The Costs of Nitrate Pollution in Drinking Water*

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Abstract

Nitrate contamination of drinking water is a widespread environmental concern and threatens human health. The magnitude of the environmental health consequences depend on an individuals' ability to avoid exposure. This paper uses an event-study framework to uncover the heterogeneity in avoidance behavior following Safe Drinking Water Act nitrate violations. Using weekly store-level scanner data, I estimate that consumers spend approximately $4.7 million annually on bottled water and soda to avoid nitrate contaminated drinking water. However, consumers in resource-constrained areas exhibit substantially less protective behavior. This leads to 143 additional infant deaths per year relative to areas with less-costly access to safe drinking water. These results underscore substantial costs from nitrate pollution and that these costs are disproportionately distributed to those with less ability to protect themselves.

1 Introduction

Nitrate pollution is one of the United States' most costly and widespread environmental problems (Environmental Protection Agency, 2022). Nitrogen contamination in water systems harms aquatic life, limits human recreational activity, and threatens human health. Nitrates, when ingested at excessive levels, affect infant health, causing "blue-baby syndrome" (or methemoglobinemia), which may be deadly (Walton, 1951). Other evidence also suggests that nitrates annually lead to about 1,700 occurrences of pre-term births and 6,500 nitrate-attributable cancer cases (Temkin et al., 2019). Rural areas are especially vulnerable since agricultural production is nitrogen-intensive, and nitrogen fertilizers leach into water systems over time (Paudel and Crago, 2020; Metaxoglou and Smith, 2022).

The magnitude of the public health damages from pollution largely depends on individuals' ability to avoid the environmental hazard. Many environmental regulations, like the Safe Drinking Water Act (SDWA), use information disclosures and public notices to alert consumers of drinking water quality violations in an effort to mitigate the public health risks. However, consumers respond to water quality information heterogeneously (Zivin, Neidell, and Schlenker, 2011; Allaire et al., 2019; Marcus, 2021). Resource constraints, like income, market access, and other infrastructure gaps, may limit individuals' ability to reduce exposure to drinking water pollution (De Janvry, Sadoulet, and Murgai, 2002). These factors may be particularly acute in rural areas, where residents disproportionately experience SDWA nitrate violations (Allaire, Wu, and Lall, 2018).

This paper quantifies the willingness to pay to avoid nitrate contamination in drinking water and how avoidance behavior and the subsequent health impact differs across demographics. I study this in the context of SDWA nitrate violations in the United States using an event-study framework. SDWA violations simultaneously indicate an increase in nitrate contamination to a dangerous level and serve as information shocks about water quality, where the latter may induce a consumer response.[1] I uncover how this response differs for

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[1]Residents typically have imperfect information about local water quality (Keiser and Shapiro, 2018) and

residents in areas that are income-constrained and those living in food deserts.[2] I use the timing of SDWA violations to estimate the net health impacts on birth outcomes and infant mortality, and how the health impact differs based on characteristics correlated with levels of protective behavior.

Building on Harrington and Portney (1987), I propose a theoretical framework to illustrate that the net effect of worsening water quality on health is ambiguous. Worsening drinking water quality, which triggers SDWA violations, heightens the risk to the public health of those residents. However, public notifications that accompany violations likely causes consumers to engage in more protective action, like relying on bottled water and other beverages, which may improve health outcomes ceteris peribus. I extend Harrington and Portney (1987) to allow individuals to face differential implicit prices for protective behavior, where differences arise from geographic or socioeconomic resource constraints. The analytical results from this model predict that individuals facing higher implicit prices will engage in less averting behavior, and as a result, there are higher realized human health costs.

To empirically test for avoidance behavior, I estimate the effect of different water quality violations and subsequent public notifications on beverage purchases, as measured by bottled water and soda sales at local retail outlets, using an event-study framework. The staggered timing of violations in public water systems (PWS) across the United States represent shocks to both water quality and consumers' information, which allows the estimation of the response after a violation occurs relative to the weeks preceding a violation. Two-way fixed effects control for fixed differences across stores and seasonality in bottled water sales. To account for potential bias in heterogeneous treatment across time, I use

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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.

[2]Importantly, the behavioral response is only a portion of the total economic costs of nitrate violations because it fails to account for the health consequences imposed on those who remained exposed (Harrington and Portney, 1987).

an unbiased estimator proposed by Gardner (2021).[3] I also allow for heterogeneity in the estimates of avoidance behavior by census tract 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 notifications. In the second stage of the analysis, I estimate the effect of nitrate violations and subsequent public notifications on health. I uncover the average net effect on health, as well as, heterogeneous impacts based on factors that may limit avoidance behavior.

I use data from the Safe Drinking Water Information System (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 weekly store-level retail scanner data from 2010 to 2019. The weekly panel of beverage sales allows me to measure the response each week following a violation event and the average treatment effect of an active violation. This empirical design also investigates anticipatory action or uncovers other pre-trends. I interact census tract demographics and measures of grocery-store accessibility to test for heterogeneity in response. Lastly, I use within county variation of proprietary, monthly infant health statistics to estimate the effects of nitrate exposure in drinking water with varying levels of protective behavior on health outcomes.

