The Costs of Nitrate Pollution in Drinking Water *

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July 22, 2022

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Abstract

Nitrate contamination of drinking water is a widespread and worsening environmental concern. The magnitude of the environmental health consequences depend on an individual's ability to avoid exposure. However, there are a number of factors which may undermine one's ability to avoid pollution exposure. This paper studies the heterogeneity in avoidance behavior following Safe Drinking Water Act nitrate violations. I find that consumers exhibit averting response through both bottled water and sugar-sweetened beverages. However, consumers in food deserts show a 31 percentage points lower response relative to consumers with supermarket and grocery access. These results are informative to the mechanisms through which individuals are persistently exposed to environmental pollution despite the presence of regulation.

*Thank you to seminar participants at UC Davis's Dissertation Workshop, as well as, Jamie Hansen-Lewis, Aaron Hrozencik, Aaron Smith, Sarah Smith, and Shu Shen for helpful comments and Kyle Butts for guidance on the empirical implementation. I also appreciate continued guidance from Katrina Jessoe and Richard Sexton. This project was supported by funding from USDA-ERS Rural and Resource Economics Division.

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1 Introduction

Nitrate pollution in drinking water poses a significant health threat and is a widespread and worsening issue. Excessive levels of ingested nitrates particularly affect infants – being a well-known cause of "Blue-Baby Syndrome" (or methemoglobinemia) – potentially resulting in death (Walton, 1951). Recent evidence also suggests that nitrates lead to other birth defects and cancer (Temkin et al., 2019). Rural areas are especially vulnerable with nitrogen-intensive agricultural production contributing to nitrate pollution (Metaxoglou and Smith, 2022). The extent of these public health damages largely depends on individuals' ability to avoid the environmental hazard.

Many environmental regulations are conceptualized around the assumption that those exposed to pollution have the ability to avoid the negative externality once information about the local environmental hazard is revealed. The Safe Drinking Water Act (SDWA) uses information disclosures and public notices to alert consumers of drinking water quality violations and mitigate the risks to public health. However, Marcus (2021) and others show that consumers respond to water quality information heterogeneously.[1] Heterogeneous adaptation to environmental hazards may leave subsets of the population differentially exposed to the harmful health effects of nitrate exposure.

Furthermore, a variety of constraining factors may limit pollution avoidance. These factors may be particularly acute in rural areas, where residents disproportionately experience SDWA nitrate violations, often due to agricultural pollution (Allaire, Wu, and Lall, 2018; Paudel and Crago, 2020). Income constraints, market accessibility, and other infrastructure gaps may limit rural residents' ability to protect themselves from drinking water pollution (De Janvry, Sadoulet, and Murgai, 2002). Greenstone and Jack (2015) hypothesize that marginal willingness to pay for environmental goods is often low in developing country settings due to low incomes and high marginal costs of environmental quality improvement. These factors may similarly lead to smaller behavioral responses to drinking water contam-

[1] Also see Zivin, Neidell, and Schlenker (2011) and Allaire et al. (2019).

ination in the rural United States, where quality improvements should be valuable because of the high rates of violations.

The objectives of this paper are to estimate the costs of nitrate contamination in drinking water and disentangle the distributional relationship of avoidance behavior and the subsequent health consequences. While several papers estimate the extent of avoidance behavior through bottled water retail sales after nitrate violations (Zivin, Neidell, and Schlenker, 2011; Allaire, Wu, and Lall, 2018), these are derived from two-way fixed effect estimation and may suffer from bias.[2] I update these established estimates of the behavioral response to nitrate violations with an unbiased estimator proposed by Gardner (2021). Additionally, the behavioral response is only a portion of the economic costs of nitrate violations because it fails to account for the health consequences imposed on those who remained exposed (Harrington and Portney, 1987). The epidemiological literature identifies the potential health risks associated with nitrate ingestion, but these studies do not account for the behavioral response. I account for both the behavioral and health costs and provide a more comprehensive estimate of the economic costs of nitrate violations in drinking water.

In doing so, this paper contributes to the literature in three primary ways. First, the costs of nitrate pollution in surface water, resulting in algal bloom and "dead-zone" (or hypoxic zones) in the Gulf of Mexico, are substantial (Hendricks et al., 2014; Taylor and Heal, 2022). However, despite being a critical focus for local and federal environmental regulators, less is known about the extent of economic damages of nitrate pollution in groundwater and drinking water.[3] Identifying the damages in this context are empirically challenging due to endogenous sorting, and much of the current knowledge about nitrate's impact on health relies on case-studies or cross-sectional exposure analyses (Walton, 1951; Ward et al., 2018; Temkin et al., 2019). I overcome this empirical challenge by using quasi-random shocks to

[2]Goodman-Bacon (2021) and others document the potentially severe treatment effect bias when using two-way fixed effects when treatment is heterogeneous over time. I expand on these issues in the empirical section.

[3]Nitrate contamination issues in drinking water are sourced almost exclusively from groundwater. Pennino, Compton, and Leibowitz (2017) states that about 95% of the SDWA violations occur in groundwater sources.

water quality within each location, controlling for time-invariant location characteristics.

Second, I add to the literature on drinking water pollution and regulation. Bennear and Olmstead (2008) and Bennear, Jessoe, and Olmstead (2009) study the effectiveness of SDWA regulations on monitoring and water quality. A more recent body of work has uncovered novel significant health impacts of drinking water pollution for a variety of contaminants (Currie et al., 2013; Christensen, Keiser, and Lade, 2019; Marcus, 2020, 2021; Hill and Ma, 2022). However, the impacts of water pollution on health remains understudied (Keiser and Shapiro, 2018), especially compared to air pollution. I add to these works by estimating both the behavioral and health impacts of nitrate pollution, and highlight some areas where the SDWA falls short in mitigating public health externality.

Lastly, the recent environmental justice literature has revealed that low socioeconomic groups are unequally exposed to pollution (Banzhaf, Ma, and Timmins, 2019), especially in the context of air pollution in urban areas (Currie, 2011). These sub-populations also may exhibit a dampened behavioral response, exacerbating the inequality of environmental health damages. I demonstrate that geographic constraints – specifically food deserts – also limit individual's ability to protect themselves from the negative health consequences of nitrate pollution. This paper documents that environmental justice is also concerning in the rural United States primarily through water pollution.

My conceptual model builds on Harrington and Portney (1987), which decomposes the net health effect of worsening pollution into direct health and behavioral components. I extend this model to allow individuals to face differential implicit prices for protective behavior. These unique implicit prices potentially arise from geographic or socioeconomic resource constraints. The analytical results from this model predict that individual facing higher implicit prices will engage in less averting behavior, leaving these populations differentially exposed to pollution.

I empirically test these theoretical hypotheses in the context of drinking water and nitrate pollution in the United States. All public drinking water systems that serve over 25 people are required to maintain reporting, monitoring, and minimum standards of drinking water quality through the SDWA. The SDWA serves both to ensure local public water system (PWS) compliance and to notify citizens of the possibility of harmful exposure. These events simultaneously indicate an increase in nitrate contamination to a dangerous level and serve as an exogenous information shock about water quality, inducing an consumer response.[4] I exploit the exogenous timing of these to events to estimate both the behavioral response through local retail beverage sales and the net infant health impact.[5]

I use data from the Safe Drinking Water Information Systems (SDWIS) through the Environmental Protection Agency (EPA) on PWS characteristics, violation, and enforcement data from 2010 to 2020. These data report the date of violation and public notification and the subsequent return to compliance for SDWA contaminant rules. I pair these violation and notification records with retail scanner data from Information Resources Inc (IRI) for retail stores across the United States from 2010 to 2019. IRI retail scanner data contain precise store locations – including grocery, convenience, dollar and mass merchandising stores – and are the most comprehensive retail data available. I utilize food accessibility statistics from the Food Access Research Atlas provided by United States Department of Agriculture Economic Research Service (USDA-ERS) to determine the geographic dispersion of the population relative to grocery store location.

Lastly, exposure to heightened levels of nitrates are most concerning for infants and pregnant mothers. I use National Vital Statistics from the Center for Disease Control (CDC) to study the impacts of these interventions and varying-levels of avoidance behavior on infant health outcomes. I study the impacts on the outcomes of infant birthweight, APGAR (Appearance, Pulse, Grimace, Activity, and Respiration) score, and infant mortality. For

[4] Residents typically have imperfect information about local water quality (Keiser and Shapiro, 2018) and would have limited ability to anticipate a SDWA violation. The exception may be for SDWA violations that coincide with natural disaster events, like hurricanes and bacterial coliform (Beatty, Shimshack, and Volpe, 2019). Chemical nitrate contamination, however, builds gradually as a legacy contaminant and is unlikely to be correlated with extreme events.

[5] The quasi-experimental setting of SDWA violations and public notifications have similarly been used by Zivin, Neidell, and Schlenker (2011) and Allaire et al. (2019) to measure the behavioral response to a variety of pollutants and Currie et al. (2013) to measure the infant health impact in New Jersey.

populations that exhibit lower levels of averting action, the theoretical model predicts that infant health will decline relative to populations that engage in sufficient averting behavior.

I empirically test the hypotheses of this paper through two stages. First, I estimate the effect of different water quality violations and subsequent public notification on avoidance behavior through beverage purchases – disaggregated into bottled water and sugar-sweetened beverage sales – using an event study framework. The main outcome of interest is the value of logged bottled beverage sales (in cents) at the store-week level. Store and week fixed effects control for fixed differences across stores and seasonality in bottled water sales. The main coefficients of interest can be interpreted as the percent increase in bottled beverage sales for each event-week following the notification relative to the store and calendar week's expected outcome in the absence of a violation. This percent increase measures the behavioral response by residents to the public notification. I also allow for heterogeneity in the estimates of avoidance behavior by census tract through measures of income, percent of population in food deserts, SNAP participation, and vehicle access. This analysis highlights factors that may leave vulnerable populations exposed even after SDWA public notification.

In the second stage of the analysis, I study the impacts of nitrate violations and subsequent public notifications on health. The net impact of these events on health are ambiguous. On one hand, worsening drinking water quality, which induces the violation, heightens the risk to the public health of those residents. On the other hand, the public notification likely causes consumers to engage in more protective action, like relying on bottled water and other beverages, which may improve health outcomes in the weeks after a violation. I uncover the average net effect on health, as well as, the heterogeneous impacts on health based on the same factors that may limit avoidance behavior.

