# Benefits of Avoiding Nitrates in Drinking Water*

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**Abstract**

Nitrate contamination of drinking water is a widespread concern and threatens human health. The magnitude of the health consequences depends on individuals' ability to avoid exposure. This paper uses an event-study framework to uncover avoidance behavior and infant mortality outcomes following public notifications required by the Safe Drinking Water Act. Using store-level scanner data, I estimate that consumers spend $4.5 million annually on bottled water to avoid nitrate-contaminated drinking water. This protective behavior leads to 20 avoided infant deaths per year or $223 million in monetized benefits. These results underscore the benefits and role of environmental information policy in inducing avoidance of environmental hazards.

**Keywords:** drinking water, nitrates, infant health, information, environmental justice

**JEL Codes:** Q53, Q25, Q58

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# 1 Introduction

Nitrates are among the most costly and widespread water pollutants in the United States (Environmental Protection Agency, 2022). Nitrogen contamination in water systems harms aquatic life, limits recreational activity, and threatens human health. When ingested at excessive levels, nitrates are a well-known cause of "blue-baby syndrome" (or methemoglobinemia), which may be deadly (Walton, 1951). Although blue-baby syndrome occurrence is believed to be rare, other evidence suggests that even modest levels of nitrates lead to other health complications. For example, epidemiological studies suggest that about 1,700 occurrences of pre-term births annually and 6,500 cancer cases in adults are attributable to nitrate exposure (Ward et al., 2018; Temkin et al., 2019).

The magnitude of the public health damages from nitrate pollution largely depends on an individual's ability to avoid the polluted source. Many environmental regulations, like the Safe Drinking Water Act (SDWA), use information disclosures and public notices to alert consumers of potential environmental hazards in an effort to mitigate the public health risks. However, consumers may differentially respond to information about water quality (Zivin, Neidell, and Schlenker, 2011; Allaire et al., 2019; Marcus, 2021), and not all drinking water sources are tested and reported regularly (Lade et al., 2024). Resource constraints, like income, market access, and other infrastructure gaps, may further limit individuals' ability to reduce exposure to drinking water pollution.

This paper quantifies behavioral responses to nitrate contamination in drinking water and how these responses and the subsequent health impacts differ across demographics. Using an event-study framework, I quantify these responses in the context of SDWA nitrate violations and public notifications in the United States. The SDWA necessitates that public water systems must notify consumers within 24 hours of detecting nitrates above a regulatory threshold, and this prompt notification may induce an immediate and persistent consumer response. I use the timing of SDWA notifications following nitrate violations to estimate changes in bottled water purchases at local retail stores and the net health impacts on infant mortality. I further explore how the avoidance behavior and health impact differ based on socioeconomic characteristics.

I build a stylistic model to illustrate the value of pollution information and avoidance behavior. The model illustrates that, although violations reflect worsening drinking water quality, the accompanying information disclosures create an ambiguous net health response. On the one hand, if individuals' drinking water consumption behavior does not change, they are drinking tap water that is worse than before and negative health outcomes may result. On the other hand, public notifications may induce consumers to engage in more protective action and to drink cleaner water than prior to the violation, like relying on bottled water, which may improve health outcomes *ceteris peribus*.

To empirically test for avoidance behavior, I estimate the effect of SDWA public notifications from nitrate violations on changes in drinking water sources, as measured by bottled water sales at local retail outlets. My primary treatment variable is derived from 1,700 SDWA nitrate notification events that occurred between 2010 and 2019 across the United States. The staggered timing of notification in public water systems (PWS) across the United States reflects shocks to consumers' perceptions about their drinking water quality, which gives rise to an event study design. The first outcome variable measures weekly bottled water sales at the retail store level. I use this outcome to measure the consumer response to information in the weeks following a public notification from a nitrate violation, and the event study design allows me to uncover potential pre-trends and anticipation. The primary results measure the treatment effect from about 1,400 unique store-notification events across the period. My second outcome is proprietary county-month infant health outcomes across the entire U.S. during the sample period, which allows me to measure the net-health impact of SDWA nitrate violations and notifications relative to the months just before information disclosures happen. As discussed above, the expected sign of the coefficient of interest may be positive, negative, or net neutral depending on which effect dominates. In both sets of regressions, two-way fixed effects control for fixed differences across locations and nationwide seasonality in bottled water sales and infant health measures. To account for potential bias in heterogeneous treatment across time, I use an unbiased estimator proposed by Gardner (2021).

The first central result is that SDWA nitrate notifications lead to significant avoidance behavior through bottled water purchases. Public notifications due to nitrates induce an approximately 32% increase in bottled water sales on average across all violation weeks relative to the weeks preceding a violation. Avoidance is the strongest in the first three weeks following the notification, peaking at a 64% increase, and gradually diminishes back to baseline levels thereafter. This translates to $4.5 million annually in the United States to avoid nitrate-contaminated drinking water, which is relatively inexpensive compared to other forms of environmental damages of nitrate pollution (Dodds et al., 2009; Taylor and Heal, 2022). Second, avoidance behavior differs across poverty quartiles, where poverty rates are negatively correlated with avoidance behavior. This heterogeneity in response illustrates that not all populations uniformly respond to the notification and some may remain exposed to the health threat.

The second key finding is that public notifications from SDWA nitrate violations significantly decreases the rate of infant mortality rate by 0.74 in the same month of the notification. But this effect dissipates after the first month, following the pattern of bottled water purchases. This reduction implies that an annual 20 infant deaths are avoided per year or $223 million in monetized benefits due to SDWA notifications. This is consistent with the conceptual model in which information about the hazard induces protective behavior among affected households towards a safer drinking water source and that behavior is net beneficial. However, the highest poverty rate census tracts – who are the least responsive in bottled water purchases – see an increase in infant mortality in the months during an ongoing violation.

This paper adds to a growing literature that calculates the responses to and the human health impacts of drinking water pollution in the U.S. Despite relatively advanced regulation and infrastructure, poor drinking water in the U.S. in many forms has been linked to adverse health impacts (Currie et al., 2013; Marcus, 2021; Hill and Ma, 2022; Frye and Kagy, 2023; Christensen, Keiser, and Lade, 2023; Jacqz, Somunc, and Voorheis, 2024). Conversely, investment in U.S. drinking water systems and stricter standards for monitoring and reporting improve drinking water quality and human health (Bennear and Olmstead, 2008; Keiser et al., 2023). In particular, accurate and timely information about drinking water quality allows individuals to adjust their behavior and protect themselves (Zivin, Neidell, and Schlenker, 2011; Allaire et al., 2019). Most similar to this paper, Marcus (2020) shows that information about total coliform bacteria in drinking water induces individuals to better protect themselves, yielding large net social benefits through avoided health costs. In the same setting, (Marcus, 2025) shows that students uninformed about coliform pollution lead to lower math test scores.

This paper's relative contribution to this literature isolates the consequences of nitrates, specifically, and the costs and benefits of current SDWA regulation in protecting individuals from exposure. Nitrates are unique relative to many other common contaminants because they pose an immediate health concern to infants who consume even a small amount of nitrate-contaminated drinking water. Therefore, the behavioral response to timely pollution information by potentially affected individuals may be a primary determinant of the health consequences. Indeed, my findings demonstrate that avoiding nitrate-contaminated drinking water, induced by SDWA regulations, is an important determinant of the health consequences. These findings reinforce the high social value of safe drinking water and the role of informational regulations in preventing environmental harm to human health at a national scale.

This paper also contributes to the social costs of agricultural nutrient pollution. 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; Del Rossi et al., 2023). External costs are also borne by public water systems or households that must treat their source water or identify new sources (Keeler et al., 2016; Mosheim and Ribaudo, 2017). However, causal links between nitrate exposure and health have been elusive. 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). This study is the first to link both the behavior and health impacts of nitrate-polluted drinking water, and I give evidence that the two are closely tied to one another. I estimate in this paper that consumers spend an extra \$4.5 million annually on bottled water due to nitrates in public drinking water – a small amount relative to past estimates of environmental damage through other channels. Although, the annual human health costs of nitrates would be substantially larger, about $223 million, if not for SDWA interventions.

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). I document a case where sub-populations also exhibit a dampened behavioral response to pollution information, exacerbating inequality of environmental health damages. In the case of nitrate pollution in drinking water, lower socioeconomic status is associated with limited responses from individuals to protect themselves from negative health consequences. Targeted support beyond information may be needed in socioeconomically vulnerable populations to further limit nitrate exposure in drinking water.

# 2 Background

## Safe Drinking Water Act

The SDWA, passed in 1974, regulates drinking water systems that serve at least 25 people and aims to protect individuals from drinking water pollution or waterborne illness. It requires administrators of the systems to regularly monitor and report drinking water quality, and it establishes maximum contaminant levels (MCL) for over 90 contaminants. Testing is typically required annually for each of the 90 contaminants, but state officials may request more additional testing for systems vulnerable to a particular contaminant. Some contaminants are short-lived and/or 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 are believed to pose a health threat to certain populations.

A violation occurs if any of the regular testing results in water quality measures above the MCL for each of the contaminants. 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, which include nitrate violations, pose an immediate and acute threat to human health.

For Tier 1 violations, public notification must occur within 24 hrs of detecting contaminants above the MCL. As shown in Figure A1, nitrate contamination is a perennial issue and is typically the most prevalent acute health threat in public drinking water systems. Notices are required to be hand delivered, published in local news outlets, and posted in public areas. An example of a Tier 1 public notification and the required elements is provided in Figure A2. Tier 2 violations include non-acute health-based violations (e.g. lead, arsenic, copper, and some Coliform) and administrative rules (e.g. monitoring, reporting, overdue fees). Notification must also occur for tier 2 and 3 violations, but within 30 days and 365 days, respectively.

Aside from annual consumer confidence reports[1], public notifications are the primary mechanisms through which consumers' beliefs about water quality may be updated. SDWA violations and subsequent notifications have been widely used in economic studies as shocks to drinking water quality perceptions (Bennear and Olmstead, 2008; Zivin, Neidell, and Schlenker, 2011; Allaire et al., 2019; Marcus, 2020). Figure 1 reinforces the point that SDWA notification trigger a change in the public's perception about drinking water quality. It plots standardized Google Search hits for Columbus, OH around two notable SDWA nitrate notification events. This figure anecdotally supports the idea that public notifications provide an immediate shock to consumer awareness about their drinking water quality.[2]

## Nitrate Pollution

While nitrate 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.[3] Nitrogen fertilizers provide substantial benefits to farmers through increased yields and profits and have lowered the price of key food staples to consumers.

[1]The SDWA also requires annual consumer confidence reports that inform residents about water quality levels and notify them of any administrative or other Tier 3 violations.

[2]Google search data can only be provided at the U.S. metropolitan statistical area level. Since the majority of SDWA nitrate violations occur in more rural, small public water systems, linking nitrate notification events and Google search trends data is only possible for U.S. metropolitan areas that experienced a nitrate violation over the sample period, which is limited to one event in Columbus, OH.

