DOES WATER QUALITY MATTER FOR RECREATION? EVIDENCE FROM MICRO PANEL DATA

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1) Introduction

The Clean Water Act (CWA) of 1972 is among the farthest reaching environmental laws in the United States. Read literally its objectives include the complete elimination of toxic and conventional discharges into the nation's waterways, and the assurance that surface water quality standards needed for recreation and other direct uses are obtained. While these ambitious goals are unlikely to ever be met in practice, progress has been made in improving water quality across the nation. For example, the US Environmental Protection Agency (EPA) estimates that phosphorous levels have decreased in 25 percent of lakes since passage of the Act (USEPA, 2009); similar improvements have also been seen in streams and rivers (Bingham et al., 2000). These quality gains have, however, come with a cost. The US Department of Commerce estimates that in 2005 the industrial sector alone spent $1.35 billion on pollution abatement capital and $6.73 billion on abatement-related operations to comply with the Act (USDC, 2008). Furthermore, there are many remaining problems. The main regulatory focus during the first three decades of the CWA was on point sources, with particular emphasis on municipal waste water treatment plants. As a result levels of biological pollutants such as fecal matter and bacteria have decreased to the point that they are no longer the main threat to rivers, streams, and lakes. Instead, nutrient pollution from non-point sources is now the primary cause of water bodies failing to meet their designated uses. Indeed the same EPA report documenting overall improvements in lake water quality also notes that more than 40% of lakes are impaired due to excess nutrients (USEPA, 2009). If nutrient pollution levels are to be reduced further, abatement will need to focus non-point sources, which presents non-trivial regulatory challenges and expense.

These specific points suggest in general that water quality has improved since the early 1970s, additional reductions in nutrient pollution would be needed to comply with the letter and spirit of the CWA, and these reductions would likely involve non-trivial expensive. They do not address the economic benefits of the CWA, which requires a link between water quality and human well-being. Among the more obvious links is between water quality and recreation, and it has been suggested that the majority of CWA benefits flow through this mechanism. For example, in an aggregate retrospective analysis EPA contractors estimated a lower bound on the non-market recreational benefits of water quality improvements stemming from the CWA at $11 billion annually (Bingham et al., 2000). The accuracy of this estimate and others like it, however, depends critically on the assertion that there is a causal relationship between surface water quality and recreation behavior. The overall objective of this paper is to rigorously examine this assertion.

At some level a causal relationship between water quality and recreation behavior is self-evident, in that people are unlikely to fish, swim, or boat in heavily polluted waters. Once a quality threshold is reached, however, the existence and size of behavioral responses to further quality improvements is less obvious. Though there is substantial spatial variability, it seems fair to say that the first-order water quality problems that were present in the United States in the 1960s and 1970s have largely been solved. Current problems are based primarily on non-point source nutrient pollution that can degrade the quality of recreation at particular water bodies, but may not affect their actual use. Thus establishing a causal relationship between recreation behavior and water quality improvements arising from future regulation under the CWA (and hence between abatement effort and benefits) requires examination of a potentially subtle behavioral response.

There is ample evidence of an association between nutrient pollution and water recreation behavior. This evidence, however, is based almost entirely on revealed preference cross-sectional (e.g. Phaneuf et al., 2009) or stated preference (e.g. Whitehead et al., 2010) studies.

The former typically uses variability in water quality conditions and behavior across recreation sites at a point in time to show that, all else equal, people tend to visit sites that have higher water quality. Two problems threaten identification in these types of studies. First, as with all cross-sectional approaches it is difficult to adequately control for confounding determinants of behavior. Specifically, it may be that good water quality is correlated with other attractive but unmeasured aspects of recreation sites, leading to an upward bias in estimates of the behavioral response to water quality improvements. Second, there is often a spatial and temporal mismatch between observed behavior and the measurement of water quality. This arises because data collection for these two information types is rarely coordinated. Typically economists must make do with secondary data on water quality collected for other purposes to estimate their models. Thus revealed preference studies may suffer from both endogeneity and measurement error problems. In contrast, stated preference approaches can limit endogeneity problems via well-constructed experimental designs. However, communicating water quality variability in a survey context is a non-trivial challenge, and concerns about hypothetical bias cannot be readily dismissed. Thus, while many careful studies of water quality and recreation behavior exist, to our knowledge there have been no studies that rigorously establish causality using panel or quasi-experimental analysis. This is almost certainly because of the dearth of panel recreation data sets collected at a micro scale, which are also temporally and spatially matched to appropriate water quality measures.

