Don’t Drink the Water! The Impact of Harmful Algal Blooms on Household Averting Expenditure

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Abstract

Increasingly frequent Harmful Algal Blooms (HABs) are generating growing public concern and attracting new policy focus both across the United States and globally. One particularly acute problem with HABs is the potential impact on drinking water supplies due to high levels of microcystin toxins. We study households' averting expenditure in response to a HAB outbreak in the Toledo, OH water supply. Using household level data from the NielsenIQ consumer panel for bottled water purchases, we estimate both post-matching difference-in-difference models and household panel models of averting behavior. Our estimates provide the first revealed preference estimates of averting expenditure associated with drinking water contamination by HABs. We find that per household averting expenditure ranges between \$2.60 and \$4.12 for the three-day drinking water advisory in Toledo, providing a lower bound willingness to pay to avoid HABs in public drinking water supplies. Our results imply a total averting expenditure of \$828,193 across all affected households serviced by the Toledo public water supply.

1. Introduction

Freshwater eutrophication, especially overgrowth of toxic algae is recognized as a major water quality problem in all states and across the globe. When toxin-producing algae grows excessively in a waterbody, a harmful algal bloom (HAB) occurs. According to the 2017 National Lakes Assessment, HABs are present in 19.83% of samples across 1,210 lakes in the United States (Environmental Protection Agency 2021). Toxic algae releases *Cyanotoxins* into the surrounding water which poses a threat to the aquatic ecosystem, local economies, public health and drinking water safety (Griffith and Gobler 2020). The Lake Erie region is particularly vulnerable to HABs due to extensive agricultural land use and presence of shallow lakes resulting in less water volume per surface area (Tian et al. 2017). Since the mid-1990s, this region has seen increasingly frequent HAB outbreaks causing significant impacts on as many as 11 million residents in the United States and Canada (Bridgeman, Chaffin and Filbrun 2013). In Ohio alone, more than $3 billion has been spent to address HABs in Lake Erie since 2011 (Environmental Protection Agency 2015). An additional $1 billion investment has been announced in February 2022 for the Great Lakes Restoration Initiative to address HABs and other threats facing Lake Erie and the Great Lakes (Environmental Protection Agency 2022).

Farmers, conservation authorities and governments are collaborating at the regional, national and state levels to mitigate nutrient runoff from agricultural activities which has been identified as the primary cause of HABs in Lake Erie (Michalak et al. 2013; Scavia et al. 2014). The U.S. and Canada updated the Great Lakes Water Quality Agreement (GLWQA) in 2012[1] to place more emphasis on mitigating nutrient loadings (GLWQA 2016). In 2015, the Ohio Senate

[1] The Great Lakes Water Quality Agreement (GLWQA) was first signed in 1972. It has been revised in 1878 aiming at a broadened goal of protecting the entire Great Lakes ecosystem.

passed a bill to restrict farmers' nutrient management practices aimed at limiting nutrient application and loading into Lake Erie. Federal and state programs also provide multiple incentives to promote adoption of Best Management Practices (BMPs) on farms to reduce nutrient loadings (Garnache et al. 2016; Liu et al. 2020). Despite efforts to reduce nutrient runoff and HABs, the frequency of HABs is increasing, often with a greater spatial extent (Gobler 2020).

For inland lakes and reservoirs used for drinking water source, HAB contamination results in costly filtering expenditure and water system upgrades, and if insufficient, poses significant risks to households (Bingham, Sinha, and Lupi 2015). Given the absence of federal and state regulation on HABs (Henrie, Plummer, and Roberson 2017; Treuer et al. 2021), drinking water systems across the country often lack clear protocols for monitoring and responding to HAB outbreaks placing residents at risk of contaminated water supplies.[2] Recent water advisories of public water supply contamination caused by HABs are widespread across the nation including, Carroll township, Ohio in 2013 and Toledo city, Ohio in 2014 as a result of HABs in Lake Erie, City of Ingleside, Texas with a 13-day advisory in 2016, City of Salem, Oregon, village of Rushville, New York and Greenfield, Iowa in 2018, West Palm Beach, Palm Beach and South Palm Beach, Florida in 2021. The potential impact from HABs was highlighted by the Toledo water crisis in 2014 with the discovery of alarming levels of *Microcystin (MC)*, the most ubiquitous *Cyanotoxin* in freshwater systems worldwide (World Health Organization 2003), in the treated water of Toledo, Ohio's public water system. About 500,000 residents were

[2] At present, Cyanotoxins are not regulated under Safe Drinking Water Act. To reduce drinking water risks from cyanotoxins with accelerating HABs, the EPA developed Health Advisories for two cyanotoxins (Cylindrospermopsin, and Microcystins) in 2015. The EPA also include Cyanotoxins on the drinking water priority Contaminant Candidate List and are monitoring ten Cyanotoxins under the fourth Unregulated Contaminant Monitoring Rule. However, all of these are non-enforceable and non-regulatory.

without potable water on tap for three days and over 100 individuals became ill after exposure to the contaminated water supply. To recover Toledo's drinking water systems, over $200,000 was spent per month for additional powdered activated carbon treatment. After the crisis, Toledo also began a 10-year, $500 million project to upgrade the water intake and treatment system.

Growing concerns over HABs makes evaluation of evolving policies and programs targeting HABs reduction of significant importance to policymakers seeking to balance costs and benefits of policy intervention. There is an increasing body of literature investigating the impacts of HABs using stated and revealed preference methods. Existing studies primarily assess the impacts in terms of property values (Leggett and Bockstael 2000; Walsh, Milon, and Scrogin 2011; Wolf and Klaiber 2017; Liu et al. 2019; Wolf et al. 2019; Wolf, Gopalakrishnan and Klaiber 2022), recreational visits (Hanley, Bell, and Alvarez-Farizo 2003; Keeler et al. 2015; Wolf, Georgic, and Klaiber 2017; Palm-Forster, Lupi and Chen 2016) and fisheries (Weicksel and Lupi 2013; Bingham, Sinha, and Lupi 2015; Wolf et al. 2017; Zhang and Sohngen 2018; Gill, Rowe, and Joshi 2018). For instance, Zhang and Sohngen (2018) apply survey data from Ohio recreational anglers to evaluate their willingness to pay for reducing HABs in Lake Erie. They found that on average, anglers are willing to pay over $8 per trip for a one-mile reduction of HABs to a fishing site. Using housing market data, Wolf, Gopalakrishnan and Klaiber (2022) report that households near Lake Erie are willing to pay $2,205 on average for a $1\mu g/L$ reduction in algae concentrations. Complementing these existing studies, we provide the first revealed preference estimates of the economic impacts of HABs on household welfare associated with drinking water safety.

In response to the HAB contamination of drinking-water, households are expected to use alternative water sources, such as bottled water, water purifiers or private wells. Averting behavior is a commonly used non-market valuation technique to measure welfare changes when households alter behaviors to avoid or reduce environmental risks. Existing studies have found significant increases in averting expenditure of bottled water in response to groundwater contamination (Abdalla, Roach, and Epp 1992), water quality violations (Zivin, Neidell, and Schlenker 2011; Allaire et al. 2019), hurricanes (Beatty, Shimshack, and Volpe 2019) and shale gas development (Wrenn, Klaiber, and Jaenicke 2016). These averting expenditures are undertaken by consumers based on personal perceptions of risks (Abrahams, Hubbell, and Jordan 2000; Anadu and Harding 2000; Um, Kwak, and Kim 2002; Jakus et al. 2009; Hu, Morton, and Mahler 2011; Bontemps and Nauges 2016). However, all of these studies apply survey data or store-level data apart from Wrenn, Klaiber, and Jaenicke (2016). These authors use household data on bottled water purchases to examine impacts of risk perceptions of shale gas development in Pennsylvania and report an annual averting expenditure of $10.74 for each household per year due to nearby shale gas activity. We contribute to this literature and provide revealed preference estimates of averting expenditure based on observed behaviors using market transaction data at the household level.