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

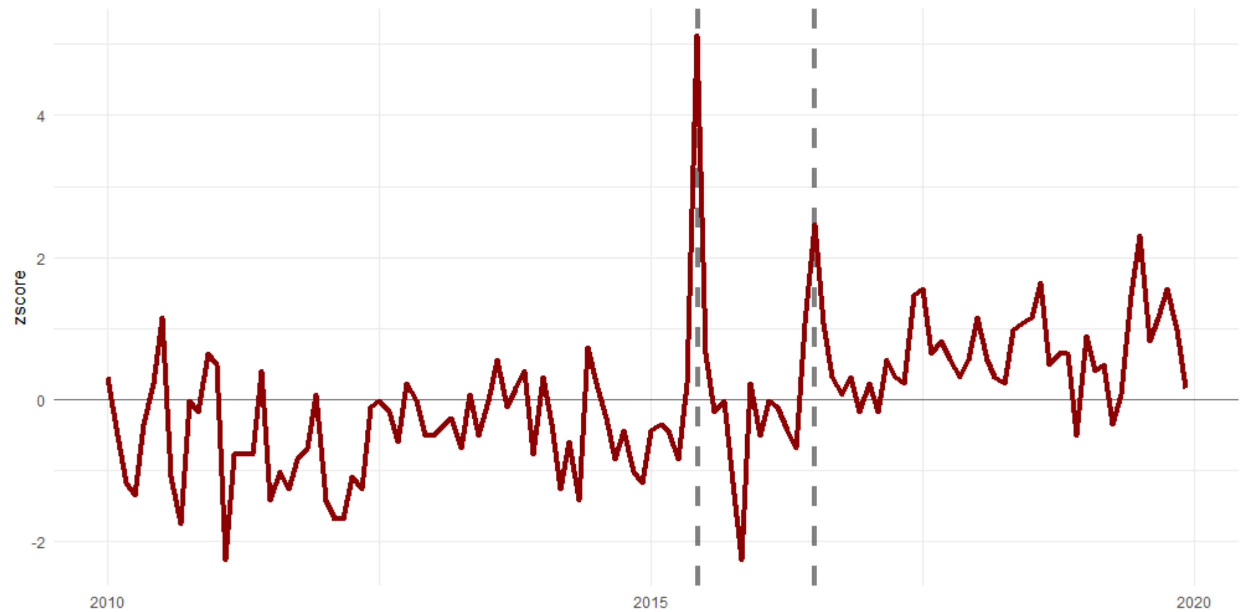


Figure 1: Google Search Trends in Columbus, OH

Note: Figure displays standardized Google search hits in Columbus, OH from 2010-2017. Keywords for selected hits include, "nitrate","drinking water quality","blue baby", "methemoglobinemia", and "Columbus Water". Dashed lines indicate the timing of two SDWA Nitrate Violation events in June 2015 and July 2016.

However, nitrogen fertilizer is often applied in excess of socially optimal levels, and the marginal social benefits of reducing nitrogen fertilizer are believed to be greater than the marginal private costs incurred by the farmer (Gourevitch, Keeler, and Ricketts, 2018). Excess nitrogen is leached through the soil into groundwater basins over time, and, depending on the texture of the soil and weather, may not reach the groundwater until many years after the initial application (Harter et al., 2012; Metaxoglou and Smith, 2022).

Figure 2 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. PWSs that source from groundwater, as opposed to surface water, are more vulnerable to nitrate loading, and they account for 95% of the historical SDWA violations (Pennino, Compton, and Leibowitz, 2017). A heavy concentration of violations through Texas, Oklahoma, and Kansas closely follow the boundaries of the High Plains Groundwater Aquifer. The same is true of California's Central Valley Aquifer. These at-risk areas are also agriculturally intensive and apply nitrogen fertilizer at

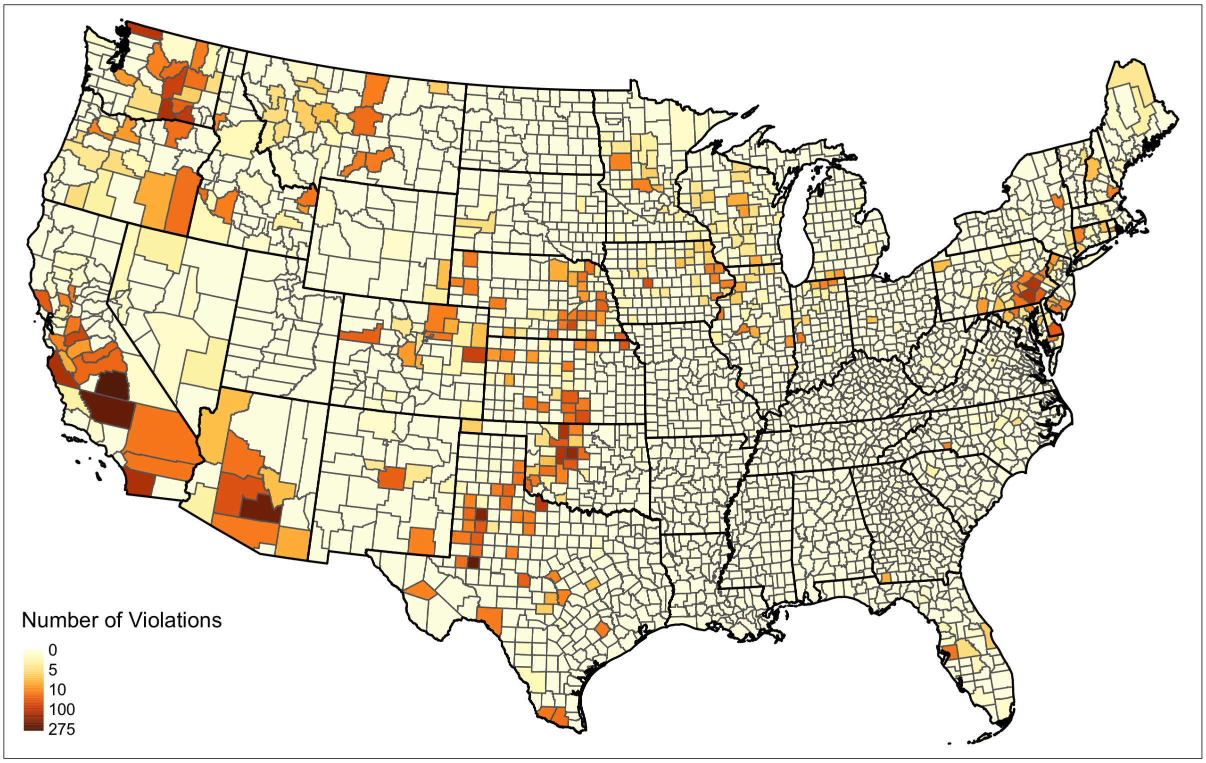


Figure 2: Number of SDWA Nitrate Violations, 2010-2019

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

high rates.

Once present in the groundwater, nitrates are an irreversible pollutant and often require households or water suppliers to identify new sources or costly filtration. Unlike bacterial contamination, boiling water and basic carbon filters do not eliminate nitrates. Thus, households have few options other than purchasing bottled water in the short run to access safe drinking water. In the long run, public water systems must identify alternative sources of water, build an industrial water treatment plant, or individuals must install expensive reverse-osmosis (RO) water filters (Jensen et al., 2012; Mosheim and Ribaudo, 2017). RO filters are often much more expensive than conventional filters, and are not widely available at supermarkets and grocery stores.

### Human Health Impacts

Exposure to nitrates poses the highest health risk for infants and pregnant mothers. Most notably, ingestion of high-levels of nitrates limits adequate oxygenation of the blood and may result in death. This condition is known as methemoglobinemia (or blue-baby syndrome) and has well-known links to nitrate-contaminated drinking water. The U.S. EPA and the World Health Organization set 10 mg/L MCL as the threshold for nitrates. This threshold is set by a 1951 survey, which identified that 2.3% of Methemoglobinemia cases were associated with nitrate concentrations above 10 mg/L (Walton, 1951). More recent epidemiological studies have argued that increased incidence of birth defects, Sudden Infant Death Syndrome (SIDS), and pre-term birth are connected to nitrate levels much lower than federal thresholds (George et al., 2001; Ward et al., 2018; Temkin et al., 2019). These findings suggest that many more individuals may benefit by avoiding tap water with nitrates even at more modest levels.

Nitrates pose an acute health threat, and perverse health outcomes may occur almost immediately after ingestion. While *in utero* exposure is a concern and pregnant mothers are advised against drinking contaminated water, most of the documented cases of blue-baby syndrome resulted from newborns' exposure through formula (Walton, 1951). Therefore, nitrates are distinct from other environmental toxins for two reasons. First, the health impacts of nitrates may manifest shortly after exposure. Second, preventing exposure to nitrate-contaminated drinking water is relatively straightforward if one knows the hazard exists. Whereas, with many environmental toxins, exposure is not as easily avoided (e.g. air pollution) and health detriments may occur *in utero* or take years materialize.

## 3 Conceptual Model

I develop a stylized conceptual framework to capture the relationships between pollution, avoidance behavior, and health outcomes. Individuals derive utility from health, $H$, and a composite good, $X$, based on a concave, continuously differentiable function, $U$. $H$ is a dose-response function of health, dependent on pollution, $T$, and avoidance behavior, $B$. $B$ in the context of drinking water pollution can be thought of as consumption of a safe alternative source, like bottled water. The dose-response function for health is a decreasing function of pollution, $H_T \leq 0$. Bottled water provides 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 $B_T$. Together, $\frac{dH}{dT}$ in equation 2 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 typically observed. If the second term is ignored, estimating the effects of ambient levels of environmental pollution on population health may underestimate the true dose-response function. Importantly, the direction of the net health effect is ambiguous, as health benefits from avoidance behavior may offset the direct health effect.