The specific objective of this paper is to fill this void by presenting the first micro panel analysis of the relationship between water quality and recreation behavior. We exploit a unique dataset tracking lake visits by a random sample of Iowa residents for the years 2002, 2003, 2004, and 2005. Trip records were gathered for each time period using annual surveys containing identical questions on individuals' visits to each of the 128 primary lakes in the state. To our knowledge this is the only micro level, spatially explicit, panel recreation data base constructed to date. At the same time that the behavioral data was gathered a coordinated limnology survey was undertaken, so that water quality measures are available for all individual lakes in the state for the same time periods that we observe behavior. Thus in addition to the panel feature of the data, we are able to match water quality measures at comparable spatial and temporal scales.

We use this data base to carry out several analyses designed to measure the causal effect of water quality on recreation behavior. We find convincing evidence that better water quality leads to a higher likelihood that an individual will visit a particular lake. Using different water quality measures and model specifications we find that the elasticity of participation with respect to water quality indicators is consistently near 0.30. We find mixed evidence that better water quality leads to a higher frequency of site visitation, and that the behavioral response to water quality at this margin is smaller than for participation.

2) Study Area, Data Sources, and Research Strategy

The laboratory for our study is the state of Iowa, which has 128 primary lakes distributed throughout the state. The majority of these are man-made reservoirs, though the state does include some natural lakes. As we discuss below, residents of Iowa are relatively active participants in outdoor recreation and its lakes are regularly visited for boating, swimming, angling, and other purposes. In general water quality problems in the state are the result of non-point source pollution stemming from agricultural operations, with excess nutrients and sediments being the primary cause of impairment. The Iowa Department of Natural Resources classifies 47 percent of lakes in the state as impaired due to nutrient and sediment pollution. In this sense Iowa is representative of inland lakes in much of the rest of the country, where nitrogen and phosphorous pollution from non-point sources are the primary regulatory challenge.

Water pollution problems in Iowa, however, are not uniformly distributed across the landscape. Indeed the state contains some of the country's cleanest and dirtiest lakes, which provides useful variability that we exploit in this study.

Data Sources

The data for our study come from two coordinated information gathering efforts. The behavioral data are based on a multi-year assessment of lake recreation in Iowa. Beginning in 2003 and continuing annually through 2006 researchers at Iowa State University surveyed a sample of state residences about their visits to lakes in the state during the previous year. In the first year 8000 households were randomly selected and mailed a survey; following standard Dillman (1978) procedures 4254 useable surveys were eventually returned for an overall response rate of 53 percent. In 2004, 2005, and 2006 these same households were contacted again by mail and asked to answer identical questions about their lake use patterns. To limit the effect on sample size of attrition in the panel, each year new households were also included in the contact sample. The result is an unbalanced panel to which 6261 unique individuals contributed at least one year's worth of trip records. Table 1 summarizes the panel features of the behavioral data. There is evidence of attrition in the panel, in that only 2354 of the original 4254 people (55 percent) participating in the 2003 survey contributed records to all four years of the panel. If people who are less avid lake visitors selected out of the panel it may be that the observed and unobserved characteristics of the sample change from year to year. While the effect of this on identification may be partially attenuated by the new entrants to the sample in each year, additional analysis is needed to fully understand the selection aspects of our data and its impact on our analysis.

Table 2 shows aggregate trip-taking behavior broken out by year. Each year approximately 60 percent of people in the sample report making at least one trip to a lake in the state. The mean frequency of visit among these users is between ten and eleven each year; the large standard deviation in trip frequency suggests there is substantial variability in this margin of behavior. Finally, as is typical for recreation data sets the distribution of aggregate behavior is skewed to the right by the presence of some avid visitors. Given this the median trip count of six for the first year and seven for subsequent years is a better indicator of central tendency.