In this paper we investigate the case of the Toledo water crisis to evaluate the impacts of HABs on household averting expenditure. We model household expenditure on bottled water in response to the three-day drinking water advisory in Toledo to quantify the impact of HABs on household averting expenditure. Using household level data from the NielsenIQ consumer panel, we develop a dataset of household biweekly expenditure on bottled water within the three months prior to and after the crisis. We apply both post-matching difference-in-difference models and household panel models to empirically estimate averting expenditure. We find that averting expenditure is between $2.60 and $4.12 per household in response to the three-day water advisory. The estimates are robust and consistent across various model specifications and matching procedures. These estimates provide a lower bound of the willingness to pay to mitigate HAB contamination in drinking water supplies as we do not consider other long-term defensive behaviors and alternative water supply sources. Our results imply a total averting cost of at least $828,193 across all affected households serviced by the Toledo public water supply.

The rest of the paper proceeds as follows. We first describe the theoretical methodology, and then introduce the Toledo water crisis and household bottled water purchase data. We continue with a description of our post-matching difference-in-difference and panel data models, followed by a description of the estimation results along with a series of robustness checks. Finally, we discuss welfare and policy implications in the concluding section.

2. Averting Behavior

Drinking water affects household welfare substantially serving as a fundamental input into the household production function. Each household is assumed to choose a level of numeraire consumption alongside drinking water quality to maximize their utility subject to a budget constraint. The ambient water quality does not affect household utility directly, though it enters the budget constraint by determining the cost to achieve a desired level of drinking water quality. It is expected that household expenditure is higher with a lower level of ambient water quality as the household will have to allocate additional budget to obtain improved water quality. The averting behavior model assumes that consumers make changes in their behavior and consequently spend additional money to avoid an undesirable outcome from exogeneous changes in the environment (Courant and Porter 1981; Bartik 1988). Observed changes in defensive behaviors help to reveal averting expenditure and economic benefits associated with removing threats to drinking water supplies.

We follow Bartik (1988) and construct the theoretical framework with a household maximization problem in equation (1):

$$\max_{X,Q} U(X,Q)$$
$$s.t.\ X + D(Q,P) = Y \qquad (1)$$

where X is the numeraire commodity, Q is the drinking-water quality chosen by a household, P is the exogeneous ambient water quality, $D(Q,P)$ is the averting cost function showing the defensive expenditure required to reach a particular drinking water quality Q given P, and Y is household income. The first-order conditions at maximization yield the indirect utility of $V(P,Y)$. Under the assumption that numeraire consumption and original drinking water quality remain unchanged when P varies, D_p provides an estimate of the marginal willingness to pay (MWTP) as shown in equation (2). The integral of MWTP over changes in ambient water quality gives the total defensive expenditures of mitigating drinking water risks from HABs.

$$\frac{dY}{dP}|_{dV=0} = -\frac{V_P}{V_Y} = D_p \quad (2)$$

Tap water is considered as the primary drinking water source as it provides the cheapest, generally safe and clean potable water to households through the public water system. When tap water is regarded as unsafe or of low quality, consumers are more likely to use bottled water as alternative water sources (Ferrier 2001; Hu, Morton, and Mahler 2011). Substituting bottled water for tap water results in additional costs[3] which reveals the averting costs associated with

[3] According to water rate in Toledo city, tap water rate is $2.742 per 100 cubic feet (i.e. 748 gallons) in 2020, that is $0.0037/gallon. In comparison, the average price of wholesale bottled water is about $1.18/gallon according to the Beverage Marketing Corporation (BMC). The price of bottled water is much higher than tap water from municipal water systems by over 300 times.

water quality degradation. Using the averting behavior framework, we can empirically model household expenditure of bottled water to measure the costs of achieving safe drinking water in response to water supply contamination by HABs.

3. The Toledo Water Crisis and Household Bottled Water Purchases

Increasingly frequent HABs in Lake Erie combined with outdated water supply systems triggered the largest water crisis in the region, the Toledo water crisis. The city of Toledo, Ohio issued a "Do Not Drink" water advisory on August 2nd, 2014 after two sample readings of *Microcystin* exceeded the safe drinking water threshold.[4] The water advisory was communicated widely via radio, television, newsprint and social media to notify residents of the contaminated water supply. The advisory was in effect for three days and ended on August 4th. Approximately 500,000 water users from Lucas, Fulton, Wood and Monroe counties were exposed to harmful algal toxins and without drinkable water on tap. Local restaurants, universities and public libraries closed during the advisory and more than 100 people became ill after exposure to the contaminated tap water (Henry 2014).

The water crisis was covered nationally and featured prominently on local and national news media coverage. National press including the New York Times, the Washington Post, Los Angeles Times, and the Wall Street Journal[5] provided detailed coverage about the water crisis

[4] According to EPA, the threshold of *Microcystins* for children six and older and adults for safe drinking water is $1.6\mu g/L$ while the level should be less than $0.3\mu g/L$ for the group of children under six and sensitive populations. When the levels of Cyanotoxins are above the thresholds in the finished drinking water, response strategies include additional monitoring, treatment optimization and potentially other actions, such as public notification or drinking water advisories. Issue of a drinking water advisory requires two consecutive detections of exceeding levels of Cyanotoxins.

[5] For instance, "Behind Toledo's water crisis, a long-troubled Lake Erie" by the New York Times, "Ohio's water crisis is a warning to all states". "Toledo can't drink its water. There's an economics lesson there", "The toxin that shut off Toledo's water? The feds don't make you test for it." by the Washington Post, "Water ban over, Toledo drinks from tap again" by Los Angeles Times, "Algae blooms making Toledo water undrinkable are thriving", "Five years later: lessons from the Toledo water crisis" by the Wall Street Journal.

and urged actions to deal with algae blooms in Lake Erie. Extensive media coverage resulted in Google Trends' searches of "harmful algal bloom" reaching the peak in Ohio as shown in Table A1 in the Appendix. Public concerns over harmful algal blooms increased substantially after the crisis, particularly in 2016 and 2019.

Given the acute health impacts of contaminated water by *Microcystin*, water users were warned not to drink, cook with or even bathe in the city's tap water.[6] Residents were recommended to use bottled water for daily use instead of tap water, which spurred a regional shortage of bottled water in and around Toledo. Local social media feeds were occupied by pictures of long lines, empty shelves in water aisles, and "out of water" signs in local grocery stores. In search of bottled water, Toledo residents were traveling as far away as Lima, Delaware and north of Ann Arbor (Dungjen 2014). Ohio governor John Kasich announced a state of emergency and ordered a contingent of Ohio National Guard to deliver thousands of gallons of bottled water to residents in Toledo area (Ohio National Guard 2014).