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

Now, assume that individuals have imperfect knowledge about the levels of drinking water contamination they face.[4] Therefore, individuals make decisions about perceived levels of pollution, denoted by $T_p$, while health is impacted by actual levels of pollution. 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 avoidance behavior by $p_B$. The price of the composite good is normalized to 1, and utility is monotonically increasing in the composite good. Under the latter assumption, the budget constraint holds with equality and can

[4] This assumption is similar to that of Barwick et al. (2023), but theirs is in the context of air pollution in China.

be substituted as an argument into the utility function. Therefore, the consumer solves the utility maximization problem with one choice variable, $B$:

$$\max_{B\geq 0} U(H(T,B(T_p)),Y-p_B\times B(T_p)) \tag{3}$$

The first order condition that defines an interior solution for avoidance behavior for this problem is:

$$a := \frac{\partial U}{\partial B} = U_H H_B(T) - U_X(p_B) = 0 \tag{4}$$

Assume that $\frac{\partial H^2}{\partial B \partial T} \geq 0$. This weak inequality states that there are greater marginal health benefits of avoidance at higher levels of pollution than at a lower levels of pollution. This relationship is realistic and underlies many information-based environmental regulations: When pollution is below a certain threshold, there is little to no health risk nor reason to adjust behavior. However, as pollution worsens above a threshold the gains (or public health risk reduction) from pollution avoidance are believed to be high enough to warrant informational intervention. With this setup and under the implicit function theorem, we can conclude that avoidance behavior is weakly increasing in the level of pollution:

$$\frac{dB}{dT} = -\frac{\frac{\partial a}{\partial T}}{\frac{\partial a}{\partial B}} = -\frac{U_{HH}\frac{\partial H}{\partial B}\frac{\partial H}{\partial T} + U_H\frac{\partial^2 H}{\partial B \partial T}}{U_{HH}(\frac{\partial H}{\partial B})^2 + U_H\frac{\partial^2 H}{\partial^2 B}} \geq 0 \tag{5}$$

Consider the case where actual pollution worsens more than perceived pollution does, $dT \geq dT_p$. By equation 5, we arrive at the intuitive conclusion that change in avoidance behavior is weakly higher if individuals have more accurate information about the level of pollution, $dT \cdot B_T \geq dT_p \cdot B_T$. From equation 2, we would expect $dT \cdot H_T + dT \cdot H_B \cdot B_T \geq dT \cdot H_T + dT_p \cdot H_B \cdot B_T$ – that the informed individual's net health effects from a given increase in pollution are better than the uninformed.

In the remainder of this paper, I empirically test several conclusions from this stylized model in the context of worsening nitrate pollution in drinking water. First, I will estimate the relationship $dT \cdot B_T \cdot p_B$, which determines the annual monetary value that consumers spend as a result of information about worsening nitrate pollution. Second, because a direct dose-response function cannot be estimated with observational data, I will estimate the net health effects after individuals are informed, $\frac{dH}{dT}$. With a value of statistical life and the estimated value of this term, I will then compare the relative health benefits with the additional costs that the informational intervention induced.

# 4 Data

I assemble a panel dataset from 2010-2019 that includes the timing of SDWA nitrate violations and notifications, week-store level scanner data on bottled water sales, and county-month infant health outcomes. My empirical strategy will leverage variation in bottled water sales and infant health outcomes to estimate the impact that SDWA public notification has on averting behavior and health. Table 1 provides the summary statistics for the primary variables used in my analysis.

## SDWA Nitrate Violations

I gather SDWA violation, enforcement, and notification records from the EPA's Safe Drinking Water Information System database. These data report the history of SDWA violations and notifications, their timing, and the characteristics of the violating PWS. I select only the occurances that violate the nitrates rule and were considered acute health-based violations, requiring immediate consumer notification. From 2010-2019, about 1,800 such events occurred in the U.S., and these events will serve as the primary treatment timing in my analysis. By rule, violations and notifications are supposed to occur in the same 24-hour period. However, in the instances in which there are different dates reported for the same violation (whether due to real-life delays or measurement error), I select the date that the public notification was confirmed by the PWS to the reporting agency to ensure accurate timing of the information shock.

Table 1: Summary Statistics of Main Variables

| Variable | N | Mean | Sd | Min | Max |
|---|---|---|---|---|---|
| Birth Count | 189,090 | 156 | 539 | 1 | 4,988 |
| Infant Mortality Count | 189,090 | 0.77 | 2.8 | 0 | 37 |
| Infant Mortality Rate (per/1,000) | 189,090 | 4.8 | 21 | 0 | 1,000 |
| arcsin(IMR) | 189,090 | 0.78 | 1.4 | 0 | 7.6 |
| Low Birthweight Count | 189,090 | 12 | 39 | 0 | 378 |
| arcsin(Low Birthweight) | 189,090 | 3.7 | 2.3 | 0 | 7.6 |
| Minimum Temperature (C) | 189,090 | 5 | 10 | -25 | 27 |
| Maximum Temperature (C) | 189,090 | 18 | 11 | -16 | 41 |
| % of Month in Violation | 189,090 | 0.0075 | 0.078 | 0 | 1 |
| Bottled Water Purchases ($) | 457,817 | 719.12 | 972.71 | 0.02 | 24,278.05 |
| Bottled Water Volume (L) | 457,817 | 1,691.85 | 3,099.19 | 0.01 | 105,393.76 |
| Bottled Water Price ($/L) | 457,817 | 0.72 | 0.42 | 0.11 | 3.36 |
| Minimum Temp. (C) | 457,817 | 8.77 | 10.01 | -28 | 28.64 |
| Maximum Temp.(C) | 457,817 | 22.11 | 11.17 | -15.23 | 44.2 |
| Precip. (mm) | 457,817 | 15.4 | 19.69 | 0.34 | 248.52 |
| Poverty Rate (%) | 457,817 | 18.66 | 12.25 | 0 | 90 |
| % Food Desert | 457,817 | 20.79 | 27.34 | 0 | 100 |
| % Hispanic | 457,817 | 23.25 | 25.42 | 0.65 | 94.98 |
| % White | 457,817 | 76.87 | 17.31 | 4.59 | 98.71 |

Since the outcomes measures are temporally aggregated, it is necessary to define treatment at the week (or month) level. Therefore, treatment is defined as the proportion of the week (or month) that has an active nitrate violation. This adjusts for the fact that some location-weeks may experience differential treatment intensity in the initial week based on which day it occurred (e.g. a violation on a Monday might trigger more observed weekly averting behavior than a violation on a Friday).

PWSs return to compliance from nitrate violations at different rates depending on contamination levels of follow-up tests or the ability of the PWS to procure safe sources. The return to compliance dates in the SDWIS dataset are incompletely reported, and therefore, my analysis uses the subset of total violations with a known return to compliance date. Violations last anywhere from 1 to 357 days and 135 days on average across violations. For violations of the longest duration violations, I cap treatment (i.e. treatment turns off) at 150 days (the 75th percentile violation length) to isolate the short-term averting response.[5] Similar to the violation start date, the return to compliance date may occur mid-week (or mid-month), and therefore, I adjust the treatment indicator in the end-weeks (or months) to reflect the proportion that the violation is active.

## Bottled Water Sales

Bottled water sales data come from scanner data from Circana (formerly Information Resources Inc.), which provides the most geographically comprehensive scanner data available.[6] These retail scanner data cover over 48,000 stores nationally and span dollar, convenience, grocery, and mass merchandiser stores. The widespread coverage of these data is particularly helpful in measuring the impacts among small public water systems located in more rural areas. The primary outcome measures weekly sales by product code (UPC). I collect all UPCs categorized as "bottled water", which includes small individual bottles, packages of small bottles, and refillable jugged water from in-store dispensers. My final measure sums all sales from these products and aggregates to the store-week level. These data are reported for a variety of store types as exhibited in Figure A3. Also from this dataset, I use the price of bottled water ($/L) as a control variable, and in alternative specifications, I use variation in bottled water volume (in Liters) and carbonated beverages (i.e. soda and seltzers) as outcomes that are similarly constructed.

I merge this data to the record of nitrate violations based on week and whether the store is located in the same zip code as the PWS. Therefore, multiple stores in the same city may be affected by the same SDWA violation. After this merge and cleaning, there remain about 1,400 store-violations pairings that will be used to identify avoidance behavior to nitrate in drinking water.

[5] In the longer run, individuals may protect themselves through more permanent measures, like installing reverse-osmosis filtration systems, which tend to be costly and take time to install. However, in the short-run bottled water is the only means of protecting oneself if they did not already have a filtration system installed.

[6] The Circana data's advantage is that the reported store characteristics contain zip codes and data is reported weekly. Whereas, other commonly used alternatives only offer monthly sales data and a store's county is the most granular geographic information offered.

## Infant Health Outcomes

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 infant mortality rate to study how being notified of nitrate contamination impacts infant health in the mother's resident county. 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, my primary health outcomes measure total infant mortality stemming from all causes.

There are two primary limitations to using health outcomes at the county-month level. First, nitrate exposure may occur both *in utero* and neonatal, but the appropriate health outcomes may differ based on the pathway of exposure. For this reason, I conservatively focus just on reported health outcomes in the months that an SDWA is active. This may fail to capture the health impacts of infants who were exposed *in utero*, whose health outcomes were reported after their PWS returned to compliance. A second limitation is the inability to precisely identify whether infants and mothers reside within a PWS in a given county. It is unlikely that all individuals in the county are exposed to the contamination, and not all individuals will directly receive information about the threat. Therefore, this is a potential source of measurement error in the primary outcome variable that may bias the results towards zero.

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 identifying variation to estimate health effects to environmental contaminants and are used in many other settings (e.g. Taylor (2022); Hansen-Lewis and Marcus (2022)).

## Weather

The empirical strategy will leverage variation in averting behavior and health outcomes within the location after violations and subsequent notification. It is plausible to believe that weather influences both bottled water purchases and infant health and may be correlated with the timing of nitrate violations. For this reason, I control for local weather using data obtained from Schlenker and Roberts (2009). These data report daily minimum and maximum temperature and precipitation on a 2.5 km by 2.5 km grid throughout the U.S. dating back to 1950. I aggregate these data by taking the average weather observations across all grid cells within a county for a given day. Then, I take the average minimum and maximum temperature across the days of the week and sum daily precipitation to obtain the final county-week and county-month weather variables. In some specifications, I also control for the quadratic and cubic transformations of these variables to account for non-linear impacts of heat on behavior and health.

## Demographics

Lastly, I will test how averting behavior and health effects varies across demographic characteristics. Demographic data are obtained from USDA's Food Research Atlas, which provides cross-sectional information about race, income, and grocery accessibility for census tracts in the U.S.[7] 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 my analysis. For ease of interpretation, I convert these demographic measures into dummy variables for either above/below the median or quartiles for the heterogeneity analysis that is described below.

[7] Since it is cross-sectional, I will be unable to capture changes in demographics across my sample. However, since the analysis will identify short-term responses, it is unlikely that demographics will change within the few-week window around treatment.

# 5 Empirical Model

The empirical model will test the extent to which notifications about nitrate contamination in drinking water will trigger individuals to purchase more bottled water to protect themselves and whether that protection results in meaningful differences in health outcomes. I first estimate how avoidance behavior changes in the weeks following a SDWA public notification about nitrates. I then estimate the changes in infant mortality in the months during an active violation. Finally, I explore how the patterns in both of these treatment effects differ based on demographic characteristics.

## Nitrate Avoidance

The staggered nature of SDWA violations in PWSs 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 staggered timing of SDWA violations as a quasi-experimental research design to identify causal effects (e.g. Zivin, Neidell, and Schlenker (2011); Marcus (2020)). 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 for time-invariant differences that differ across space and macroeconomic shocks that differ over time. The magnitude of the TWFE bias is dependent on the degree of treatment effect heterogeneity across time and has potentially severe consequences for the interpretation of TWFE coefficients.

While this potential bias is now well understood, subsequent work has proposed alternative estimators to traditional 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. For the results, I report both traditional TWFE estimates and estimates from Gardner (2021)'s two-stage DD (hereafter referred to as DiD2s).