A first central result is that nitrate violations lead to of significant avoidance behavior through bottled water and soda purchases. Public notifications due to nitrates induce an approximately 17% increase in bottled water sales and 11% in soda sales relative to the weeks preceding a violation. This translates to $4.7 million annually in averting expenditures in the United States, which is relatively inexpensive compared to other environmental damages of agricultural fertilizer pollution (Dodds et al., 2009; Taylor and Heal, 2022). Second, food ac-

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[3]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.

cessibility and income constraints significantly limit avoidance behavior through purchasing bottled beverages by 31 and 26 percentage points, respectively, which illustrates the implicit higher barrier these residents face to avoid contaminated water.

Finally, I find that the public notifications from SDWA nitrate violations improve the rate of infant mortality by 7.7% in areas that have proximate access to alternative beverage sources. This is consistent with the model in which informational provisions induce protective behavior among affected households. However, areas with food-access constraints experience a net 6.3% increase in infant mortality relative to pre-violation weeks. This implies that roughly 143 infant deaths each year, or health costs of $1.5 billion, in the United States are attributable to nitrate violations in vulnerable populations.

This paper contributes to the social costs of nitrate pollution from agricultural production by uncovering the substantial health costs associated with nitrogen exposure in drinking water. The costs of nitrate pollution in surface water, resulting in algal bloom and "dead-zone" (or hypoxic zones) in the Gulf of Mexico, are estimated to be large, ranging between $2.2 to $7.3 billion annually (Dodds et al., 2009; Taylor and Heal, 2022). Less is known about the extent of economic damages of nitrate pollution in drinking water sourced from groundwater.[4] Zivin, Neidell, and Schlenker (2011) estimate that consumers spend $1.7 million annually to avoid nitrate contaminated drinking water, but do not incorporate the health costs. Identifying the health costs in this context is empirically challenging due to endogenous sorting, and much of the current knowledge about the impact of nitrates on health relies on case-studies or cross-sectional exposure analyses (Walton, 1951; Ward et al., 2018; Temkin et al., 2019). I give evidence that the human health costs of nitrate pollution far exceed the avoidance behavior costs and that the health costs are disproportionately realized despite existing regulation.

Second, I add to the body of work that calculates the health costs of water pollution

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[4]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.

and the effectiveness of current regulation. The economic impacts of water pollution remains understudied, especially relative to air pollution (Keiser and Shapiro, 2018). 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). I contribute to these studies by estimating both the behavioral and health impacts of nitrate pollution and highlight an area 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. My results suggest that geographic constraints – specifically food deserts – also limit individuals' ability to protect themselves from the negative health consequences of nitrate pollution. This paper documents that environmental justice is a concern in the rural United States primarily through water pollution.

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 at 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 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.[5] This pattern also loosely follows the spatial variation of farm nitrogen application in the United States, discussed in the next section.
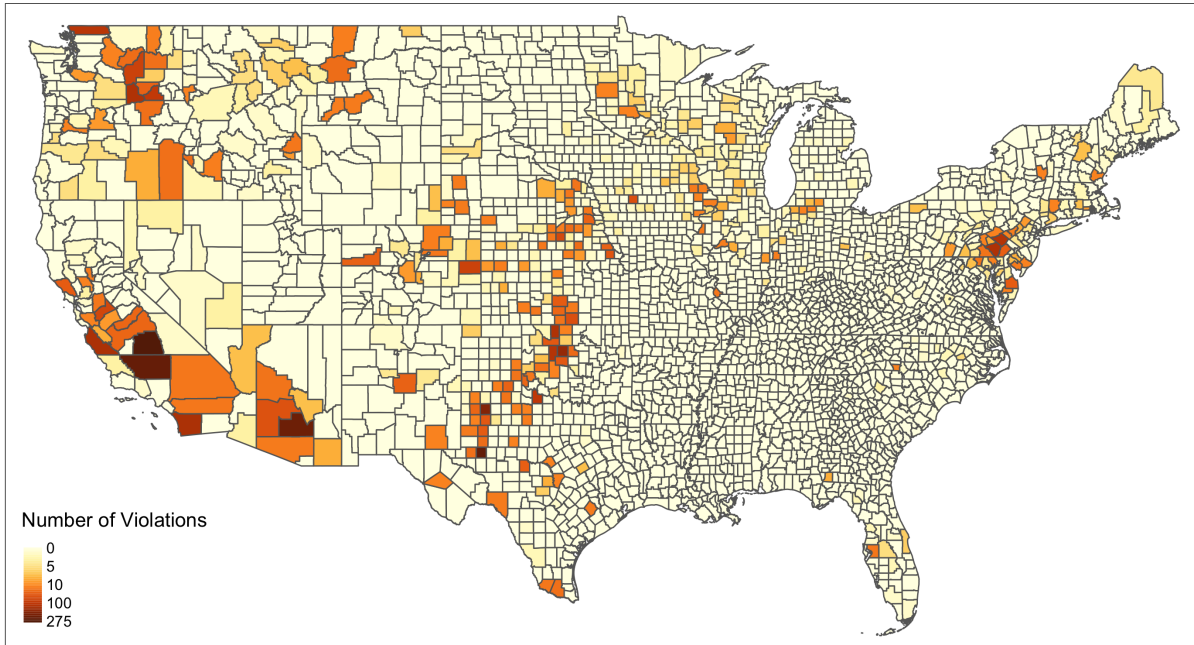
Figure 1: Number of SDWA Nitrate Violations, 2010-2019

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

While nitrogen pollution is the result of a number of anthropogenic activities, agriculture is the primary source. In the United States, agricultural fertilization accounted for approximately 93% of commercial nitrogen use in 2010.[6] 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.