To quantify averting behavior during this time period, we obtained household purchase data from the Consumer Panel collected by NielsenIQ. The dataset represents a longitudinal panel of about 60,000 geographically dispersed and demographically balanced households in the U.S. and includes information on their demographic characteristics, products purchased, and shopping trip information.[7] We follow the literature and generate the biweekly purchase data on bottled water (Wrenn, Klaiber, and Jaenicke 2016; Zhen et al. 2011). Specifically, we first identify all transactions on bottled water, which includes 5,354 Universal Product Codes (UPCs), and then aggregate all bottled water expenditure by household ID and biweek number. Each

[6] According to Environmental Protection Agency, acute health effects in humans after exposure to Cyanotoxins include fever, headache, sore throat, vomiting, diarrhea and death in rare circumstances.
[7] See Kilts Center at https://www.chicagobooth.edu/research/kilts/datasets/nielsenIQ-nielsen for a more detailed overview of the NielsenIQ data.

resulting observation represents household total expenditure on bottled water in each biweek. Households outside the study area are identified and dropped. We attach demographic information for each household by the unique household ID. Household income are category variables which are transformed into numeric values using the mean value of each category.

To create the difference-in-difference design, we define the treated area for our study as the region receiving water from the City of Toledo, as shown in Figure 1.[8] We select a different, unimpacted metropolitan area in Ohio that is adjacent to the Lake Erie to construct a control sample as these lake adjacent communities share similar geographic characteristics and recreation patterns which may lead to similar bottled-water purchasing patterns. We use the Cleveland water service area as the control area as this area is also bordering Lake Erie but geographically far from the HAB region in Toledo and has historically not been subjected to significant HAB events as those tend to occur in the shallower and warmer regions in the western basin of Lake Erie (Environmental Protection Agency 2018). We improve upon our naïve treatment and control designation using genetic matching and nearest neighbor matching techniques to construct a matched control described in the following section.

To assess the plausibility of Cleveland as a valid counterfactual, we examine whether biweekly household expenditure on bottled water from treated and control area follows the same trends prior to the advisory by visual examination and statistical test. Figure 2 compares the average biweekly expenditure within three months from biweek 12 to 19[9] in the Toledo treatment group and Cleveland control group. Overall, the treatment group and control group share a similar trend prior to biweek 16. Households in the treated area generally consume more

[8] We delineate the treatment and control area using zip codes in order to trace household transaction data of bottled water using Consumer Panel data from NielsenIQ.

[9] We define the first day of biweek 16 as August 2nd (Saturday) to exactly capture the impacts of Toledo water crisis. Each biweek starts from Saturday until the next Friday.

bottled water, although this difference remains roughly constant prior to the water quality advisory. What is immediately clear from this plot is the significant change in bottled-water purchases during the advisory period which forms the basis for our treatment effect. In addition, we also test the parallel trends assumption statistically (Table A3) and provide a detailed discussion in the results section. Our results confirm that the treatment group and control group share a similar trend in bottled water purchases before the water advisory.

Table 1 compares demographic and socioeconomic characteristics of treated sample household with control group, as well as matched control group. There are 482 households with 2,665 biweekly transactions of bottled water recorded in the full sample. The average household income in the treatment group is $52,320, with over 2 persons in the household. Most household heads are over 50 years old and have a college degree. To test for covariate balance, we calculate the standardized mean difference between treatment and control groups before and after matching (Stuart 2010). The values of standardized mean differences decrease substantially after matching in terms of household income, size, presence of children and education level, and all of them are close to zero.

4. Econometric Estimation

To disentangle the effects of HABs on drinking water safety from other related aspects, such as recreational behavior or fishing, we apply a difference-in-difference (DID) design to evaluate how a drinking water advisory affects household biweekly expenditure on bottled water. Demand for bottled water is expected to increase as a result of substitution from tap water to bottled water as households seek to maintain water quality levels when their existing tap water quality degrades. The baseline DID model we estimate is as follows:

$$y_{ict} = \alpha_0 + \alpha_1(Treat_i \times Post_t) + \alpha_2 Treat_i + \alpha_3 Post_t + \boldsymbol{\gamma x_i} + \delta_c + \epsilon_{ict} \quad (3)$$

where y_{ict} is the biweekly expenditure on bottled water of household i in county c and time t. $\boldsymbol{x_i}$ is a vector of observed demographic characteristics of household i, such as household income, size, presence of children, age, education of household head, and race. δ_c is a dummy variable of county. $Treat_i$ is an indicator of treatment, which equals 1 if household i receives water supply from Toledo, and 0 otherwise. $Post_t$ equals 1 if the purchase is made after the Toledo water crisis (from biweek 16 onwards). α_1 is the key DID interaction of post-treatment period and treatment group, which provides an estimate of the biweekly averting expenditure caused by the HAB outbreak on Toledo residents. We primarily investigate a three-month time window which covers 3 biweeks prior to the HAB outbreak (biweek 13 to 15) and 3 biweeks after the HAB outbreak (biweek 16 to 18). We also look at a shorter and longer time periods of 4 biweeks (biweek 14 to 17) and 8 biweeks (biweek 12 to 19) in the results section.

We extend our baseline DID to allow for time-varying effects in equation (4). We interact the treatment variable with a set of biweekly fixed effects $\sum_{t=14}^{T=18} d_t$ using a six-biweek time window. Impacts of HABs on household drinking water are revealed by the changes over time relative to the base biweek of 13. We replace the biweek dummies with $\sum_{t=15}^{T=17} d_t$ or $\sum_{t=13}^{T=19} d_t$ respectively when we look at a four-biweek or eight-biweek time window with the first biweek omitted as the base time period.

$$y_{ict} = \beta_0 + \sum_{t=14}^{T=18} \beta_{1t}(Treat_i \times d_t) + \beta_2 Treat_i + \sum_{t=14}^{T=18} d_t + \boldsymbol{\theta x_i} + \delta_c + \mu_{ict} \quad (4)$$

While the DID model seeks to limit the potential scope for unobservables to bias results, we can potentially improve on the baseline model using matching to ensure greater comparability between treatment and control groups (Smith and Todd 2005; Imbens and

Wooldridge 2009). To maximize covariate balance, we follow previous studies (Ferraro, Mclntosh, and Ospina 2007; Arriagada et al. 2012; Brent and Ward 2019; Carlsson, Jaime, and Villegas 2021) and use one-to-one genetic matching with replacement to construct a matched control group (Diamond and Sekhon 2013; Sekhon 2008). In addition, we also employ the widely used one-to-one nearest neighbor covariate matching with replacement using Mahalanobis distance.[10] Genetic matching is a form of nearest neighbor matching that uses a genetic matching algorithm to identify an optimal weight for each covariate to minimize the generalized Mahalanobis distance.[11] We match each treated household to the closest household from the control area using the full set of household demographics $\boldsymbol{x_i}$ as well as exact matching on the treatment period (before or after the water advisory in biweek 16).[12] The goal of the matching routine is to further reduce the potential for unobservable differences in households between treatment and control groups. We can empirically assess the improvement in observed characteristics using summary statistics of treatment and control groups which are discussed in the previous section. Overall, genetic matching appears to perform better than nearest neighbor covariate matching in balancing covariates between the treatment group and control group in the pre-treatment period.

[10] It is a tradeoff between bias and variance to allow replacement or not (Smith and Todd 2005). Allowing for replacement yields better balance by reusing observations. However, it decreases the effect sample size thereby increasing the variance and worsening precision in some case. We are using matching with replacement after comparing matching quality and regression results. As present in Table 1, standardized mean difference between matched control and treatment households significantly reduce after matching with replacement. We also compare regression results of DID-genetic matching without replacement in appendix Table A1. Estimates are similar in comparison to genetic matching with replacement in Table 2 and 4, but slightly larger in magnitude overall.

[11] See Diamond and Sekhon (2013) for further discussion of generalized mahalanobis distance and genetic matching.

[12] We use package "Matching" in R to conduct the matching. Various calipers can be added to the matching approach, and narrower calipers will produce less bias on covariates and produce more accurate estimates on treatment effects (Austin 2009). We do not restrict any calipers to further reduce bias on covariates for two reasons. Firstly, given so few observations, we want to keep as many observations as possible. Secondly, results are not highly dependent on matching methods as unmatched results are similar as matched result.

