Delayed Information and Behavioral Spillovers: Evidence from U.S. Drinking Water Violations

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January 28, 2026

Abstract

Timely public disclosure is a central component of environmental regulation, yet little is known about how delays in mandated notifications affect protective behavior and its spillovers across communities. This paper studies how the timing of public notification influences household avoidance behavior following acute microbial drinking water violations in the United States. I combine administrative data on drinking water violations and enforcement actions with high-frequency retail scanner data on bottled water sales from 2006–2019. I show that avoidance behavior responds sharply to timely public notification but is substantially muted when notification is delayed or missing. Event-study evidence indicates that households do not respond to the onset of contamination itself, but rather to the arrival of salient public information. I further document spillover effects in neighboring communities that are not directly affected by violations. These spillovers arise primarily within shared media markets and dissipate with geographic and informational distance, highlighting the role of local media in transmitting risk information. Alternative channels such as social connectedness and socio-demographic similarity do not generate comparable spillovers in the absence of media exposure. Together, the results demonstrate that the effectiveness of right-to-know policies depends critically on implementation, particularly the timing of information release, and that information disclosure can induce behavioral responses beyond the targeted population.

1 Introduction

Mandatory information disclosure about environmental hazards has become an integral part of public policy. Governments increasingly rely on transparency to help citizens recognize and avoid health risks associated with environmental pollution. They are used widely to warn about risks from various sources, including air quality, drinking water quality, toxic release, and product safety, reflecting a broad consensus on the importance of information provision in regulation. Yet the effectiveness

* *Indiana University, Kelley School of Business. email: rbaizak@iu.edu.* Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

of these policies depends on *when* and *how* information reaches the public. When citizens receive warnings too late, or when awareness spreads through informal channels rather than official notices, their behavioral responses can be misaligned with the actual pattern of risk. These frictions can lead to insufficient protection where hazards truly exist or costly overreactions in unaffected areas.

This paper studies how such informational frictions shape the public response to drinking water quality violations in the U.S.. Safe drinking water is fundamental to public health, yet drinking water contamination remains a widespread concern in the United States. In a typical year, 10–20% of Americans are served with water that violates health-based standards under the Safe Drinking Water Act (SDWA) (Allaire, Wu, and Lall 2018; Keiser et al. 2023). Waterborne contaminants, from microbial pathogens to toxic chemicals, cause both acute illnesses and long-term health risks; for example, waterborne pathogens alone are estimated to cause around 7 million cases of sickness annually in the U.S. (Keiser et al. 2023). High-profile drinking water crises such as the Flint, Michigan lead contamination disaster have underscored the stakes: delayed or insufficient communication of water safety problems can lead to severe health consequences, public outrage, and a lasting erosion of trust in authorities (Christensen, Keiser, and Lade 2021). These events highlight that effective information disclosure is as critical as infrastructure investments in ensuring safe tap water.

Under the SDWA's information policy, community water systems are legally required to inform the public when a health-based water quality violation occurs. The Public Notification (PN) Rule ensures consumers have a "right to know" about unsafe water and instructs water suppliers to issue notices within strict timeframes depending on the severity of the violation. In particular, Tier 1 violations, those posing an immediate danger, such as microbial contaminants, must be reported to consumers within 24 hours, often via media alerts or door-to-door notices. In practice, however, challenges in implementation have frequently undermined these goals. Federal oversight has long documented persistent failures in the enforcement of public notification requirements under the Safe Drinking Water Act. As early as 1992, U.S. Government Accountability Office (GAO) investigation found that systems issued public notices for only 68 out of 167 serious violations reviewed, and that over 70% of those notices were delivered late, often weeks or months after the violation occurred, rendering them ineffective as timely health warnings (USGAO 1992). More recent audits confirm that these problems remain widespread. A 2011 GAO report estimated that 26% of health-based violations and 84% of monitoring violations were either not reported or inaccurately reported by states, limiting EPA's ability to monitor compliance or ensure the public was adequately informed (USGAO 2011). The Environmental Protection Agency's (EPA) Office of Inspector General (OIG) further concluded in 2019 that several state primacy agencies did not ensure that water systems consistently issued

required public notices, particularly for lower-tier violations, resulting in gaps, delays, and inconsistencies in how consumers across the country learn about drinking water risks (USEPAOIG 2019). Together, these audits highlight that public notification practices remain unreliable and unevenly enforced, undermining the effectiveness of right-to-know provisions.

Even when official notifications are delayed, information about local water problems may still emerge through informal or media channels, but this too can have complex effects. Local news outlets and social networks sometimes disseminate reports of drinking water violations beyond the immediately affected community, especially for severe incidents that garner regional coverage. For example, a contamination event in one county might be reported on television or newspapers, alerting residents in neighboring counties who share the same media market. In these cases, information spillovers can occur: people outside the contaminated area become aware of the problem and might change their behavior out of precaution or concern. On the one hand, such spillovers can be beneficial if they warn a broader population about a genuine risk (for instance, downstream communities or those on interconnected water systems). On the other hand, diffuse communication can also induce unintended costs or overreactions. Individuals in areas not affected by the violation may nonetheless engage in costly avoidance behaviors, for example, purchasing bottled water or filters "just in case", even though their own water supply is compliant. Prior research on risk perception provides reason to expect these kinds of responses. Cognitive biases like availability heuristics can lead people to overestimate risks when a vivid incident (like a neighboring county's water scare) comes readily to mind (Tversky and Kahneman 1974) or people behave altruistically to high-risk event (Viscusi 1997). Similarly, studies of other health advisories have documented spillover effects to non-targeted populations: for instance, public advisories about mercury in fish led even low-risk consumers to reduce fish consumption, suggesting that news of hazards can trigger broad behavioral changes beyond the intended audience (Shimshack and Ward 2010). In the context of drinking water, however, little is known about how far and through what mechanisms information about a local violation travels, nor how people in unaffected areas respond when they hear of a water safety issue elsewhere.

This paper examines how delayed information and cross-community information spillovers influence pollution avoidance behavior in the drinking water context. I focus on a specific defensive behavior, purchases of bottled water, as a tangible measure of the public's response to perceived tap water risks. My analysis is built on a novel dataset that combines administrative records of drinking water violations and enforcement actions with high-frequency store sales data across the United States. First, I compile detailed violations related to microbial contaminants from EPA's federal Safe Drinking Water Information System (SDWIS) database for 2006 to 2019, including the week each

health-related violation occurred. Second, by relying on EPA's Enforcement and Compliance History Online (ECHO) system database, I am able to quantify the public notification delay for each violation – essentially, the lag between the violation event and the time the public was officially informed. Particularly, I take advantage of the records about informal enforcement actions that can be linked to SDWIS violations and which provide information about the type, originator and the date of enforcement action. Some of the enforcement action types provide information about the public notification of the violations, such as when state received confirmation from the water system about its compliance with the Public Notification rule. These data allow me to determine whether notices were delivered on time according to regulatory guidelines (e.g., within 24 hours) and if there were delays in alerting the public or if they were missing altogether. I then link each microbial violation incident to consumer behavior using NielsenIQ retail scanner data covering the same period (2006–2019). I also use NielsenIQ Homescan data at the household level in my robustness analysis. Merging these with the violation records yields a balanced panel of over 2,283 counties observed weekly over 14 years, in which I can observe changes in bottled water buying in response to local water quality violations.

I begin my analysis with a difference-in-differences event-study design focusing on twenty-eight acute microbial violation events in the United States between 2006 and 2019, where a single community water system serves the majority of the county population. Fourteen of these events involve timely public notification, while the remaining fourteen involve delayed notification. For each event county I identify a neighboring county that didn't have any acute pathogen or no significant health-based violation one year before and one year after the event time. I form control group counties for both directly affected and indirectly exposed counties by matching based on the set of eleven socio-demographic variables.

The event-study results indicate that bottled water sales increase sharply in directly affected counties at the time of timely public notification, rising by approximately 22%; this effect is statistically significant at the 10% level. Indirectly exposed neighboring counties exhibit a smaller increase of about 14%, though this estimate is not statistically distinguishable from zero. In contrast, for violations with delayed public notification, I find no detectable increase in bottled water sales at the time of disclosure in either directly affected or indirectly exposed counties.

Next, I extend my analysis to the full set of NielsenIQ counties, covering about 95% of the U.S. population for all the acute microbial violations between 2006-2019, where I aggregate community water system violations to the county-by-week level using population weights and the share of days

in the violation. I evaluate both the direct impact of drinking water violations on consumer behavior in affected communities and the spillover impact on surrounding communities that were not themselves in violation. The empirical strategy exploits variation in the timing and location of violation events to identify changes in bottled water purchases attributable to new information about water contamination. In essence, I treat an acute microbial violation as a shock to perceived water risk in the community, and I ask how bottled water sales in that community evolve in the weeks after the violation, compared to baseline trends incorporating a rich set of fixed effects and controls.

Crucially, I differentiate between cases where the public was notified immediately and cases where notification was delayed or absent. This allows me to test how the public responds to violations with different timings of the notification. To study information spillovers, for each "treated" county (where a violation occurred), I identify a set of neighboring counties.

The findings show that the timing and reach of information are critical determinants of public response. For acute pathogen violations, issuing a prompt public notice triggers an avoidance response. I estimate that timely public notification leads to about a 14.7% increase in bottled water sales in the affected county (for a fully exposed population). By contrast, when notification is delayed, the increase in bottled water purchases is only around 6%, and if a notice is never issued, I observe a similar but statistically insignificant change in purchasing behavior. These differences underscore the crucial role of timely risk communication in prompting protective action.

Beyond the directly affected communities, I also find evidence of spillover effects in nearby areas: a comparable full exposure from all adjacent counties with timely notification is associated with about an 9% increase in sales in the unaffected county. Estimated spillover effects from neighboring counties' violations with delayed notification are smaller but statistically significant, while violations with missing public notification are associated with positive but statistically insignificant effects.

Since PN Rule guidance suggests using media such as television and radio for acute health-based violations, I decompose neighboring-county exposure according to potential information channels. I find that spillover behavior in avoidance behavior is strongest when the neighboring county shares the same media market with the affected county than those outside of it. Media markets are identified using Nielsen Designated Market Area (DMA) boundaries, which group counties based on the largest audience achieved by commercial TV stations. I find that spillover behavior dissipates with greater distance or when counties do not share media coverage. In other words, public awareness, often via local media, can extend defensive behavior to surrounding communities, but this effect decays when informational and geographic links are weaker.

To explore alternative information channels that could potentially drive spillover behavior, I examine the roles of social connectivity and socio-demographic similarity across counties. First, I use Facebook's Social Connectedness Index (SCI), which measures the intensity of social ties between all U.S. county pairs based on Facebook friendship links. I construct population-weighted measures of social connectedness between affected counties and their neighbors, but find no evidence that higher social connectivity amplifies spillover responses among adjacent counties within the same media market. Moreover, even counties with very high social connectivity to the affected area exhibit no meaningful response when they are neither geographically adjacent nor located in the same DMA. This suggests that social connectedness alone is insufficient to generate spillover behavior in the absence of exposure to local public warnings.

Second, I examine socio-demographic similarity between counties. In contrast to a homophily-based interpretation, I find that spillover responses are not stronger among socio-demographically similar neighboring counties. Instead, spillover effects tend to be larger for neighbors that are *less* socio-demographically similar to the affected county, consistent with spillovers flowing from larger or more urban counties to smaller or more rural ones rather than along similarity-based social ties. Taken together, these findings reinforce the conclusion that spillover behavior is primarily mediated by media exposure and geographic proximity, rather than by social connectedness or demographic similarity per se.

Given that a substantial share of acute pathogen violations are associated with delayed or missing public notification, I also examine whether such violations are accompanied by short-run health-related responses, using NielsenIQ retail sales of over-the-counter (OTC) gastrointestinal (GI) medications. Purchases of these products may provide an indirect indicator of acute gastrointestinal illness if exposure to contaminated drinking water leads to symptomatic responses. Overall, the evidence is limited. However, for violations that were never publicly notified, I find a suggestive increase in GI medication purchases: sales rise by approximately 12% one week after the violation onset, while other lags show no consistent pattern. In contrast, I find no systematic changes in GI medication sales following violations with timely or delayed public notification.

This study contributes to several strands of literature at the intersection of environmental policy, information economics, and behavioral responses to risk.

First, I contribute to the literature on environmental regulation and information disclosure by examining how right-to-know provisions are implemented in practice. Prior research on the Safe Drinking Water Act (SDWA) has focused on the effects of disclosure requirements on regulatory

compliance and violation outcomes (Bennear and Olmstead 2008; Baker, Bennear, and Olmstead 2022), as well as on the health consequences of drinking water violations (Keiser et al. 2023). In contrast, much less is known about whether mandated public notifications are consistently delivered as intended, particularly in the context of acute health-based violations. I provide new evidence on this institutional dimension by constructing a national measure of public notification status for acute microbial drinking water violations, distinguishing between notices that are delivered on time, delivered late, or missing from administrative records. This classification allows me to document systematic variation in notification practices across space and over time, highlighting gaps between formal regulatory requirements and observed administrative implementation.

Second, this paper contributes to the literature on behavioral responses to environmental health risks. Prior research shows that when individuals become aware of contamination in their environment, they often undertake costly avoidance measures, a form of defensive expenditure that reveals their private valuation of health risks. In the context of drinking water, earlier studies document increased bottled water purchases and other protective behaviors following contaminant violations (Zivin, Neidell, and Schlenker 2011; Allaire et al. 2019; Marcus 2022; Christensen, Keiser, and Lade 2021). This paper extends that literature by emphasizing the role of information timing and credibility in mediating these behavioral responses. I show that the occurrence of a contamination event alone is not sufficient to induce strong avoidance behavior. Instead, residents respond most strongly when public notification is issued promptly, as intended under regulatory guidelines. When notification is delayed or missing, behavioral responses are substantially weaker, despite the presence of an underlying health risk. These findings suggest that delayed or opaque communication can significantly blunt the protective effects of information disclosure, with implications for how the benefits of right-to-know policies are assessed.

Third, this paper contributes to the economics literature on spillovers and information diffusion across communities. I provide evidence that acute drinking water violations generate behavioral responses beyond the directly affected area, as information about health risks spreads through shared media environments. Using bottled water purchases as a revealed-preference measure, I show that spillover effects are concentrated among counties that share the same local media markets, and attenuate sharply outside these boundaries. By identifying the role of media-market overlap in shaping spillover behavior, this paper bridges environmental economics with insights from communication and network economics, demonstrating that precautionary responses depend not only on geographic proximity but also on informational connectivity. These findings complement evidence of spillovers in other environmental and health contexts (Wrenn, Klaiber, and Jaenicke 2016; Shimshack and

Ward 2010; Gallagher 2014; Hu 2022), while providing the first national evidence of such effects in the context of drinking water safety. From a policy perspective, the results highlight that information disclosure can generate unintended behavioral responses outside the target population, underscoring the importance of carefully designed communication strategies that clearly delineate affected areas.

Finally, this paper contributes to the literature on belief updating and information salience by showing that the behavioral impact of regulatory disclosure depends critically on timing and transmission. Although unsafe drinking water is experienced during the violation period, households respond sharply only when public notification is issued promptly. This pattern is consistent with salience-based accounts of belief updating, in which individuals place disproportionate weight on information that is immediate, publicly framed, and attention-grabbing (Bordalo, Gennaioli, and Shleifer 2013, 2022). (Bordalo, Gennaioli, and Shleifer 2013, 2022). This interpretation aligns with evidence from other policy contexts showing that information affects behavior primarily when it is salient and visible at the point of decision-making (Chetty, Looney, and Kroft 2009; Finkelstein 2009; Busse et al. 2015; Dessaint and Matray 2017). Spillover effects further reinforce this mechanism: precautionary behavior propagates primarily through shared media markets, which synchronize the salience of public information across locations, rather than through social connectedness alone.

In summary, this paper sheds light on how the effectiveness of an environmental right-to-know policy, specifically, the timeliness of public notification, and the structure of media markets jointly shape behavioral responses to drinking water contamination. The findings are relevant for ongoing efforts to improve drinking water safety and transparency. They indicate that rapid public communication substantially amplifies protective behavior in directly affected communities, while delayed or missing notification weakens these responses. At the same time, the presence of spillover effects implies that information disclosure can influence behavior beyond the targeted population, particularly in areas that share local media coverage. This highlights the importance of communication strategies that clearly delineate affected areas and provide accurate, timely information to surrounding communities. Taken together, the results contribute to a more nuanced understanding of both the benefits and the limits of information-based environmental policy. As an illustration of economic magnitude, back-of-the-envelope calculations reveal that acute microbial violations generated an additional $2.4 million in sales of bottled water in 2,283 counties between 2006-2019 in directly affected counties. If violations with delayed and missing public notification had instead been notified on-time, based on the estimated coefficients, it would have brought additional bottled water sales of about $2 million. Spillover responses generated an additional $2.1 million in purchases in

unaffected neighboring counties within the same media markets.

The remainder of the paper is organized as follows. Section 2 describes the institutional framework governing drinking water regulation and public notification. Section 3 details the data sources and construction. Section 4 outlines the empirical strategy, including the identification of notification timing and spillover exposure. Section 5 presents the main results, Section 6 reports robustness checks and extensions, and Section 7 concludes.

2 Background

2.1 Safe Drinking Water Act

The 1974 Safe Drinking Water Act (SDWA) is the main statute that regulates the national public drinking water supply with the goal of protecting public health from contaminants in the water. The law governs around 150,000 public water systems, which are classified into three types based on the number of people served and the length of the service period. The first and major type is comprised of 50,000 community water systems (CWS) that supply drinking water to nearly 90% of the U.S. population year-round. The rest are non-community water systems, which furnish water in areas where people do not spend extended periods of time. Private wells are not regulated under the SDWA, which mostly operate in rural areas (USEPA 2023b).

The SDWA authorizes the Environmental Protection Agency (EPA) to set national drinking water standards for public water systems. The National Primary Drinking Water Regulations (NPDWR) include enforceable Maximum Contaminant Level (MCL) standards for over 90 contaminants, as well as Maximum Residual Disinfectant Level (MRDL) and Treatment Techniques (TT) requirements to ensure public water safety (USEPA 2023a). When systems violate these standards, they incur health-based violations. The EPA also establishes monitoring and reporting requirements, such as the frequency of monitoring a specific contaminant or the reporting frequency of the contaminant levels in the water system to regulators and the public. Violations of these requirements are referred to as monitoring and reporting violations. Because health-based violations indicate potential exposure to contaminants with direct implications for human health, they trigger public notification requirements under the SDWA and form the focus of the empirical analysis in this paper.

The EPA has delegated enforcement responsibility under the SDWA, known as *primacy*, to 49

states, territories, and indian tribes[1]. To retain this authority, primacy agencies must continuously meet certain requirements, such as promulgating regulations with at least the same degree of stringency as at the federal level. They also must monitor public water systems and maintain record-keeping. The states have the authority to take enforcement actions against public water systems to compel compliance with the federal and local drinking water regulations. The EPA and its ten regional offices maintain the oversight of the states' drinking water programs and when needed overtake the enforcement in place of a state.

2.2 Public Notification Rule

Public water systems are required to monitor their finished water for regulated contaminants and to inform consumers when standards are violated. Under the Public Notification (PN) Rule, systems must notify the public whenever there is a violation of a Maximum Contaminant Level (MCL), Maximum Residual Disinfectant Level (MRDL), treatment technique (TT), or certain monitoring and reporting requirements. The rule specifies the content, timing, and delivery methods of these notices.