I find evidence of significant avoidance behavior through bottled water purchases for nitrate contaminant violations. Public notifications due to nitrates induce behavioral adaptation of approximately 17% increase in bottled water sales and 11% in sugar-sweetened beverages in the weeks following notification. This translates roughly to $4.7 million annually in averting expenditures due to nitrate contamination - a relatively inexpensive form of protection for those with access.

Food accessibility and income constraints significantly limit avoidance through beverage sales by 31 and 26 percentage points, respectively, illustrating the implicitly higher barrier these residents face to avoid contaminated water (or access costs are elevated) compared to residents with proximate grocery access. These food access constraints also lead to a 6.3% increase in infant mortality relative to pre-violation weeks and 4.4% increase in low-income populations, suggesting that the lack of averting response leads to detrimental health consequences.

These findings result in three relevant policy conclusions. First, there are both behavioral and health costs associated with nitrate pollution in drinking water. This study quantifies the extent of those costs, which can help identify appropriate policy responses. Second, current regulatory measures that aim to protect citizens from drinking water pollution may be ineffective in resource constrained areas; in the future, these areas may need a multifaceted policy approach, like ensuring those affected have the opportunity for a safe alternative, to lessen damages to public health. Lastly, policy measures that are ineffective in some populations may leave vulnerable communities continually exposed to environmental health impacts, worsening environmental inequality.

2 Background

Safe Drinking Water Act

The SDWA, initially passed in 1974, regulates drinking water systems that serve at least 25 individuals and aims to protect individuals from drinking water pollution or waterborne illness. It requires regular monitoring and reporting of drinking water quality by systems and establishes maximum contaminant levels (MCL) for over 90 contaminants. Some contaminants are short-lived and quickly treatable in-home, while others are legacy pollutants and are costly to rectify by households or public water systems. MCLs are determined by the threshold which contaminants pose a potential health threat to certain populations.

Once a violation occurs, the SDWA relies on public notifications to alleviate the public health risk. The public notification requirements establish 3 tiers. Tier 1 violations pose immediate threat to human health and notification must occur within 24 hrs of detecting contaminants above the MCL. Nitrates and some violations of the Total Coliform Rule are the two contaminants classified as Tier 1 violations. These notices are required to be hand delivered, published in local news outlets, and posted in public areas based on these tiers. An example of a Tier 1 public notification and the required elements is provided in figure B1. Tier 2 violations include arsenic, lead, copper, among others. Tier 3 violations are often due to reporting or monitoring failures. Notification must occur within 30 days and 365 days, respectively, for tier 2 and 3 violations.

SDWA violations and subsequent notifications have been widely used in economic studies as exogenous treatment in quasi-experimental settings (Bennear and Olmstead, 2008; Zivin, Neidell, and Schlenker, 2011; Allaire et al., 2019). Most recently, Marcus (2020) utilizes the variation in public notification tiers to identify health and averting behavior for TCR violations in North Carolina. Similarly, this paper uses SDWA public notification to study the mechanisms through which notification-based environmental regulation yields limited response in some populations and the related health costs.

Figure 1 plots the spatial variation in nitrate violations by county in the United States from 2010 to 2019. Larger numbers of violations happen in the Great Plains and the West.[6] This pattern also loosely follows the spatial variation of farm nitrogen application in the United States, discussed in the next section.

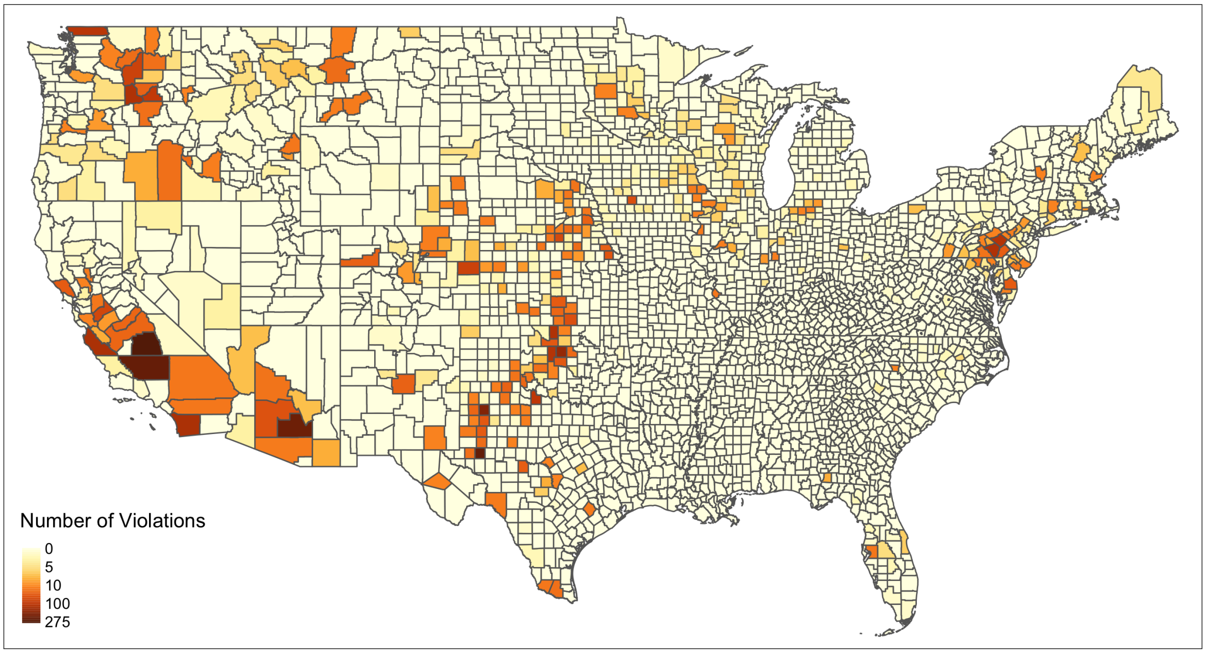

Figure 1: Number of SDWA Nitrate Violations, 2010-2019
Note: Author's creation from EPA's SDWIS database. Figure displays the count of nitrate SDWA health-based violations from 2010 to 2019.

Nitrate Pollution

The EPA describes nitrogen pollution as one of the most most widespread and costly forms of environmental pollution in the United States. While this pollution is the result of a number of anthropogenic activities, agriculture is the primary. In the United States, agricultural fertilization accounted for approximately 93% of commercial nitrogen use in 2010.[7] Figure 2 plots 2010 agricultural nitrogen use by county. Unsurprisingly, the most heavily concentrated areas span across the Corn Belt and in California's Central Valley.

Global use of agricultural nitrogen fertilizer has steadily risen over the last century (FAO, 2020). This trend is, in part, driven by an increasing global population and demand for food. In the last two decades, expanded use of biofuels due to the Renewable Fuel Standard

[6]This relationship also coincides with a greater dependency on groundwater as approximately 95% of all nitrate violations are sourced from groundwater Pennino, Compton, and Leibowitz (2017). A heavy concentration of violations through Texas, Oklahoma and Kansas closely follow the boundaries of the Ogallala Aquifer. The same is true in California's central valley.

[7]Authors calculations from John and Gronberg (2017)

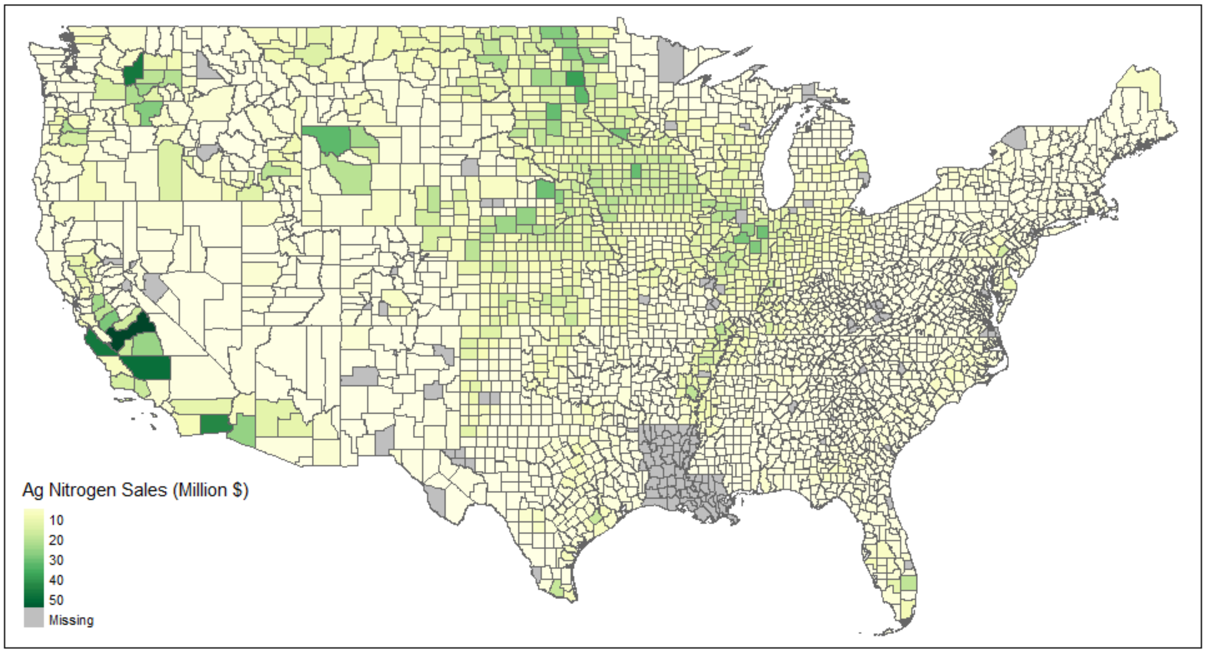

Figure 2: Agricultural Nitrogen use by County, 2010

Note: Author's creation from USGS data John and Gronberg (2017). Figure displays estimated county-level agricultural nitrogen use in 2010.

resulted in additional demand for fertilizer (Lark et al., 2022). Advances in production technology (i.e. the Haber Bosh process) in the early 20th century and low energy prices also contributed to increased fertilizer use from the supply side.