To complement the DID models, we also estimate a household fixed effect model using household data in the treated area to identify the effects of HABs on drinking water.[13] This panel model allows us to capture the bottled water expenditure of each household over time controlling for all household specific characteristics that are time-constant, regardless of whether they are observed or unobserved. The model is specified in equation (5)

$$y_{it} = \sum_{t=14}^{T=18} \gamma_t biweek_{it} + \boldsymbol{\phi x_i} + \pi_i + \omega_{it} \quad (5)$$

where $biweek_{it}$ indicates biweek number for household i at time t, π_i represents a household fixed effect, and other notations are consistent with the DID design. Similarly, the series of biweek dummies depend on the sampling time window.

5. Results

Our econometric approach begins with a standard DID model using full sample and matched sample to estimate the change in bottled water expenditure in response to the drinking water HAB advisory. We further investigate the potential for time-varying effects by adding a series of time dummies preceding and following a HAB outbreak. We also estimate a household fixed effect model to trace impacts on household expenditure using a panel data frame. Finally, we estimate a series of models to examine the robustness of our results.

[13] The Consumer Panel Data is not a conventional panel as households do not have records in every period and households may enter or exit. For example, around 18% of sampled households in our study area do not have observations in each biweek. Considering the attributes of Consumer Panel Data, we believe that missing records in household purchases are random which are unrelated with unobservables (See Bharadwaj et al. 2017 for a discussion on balanced versus unbalanced panel). As a result, we are using an unbalanced panel data for estimation to incorporate all observations in the treatment area. We also apply the household fixed effect model to a balanced panel data in appendix Table A2 for comparison. Estimates are quite similar to the unbalanced approach, but slightly larger in magnitude in all time windows.

Difference-in-Difference Estimates for Averting Expenditures

Before presenting our DID results, we first return to an examination of parallel trends. In additional to a visual inspection as mentioned previously, we statistically test the parallel trend assumption using equation (4) for the pre-treatment period before biweek 16. This specification considers non-linear trends in bottled water consumption with kinks. Interacting pre-treatment biweeks with $Treat_i$ allows us to examine whether there is a parallel trend in bottled water consumption between treatment and control group. All interaction terms using both the full sample and matched sample are insignificant (Table A3), which implies no significant difference in the treatment and control group trends prior to the drinking water advisory. These results support our DID strategy by showing that the treatment group, control group and matched control group follow the same trend before the water advisory.

Turning to our primary results, Table 2 shows the regression results for five DID specifications following equation (3) with the full and post-matching data sample. A 6-biweek sampling window is chosen as the primary time window so as to avoid potential contamination of our treatment effect by extending the window far beyond the advisory event. Given that estimates of the average treatment effect may be sensitive to the study period, we also compare the 6-biweek window with a 4-biweek and 8-biweek period respectively, as shown in column 3 and 5. Robust standard errors are clustered at the county level, which are shown in parentheses. Across all specifications we find that the coefficients on control variables are as expected, although many of these coefficients are insignificant.

Turning attention to the DID results of interest, columns 1 and 2 in Table 2 present estimates using the full data sample with the second column adding county fixed effects. The results of these two specifications are quite similar. The significant coefficient on the interaction term *Post*×*Treat* indicates the existence of biweekly averting expenditure in response to the water advisory. For households who receive water from Toledo, we find that each household increased water purchases by an average of \$1.15 each biweek in response to the advisory. The last four columns show estimates of the DID model in equation (3) using matched sample data replying on nearest neighbor matching and genetic matching. Estimates of averting expenditure using the genetic matching algorithm are quite similar with an increase in expenditure of \$1.20 per biweek per household whereas nearest neighbor matching reveals a slightly smaller value at \$0.93. For clarity and consistency, we will continue our analysis using our preferred genetic matching method. We next compare different time windows in column 4 and 6. The average biweekly averting expenditure increases to \$1.67 using a shorter time period of 4 biweeks and intuitively decreases to \$0.96 using a longer time period of 8 biweeks. This finding suggests that the treatment effect is highest in close temporal proximity to the water advisory and attenuates over time.

To explore heterogeneity in household averting expenditure, we add a series interaction terms for socio-demographic variables including income, education, race, presence of children and age with the treatment variables in equation (3). For example, to examine heterogeneity across income, we divide household income into a low-income level (less than \$40,000), medium-income level (between \$40,000 and \$70,000) and high-income level (higher than \$70,000), and then interact these variables (omitting low) with treatment variables as shown in equation (6). We follow a similar approach for other demographic variables.

$$
\begin{aligned}
y_{ict} = \alpha_0 + \alpha_1(Treat_i \times Post_t) + \alpha_2 Treat_i + \alpha_3 Post_t \\
+ \rho_1(MediumIncome_i \times Treat_i \times Post_t) \\
+ \rho_2(HighIncome_i \times Treat_i \times Post_t) + \rho_3(MediumIncome_i \times Treat_i) \\
+ \rho_4(HighIncome_i \times Treat_i) + \rho_5(MediumIncome_i \times Post_i) \\
+ \rho_6(HighIncome_i \times Post_i) + \boldsymbol{\gamma x_i} + \delta_c + \epsilon_{ict} \ (6)
\end{aligned}
$$

We find heterogeneous effects on households with different income, education and race. Households with medium income and lower education levels are found to have a higher averting expenditure. As shown in Table 3, households with medium annual income purchase an additional \$1.53 in each biweek compared with the omitted low income category. Interestingly, we find no significant differences between the low income and high income groups suggesting a nonlinear response to the water crises across this demographic dimension. We also find that households with postgraduate education spend \$1.05 less than other lower-income households. As revealed by the higher expenditure on bottled water, our results imply significant distributional effects across households which is similar to related studies on perceived drinking water risks (Onufrak et al. 2012; Javidi and Pierce 2018).

We next investigate whether the averting expenditure varies over time by adding a series of time dummies following equation (4). Table 4 displays DID estimates with time varying treatment using the full sample and genetic-matched sample over various time periods. Based on the results in column 1, each household is observed to increase water expenditure by \$2.78 in the first biweek after the crisis, and another \$0.87 in the following biweek. The impacts on households are no longer significant by the third biweek. Summing the two significant biweeks, we find that the water advisory results in increased household expenditure of \$3.64, on average.

Using the matched sample, the estimates range from \$2.60 to \$4.12 as shown in columns 2 to 4 with different time windows. Estimate using nearest neighbor matching fall in this range as reported in appendix Table A6. Overall, these results suggests that for the three-day water advisory, the impacts on households generally remain up to a month (i.e. two biweeks) with total averting costs for each household at \$3.76 using a post-matching sample and six-biweek time window.

Table 5 reports estimates of household fixed effect model following equation (5). Depending on the sampling time periods, averting expenditure for each household ranges from \$2.56 to \$3.65 For our primary time window of six biweeks, our panel estimates are nearly identical to the DID estimates with time-varying treatment in Table 4, with \$2.77 in biweek 16 and \$0.88 in biweek 17. We also find positive although insignificant averting expenditure in the following biweeks after the crisis using four-biweek and eight-biweek time windows. The similarity in estimates across our model specifications suggests limited scope for unobservables to influence our DID findings. The results confirm that impacts of HABs on household averting behavior extend beyond the duration of water advisory, with a declining magnitude over time.

