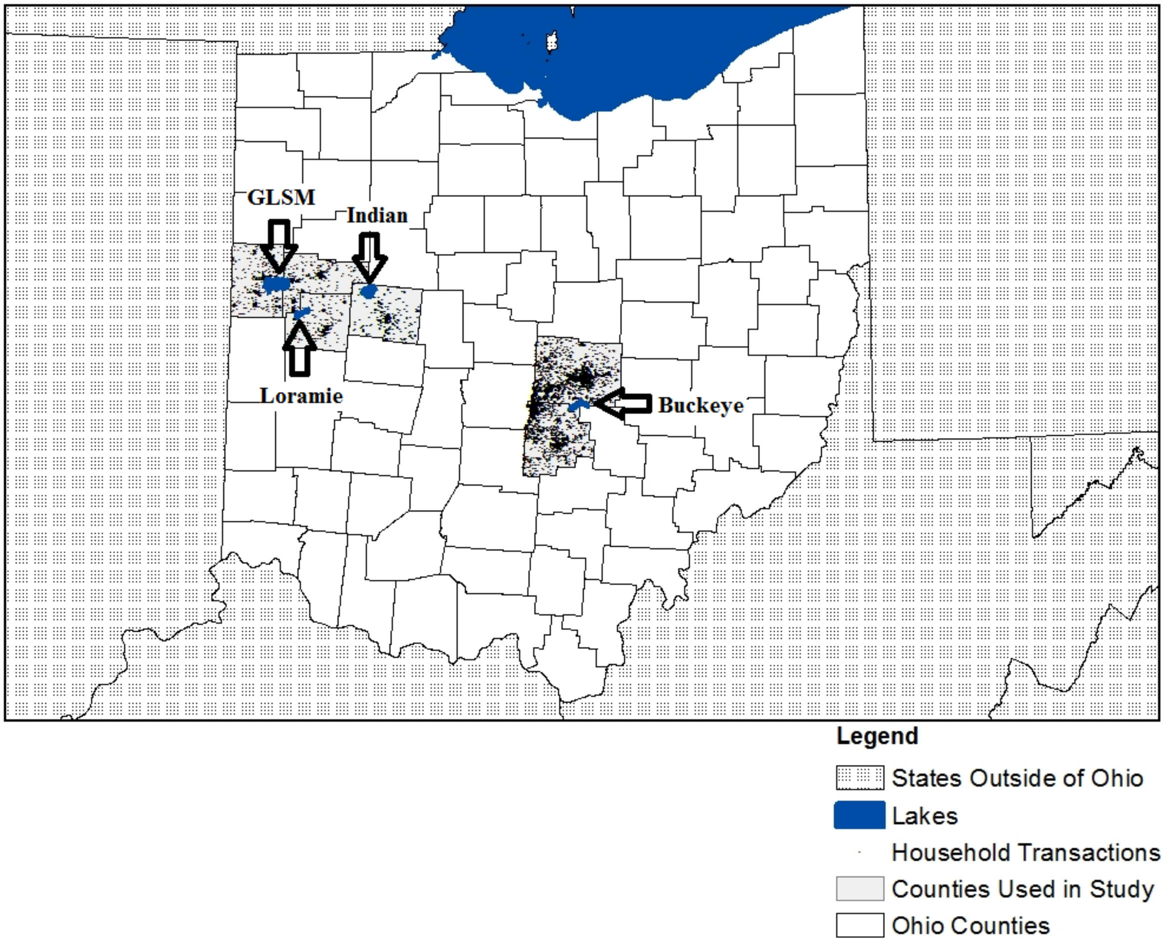


Figure 4 –Transaction near GLSM