To estimate the response to tier 1 SDWA public notifications, I estimate equation (6), where $B_{iwy}$ are bottled water sales in \$ at store $i$ and in week-year $wy$. Treatment, $Notif_{iwy}$ is the share of week-year $wy$ after a public notification is released (equals 0 before treatment and after systems return to compliance). I multiply treatment by $w_i$, which is the percentage of the store's census tract affected by the violation. Together, $Notif_{iwy} \times w_i$ capture the community treatment intensity. The vector $X_{iwy}$ captures time-varying weather controls. The most simplified specification includes store fixed effects, $\alpha_i$, which capture time-invariant factors, like store location and size of the consumer population. The complete specification also includes week-by-year fixed effects denoted by $\lambda_{wy}$, which absorbs national seasonality in beverage sales and macroeconomic shocks; store-by-year fixed effects, $\phi_{iy}$ and store-week, $\psi_{iw}$, capture store-specific trends or seasonality that may not be absorbed by $\alpha_i$ and $\lambda_{wy}$. 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, similar to (Zivin, Neidell, and Schlenker, 2011). Following Gardner (2021), I estimate equation 6.

$$\begin{gathered}\textit{With not yet treated sample: } \log(B_{iwy}) = \phi' X_{iwy} + \lambda_{wy} + \alpha_i + \phi_{iy} + \psi_{iw} + \varepsilon_{iwy} \\ \textit{With full sample: } \hat{\varepsilon_{iwy}} = \beta Notif_{iwy} \times w_i + \phi' X_{iwy} + \mu_{iwy}\end{gathered} \tag{6}$$

I additionally estimate the dynamic version (or event-study) of equation 7 to offer insight into the evolution of the treatment effect in the weeks following a violation notification. This specification also offers evidence to support the identifying assumption that, conditional on fixed effects and covariates, bottled water purchases would not have significantly differed in the absence of public notification. For the event study, I use a ten-week window before and after the notification. For this exercise, I drop stores that do not have a balanced panel within 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 before public notification 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 7, where $Week_{it}$ indicates if store $i$'s observation is $t$ weeks away from the nitrate violation notification.

$$\begin{aligned}
\textit{With not yet treated sample: } \log(B_{iwy}) &= \phi' X_{iwy} + \lambda_{wy} + \alpha_i + \phi_{iy} + \psi_{iw} + \varepsilon_{iwy} \\
\textit{With full sample: } \hat{\varepsilon_{iwy}} &= \sum_{w=-10}^{w=10} \beta_{1t} Week_{it} \times w_i + \phi' X_{iwy} + \mu_{iwy}
\end{aligned} \tag{7}$$

An identifying assumption of this event-study framework is that bottled water sales would not have changed in the absence of notification. In equation (7), this assumption is supported if $\beta_{1w}$ for all $w \in [-10, -1]$ are not statistically distinguishable from zero.

## Infant Health Impacts

The SDWA public notification primarily serves to protect consumers from contaminated drinking water and its 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 implications of averting behavior, or lack thereof, using infant health statistics and drinking water violation and quality records.

To estimate the impacts of nitrate violation notifications on infant health, I use the same exogenous treatment timing of 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. Hence, the variables indicate the measure in county $c$ in month-year $my$. Second, in addition to estimating the effects for the duration of the violation, I also report the results for just the initial month of the notification since this is when they are expected to have the biggest impact on protective behavior. Vector $X_{cmy}$ controls for linear, quadratic, and cubic weather controls to control for the nonlinear impacts of heat on mortality. I estimate equation 8 for my primary health analysis.

$$\begin{aligned} \textit{With not yet treated sample: } Y_{cmy} &= \phi' X_{cmy} + \alpha_c + \lambda_{my} + \phi_{cm} + \varepsilon_{cmy} \\ \textit{With full sample: } \hat{\varepsilon_{cmy}} &= \beta Notif_{cmy} + \phi' X_{cmy} + \mu_{cmy} \end{aligned} \tag{8}$$

# 6 Results

## Bottled Water

Bottled water is a relatively safe alternative drinking water source in the presence of local contamination, and affected residents are specifically urged to purchase bottled water. Therefore, changes in bottled water purchases after SDWA nitrate violations are the primary form of immediate private protection individuals can take.[8] Additional expenditure on bottled water caused by nitrate violations reflects one societal cost of increased nitrate contamination, as individuals spend more than they otherwise would have in the absence of contamination.

Figure 3 displays the coefficients of the dynamic response of bottled water sales for the weeks before and after nitrate violations. All coefficients are relative to the baseline period, which is the third week prior to the violation. The parallel trends assumption is supported and suggests that consumers do not display a systematic pattern of bottled water purchasing prior to violations (i.e., no anticipation). Figure A4 results from the same event study, but with the outcome reported in levels rather than logs. Similarly, Figure A5 presents results for logged bottled water purchases in volume rather than dollars. Results are consistent for any of these measures of the dependent variable.

Following a nitrate violation, bottled water purchases significantly increase by as much as 67% in the third week after a violation. After 9 weeks, this increase is no longer statistically different from the baseline period. This gradual shift back to baseline levels of bottled water may stem from several explanations: i) The recency of the initial shock induces significant behavioral

[8] Boiling water does not eliminate nitrates and may even make nitrates more concentrated in the water. Standard carbon water filters also do not filter out nitrates. Reverse osmosis filters are the only other effective means of protection, but these systems are much costlier than carbon filters and household reverse osmosis systems typically require a professional to install.

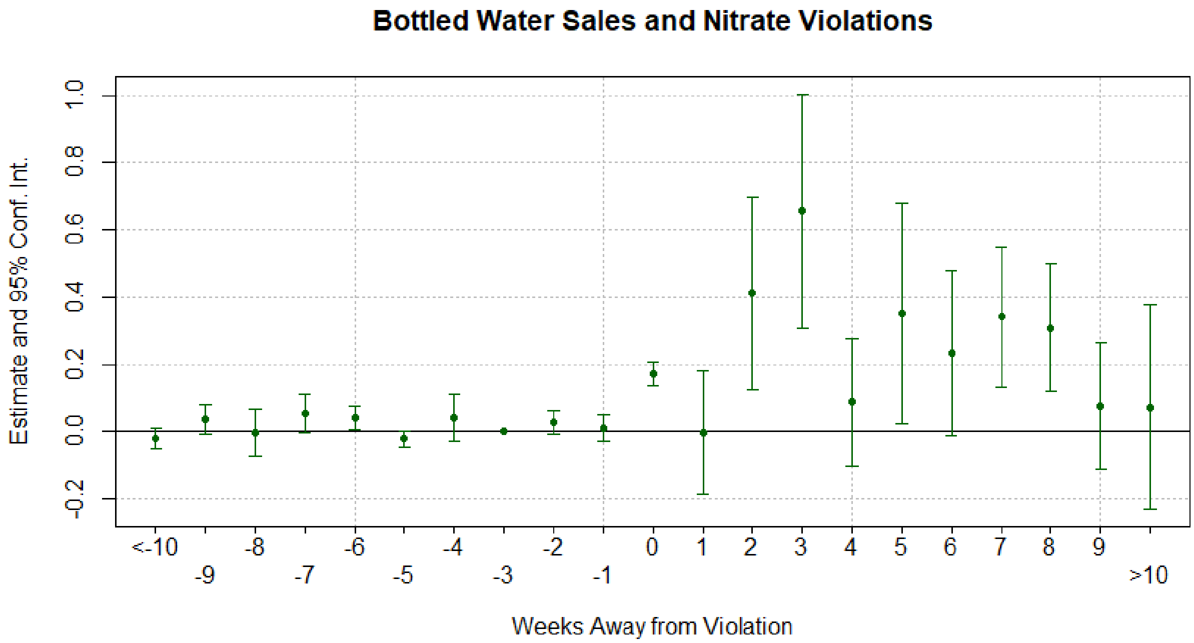


Figure 3: Event-Study Results: Bottled Water Sales Pre- and Post- SDWA Violation
Note: Presents the two-stage difference in difference event-study coefficients of logged bottled water sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in bottled water sales relative to 3 weeks prior to the violation. 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.

change. But as time passes, whether because of ignorance, complacency, or individual preferences, the affected population reverts to prior behaviors. ii) As time passes, individuals engage in longer-term forms of averting behavior, like installing durable reverse osmosis filters in their homes. Within the scope of this study, I am not able to empirically distinguish between these two possibilities.

Table 2 displays the results of the average treatment effect on the treated across all active violation weeks. Panel A reports the results from traditional two-way fixed effect estimation and panel B reports results robust to potential bias from the staggered treatment via the Two-Staged Difference-in-Difference estimation. The full model in column 5 in Panel B, reports that consumers increase bottled water purchases by 32% when violations are active. This estimate is robust across different levels of fixed effects and only displays small differences to the traditional two-way fixed effect estimate in this setting, and if anything, suggests that two-way fixed effects

Table 2: Bottled Water Sales during SDWA Nitrate Violations

| | log(Bottled Water Sales) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A. TWFE* | | | | | |
| Nitrate Notif. x $w_i$ | 0.397** | 0.161 | 0.285* | 0.287* | 0.287* |
| | (0.137) | (0.190) | (0.137) | (0.137) | (0.137) |
| Num.Obs. | 457 817 | 457 817 | 457 817 | 457 817 | 457 817 |
| *Panel B. DiD2s* | | | | | |
| Nitrate Notif. x $w_i$ | 0.398** | 0.348** | 0.319** | 0.321** | 0.321** |
| | (0.124) | (0.128) | (0.115) | (0.115) | (0.115) |
| Num.Obs. | 457 713 | 457 713 | 457 458 | 457 458 | 457 458 |
| Store | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week | | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ | ✓ |
| Week-Year | | | ✓ | ✓ | ✓ |
| Violation | | | | ✓ | ✓ |
| Store-year | | | | | ✓ |
| Store-week | | | | | ✓ |

Note: Dependent variable is logged bottled water sales in dollars. 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. All regressions include controls for price and local weather and are weighted by the number of people served by the violating PWS. Standard Errors are multi-clustered at the store and violation level.

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

are biased towards zero in this setting.

I show robustness to these main results through several alternative specifications presented in the appendix. First, Table A1 shows point estimates of similar magnitude in the full specification, but with more noise. This finding implies that notifications from larger water systems result in a more consistently positive and large response than those of small water systems.[9] Second, I also explore the consumer's response to carbonated beverages (including sparkling water), which they may purchase as a substitute for contaminated tap water. However, the results shown in Table A2 do not support a strong shift towards carbonated beverages as a result of nitrate contamination

[9]This heterogeneity is reinforced in Figure A8, which decomposes the response by PWS size.

in their tap water.