Robustness

We conduct several robustness exercises to examine the stability of our primary results. Firstly, we examine whether household expenditure on non-water alternatives, including sugar sweetened or sugar free beverages, increases in response to the water advisory. This would be expected if households substitute to other beverages given unsafe tap water (Javidi and Pierce 2018). We report our findings in Table A4 and find no significant increases in household purchases of non-water alternatives. We find little evidence to show that households are substituting sugar or sugar-free beverages with unsafe tap water.

Our second robustness specification examines the potential for spillover effects to surrounding areas not serviced by the Toledo water supply. This spillover behavior is likely if households in nearby areas respond to the news coverage and may not know whether their own water supply is impacted by HABs or is sourced from Toledo. To measure any potential spillover effects, we add the additional variable $spillover$ into the model which indicates whether households live in bordering zip codes and then interact this variable with the $Post$ advisory indicator. We find no significant increase in bottled water expenditure among those households living in bordering area (Table A5). This suggests that consumers were well-informed of their water provider and the communications on potential water quality risks due to HABs. There is little evidence to show that risk perceptions over HABs have an impact on households outside the advisory area.

6. Conclusion

This study focuses on a timely policy issue in the light of increasing frequent HABs nationwide and lack of federal regulations to monitor, manage or remove Cyanotoxins from water supply systems. The economic welfare evaluation of HABs impacts is limited from the literature, particularly as it relates to revealed preference studies. There are no existing studies that have evaluated the economic impacts of HABs on drinking water safety. We contribute to the literature and investigate the case of the Toledo water crisis to quantify the impacts of water quality advisories caused by HABs on household behaviors. We model household expenditure on bottled water, the primary substitute for conventional tap water, to quantify the averting expenditure in response to the three-day drinking water advisory in Toledo, Ohio.

Using a post-matching difference-in-difference design and a household fixed effect panel model, we estimate the average averting cost is $3.76 for each household, with the impacts on averting expenditure persisting for up to one month. The estimates are robust and consistent across various model specifications and matching procedures. These estimates provide a lower bound of the willingness to pay to mitigate HAB contamination in drinking water supplies. Using these estimates, we calculate a total averting expenditure due to the three-day water advisory of $828,193 after multiplying the average averting cost per household by the total number of households affected.[14] To help place this expenditure in context we compare this expenditure to typical tap water costs. The 2014 annual residential water rate in Toledo is $204 which results at an average water fee of $17 per month (Ohio Environmental Protection Agency 2021). The averting expenditure in response to the 3-day HAB water advisory is therefore equivalent to an increase in the monthly water expenditure on tap water of over 20%.

In a series of robustness results, we find a general lack of spillover effects in surrounding areas suggesting that our difference-in-difference estimates are capturing the majority of the averting expenditures associated with the Toledo water advisory. However, we should note that during the crisis, state agencies including the Ohio National Guard were delivering bottled water and also used water purification systems to produce potable water. Households may have traveled a much longer distance to purchase bottled water than their conventional grocery stores nearby as there were news reports of shortages of bottled water in local stores. Given these

[14] There are around 220,264 households affected by the crisis, which is estimated by dividing total affected population 500,000 by average household size of 2.27 according to census data between 2015 to 2019.

concerns, our results are best interpreted as providing a lower bound of total averting expenditure associated with HAB advisories on drinking water.

Our results have direct implications for policymakers seeking to balance costs and benefits of costly policy intervention targeting HAB reductions through regulating nutrient application and management practices on farms. More importantly, our study links HABs to household behavior as shown by averting expenditure on bottled water. It is expected that increasing frequency and intensity of HABs in inland lakes pose a growing challenge to both public water systems and regulatory agencies. If no policy interventions for managing HABs in public water systems were to occur alongside the predicted increases in HABs in inland lakes and reservoirs due to climate change, households stand to experience significant welfare losses as they seek to avoid potential water quality degradation through averting expenditure.

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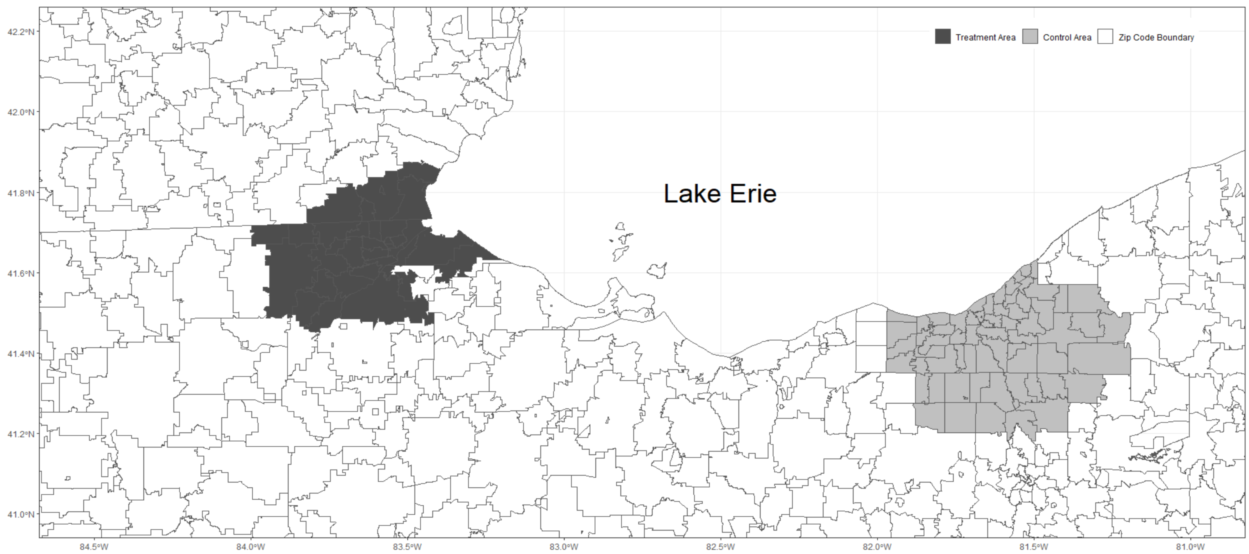

Figure 1. Treatment area and control area

Note: Treatment area include households who receive drinking water from the City of Toledo while control area covers all the households that receive water from the City of Cleveland. We use zip code to delineate treatment and control regions, which match water supply areas closely.