EPA distinguishes three public notification tiers. Tier 1 notices apply to violations that pose an *acute* and serious risk to public health from short-term exposure. For these violations, systems must issue a public notice within 24 hours of learning of the violation, typically through high-visibility channels such as local television and radio, newspaper notices, public postings, or direct delivery. Tier 1 notices generally advise consumers not to drink the water without boiling it first, or to use an alternative source such as bottled water. Table 1 maps specific contaminants and rules to required public notification content such as the mentioned at-risk populations, health risks and recommended actions. Majority of them urge to boil water before drinking or using it or buy bottled water. Tier 2 and Tier 3 notices apply to less urgent violations involving long-term risks or monitoring and reporting failures and allow substantially longer notification timelines and lower-salience delivery methods (USEPA 2010, 2023d; USEPAOIG 2019). Because these notices are not designed to prompt immediate protective action, they are not the focus of this study.

All three tiers share core content requirements: the notice must describe the violation and when it occurred, identify the population at risk and potential health effects, explain what the system is doing to correct the problem, provide recommended consumer actions (including whether alternative water should be used), and indicate when the system expects to return to compliance. Systems must

1. I refer to them as *states* or *primacy agencies* in the subsequent text.

also submit a "certification" to the primacy agency within ten days of issuing a public notice, including a copy of the notice and the method and date of distribution (USEPA 2023d).

In this paper, I focus on Tier 1 health-based violations whose notices require rapid communication and typically recommend boiling water or using bottled water. I refer to this group as *Acute Pathogens* violations. These include MCL exceedances for fecal indicators (e.g., fecal coliforms and *E. coli*), high levels of disinfectants such as chlorine dioxide, and elevated turbidity that signals potential pathogen breakthrough. See Appendix A.2 for additional details on the PN rule.

3 Data

3.1 Drinking water violations

I use the EPA Safe Drinking Water Information System (SDWIS) Federal Reporting Services' National Downloads data from the Enforcement and Compliance History Online (ECHO) system to gather information about public water systems and their compliance history. States are responsible for maintaining inventory and record-keeping of the activities of the public water systems under their jurisdiction. Often, they store their data at the SDWIS/State system designed to be used by states. Each quarter, states must submit updates about public water systems' performance to the SDWIS/Fed national database. The federal database contains information about all the water systems, such as geographic area or service population. The violations section contains the noncompliance period start and end date, the rule being violated, and the main contaminant. Since the system also records the return to the compliance date, I follow USEPA (2013) to find an effective violation end date. Noncompliance period usually lasts a month or a quarter, depending on the type of violation, as can be seen in Table 2. Violations may affect the entire service population or only a portion of the distribution system; however, SDWIS does not provide information on the spatial extent of exposure within a system.

I focus only on on an *Acute Pathogens* category. Following Allaire et al. (2019), I construct this category by grouping Tier 1 MCL violations for fecal indicators (e.g., fecal coliforms and *E. coli*), violations of the MRDL for chlorine dioxide, and turbidity exceedances that indicate potential breakthrough of pathogens. Their corresponding Tier 1 notices explicitly describe acute gastrointestinal or nervous system symptoms, identify populations at risk, and recommend averting actions such as boiling water or using bottled water.

3.2 Public Notification Timing

The EPA's Enforcement and Compliance History Online (ECHO) database also records enforcement actions taken by primacy agencies in response to drinking water violations. These actions are classified as formal or informal, with informal actions typically consisting of correspondence between regulators and water systems, such as notifications regarding violations or public notification compliance. Enforcement actions can be linked to specific violations and include information on the action date, the originator (state or EPA region), the enforcement category, and the action type.

Several types of informal enforcement actions explicitly reference public notification, including records indicating when a state requested, received, or issued a public notice. As discussed in Section 2.2, water systems are required to submit a public notification certification to the primacy agency within ten days of issuing a notice to the public. In addition, each violation tier is subject to a regulatory deadline for issuing public notification, which is 24 hours for Tier 1 health-based violations.

I use the timing of these enforcement action records to classify public notification associated with each health-based violation as *on-time*, *late*, or *never notified*. Appendix B.2 provides additional detail on the construction of these measures, and Figure A1 illustrates the distribution of public notification timing across violation categories.

3.3 Sales data

My primary outcome data come from NielsenIQ Retail Scanner (RMS) data provided by the Kilts Center at the University of Chicago. These data report weekly store-level revenue and quantities sold for over 30,000 retail stores across most of the United States, with products observed at the UPC (barcode) level. A product is defined as a UPC–version combination. I use RMS data from 2006 to 2019 and focus on NielsenIQ's bottled water product module. Bottled water sales are defined as total dollar sales (in constant 2019 dollars) across all bottled water UPCs, aggregated to the county–week level. To ensure stable store participation over time, I retain only stores with positive sales in at least 12 years of the sample period. The resulting balanced panel covers 2,283 counties observed over 730 weeks. Because RMS stores are observed consistently over time and across counties, these data provide the statistical power needed to identify responses to relatively rare acute violation events.

In addition to bottled water, I also use RMS data on over-the-counter gastrointestinal (GI) medications to examine potential health-related responses to delayed or missing public notification of acute pathogen violations. These products include diarrhea remedies, electrolyte oral rehydration solutions, and antacids.

3.4 Weather controls

I use county-level daily historical nClimGrid-Daily weather data from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA)

for my sample period to control for temperature and precipitation. I calculate the weekly maximum temperature for a county in Celcius degrees and create a factor variable with ten bins starting from less and equal to 0 degrees up to equal to or greater than 40 degrees with 5-degree steps. Similarly, I calculate weekly total precipitation in millimeters and create a factor variable with eight bins starting from 0 mm to greater than 100 mm.

3.5 Spatial and Information Structure

3.5.1 Neighboring Counties (NCs)

I define neighboring counties using the 2023 Census County Adjacency file. This file identifies all directly adjacent counties for each focal county and is used to measure geographic spillover exposure. To construct the set of neighboring counties used in the spillover analysis, I use the 2023 County Adjacency File from the U.S. Census Bureau. [2]

3.5.2 Designated Market Areas (DMAs)

In addition to geographic adjacency, I use Nielsen Designated Market Areas (DMAs) to capture media markets through which information may spread. DMAs are geographic regions defined by Nielsen based on television viewership patterns and represent the primary media markets in which households receive local news. I use Nielsen's crosswalk between counties and DMAs for 2017. Each county belongs to exactly one DMA. Because public notification of drinking water violations requires notifying through local television, DMA boundaries determine which counties share the same information environment.

For each county, I identify (i) neighboring counties inside the same DMA, (ii) neighboring counties outside the DMA, and (iii) other non-neighbor counties in the same DMA. These distinctions are used to construct measures of potential information spillovers through geography and media markets.

3.5.3 Social Connectedness Index (SCI)

To study non-geographic spillovers, I incorporate the Facebook Social Connectedness Index (SCI), which measures the intensity of social ties between all U.S. county pairs. Bailey et al. (2018) con-

2. The next most recent adjacency file is from 2010; adjacency relationships are highly stable over time.

structed the SCI based on the snapshot of the universe of all Facebook friendships in 2016. They construct the SCI between two counties based on the number of Facebook connections among users in these locations, divided by the product of the total number of users in each county. Thus, it captures a relative probability that a random Facebook user in county i is friends with a user in county j. Facebook's SCI can be used as a reasonable approximation of the real-world social interactions in the U.S. as it serves for online interactions mostly between real-world friends, and based on about 239 million active users in the U.S. and Canada (Bailey et al. 2018; Hu 2022).

4 Empirical Framework: Effects of Public Notification Timing on Avoidance Behavior and Spillover Effects

4.1 Event Study Evidence: Large Community Water Systems with County-Level Coverage

Event Definition and Sample Construction. I begin with an event study analysis of acute microbial drinking water violations to examine the timing and spatial reach of avoidance behavior in a transparent setting. Acute microbial violations are subject to the Tier 1 Public Notification (PN) rule, which requires public disclosure within 24 hours due to the risk of short-term adverse health effects. I restrict the sample to violations associated with large Community Water Systems (CWS) serving populations of at least 100,000 people. As described in Appendix A.1 CWSs are highly local, and there are often multiple systems operating within a single county. To align the treatment unit with the outcome unit, I further retain only events in which the affected CWS serves at least 75 percent of the county population. This restriction reduces attenuation arising from partial exposure within a county.[3]

This selection yields 33 acute violation events, consisting of 14 violations with on-time public notification, 16 violations with delayed notification, and 3 violations for which public notification was never issued. Violations without public notification are excluded from the event-study analysis, as they lack a well-defined notification date. Among delayed-notification events, I restrict attention to violations for which public notification occurred sufficiently close to the violation start to be observed within the event-study window.[4] The resulting event-study sample consists of 28 acute microbial

3. The finest geographic identifier available in the NielsenIQ Retail Scanner dataset is the county of the store.

4. Specifically, I retain delayed-notification events for which public notification occurred within 100 days of the violation start. This restriction ensures that public disclosure falls within the symmetric pre- and post-event window used in the

violation events. I refer to the counties in which the violation CWS is located as "*directly exposed*" counties.

For each event county I identify a neighboring county that didn't have any acute pathogen or no significant health-based violation one year before and one year after the event time. I refer to them as "*indirectly exposed*" counties. This allows the event study to trace behavioral responses not only in areas directly affected by the violation, but also in nearby areas that may be exposed to information spillovers through shared media markets, social connections, or precautionary behavior.

Control Group Construction. For both directly and indirectly exposed counties, I construct control counties using a matching procedure based on pre-determined socio-demographic characteristics, similar in spirit to matched-location approaches used in prior work on environmental crises (e.g., Christensen, Keiser, and Lade (2021).

Specifically, I compute a county-level socio-demographic distance using eleven standardized characteristics drawn from the 2012 American Community Survey and 2012 Republican vote share, including an ordered population-density-bin measure. For counties i and j, the distance is defined as a normalized Euclidean distance, $D_{ij} = \sqrt{\sum_{k=1}^{11}(X_{ik} - X_{jk})^2}$, and is normalized to the unit interval: $D_{ij}^{\text{norm}} = \frac{D_{ij} - \min_{(i',j')} D_{i'j'}}{\max_{(i',j')} D_{i'j'} - \min_{(i',j')} D_{i'j'}}$, where X_{ik} denotes the standardized value of characteristic k for county i and $K = 11$. Additional details on the construction of the distance metric and the underlying covariates are provided in Appendix B.7.

For each treated county, I restrict the pool of potential control counties to those observed in the NielsenIQ Retail Scanner data and exclude counties that share a border with, or are located in the same state as, the treated county. From this restricted pool, I form a candidate set consisting of the 50 nearest counties according to the socio-demographic distance measure. For directly exposed counties, I select as the control county the closest candidate with no recorded county-month drinking water violations within one year before or after the compliance period associated with the event. For indirectly exposed counties, I impose an additional restriction that none of the candidate county's bordering counties experienced a violation within the same window. [5]

Appendix Tables A2 and A6 report information on the violating Community Water Systems, the timing of noncompliance, and the corresponding control counties selected for events with on-time and delayed public notification, respectively. Appendix Tables A3 and A4 summarize socio-

event-study analysis. Applying this restriction yields 14 delayed-notification events, which are paired with the 14 on-time events in the event-study sample.

5. In a small number of cases, no candidate county satisfies this additional restriction. In these instances, I assign the closest feasible control county based on inspection of violation histories.

demographic characteristics and distance measures for directly and indirectly exposed counties and their matched controls for on-time notification events. Appendix Tables A7 and A8 provide the analogous information for events with delayed public notification. Public notification delays in these violations range from a month to about a quarter. Across both notification regimes, treated and control counties appear broadly similar in terms of population size and density, demographic and racial composition, economic characteristics, and political orientation, supporting the comparability of the matched samples.

Event Time and Specification. Event time is defined relative to the public notification week. Let k denote the number of weeks between calendar week t and the Public Notification (PN) week associated with event e. The following event-study specification is estimated at the store-by-event-by-week level:

$$y_{est} = \alpha + \sum_{\substack{k=-24 \\ k\neq -1}}^{24} \beta_k^D \, \mathbf{1}\{\kappa_{et} = k\} \cdot \textit{Direct}_{ec} + \sum_{\substack{k=-24 \\ k\neq -1}}^{24} \beta_k^I \, \mathbf{1}\{\kappa_{et} = k\} \cdot \textit{Indirect}_{ec} + W_{ct}'\delta + \gamma_{es} + \tau_{eyw} + \varepsilon_{est}. \tag{1}$$

Equation (1) is estimated using a stacked difference-in-differences event-study design, in which each violation event defines a separate cohort that is stacked into a single estimation sample. This approach accommodates overlapping events in calendar time and allows for flexible event-specific fixed effects, following the stacked event-study framework formalized by Cengiz et al. (2019) and implemented in related applied work such as Butters, Sacks, and Seo (2022). Here, y_{est} is the log of bottled water sales in store s, county c, event e and week t. The indicator $\textit{Direct}_{ec}$ equals one if county c is the directly exposed county for event e, while $\textit{Indirect}_{ec}$ equals one if county c is a geographically adjacent county that did not experience any acute pathogen or other significant health-based violation one year before and one year after the event time. The vector W_{ct} includes a vector of weather controls (maximum temperature and precipitation bins), as weather can affect both the occurrence of microbial violations and demand for bottled water. The specification includes event-by-store fixed effects γ_{es} and event-by-year-by-week fixed effects τ_{eyw}, which absorb time-invariant store characteristics and common shocks within each event week. The coefficients β_k^D and β_k^I trace the dynamic response of bottled water purchases in directly and indirectly exposed counties relative to the week prior to public notification.

Under an information-driven response, bottled water purchases should remain flat prior to public notification and increase sharply following disclosure, particularly for events with timely notification.

In contrast, if avoidance behavior is driven primarily by contemporaneous exposure or sensory cues, responses should occur at the onset of the violation regardless of notification timing. The event-study design therefore provides a transparent test of whether information timing, rather than the biological shock itself, governs consumer behavior.

While informative, this event-study analysis relies on a small, selected sample of high-coverage events. I therefore turn next to a fixed-effects framework that exploits the full panel of county-week observations to estimate average direct and spillover effects across all violations.

4.2 Evidence from the National Sample of Drinking Water Violations

Building on the event-study evidence, I estimate the average effects of drinking water violations using a fixed-effects framework for the full national sample. I use fixed effects models to estimate avoidance responses to acute pathogen violations under different notification regimes. Bottled water sales provide information about pollution avoidance behavior. I constructed a balanced panel of 2,283 counties for 730 weeks from 2006 to 2019. The baseline specification is

$$\begin{aligned} S_{cyw} = \beta_1 V_{cyw}^{\text{On}} + \beta_2 V_{cyw}^{\text{Late}} + \beta_3 V_{cyw}^{\text{Never}} + \theta_1 V_{cyw}^{\text{On,NC}} + \theta_2 V_{cyw}^{\text{Late,NC}} + \theta_3 V_{cyw}^{\text{Never,NC}} \\ + \delta W_{cyw} + \alpha_{cy} + \mu_{pm} + \gamma_{ym} + \varepsilon_{cyw}, \end{aligned} \tag{2}$$

where S_{cyw} is the log of weekly bottled water sales in county c. The coefficients β_1, β_2, and β_3 measure avoidance behavior to acute pathogen violations in the home county under each notification regime. The parameters θ_1, θ_2, and θ_3 capture spillover responses arising from violations in geographically adjacent counties. Home county's violation indicators (V_{cyw}^{On}, V_{cyw}^{Late}, and V_{cyw}^{Never}) are adjusted by the number of days in a week a water system was out of compliance and the share of the county population affected. Similarly, violation indicators of neighboring counties ($V_{cyw}^{\text{On,NC}}$, $V_{cyw}^{\text{Late,NC}}$, and $V_{cyw}^{\text{Never,NC}}$) are population-weighted measure of the violation indicators for all counties neighboring county c (see B.3 for more details).

The vector W_{cyw} includes a vector of weather controls (maximum temperature and precipitation bins), as weather can affect both the occurrence of microbial violations and demand for bottled water. I include county-by-year fixed effects α_{cy}, which absorb all time-invariant county characteristics as well as annual county-level shocks or trends that may affect bottled water sales. These fixed effects also flexibly capture any county-level differences in public-notification practices and coordination between local health departments and water systems. Primacy agency-by-month fixed effects μ_{pm}

control for region-specific seasonal patterns, allowing seasonality to vary across primacy agencies or states. γ_{ym} is year-by-month fixed effects, which absorb national-level trends and fluctuations. Standard errors are clustered at the county level.

Identification. Our identification relies on week-to-week changes in Acute pathogen violations and PN timing within counties, after removing county-specific trends, region-specific seasonal patterns, national shocks, and weather-driven shifts in water demand. Given this structure, the timing of violation events is plausibly exogenous to short-run bottled water purchasing behavior. Identification could be threatened if unobserved short-run shocks simultaneously affected treated water quality and bottled water demand. Acute microbial violations, however, generally reflect unexpected infrastructure or treatment failures rather than conditions tied to weekly fluctuations in consumer demand.

4.3 Behavioral Spillovers and Information Channels

To examine whether violation events outside the focal county are associated with changes in local bottled water sales, I extend the baseline specification by decomposing neighboring-county exposure according to potential information channels. These extensions allow the model to flexibly estimate associations between local outcomes and violations occurring in different parts of the surrounding information environment.

First, I distinguish between adjacent counties that share the same Designated Market Area (DMA) and those located outside it. DMAs define the geographic boundaries of local broadcast media markets and therefore determine which counties receive the same television and radio coverage - delivery methods explicitly specified for Tier 1 public notices. For each county, I construct three separate timing-specific exposure measures: (i) adjacent counties inside the same DMA, (ii) adjacent counties outside the DMA, and (iii) non-adjacent counties in the same DMA. These measures allow the empirical model to differentiate between geographic proximity and shared media markets as potential channels through which information about violations may reach households.

To implement this decomposition, I replace the single neighboring-county term in equation (2)

with timing- and channel-specific exposure measures. The main specification is

$$S_{cyw} = \sum_{s \in \{\text{On,Late,Never}\}} \left(\beta_s V_{cyw}^{s} + \theta_s^{\text{In}} V_{cyw}^{s,\text{NC-InDMA}} + \theta_s^{\text{Out}} V_{cyw}^{s,\text{NC-OutDMA}} + \kappa_s V_{cyw}^{s,\text{DMA-NonNC}} \right) + \delta W_{cyw} + \alpha_{cy} + \mu_{pm} + \gamma_{ym} + \varepsilon_{cyw}, \tag{3}$$

where $s \in \{\text{On}, \text{Late}, \text{Never}\}$ indexes the public notification timing regime. As before, V_{cyw}^{s} denotes the home-county acute-pathogen exposure under timing state s, scaled by days out of compliance and the affected share of the county population. The variables $V_{cyw}^{s,\text{NC-InDMA}}$, $V_{cyw}^{s,\text{NC-OutDMA}}$, and $V_{cyw}^{s,\text{DMA-NonNC}}$ are population-weighted acute-pathogen exposure measures for, respectively, (i) geographically adjacent counties in the same DMA as county c, (ii) geographically adjacent counties outside county c's DMA, and (iii) non-adjacent counties that share county c's DMA.[6] The coefficients θ_s^{In}, θ_s^{Out}, and κ_s therefore capture associations between bottled water sales in county c and violations occurring in these distinct parts of the surrounding information environment, conditional on the same set of weather controls and fixed effects as in equation (2).

5 Regression Results

5.1 Dynamic Responses to Public Notification

I begin by presenting event-study estimates for acute microbial drinking water violations in large Community Water Systems with county-level coverage. Recall that acute violations are subject to the Tier 1 Public Notification (PN) rule, which requires disclosure within 24 hours of system awareness.

Figure 3 presents event-study estimates of bottled water purchases around violations with timely public notification, separately for directly exposed counties (purple) and indirectly exposed neighboring counties (teal), as specified in Equation 1. The specification includes controls for precipitation and temperature, as well as store fixed effects and event-by-year-by-week fixed effects. Estimated coefficients are flat and statistically indistinguishable from zero in the pre-period for both directly and indirectly exposed counties.