Back-of-the-envelope costs associated with avoiding contaminated tap water due to nitrate violations can be estimated by equation 9. The raw SDWA violations dataset contains summary statistics for annual nitrate violations in the U.S. On average, 650,000 people are exposed for an average of 135 days per year. The bottled water data used for the analysis is only a share of total bottled water purchases in the U.S. Therefore, I must rely on aggregated statistics to determine an estimate of $19.4 billion in annual bottled water sales (or about $59 per person per year) (International Bottled Water Association, 2019). Distributing each of these figures uniformly across the population of the United States and the weeks of the year, $BW_{pw}$ captures the average expenditure per person per week on bottled water and $\beta^{BW}$ the increase due to nitrate violations. I sum over the duration in weeks ($w$) and over each person affected ($p$) to attain an annual measure of behavioral costs.

$$\text{Behavioral Costs} = \sum_{p}\sum_{w}(\hat{\beta}^{BW} \times BW_{pw}) \tag{9}$$

This exercise indicates that consumers spend approximately $4.5 million (about $7 per affected person) annually on bottled water in the United States as a result of nitrate violations. This first primary finding is relatively larger than previous studies that estimate the impacts of water quality violations on bottled water purchases. In their main findings, Allaire et al. (2019) and Zivin, Neidell, and Schlenker (2011) estimate an impact of 14% and 25% increases, respectively, but neither result is statistically significant. More granular data on bottled water purchases, which provides better geographic matching, is one reason why these estimates are more precise in this paper. Still, $7.75 per person is a relatively low-cost incurred to avoid the potentially large health costs.

I also explore heterogeneity along demographic and PWS characteristics. Most notably, Figure 4 displays the treatment effect broken down into poverty rate quartiles. The lowest quartile (i.e. lowest share below the poverty threshold) displays the highest averting behavior, whereas the highest poverty quartile reports noisy treatment effects centered around zero. This is suggestive

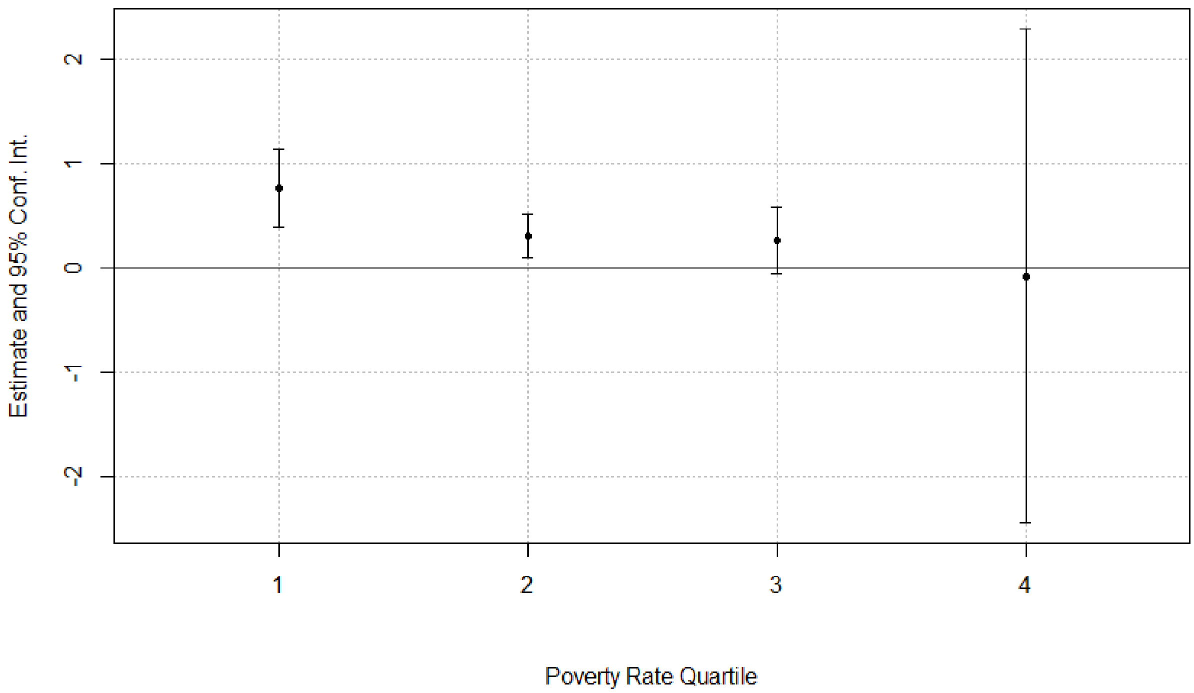


Figure 4: Averting Behavior Heterogeneity: By Poverty Quartile

Note: Presents the two-stage difference in difference coefficients of logged bottled water sales for the weeks before and after a SDWA violation broken down by poverty rate quartiles. The vertical axis measures the % difference in bottled water sales during active violations. 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. Census tracts with lower poverty rates tend to purchase more bottled water in response to nitrate violations.

that income, or characteristics correlated with poverty, lead individuals to protect themselves differentially, and high-poverty areas may remain exposed to the health effects of ingesting nitrates after the violations occur. I explore other dimensions of heterogeneity based on demographics in Figure A7. Here, individuals in food deserts, more rural areas, and more non-white census tracts all display lower averting behavior. Figure A8 shows heterogeneity based on PWS and store characteristics. Higher-price bottled water and the smallest PWS in terms of populations served display smaller averting responses. While these factors should not be interpreted as causal mechanisms, they are indicative that some populations protect themselves more than others, leaving some exposed to nitrates.

### 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, public notifications following a nitrate violation significantly increase bottled water purchases, but some populations are more responsive than others. If the hypothesis in the conceptual model holds, I expect bottled water purchases and infant mortality to move in opposite directions of each other. That is, if nitrates are harmful to infants, consuming safe water should induce a health improvement, but infant mortality may worsen due to heightened nitrate levels in the post-violation weeks if little or no protective behavior happens.

I test this hypothesis by estimating equation 8. The primary outcome of interest is the infant mortality rate (per 1,000 births) in levels. Hence, the main coefficients report the change in infant mortality in the months after a SDWA nitrate violation. Table 3 displays the net impact on infant mortality for just the first month of the violation (Panel A) when bottled water purchases increased the most, and all months of an active violation (Panel B). Appendix Table A3 also reports from the same base model but with the infant mortality rate transformed by the inverse hyperbolic sine. Results from this specification are consistent in sign and magnitude.

The results imply there is a large and statistically significant 0.74 (15%) decline in infant mortality in the initial month of nitrate violations. The event study results in Figure A6 reinforce this finding, showing a significant decline in infant mortality in the initial month after the notification, but all other months show no significant difference relative to the month prior to the notification. When paired with the behavioral response through bottled water, these results indicate that public notification interventions initially provide strong benefits to affected populations. On average, over the duration of the violation, the effects on infant mortality become noisier and statistically insignificant. The magnitude and standard errors of Panel B result mirrors the event study for the behavioral response in Figure 3, where bottled water purchases increase most in the first weeks after the violation occurs but diminish as time passes.

In Appendix Table A4, I also explore whether SDWA nitrate notifications affect the oc-

Table 3: Impact of SDWA Nitrate Notifications on Infant Mortality

| | Infant Mortality Rate | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A. First Month Only* | | | | |
| % of 1st month | −1.060*** | −0.832*** | −0.591* | −0.741* |
| | (0.213) | (0.202) | (0.293) | (0.315) |
| Num.Obs. | 189090 | 189090 | 189090 | 188808 |
| *Panel B. All Active Months* | | | | |
| % of Month | −0.370 | −0.269 | −0.198 | −0.251 |
| | (0.204) | (0.154) | (0.158) | (0.157) |
| Num.Obs. | 189090 | 189090 | 189090 | 188808 |
| County | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ |
| Month | | ✓ | ✓ | ✓ |
| Year-Month | | | ✓ | ✓ |
| County-Month | | | | ✓ |

Dependent variable is the infant mortality rate (per 1,000 births). Treatment variable is the percent of the month a county experienced an active nitrate violation. All regressions are weighted by the total number of births in the county-month, and each regression controls for linear, quadratic, and cubic average minimum and maximum temperature. Standard errors are clustered at the county level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

currence of low birth weight. Results from this table similarly show an improvement in the rate of low birthweight following notification, but these results are estimated with less precision than infant mortality. There are two plausible reasons for this result: First, due to the acute health risk nature of nitrates, infant exposure (e.g., through formula) may be more consequential than *in utero* exposure. Second, there may be a disconnect between when exposure happens and when low birthweight occurrences are recorded. Therefore, measurement error may prevent precise identification of the low birth weight outcome in this setting.

I also explore heterogeneity in treatment effects for infant morality along the same dimensions as bottled water. Figure 5 displays the treatment effects differentiated by poverty rate quartile for all months with an active violation. The lowest poverty rate quartiles, who purchase

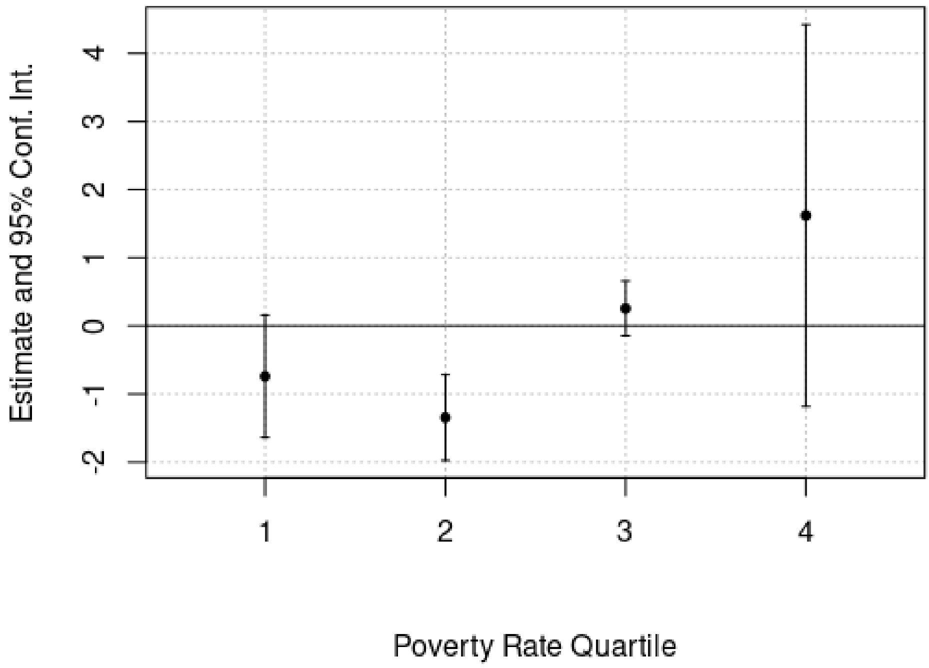


Figure 5: Infant Mortality Heterogeneity: By Poverty Quartile

Note: Presents the two-stage difference in difference coefficients of the infant mortality rate for the months with a SDWA violation broken down by poverty rate quartiles. The vertical axis measures the % difference in infant mortality rate during active violations. The regression includes county, month-by-year, county-by-month fixed effects, and weather controls. Standard errors are clustered at the county level. Counties with lower poverty rates experience the largest improvements in infant mortality after violation and public notification.

relatively more bottled water after violations, see a decline in infant mortality. Whereas, the higher poverty quartiles experience increased infant mortality during nitrate violations. Importantly, poverty should not be interpreted as a causal mechanism. Rather, taken in tandem with Figure 4, they show that the sub-populations that protect the most following violations see meaningful improvement in health outcomes and *vice versa*.