Nitrates in groundwater are an irreversible pollutant and often require households or water suppliers to identify new sources once detected. Approximately 90% of rural residents in the United States rely on groundwater for domestic use (Power and Schepers, 1989). PWS that source from groundwater account for 95% the historical SDWA violations (Pennino, Compton, and Leibowitz, 2017).[8] Nitrates are leached through the soil into groundwater basins over time, so the full externality is not realized until many years, even decades, after the polluting activity (Harter et al., 2012). Unlike bacterial contaminants, boiling the water does not eliminate the concentration and the long-term solutions are costly to the public

[8]This does not include households that rely on private wells for domestic use. Private groundwater wells are perhaps even greater risk of environmental harm since these wells are outside the jurisdiction of the SDWA and do not require regular monitoring.

water system. Once a groundwater source is contaminated with nitrates, contamination levels persist – they are unlikely to decline. Thus, public water systems must identify new sources of water, which are also susceptible to contamination, or build an expensive water treatment plant.[9]

Assessing the total environmental costs of nitrogen pollution is a multi-disciplinary task and remains a challenge for economic researchers (Keiser, Kling, and Phaneuf, 2020). Nitrogen contamination in surface waste and associated environmental harm manifests primarily through algal blooms (Hendricks et al., 2014). Algal blooms create dead zones (or hypoxic zones) in bodies of surface water, which are detrimental to aquatic life and costly to human recreation (Egan et al., 2009). Tracking non-point source nitrogen pollution in surface water remains an active field of research (Paudel and Crago, 2020; Taylor and Heal, 2022).

Human Health Impacts

While (Temkin et al., 2019) argue that nitrate ingestion is also carcinogenic, and that current EPA thresholds should be much lower, identifying the health risks to adults is empirically challenging due to the unobserved exposure risks over the entire lifetime of an adult. For these reasons, infant health outcomes are typically assessed in the environmental health economic literature (Almond and Currie, 2011). Infants have a relatively short window for which exposure, either *in utero* or postnatal, leads to adverse health outcomes.

Furthermore, exposure to nitrates pose the highest health risk for infants and pregnant mothers. High levels of nitrate exposure is correlated with an increased risk of methemoglobinemia (or blue-baby syndrome), which limits adequate oxygenation of the blood. The 10 mg/L MCL threshold set by the EPA is based on a 1951 survey, which identified 2.3 percent of Methemoglobinemia cases were associated with nitrate concentrations above 10 mg/L (Walton, 1951). The World Health Organization shares this same guideline inter-

[9] Anecdotal evidence suggest industrial water treatment cost upwards of $3 million, and require additional year-to-year operational costs.

nationally. Once a water system's report nitrate level in excess of this threshold, pregnant mothers are advised to identify a safe source and that the tap water should not be used in infant formula.

Constraints to Averting Response

A number of economic factors may limit an individual's ability to respond to information about environmental quality. These factors lead to smaller observed marginal willingness to pay (MWTP) for environmental improvement. However, estimates of MWTP in the presence of significant constraints underestimate the true MWTP. The lack of reliable news outlets in an area, for example, leads to a dampened local response to public notifications of pollution (Marcus, 2021). However, the same individuals may chose a meaningfully different response in the presence of broadly communicated information about pollution to a population. Policy aimed at limiting pollution exposure must also carefully consider constraints that may vary across populations.

This study highlights the interaction between food deserts and SDWA nitrate violation, two realities that are acute in the rural United States (Bitler and Haider, 2010). Generally, food and beverage items have higher retail prices in food deserts due to higher operating costs. Residents living in food deserts also face higher access costs through travelling longer distances to travel to a supermarket. The presence of food deserts and their implication inequality and nutrition have long been debated (Allcott et al., 2019).

For this paper, I use USDA's definition of a food desert (or low access) as a census tract with at least 500 people, or 33 percent of the population, living more than 1 mile in urban or more than 10 miles in rural areas from the nearest supermarket, supercenter, or large grocery store. Figure 3 plots rural food deserts in the United States. Again, rural food deserts are highly prevalent in the Western United States. Tables B1 and B2 show that consumers in food deserts and rural areas both face higher prices for bottled water and sugar-sweetened beverages, respectively.

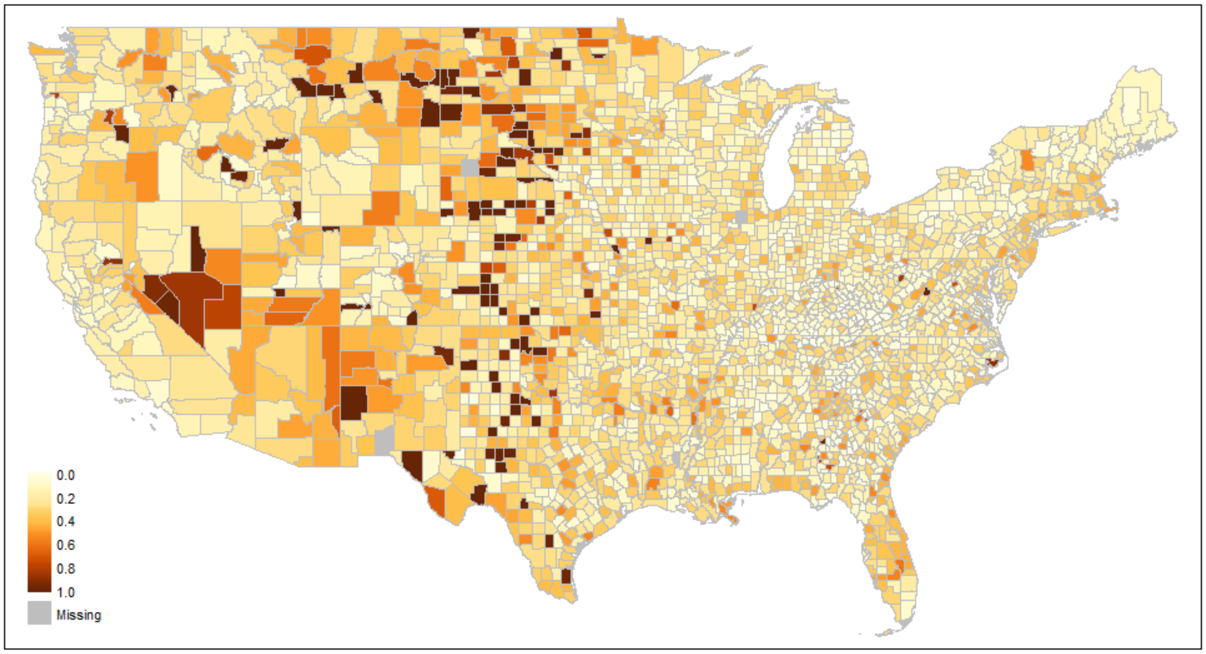

Figure 3: Share of County Population in Food Desert, 2015

Note: Author's creation from USDA Food Research Atlas data. Figure displays the share of the county's population that are over 10 miles away from a grocery store in rural areas or 1 mile away in urban areas.

3 Conceptual Model

I develop a stylized conceptual framework similar to Harrington and Portney (1987), which I extend to illustrate how resource constraints may limit averting behavior. Consumers derive utility from health, H, and a composite good, X. H is a dose-response function of health, dependant on pollution, T, and protective behavior, B. In the context of this paper, T is a binary variable equal to one if tap water is contaminated and zero otherwise. B is consumption of a safe alternative beverage. The dose-response function for health is a decreasing function of pollution, $H_T < 0$. Alternative beverages provide a means to lessen exposure to the potential pollutant.

$$
\begin{aligned}
U &= U(H, X) \\
H &= H(T, B(T)))
\end{aligned}
\tag{1}
$$

Totally differentiating H with respect to T yields equation 2, where the first term, H_T, indicates the direct health effect of exposure to the pollutant. The second term indicates the behavioral response through which consumers may choose to protect themselves to some extent through pollution avoidance behavior, indicated by B. Together, $\frac{dH}{dT}$ yields the net effect of an exogenous change in pollution on health. In observational studies, the net effect, rather than the direct effect, of pollution on health is observed in practice. Failing to account for this reality will undoubtedly lead to inaccurate conclusions about the pollutant's effect on health.

$$
\frac{dH}{dT} = H_T + H_B B_T \tag{2}
$$

Consumers maximize utility subject to a budget constraint, Y. I follow Abrahams, Hubbell, and Jordan (2000) and assume that the price of tap water is equal to zero, and denote the price of purchasing beverages at retail by p_B. Each consumer must also experience an unique implicit price, $p_I^i \geq 0$, in order to obtain the safe alternative. For the context of this paper, implicit prices arise due to limited accessibility. The price of the composite good is normalized to 1 and utility is monotonically increasing in the composite good. Therefore, the consumer solves the utility maximization problem:

$$
\max_B \; U(H(T, B), Y - (p_I^i + p_B)B) \;\; \text{s.t.} \qquad B \geq 0 \; [\mu] \tag{3}
$$

The solutions to this maximization problem, which are derived further in the appendix, yield a demand function for the protective behavior that is dependant on pollution, T, and the total price of averting response, $p_I^i + p_B$. An exogenous change in T will yield a non-negative change in demand for safe beverages, represented by the partial $B_T(Y, p_I^i + p_B)$.

In empirical settings, this reduced-form change in demand for an exogenous environmental quality change captures the *average* averting response in the sample. The average behavioral response, however, fails to express the distribution of avoidance behavior. Implicit costs are one explanation why the behavioral response differs by sub-populations. That is, $B_T(Y, p_B) \geq B_T(Y, p_I^i + p_B)$ for $p_I \geq 0$. High implicit costs, p_I^i, may contribute to why the valuation for environmental goods has been found to be lower in developing country setting.

Bottled water and other beverages for residents in food deserts in rural areas may be relatively more expensive due to either higher transportation costs or higher baseline retail prices. Grocery access in food deserts increases the cost for consumers to substitute bottled water for tap water consumption. Holding all other factors constant, I hypothesize that averting behavior is dampened in food deserts due to the interaction of costly grocery access in rural areas. I measure this effect by interacting food access statistics with the public notification information shock.