Nitrogen fertilizers are an integral part of the agricultural supply chain by increasing agricultural yields, and global use 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 resulted in

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[5]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.

[6]Authors calculations from John and Gronberg (2017)
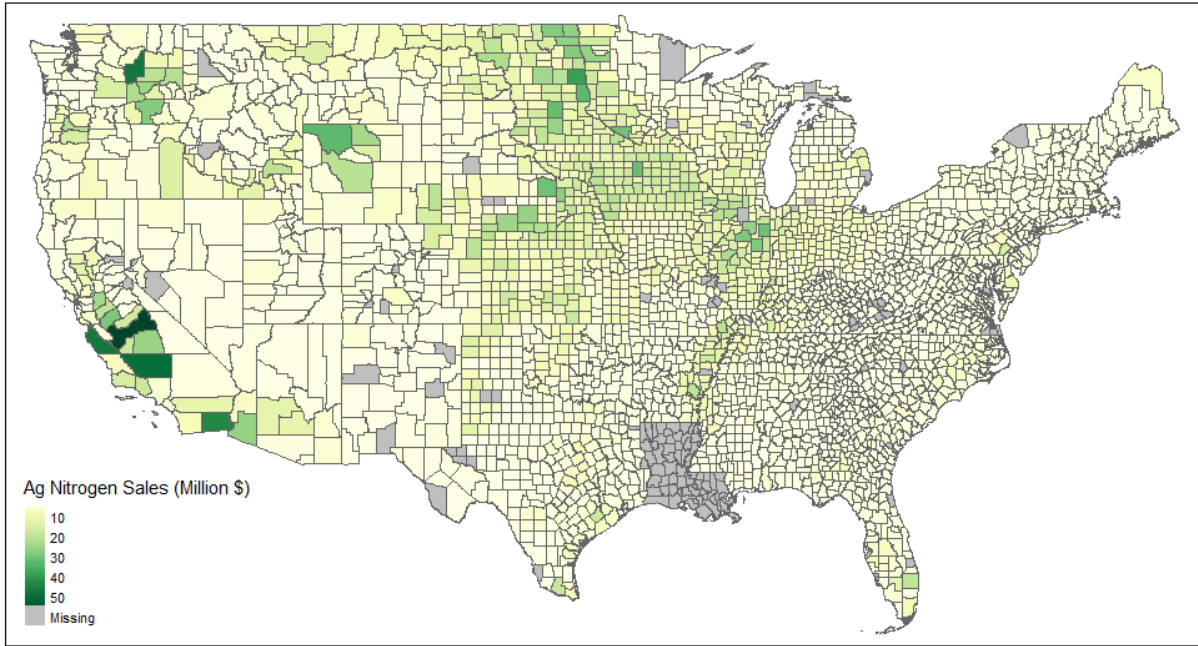
Figure 2: Agricultural Nitrogen use by County, 2010

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

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).[7] 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

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[7]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.[8]

Assessing the total environmental costs of nitrogen pollution 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 that 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 internationally. Once a water system reports nitrate level in excess of this threshold, preg-

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

nant 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. Food deserts and their impacts on 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 soda, respectively.
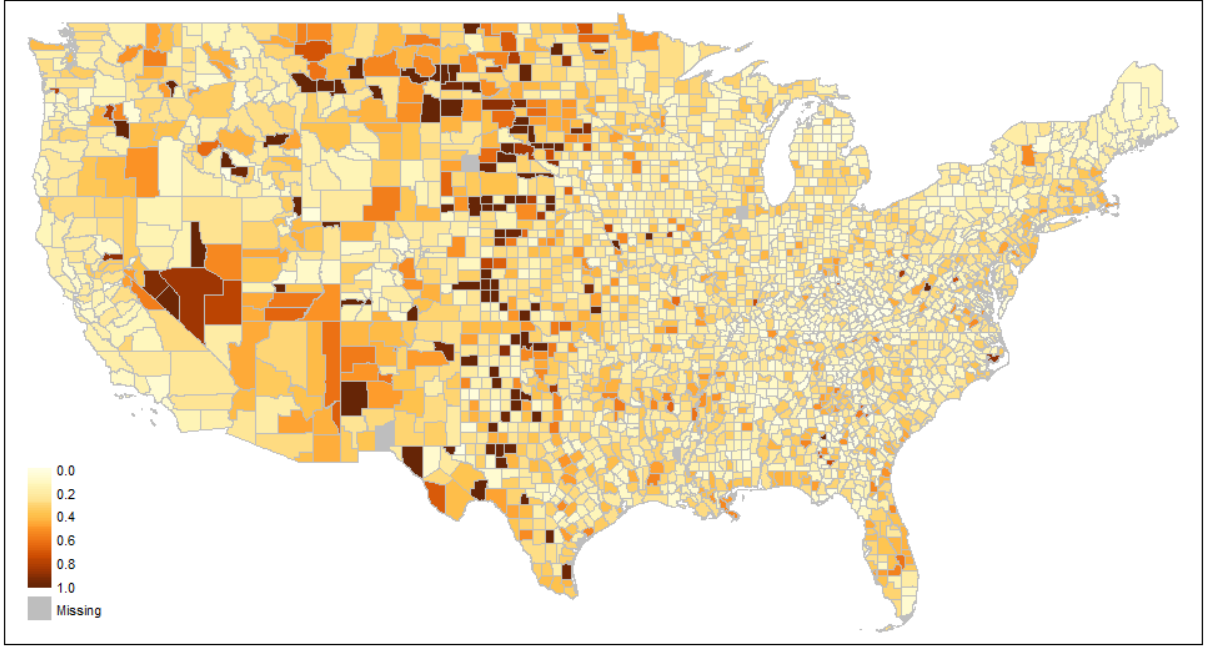
Figure 3: Share of County Population in Food Desert, 2015

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. 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.

$$U = U(H, X)$$

$$H = H(T, B(T)))$$

(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.