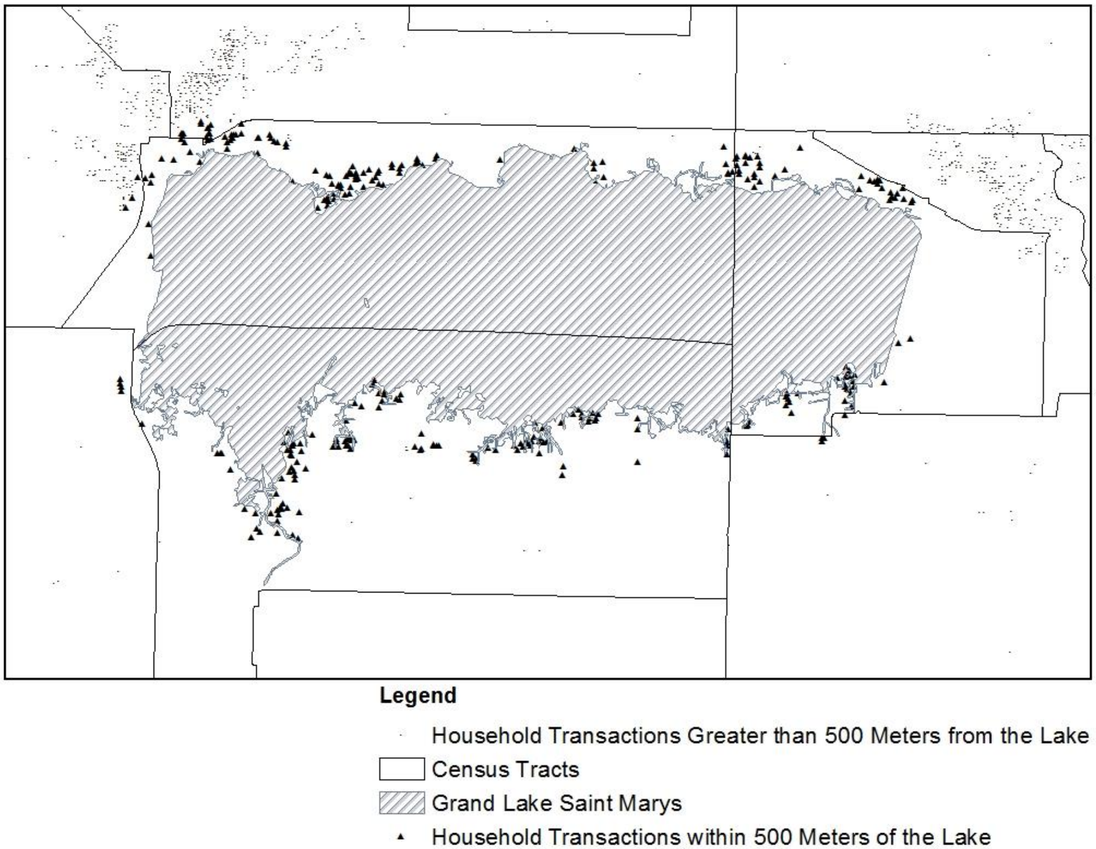
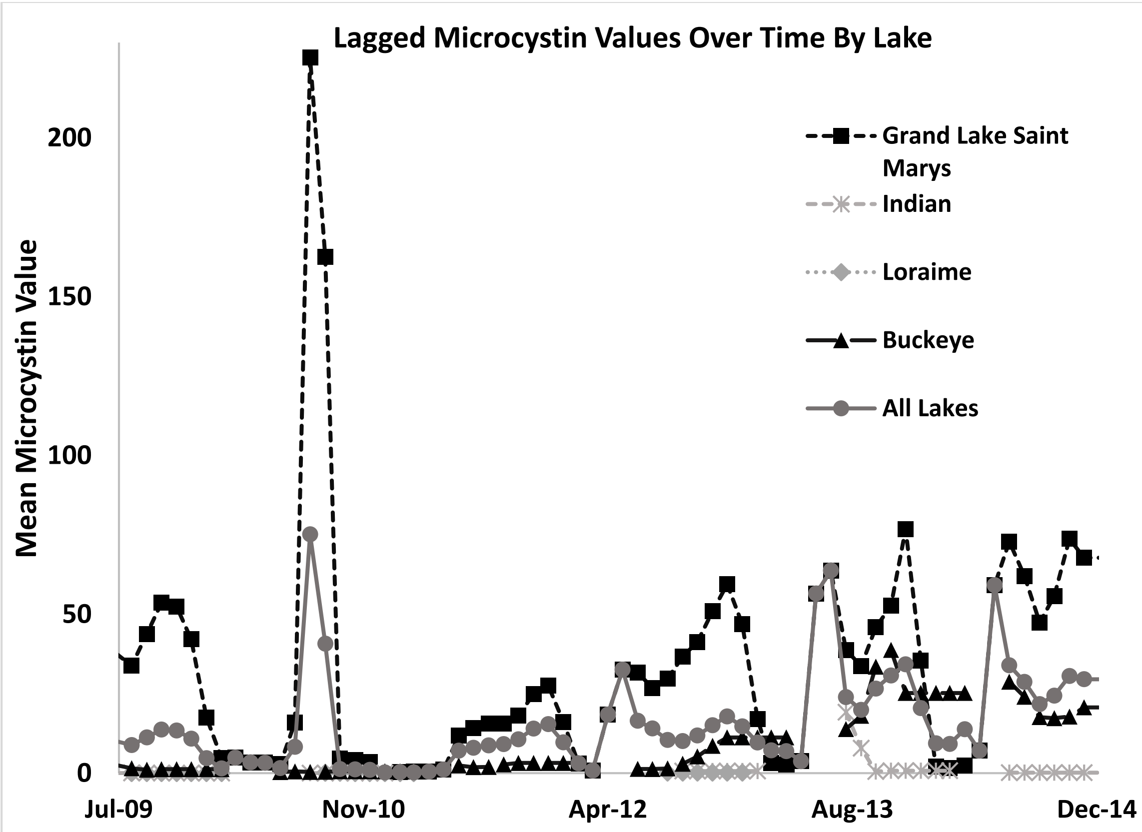