Consumers in food deserts also may be less likely to consume bottled water due to a higher retail price in the local retail stores. As the price of bottled water increases in equation (A2), the necessary marginal utility of the composite good for a corner solution becomes smaller. Hence, even in the event of a positive shock to T, the shadow value remains small enough for consumers to stay at the corner solution.

Importantly, a distribution of B_T can also be informative of the direct health impacts of the pollutant. Consider, again, equation 2. For smaller values of B_T, the gap between the net health effect and the direct health effect, $\frac{dH}{dT} - H_T$, lessens. This theoretical model underscore the distributional relationship to empirically estimate both the behavioral and health response to nitrate pollution, which may differ by an individual's context.

4 Data

SDWA violations and subsequent notifications provide a quasi-experimental context to study averting behavior. This research design assumes that consumers cannot predict an impending SDWA violations and that notification serves as an exogenous shock to perceived water quality. I provide evidence that consumers only respond in the weeks after a violation occurs, not prior, which is a necessary exogeneity condition for this design. To measure averting response heterogeneity, I assemble a store-by-week panel from 2010-2019. I exploit weekly within-store variation SDWA nitrate violation events to identify average treatment effects and observe cross-sectional heterogeneity across resource constraints.

Water Quality Violations

Enforcement and Compliance History Online (ECHO) through the EPA contains a record of SDWA violations and enforcement actions for PWS across the United States. To ensure a precisely identified exogenous shock to perceived water quality, I use tier 1 public notifications from SDWA nitrate violations and notifications as the main sample for my estimation strategy.[10] Throughout the remainder of the paper, I use the terms violations and notifications interchangeably since the events occur on the same day for tier 1 violations.

I define that treatment occurs in the weeks between the date of public notification to the return to compliance date. Figure B2 illustrates the timing of these occurrences throughout the year, showing that some violation types are more seasonal than others.

Beverage Sales

Beverage sales data come from Information Resources Inc (IRI), which is the most geographically comprehensive scanner data available. These retail scanner data cover over 48,000 stores

[10] While the public notification date is included in the data, leakages of information or slow dissemination of water quality information may happen between the violation date and the public notification. This possibility threatens the experiment design and may lead to an anticipation effect.

nationally and measure weekly sales by product code (UPC). The widespread coverage of these data is particularly helpful in measuring the impacts in rural areas, where data availability is typically sparse. I disaggregate beverage sales into two categories: bottled water and sugar-sweetened beverages. Each measure is the sum of weekly store revenue from all types of bottled water or sugar-sweetened beverages. These data are reported for a variety of store types as exhibited in Figure B3.

Infant Health Outcomes

Nitrate contamination in drinking water poses the most serious health threat to infants and pregnant mothers. I use proprietary infant health statistics from the CDC's National Center for Health Statistics. I aggregate birth statistics in the United States from 2010-2019 to about 190,000 county-month observations across the United States. Specifically, I use the rate of birthweight and infant mortality rates to study how SDWA public notification, and heterogeneous levels of averting response affect infant health outcomes.

A limitation of this study is the inability to precisely identify the residence of infants and mothers. Several recent studies use birth-certificate records, latitude and longitude of residence, and mother-fixed effects to control for unobservable characteristics (Currie et al., 2013; Marcus, 2021; Hill and Ma, 2022). However, at a national level, county-month observations provide the most geographic and temporal granularity and provide sufficient power to identify environmental health effects (Taylor, 2022; Hansen-Lewis and Marcus, 2022).

Grocery Access & Demographics

The Food Access Research Atlas from the USDA provides cross-sectional census-tract level food access statistics determined by the distance to the nearest grocery store or source of healthy food. The Food Access Research Atlas also contains characteristics that may limit food access, like income and vehicle ownership. This dataset is primarily derived from the 2010 Census, the 2014-2018 American Community Survey, and the 2019 STARS (Store Tracking and Redemption System). These data provide the primary community characteristics through which I evaluate heterogeneity in averting behavior.

Given that these data are cross-sectional, they will be unable to capture any variation in demographics over the course of the sample. For example, water pollution may cause local residents to move to reduce exposure to the pollutant – a more long-run and extreme form averting behavior. However, given that this type of out-migration could take years to be fully realized, this possibility is unlikely to bias the short-run averting response through beverage sales.

5 Empirical Model

Averting Behavior and Heterogeneity

The staggered nature of SDWA violations in communities across the United States allows for the implementation of a dynamic difference-in-difference (DD) empirical specification. A number of studies have similarly used the exogenous and staggered timing of SDWA violations as a quasi-experimental research design. However, a large and growing literature documents the potential bias in difference-in-difference estimated using two-way fixed effects (TWFE) with variation in treatment timing (Goodman-Bacon, 2021). Generally, TWFE controls time-invariant differences and macroeconomic shocks. However, the bias arises because TWFE also residualizes the treatment variable, and already treated units are used as implicit counterfactuals. The magnitude of the TWFE bias is dependant on the degree of heterogeneity across time and has potentially serve consequences of the interpretation of TWFE coefficients.

While this potential bias is now well understood, subsequent work has proposed alternative estimators to TWFE to uncover unbiased estimates in staggered DD settings (Callaway and Sant'Anna, 2019; Gardner, 2021). For this setting, Gardner (2021) provides an ideal estimator, estimating DD estimates in two-stages. Using only pre-treated units, the time and individual fixed effects are estimated in the first stage. The remaining variation in the outcome variable, after controlling for fixed effects, is used to identify the unbiased treatment effect in the second stage. I demonstrate this small bias by comparing the TWFE estimates, which are similar to Allaire et al. (2019), with the estimator from Gardner (2021).

To estimate the response to tier 1 SDWA public notifications, I estimate equation (4), where B_{ist} are beverage sales in cents at store i and in state s in week-year t. Treatment, Vio_{ist} is equal to 1 during active violation weeks, and 0 otherwise. I multiply treatment by w_i, which is the percentage of the store's census-tract affected by the violation. Together, $Vio_{ist} \times w_i$ capture the community treatment intensity. The vector $\boldsymbol{X_{ist}}$ captures time-varying controls (e.g., weather). The base specification uses week-by-year fixed effects denoted by λ_t, which absorbs national seasonality in beverage sales and macroeconomic shocks. I also include store-by-event fixed effects, α_i, which capture time-invariant factors, like store location and size of the consumer population.[11] Additionally, state-by-year fixed effects, ϕ_s, capture state-year specific regulatory differences.[12] Standard errors are multi-clustered at the store and violation level (Cameron, Gelbach, and Miller, 2011). This accounts for potential serial correlation within individual stores over time and between stores affected by the same violation. Following Gardner (2021), I estimate equation 4.

$$\begin{aligned} &\textit{With not yet treated sample: } \log(B_{ist}) = \boldsymbol{\phi' X}_{ist} + \lambda_t + \alpha_i + \phi_s + \varepsilon_{ist} \\ &\textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\phi' X}_{ist} + \mu_{ist} \end{aligned} \tag{4}$$

I additionally estimate the dynamic version (or event study) of equation 5 to offer

[11] Population size and demographics of the local population could obviously change over the course of the panel. This change is a potential omitted variable if it correlated with treatment timing (i.e. out-migration due to poor water quality). This implies that my point estimates underestimate the full averting behavior taken by consumers, but estimating the out-migration effect is beyond the scope of this paper.

[12] State agencies carry out the enforcement and monitoring of SDWA requirements among PWS.

insight into the evolution of the treatment effect in the weeks following a violation and detect persisting effects beyond a return to compliance. This specification also allows a test of the identifying assumption that, conditional on fixed effects and covariates, beverage purchases would have not significantly differed in the absence of violation. Parallel pre-treatment trends in the weeks leading up to a violation supports this assumption. For the event study, I use an eight week window before and after the violation.[13] I ensure a balanced panel during the event study window. Following Schmidheiny and Siegloch (2020), I bin all other observations outside the event study window into the window endpoints. I use the third week prior to violation as the baseline week, which allows this specification to detect any anticipatory effect in the two prior weeks.

The event study results are estimated with equation 5, where $Week_{iw}$ indicates if store i's observation is w weeks away from the violation. I also interact this event-week dummy with Vio_{iswt} because PWS return to compliance at different points post-violation. Therefore, a PWS that returns to compliance seven weeks post-violation may yield a more lasting response than a PWS with only a week-long violation. This specification tests for the differing effects between post-violation and compliant versus post-violation with an active violation.

$$\textit{With not yet treated sample: } \log(B_{iswt}) = \boldsymbol{\phi' X}_{iswt} + \lambda_t + \alpha_i + \phi_s + \varepsilon_{iswt}$$

$$\textit{With full sample: } \hat{\varepsilon_{iwt}} = \sum_{w=-8}^{w=8} \beta_{1w} Week_{iw} + \sum_{w=-8}^{w=8} \beta_{2w} Week_{iw} * Vio_{iswt} + \boldsymbol{\phi' X}_{iswt} + \mu_{iswt} \tag{5}$$

The primary identifying assumption of the event study framework is parallel trends in the pre-treatment periods. In equation (5), this assumption is supported if β_w for $w \in [-8, -1]$ is not statistically distinguishable from zero.

To test for heterogeneity by community demographics, I will estimate equation (6),

[13] Eight weeks is chosen as the window since all nitrate violations in the sample are resolved in 7 weeks or prior of initial violation.

which interacts the violation and public notification dummy variable with cross-sectional characteristics. The vector $\boldsymbol{Z_i}$ contains time-invariant demographic variables for socio-economic indicators or resource access measures. Elements of $\boldsymbol{\gamma}$ will report the difference relative to β across values of $\boldsymbol{Z_i}$.

$$\begin{aligned} &\textit{With not yet treated sample: } \log(B_{ist}) = \boldsymbol{\phi' X}_{ist} + \lambda_t + \alpha_i + \varepsilon_{ist} \\ &\textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\gamma Z_i} * Vio_{ist} * w_i + \boldsymbol{\phi' X}_{ist} + \mu_{ist} \end{aligned} \tag{6}$$

Infant Health Impacts

The SDWA public notification primarily serves to protect consumers from contaminated drinking water and the negative health impacts. Averting behavior through beverage sales protects consumer from that threat. However, where aversion does not take place, residents may remain exposed to the potential health consequences. This project will study the health implication of averting behavior, or lack thereof, using infant health statistics and drinking water violation and quality records.