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

(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^i, which is the unique price faced by each individual. Each consumer also experiences a 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:

$$\max_{B \geq 0} \ U(H(T, B), Y - (p_I^i + p_B^i)B)$$

(3)

The solutions to this maximization problem, which are derived further in appendix A, yield a demand function for the protective behavior that is dependant on the level of pollution,

T, and the total price of averting response, $p_I^i + p_B^i$. An exogenous change in T will yield a non-negative change in demand for safe beverages, represented by the partial $B_T(Y, p_I^i + p_B^i)$.

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, $B_T(Y, p_B^i) \geq B_T(Y, p_I^i + p_B^i)$ 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 settings.

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. 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 underscores 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 violation 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 in 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.[9] 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 provides the most geographically comprehensive scanner data available. These retail scanner data cover over

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[9]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.

48,000 stores 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 soda. Each measure is the sum of weekly store revenue from all types of bottled water or soda. Soda sales are the cumulative of carbonated beverage, sugar- and calorie-reduced beverage (i.e. diet sodas), and seltzer sales. Bottled water captures non-carbonated, natural or regular water in both small bottles and multi-gallon, refillable jugs. 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 low-birthweight and infant mortality to study how SDWA public notification, and how heterogeneous levels of averting response affect infant health outcomes. Though nitrate ingestion is a known cause of infant deaths related to "blue-baby syndrome", the CDC does not uniquely categorize these deaths in the data. Instead, the primary health outcomes measures total infant mortality in a county measures death stemming from all causes.

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 available and provide sufficient power to identify environmental health effects and are used in a number of settings (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 alternative, estimating DD 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.[10] Additionally, state-by-year fixed effects, ϕ_s, capture state-year specific regulatory differences.[11] 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.

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[10]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.

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

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

$$\text{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\phi}' \boldsymbol{X}_{ist} + \mu_{ist} \tag{4}$$

I additionally estimate the dynamic version (or event-study) of equation 5 to offer 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 offers evidence to support the identifying assumption that, conditional on fixed effects and covariates, beverage purchases would have not significantly differed in the absence of violation. For the event-study, I use an eight week window before and after the violation.[12] 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.

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

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

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

$$(5)$$

An identifying assumption of this event-study framework is that beverage sales would not have changed in absence of treatment. In equation (5), this assumption is supported if β_{1w} for all $w \in [-8, -1]$ are not statistically distinguishable from zero.

To test for heterogeneity by community demographics, I will estimate equation (6), 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 $\boldsymbol{Z_i}$. Importantly, the heterogeneity analysis should not be interpreted as causal estimates since Z_i is non-randomly distributed. However, γ can still uncover true heterogeneous treatment effects and this analysis can be suggestive of the causal mechanisms.

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

$$\text{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\gamma Z_i} * Vio_{ist} * w_i + \boldsymbol{\phi'X}_{ist} + \mu_{ist}$$

$$(6)$$

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 consumers 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.[13] 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 themselves 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.

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

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 months. 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 soda. For nitrate violations, bottled water is the recommended alternative source included in public notifications. Boiling water, for example, does not eliminate nitrates and potentially

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

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.

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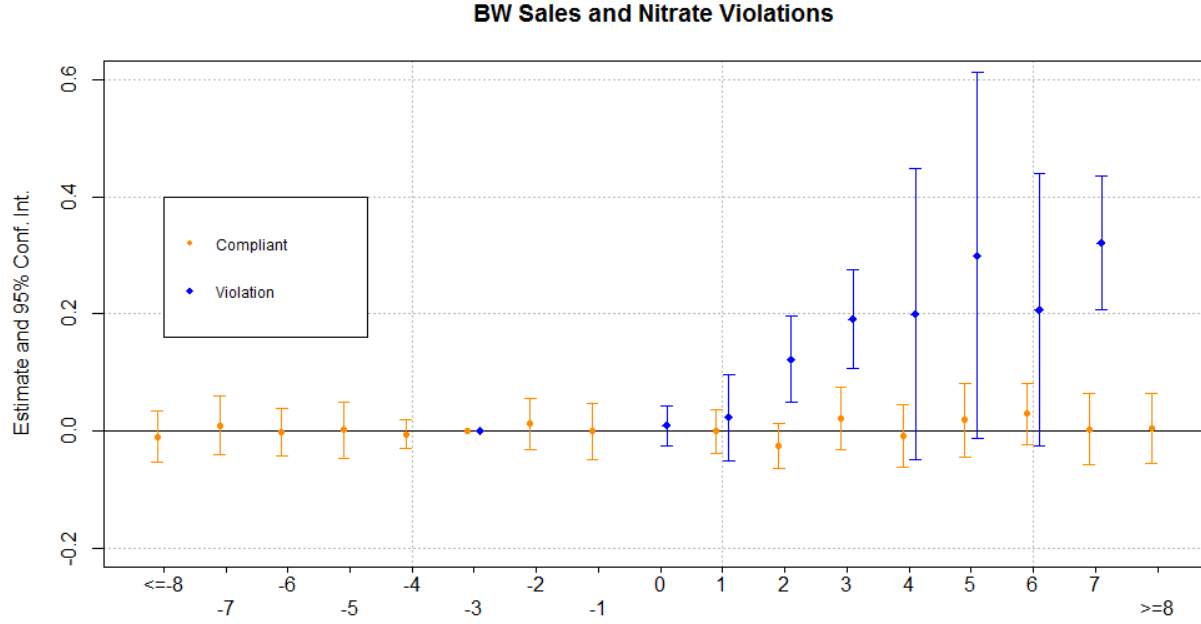
Figure 4: Event-Study Results: Bottled Water Sales Pre- and Post- SDWA Violation

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.