The water quality data are based on a census of quality conditions in Iowa's lakes that was timed to coincide with when the behavioral data was gathered. This effort was coordinated by limnologists at Iowa State University. It involved sampling conditions at each of the 128 lakes included in our study three times per year during the recreation season, for each of the four years of the study. The three sample events were targeted to occur approximately at the beginning of June, July, and August each year. During each sample event common indicators of water body health such as ambient nitrogen and phosphorous, chlorophyll a, and dissolved oxygen were measured, and technicians assessed the water's clarity using a Secchi disk. Additional features of the lake at the time of the sample event were also recorded, with the end result being an unusually rich characterization of quality conditions at the lakes throughout our study period.

In this initial modeling effort we focus on two classes of water quality variables. Runoff of nitrogen and phosphorous (and sediments) tend to be the primary catalysts for subsequent events associated with poor lake water quality – e.g. impaired aquatic life, algae blooms, and limited water clarity. Given this we focus on total nitrogen and total phosphorous as our direct measures of pollution in the study lakes, and refer to them as primary pollutant variables. The actual levels of these pollutants, however, are not perceptible by potential lake visitors. Rather, it is the ramifications of elevated nutrients that are more likely to be visible to visitors, and hence more likely to influence behavior. Given this we also focus on three secondary response measures of the impact of nutrient and sediment runoff in our study lakes: ambient dissolved oxygen, Secchi depth, and ambient chlorophyll a. Higher dissolved oxygen levels suggest healthier aquatic life in general, and the potential for greater numbers of game (as opposed to rough) fish. Secchi depth is a direct measure of water clarity; chlorophyll a measures algae presence and is therefore an indicator of enhanced productivity stemming from nutrient enrichment.

Table 3 provides a summary of the water quality variables that we have constructed for our initial analysis. Since our models require a measure of quality for each lake during each time period, we first needed to collapse the results of the three annual sampling events into a single measure. We use a simple mean over the three measurements to construct the quality value for a particular variable/lake/time combination. The table summarizes these values for total nitrogen (TN), total phosphorous (TP), dissolved oxygen (DO), Secchi depth measure, and chlorophyll a (CLA) for each year across all 128 lakes, with standard deviations given in parentheses. The mean to standard deviation ratios for the quality variables suggest (with the possible exception of DO) that there is substantial variability across lakes in each time period. This variability arises primarily from differences in pollution loads across space. The variability across time is likely due more to stochastic features such as changes in precipitation year to year, though the impact of policy initiative may also contribute to changes across time. We exploit both the temporal and spatial variability in water quality conditions in our analysis.

Research Design

As noted above, our primary objective is to assess the causal relationship between recreation behavior and water quality. Past studies of recreation behavior suggestion there are two behavioral margins that might be influenced by site characteristics: participation (extensive margin) and trip frequency (intensive margin). The former relates to a person’s propensity to visit a particular destination at least once during a recreation season. This decision is likely to depend on the person's general interest in the recreation possibilities at the site, the proximity of the site to his home, and environmental quality characteristics at the site. Since most participants make relatively infrequent trips to specific recreation sites the extensive margin likely provides the clearest behavioral footprint on the role of site quality. For people who are more avid visitors the intensive margin may also respond to quality characteristics. Thus a person might decide to take greater numbers of trips to a destination exhibiting better quality, conditional on having decided to visit the site for at least one trip. In this study we begin by examining the participation and trip frequency decisions separately using reduced form panel models. This allows us to assess, using a relatively well-controlled design, the different means by which people might respond to improvements in water quality. We then use the reduced form evidence to guide our specification of structural models that combine both the intensive and extensive decisions, and allow us to measure the non-market values of marginal changes in lake water quality.