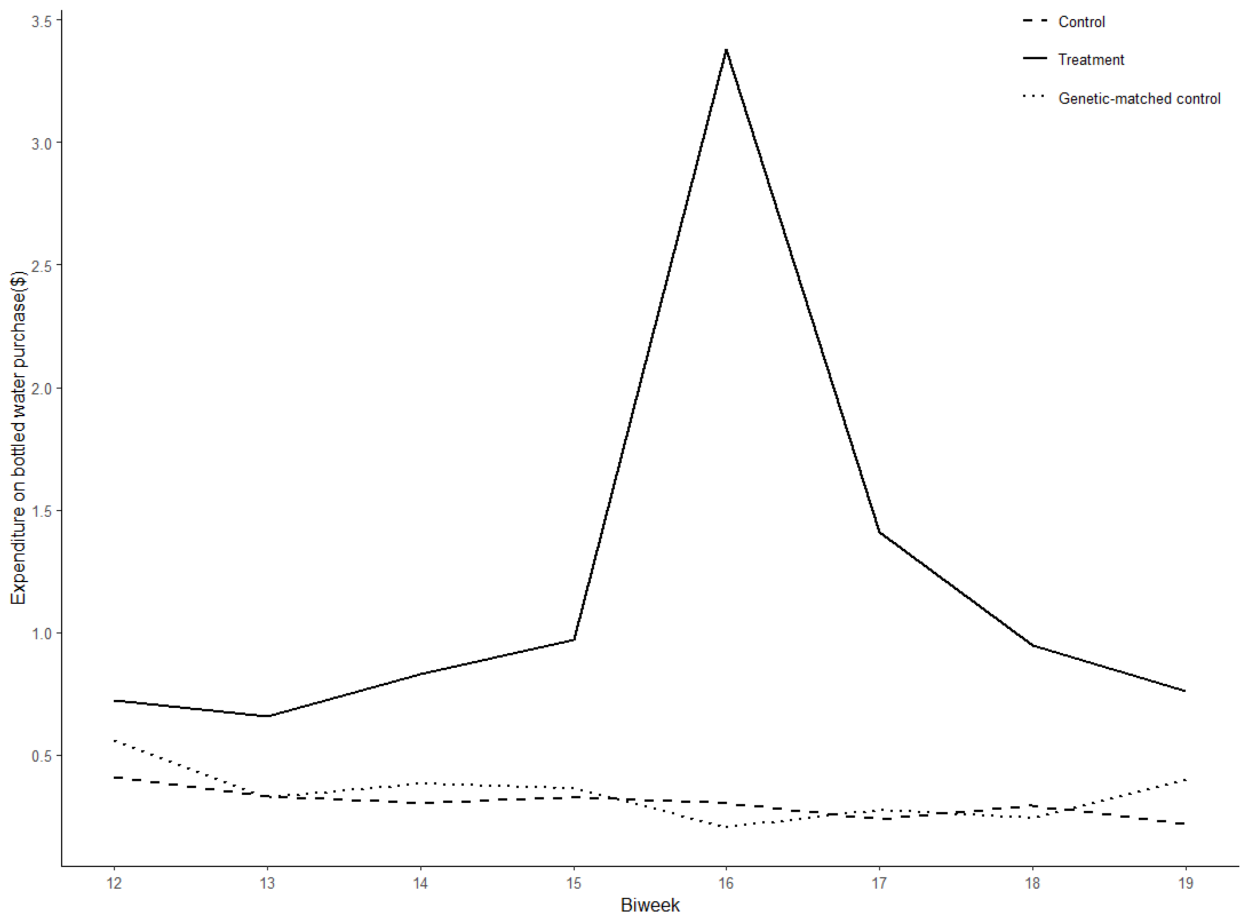

Figure 2. Average biweekly expenditure on bottled water in treatment and control group
Note: Biweekly expenditure sums up each household's expenditure on bottled water for two weeks starting from Saturday. Toledo water crisis occurs on August 2nd, 2014 (Saturday), which is the biweek of 16.

Table 1. Comparison of Households Characteristics in Treatment and Control Sample

Variable	Treat	Control		Nearest Neighbor		Genetic	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD
Outcome							
Expenditure (before)	0.82	0.32		0.19		0.42	
Expenditure (after)	1.92	0.28		0.36		0.31	
Controls							
Household Income($/1000)	52.32	57.40	-0.17	52.34	-0.00	52.47	-0.01
Household Size 1(0/1)	0.30	0.28	0.06	0.30	0.02	0.30	-0.00
Household Size 2(0/1)	0.41	0.42	-0.02	0.45	-0.08	0.42	-0.02
Household Size 3(0/1)	0.16	0.13	0.08	0.13	0.07	0.16	0.00
Household Size 4 or more(0/1)	0.13	0.17	-0.14	0.12	0.02	0.12	0.02
Have Children(0/1)	0.16	0.21	-0.11	0.14	0.07	0.17	-0.02
Married(0/1)	0.58	0.61	-0.06	0.60	-0.06	0.58	-0.02
Younger than 30(0/1)	0.12	0.13	-0.04	0.12	0.00	0.11	0.02
Age 30 to 49(0/1)	0.28	0.29	-0.03	0.25	0.07	0.28	0.01
Age 50 and older(0/1)	0.68	0.69	-0.03	0.71	-0.07	0.69	-0.03
High school or less(0/1)	0.34	0.27	0.15	0.30	0.09	0.34	0.00
College graduate(0/1)	0.54	0.56	-0.05	0.61	-0.14	0.54	-0.01
Postgraduate(0/1)	0.10	0.15	-0.17	0.07	0.09	0.09	0.02
White(0/1)	0.83	0.81	0.06	0.85	-0.04	0.84	-0.03
Black African(0/1)	0.12	0.14	-0.06	0.11	0.04	0.11	0.03
Hispanic(0/1)	0.03	0.01	0.11	0.03	0.00	0.03	0.00
Other race(0/1)	0.04	0.04	-0.00	0.04	0.00	0.04	0.00
Number of observations	816	1849		816		816	

Note: Expenditure (before) measure average biweekly expenditure on bottled water from biweek 13 to 15, while after treatment covers biweek 16 to 18. Standardized mean difference (SMD) is calculated by dividing the difference in means by the square rood of the sum of variances to check balance between treatment and control group.

Table 2. Impacts of Toledo Water Crisis on Averting Expenditures

	DID		NN-DID	Genetic-DID		
	6 biweeks	6 biweeks	6 biweeks	4 biweeks	6 biweeks	8 biweeks
Post×Treat	1.1486***	1.1451***	0.9268***	1.6659***	1.2043***	0.9593***
	(0.2052)	(0.2053)	(0.2934)	(0.4139)	(0.2944)	(0.2327)
Treat	0.4709***	0.3896	0.4227	0.2897	0.3350	0.5176*
	(0.1470)	(0.3058)	(0.3898)	(0.5461)	(0.3897)	(0.3096)
Post	-0.0431	-0.0430	0.1733	-0.1477	-0.0992	-0.1235
	(0.1135)	(0.1136)	(0.2075)	(0.2932)	(0.2084)	(0.1646)
Household Income($/1000)	0.0012	0.0013	0.0008	0.0043	0.0035	0.0028
	(0.0018)	(0.0018)	(0.0031)	(0.0043)	(0.0030)	(0.0024)
HouseholdSize 2	0.0922	0.1030	0.1841	0.1231	0.3150	0.2225
	(0.1727)	(0.1740)	(0.2832)	(0.3976)	(0.2799)	(0.2186)
HouseholdSize 3	0.3117	0.3147	0.3522	0.5535	0.6998**	0.7903***
	(0.2243)	(0.2258)	(0.3463)	(0.5015)	(0.3550)	(0.2796)
HouseholdSize 4 or more	0.3263	0.3401	0.1031	0.1087	0.4610	0.7036**
	(0.2479)	(0.2494)	(0.3868)	(0.5594)	(0.3994)	(0.3032)
Children	0.0353	0.0348	0.0510	0.3038	-0.1165	-0.5050**
	(0.1841)	(0.1842)	(0.3157)	(0.4248)	(0.3086)	(0.2404)
Married	0.0773	0.0631	0.1790	0.0037	-0.1307	0.0070
	(0.1595)	(0.1607)	(0.2538)	(0.3467)	(0.2458)	(0.1930)
Age 30 to 49	-0.5071	-0.5293	-0.2671	-0.9562	-0.4068	-0.5939
	(0.3427)	(0.3446)	(0.4101)	(0.5993)	(0.4273)	(0.3887)
50 and Older	-0.3914	-0.4374	-0.3959	-0.6590	-0.3468	-0.4562
	(0.3391)	(0.3421)	(0.3963)	(0.5721)	(0.4124)	(0.3804)
College graduate	-0.2217**	-0.2441**	-0.3925**	-0.2518	-0.1836	-0.2779**
	(0.1090)	(0.1100)	(0.1679)	(0.2389)	(0.1686)	(0.1341)
Postgraduate	-0.2211	-0.2308	-0.3003	-0.1558	-0.3505	-0.3070
	(0.1687)	(0.1710)	(0.3213)	(0.4374)	(0.3054)	(0.2432)
Black	0.3633**	0.3764***	0.4422*	0.9045***	0.5542**	0.5626***
	(0.1421)	(0.1429)	(0.2413)	(0.3331)	(0.2352)	(0.1824)
Hispanic	1.0410***	1.0916***	0.9981**	2.0837***	1.5488***	1.7615***
	(0.3509)	(0.3572)	(0.4300)	(0.6979)	(0.4808)	(0.4099)
Other race	0.4793*	0.5316**	0.8509**	1.3244**	1.0395**	0.8656**
	(0.2452)	(0.2482)	(0.3918)	(0.6251)	(0.4384)	(0.3604)
Constant	0.5474	0.5854	0.4144	0.5895	0.3245	0.5135
	(0.3699)	(0.3737)	(0.4584)	(0.6544)	(0.4705)	(0.4245)
R-Squared	0.0677	0.0704	0.0687	0.0999	0.0726	0.0717
N	2,665	2,665	1,632	1,084	1,632	2,202
County Fixed Effect	NO	YES	YES	YES	YES	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01. The last four columns present difference-in-difference (DID) estimates with matched sample using nearest neighobor (NN) matching and genetic matching as describe in econometric estimation section.