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.

	log(Bottled Water Sales)				
	(1)	(2)	(3)	(4)	(5)
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				Linear	Quadratic

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

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.

Soda

Instead of substituting bottled water, some consumers may substitute contaminated tap water with other beverage options, like soda. Soda sales are an alternative form of averting behavior and should not be ignored in calculating the full response from exogenous changes in nitrate contamination in drinking water. Analysis of soda 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.
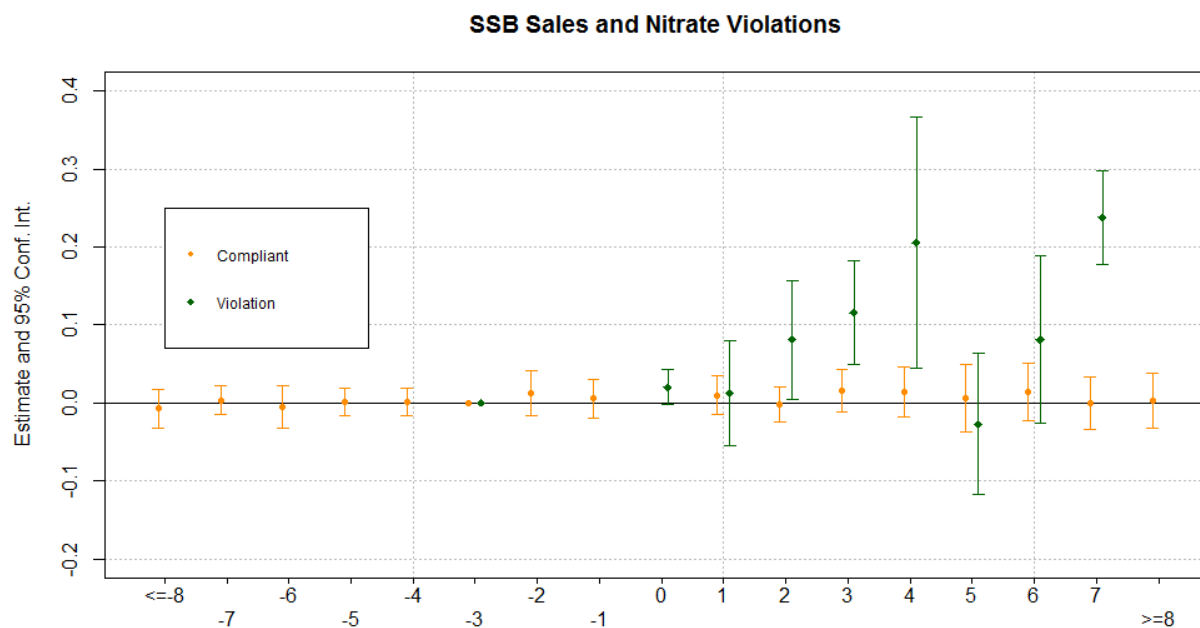
Figure 5: Event-Study Results: Soda Sales Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event-study coefficients of logged soda sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in soda 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 soda. Again, the parallel trends assumption prior to a violation holds. Similar to bottled water, soda 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.

| | log(Soda Sales) | | | | |
	(1)	(2)	(3)	(4)	(5)
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				Linear	Quadratic

Note: Dependant variable is logged soda 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 Soda

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

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 sales)					
	(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.

	log(Soda sales)					
	(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 soda 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: Soda Sales

Second, table 4 displays the results for soda sales. Similarly, food desert census-tracts display negative, but not significant, 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 soda purchases – suggesting that the resource constraints limit the purchasing ability for all products, rather than capturing a systematic correlation between

consumer preferences between soda and bottled water.[14]

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 approximately report the proportional change in infant mortality in the nine months after a SDWA nitrate violation (i.e. $\beta \times 100 = \%$ change) (Bellemare and Wichman, 2019). 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.[15]

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[14]One long-standing claim is that consumers use SNAP funds to purchase more soda compared to the 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.

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

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 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)				
	(1)	(2)	(3)	(4)	(5)
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)				
	(1)	(2)	(3)	(4)	(5)
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.