Using the estimates from Table 3 and EPA's value of statistical life (VSL)[10], I monetize the infant mortality benefits of avoiding nitrate-contaminated drinking water. Over the sample, the infant mortality rate was 4.8 infant deaths per 1,000 births. If infant mortality improved 0.74

[10]See `https://www.epa.gov/environmental-economics/mortality-risk-valuation` for details on EPA's mortality risk valuation.

in the first month of a violation event and 1,746 such events happened during the sample, about 20 infant deaths were prevented annually (or 201 total deaths across the ten-year sample) from public notification interventions. Using a VSL of $11.17 million, the information interventions provide $223 million in annual benefits, which far outweigh the annual expenditure of $5 million spent on additional bottled water. Thus, SDWA public notifications for nitrates provide large social welfare improvements. This finding reinforces that of Marcus (2020) and Marcus (2025), where timely notification in the context of North Carolina and total coliform violations provides large net welfare benefits. But importantly, I show that these improvements do not accrue uniformly across the population, and the treatment effect heterogeneity suggests that targeted interventions for socioeconomically vulnerable populations may yield even greater social benefits.

# 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 respond 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 themselves against environmental hazards, leaving them exposed to negative health consequences. In this paper, I show that consumers respond to SDWA nitrate violations by purchasing 32.1% more bottled water on average. These are relatively cheap forms of protection, which translates to roughly $4.5 million in annual averting expenditures. However, some demographics respond less than others, where the highest-poverty census tracts' bottled water purchases do not statistically differ from pre-violation periods. These results establish that the protective behavior that occurs as a result of these SDWA public notifications is relatively inexpensive, but some may be left exposed to the hazard.

Second, I show that the infant mortality rate improves by 0.74 in the initial month following the notification event, demonstrating that individuals' protective behavior has a positive and meaningful impact on infant health. In a typical year, this behavior prevents about 20 infant deaths valued at around $223 million annually. However, like bottled water purchases, these positive health effects dissipate over time and revert to pre-violation levels. Furthermore, reflecting the disparities in protective behavior, the highest poverty rate census tracts experience increased infant mortality post-violation.

Drinking water quality remains a concern in the United States despite relatively advanced regulations, monitoring, and technology that is available. This work, along with others (e.g. Marcus (2020, 2025)), shows that accurate and timely information about drinking water quality can provide large social net benefits can reduce potential health costs. Similar evidence has been shown in the context of air pollution (Barwick et al., 2023), suggesting that investments in pollution information and dissemination are a cost-effective way of reducing the health impacts of pollution more generally.

The environmental justice literature documents many instances where populations are disproportionately exposed to environmental harm (Banzhaf, Ma, and Timmins, 2019). In the case of nitrate pollution, I also show socioeconomic characteristics limit the avoidance response, which in turn, results in further disparities in health outcomes from environmental pollution. Therefore, while pollution information is valuable to society in general, additional efforts may be warranted when environmental threats are present among socioeconomically vulnerable populations.

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# For Online Publication: Appendix

## A Additional Tables and Figures

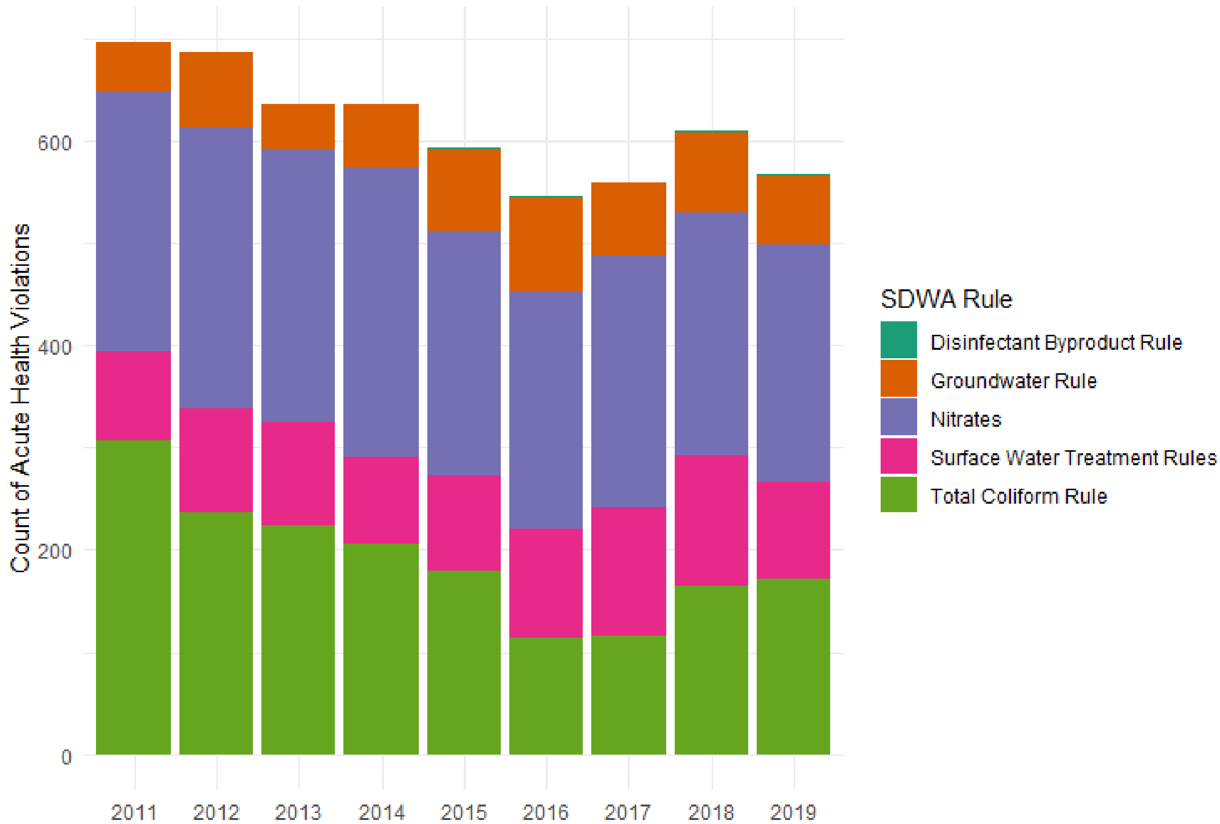



Figure A1: Count of Acute Health Based SDWA Violations

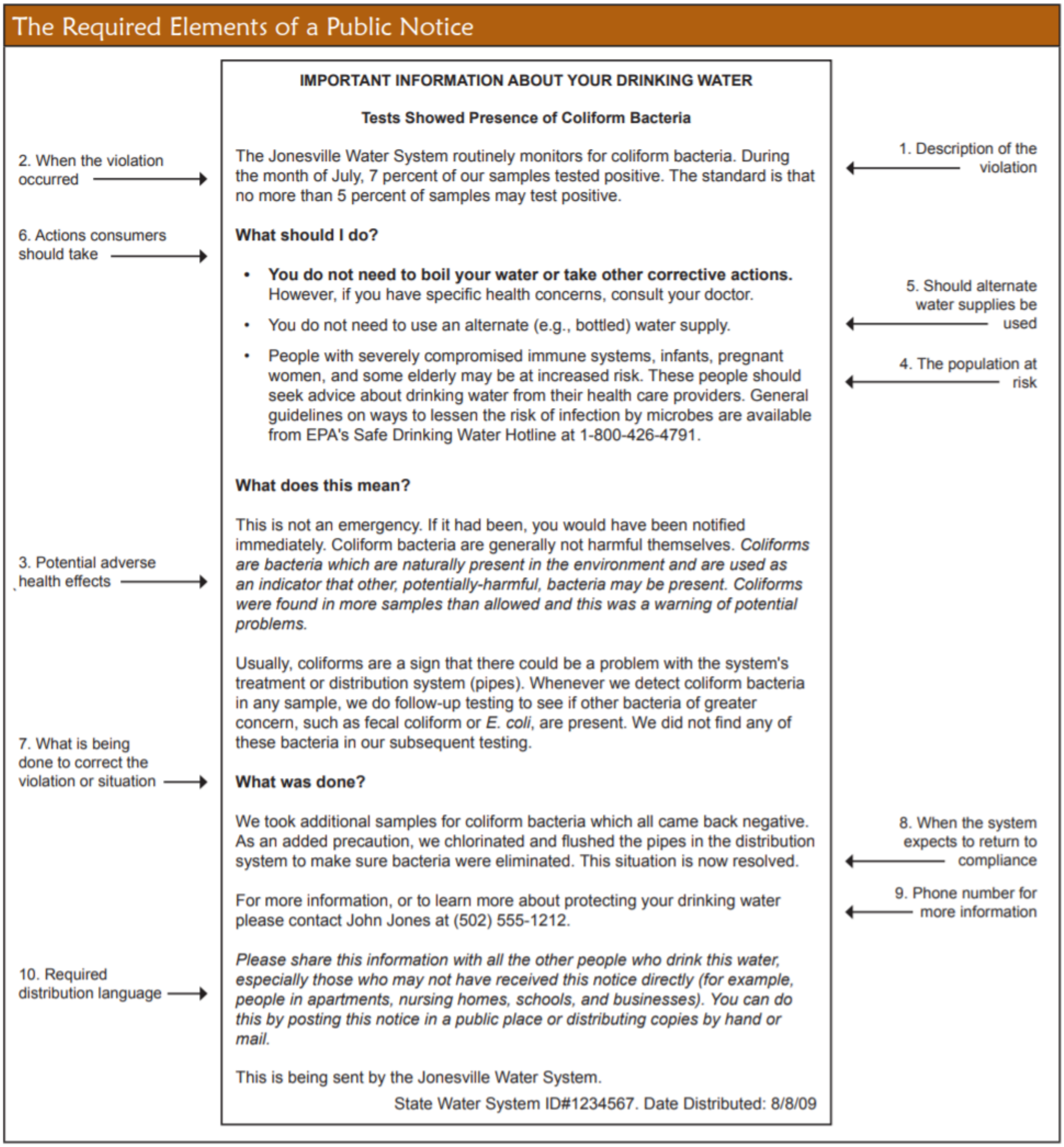
Note: Figure displays the annual count of SDWA acute health based violations broken down by contaminant type. Nitrates violations are typically a leading cause of acute health based violations in the U.S. Author's creation from U.S. EPA SDWIS data.