At the time of public notification, bottled water sales increased sharply in directly exposed counties, rising by approximately 23% in the notification week (statistically significant at the 10 percent

6. Construction of these variables follows the same aggregation procedure as in Appendix B.3, with the relevant county sets defined by adjacency and DMA membership.

level) before returning to baseline in subsequent weeks. Bottled water sales in indirectly exposed neighboring counties also increase at the time of notification, by approximately 14%, although this estimate is not statistically significant.

Figure 4 reports analogous estimates for violations with delayed public notification. Pre-trends are generally flat and stable. In contrast to timely-notification events, there is no detectable increase in bottled water sales at the time of public notification in either directly or indirectly exposed counties. For violations with delayed public notification, the absence of a detectable response at the notification week likely reflects the diminished salience of information that is disclosed well after the underlying violation has occurred. In contrast to timely notifications, which are intended to alert consumers to an ongoing or imminent health risk, delayed notifications are often issued after conditions have normalized and may therefore convey limited actionable information at the time of disclosure.

As a diagnostic check, Appendix Figures A2 and A3 report event-study estimates when event time is anchored to the violation start date rather than the public notification week. For violations with timely public notification, modest increases in bottled water purchases appear several weeks after the violation start, coinciding with the notification week, which typically occurs within the violation month or shortly thereafter. In contrast, for violations with delayed notification, there is no systematic response at the violation start. These patterns reinforce the interpretation that avoidance behavior is driven by the timing of public disclosure rather than by the onset of contamination itself.

Results are robust to using the log share of bottled water sales as the outcome variable rather than log levels (see Appendix Figures A4 and A5).

5.2 Average Effects Across All Violations

This section examines average responses to acute microbial drinking water violations using the full national sample. I first describe descriptive patterns in sales and violations, and then present fixed effects estimates of the average effects under different public notification regimes

Panel *a* of Figure 2 plots total national bottled water sales over time for the 2,283 counties in the balanced panel. Sales exhibit seasonality, with peaks during the summer months, and week-to-week variation. In addition, there is a clear upward trend beginning around 2015, including during winter months, consistent with the longer-run growth of bottled water consumption. Panel b shows bottled water sales per capita across counties. Panel *b* shows total bottled water sales per capita

across the counties. The panel covers approximately 310 million people—about 95% of the U.S. population. Counties not covered by NielsenIQ data are primarily located in the parts of the Great Plains, Northwest and Southeast. Counties with the highest per-capita sales are concentrated in the Southwest, Mountain States, Appalachian Region, and the Northeast.

As described in Section B.3, I aggregate community water system (CWS) violations to the county-by-week level using population weights and the share of days in violation. Table 2 reports summary statistics at the CWS level by National Primary Drinking Water Regulation (NPDWR) rule and contaminant code. All acute microbial violations have a median duration of 30 days. The most common violations are turbidity exceedances, followed by total coliform violations.

Panel a of Figure 2 plots the total number of acute microbial violations across all counties over time, disaggregated by public notification timing. Violations display seasonality, with the highest incidence during summer months. Although the total number of violations declines after 2017, a consistently large share of violations is associated with delayed public notification. Panel b of Figure 2 illustrates cross-sectional variation in violations. The heatmap shows the cumulative number of acute microbial violations by county and highlights the dominant public notification timing. Counties with the highest number of violations are concentrated in the Central and Southern Great Plains and parts of the Appalachian region. States such as Oklahoma, Arkansas, Texas, and Kentucky exhibit both high violation intensity and a predominance of delayed notification. In contrast, Western states, Wyoming and Massachusetts have fewer violations overall but a high share of counties with missing public notification.[7] Recall that public notification timing is measured using the date on which the state primacy agency records receipt of the notification, which federal rules require to occur within 10 days after the water system issues the notice. Violations are classified as having on-time or delayed notification based on whether this statutory reporting window is met. When no receipt date is recorded, the violation is classified as having a missing public notification.

I now turn to the estimation results. Figure 5 presents estimates from Equation 2, separately by public notification timing and for home versus neighboring counties. Identification comes from within-county variation in violations under different notification regimes at the county-by-year-by-week level, after controlling for county-by-year fixed effects, state-by-month fixed effects, year-by-

7. USEPAOIG (2019) documents systematic gaps in public notification tracking across EPA regions. In particular, Regions 9 and 10 (western states) do not consistently track Tier 3 public notices, which are used to notify the public when systems fail to perform required monitoring. EPA Region 8, which oversees states in the northern Rocky Mountains area and implements the drinking water program in Wyoming, was noted as not recording public notification violations when water systems fail to issue mandated public notices. The OIG report noted that Region 8 personnel cited a lack of resources to allocate a public notice rule manager.

month fixed effects, and categorical controls for temperature and precipitation. Bottled water sales increase by about 14.7% in home counties during acute microbial violations when public notification is issued on time. Violation with delayed public notification are associated with a smaller but still statistically significant increase of about 5.7%. Violations without any inferred public notification exhibit a positive point estimate of similar magnitude, but the effects is not statistically distinguishable from zero.

Beyond the directly affected communities, I also find evidence of spillover effects in nearby areas. A comparable full exposure from all adjacent counties with timely notification is associated with about a 9% increase in sales in the unaffected county. Estimated spillover effects from neighboring counties' violations with delayed notification are approximately 7% (statistically significant at the 5% level), while violations with missing public notification are associated with a smaller increase of about 2% that is not statistically distinguishable from zero.

Across both home and neighboring counties, estimated effects are largest for on-time notification, smaller for delayed notification, and weakest and statistically indistinguishable from zero when notification is missing.

5.3 Spillovers by Geography and Information Environment

I next examine heterogeneity in spillover effects across geographic and media-market boundaries. Since PN Rule guidance suggests using media such as television and radio for acute health-based violations, I decompose neighboring-county exposure according to potential information channels. Figure 6 presents estimates from Equation 3, separately by public notification timing and by whether neighboring counties are located within the same Designated Market Area (DMA), outside the DMA, or are non-adjacent counties within the same DMA. Table 4 reports the point estimates and the figure plots the coefficients from column (4). Media markets are identified using Nielsen Designated Market Area (DMA) boundaries, which group counties based on the largest audience achieved by commercial TV stations.

Spillover effects in avoidance behavior are strongest when neighboring counties share the same media market as the affected county. Estimated spillover effects from neighboring counties' violations with on-time and delayed public notification within the same DMA are both approximately 7% and are statistically significant at the 5% level. Spillovers of similar magnitude are also observed for non-neighboring counties within the same DMA, with estimated effects of about 7% for both on-time and

delayed notification, significant at the 10% and 5% levels, respectively.

For neighboring counties outside the DMA, violations with on-time notification are associated with a smaller increase of about 5% (statistically significant at the 10% level), while the corresponding estimate for delayed notification is approximately 2% and not statistically distinguishable from zero. Although delayed public notification does not generate sharp responses at the time of disclosure in the event-study analysis, the positive average spillover effects documented here suggest that information about these violations may affect behavior in a diffuse and temporally dispersed manner that is not concentrated at a specific event week. Across all types of neighboring counties, violations with missing public notification generate effects close to zero and are not statistically distinguishable from zero.

Overall, these results indicate that spillover behavior dissipates with greater geographic distance and weaker informational links, and is strongest when counties share local media coverage. This pattern is consistent with spillovers operating primarily through media exposure rather than through purely geographic proximity. Spillover effects are highly localized: Appendix Figure A6 shows that estimated effects attenuate sharply and do not extend to second-degree neighboring counties (See Section 6.1 for details).

5.4 Heterogeneity Analysis

This section analyzes socio-demographic heterogeneity in avoidance behavior and spillover effects. Table 5 reports coefficients from regressions that interact the exposure variables with binary indicators for county characteristics, where each characteristic is split at the national median. The table separately reports exposure from own-county violations, neighboring counties within the same DMA, neighboring counties outside the DMA, and non-neighboring counties within the same DMA, focusing on violations with timely public notification. For each characteristic, the table also reports the p-value from a test of equality between the coefficients for the two subgroups.

Table 5 finds limited heterogeneity in avoidance behavior and spillover responses across socio-demographic characteristics. The main exception is rural status: own-county responses to timely public notification are substantially larger in rural counties, and spillover responses for more distant counties, particularly non-neighboring counties within the same DMA, are also stronger in rural areas. For most other characteristics, including income, education, race, age composition, political affiliation, language barriers, and measures of technological connectivity, differences in coefficients

across subgroups are small and statistically indistinguishable. Overall, these results indicate that avoidance behavior and spillover responses are broad-based rather than concentrated in narrowly defined demographic groups.

6 Robustness Checks and Extensions

6.1 Spatial Decay of Spillover Effects

In the previous section, I find that avoidance behavior responds not only to violations in neighboring counties but also to violations in non-neighboring counties when they share the same media market. It is therefore important to assess whether spillover effects attenuate with greater geographic distance. Table A13 reports estimates from Equation 3 augmented to include indicators for second-degree neighboring counties (neighbors of neighbors), both within the same DMA and outside the DMA, by public notification timing. Figure A6 plots the corresponding coefficient estimates from column (6).

Across specifications, spillover estimates for second-degree neighboring counties are small and statistically indistinguishable from zero. In addition, once second-degree exposure is included, spillover effects for first-degree neighboring counties outside the DMA also become statistically insignificant. In contrast, estimated effects for violations with on-time and delayed public notification in the home county and in first-degree neighboring counties within the same DMA remain stable. Spillovers from non-neighboring counties within the same DMA persist only for violations with on-time public notification.

Taken together, these results indicate that spillover effects are geographically localized and attenuate rapidly with distance, reinforcing the interpretation that both spatial proximity and shared information environments are necessary for spillovers to arise.

6.2 Alternative Definitions of Indirect Exposure

As a further exploration of possible information pathways, I estimate specifications that incorporate exposure measures based on (i) the Facebook Social Connectedness Index (SCI) and (ii) a socio-demographic similarity index. These measures are constructed analogously to the baseline DMA-based exposure variables but replace geographic adjacency or media-market overlap with alternative definitions of cross-county linkages. Each measure is defined separately for violations with on-time and delayed public notification using population-weighted exposure. Appendix Section C.1 provides details on variable construction and regression specifications.

Table A10 reports estimates from Equation A1, focusing on acute microbial violations occurring

in (i) the top five and bottom five socially connected counties based on Facebook friendship links and (ii) the top five socio-demographically closest counties based on the constructed distance metric. By construction, these groups exclude all geographic neighbors and counties within the same DMA.

Overall, the results indicate limited spillover effects through these alternative indirect exposure channels. Estimated coefficients for both on-time and delayed public notification are generally small and statistically indistinguishable from zero. While a few estimates for delayed notifications among highly socially connected or socio-demographically similar counties are marginally significant at the 10% level, these effects are not robust across specifications and are substantially smaller than the spillovers observed through shared media markets. These findings reinforce the interpretation that spillover behavior operates primarily through local media exposure rather than through broader social or demographic similarity alone.

6.3 Heterogeneity in Spillover to Neighboring Counties by Social Connectivity, Socio-Demographic Similarity and Prior Experience

While the previous subsection finds no evidence of spillovers from alternative indirect exposure channels, it remains possible that social connectedness or socio-demographic proximity moderates spillover effects originating from geographically proximate or media-linked counties. To examine this possibility, Table A11 reports estimates from regressions that interact exposure from all neighboring counties with binary indicators for above- versus below-median social connectedness, socio-demographic similarity, and recent experience with acute microbial violations. For each characteristic, the table also reports p-values from tests of equality between the coefficients for the two subgroups. Appendix Section C.1 provides details on variable construction.

Overall, the results indicate limited heterogeneity in spillover effects across these dimensions. Spillover responses do not differ systematically by social connectedness or by prior experience with acute microbial violations. The main exception concerns socio-demographic similarity: spillover effects are concentrated in counties that are less socio-demographically similar to their neighbors. This pattern suggests that spillovers may be stronger when violations occur in demographically distinct or larger neighboring counties, rather than reflecting homophily-based information transmission.

Consistent with this interpretation, Table A12 shows no evidence that social connectedness moderates spillover effects across different neighbor categories. Estimated differences between above- and below-median SCI counties are small and statistically insignificant for neighboring counties

within the same DMA, neighboring counties outside the DMA, and non-neighboring counties within the same DMA.

6.4 Health-Related Responses: OTC Gastrointestinal Medication Sales

Given that a substantial share of acute pathogen violations are associated with delayed or missing public notification, I next examine whether such violations are accompanied by increases in over-the-counter (OTC) gastrointestinal (GI) medication sales. Using NielsenIQ retail scanner data, these sales provide a proxy for short-run health responses if contaminated drinking water leads to acute gastrointestinal symptoms. Because symptom onset may occur with a delay, I estimate distributed-lag specifications that include up to four weeks following the violation start.

Table A14 reports coefficient estimates from regressions analogous to Equation 2, but with OTC GI medication sales as the outcome. Column (1) uses total GI medication sales, while Columns (2)–(4) separately consider diarrhea remedies, oral rehydration solutions, and antacids. All specifications focus on home-county violations and distinguish between timely, delayed, and missing public notification. Figure A7 plots the estimated dynamic responses for total GI medication sales.

Overall, the evidence of increased GI medication purchases is limited. For violations that were never publicly notified, there is a suggestive increase in total GI medication sales approximately one week after the violation start, corresponding to an increase of about 12%. In contrast, other lags exhibit no consistent pattern, and no systematic changes in GI medication sales are observed following violations with timely or delayed public notification. Taken together, these results provide a modest evidence of short-run health-related responses associated with unnotified acute pathogen violations. While these results should be interpreted cautiously, they are consistent with the idea that the absence of timely public notification may increase the risk of short-run health impacts.

7 Discussion and Conclusion

This paper shows that the timing of public notification plays a central role in inducing avoidance behavior during acute microbial drinking water violations. Such events are required to be reported to consumers within 24 hours, often through media alerts or door-to-door notices. I find that timely public notification substantially increases bottled water purchases, whereas delayed notification generates much weaker responses, and missing notification generates no detectable response. Event-study evidence further indicates that households do not respond to the onset of contamination itself, but rather to the arrival of salient public information.

In the full national sample, timely notification of acute microbial violations increases bottled water sales in fully exposed counties by 14.7%, while delayed notification increases sales by only 6%. Back-of-the-envelope calculations suggest that this is equivalent to additional sales of bottled water of about $2,4 million across the 2,283 counties in the sample between 2006-2019 (see Table A15) [8]. If violations with delayed and missing public notification had instead been reported on-time, the estimates imply an additional $2 million in bottled water sales (see Table A16. These differences underscore the importance of timely risk communication in prompting protective behavior.

Beyond directly affected communities, I also document spillover effects in nearby areas, particularly among counties that share the same local media market. A comparable full exposure from adjacent counties within the same Designated Media Market (DMA), with timely or delayed notification, is associated with 7% increase in bottled water sales in unaffected counties, which is equivalent to about $2.1 million additional purchases. Spillover effects attenuate with geographic distance and are largely absent outside shared media markets, suggesting that mass media plays a central role in transmitting risk information beyond the directly exposed population. Consistent with this interpretation, even counties with high social connectedness to the affected area exhibit no meaningful response when they are neither geographically adjacent nor located within the same DMA, indicating that social ties alone are insufficient to generate spillover behavior in the absence of exposure to local public warnings.

For violations that were never publicly notified, I find suggestive evidence of health-related responses in the form of increased over-the-counter gastrointestinal (GI) medication purchases. Sales rise by approximately 12% one week after the violation onset, corresponding to about $62,000 in additional purchases over the sample period (see Table A17). While this pattern is consistent with de-

8. This calculation is based on average bottled water sales of $23,717 and cumulative violation exposure across counties over the sample period.

layed or absent notification shifting responses away from preventive behavior and toward treatment, these estimates capture only a narrow subset of potential health-related costs. A full accounting of health impacts would require data on medical utilization, morbidity, or foregone earnings, which are beyond the scope of this study.

Taken together, the findings have direct relevance for ongoing efforts to improve drinking water safety and transparency. They indicate that rapid public communication substantially amplifies protective behavior in directly affected communities, while delayed or missing notification weakens these responses. At the same time, spillover effects imply that information disclosure can influence behavior beyond the targeted population, particularly in areas that share local media coverage. These results highlight the importance of communication strategies that deliver timely, salient information to affected communities while clearly delineating the geographic scope of risk to surrounding areas. Future research could examine how notification timing translates into health or economic outcomes beyond short-run avoidance behavior. Overall, the paper contributes to a more nuanced understanding of both the benefits and the limits of information-based environmental policy.