To estimate the impacts of nitrate violations on infant health, I use the same exogenous treatment timing of SDWA violations and public notifications used above to estimate the behavioral response. However, this specification deviates in two primary ways. First, at the national level, proprietary infant health outcomes are only available at the county-month level.[14] Second, SDWA informational provisions identify infants under 6 months and pregnant mothers as the subset of population most susceptible to nitrate exposure. Therefore, the harmful health impacts of nitrate exposure may manifest itself anytime nine months after the violation. I estimate the average local infant health impacts for the nine months after violation. I uncover the reduced form health impacts by estimating equation 7.

[14]Some states provide researches access to birth-certificate level data. However, county-month is the most granular available for a national assessment.

$$\begin{aligned} &\textit{With not yet treated sample: } \log(Y_{it}) = \boldsymbol{\phi}'\boldsymbol{X}_{ist} + \lambda_t + \alpha_i + \varepsilon_{ist} \\ &\textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Exp_{ist} + \boldsymbol{\gamma}\boldsymbol{Z_i} * Exp_{ist} + \boldsymbol{\phi}'\boldsymbol{X}_{ist} + \mu_{ist} \end{aligned} \tag{7}$$

Here, Y_{it} are infant health outcomes in county i in month t. Exp_{ist} is a dummy equal to 1 if a public water system in county i in state s experienced a SDWA nitrate violation anytime in the previous nine month. Similar to the behavioral response, I also test for heterogeneous treatment effects across possible geographic and socioeconomic constraints.

6 Results

Bottled Water

For the baseline estimates of averting behavior, I disaggretate beverage sales into bottle water sales – the traditional measure of averting behavior in averting behavior studies – and sugar-sweetened beverage. For nitrate violations, bottled water is the recommended alternative source included in public notifications. Boiling water, for example, does not eliminate nitrates and potentially makes nitrates more concentrated. One alternative in-home treatment method that removes nitrates from water is a costly water-treatment system. Purchasing one of these systems reflects a long-run response since it would protect against all future potential water quality risks. Therefore, bottled water sales capture the short-run, lower-bound of averting response by consumers.

Figure 4 displays the dynamic response of bottled water sales for the weeks around nitrate violations. The parallel trends assumption is supported since no pre-treatment week (or binned pre-treatment) is significantly different than the baseline week (i.e. three weeks prior to violation). Positive averting response occurs for active violation the 2nd through the 7th weeks after the initial violation. This delayed response is suggestive of slow dissemination of information throughout a community. There does not appear to be a persistent effect after water systems return to compliance.

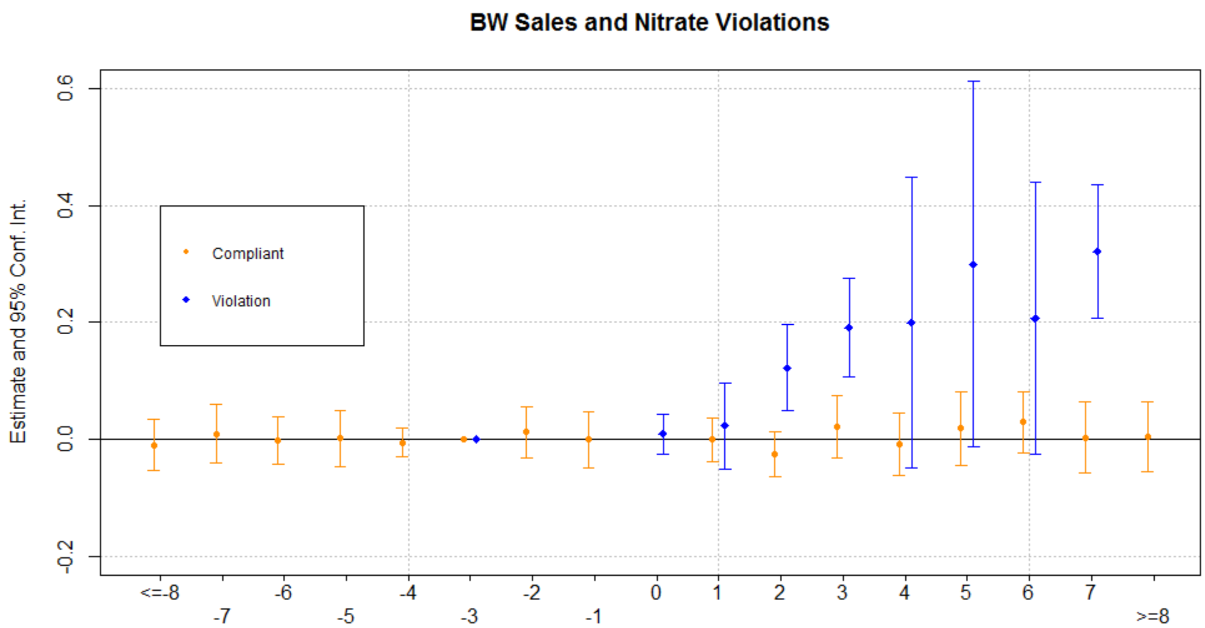

Figure 4: Event Study Results: Bottled Water Sales Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event study coefficients of logged bottled water sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in bottled water sales relative to 3 weeks prior to the violation. Violation indicates that the observation remained in an active violation, and compliant indicates the local PWS returned to compliance. The regression includes, event by store, week-by-year, state-by-year fixed effects, and weather controls. Standard errors are multi-clustered at the store and violation level.

Table 1 displays the results of the average treatment effect across all active violation weeks. Columns (1) and (2) report the biased estimates from TWFE. These point estimates are similar to those of Allaire et al. (2019), suggesting that my sample doesn't differ in a statistically meaningful way. Columns (3) and (4) report the two stage DD results from Gardner (2021) and an intention-to-treat effect of 17.3%. In this context, the TWFE does bias the point estimate to zero, but the bias is economically small.

A back of the envelop calculation implies that individuals spend approximately \$2.5 million on bottled water purchases annually in the United States as a result of nitrate violations. This figure is similar to that of Zivin, Neidell, and Schlenker (2011). To compute this figure, I use national statistics on bottled water sales and nitrate violation statistics

Panel A. TWFE					
Nitrate Vio x w_i	0.170	0.164	0.229*	0.128*	0.124*
	(0.103)	(0.104)	(0.112)	(0.055)	(0.053)
Num.Obs.	721 897	721 897	721 897	721 897	721 897
Panel B. DiD2s					
Nitrate Vio x w_i	0.273*	0.303*	0.315*	0.173***	0.185***
	(0.122)	(0.124)	(0.125)	(0.032)	(0.033)
Num.Obs.	721 897	718 634	614 478	614 478	614 478
Std.Errors	Store & Vio	Store & Vio	Store & Vio	Store & Vio	Store & Vio
Event by Store	X	X	X	X	X
Week	X	X	X	X	X
Year	X	X	X	X	X
Week-Year		X	X	X	X
State-Year			X	X	X
Weather Controls				1	2

Note: Dependant variable is logged bottled water sales in cents. Each regression includes store by event, week by year, and state by year fixed effects and are weighted by the percent of population affected by the violation. Standard errors are multi-clustered at the store and violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Bottled Water Sales during SDWA Nitrate Violation

from Pennino et al. (2020). This number understates the full amount that individuals spend on averting actions as a result of nitrate violations due to a number of other, long-term protective actions, like water filtration systems. However, bottled water provides a relatively inexpensive alternative for protection against the potentially harmful health effect. Furthermore, I show that this averting response differs across resource constraints and demographics, which may result in some populations remaining exposed to nitrate pollutants.

Sugar-Sweetened Beverages

Instead of substituting bottled water, some consumers may substitute contaminated tap water with other beverage options, like sugar-sweetened beverages (SSB). SSB sales are an alternative form of averting behavior and should not be ignored in calculating the the full response from exogenous changes in nitrate contamination in drinking water. Analysis of SSBs additionally gives insight into the indirect effects of drinking water pollution, as consumers may substitute to beverage options that have their own set of health externalities.

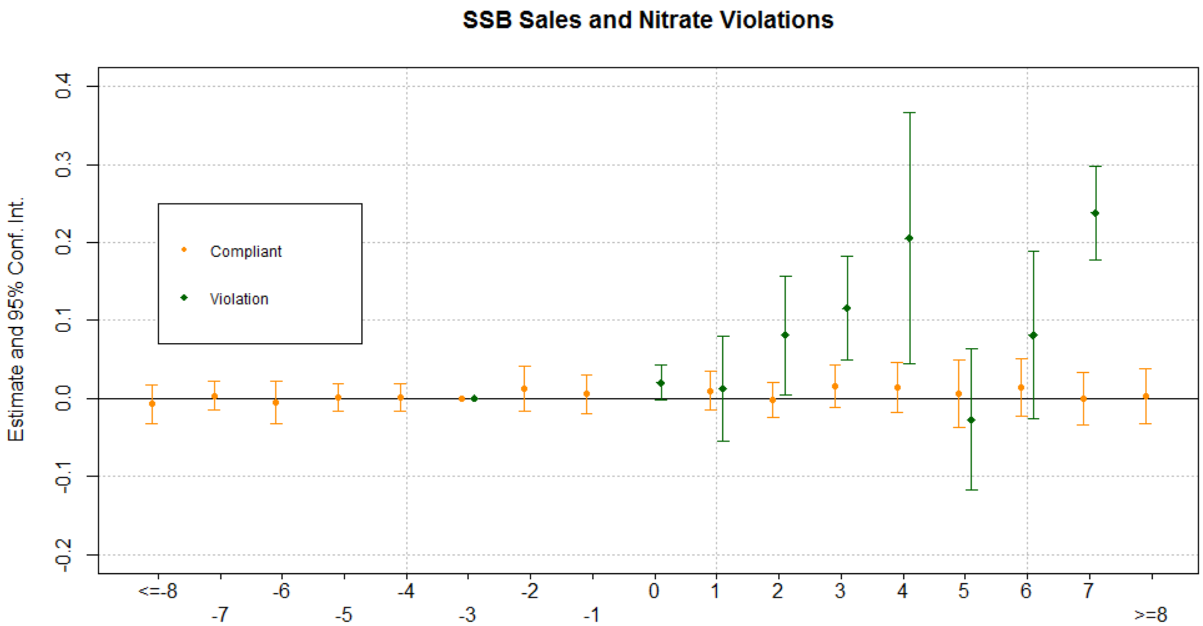

Figure 5: Event Study Results: Sugar-Sweetened Beverage Sales Pre- and Post-SDWA Violation

Note: Presents the two-stage difference in difference event study coefficients of logged sugar-sweetened beverage sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in bottled water sales relative to 3 weeks prior to the violation. Violation indicates that the observation remained in an active violation, and compliant indicates the local PWS returned to compliance. The regression includes, event by store, week-by-year, state-by-year fixed effects, and weather controls. Standard errors are multi-clustered at the store and violation level.