Table 3. Demographic Heterogeneity in Averting Expenditures using Genetic Matched Control

	Income	Education	Race	Children	Age
Post×Treat×Medium_Income	1.5284**				
	(0.7656)				
Post×Treat×High_Income	-0.4337				
	(0.6677)				
Post×Treat×College		-0.6331			
		(0.6295)			
Post×Treat×Postgrad		-1.0529**			
		(1.0743)			
Post×Treat×Black			-0.1630		
			(0.9124)		
Post×Treat×Hispanic			0.7557		
			(2.0970)		
Post×Treat×OtherRace			2.9078***		
			(1.8876)		
Post×Treat×Children				0.1920	
				(0.7880)	
Post×Treat×Age30to49					0.3729
					(1.6600)
Post×Treat×Age50older					0.3531
					(1.6034)
Constant	0.1511	0.0794	0.4254	0.3421	-0.4093
	(0.5036)	(0.4992)	(0.4729)	(0.4732)	(0.8391)
R-Squared	0.0917	0.0778	0.0841	0.0745	0.0741
N	1,632	1,632	1,632	1,632	1,632
Controls	YES	YES	YES	YES	YES
County Fixed Effect	YES	YES	YES	YES	YES

Note: Results are based on the baseline model of 6 biweeks. According to 2012 census, households are classified into low income with less than \$40,000, medium income between \$40,000 to \$70,000 and high income of over \$70,000.

Table 4. Impacts of Toledo Water Crisis on Averting Expenditures by Biweeks

	DID	Genetic-DID		
	6 biweeks	4 biweeks	6 biweeks	8 biweeks
Biweek13×Treat				0.1860
				(0.4752)
Biweek14×Treat	0.2109		0.2125	0.3815
	(0.3515)		(0.5105)	(0.4612)
Biweek15×Treat	0.3453	-0.0474	0.1494	0.5043
	(0.3518)	(0.5869)	(0.5074)	(0.4518)
Biweek16×Treat	2.7749***	2.6007***	2.8579***	3.0596***
	(0.3493)	(0.5754)	(0.5119)	(0.4666)
Biweek17×Treat	0.8671**	0.6780	0.9026*	1.0638**
	(0.3494)	(0.5789)	(0.4991)	(0.4625)
Biweek18×Treat	0.3202		0.1506	0.4972
	(0.3505)		(0.5125)	(0.4535)
Biweek19×Treat				0.2941
				(0.4590)
Constant	0.6110	0.4866	0.2826	0.7405
	(0.3860)	(0.6731)	(0.5059)	(0.4669)
R-Squared	0.0985	0.1202	0.1043	0.1074
N	2,665	1,084	1,632	2,202
Controls	YES	YES	YES	YES
Biweek Fixed Effect	YES	YES	YES	YES
County Fixed Effect	YES	YES	YES	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01.

Table 5. Impacts on Biweekly Expenditure in Treated Area using Household Fixed Effect

	4 biweeks	6 biweeks	8 biweeks
Biweek13			-0.174
			(0.413)
Biweek14		0.236	0.047
		(0.467)	(0.416)
Biweek15	0.187	0.420	0.206
	(0.541)	(0.469)	(0.418)
Biweek16	2.556^{***}	2.770^{***}	2.581^{***}
	(0.535)	(0.462)	(0.411)
Biweek17	0.648	0.877^{*}	0.668
	(0.538)	(0.465)	(0.413)
Biweek18		0.360	0.180
		(0.464)	(0.413)
Biweek19			-0.018
			(0.412)
R-Squared	0.069	0.068	0.065
N	542	816	1,101

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01.

Appendix

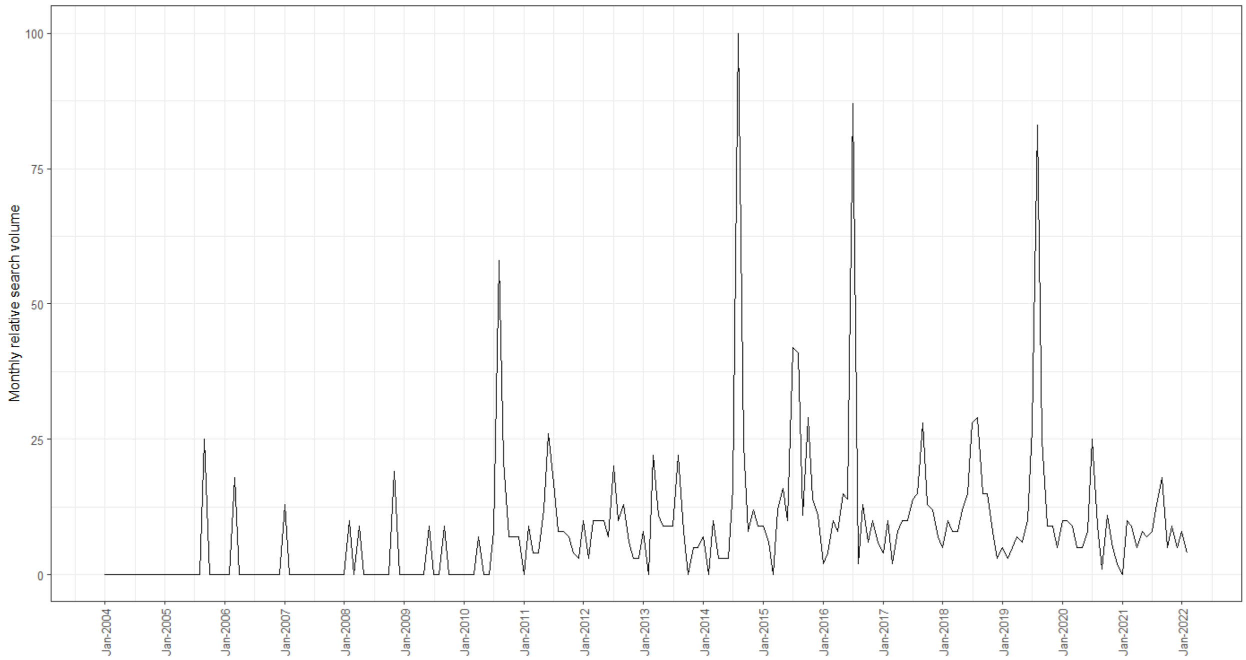

Table A1. Google Relative Search Volume for "Harmful Algal Bloom" in Ohio across Time

Note: Google search volume represents search interest relative to the highest point given the chosen region and time. The peak popularity for the term "harmful algal bloom" is in August 2014 when the Toledo water crisis happens.