There are three main challenges we need to overcome in carrying out this research. First, theory does not provide guidance on how water quality variables should enter estimating equations describing recreation behavior. While it seems sensible to assert that objective measures of water quality measures correlate with the latent, subjective impressions that govern people's actual choices, the precise relationship between the objective and subjective measures cannot be known. At this stage of research we address this by looking at how different classes of quality variables (i.e. the primary pollutant and secondary response measures) explain behavior. In the future we plan to also look at water quality indices, which are designed to aggregate several individual objective measures into an ordinal reflection of the water quality available at a water body. Related to this, there may be heterogeneity in how individual visitors respond to the different measures of quality. For anglers some moderate elevation in nutrient levels might be preferred, if it stimulates biological production, reduces water clarity, or otherwise improves the likelihood of catching fish. Swimmers, in contrast, are likely to prefer water clarity and cleanliness above all else. Finally, water quality is likely to be a second order determinant of behavior for many visitors, in the sense that driving distance, built infrastructure, and the convenience of use may be more important. For this reason it is essential that we control for as many drivers of behavior as possible using individual fixed effects and temporally and spatially varying controls.

3) Reduced Form Panel Analysis

We begin by considering a reduced form analysis of individuals' participation decisions across the four years of our study. Our basic model is

$$y_{ijt} = \gamma_j Q_{jt} + \beta_j X_{ijt} + c_{ij} + \varepsilon_{ijt}, \quad j = 1,...,128, \quad t = 2002,...,2005. \tag{1}$$

In (1), y_{ijt}=1 if person *i* visited lake *j* during year *t*, and zero otherwise. Thus we have a linear probability model that can be estimated by least squares, with minimal distributional assumptions. The additional notation in (1) is as follows: Q_{jt} is a collection of water quality measures for lake *j* at time *t*, X_{ijt} contains other controls, γ_j and β_j are vectors of parameters to be estimated, c_{ij} is a person/site specific fixed effect, and ε_{ijt} is the idiosyncratic error. The model is general in that, as written, it allows for different responses to water quality variables at different lakes across the state. At this level of generality, however, it is only cross-time variability in water quality that identifies γ_j. This precludes the use of time fixed effects to control for unobserved, temporally varying determinants of behavior – most notably weather. It also relies on the source of water quality variability that is more likely subject to random fluctuations unrelated to the underlying pollution conditions at the lake. Thus at this stage of the research we use a restricted version of (1) given by

$$y_{ijt} = \gamma Q_{jt} + \beta X_{ijt} + c_{ij} + \varepsilon_{ijt}, \quad j = 1,...,128, \quad t = 2002,...,2005. \tag{2}$$

By restricting $\gamma_j = \gamma$ for all lakes in the study we are able to exploit both temporal and spatial variations in water quality.

Equation (2) is in essence a system of linear probability model equations with cross-equation restrictions. An observation is a person/site/time combination, and the unit of panel analysis is a person/site combination. We estimate the parameters in (2) by stacking all the observations, and using a fixed effects linear panel model to account for the c_{ij} terms. To avoid placing extra structure on the model we do not explicitly account for the correlation among the ε_{ijt} terms for a given person i at a particular time. Thus our estimates are consistent but not efficient. To account for the bias in standard errors that this omission implies all standard error estimates are computed using robust methods. Finally, for our main results we use the unbalanced panel. We subsequently assess robustness by restricting our sample to the 2354 people who contributed all four years of records to the study.

Table 4 contains selected parameter estimates for our first class of models, which focuses on using measures of primary pollution as explanatory variables. In all cases the variables enter in logs, implying the coefficient estimates are semi-elasticities of the form

$$\gamma_k = Q_{jt}^k \frac{\partial y_{ijt}}{\partial Q_{jt}^k}, \tag{3}$$

where k indexes the particular pollution measure. Thus the coefficient estimates are comparable in magnitude, and the elasticity of participation with respect to water quality is obtained by dividing γ_k by an average participation rate. Across all observations (people, sites, and time periods) the average proportion of people visiting a site is 0.018.

We consider three models with increasing levels of extra controls. In model I we only include the two pollution measures, and so the identifying assumption is that there are no unobserved time varying determinants of behavior that are correlated with total nitrogen and phosphorous. This is unlikely to be the case, since annual weather fluctuations are likely to affect both recreation participation and (via precipitation) measured ambient water quality. Nonetheless coefficient estimates on TN and TP are solidly negative, as expected. In model II we add time dummy variables that control for time varying determinants of behavior that are constant across space. For example, state-wide fluctuations in weather or macroeconomic conditions influencing recreation would be accounted for by these variables. In model III we allow the time effects to vary in size across the state by interacting the time dummy variables with regional indicators that map the lakes' locations into five geographical regions across the state. In both models II and III the coefficient estimates are solidly negative and significant as well. Model III is our preferred specification in that it includes the most robust set of controls. For the primary pollution specifications, we find average elasticity of participation with respect to water quality of −0.35. This estimate suggests water quality is an economically significant determinant of behavior, albeit the behavioral response to water quality change is inelastic.