Table A1: Bottled Water Sales following SDWA Nitrate Notificiation: Unweighted

| | log(Bottled Water Sales) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A. TWFE* | | | | | |
| Nitrate Vio x $w_i$ | 0.027 | 0.161 | 0.152 | 0.161 | 0.164 |
| | (0.428) | (0.190) | (0.200) | (0.211) | (0.214) |
| Num.Obs. | 457817 | 457817 | 457817 | 457817 | 457817 |
| *Panel B. DiD2s* | | | | | |
| Nitrate Vio x $w_i$ | 0.002 | 0.249 | 0.278 | 0.293 | 0.293 |
| | (0.409) | (0.174) | (0.169) | (0.169) | (0.169) |
| Num.Obs. | 457713 | 457713 | 457458 | 457458 | 457458 |
| Store | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week | | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ | ✓ |
| Week-Year | | | ✓ | ✓ | ✓ |
| Violation | | | | ✓ | ✓ |
| Store-year | | | | | ✓ |
| Store-week | | | | | ✓ |

Note: Dependent variable is logged bottled water sales in dollars. 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. All regressions include controls for price and local weather. Standard Errors are multi-clustered at the store and violation level.

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


The Required Elements of a Public Notice

**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 A2: Public Notification Example and Requirements

Note: Figure displays an example of a SDWA Public Notification and the required information that must be included. Graphic is sourced from the U.S. EPA Public Notification Rule Website: `https://www.epa.gov/dwreginfo/public-notification-rule`

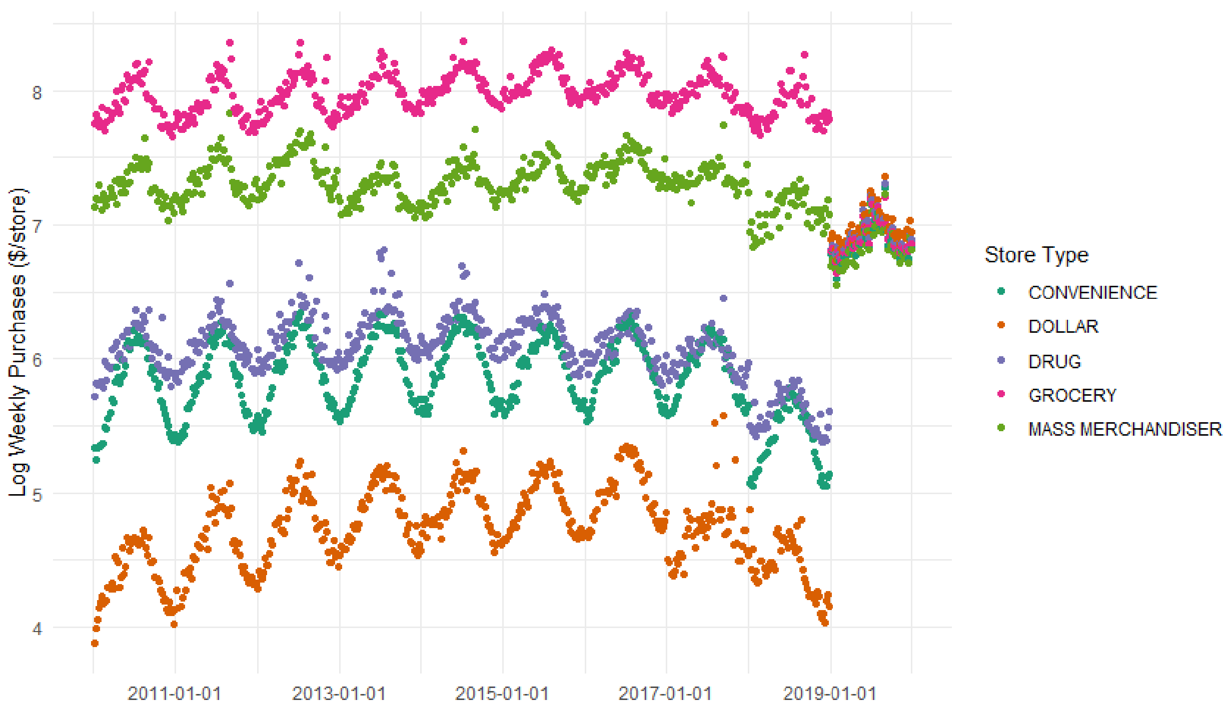



Figure A3: Raw Bottled Water Sales by Store Type

Note: Figure displays the weekly average bottled water sales by store type from 2010-2019. Author's creation from aggregated Circana retail scanner data.

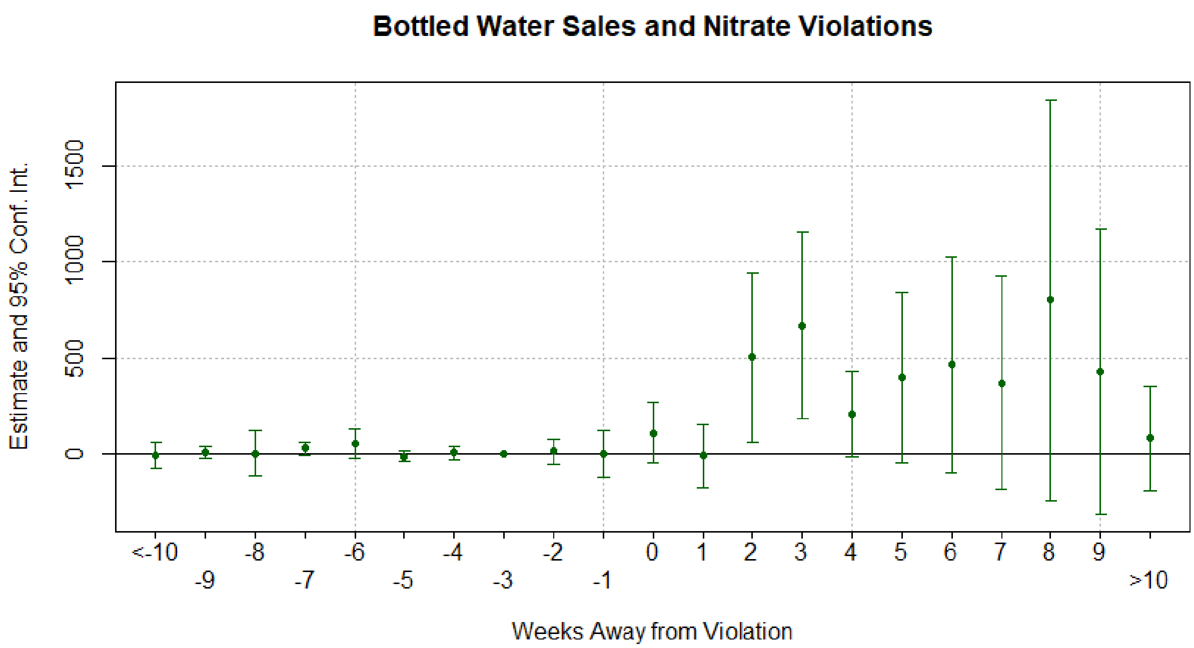



Figure A4: Event-Study Results: Bottled Water Sales (in Dollars) Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event-study coefficients of bottled water sales (in Dollars) for the weeks before and after a SDWA violation. The vertical axis measures the difference (in dollars) in bottled water sales relative to 3 weeks prior to the violation. 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.

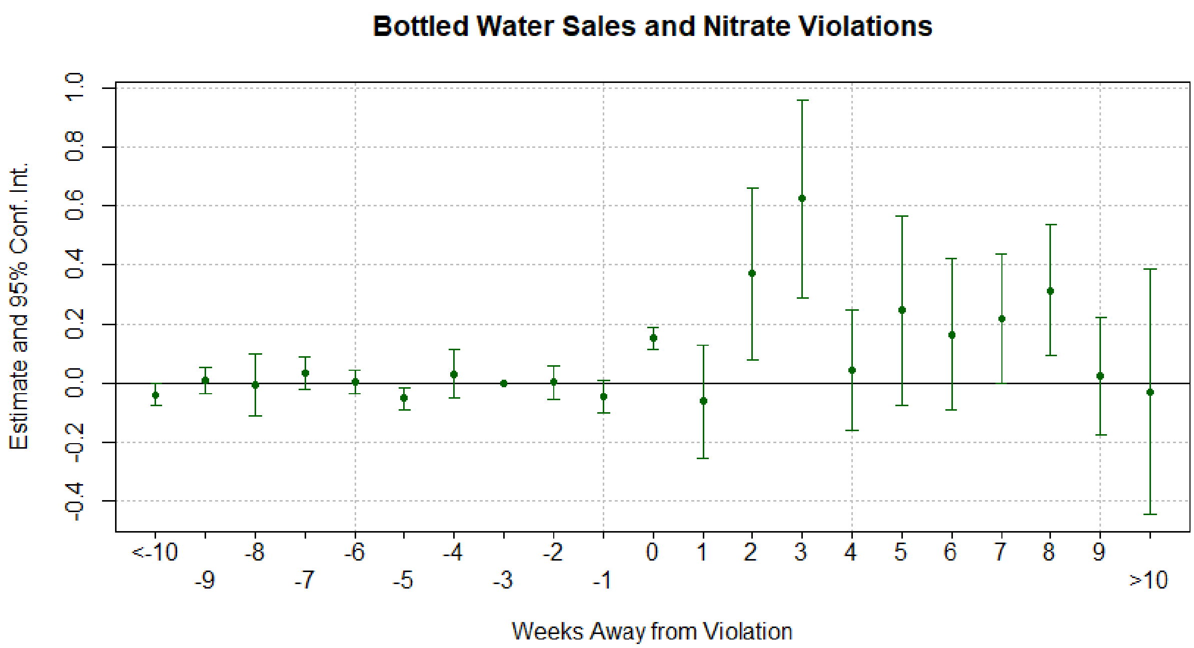



Figure A5: Event-Study Results: Bottled Water Volume Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event-study coefficients of bottled water volume (in Liters) for the weeks before and after a SDWA violation. The vertical axis measures the difference (in volume) in bottled water volume purchased relative to 3 weeks prior to the violation. 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 A2: Averting Behavior Through Carbonated Beverages

| | log(Carbonated Beverage Sales) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A. TWFE* | | | | | |
| Nitrate Vio x $w_i$ | 0.142 | 0.205 | 0.048 | 0.252 | 0.051 |
| | (0.132) | (0.137) | (0.088) | (0.148) | (0.090) |
| Num.Obs. | 386176 | 386176 | 386176 | 386176 | 386176 |
| *Panel B. DiD2s* | | | | | |
| Nitrate Vio x $w_i$ | 0.100 | 0.075 | 0.043 | 0.044 | 0.044 |
| | (0.125) | (0.089) | (0.093) | (0.093) | (0.093) |
| Num.Obs. | 386072 | 386072 | 385817 | 385302 | 385302 |
| Store | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week | | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ | ✓ |
| Week-Year | | | ✓ | ✓ | ✓ |
| Violation | | | | ✓ | ✓ |
| Store-year | | | | | ✓ |
| Store-week | | | | | ✓ |

Note: Dependent variable is logged carbonated beverage sales in dollars. 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. All regressions include controls for price and local weather and are weighted by the number of people served by the violating PWS. Standard Errors are multi-clustered at the store and violation level.