Figure 5 present the event study results, where the outcome are sales of SSB. Again, the parallel trends assumption prior to a violation holds. Similar to bottled water, SSB sales generally increase as a result of active nitrate violations. These coefficients are dampened relative to bottled water, but consumers do respond through alternative beverage forms other than just bottled water – indicating that local drinking water contamination induce a secondary effect on those affected, which have negative ramifications for health.

Table 2 presents the average treatment effect over all active violation weeks. As with the bottled water sales, there is bias in the TWFE estimates, but the corresponding point

Panel A. TWFE					
Nitrate Vio x w_i	0.174**	0.149**	0.142*	0.094*	0.093*
	(0.053)	(0.050)	(0.055)	(0.037)	(0.037)
Num.Obs.	621 618	621 618	621 618	621 618	621 618
Panel B. DiD2s					
Nitrate Vio x w_i	0.217***	0.220***	0.179***	0.113**	0.127***
	(0.054)	(0.057)	(0.040)	(0.039)	(0.033)
Num.Obs.	621 618	618 423	516 315	516 315	516 315
Std.Errors	Store & Vio	Store & Vio	Store & Vio	Store & Vio	Store & Vio
Event by Store	X	X	X	X	X
Week	X	X	X	X	X
Year	X	X	X	X	X
Week-Year		X	X	X	X
State-Year			X	X	X
Weather Controls				1	2

Note: Dependant variable is logged bottled water sales in cents. Nitrate Vio equals 1 when the local PWS has an active violation. w_i is the percent of the census tract affected by the violation. Each regression includes store by event, week by year, and state by year fixed effects and is weighted by w_i. Standard Errors are multi-clustered at the store and violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Averting Behavior Through Sugar-Sweetened Beverages

estimates are not significantly different than each other. Therefore, the TWFE bias is small in this setting.

A back-of-the-envelope calculation indicates that consumers spend an additional $2.2 million annually on SSB as a result of nitrate violations. A large literature studies the effects of SSB consumption and the impacts of obesity (Bleich and Vercammen, 2018). An indirect effect of drinking water contamination may lead to alternative health impacts, like increased obesity rates, if consumers opt to substitute water consumption with SSBs.

Treatment Effect Heterogeneity

A key contribution of this paper studies the mechanisms through which demographics and resource constraints limit observed averting behavior. To estimate these effects, I estimate equation 6. For ease of interpretation, I convert all continuous demographic variables into discrete indicators, where $Z_i = 1$ if census-tract $i's$ proportion of the population for measure Z above the sample median.

	log(Bottled Water)					
	1	2	3	4	5	6
Nitrate Vio*w_i	0.173***	0.463***	0.249***	0.407***	0.180***	0.161***
	(0.032)	(0.128)	(0.042)	(0.078)	(0.027)	(0.026)
x Food Desert		−0.314*				
		(0.122)				
x Low Income			−0.264**			
			(0.089)			
x > Price				−0.344**		
				(0.113)		
x > SNAP					−0.075	
					(0.149)	
x > Low Vehicle Access						0.059
						(0.099)
Num.Obs.	614 478	614 478	614 478	614 478	614 478	614 478
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X	X	X	X
FE: Store by Event	X	X	X	X	X	X
FE: Week by Year	X	X	X	X	X	X

Note: Dependant variable is logged bottled water sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 3: Heterogeneity in Averting Behavior: Bottled Water Sales

Table 3 presents results from selected measures of heterogeneity. Most notably, column 3 shows significant 31.4% lower averting behavior in low access, food deserts relative to non-food deserts. Additionally, the average treatment effect in non-food deserts is almost twice that reported in table 1. This suggests that the implicitly higher price residents in rural food deserts have to pay in order to access safe, alternative drinking water in the weeks after a SDWA violation.

Additionally, other resource constraints are associated with lower averting response, including income and a more expensive retail price for bottled water. These results indicate that populations remain disproportionately exposed to the health impacts of nitrate contaminated drinking water. Regulation that assumes individuals have the same portfolio of averting responses available may exacerbate environmental inequality since low-resource communities are unable to protect themselves in the same manner as areas with higher-resource availability.

	1	2	3	4	5	6
Nitrate Vio*w_i	0.113**	0.275**	0.123**	0.303***	0.117**	0.101*
	(0.039)	(0.105)	(0.039)	(0.080)	(0.042)	(0.045)
x Low Access		−0.175				
		(0.124)				
x Low Income			−0.033			
			(0.048)			
x > Price				−0.267		
				(0.153)		
x > SNAP					−0.038	
					(0.085)	
x > Low Vehicle Access						0.063
						(0.065)
Num.Obs.	516 315	516 315	516 315	516 315	516 315	516 315
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X	X	X	X
FE: Store by Event	X	X	X	X	X	X
FE: Week by Year	X	X	X	X	X	X

Note: Dependant variable is logged sugar sweetened beverage sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Heterogeneity in Averting Behavior: Sugar-Sweetened Beverage Sales

Second, table 4 displays the results for SSB sales. Similarly, food desert census-tracts display negative, but insignificant, averting response relative to non-food deserts. While none of the heterogeneity coefficients are statistically significant, they are the same direction and similar relative magnitude to those of bottled water. These patterns are consistent across both bottled water and SSB purchases – suggesting that the resource constraints limit the purchasing ability for all products, rather than capturing a systematic correlation between consumer preferences between SSB and bottled water.[15]

[15] One long-standing claim is that consumers use SNAP funds to purchase more SSBs compared to the

Infant Health

The public health externality of drinking water pollution depends on the residents' ability to respond to the hazard. As I show in the previous section, the responses vary widely across locations. For sub-populations where the behavioral response to a change in drinking water pollution, health is expected to be relatively worse than populations that do engage in protective behavior as predicted by the stylized theoretical model.

I test this hypothesis by estimating equation 7. The first outcome of interest is infant mortality transformed by the inverse hyperbolic sin. Hence, the main coefficients report the percentage change in infant mortality in the nine months after a SDWA nitrate violation. Importantly, I also differentiate the health impacts by low-access and low-income groups, since tables 3 and 4 report consistently lower averting behavior after a SDWA nitrate violation. Table 5 displays the reduced-form net impact on infant mortality for the nine-months after a SDWA violation. Panel A tests for heterogeneity in these estimates based on low access to grocery stores, and panel B does the same for low income counties.

The results in column 1 indicate that, on average across all locations, potential exposure to dangerous levels of nitrates in drinking water does not significantly change infant health outcomes. However, columns 2 through 5 that infant mortality significantly increases in populations with lower access to grocery stores and lower incomes. The preferred specification in column 5 implies that infant morality increases by 6.3% in low-access counties and 4.4% in low-income counties where pregnant mothers or infants were potentially exposed to heightened levels of nitrates.[16]

Conversely, infant mortality rates actually improve in counties with greater access to grocery stores by 7.7% and in higher-income counties by 5.3%. In these populations, these results are suggestive that the SDWA public notifications sufficiently inform the at-risk crowd

non-SNAP population. This claim is not supported in these findings, at least in the context of averting response, comparing estimates from comparing column 5 in tables 3 and 4.

[16]The total effects for these populations are the sum of rows 1-2 and 3-4, since "x Low-Access" captures the relative effect.

of the potential health impacts, and residents take the advised action to prevent nitrate exposure. These results are both consistent with the theoretical model that individuals engage in averting action and consistent with the empirical behavioral results.

	asin(IMR)				
Panel A. Low Access					
Exp.	−0.015	−0.059***	−0.070***	−0.073***	−0.077***
	(0.011)	(0.015)	(0.015)	(0.014)	(0.013)
x Low Access		0.115***	0.119***	0.129***	0.140***
		(0.024)	(0.024)	(0.023)	(0.022)
Panel B. Low Income					
Exp.		−0.038**	−0.048***	−0.046***	−0.053***
		(0.013)	(0.013)	(0.013)	(0.012)
x Low Income		0.082***	0.086***	0.085***	0.097***
		(0.024)	(0.024)	(0.024)	(0.024)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependant variable is the inverse hyperbolic sin of infant mortality per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Nitrate exposure's impact on infant mortality

Second, table 6 reports the results of the impact of nitrate exposure on the occurance of low birthweight. Similar to infant morality, the rate of low birthweight is transformed by the inverse hyperbolic sin. The results for the rate of very low birthweight are reported in table B5, and are very similar to low birthweight. On average, counties exposed to heightened levels of nitrates in their drinking water actually see an improvement in the rate of low birthweight in the nine-months following a violation. Low-access and low-income areas experience only a negligible, and insignificant difference, contrary to the infant mortality results.

	asin(Low Birthweight)				
Panel A. Low Access					
Exposed	−0.028***	−0.026***	−0.029***	−0.030***	−0.027***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
x Low Access		0.003	0.003	0.001	−0.002
		(0.007)	(0.007)	(0.008)	(0.007)
Panel B. Low Income					
Exposed	−0.028***	−0.022***	−0.025***	−0.025***	−0.024***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
x Low Income		−0.006	−0.006	−0.009	−0.009
		(0.008)	(0.008)	(0.008)	(0.007)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependant variable is the inverse hyperbolic sin of low birthweight rate per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Nitrate exposure's impact on low birthweight occurrences.

7 Discussion

Nitrate-contaminated drinking water pose serious health threats to infants, and possibly others. The impacts of this pollution depends on individuals' abilities to adapt to the potential health threat. However, communities affected by nitrate-contaminated drinking water also often exists in resource-constrained areas. These resource constraints may prevent individuals from protecting against the environmental hazard and exposed to the negative health consequences.