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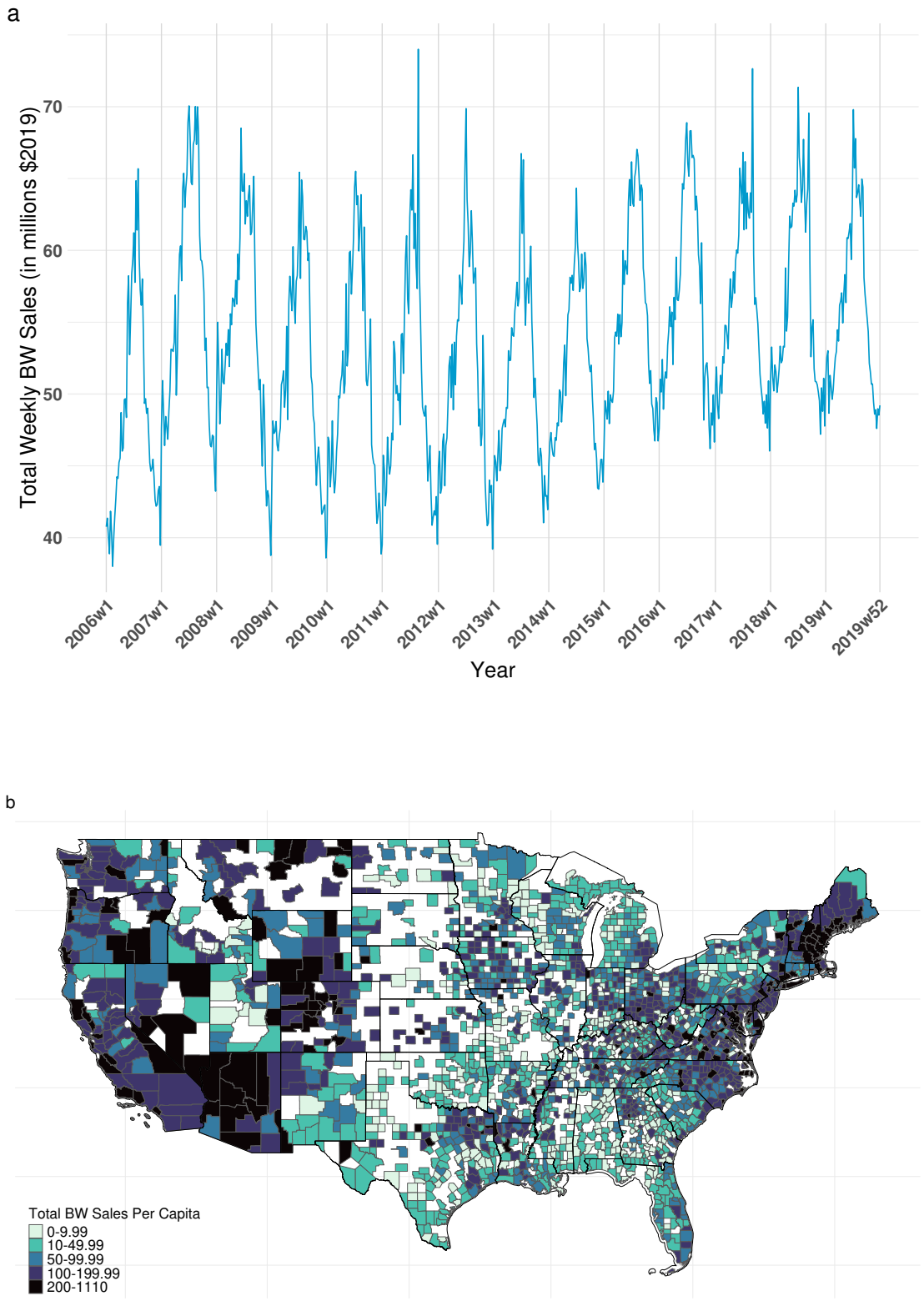
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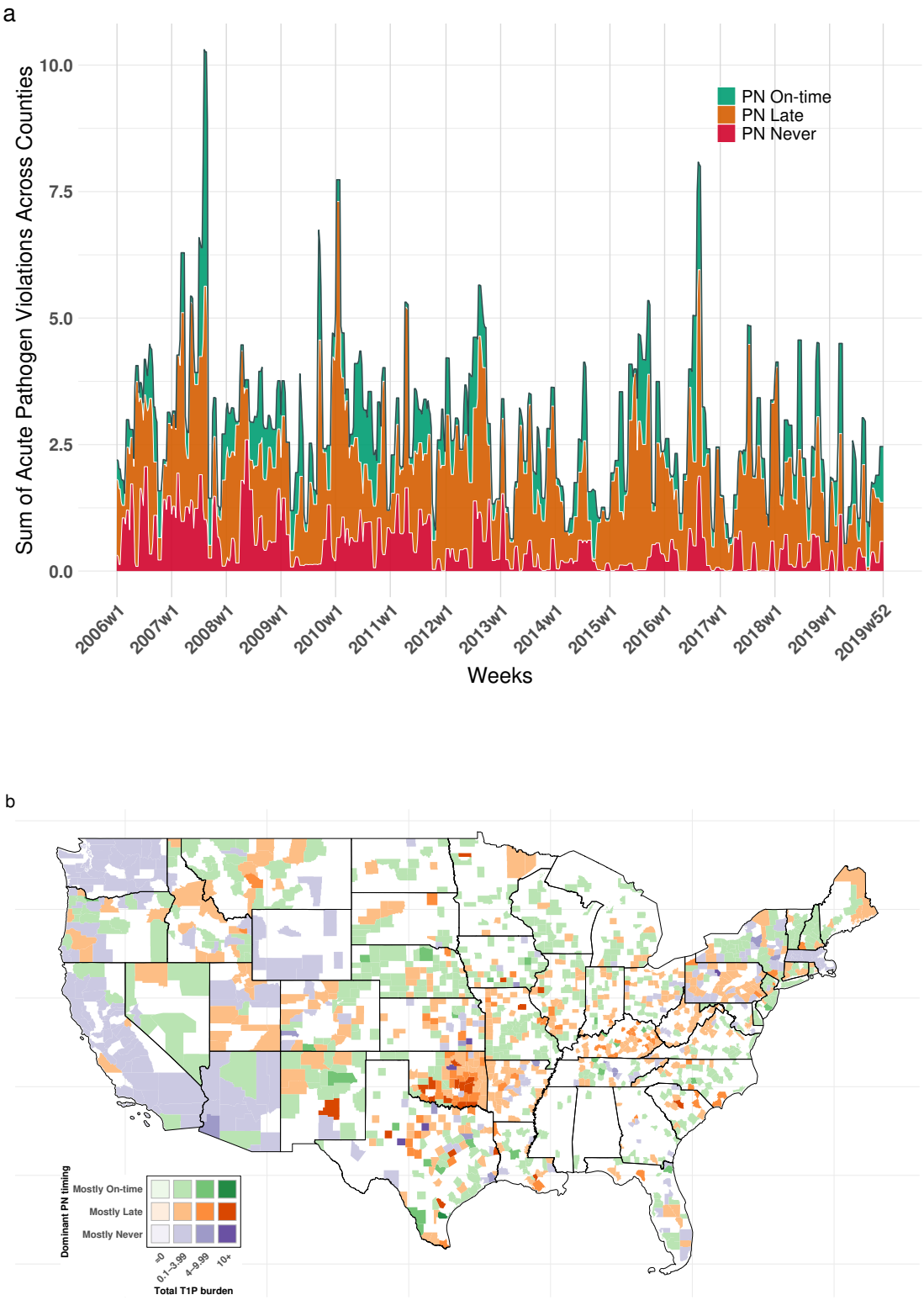
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Figure 1: Bottled Water Sales Across All Sample Counties



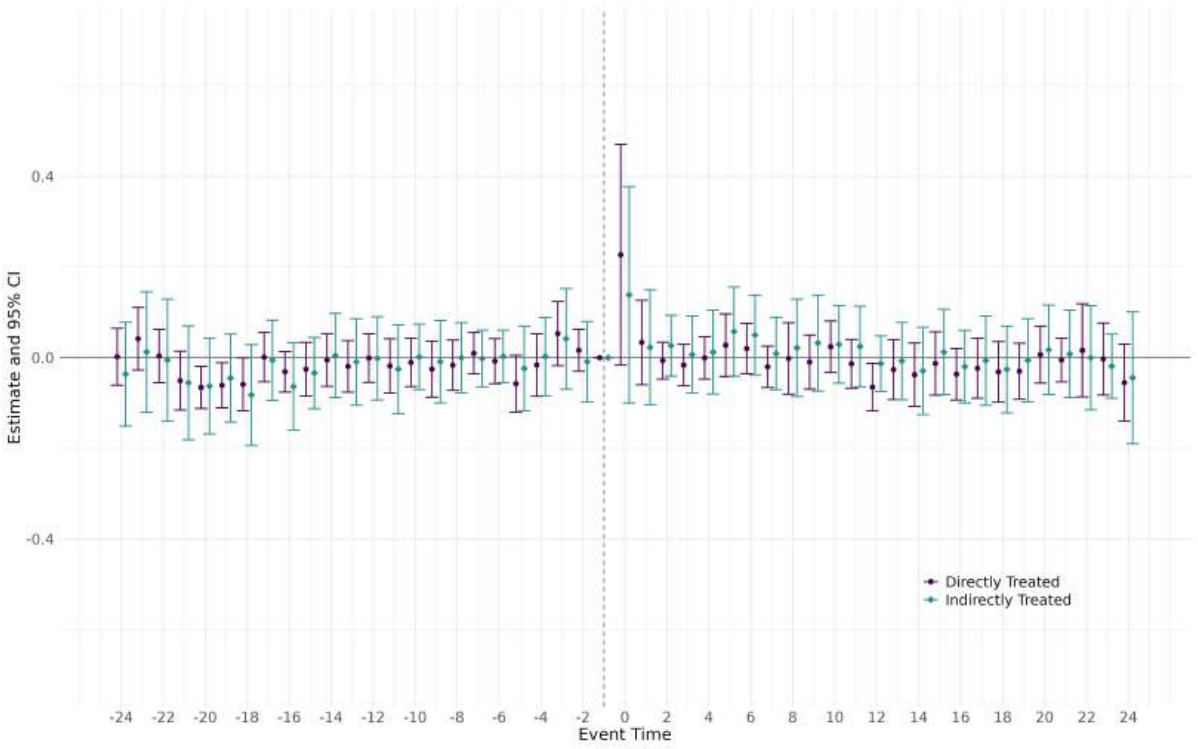
Note: Panel a graphs bottled water sales across all counties over sample period weeks (in millions \$2019). Panel b depicts total bottled water sales per capita during the sample period. White grids represent counties not present in the data due to sales not being covered by NielsenIQ. Total number of counties in sample: 2,283. Total number of weeks: 730.

Figure 2: Acute Pathogen violations by Public Notification Timing Across All the U.S. Counties



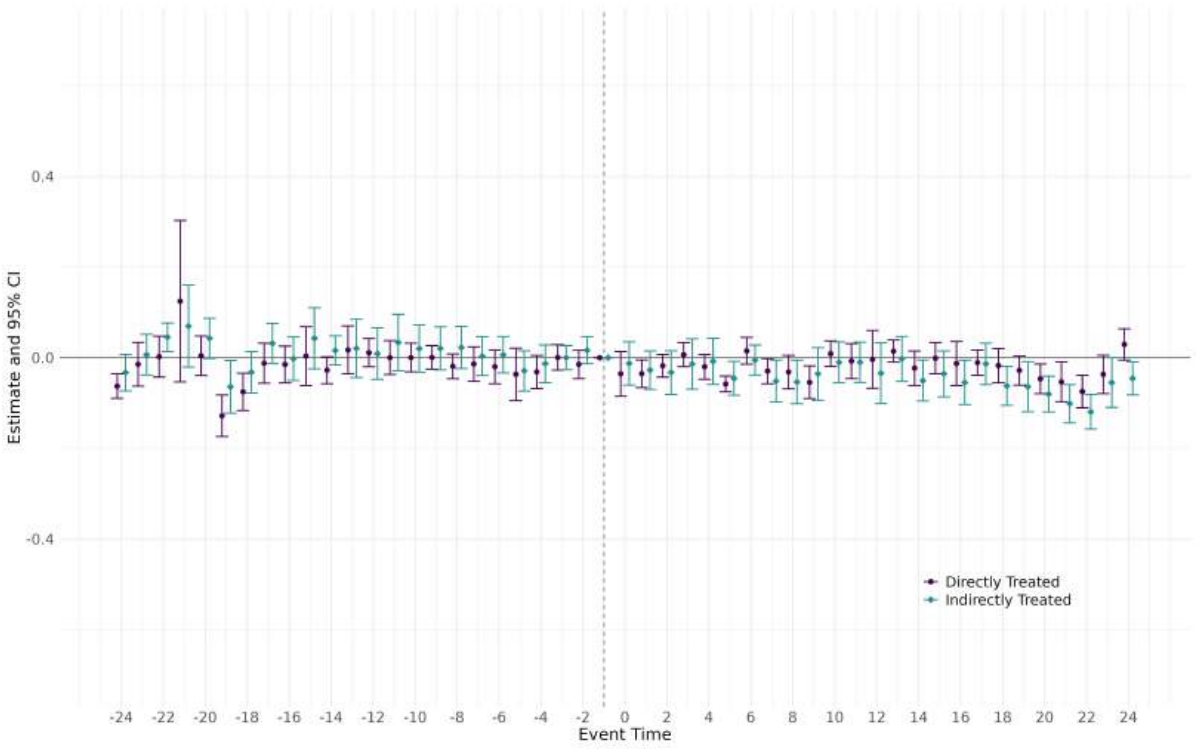
Note: Panel a graphs the total sum of Acute Pathogen violations by Public Notification Timing across all counties over the sample period. Panel b depicts the total sum of Acute Pathogen violations per county across the sample period. Total number of counties depicted: 3,108. Total number of weeks: 730.

Figure 3: Event Study of Avoidance Behavior and Spillover Effects Following Timely Public Notification of Acute Pathogen Violations



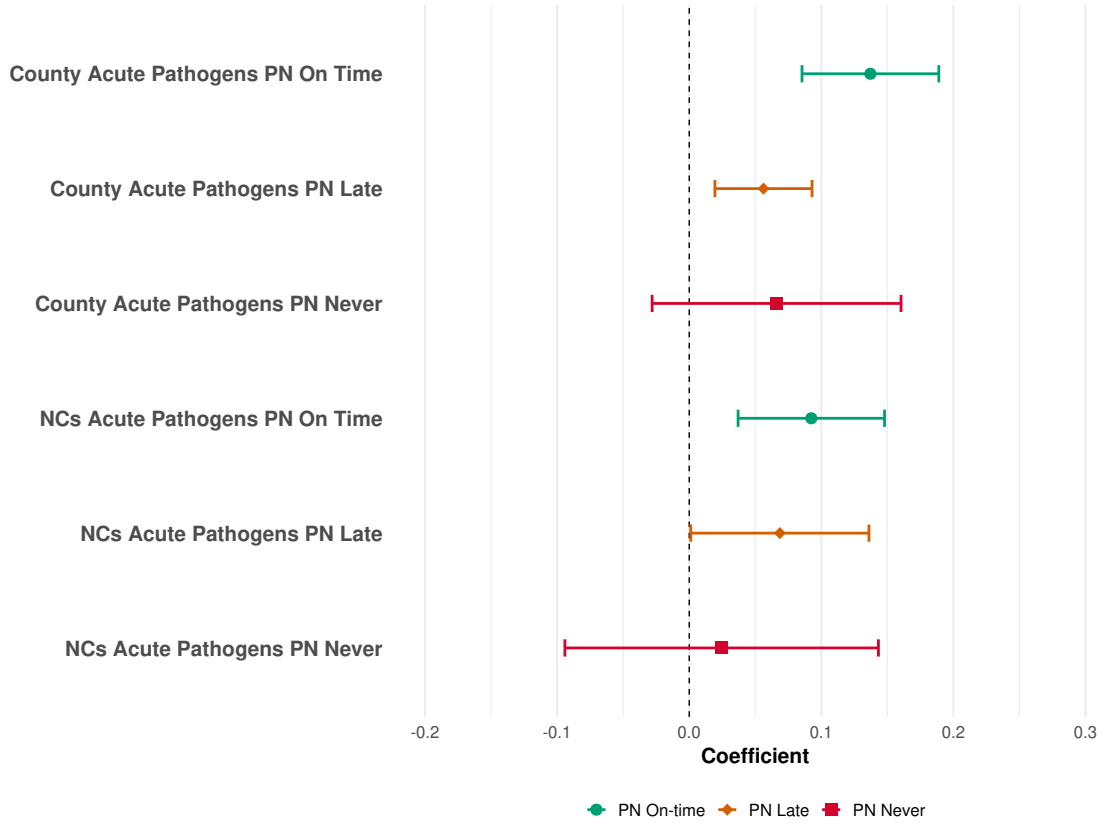
Note: Dependent variable is the log of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued on time. Event time 0 denotes the week of public notification. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure 4: Event Study of Avoidance Behavior and Spillover Effects Following Late Public Notification of Acute Pathogen Violations



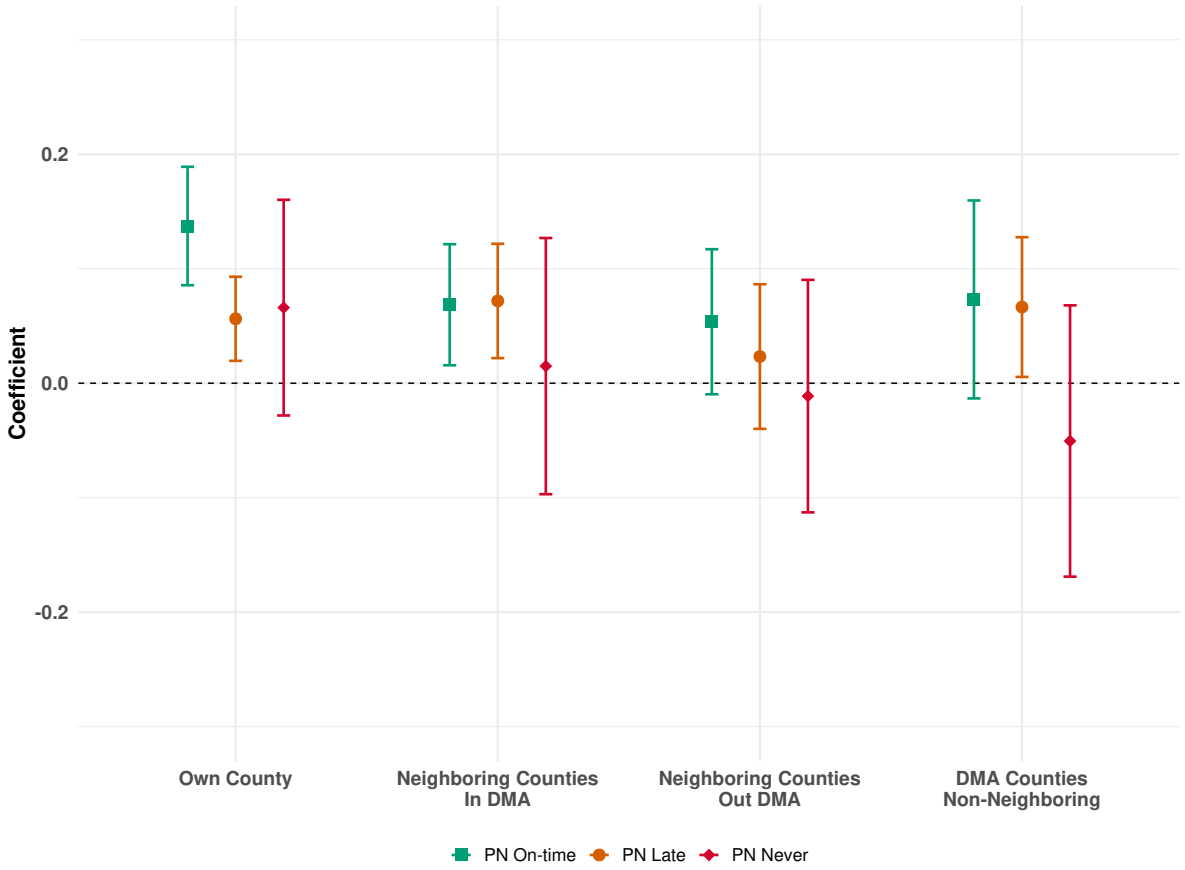
Note: Dependent variable is the log of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued late. Event time 0 denotes the week of public notification. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure 5: The Effects of Acute Pathogen Violations on Bottled Water Sales by Public Notification Timing



Note: Dependent variable is the log of bottled water sales. Horizontal lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and county×year, state×month and year×month fixed effects. Standard errors are clustered at the county level. *NCs* indicate Neighboring Counties.

Figure 6: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing



Note: Dependent variable is the log of bottled water sales. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and county×year, state×month and year×month fixed effects. Standard errors are clustered at the county level. *Neighboring Counties In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Table 1: Federal Regulatory Standards and Public Notification Requirements for Acute Pathogens

Rule	Contaminant	Standard	Population at Risk in PN	Health Effects in PN	Recommended Actions in PN
Total Coliform Rule (TCR), Revised Total Coliform Rule (RTCR)	Fecal Coliform, E. Coli	Maximum Contaminant Level (MCL): positive repeat sample or failure to test after positive routine sample	infants, young children, people with severely compromised immune systems	diarrhea, cramps, nausea, headaches, or other symptoms	boil water before drinking and using; use bottled water
Surface Water Treatment Rule (SWTR)	Turbidity	Treatment Technique (TT) Requirements: a single exceedance of the maximum allowable turbidity limit	NA	nausea, cramps, diarrhea and headaches	boil water before drinking and using; use bottled water
Disinfectants and Disinfection Byproducts (DBP) Rule	Chlorine dioxide	Maximum Residual Disenfectant Level (MRDL): a positive repeat exceedance or failure to sample in the next day	pregnant women, young children	problems with the nervous system and anemia	boil water before drinking and using

Note: The table summarizes the health standards, at-risk populations, and required public notification (PN) content for acute pathogen violations by rule and contaminant.

Table 2: Summary Statistics of Violation Frequency and Duration by Regulatory Rule (2006–2019)

	Rule	Contaminant	Code	Mean days	SD days	Min days	Pctl. 25	Median days	Pctl. 75	Max days	Count
1	Revised Total Coliform Rule	Revised Total Coliform Rule	Maximum Contaminant Level Violation, E. coli (RTCR)	28.26	4.45	1	29.00	30.00	30.00	31	487
2	Total Coliform Rule	Coliform (TCR)	Maximum Contaminant Level Violation, Acute (TCR)	30.25	9.41	4	29.00	30.00	30.00	91	1633
3	Stage 1 Disinfectants and Disinfection Byproducts Rule	Chlorine dioxide	Acute Maximum Residual Disinfectant Level	29.25	0.97	27	29.00	29.50	30.00	30	28
4	Interim and Long Term 1 Enhanced Surface Water Treatment Rule	Interim Enhanced Surface Water Treatment Rule	Monthly Turbidity Exceed (Enhanced SWTR)	29.38	1.62	2	29.00	30.00	30.00	30	2302
5	Interim and Long Term 1 Enhanced Surface Water Treatment Rule	Interim Enhanced Surface Water Treatment Rule	Single Turbidity Exceed (Enhanced SWTR)	29.05	2.70	2	29.00	30.00	30.00	31	1128

Note: The sample covers all community water systems (CWS) in the United States from 2006 to 2019. *Count* refers to the total number of violation events recorded during the sample period. *SD* denotes Standard Deviation; *Pctl* denotes Percentile.