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

Table A3: Impact of SDWA Nitrate Notifications on Infant Mortality

| | asin(Infant Mortality Rate) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A. First Month Only* | | | | |
| % of First Month | −0.199*** | −0.155*** | −0.098 | −0.114* |
| | (0.047) | (0.042) | (0.055) | (0.056) |
| Num.Obs. | 189 090 | 189 090 | 189 090 | 188 808 |
| *Panel B. All Violation Months* | | | | |
| % of Month with Violation | −0.062 | −0.043 | −0.030 | −0.019 |
| | (0.049) | (0.039) | (0.039) | (0.037) |
| Num.Obs. | 189 090 | 189 090 | 189 090 | 188 808 |
| County | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ |
| Month | | ✓ | ✓ | ✓ |
| Year-Month | | | ✓ | ✓ |
| County-Month | | | | ✓ |

Dependent variable is the inverse hyperbolic sine of infant mortality (per 1,000 births). Treatment variable is the percent of the month a county experienced an active nitrate violation. All regressions are weighted by the total number of births in the county-month and each regression controls for linear, quadratic, and cubic average minimum and maximum temperature. Standard errors are clustered at the county level.

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

Table A4: Impact of SDWA Nitrate Notification on Low Birth Weight Rate

| | Low Birth Weight Rate (per 1,000) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A. First Month Only* | | | | |
| % of First Month | −0.770 | −2.616* | −1.965 | −1.680 |
| | (1.475) | (1.106) | (1.292) | (1.338) |
| Num.Obs. | 189090 | 189090 | 189090 | 188808 |
| *Panel B. All Active Months* | | | | |
| % of Month | 0.095 | −0.936 | −0.980 | −1.062 |
| | (0.865) | (0.602) | (0.629) | (0.692) |
| Num.Obs. | 189090 | 189090 | 189090 | 188808 |
| County | ✓ | ✓ | ✓ | ✓ |
| Year | | ✓ | ✓ | ✓ |
| Month | | ✓ | ✓ | ✓ |
| Year-Month | | | ✓ | ✓ |
| County-Month | | | | ✓ |

Dependent variable is low birthweight (per 1,000 births). Treatment variable is the percent of the month a county experienced an active nitrate violation. % of the first month is a variable that only takes a positive value in the initial month of the violation. All regressions are weighted by the total number of births in the county-month and each regression controls for linear, quadratic, and cubic average minimum and maximum temperature. Standard errors are clustered at the county level.

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

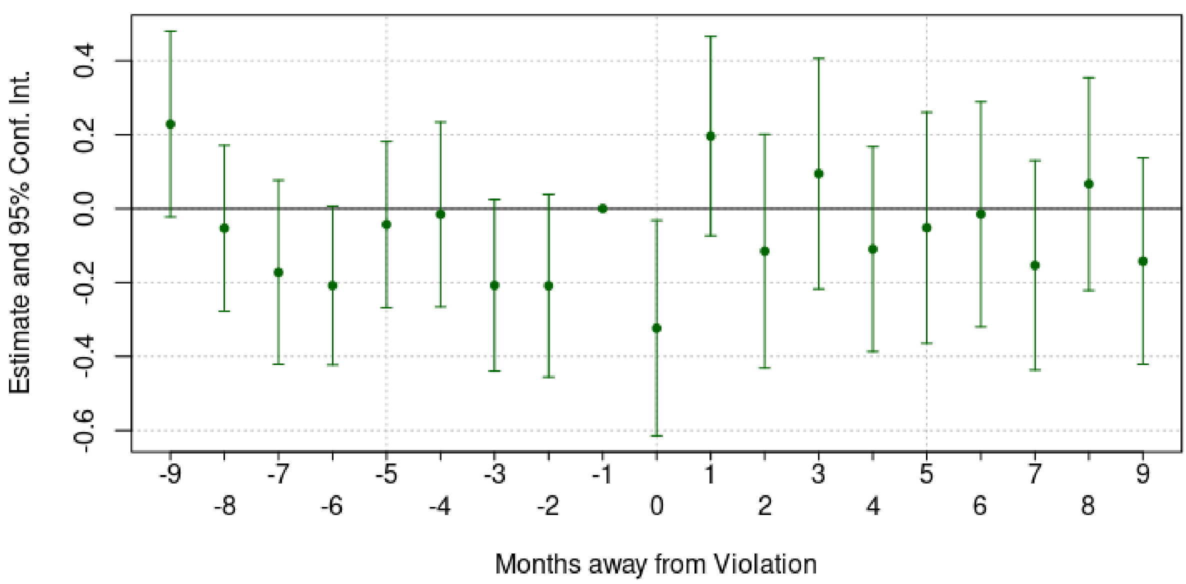



Figure A6: Event Study Results: Infant Mortality Rate Pre- and Post- SDWA Notification

Note: Presents the two-stage difference in difference event-study coefficients of infant mortality for the months before and after a SDWA notification. The vertical axis measures the difference (in levels) of infant mortality rate relative to the month prior to the notification. The regression includes county-month and year-month fixed effects and controls for linear, quadratic, and cubic monthly temperature. Standard errors are clustered at the county level.

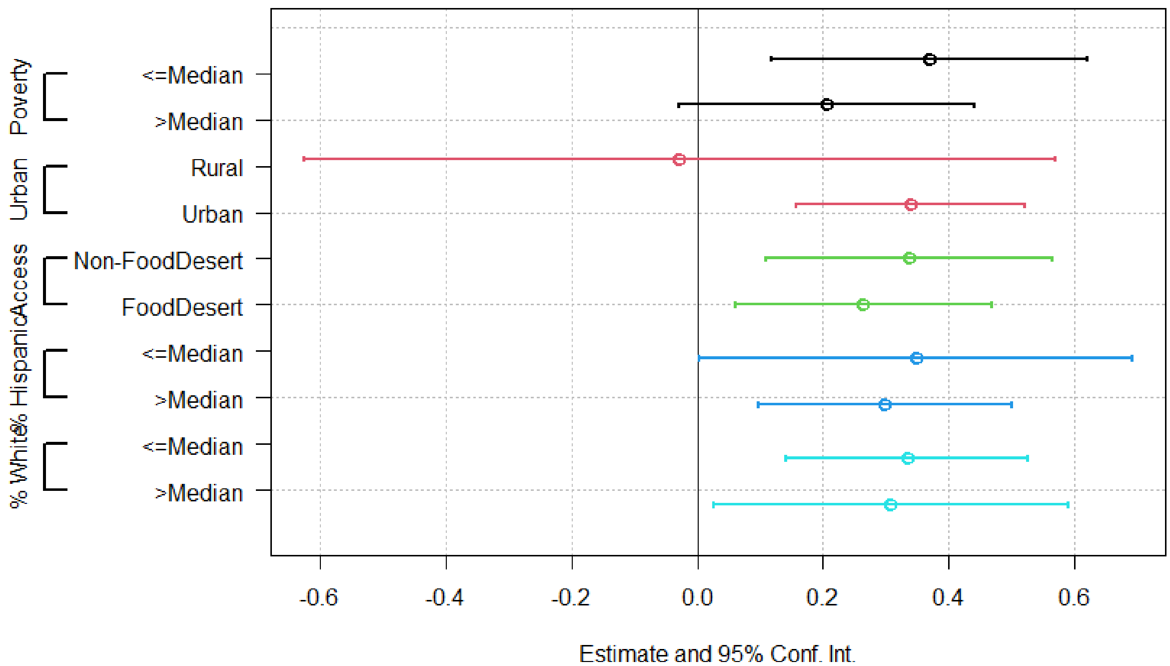



Figure A7: Averting Behavior Heterogeneity: By Population Demographics

Dependent variable is logged bottled water sales in dollars. Treatment variable is the % of the population that received a SDWA nitrate notification, matching treatment variable in Table 2. All regressions include controls for price and local weather and are weighted by the number of people served by the violating PWS. Standard Errors are multi-clustered at the store and violation level.

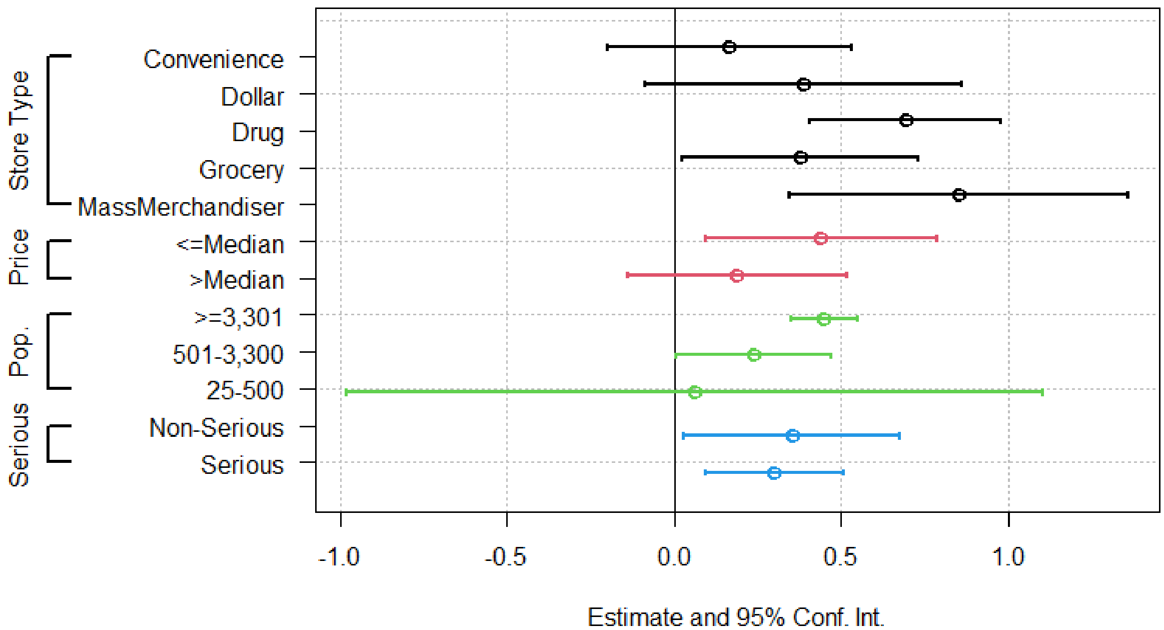



Figure A8: Averting Behavior Heterogeneity: By Public Water System Characteristics

Dependent variable is logged bottled water sales in dollars. Treatment variable is the % of the population that received a SDWA nitrate notification, matching treatment variable in Table 2. All regressions include controls for price and local weather and are weighted by the number of people served by the violating PWS. Standard Errors are multi-clustered at the store and violation level. Standard Errors are multi-clustered at the store and violation level.