Table A1. Estimates of Postmatching Difference-in-Difference without Replacement

	4 biweeks	6 biweeks	8 biweeks
		Panel A	
Post×Treat	1.6381***	1.1835***	0.9693***
	(0.4116)	(0.2913)	(0.2336)
Treat	0.2685	0.3516	0.4966
	(0.5449)	(0.3876)	(0.3112)
Post	-0.1269	-0.0790	-0.1352
	(0.2912)	(0.2061)	(0.1653)
Constant	1.0086	0.7171	0.4979
	(0.7309)	(0.5269)	(0.4217)
R-Squared	0.0973	0.0706	0.0574
N	1,084	1,632	2,202
Controls	YES	YES	YES
County Fixed Effect	YES	YES	YES
		Panel B	
Biweek13×Treat			0.0674

			(0.4574)
Biweek14×Treat		0.1650	0.2266
		(0.5028)	(0.4571)
Biweek15×Treat	0.1215	0.2431	0.3576
	(0.5826)	(0.5000)	(0.4597)
Biweek16×Treat	2.6223***	2.7618***	2.8724***
	(0.5780)	(0.4966)	(0.4594)
Biweek17×Treat	0.7562	0.8607*	1.0057**
	(0.5758)	(0.4964)	(0.4543)
Biweek18×Treat		0.2994	0.3829
		(0.5039)	(0.4555)
Biweek19×Treat			0.2385
			(0.4564)
Constant	0.9611	0.6846	0.6068
	(0.7532)	(0.5641)	(0.4612)
R-Squared	0.1176	0.1023	0.0929
N	1,084	1,632	2,202
Controls	YES	YES	YES
Biweek Fixed Effect	YES	YES	YES
County Fixed Effect	YES	YES	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01.

Table A2. Impacts on Biweekly Expenditure in Treated Area using Balanced Panel Data

	4 biweeks	6 biweeks	8 biweeks
Biweek13			-0.055
			(0.472)
Biweek14		0.321	0.237
		(0.558)	(0.472)
Biweek15	-0.218	0.018	-0.199
	(0.574)	(0.558)	(0.472)
Biweek16	2.662***	3.213***	2.683***
	(0.574)	(0.558)	(0.472)
Biweek17	0.339	0.659	0.624
	(0.574)	(0.558)	(0.472)
Biweek18		0.174	0.102
		(0.558)	(0.472)
Biweek19			0.055
			(0.472)
R-Squared	0.088	0.091	0.077
N	448	600	776

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01.

Table A3. Test for Parallel Time Trend in Pre-Treatment Period

	DID		NN-DID		Genetic-DID	
	3 biweeks	4 biweeks	3 biweeks	4 biweeks	3 biweeks	4 biweeks
*Biweek13*Treat*		0.0026		0.1141		0.1519
		(0.2607)		(0.4722)		(0.3635)
*Biweek14*Treat*	0.2069	0.2059	0.6703	0.7584	0.2040	0.3376
	(0.2636)	(0.2617)	(0.5091)	(1.0599)	(0.3721)	(0.3532)
*Biweek15*Treat*	0.3410	0.3415	0.9137	1.0065	0.1614	0.5193
	(0.2638)	(0.2619)	(1.2100)	(1.0439)	(0.3701)	(0.3464)
Biweek13		-0.0854		-0.2080		-0.2553
		(0.1463)		(0.4098)		(0.2697)
Biweek14	-0.0340	-0.1176	-0.4994	-0.6833	-0.0289	-0.2692
	(0.1462)	(0.1462)	(0.4770)	(1.0335)	(0.2676)	(0.2543)
Biweek15	-0.0149	-0.0994	-0.5877	-0.7640	0.1782	-0.2784
	(0.1453)	(0.1453)	(1.1854)	(1.0168)	(0.2638)	(0.2437)
Treat	0.2514	0.3465	0.2609	0.3345	0.2658	0.2092
	(0.3380)	(0.3030)	(0.3760)	(0.3224)	(0.4257)	(0.3748)
Constant	0.3479	0.3039	0.1797	0.4370	-0.1439	0.4252
	(0.3973)	(0.3453)	(0.4341)	(0.3582)	(0.4779)	(0.4641)
R-Squared	0.0513	0.0508	0.0622	0.0835	0.0868	0.0847
N	1,327	1,783	806	1,098	806	1,098
Controls	YES	YES	YES	YES	YES	YES
County Fixed Effect	YES	YES	YES	YES	YES	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01.

Table A4. Impacts on Household Expenditure of Various Beverages

	Sugar Free Beverages	Sugar Sweetened Beverages	Diet Soda	Regular Soda	Juice	Fruit Flavored Drinks
Post×Treat	0.1145	0.1153	0.0198	0.3332	0.0947	-0.2179
	(0.2611)	(0.4089)	(0.1711)	(0.3665)	(0.1978)	(0.1724)
Treat	0.8110**	1.4978**	0.1332	0.5850	0.6778**	0.9128***
	(0.3889)	(0.6091)	(0.2548)	(0.5460)	(0.2946)	(0.2568)
Post	0.1315	-0.0274	0.0161	-0.1057	0.1154	0.0783
	(0.1444)	(0.2262)	(0.0947)	(0.2028)	(0.1094)	(0.0954)
Constant	0.9971**	2.0257***	0.1862	2.0333***	0.8110**	-0.0076
	(0.4752)	(0.7444)	(0.3115)	(0.6673)	(0.3600)	(0.3139)
R-squared	0.0341	0.0449	0.0232	0.0451	0.0335	0.0298
Observations	2,665	2,665	2,665	2,665	2,665	2,665
Controls	YES	YES	YES	YES	YES	YES
County Fixed Effect	YES	YES	YES	YES	YES	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01. Sugar free beverages include diet soda and juice and sugar sweetened beverages include regular soda and fruit flavored drinks.

Table A5. Spillover effects of Toledo Water Crisis

Variable	border zip codes	non-treated area in affected counties
Post×Spillover	0.5708	0.3632
	(0.3650)	(0.2953)
Post×Treat	1.1443***	1.1448***
	(0.2028)	(0.2003)
Spillover	0.2917	0.2913
	(0.2991)	(0.2547)
Treat	0.6073**	0.7333***
	(0.2631)	(0.2497)
Post	-0.0427	-0.0428
	(0.1122)	(0.1108)
Constant	0.4019	0.4024
	(0.3501)	(0.3445)
R-Squared	0.0682	0.0658
N	2,858	2,968
County Fixed Effect	YES	YES

Note: Spillover effects are based on DID model of 6 biweeks. Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01; Border zip codes include treatment area and bordering zip codes. Border counties include full region of Lucas, Fulton, Wood and Monroe

Table A6. Estimates of Averting Expenditures by Biweeks using Nearest Neighbor Matching

	6 biweeks
Biweek14×Treat	0.7345
	(0.7079)
Biweek15×Treat	0.5011
	(1.7450)
Biweek16×Treat	2.6137***
	(0.4114)
Biweek17×Treat	0.4985
	(0.6612)
Biweek18×Treat	0.0300
	(1.1753)
Constant	0.4793
	(0.4616)
R-Squared	0.1005
N	1,632
Controls	YES
Biweek Fixed Effect	YES
County Fixed Effect	YES

Note: Standard errors are clustered by county level. *p<0.1**p<0.05***p<0.01