Figure 5 – Algal readings by month



Appendix

Table A1. Robustness to spatial scale of unobservables (semi-log)

Variable	(1) Blockgroup	(2) Blockgroup*Year	(3) Tract*Year
LakeAdj*Algae	-0.300***	-0.390***	-0.312***
	(0.108)	(0.115)	(0.103)
Lake250*Algae	-0.133**	-0.105	-0.0912
	(0.0659)	(0.0908)	(0.0889)
Lake500*Algae	0.0132	0.0546	0.0318
	(0.0678)	(0.0914)	(0.0802)
Stories	-0.0500***	-0.0547***	-0.0574***
	(0.00886)	(0.00714)	(0.00743)
totalrooms	0.00674***	0.00682***	0.00891***
	(0.00239)	(0.00238)	(0.00248)
totalbaths	0.0916***	0.0922***	0.0935***
	(0.00614)	(0.00585)	(0.00551)
Sqft (100s)	0.0511***	0.0490***	0.0527***
	(0.00305)	(0.00239)	(0.00227)
acres	0.136***	0.138***	0.146***
	(0.0135)	(0.0119)	(0.0124)
age	-0.0105***	-0.0113***	-0.0101***
	(0.000660)	(0.000500)	(0.000494)
fireplace(0/1)	0.0573***	0.0604***	0.0605***
	(0.00531)	(0.00515)	(0.00506)
garage(0/1)	0.0148*	0.0164**	0.0252***
	(0.00853)	(0.00712)	(0.00727)
LakeAdj	0.739***	0.818***	0.787***
	(0.0878)	(0.103)	(0.0860)
Lake250	0.169*	0.193*	0.252***
	(0.102)	(0.0988)	(0.0922)
Lake500	-0.0825	-0.0825	-0.0196
	(0.0671)	(0.0899)	(0.0817)
Sqft Squared (10000s)	-0.000516***	-0.000478***	-0.000521***
	(7.35e-05)	(5.41e-05)	(5.07e-05)
Acres Squared	-0.0186***	-0.0195***	-0.0214***
	(0.00266)	(0.00264)	(0.00275)
Age Squared	6.47e-05***	7.15e-05***	5.99e-05***
	(7.27e-06)	(5.70e-06)	(5.57e-06)
Constant	10.64***	10.87***	10.63***
	(0.0383)	(0.0298)	(0.0326)
Blockgroup*Year FE	360	2,100	683
Year FE	6	0	0
Monthly FE	11	11	11
Observations	16589	16589	16589
R-squared	0.733	0.769	0.729

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the level of spatial fixed effectsl.