Models based on secondary response measures of pollution are shown in table 5. Models I through III once again show results associated with the gradual increase of additional controls. Models I and II complement our findings from the primary pollution models, in that all estimates are significant and intuitively signed. Dissolved oxygen and Secchi depth are positive indicators of quality, and so the positive signs are expected. The parameter estimates in these models suggest elasticity measures ranging from −0.14 for chlorophyll a to 0.52 for dissolved oxygen. These findings, however, are not fully robust to the inclusion of additional controls in model III. While the coefficients on Secchi depth and Chlorophyll a are still intuitive, the estimate for dissolved oxygen flips signs and loses significance. This is likely due to the reduction in useable variable that is a consequence of including the additional spatial controls (recall from table 3 that dissolved oxygen had the least amount of cross-lake variability among the five variables). Because of the non-intuitive sign on dissolved oxygen, table 5 also shows a restricted model that eliminates DO from the specification. Estimates of the remaining two coefficients are largely unaffected.

To complete our analysis of the participation margin, table 6 displays two specifications – both with the full set of spatial and temporal controls – with combinations of the primary pollutant and secondary response variables. Aside from the counterintuitive sign on DO in model I, these results largely confirm our findings from the separate analyses. In particular our results provide strong evidence of a causal relationship between water quality and decisions related to whether or not to select a given site for a visit. The ranked magnitudes of our estimates suggest absolute value participation elasticities centered on 0.30 to 0.35.

Frequency Analysis

We now turn to a reduced form analysis of the frequency of visit decision. Our objective is to examine the conditional behavior of people who have decided to visit a site, to assess whether better water quality causes them to visit a lake more often. This is a more complicated econometric environment, in that the dependent variable is now quantitative rather than qualitative. Furthermore we need to address censoring and small integer outcomes: a person may visit a lake in one year, but take no visits in the following year; visit counts are also likely to be too small to effectively approximate with a continuous distribution. Thus for this analysis we therefore use a specific parametric assumption leading to a fixed effects Poisson count data model.

We denote the number of trips person i made to lake j during year t by Y_{ijt} and assume that Y_{ijt} follows a Poisson distribution with conditional mean

$$\lambda_{ijt} = E(Y_{ijt}) = \exp\left(\gamma Q_{jt} + \beta X_{ijt} + c_{ij}\right), \quad j = 1,...,128, \quad t = 2002,...,2005, \tag{4}$$

where the c_{ij}'s are person/site specific fixed effects that are constant over the panel. Thus (4) is a specification of the Poisson panel fixed effect model, written in a system context with cross-equation restrictions. We have chosen this specification because, unlike most non-linear models, the fixed effect Poisson model does not suffer from an incidental parameters problem, and so consistent estimation of the parameters of interest is possible while also controlling for time constant unobservable determinants of behavior via the c_{ij}'s (Cameron and Trivedi, 1998, pp. 281-82). However, the fixed effects model requires that all panel units included in the estimation sample have at least one non-zero outcome in the panel. In (4) the panel unit is a person/lake combination, and so individuals contribute a person/lake/time observation indexed *i*, *j*, *t* only if they have visited lake *j* at least once during the four years of the study (Cameron and Trvedi, 2009, pp. 624-25). Thus the size and composition of the sample used for estimation in this analysis is different than what we used for the participation analysis.

Table 7 contains estimates for models that use the primary pollutants as quality variables. We have once again included the quality variables in log form. Equation (4) shows that this decision results in a log-log model, so that the estimated coefficients are interpretable as elasticities. In particular, γ_k in this case is the elasticity of trip frequency with respect to quality measure *k*. As with the participation analysis, we consider three specifications that include progressively more controls. Model III is our preferred specification; we nonetheless find negative and significant estimates for parameters on both total phosphorous and nitrogen for all models. The elasticity estimates from model II are −0.10 and −0.24, respectively, suggesting the behavioral response in this dimension is smaller than in the participation case. These estimates, however, still seem economically significant.