Table 3: Summary Statistics of Key Variables in the National Sample (2006–2019)

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water sales (2019$)	23,717	94,237	0.1	489	3,356	13,112	4,283,638
Log bottled water sales	7.9	2.2	-2.3	6.2	8.1	9.5	15
Direct Violation Exposure by Public Notification Timing							
Own County Acute Pathogens — any PN timing	0.00087	0.019	0	0	0	0	1
Own County Acute Pathogens — PN on time	0.00023	0.01	0	0	0	0	1
Own County Acute Pathogens — PN late	0.00049	0.015	0	0	0	0	1
Own County Acute Pathogens — PN never	0.00016	0.008	0	0	0	0	1
Spillover Exposure							
NCs (all) Acute Pathogens — any PN timing	0.00092	0.013	0	0	0	0	0.85
NCs (all) Acute Pathogens — PN on time	0.00026	0.0081	0	0	0	0	0.8
NCs (all) Acute Pathogens — PN late	0.00052	0.0091	0	0	0	0	0.85
NCs (all) Acute Pathogens — PN never	0.00014	0.0044	0	0	0	0	0.78
NCs (In-DMA) Acute Pathogens — PN on time	0.00026	0.0089	0	0	0	0	0.96
NCs (In-DMA) Acute Pathogens — PN late	0.00049	0.011	0	0	0	0	0.95
NCs (In-DMA) Acute Pathogens — PN never	0.00013	0.005	0	0	0	0	0.8
NCs (Out-DMA) Acute Pathogens — PN on time	0.00015	0.0063	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN late	0.00046	0.011	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN never	0.00012	0.0046	0	0	0	0	0.72
DMA Non-NC Acute Pathogens — PN on time	0.00026	0.0063	0	0	0	0	0.82
DMA Non-NC Acute Pathogens — PN late	0.00051	0.0076	0	0	0	0	1
DMA Non-NC Acute Pathogens — PN never	0.00014	0.0039	0	0	0	0	0.68
Total number of neighboring counties (NCs)	6	1.3	1	5	6	7	14
Number of NCs in DMA	4.2	1.7	0	3	4	5	11
Number of NCs out of DMA	1.8	1.6	0	0	2	3	9
Controls							
Weekly max temperature	24	9.6	-20	18	26	31	49
Weekly total precipitation	20	25	0	2.5	12	29	963
Socio-Demographic Variables							
County Median HH Income ($2012)	46,416	12,344	19,624	38,387	44,253	51,641	122,068
County Share Child Pop.	0.19	0.028	0.073	0.18	0.19	0.21	0.35
County Share Elderly Pop.	0.15	0.038	0.046	0.13	0.15	0.17	0.45
County Share Coll. Degree	0.22	0.039	0.087	0.19	0.22	0.24	0.35
County Share Black	0.098	0.15	0	0.0077	0.029	0.12	0.84
County Share Hispanic	0.086	0.13	0	0.018	0.036	0.089	0.98
County Share Presid Votes Republican	0.33	0.086	0.034	0.28	0.33	0.38	0.64
Share Rural Pop.	0.75	0.36	0	0.45	1	1	1
Share Lang. Barrier Pop.	0.18	0.07	0.051	0.13	0.17	0.21	0.58
Share No Fixed Broadband Pop.	0.13	0.17	0	0.015	0.061	0.18	1
Share No Broadband or Computer Pop.	0.19	0.081	0.028	0.13	0.17	0.23	0.61
County Population	137,132	382,265	1,642	19,725	40,403	103,514	10,081,570

Note: Number of counties in the sample is 2,283. *NCs In-DMA* (*Out-DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-NC* refers to non-adjacent counties within the same DMA.

Table 4: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing

	Log Sales BW			
	(1)	(2)	(3)	(4)
Own County Acute Pathogens — PN on time	0.1380***	0.1376***	0.1372***	0.1373***
	(0.0264)	(0.0264)	(0.0264)	(0.0264)
Own County Acute Pathogens — PN late	0.0561***	0.0561***	0.0562***	0.0563***
	(0.0187)	(0.0188)	(0.0188)	(0.0187)
Own County Acute Pathogens — PN never	0.0660	0.0660	0.0661	0.0660
	(0.0481)	(0.0481)	(0.0481)	(0.0481)
NCs (In-DMA) Acute Pathogens — PN on time		0.0707***	0.0703***	0.0685**
		(0.0268)	(0.0269)	(0.0270)
NCs (In-DMA) Acute Pathogens — PN late		0.0731***	0.0731***	0.0719***
		(0.0255)	(0.0255)	(0.0255)
NCs (In-DMA) Acute Pathogens — PN never		0.0151	0.0151	0.0149
		(0.0571)	(0.0571)	(0.0571)
NCs (Out-DMA) Acute Pathogens — PN on time			0.0534*	0.0537*
			(0.0323)	(0.0323)
NCs (Out-DMA) Acute Pathogens — PN late			0.0233	0.0233
			(0.0322)	(0.0322)
NCs (Out-DMA) Acute Pathogens — PN never			-0.0114	-0.0113
			(0.0519)	(0.0518)
DMA Non-NC Acute Pathogens — PN on time				0.0732*
				(0.0441)
DMA Non-NC Acute Pathogens — PN late				0.0665**
				(0.0311)
DMA Non-NC Acute Pathogens — PN never				-0.0505
				(0.0605)
Temp Max Control	Yes	Yes	Yes	Yes
Total Precip. Control	Yes	Yes	Yes	Yes
R^2	0.99193	0.99193	0.99193	0.99193
Observations	1,649,604	1,649,604	1,649,604	1,649,604
County–Year fixed effects	✓	✓	✓	✓
State-Month fixed effects	✓	✓	✓	✓
Year–Month fixed effects	✓	✓	✓	✓

Note: Clustered (County) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. *Neighboring Counties In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Table 5: Heterogeneity in Spillover Behavior Across Socio-Demographic Characteristics

	Violation Exposure Specification			
Row	Own (PN On-time)	NC in DMA (PN On-time)	NC out of DMA (PN On-time)	DMA non-NC (PN On-time)
Below Median HH Income	0.139*** (0.033)	0.082* (0.034)	0.027 (0.052)	0.028 (0.047)
Above Median HH Income	0.134** (0.044)	0.054 (0.042)	0.066 (0.040)	0.109 (0.065)
p(diff)	p=0.929	p=0.606	p=0.548	p=0.313
Below Median Coll Degree	0.125*** (0.036)	0.085* (0.033)	0.019 (0.040)	0.109 (0.059)
Above Median Coll Degree	0.151*** (0.039)	0.050 (0.043)	0.071 (0.044)	0.032 (0.062)
p(diff)	p=0.623	p=0.524	p=0.385	p=0.372
Below Median Child Pop	0.165*** (0.041)	0.073 (0.042)	0.128* (0.051)	0.128 (0.066)
Above Median Child Pop	0.122*** (0.034)	0.069* (0.034)	0.018 (0.041)	0.015 (0.049)
p(diff)	p=0.426	p=0.936	p=0.088	p=0.168
Below Median Elderly Pop	0.125*** (0.033)	0.050 (0.031)	0.038 (0.032)	0.012 (0.068)
Above Median Elderly Pop	0.167*** (0.042)	0.123* (0.053)	0.104 (0.084)	0.164*** (0.048)
p(diff)	p=0.437	p=0.237	p=0.463	p=0.066
Below Median Hispanic Pop	0.131*** (0.030)	0.009 (0.046)	0.157 (0.087)	-0.025 (0.061)
Above Median Hispanic Pop	0.141*** (0.039)	0.095** (0.031)	0.021 (0.032)	0.114* (0.054)
p(diff)	p=0.836	p=0.117	p=0.142	p=0.087
Below Median Black Pop	0.184*** (0.047)	0.124** (0.044)	0.075 (0.053)	0.096 (0.051)
Above Median Black Pop	0.114*** (0.032)	0.023 (0.030)	0.035 (0.038)	0.061 (0.067)
p(diff)	p=0.216	p=0.055	p=0.536	p=0.676
Below Median Republican	0.138*** (0.032)	0.049 (0.034)	0.061 (0.034)	0.101 (0.060)
Above Median Republican	0.135** (0.045)	0.105* (0.043)	0.041 (0.074)	0.035 (0.058)
p(diff)	p=0.951	p=0.315	p=0.799	p=0.431
No Large Language-Barrier Pop.	0.162*** (0.037)	0.073 (0.039)	0.136* (0.056)	0.086 (0.049)
Large Language-Barrier Pop.	0.119** (0.036)	0.069 (0.036)	0.035 (0.037)	0.070 (0.062)
p(diff)	p=0.412	p=0.932	p=0.132	p=0.839
No Large Fixed-Broadband-Limited Pop.	0.197*** (0.052)	0.033 (0.044)	0.071 (0.050)	0.101* (0.049)
Large Fixed-Broadband-Limited Pop.	0.113*** (0.031)	0.086** (0.032)	0.038 (0.042)	0.051 (0.073)
p(diff)	p=0.164	p=0.324	p=0.620	p=0.567
No Large Broadband+Computer-Limited Pop.	0.162*** (0.047)	0.066 (0.043)	0.063 (0.042)	0.079 (0.074)
Large Broadband+Computer-Limited Pop.	0.127*** (0.032)	0.074* (0.033)	0.036 (0.045)	0.072 (0.038)
p(diff)	p=0.548	p=0.892	p=0.665	p=0.934
Non-Rural	0.075* (0.034)	0.061 (0.036)	-0.026 (0.046)	-0.048 (0.053)
Rural	0.215*** (0.042)	0.079* (0.039)	0.094* (0.044)	0.119* (0.055)
p(diff)	p=0.010	p=0.738	p=0.060	p=0.028

Note: The table reports coefficients from interactions between the exposure variable and binary indicators for county characteristics (split at the national median). $p(diff)$ reports the p-value from a test of equality between the coefficients of the two subgroups. Regressions include categorical controls for precipitation and temperature and county×year, state×month and year×month fixed effects. Standard errors clustered at the county level are shown in parenthesis. Number of observations: 1,649,604. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

A Background: Additional Details

A.1 Community Water Systems

Among the community water systems, more than 54% are of very small size, serving less than 500 people and about 500 systems are characterized by the EPA as "very large" which have service population of greater than 100,000 people. Commonly they are owned and operated by local governments except for a small percentage that are run by private organizations (Keiser et al. 2023). Their operations begin with getting the water from groundwater or surface waters, such as lakes and rivers. Next they treat the sourced water from manmade and biological contaminants using different processes. The cleaned water is then distributed to consumers.

A.2 Public Notification Rule

EPA distinguishes three public notification tiers. Tier 1 notices apply to violations that pose an *acute* and serious risk to public health from short-term exposure. For these violations, systems must issue a public notice within 24 hours of learning of the violation, typically through high-visibility channels such as local television and radio, newspaper notices, public postings, or direct delivery. Tier 2 notices cover other health-based violations that present serious health risks from *long-term* exposure rather than immediate acute illness. Because these situations are less urgent, systems have up to 30 days to notify consumers, and the notices can be mailed, included in water bills, or published in a local newspaper. Tier 3 notices are used for the remaining situations, most commonly monitoring and reporting violations. These notices may be combined with annual Consumer Confidence Reports and must be provided within one year of the system learning of the violation (USEPA 2010, 2023d; USEPAOIG 2019).

The SDWA included provisions to notify public about their systems' drinking water quality and EPA established its first public notification (PN) rules in 1976 with later revisions in 1987. The 1992 Government Accountability Office (GAO) review found low level of compliance with the PN rules across water utilities and insufficient enforcement by states and criticized the PN process to be too burdensome for systems (USGAO 1992). The 1996 amendments to the SDWA called EPA to change the regulation to focus on notifying during acute serious violations and making the PN process less cumbersome for systems. These changes were implemented in the revised PN rule issued in 2000. Later promulgations of the NPDWR also amended related PN regulations. EPA issued PN guidance

documents to water systems and states in 2010 and 2023 (USEPA 2023d).

Although the PN rule was last updated in 2000 and specifies only media outlets common at that time, the PN Handbook update in 2010 discusses the possibility of using e-mails and the internet. But it cautions against relying on it as a main delivery method (USEPA 2010). The 2023 update of the PN Handbook adds that large systems should use email, website and social media platforms in addition to traditional methods, however, it doesn't apply to our analysis as the sample covers the pre-2023 period (USEPA 2023c).

During the violation period, some systems might provide free or discounted bottled water to the service population (Allaire et al. 2019; Christensen, Keiser, and Lade 2019). The PN Rule suggests following up with the public or providing "problem corrected" notices via radio, television, public posting or personal delivery methods once the violation is resolved but leaves the requirement to be decided by each state (USEPA 2010). It also requires providing notifications in other languages if a "large proportion" of the population served by a water system does not speak English (USEPA 2010). However, the rule leaves it to states to define what constitutes a "large proportion" or in the absence of such state-level regulations, the rule lets the systems decide it.

The PN Handbook provides suggestions on how to prevent overreactions to a public notice. It discusses the role of public education, especially for recurring problems such as nitrate violations, and working with experts such as local healthcare professionals, university experts, or advocacy group leaders.

B Data: Additional Details

B.1 Drinking Water Violations

I focus on Tier 1 violations whose public notices require rapid communication, including via media, and typically advise consumers to boil water or use an alternative source; I refer to this group as *Acute Pathogens* (see Section 3.1). I follow Allaire et al. (2019) in violation classification. Table 1 summarizes the mapping from specific SDWA rules and contaminants to these categories, along with the populations at risk, stated health effects, and recommended actions in the corresponding public notices (USEPA 2010).

Compared to Allaire et al. (2019), I also keep systems that serve less than 500 people, which comprise about 50% of community water systems. The authors motivated the exclusion of the very small community water systems by their having different monitoring requirements and irregular reporting (Allaire et al. 2019). However, Michielssen, Vedrin, and Guikema 2020 note that after the 2015 Revised Total Coliform Rule (RTCR), very small systems accounted for an increased share of health-based violations. Including very small systems does not affect the interpretation of the results, as the empirical analysis aggregates violations to the county level using population weights, limiting the influence of any single small system.

B.2 Public Notification Timing

The SDWIS database does not record the exact dates when contamination begins or ends. Instead, it reports the start and end of the administrative noncompliance period, as well as the date when a system returned to compliance. These fields are defined in the SDWIS data dictionaries as regulatory noncompliance windows rather than the physical duration of unsafe water exposure. Consistent with EPA guidance, pathogen rules such as the Total Coliform Rule are evaluated over monthly compliance periods. As a result, SDWIS typically records Tier 1 pathogen violations with noncompliance durations of approximately 30 days, as shown in Table 2. These patterns reflect regulatory compliance structures rather than the underlying length of contamination. Importantly, however, the SDWIS noncompliance period corresponds to the window during which a violation is formally recognized by regulators and therefore constitutes the relevant reference period for public notification and enforcement actions, even if it does not coincide exactly with the physical duration of unsafe water.

Using this information, I construct measures of public notification timing based on the effective violation end date, the date a primacy agency received or issued a public notification, and the date a boil water order (BWO) was issued, when available. A public notification is classified as *on-time* under either of the following conditions: (i) the state issued a public notification or boil water order on or before the effective violation end date; or (ii) the state received certification of public notification from the water system on or before the effective violation end date or within eleven days thereafter, consistent with the ten-day certification requirement specified in the Public Notification Rule. If the state received certification of public notification after this window, the notification is classified as *late*. Violations for which there is no record of any public-notification-related informal enforcement action are classified as *never notified*. Figure A1 displays the distribution of the constructed public notification timing measures at the system level across all violation categories.

B.3 Violation Measures Construction

Aggregation to County-Week Violations. Counties may be served by multiple community water systems (CWSs). I aggregate CWS-level violations to the county-week level using population weights. Let P_{ic} denote the population served by system i in county c, and let $P_c = \sum_{i \in I_c} P_{ic}$ denote the total county served population. Let $k_{i,cyw}$ denote the number of days in week w of year y during which CWS i serving county c was out of compliance. The weekly acute-pathogen exposure for county c is defined as $V_{cyw} = \sum_{i \in I_c} \left(\frac{k_{i,cyw}}{7} \cdot \frac{P_{ic}}{P_c} \right)$.

I similarly construct timing-specific measures. For example, the on-time exposure is $V_{cyw}^{\text{On}} = \sum_{i \in I_c} \left(\frac{k_{i,cyw}}{7} \cdot \frac{P_{ic}}{P_c} \cdot \mathbf{1}\{\text{on-time}\} \right)$, with analogous definitions for V_{cyw}^{Late} and V_{cyw}^{Never}. These three measures are mutually exclusive and exhaustive by construction.

Neighboring-County Exposure. To quantify potential behavioral spillovers, I construct timing-specific acute-pathogen exposure measures for counties that share a physical border with county c. Let $N(c)$ denote the set of neighboring counties, as defined by the U.S. Census adjacency file. For each timing state $s \in \{\text{On}, \text{Late}, \text{Never}\}$, I define $V_{cyw}^{s,\text{NC}} = \sum_{n \in N(c)} \left(V_{nyw}^{s} \cdot \frac{P_n}{\sum_{n \in N(c)} P_n} \right)$.

These measures capture the population-weighted intensity of acute-pathogen violations occurring in the immediate geographic surroundings of county c, with each neighboring county's exposure weighted by its population share among all adjacent counties.

B.4 Scanner Data: GI Medication Sales

Gastrointestinal (GI) medications include the product modules for diarrhea remedies, electrolyte oral rehydration solutions (ORS), and antacids. To construct the ORS subset, I begin with the Nutritional Supplements module and filter products based on retailer UPC descriptions. I retain items explicitly marketed as oral rehydration or electrolyte replacement products, including liquids, powders, freezer pops, and strips, and exclude sports drinks, energy beverages, lifestyle hydration products, and general nutritional supplements [9]

B.5 NielsenIQ Homescan (HMS) Data

As a robustness check, I complement the RMS store-level sales data with household-level purchase data from the NielsenIQ Consumer Panel (Homescan), provided by the Kilts Center. The Homescan panel includes approximately 40,000–60,000 households per year and records UPC-level purchases across all retail formats, including outlets not covered by RMS. For each transaction, the data report the purchase date, UPC, quantity, expenditure, and the household's three-digit ZIP code, along with detailed demographic characteristics.

Households remain in the panel for at least one calendar year, though panel tenure varies. Because prices are self-reported for purchases made outside RMS-covered stores, measurement error is greater than in scanner data. Following Einav, Leibtag, and Nevo (2010), I trim observations below the 1st percentile and above the 99th percentile of the within-year bottled water price distribution. I construct household–month bottled water spending as the sum of constant-2019-dollar expenditures across all bottled water UPCs. After cleaning, the analysis sample contains 165,082 households with positive bottled water purchases at the monthly level between 2006 and 2019.

B.6 Sociodemographics and Broadband Access

I use county-level sociodemographic variables from the 2015-2019 5-year American Community Survey (ACS) data for 2012 to apply in my heterogeneity analyses. I focus on household median income and composition of the population for factors such as college education degree, children

9. Inclusion requires electrolyte-related terms in the UPC description (e.g., "electrolyte," "ELC," "oral rehydration," "ORS") or membership in well-known ORS product families such as *Pedialyte*, *Enfalyte*, *Liquilytes*, *Oralyte*, or *Suero*. I additionally retain pediatric or medical cues when present (e.g., "pediatric," "PDTRC"). I exclude products whose branding or descriptors indicate energy or performance positioning, vitamin or protein blends, or general wellness beverages (e.g., sports drink lines or lifestyle hydration mixes).