In this paper, I show that consumers respond, on average, by purchasing 17.3% more bottled water and 11.3% more sugar-sweetened beverages as a response to nitrate violations. These are relatively cheap forms of protection, which translates to roughly \$4.7 million in annual averting expenditures. This amount is likely far less the counterfactual health damages if all individuals remained exposed to heightened levels of nitrates. However, individuals in food deserts and low-income populations exhibit a significantly dampened response.

In reduced-form evidence, I also show that the same constraints which limit averting response are associated with detrimental infant health impacts. In the nine-months following a nitrate SDWA violation, low access counties experience a 6.3% increase in the infant mortality rate and 4.3% increase in low income counties. Whereas, counties with fewer constraints actually see an improvement in infant health outcomes. These findings are consistent with the theoretical framework that avoidance behavior protects against the harmful health impacts of nitrate pollution in drinking water. Regulations that induce avoidance behavior through informational provisions do appear to protect some from these affects. However, in populations where response is limited, they experience net negative impacts on infant health.

The results of this paper quantify the externality of nitrate pollution in drinking water both through the channels of behavioral response and net health impacts. While there are no federal policies considering the regulation of nitrogen use in agriculture in the United States, I provide further evidence that the costs of nitrate pollution are large and far-reaching. I also show that the SDWA sufficiently protects some residents from the health costs associated with drinking water pollution, but others remain exposed and experience these health impacts, potentially worsening environmental health inequality.

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Appendix

A Theoretical Solutions

This utility maximization problem yields the following set of first order conditions:

$$\begin{aligned} &U_H H_B(T) - U_X(p_I^i + p_B) + \mu = 0 \\ &\mu B = 0 \\ &\mu \geq 0 \end{aligned} \tag{A1}$$

Case 1: $(B = 0)$

Under this scenario, consumers utilize only tap water for their residential and drinking needs. For a corner solution to exist for other beverage consumption the inequality in equation (A2) must hold, where the right-hand side represents the shadow value of avoiding health damages from tap water consumption. The corner solution emerges when the marginal rate of substitution between the composite good and health is greater than the shadow price of perceived health damages. Equation (A2) implies that either (i) the perceived damages from drinking tap water are sufficiently small and (ii) that the price of alternative beverages are sufficiently high relative to the marginal utility of the composite good, X, so that the consumer chooses to not purchase other beverages.

$$\frac{U_X}{U_H} > \frac{-H_T}{p_I^i + p_B} \tag{A2}$$

Case 2: $(B > 0)$

In case 2, the consumer purchases a positive amount of the alternative source. Demand for B will satisfy equation (A3) and will be a function of the exogenous water quality (T), income (Y), the retail price (p_B), and the unique implicit price faced by each consumer, (p_I^i). This equation represents the tradeoff between investing in additional units of a clean source of drinking water and the composite good.

$$\frac{U_X}{U_H} = \frac{-H_T}{p_I^i + p_B} \tag{A3}$$

B Additional Tables and Figures

	log(Bottled Water Price)			
	1	2	3	4
(Intercept)	0.525***	0.092***	0.677***	0.648***
	(0.002)	(0.001)	(0.002)	(0.001)
Food Deserts	0.092***			
	(0.002)			
Convenience		1.081***		
		(0.001)		
Dollar		0.180***		
		(0.001)		
Drug		0.262***		
		(0.001)		
Mass Merchandiser		0.254***		
		(0.002)		
Urban			−0.081***	
			(0.002)	
Low Income				−0.111***
				(0.001)
Num.Obs.	747 449	747 449	747 449	747 449

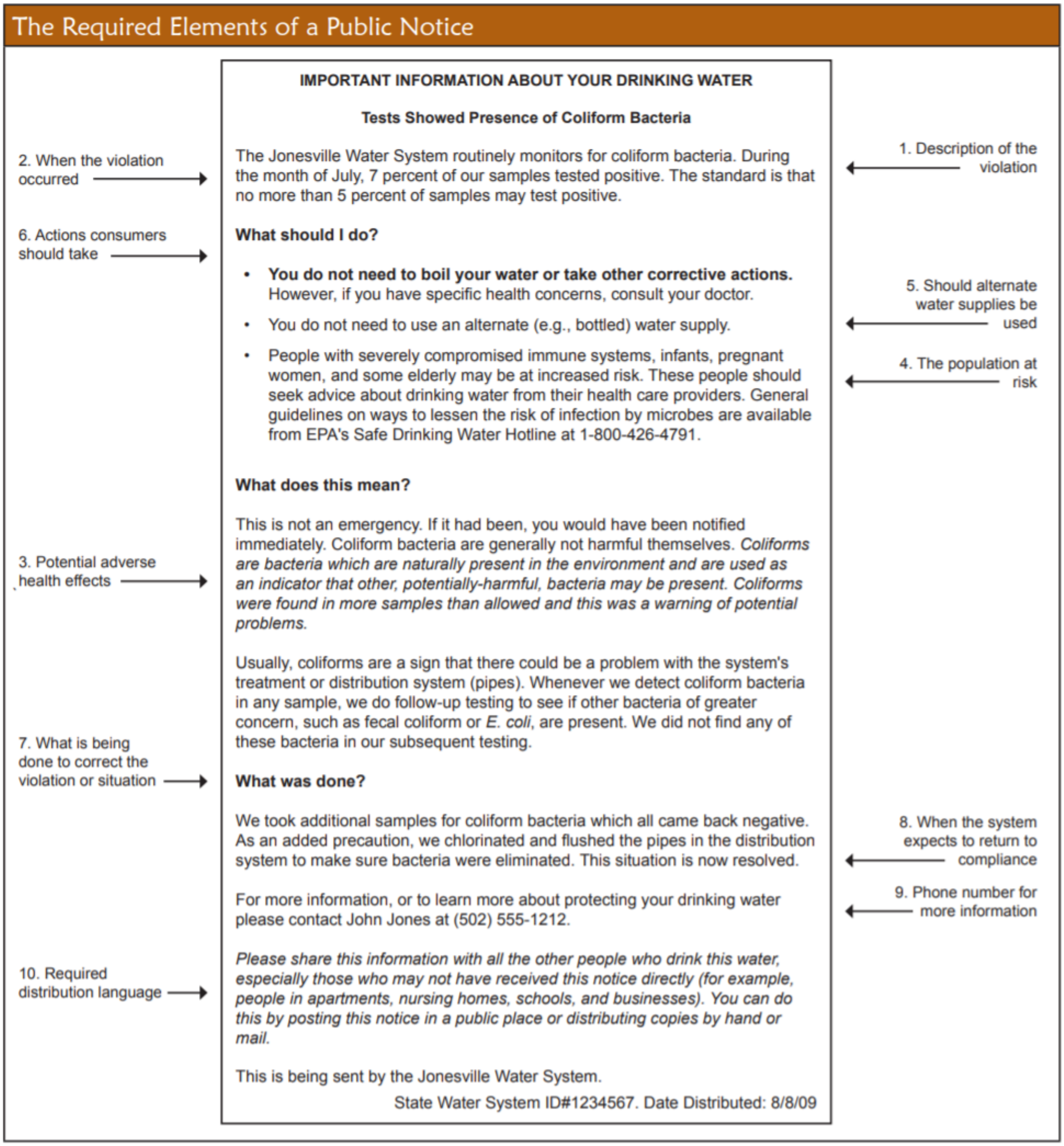
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B1: Price of Bottled Water by Store and Location Characteristics

	log(SSB Price)			
	1	2	3	4
(Intercept)	1.248***	1.016***	1.345***	1.337***
	(0.001)	(0.001)	(0.001)	(0.000)
Food Deserts	0.054***			
	(0.001)			
Convenience		0.542***		
		(0.001)		
Dollar		0.042***		
		(0.001)		
Drug		0.237***		
		(0.001)		
Mass Merchandiser		0.088***		
		(0.001)		
Urban			−0.056***	
			(0.001)	
Low Income				−0.105***
				(0.001)
Num.Obs.	644 361	644 361	644 361	644 361

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B2: Price of Bottled Water by Store and Location Characteristics



IMPORTANT INFORMATION ABOUT YOUR DRINKING WATER

Tests Showed Presence of Coliform Bacteria

The Jonesville Water System routinely monitors for coliform bacteria. During the month of July, 7 percent of our samples tested positive. The standard is that no more than 5 percent of samples may test positive.

What should I do?

- **You do not need to boil your water or take other corrective actions.** However, if you have specific health concerns, consult your doctor.
- You do not need to use an alternate (e.g., bottled) water supply.
- People with severely compromised immune systems, infants, pregnant women, and some elderly may be at increased risk. These people should seek advice about drinking water from their health care providers. General guidelines on ways to lessen the risk of infection by microbes are available from EPA's Safe Drinking Water Hotline at 1-800-426-4791.

What does this mean?

This is not an emergency. If it had been, you would have been notified immediately. Coliform bacteria are generally not harmful themselves. *Coliforms are bacteria which are naturally present in the environment and are used as an indicator that other, potentially-harmful, bacteria may be present. Coliforms were found in more samples than allowed and this was a warning of potential problems.*

Usually, coliforms are a sign that there could be a problem with the system's treatment or distribution system (pipes). Whenever we detect coliform bacteria in any sample, we do follow-up testing to see if other bacteria of greater concern, such as fecal coliform or *E. coli*, are present. We did not find any of these bacteria in our subsequent testing.

What was done?

We took additional samples for coliform bacteria which all came back negative. As an added precaution, we chlorinated and flushed the pipes in the distribution system to make sure bacteria were eliminated. This situation is now resolved.

For more information, or to learn more about protecting your drinking water please contact John Jones at (502) 555-1212.

Please share this information with all the other people who drink this water, especially those who may not have received this notice directly (for example, people in apartments, nursing homes, schools, and businesses). You can do this by posting this notice in a public place or distributing copies by hand or mail.

This is being sent by the Jonesville Water System.