Welfare and Policy Implications

The behavioral costs associated with avoiding contaminated tap water due to nitrate violations can be estimated by equation 8. Since all SDWA nitrate violations are not included in my primary estimating sample, I use data from Pennino et al. (2020) on the total number of individuals impacted each year and the average length of violation. This assumes that

the behavioral response in my sample is representative of all nitrate violations in the United States and the IRI retail data is representative of all retails.[16] The United States' generates approximately \$19.4 billion in annual bottled water sales and \$29.4 billion in soda sales (International Bottled Water Association, 2019; Beverage Industry, 2020). Distributing each of these figures uniformly across the population of the United States and the weeks of the year, BW_{pw} and $soda_{pw}$ capture the average expenditure per person per week on bottled water and soda respectively.

$$\text{Behavioral Costs} = \sum_p \sum_w (\hat{\beta}^{BW} \times BW_{pw} + \hat{\beta}^{soda} \times soda_{pw}) \tag{8}$$

This exercise indicates that consumers spend approximately \$2.5 million on bottled water purchases and \$2.2 million annually on soda annually in the United States as a result of nitrate violations.[17] This figure more than twice exceeds that of Zivin, Neidell, and Schlenker (2011) due to the downward TWFE bias and not accounting for substitution to other beverages. Yet, considering Dodds et al. (2009) estimates nitrogen pollution accounts for \$2.2 billion in damages annually in surface water, the expenses paid by the affected residents is relatively small.

However, this number understates the full behavioral costs of nitrate violations due to a number of other, long-term protective actions, like water filtration systems. Bottled beverages capture only a portion of the short-term response, but they provide a relatively inexpensive alternative for protection against the potentially harmful health effect. Furthermore, the PWS themselves and the local taxpayers they serve must undergo expenses to return to SDWA compliance. Tang et al. (2018) report that these expenses could range from anywhere between \$200,000 to \$40 million per system, depending on the size of the system

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[16]There is no way to prove that these assumptions are accurate, but Zivin, Neidell, and Schlenker (2011) make the same assumptions about a smaller subset of retail stores in only Nevada and California.

[17]A large literature studies the effects of soda consumption and the impacts of obesity (Bleich and Vercammen, 2018). An indirect effect of drinking water contamination may lead to worsened health, like increased obesity rates, if consumers opt to substitute water consumption with sodas. These indirect health impacts are not accounted for in this analysis.

and technology.

Furthermore, the economic damages to human health to those who remain exposed are likely higher than the behavioral impact. Over the 10-year panel of this study, about 4.5 million children were born in areas classified at low-access and in the nine months window following a drinking water nitrate violation. Given the estimate in table 5 that infant mortality was 6.3% higher in such counties and an average infant mortality rate of approximately 4.9 deaths per 1,000 births in these counties, this equates to roughly 143 additional infant deaths per year associated with nitrate violations in low access areas. Using EPA's value of statistical life measure of $11.17 million (in 2022 dollars), the back-of-the-envelope health costs of nitrate violations per year in food deserts exceeds $1.5 billion.[18]

It should be noted, again, that the heterogeneous treatment estimates should not be interpreted as causal estimates, but demonstrate that nitrate contamination poses severe health risk to those who do not exhibit avoidance behavior, whether food deserts are the causal mechanism or other confounding factors. The environmental health costs in exposed populations far exceeds the behavioral costs, accentuating the disparity in environmental health outcomes in resource-constrained populations.

7 Discussion

Nitrate-contaminated drinking water poses serious health threats to infants, and possibly others. The impacts of this pollution depend on individuals' abilities to adapt to the potential health threat. However, communities affected by nitrate-contaminated drinking water also often exist 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 soda as a response to nitrate violations. These are relatively cheap forms of protection, which translates to roughly $4.7 million in annual

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[18]See link for details on EPA's mortality risk valuation.

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, populations where response is limited 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:

$$U_H H_B(T) - U_X(p_I^i + p_B) + \mu = 0$$
$$\geq 0$$

(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.

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

(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

The Required Elements of a Public Notice

2. When the violation occurred →

6. Actions consumers should take →

3. Potential adverse health effects →

7. What is being done to correct the violation or situation →

10. Required distribution language →

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

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1. Description of the violation ←