[10], elderly, Black, Hispanic and Nonwhite. I use the share of votes for the Republican Presidential candidate in 2012 from National Neighborhood Data Archive (NaNDA).

I employ county-level data on the high-speed internet and computer access provided by Census and the National Telecommunications and Information Administration (NTIA) administered under Digital Equity Act (DIA) of 2021. The main variables include 2021 population estimates that lack fixed broadband service (high-speed internet) and 2019 population estimates that lack a computing device and/or broadband subscription. [11] In addition, I use other variables such as if the population is "rural" and the estimate of the population with language barriers. [12] [13] I use these variables in my heterogeneity analyses.

B.7 Information Channels

Social Connectedness-Based Exposure (SCI). To capture non-geographic information spillovers, I construct exposure measures based on social connectedness between counties using the Facebook Social Connectedness Index (SCI), which measures the relative intensity of social ties between two locations based on the number of Facebook friendship links.

Let SCI_{cj} denote the scaled Social Connectedness Index between counties c and j. For each county c, I aggregate pairwise SCI values to county-level connectivity scalars by taking population-weighted averages over predefined peer sets. Specifically, for a given peer set $G(c)$, $\overline{\text{SCI}}_c^G = \sum_{j \in G(c)} \omega_{cj} \, \text{SCI}_{cj}$ and $\omega_{cj} = \frac{\text{Pop}_j}{\sum_{k \in G(c)} \text{Pop}_k}$, where Pop_j denotes the population of county j.

I construct several SCI-based connectivity measures that parallel the geographic neighboring-county exposure. These include: (i) all geographic neighbors of c; (ii) neighboring counties within the same designated market area (DMA); (iii) neighboring counties outside the DMA; (iv) all other counties in the same DMA excluding c; and (v) DMA peers excluding geographic neighbors. These measures capture variation in the strength of social ties across geographic and media-market boundaries.

10. I use the share of the population between ages 0-10
11. That was the only available year in the data. I am making an assumption that yearly internet access for counties for the period between 2006-2019 is quite correlated with the 2021 measure.
12. Variable "rural" is based on the definition of "rural areas" from DIA.
13. Having a language barrier applies when a person speaks English less than "very well" or has low levels of literacy. It is derived from 2015-2019 ACS file and 2017 Program for the International Assessment of Adult Competencies (PIAAC) Household file and PIAAC State and County Small Area Estimates of Adult Skills on Literacy and Numeracy (for low literacy) from the National Center for Education Statistics. (US Census Bureau, National Telecommunications and Information Administration, and Department of Commerce 2023)

Socio-demographic similarity exposure (SD-Close). Socio-demographic similarity is measured using a standardized Euclidean distance between counties. For county i and county j, let X_{ik} denote the value of the k-th standardized characteristic. I use eleven characteristics: median household income, unemployment rate, share of households below poverty, share children, share elderly, share college degree, share Black, share Hispanic, share vacant housing units, the Republican share of the 2012 presidential vote, and population-density bins. The raw distance is $D_{ij} = \sqrt{\sum_{k=1}^{11}(X_{ik} - X_{jk})^2}$, and is normalized to the unit interval: $D_{ij}^{\text{norm}} = \frac{D_{ij} - \min_{(i',j')} D_{i'j'}}{\max_{(i',j')} D_{i'j'} - \min_{(i',j')} D_{i'j'}}$.

C Additional Robustness Checks

C.1 Information Channels

This section defines the alternative exposure measures used to examine whether acute-pathogen violations occurring outside the focal county may be associated with local bottled water demand through non-geographic information channels. I consider two channels: (i) social connectedness, measured using the Facebook Social Connectedness Index (SCI), and (ii) socio-demographic similarity (SD-close). Each exposure variable is defined for the three public-notification timing states $s \in \{\text{On-time}, \text{Late}, \text{Never}\}$ and is constructed analogously to the baseline neighboring-county measure.

Social Connectedness-Based exposure (SCI). For each county c, let $\mathcal{L}_c^{\text{TopSCI}}$ denote the set of the five counties with the strongest SCI links to c, excluding counties that share a border or DMA with c. The SCI-based violation exposure is then $V_{cyw}^{s,\text{TopSCI}} = \sum_{j \in \mathcal{L}_c^{\text{TopSCI}}} \omega_{cj} V_{jyw}^{s}$, where ω_{cj} are population weights normalized to sum to one over the list $\mathcal{L}_c^{\text{TopSCI}}$, and V_{jyw}^{s} is the timing-specific home-county exposure for county j as defined in Appendix B.3. Similarly, I construct $V_{cyw}^{s,\text{BottomSCI}}$ for the set of the five counties with the weakest SCI links to c, $\mathcal{L}_c^{\text{BottomSCI}}$.

Socio-demographic similarity exposure (SD-close). Let $\mathcal{L}_c^{\text{SDClose}}$ denote, for county c, the five counties with the smallest normalized socio-demographic distance, D_{cj}^{norm}, excluding (i) counties that share a border with c and (ii) counties in c's DMA. The SD-close violation exposure is then $V_{cyw}^{s,\text{SDClose}} = \sum_{j \in \mathcal{L}_c^{\text{SDClose}}} \omega_{cj} V_{jyw}^{s}$, where ω_{cj} are population weights normalized over the SD-close list.

Regression specification. For each information channel $\mathcal{L} \in \{\text{TopSCI}, \text{BottomSCI}, \text{SDClose}\}$, the estimating equation is

$$S_{cyw} = \sum_{s \in \{\text{On,Late,Never}\}} \left(\beta_s V_{cyw}^{s} + \lambda_s^{\mathcal{L}} V_{cyw}^{s,\mathcal{L}}\right) + \delta W_{cyw} + \alpha_{cy} + \mu_{pm} + \gamma_{ym} + \varepsilon_{cyw}. \tag{A1}$$

The regression includes the same set of controls and fixed effects as in Equation 2.

Above-median Social Connectedness to Neighboring Counties. To allow for heterogeneous spillover effects by the strength of social connectedness, I construct binary indicators for high SCI exposure. For each peer set G, let $\overline{\text{SCI}}_c^{G}$ denote the population-weighted average Social Connectedness Index between county c and the counties in G. I define the high-SCI indicator as $1\{\text{High SCI}_c^{G}\} =$

$1\{\overline{\text{SCI}}_c^G > \widetilde{\text{SCI}}^G(\cdot)\}$, where $\widetilde{\text{SCI}}^G(\cdot)$ denotes the relevant median threshold for peer set G. Different reference medians are used across peer sets to ensure stable classification in small groups. For geographic-neighbor peer sets, I benchmark against the state-level median.[14] For DMA-based peer sets, I benchmark against the DMA-level median when sufficiently many counties within the DMA have finite values.[15]

Above-median Socio-Demographic Closeness to Neighboring Counties. To allow for heterogeneity in spillover effects by socio-demographic similarity between counties, I construct binary indicators based on socio-demographic proximity. For each county c, let $\overline{\text{SD}}_c$ denote the mean normalized socio-demographic distance between county c and its geographic neighboring counties. Socio-demographic distance is computed using a normalized distance metric based on county-level demographic characteristics, and smaller values correspond to greater socio-demographic similarity. I define the high-proximity indicator as $1\{\text{High SD Close}_c\} = 1\{\overline{\text{SD}}_c < \widetilde{\text{SD}}\}$, where $\widetilde{\text{SD}}$ denotes the median of $\overline{\text{SD}}_c$ across all counties in the sample.

Recent violation history (past two years). To capture whether prior experience with drinking water violations affects responses to new information, I construct indicators for recent violation history at the county level. Let $V_{c\tau}$ denote the county-level weekly violation indicator for county c in week τ. I define a two-year history indicator as $\text{Past2Y}_{ct} = 1\{\max_{\tau \in [t-104,\, t]} V_{c\tau} > 0\}$, where the window spans the current week and the preceding 104 weeks. I construct analogous indicators separately for Acute pathogens overall and Acute pathogens by public-notification timing (on-time and late). These indicators are time-varying at the county level and equal one once a county has experienced at least one violation of the relevant type within the past two years.

C.2 Household-Level Evidence from NielsenIQ Homescan

To assess whether store-level responses reflect household avoidance behavior rather than retailer-side adjustments, I replicate the analysis using NielsenIQ Homescan data. Table A18 reports summary statistics for the household–month panel, with acute microbial violations aggregated to the county–month level. Table A19 reports estimates from a specification analogous to Equation 3, where the dependent variable is the log of bottled water purchases plus one, reflecting the large share of zero-purchase months at the household level.

14. When a state median is undefined (e.g., due to no finite values), I fall back to the national median.
15. If fewer than five counties in the DMA have finite values, I fall back to the state median, and if necessary, the national median.

The specification includes the same weather controls as in the county-level analysis, along with county-by-year, state-by-month, and year-by-month fixed effects. In addition, I include household fixed effects, which absorb all time-invariant household characteristics, such as baseline bottled water preferences, income, household size, and long-run health behaviors. As a result, identification comes from within-household changes in bottled water purchasing over time in response to variation in acute pathogen violations and public notification timing within counties, after accounting for county-specific trends, regional seasonality, national shocks, and weather-driven shifts in water demand. Under this design, the timing of violation events is plausibly exogenous to short-run household purchasing behavior.

Figure A8 plots the coefficient estimates from Column (4) of Table A19. Overall, the pattern of estimates closely mirrors the results from the Retail Scanner (RMS) analysis across public notification timing and exposure channels. In particular, estimated effects are largest for on-time public notification and attenuate for delayed or missing notification, with spillover responses concentrated among counties that share the same media market. At the household level, however, the estimates are generally smaller and less precisely estimated. The estimated effect of timely public notification in the home county is approximately 8% and is not statistically significant, and most spillover coefficients are positive but imprecise. The only statistically significant spillover effect appears for non-neighboring counties within the same DMA, where timely public notification is associated with an increase in bottled water purchases of approximately 20%.

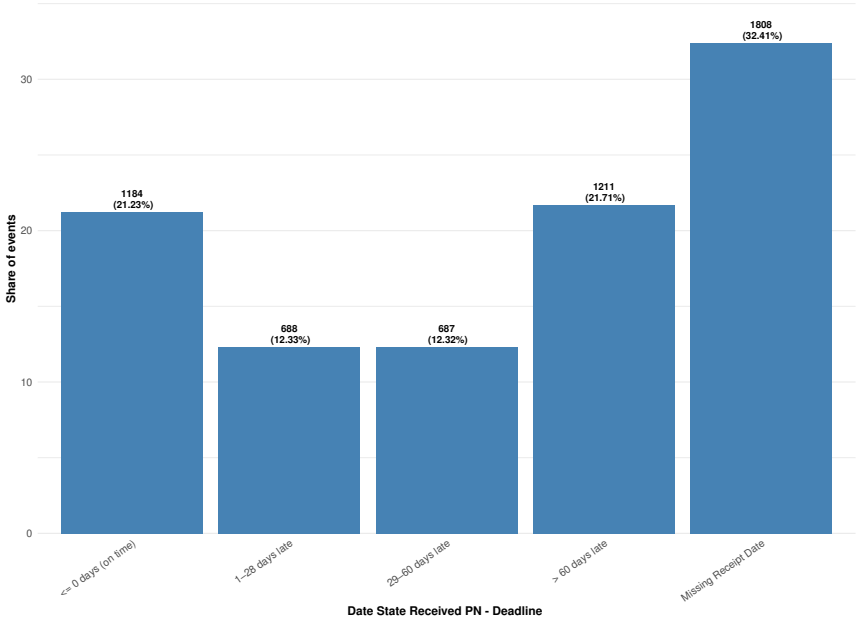
The reduced precision of the household-level estimates likely reflects features of the NielsenIQ Homescan panel. Approximately 35% of households appear in the data for only a single year, while about 20% remain for at least seven years. Although the Homescan panel spans 2,956 counties, the number of participating households per county is limited, and participation is disproportionately concentrated in higher-income, more urban, and more racially diverse counties. Figure A9 illustrates the spatial distribution of Homescan households. Panel (a) shows the number of households per county, while Panel (b) reports the median number of years households are observed. Households are concentrated primarily in urban counties in the Southwest, the Northeast, and Florida, while within-county variation in panel duration is relatively similar across states.

Taken together, these features limit the statistical power of the Homescan data to detect spillover effects at fine spatial scales and over long time horizons. In contrast, the Retail Scanner data provide substantially broader and more stable coverage across counties and time, with a larger number of continuously operating stores per county. As a result, the RMS analysis offers greater precision for

estimating spatial spillovers, while the Homescan results serve as complementary evidence that the observed patterns reflect household purchasing behavior rather than retailer-side adjustments.

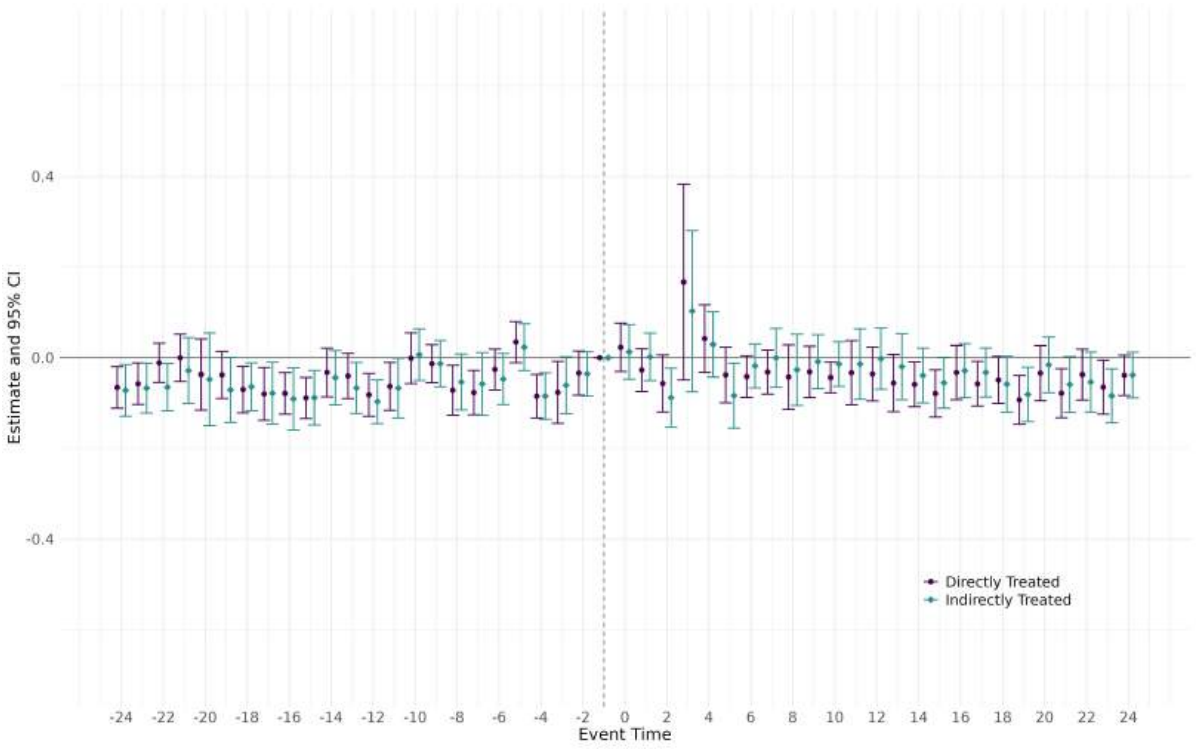
D Appendix Figures

Figure A1: Distribution of Public Notification Timing



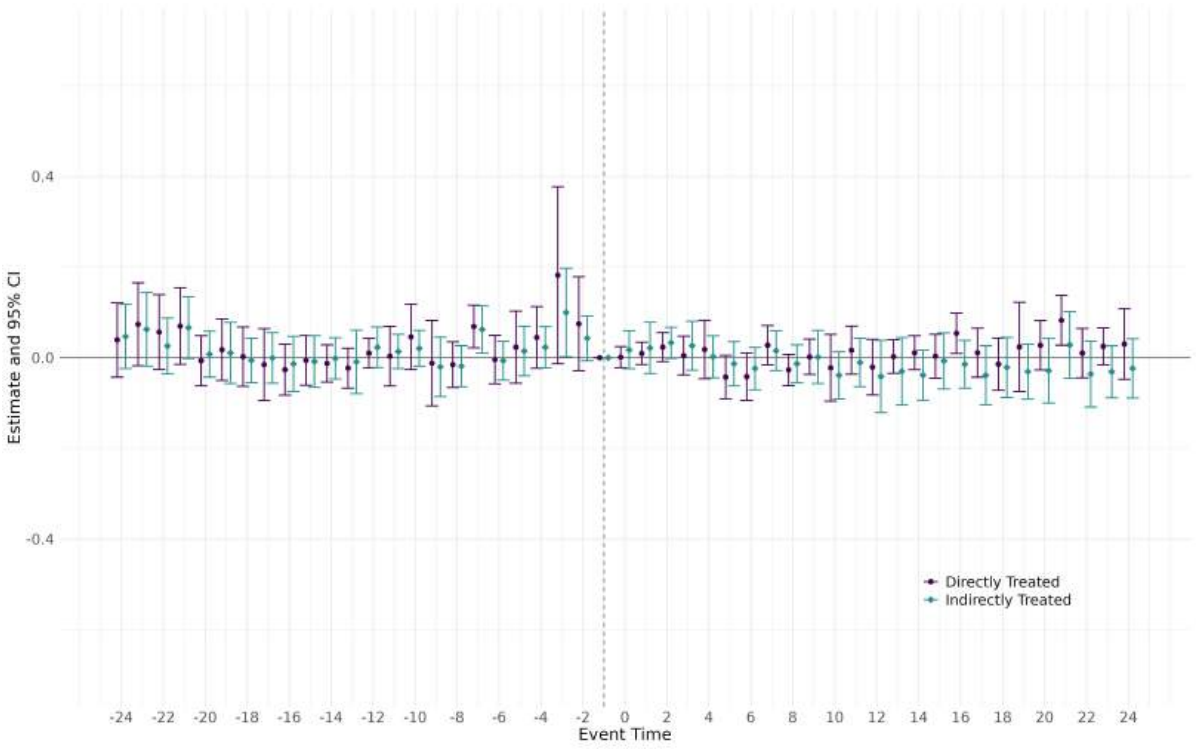
Note: historgram plots the distribution of the difference in days between the date when state received public notification from a system and its deadline period. It is computed for acute pathogen violations at the system by violation category level.