State Water System ID#1234567. Date Distributed: 8/8/09

Figure B1: Public Notification Example and Requirements

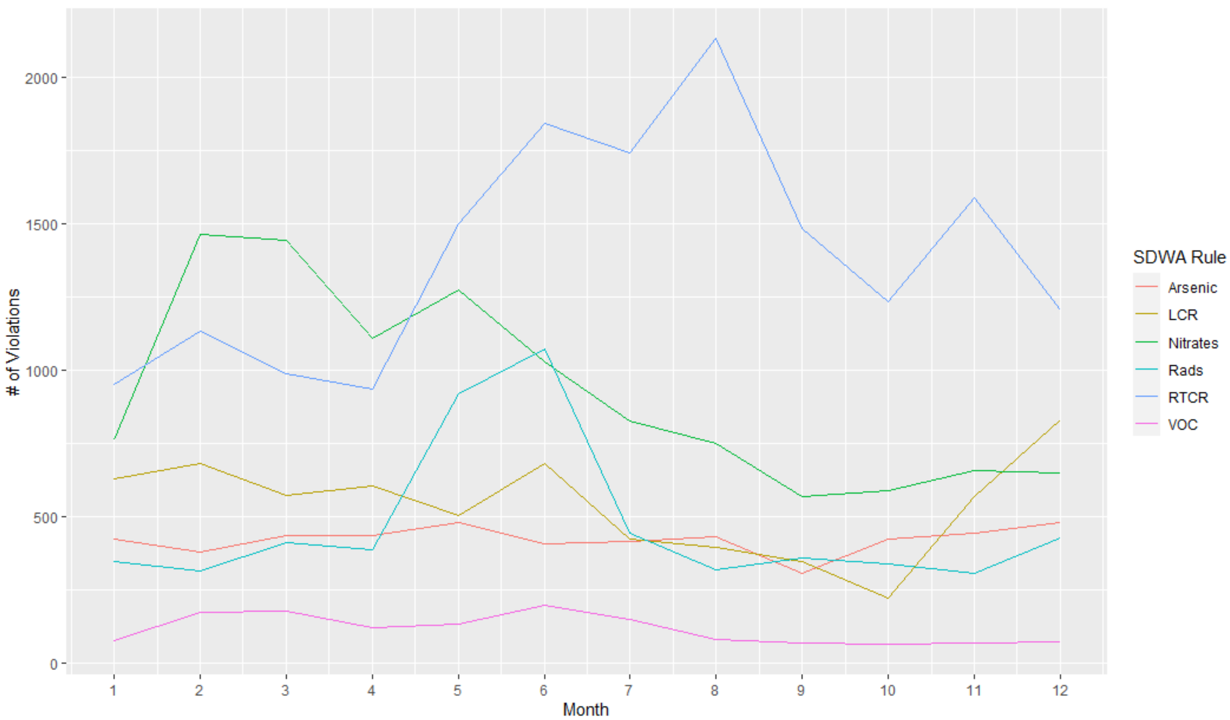


Figure B2: Sum of SDWA Violations by Type

NOTE: LCR = Lead/Copper Rule, Rads= Radionucleotides, RTCR= Revised Total Coliform Rule, VOC= Volatile Organic Compounds.

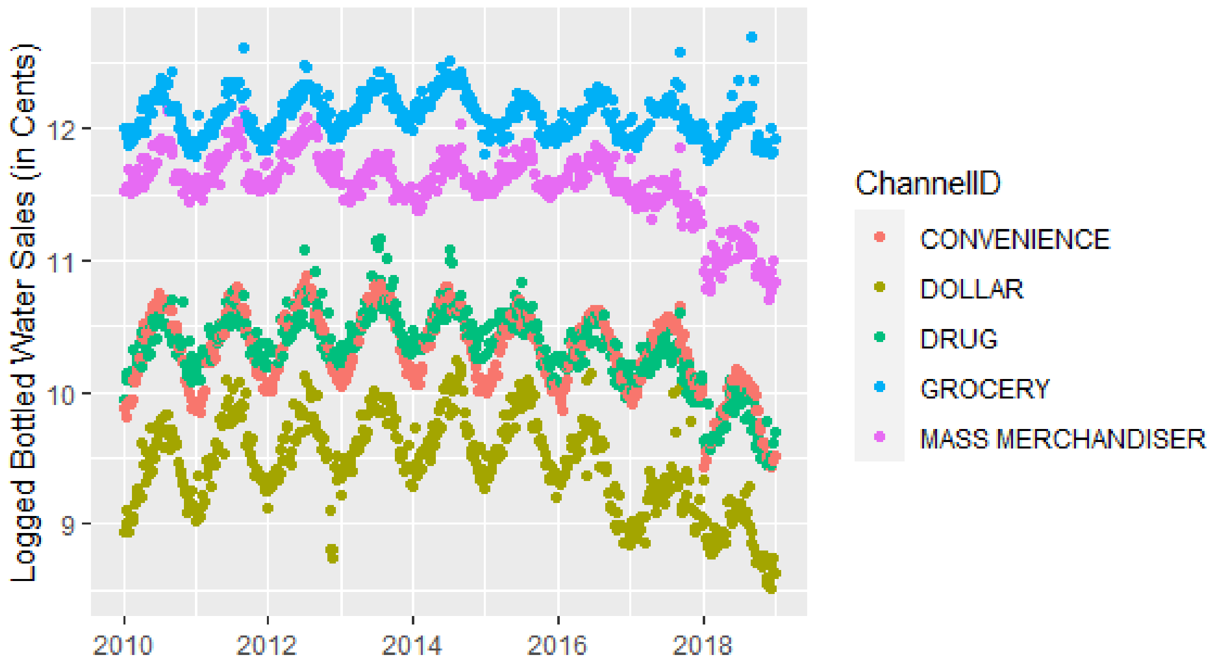


Figure B3: Raw bottled Water Sales by Store Type

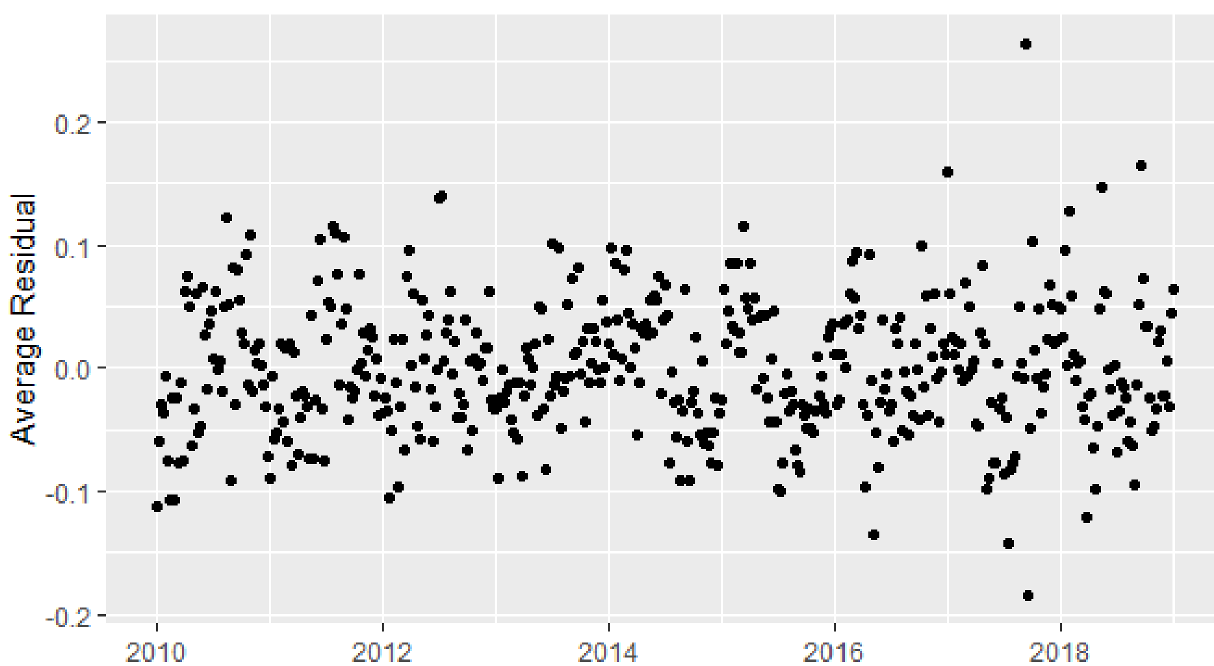


Figure B4: Identifying Variation After Conditioning on Fixed Effects

	log(Bottled Water)		
	1	2	3
Nitrate Vio	0.173***	0.266**	0.131***
	(0.032)	(0.087)	(0.035)
x> Non-White		−0.264**	
		(0.085)	
x Rural			0.164*
			(0.068)
Num.Obs.	614 478	614 478	614 478
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X
FE: Store by Event	X	X	X
FE: Week by Year	X	X	X

Note: Dependant variable is logged bottled water sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.

* p < 0.05, ** p < 0.01, *** p < 0.001

Table B3: Heterogeneity in Averting Behavior: Sugar-Sweetened Beverage Sales

	1	2	3
Nitrate Vio	0.113**	0.093**	0.084*
	(0.039)	(0.033)	(0.039)
x> Non-White		−0.084*	
		(0.042)	
x Rural			0.116*
			(0.051)
Num.Obs.	516 315	621 618	516 315
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X
FE: Store by Event	X	X	X
FE: Week by Year	X	X	X

Note: Dependant variable is logged sugar sweetened beverage sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.

* p < 0.05, ** p < 0.01, *** p < 0.001

Table B4: Heterogeneity in Averting Behavior: Sugar-Sweetened Beverage Sales

	asin(Very Low Birthweight)				
Panel A. Low Access					
Exposed	−0.032***	−0.034***	−0.035***	−0.035***	−0.032***
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
x Low Access		0.005	0.006	0.001	−0.001
		(0.015)	(0.015)	(0.015)	(0.014)
Panel B. Low Income					
Exposed	−0.032***	−0.037***	−0.037***	−0.039***	−0.038***
	(0.007)	(0.009)	(0.009)	(0.010)	(0.009)
x Low Income		0.013	0.013	0.012	0.013
		(0.016)	(0.016)	(0.016)	(0.016)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependant variable is the inverse hyperbolic sin of very low birthweight rate per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B5: Nitrate exposure's impact on the rate of very low birthweight.