5. Should alternate water supplies be used ←

4. The population at risk ←

8. When the system expects to return to compliance ←
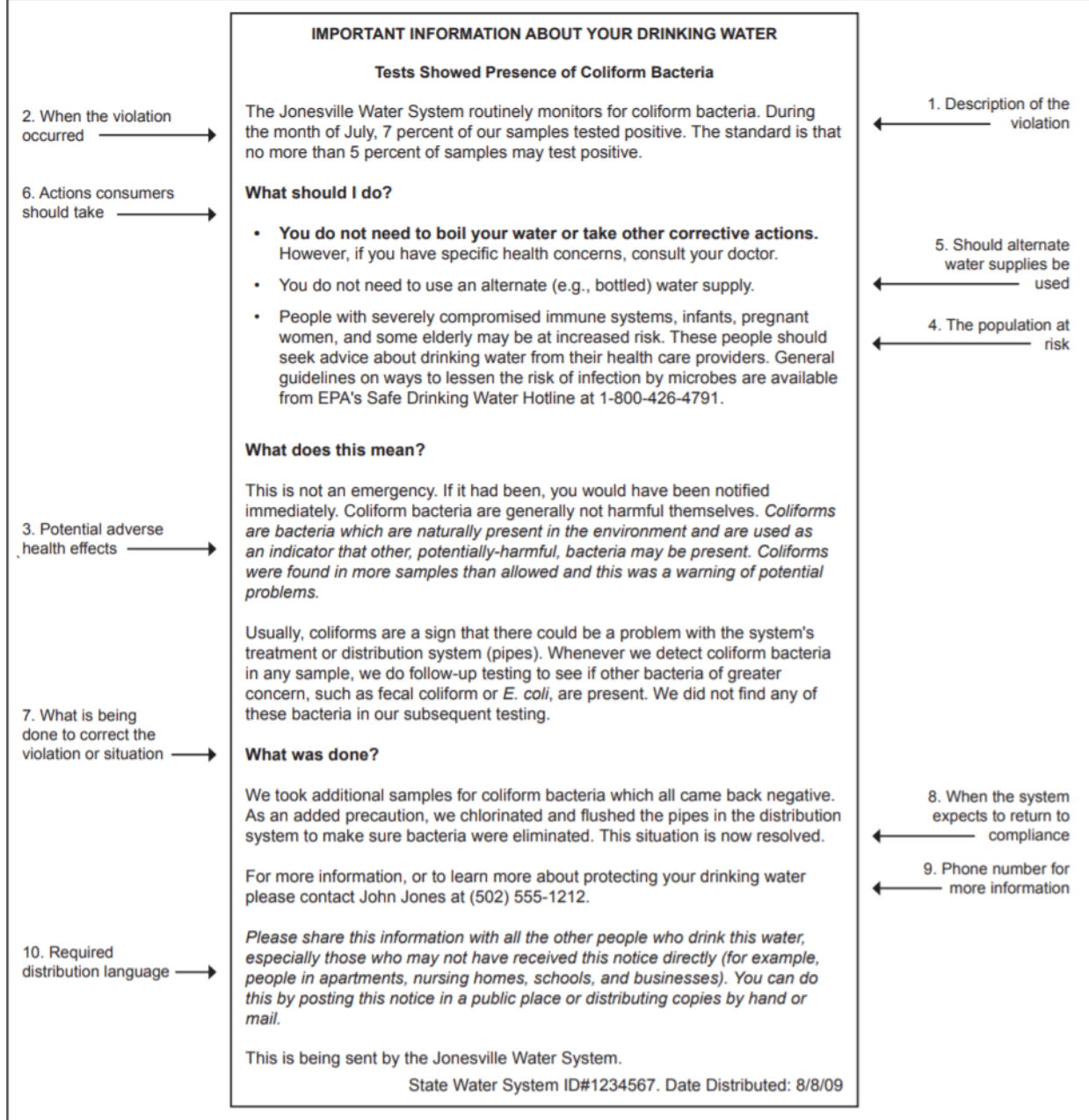
9. Phone number for more information ←

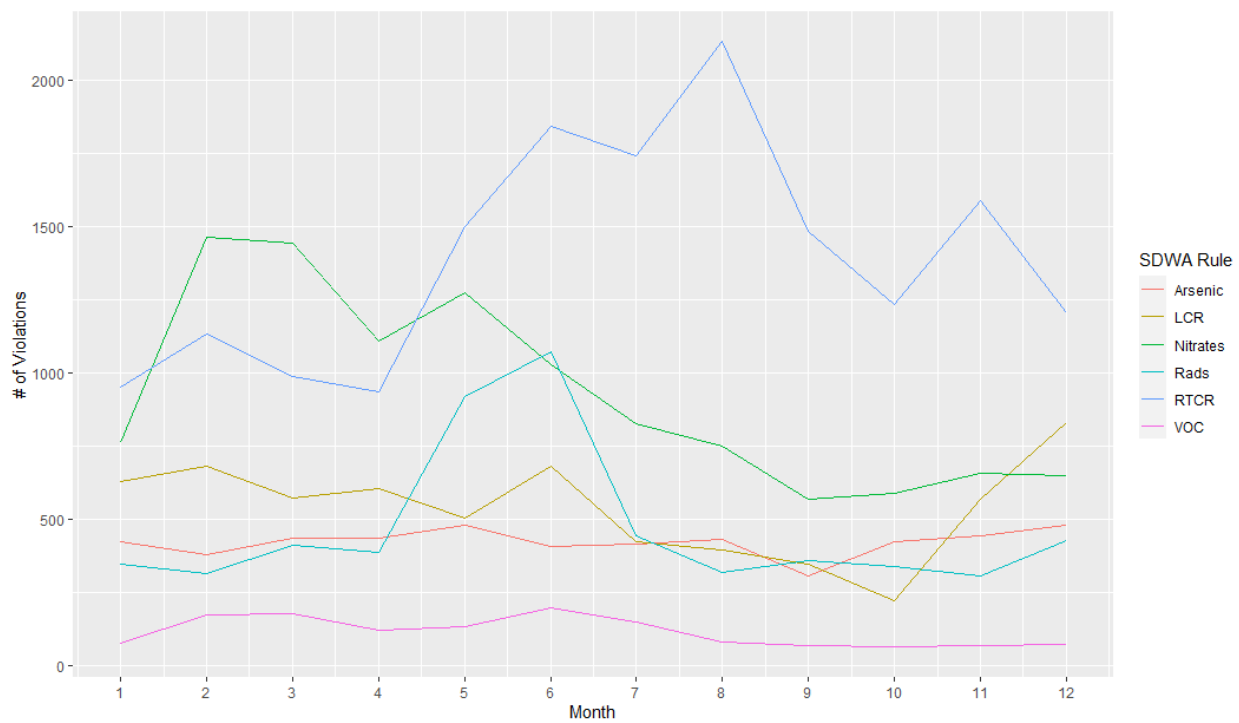Figure B1: Public Notification Example and Requirements