Figure A2: Event Study of Avoidance Behavior and Spillover Effects During Acute Pathogen Violations with Timely Public Notification



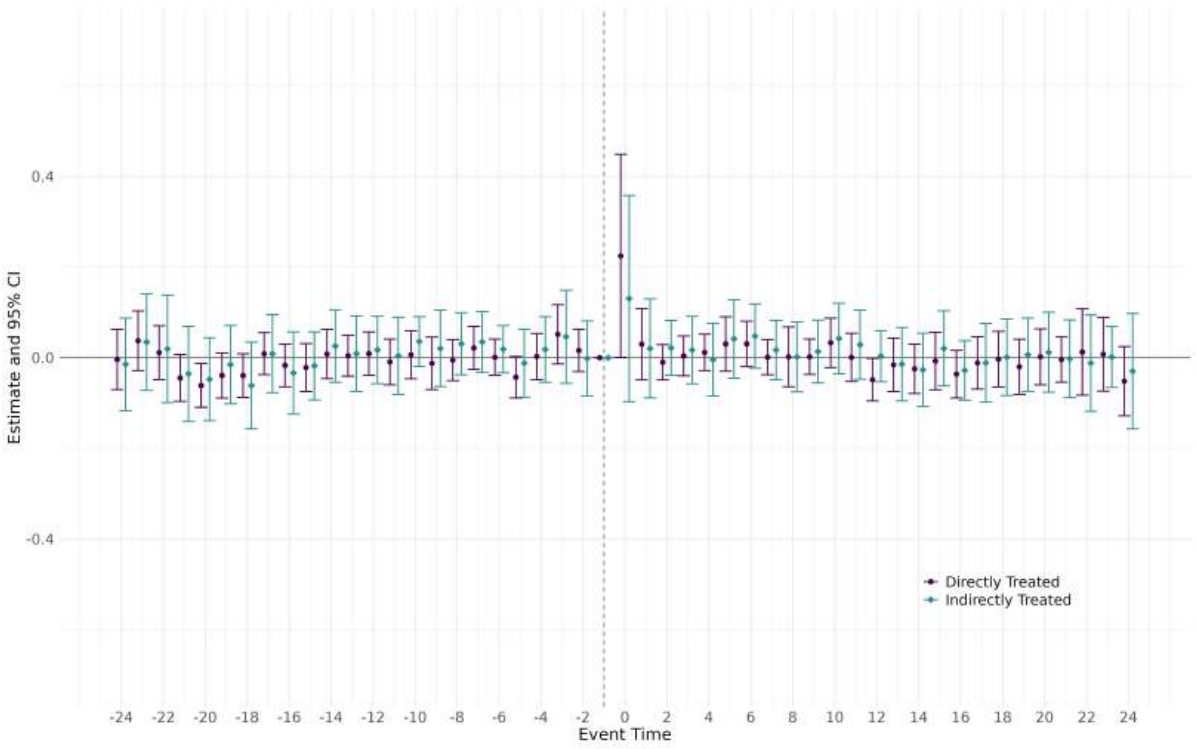
Note: Dependent variable is the log of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued on time. Event time 0 denotes the week the violation began. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure A3: Event Study of Avoidance Behavior and Spillover Effects During Acute Pathogen Violations with Late Public Notification



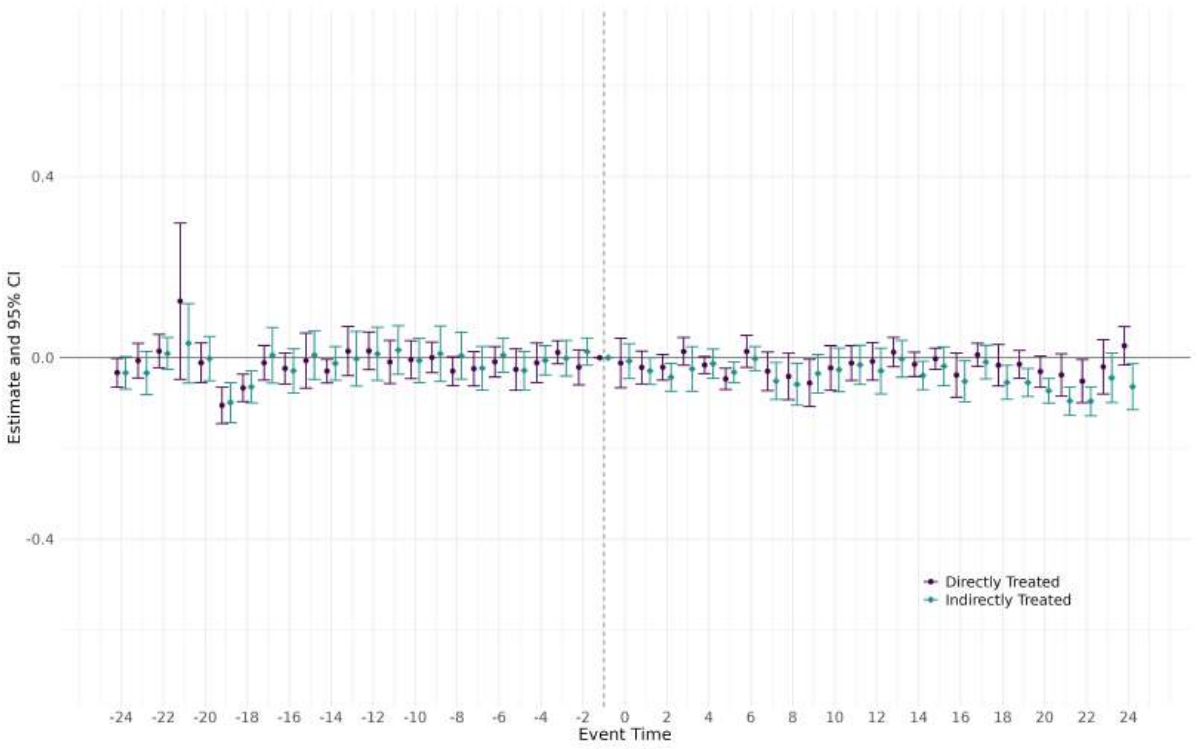
Note: Dependent variable is the log of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued late. Event time 0 denotes the week the violation began. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure A4: Event Study of Avoidance Behavior and Spillover Effects Following Timely Public Notification of Acute Pathogen Violations



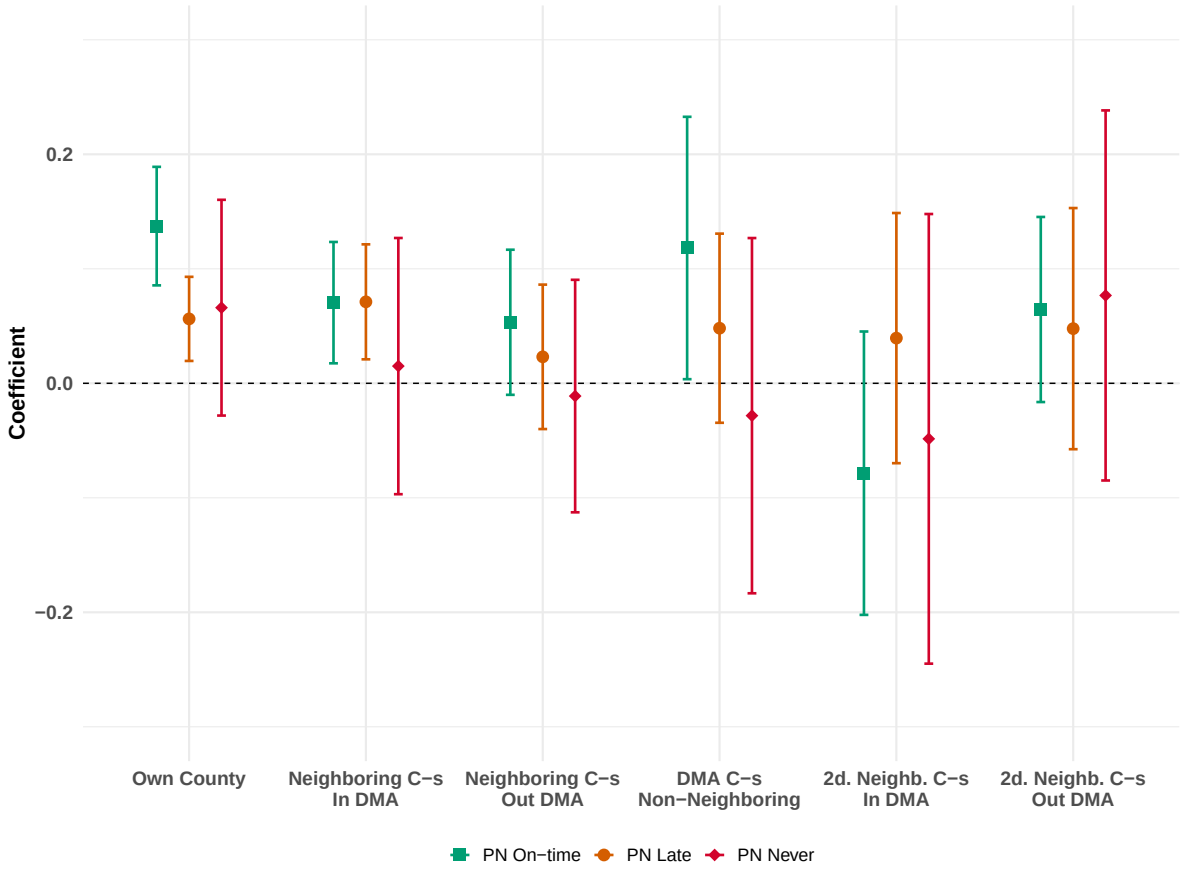
Note: Dependent variable is the log of share of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued on time. Event time 0 denotes the week of public notification. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure A5: Event Study of Avoidance Behavior and Spillover Effects Following Late Public Notification of Acute Pathogen Violations



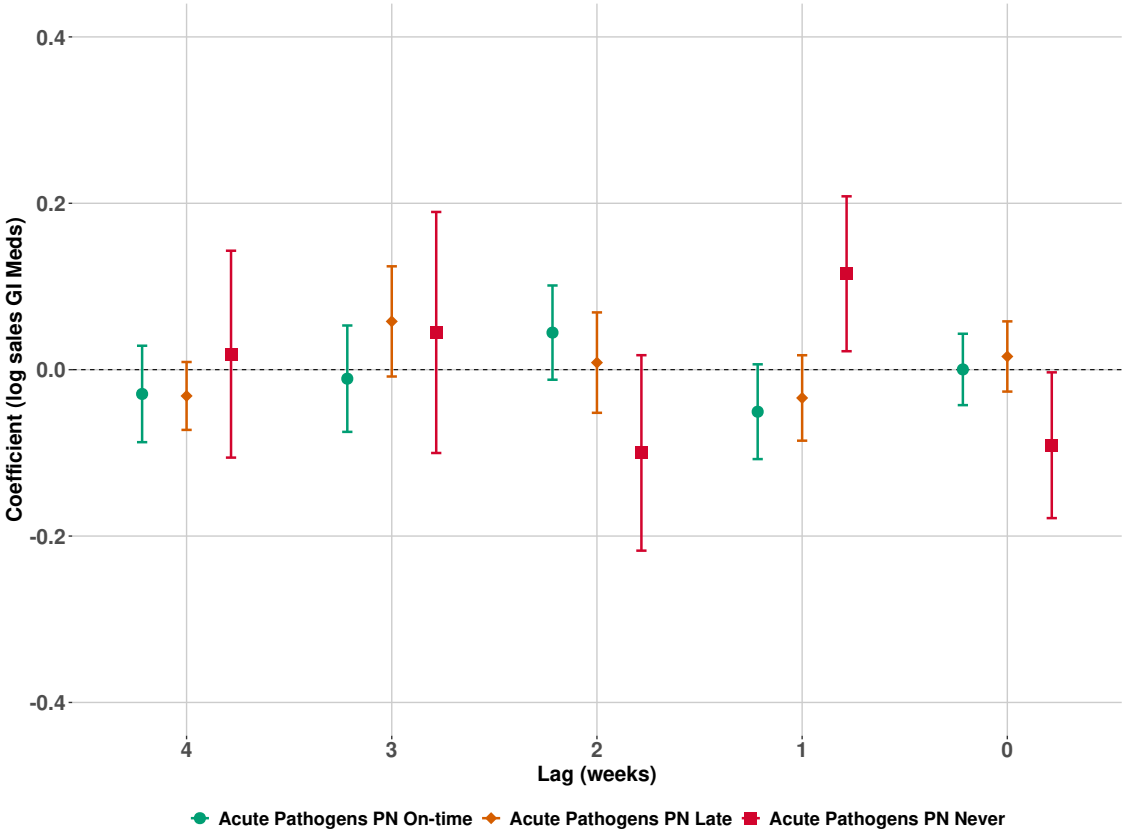
Note: Dependent variable is the log of share of bottled water sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to control counties. The sample includes fourteen acute pathogen violation events where public notification was issued late. Event time 0 denotes the week of public notification. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and event×store and event×year×week fixed effects. Standard errors are clustered at the county level.

Figure A6: Spillover Effects of Acute Pathogen Violations on First- and Second-Degree Neighbors by Notification Timing



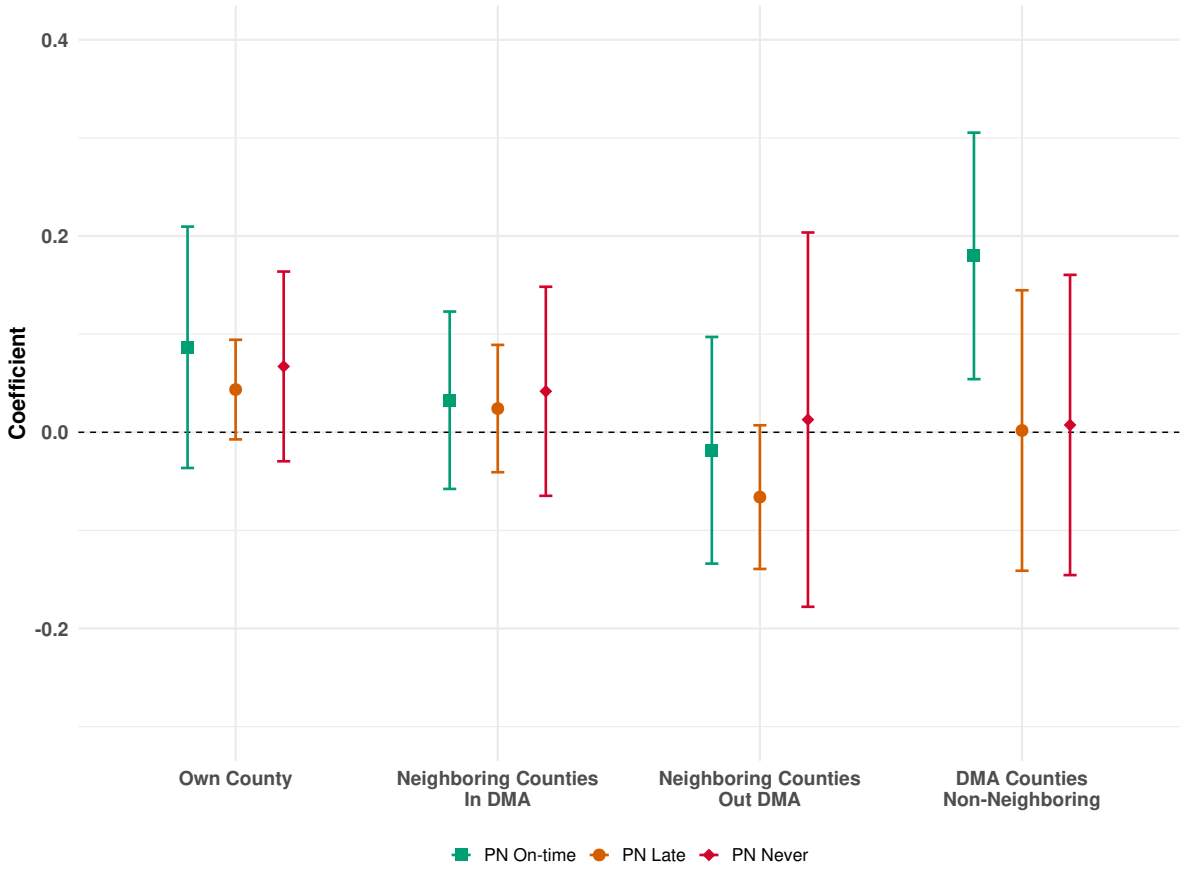
Note: Dependent variable is the log of bottled water sales. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and county×year, state×month and year×month fixed effects. Standard errors are clustered at the county level. *NCs* denotes first-degree neighboring counties; *NCs2* denotes second-degree neighboring counties. *In DMA* (*Out DMA*) refers to counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Figure A7: The Effect of Acute Pathogen Violations on OTC Gastrointestinal Medication Sales by Notification Timing



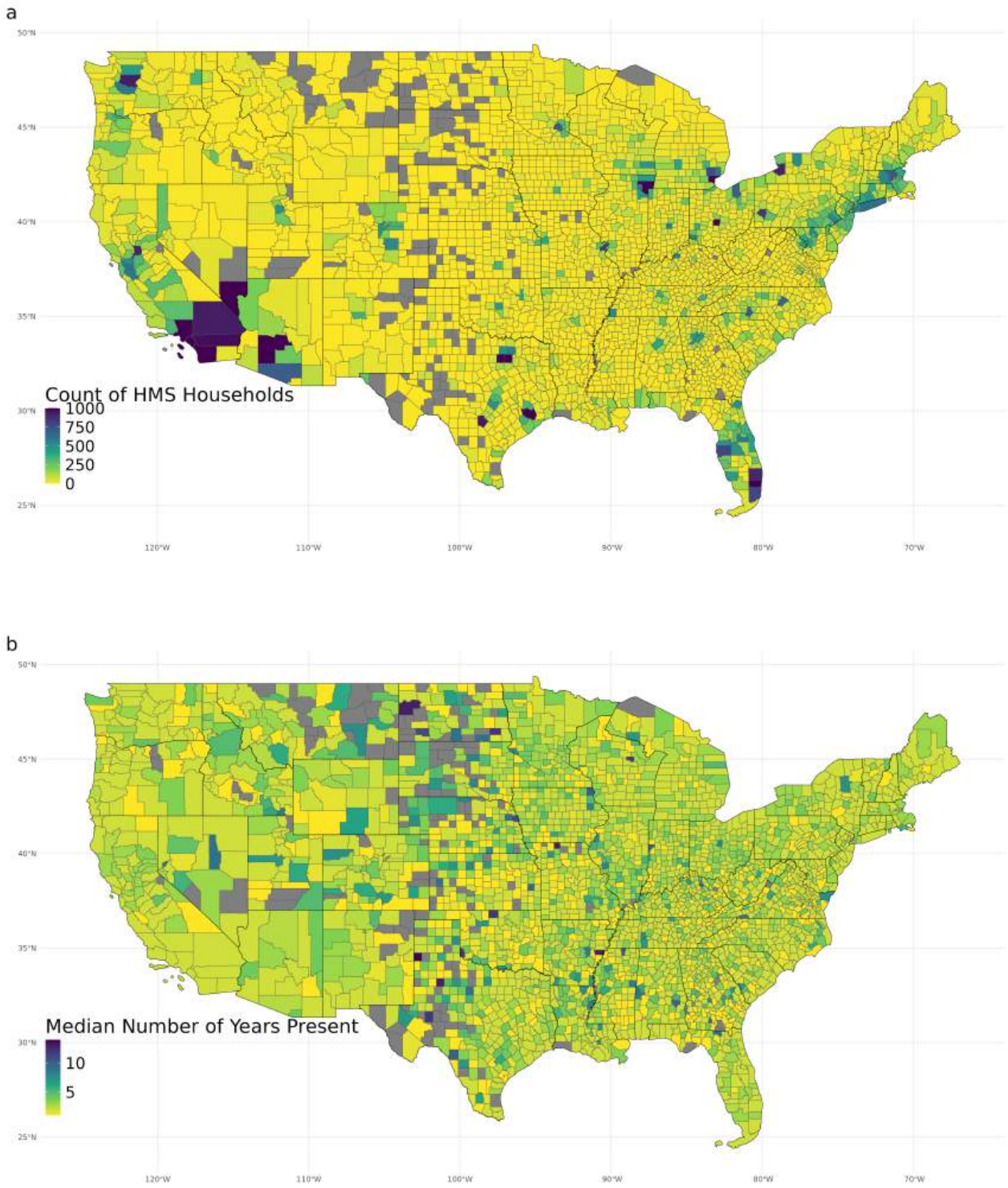
Note: Dependent variable is the log of over-the-counter gastrointestinal (GI) medication sales. The figure plots coefficients for the week of the violation (Week 0) and the four subsequent weeks (Weeks 1–4). Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature and county×year, state×month and year×month fixed effects. Standard errors are clustered at the county level.