Table 8 shows estimates for models that use the secondary response measures at quality variables. Surprisingly given the stability of estimates to now, these numbers do not make intuitive sense, nor is it straightforward to sort out the cause of these odd estimates. Indeed, incrementally removing variables does not change the sign of significance of those left in the model. At the time of writing we are still puzzling over this.

Robustness Checks

As a robustness check we run versions of both the participation and frequency panel models using the balanced panel of 2354 respondents. Table 9 shows results for the system fixed effects linear probability model, where all models include the full set of temporal and spatial controls. The two sets of results correspond to our primary pollutant (model I) and secondary response variables (Model II) strategies for including water quality variables. Coefficient estimates are essentially unchanged when we use the balanced panel in place of the unbalanced panel.

Table 10 shows results from the fixed effects system Poisson model. The specification using TN and TP as explanatory variables is qualitatively similar to what we find using the unbalanced panel, though the size of the effect on TN is larger. This is likewise for the specification using the secondary response measures, where we find estimates from the balanced panel that are similar in oddness to their unbalanced counterparts.

4) Structural Analysis

(Still to be executed)

5) Discussion

This research is still in its early stages and all of our results are preliminary. However, our estimates suggest there is reason to believe improved lake water quality does lead to an increase in the likelihood that individuals will visit a lake. Evidence of an effect related to the frequency of visit is more elusive. Nonetheless our results to some degree confirm that the associational evidence used to assess the monetary value of water quality improvements is accurate in a qualitative sense. Extrapolating from this, we can speculate that additional improvements in water quality from reduced non-point source pollution would provide positive economic benefits – though whether net benefits are positive can only be determined on a case by case basis.

The next step in this research is to complete a structural analysis of lake visit demand, which will provide a theoretically valid platform from which we can measure the marginal dollar value of changes in water quality. Additional examination of our sample – particularly as regards the threat that panel attribution poses to the validity of our estimates – is also a near term objective.

6) References

Bingham, T. et al., *A Benefits Assessment of Water Pollution Control Programs since 1972: The Benefits of Point Source Controls for Conventional Pollutants in Rivers and Streams*, RTI Project Number 6600-4, prepared for US EPA Office of Water, 2000.

Cameron, A.C. and P.K. Trivedi, *Microeconometrics using Stata*, Stata Press, 2009.

Cameron, A.C. and P.K. Trivedi, *Regression Analysis of Count Data*, Cambridge University Press, 1998.

Phaneuf, D., J. Carbone, and J. Herriges, “Non-price equilibria for non-marketed goods,” *Journal of Environmental Economics and Management* 57 (2009): 45-64.

Whitehead, J., D. Phaneuf, C. Dumas, J. Herstine, J. Hill, and B. Buerger, "Convergent validity of revealed and stated preference behavior with quality change: a comparison of multiple and single site demands," *Environmental and Resource Economics* 45 (2010): 91-112.

US Department of Commerce, *Pollution Abatement Costs and Expenditures*, April 2005.

US Environmental Protection Agency, *National Lakes Assessment: A Collaborative Survey of the Nation's Lakes*, EPA 841-R-09-001, Office of Water and Office of Research and Development, 2009.

Table 1: Panel Characteristics

Years in Panel	Respondents
1	1307
2	757
3	1843
4	2354
Total Unique Respondents	6261

Table 2: Sample Characteristics by Year

	Sample Size	Propotion with Trips ≥ 1	Mean Trips Given Trips ≥ 1	Std. Dev. Trips Given Trips ≥ 1	Median Trips Given Trips ≥ 1
2002	4254	0.57	10.63	10.93	6
2003	5277	0.62	11.06	10.51	7
2004	4244	0.61	10.69	10.42	7
2005	3993	0.62	11.08	10.77	7