Figure B2: Sum of SDWA Violations by Type

NOTE: LCR = Lead/Copper Rule, Rads= Radionucleotides, RTCR= Revised Total Coliform Rule, VOC= Volatile Organic Compounds.
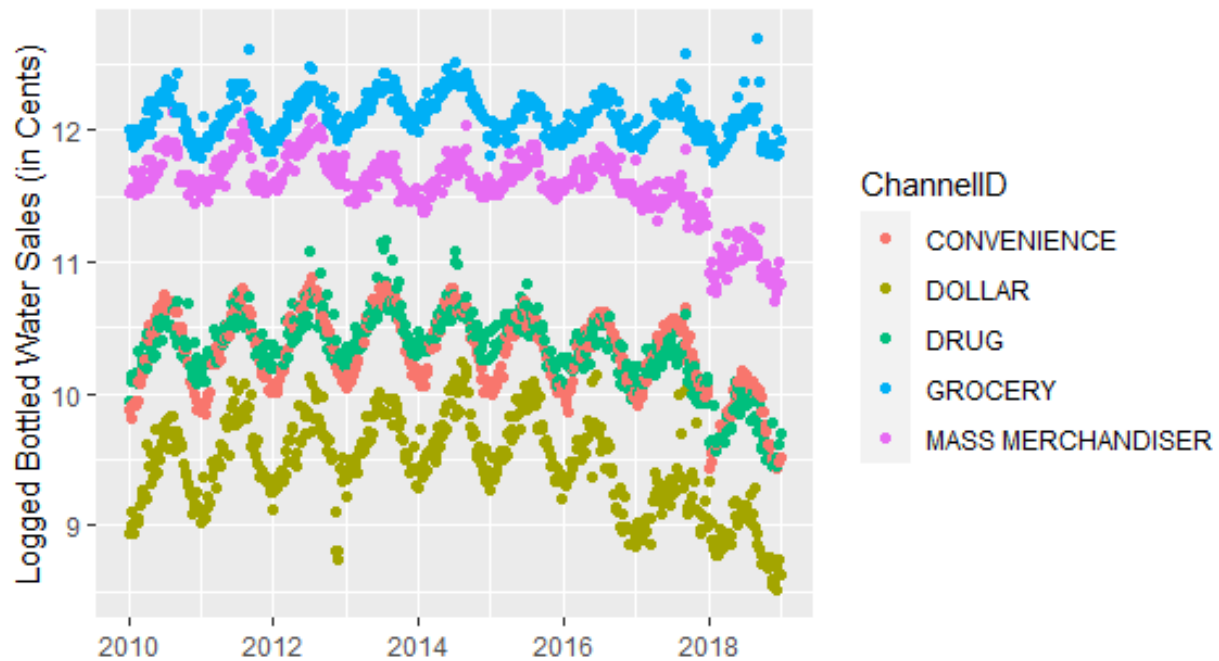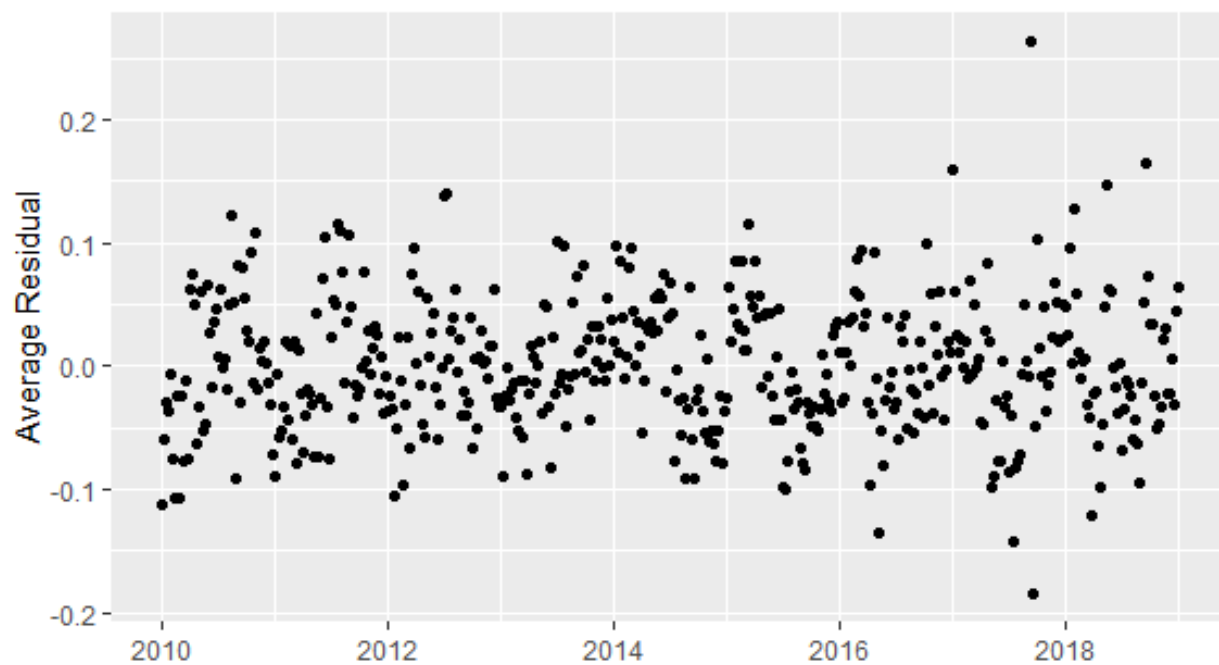
Figure B3: Raw bottled Water Sales by Store Type

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: Soda 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 soda 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: Soda 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.