Table 3: Summary of Water Quality Measures

	TN (mg/l)	TP (µg/l)	DO (mg/l)	Secchi Depth (m)	ChlA (µg/l)
2002	2.21	105.03	9.33	1.18	40.23
	(2.53)	(80.55)	(1.67)	(0.927)	(37.98)
2003	2.75	94.14	9.93	1.45	20.10
	(3.21)	(66.12)	(1.86)	(1.13)	(7.79)
2004	2.99	107.81	9.62	1.08	41.45
	(2.76)	(71.32)	(2.00)	(0.80)	(30.28)
2005	2.60	96.37	9.81	1.21	89.43
	(2.76)	(76.97)	(1.89)	(0.94)	(71.47)

Table 4: Fixed Effects Linear Probabability Model Estimates - Primary Pollutants

	I	II	III
ln(Total Phosphorous)	−0.0077	−0.0087	−0.0067
	(−26.62)	(−29.64)	(−21.67)
ln(Total Nitrogen)	−0.0094	−0.0086	−0.0063
	(−30.19)	(−26.63)	(−19.97)
Time Controls	N	Y	Y
Time x Region Controls	N	N	Y

Table 5: Fixed Effects Linear Probabability Model Estimates - Secondary Response Measures

	I	II	III	IV
ln(Dissolved Oxygen)	0.0049	0.0095	−0.0015	-
	(10.30)	(20.07)	(−3.21)	
ln(Secchi Depth)	0.0074	0.0081	0.007	0.007
	(30.16)	(32.62)	(28.51)	(28.37)
ln(Chlorophyll a)	−0.0026	−0.0051	−0.0036	−0.0038
	(−17.03)	(−31.46)	(−21.53)	(−22.40)
Time Controls	N	Y	Y	Y
Time x Region Controls	N	N	Y	Y

Table 6: Fixed Effects Linear Probabability Model Estimates - Mixed Models

	I	II
ln(Dissolved Oxygen)	−0.0012	-
	(−2.73)	
ln(Secchi Depth)	0.0057	0.0057
	(22.47)	(22.34)
ln(Chlorophyll a)	−0.0035	−0.0036
	(−20.39)	(−21.28)
ln(Total Phosphorous)	−0.0025	−0.0024
	(−7.45)	(−7.32)
ln(Total Nitrogen)	−0.0056	−0.0057
	(−17.78)	(−17.89)
Time Controls	Y	Y
Time x Region Controls	Y	Y

Table 7: Fixed Effects Poisson Model Estimates - Primary Pollutants

	I	II	III
ln(Total Phosphorous)	−0.1330	−0.1178	−0.0963
	(−13.14)	(−11.44)	(−9.27)
ln(Total Nitrogen)	−0.2114	−0.2327	−0.2390
	(−21.68)	(−22.35)	(−20.87)
Time Controls	N	Y	Y
Time x Region Controls	N	N	Y

Table 8: Fixed Effects Poisson Model Estimates - Secondary Response Measures

	I	II	III
ln(Dissolved Oxygen)	−0.3241	−0.4614	−0.3889
	(−14.49)	(−19.69)	(−15.56)
ln(Secchi Depth)	−0.0589	−0.1416	−0.0914
	(−6.39)	(−14.62)	(−8.96)
ln(Chlorophyll a)	0.0883	0.1089	0.1395
	(17.97)	(16.28)	(19.56)
Time Controls	N	Y	Y
Time x Region Controls	N	N	Y

Table 9: Fixed Effects Linear Probablity Models with Balanced Panel

	I	II
ln(Total Phosphorous)	−0.0076 (−20.1)	-
ln(Total Nitrogen)	−0.0077 (−20.43)	-
ln(Dissolved Oxygen)	-	−0.0021 (−3.71)
ln(Secchi Depth)	-	0.0081 (26.19)
ln(Chlorophyll a)	-	−0.0046 (−22.46)
Time Controls	Y	Y
Time x Region Controls	Y	Y

Table 10: Fixed Effects Poisson Models with Balanced Panel

	I	II
ln(Total Phosphorous)	−0.0829 (−6.32)	-
ln(Total Nitrogen)	−0.4263 (−29.66)	-
ln(Dissolved Oxygen)	-	−0.6367 (−19.94)
ln(Secchi Depth)	-	−0.1418 (−11.02)
ln(Chlorophyll a)	-	0.2015 (22.12)
Time Controls	Y	Y
Time x Region Controls	Y	Y