Figure A8: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing (NielsenIQ Homescan Analysis)



Note: Dependent variable is the log of (bottled water purchases+1). The figure plots point estimates and 95% confidence intervals from the household-level panel. Regressions include categorical controls for precipitation and temperature as well as household, state×month, county×year and year×month fixed effects. Standard errors are clustered at the county level. *Neighboring Counties In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Figure A9: Households' Spatial Distribution in the NielsenIQ Homescan Data.



Note: Panel a graphs the per-county total number of households in the NielsenIQ Homescan panel over the sample period (capped at 1,000; 10 counties have 1,000-3,000 households). Panel b depicts the median number of years present among households in the county.

E Appendix Tables

Table A1: Summary Statistics for Robustness Checks in the National Sample

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
OTC GI Medications Sales							
GI Medications sales (2019$)	7,797	23,033	0	484	1,558	5,642	631,251
Log GI Medications sales	7.3	1.9	-0.11	6.2	7.4	8.6	13
Diarrhea Medications sales (2019$)	866	2,639	0.01	49	164	611	149,328
Antacids sales (2019$)	6,446	18,300	0.34	410	1,321	4,761	454,616
Electrolytes ORS sales (2019$)	587	2,573	0.01	31	95	333	132,152
Social Connectedness Index (SCI)							
Top SCI Acute Pathogens – PN on time	0.00023	0.0063	0	0	0	0	0.69
Top SCI Acute Pathogens – PN late	0.00064	0.011	0	0	0	0	0.72
Bottom SCI Acute Pathogens – PN on time	0.00027	0.0097	0	0	0	0	0.99
Bottom SCI Acute Pathogens – PN late	0.00033	0.0069	0	0	0	0	0.81
Above median SCI to NCs	0.42	0.49	0	0	0	1	1
Above median SCI to NCs (In-DMA)	0.43	0.49	0	0	0	1	1
Above median SCI to NCs (Out-DMA)	0.31	0.46	0	0	0	1	1
Above median SCI to DMA (non-NC)	0.44	0.5	0	0	0	1	1
Socio-Demographically (SD) Close							
SD Close Acute Pathogens – PN on time	0.00021	0.0048	0	0	0	0	0.65
SD Close Acute Pathogens – PN late	0.00054	0.0072	0	0	0	0	0.57
Above Median SD Close to NCs	0.52	0.5	0	0	1	1	1
Second-degree Neighboring Counties (NCs2)							
NCs2 (In-DMA) Acute Pathogens — PN on time	0.00014	0.005	0	0	0	0	0.78
NCs2 (In-DMA) Acute Pathogens — PN late	0.00025	0.0057	0	0	0	0	0.59
NCs2 (In-DMA) Acute Pathogens — PN never	0.000064	0.0026	0	0	0	0	0.46
NCs2 (Out-DMA) Acute Pathogens — PN on time	0.00012	0.004	0	0	0	0	0.77
NCs2 (Out-DMA) Acute Pathogens — PN late	0.00025	0.0045	0	0	0	0	0.49
NCs2 (Out-DMA) Acute Pathogens — PN never	0.000072	0.0023	0	0	0	0	0.4
Total number of 2nd-degree neighboring counties (NCs2)	13	2.8	2	11	13	14	26
Number of NCs2 in DMA	5.9	3.1	0	4	6	8	20
Number of NCs2 out of DMA	6.9	3.5	0	4	7	9	21

Note: Number of counties in the sample is 2,283. *Top (Bottom) SCI* refers to the top (bottom) 5 connected counties based on the Social Connectedness Index (SCI). *SD Close* refers to the top 5 connected counties based on the Socio-Demographic (SD) Closeness. To isolate social/demographic channels, these groups exclude all geographic neighbors and same-DMA counties. *NCs2 In-DMA* (*Out-DMA*) refers to second-degree adjacent counties that share (do not share) the same Designated Market Area as the violation county.

Table A2: List of Community Water Systems and Violation Events in the Event Study with Public Notification On-time

	PWS Name	Violation Type	Violation Category	Compl.period begin	Compl.period end	PN week end	County Directly Tt	County Directly Tt Control	County Indirectly Tt	County Indirectly Tt Control
1	JEA MAJOR GRID	MCL Violation, Acute (TCR)	MCL	2006-10-01	2006-10-31	2006-10-21	Duval, FL	Jefferson, AL	Clay, FL	Whitley, IN
2	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	MCL Violation, E. coli (RTCR)	MCL	2015-08-01	2015-08-30	2015-09-05	Indian River, FL	Polk, NC	St. Lucie, FL	Glynn, GA
3	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	Single Turbidity Exceed	TT	2010-06-01	2010-06-30	2010-06-05	St. Louis, MO	Henrico, VA	St. Louis city, MO	Pasquotank, NC
4	NJ AMERICAN WATER - RARITAN	Single Turbidity Exceed	TT	2010-09-01	2010-09-24	2010-10-02	Union, NJ	Alameda, CA	Hudson, NJ	New Haven, CT
5	PORTLAND WATER BUREAU	MCL Violation, Acute (TCR)	MCL	2009-11-01	2009-11-30	2009-11-28	Multnomah, OR	Washtenaw, MI	Clark, WA	St. Clair, MI
6	PORTLAND WATER BUREAU	MCL Violation, Acute (TCR)	MCL	2012-07-01	2012-07-31	2012-08-04	Multnomah, OR	Ingham, MI	Clark, WA	Monroe, MI
7	COLUMBIA CITY OF (SC4010001)	Single Turbidity Exceed	TT	2009-04-01	2009-04-30	2009-04-04	Richland, SC	Shelby, TN	Kershaw, SC	Gibson, TN
8	CITY OF MIDLAND WATER PURIFICATION PLANT	Monthly Turbidity Exceed	TT	2016-07-01	2016-07-31	2016-08-06	Midland, TX	Hood River, OR	Ector, TX	Douglas, WA
9	CITY OF CORPUS CHRISTI	MCL Violation, Acute (TCR)	MCL	2007-08-01	2007-08-31	2007-08-18	Nueces, TX	Whitfield, GA	San Patricio, TX	Hood River, OR
10	CITY OF CORPUS CHRISTI	MCL Violation, Acute (TCR)	MCL	2015-07-01	2015-07-31	2015-07-25	Nueces, TX	Alamosa, CO	Aransas, TX	Benzie, MI
11	CITY OF AUSTIN WATER & WASTEWATER	Single Turbidity Exceed	TT	2018-10-01	2018-10-31	2018-10-27	Travis, TX	Denver, CO	Williamson, TX	Boone, KY
12	CITY OF LAREDO	MCL Violation, Acute (TCR)	MCL	2007-07-01	2007-07-31	2007-08-04	Webb, TX	Seward, KS	Dimmit, TX	Miami-Dade, FL
13	VIRGINIA BEACH, CITY OF	MCL Violation, Acute (TCR)	MCL	2012-05-01	2012-05-25	2012-05-26	Virginia Beach city, VA	Snohomish, WA	Currituck, NC	Glynn, GA
14	AURORA CITY OF	MCL Violation, Acute (TCR)	MCL	2011-01-01	2011-01-31	2011-02-12	Arapahoe, CO	Kenton, KY	Denver, CO	Ingham, MI

Table A3: Socio-Demographic Characteristics for Directly Exposed Counties and their Controls in the DID Event Study with PN On time

	PWS Name	Compl.period begin	County	role	Population	Median HH Income ($2012)	Unemployment Rate	Share HH Below Poverty Rate	Share Child Pop.	Share Elderly Pop.	Share Coll. Degree	Share Black	Share Hispanic	Share Vacant Houses	Population Density	Share Presid Votes Republican	SD Distance
1	AURORA CITY OF	2011-01-01	Arapahoe, CO	directly tt	574,357	60,400	0.08	0.11	0.21	0.10	0.23	0.10	0.18	0.06	720.00	0.33	0.00
2	AURORA CITY OF	2011-01-01	Kenton, KY	directly tt control	159,926	53,900	0.08	0.12	0.21	0.11	0.22	0.05	0.03	0.10	998.00	0.35	0.08
3	CITY OF AUSTIN WATER & WASTEWATER	2018-10-01	Travis, TX	directly tt	1,034,842	56,403	0.07	0.15	0.20	0.07	0.20	0.08	0.33	0.08	1,045.00	0.21	0.00
4	CITY OF AUSTIN WATER & WASTEWATER	2018-10-01	Denver, CO	directly tt control	604,356	49,091	0.09	0.16	0.19	0.10	0.19	0.10	0.32	0.08	3,950.00	0.18	0.07
5	CITY OF CORPUS CHRISTI	2007-08-01	Nueces, TX	directly tt	340,568	46,499	0.08	0.17	0.21	0.12	0.26	0.04	0.61	0.13	406.00	0.21	0.00
6	CITY OF CORPUS CHRISTI	2007-08-01	Whitfield, GA	directly tt control	102,152	41,832	0.12	0.18	0.24	0.11	0.20	0.04	0.32	0.13	352.00	0.32	0.18
7	CITY OF CORPUS CHRISTI	2015-07-01	Nueces, TX	directly tt	340,568	46,499	0.08	0.17	0.21	0.12	0.26	0.04	0.61	0.13	406.00	0.21	0.00
8	CITY OF CORPUS CHRISTI	2015-07-01	Alamosa, CO	directly tt control	15,750	38,045	0.10	0.25	0.20	0.11	0.27	0.01	0.46	0.11	22.00	0.24	0.15
9	CITY OF LAREDO	2007-07-01	Webb, TX	directly tt	250,320	38,421	0.07	0.27	0.29	0.08	0.20	0.00	0.96	0.09	74.00	0.09	0.00
10	CITY OF LAREDO	2007-07-01	Seward, KS	directly tt control	23,013	47,731	0.10	0.16	0.27	0.08	0.17	0.04	0.56	0.09	36.00	0.34	0.27
11	CITY OF MIDLAND WATER PURIFICATION PLANT	2016-07-01	Midland, TX	directly tt	138,472	59,391	0.04	0.10	0.23	0.11	0.27	0.07	0.38	0.08	154.00	0.38	0.00
12	CITY OF MIDLAND WATER PURIFICATION PLANT	2016-07-01	Hood River, OR	directly tt control	22,207	56,355	0.06	0.08	0.21	0.13	0.21	0.01	0.29	0.14	43.00	0.26	0.14
13	COLUMBIA CITY OF (SC4010001)	2009-04-01	Richland, SC	directly tt	384,596	48,420	0.10	0.16	0.19	0.10	0.23	0.46	0.05	0.11	508.00	0.19	0.00
14	COLUMBIA CITY OF (SC4010001)	2009-04-01	Shelby, TN	directly tt control	929,437	46,251	0.11	0.18	0.22	0.10	0.24	0.52	0.06	0.14	1,218.00	0.21	0.06
15	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	2015-08-01	Indian River, FL	directly tt	138,203	45,274	0.14	0.13	0.15	0.28	0.23	0.09	0.11	0.24	275.00	0.41	0.00
16	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	2015-08-01	Polk, NC	directly tt control	20,386	42,762	0.14	0.14	0.15	0.25	0.22	0.05	0.05	0.23	86.00	0.39	0.08
17	JEA MAJOR GRID	2006-10-01	Duval, FL	directly tt	866,431	48,906	0.11	0.15	0.20	0.11	0.24	0.29	0.08	0.15	1,137.00	0.34	0.00
18	JEA MAJOR GRID	2006-10-01	Jefferson, AL	directly tt control	658,464	45,415	0.10	0.16	0.20	0.13	0.23	0.42	0.04	0.14	593.00	0.29	0.06
19	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2010-06-01	St. Louis, MO	directly tt	999,147	58,485	0.08	0.10	0.19	0.15	0.22	0.23	0.03	0.08	1,968.00	0.31	0.00
20	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2010-06-01	Henrico, VA	directly tt control	307,576	61,300	0.08	0.09	0.20	0.12	0.21	0.29	0.05	0.07	1,316.00	0.33	0.05
21	NJ AMERICAN WATER - RARITAN	2010-09-01	Union, NJ	directly tt	536,383	69,347	0.10	0.10	0.20	0.13	0.17	0.22	0.27	0.08	5,215.00	0.21	0.00
22	NJ AMERICAN WATER - RARITAN	2010-09-01	Alameda, CA	directly tt control	1,515,136	71,516	0.10	0.11	0.19	0.11	0.19	0.12	0.22	0.07	2,050.00	0.11	0.08
23	PORTLAND WATER BUREAU	2009-11-01	Multnomah, OR	directly tt	737,110	51,582	0.10	0.16	0.17	0.11	0.24	0.06	0.11	0.06	1,709.00	0.14	0.00
24	PORTLAND WATER BUREAU	2009-11-01	Washtenaw, MI	directly tt control	346,010	59,063	0.09	0.13	0.17	0.10	0.20	0.12	0.04	0.09	490.00	0.22	0.09
25	PORTLAND WATER BUREAU	2012-07-01	Multnomah, OR	directly tt	737,110	51,582	0.10	0.16	0.17	0.11	0.24	0.06	0.11	0.06	1,709.00	0.14	0.00
26	PORTLAND WATER BUREAU	2012-07-01	Ingham, MI	directly tt control	281,323	45,567	0.10	0.20	0.17	0.11	0.24	0.11	0.07	0.11	506.00	0.22	0.07
27	VIRGINIA BEACH, CITY OF	2012-05-01	Virginia Beach city, VA	directly tt	439,528	65,980	0.06	0.07	0.20	0.11	0.27	0.19	0.07	0.08	1,765.00	0.31	0.00
28	VIRGINIA BEACH, CITY OF	2012-05-01	Snohomish, WA	directly tt control	714,443	68,338	0.09	0.09	0.20	0.10	0.27	0.02	0.09	0.06	342.00	0.27	0.08

Table A4: Socio-Demographic Characteristics for Indirectly Exposed Counties and their Controls in the DID Event Study with PN On time

	PWS Name	Compl.period begin	County	role	Population	Median HH Income ($2012)	Unemployment Rate	Share HH Below Poverty Rate	Share Child Pop.	Share Elderly Pop.	Share Coll. Degree	Share Black	Share Hispanic	Share Vacant Houses	Population Density	Share Presid Votes Republican	SD Distance
1	AURORA CITY OF	2011-01-01	Denver, CO	indirectly tt	604,356	49,091	0.09	0.16	0.19	0.10	0.19	0.10	0.32	0.08	3,950.00	0.18	0.00
2	AURORA CITY OF	2011-01-01	Ingham, MI	indirectly tt control	281,323	45,567	0.10	0.20	0.17	0.11	0.24	0.11	0.07	0.11	506.00	0.22	0.14
3	CITY OF AUSTIN WATER & WASTEWATER	2018-10-01	Williamson, TX	indirectly tt	426,296	70,849	0.07	0.06	0.24	0.09	0.25	0.06	0.23	0.06	381.00	0.34	0.00
4	CITY OF AUSTIN WATER & WASTEWATER	2018-10-01	Boone, KY	indirectly tt control	119,406	67,125	0.06	0.09	0.24	0.10	0.23	0.03	0.04	0.08	485.00	0.43	0.10
5	CITY OF CORPUS CHRISTI	2007-08-01	San Patricio, TX	indirectly tt	65,352	51,104	0.08	0.15	0.23	0.13	0.26	0.02	0.54	0.16	94.00	0.27	0.00
6	CITY OF CORPUS CHRISTI	2007-08-01	Hood River, OR	indirectly tt control	22,207	56,355	0.06	0.08	0.21	0.13	0.21	0.01	0.29	0.14	43.00	0.26	0.16
7	CITY OF CORPUS CHRISTI	2015-07-01	Aransas, TX	indirectly tt	23,391	44,769	0.08	0.15	0.16	0.24	0.24	0.01	0.25	0.36	93.00	0.38	0.00
8	CITY OF CORPUS CHRISTI	2015-07-01	Benzie, MI	indirectly tt control	17,554	47,491	0.11	0.11	0.17	0.21	0.23	0.00	0.02	0.38	55.00	0.37	0.13
9	CITY OF LAREDO	2007-07-01	Dimmit, TX	indirectly tt	10,054	32,960	0.10	0.28	0.24	0.15	0.16	0.01	0.86	0.21	8.00	0.11	0.00
10	CITY OF LAREDO	2007-07-01	Miami-Dade, FL	indirectly tt control	2,512,219	43,464	0.11	0.20	0.18	0.14	0.16	0.19	0.65	0.16	1,324.00	0.24	0.28
11	CITY OF MIDLAND WATER PURIFICATION PLANT	2016-07-01	Ector, TX	indirectly tt	138,193	50,851	0.06	0.15	0.25	0.10	0.25	0.04	0.53	0.08	154.00	0.28	0.00
12	CITY OF MIDLAND WATER PURIFICATION PLANT	2016-07-01	Douglas, WA	indirectly tt control	38,369	52,285	0.09	0.13	0.22	0.14	0.24	0.00	0.28	0.12	21.00	0.40	0.17
13	COLUMBIA CITY OF (SC4010001)	2009-04-01	Kershaw, SC	indirectly tt	61,583	44,068	0.12	0.16	0.20	0.14	0.22	0.25	0.04	0.13	85.00	0.36	0.00
14	COLUMBIA CITY OF (SC4010001)	2009-04-01	Gibson, TN	indirectly tt control	49,594	36,981	0.13	0.18	0.20	0.17	0.23	0.19	0.02	0.12	82.00	0.35	0.05
15	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	2015-08-01	St. Lucie, FL	indirectly tt	278,246	43,923	0.16	0.14	0.18	0.20	0.23	0.19	0.17	0.24	487.00	0.29	0.00
16	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	2015-08-01	Glynn, GA	indirectly tt control	79,628	49,986	0.11	0.15	0.20	0.15	0.24	0.26	0.06	0.23	190.00	0.36	0.13
17	JEA MAJOR GRID	2006-10-01	Clay, FL	indirectly tt	190,891	59,649	0.11	0.10	0.21	0.12	0.26	0.10	0.08	0.10	316.00	0.51	0.00
18	JEA MAJOR GRID	2006-10-01	Whitley, IN	indirectly tt control	33,234	50,568	0.10	0.08	0.20	0.14	0.23	0.00	0.02	0.08	99.00	0.41	0.11
19	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2010-06-01	St. Louis city, MO	indirectly tt	318,527	34,384	0.14	0.24	0.18	0.11	0.22	0.49	0.03	0.20	5,145.00	0.10	0.00
20	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2010-06-01	Pasquotank, NC	indirectly tt control	40,551	46,032	0.13	0.17	0.19	0.14	0.23	0.39	0.04	0.13	179.00	0.25	0.17
21	NJ AMERICAN WATER - RARITAN	2010-09-01	Hudson, NJ	indirectly tt	636,194	58,722	0.10	0.15	0.17	0.10	0.15	0.13	0.42	0.10	13,773.00	0.11	0.00
22	NJ AMERICAN WATER - RARITAN	2010-09-01	New Haven, CT	indirectly tt control	860,995	62,234	0.10	0.12	0.18	0.14	0.18	0.12	0.15	0.09	1,424.00	0.22	0.16
23	PORTLAND WATER BUREAU	2009-11-01	Clark, WA	indirectly tt	426,984	58,764	0.11	0.11	0.22	0.12	0.29	0.02	0.08	0.05	679.00	0.31	0.00
24	PORTLAND WATER BUREAU	2009-11-01	St. Clair, MI	indirectly tt control	162,978	47,877	0.15	0.13	0.19	0.15	0.27	0.02	0.03	0.11	226.00	0.32	0.11
25	PORTLAND WATER BUREAU	2012-07-01	Clark, WA	indirectly tt	426,984	58,764	0.11	0.11	0.22	0.12	0.29	0.02	0.08	0.05	679.00	0.31	0.00
26	PORTLAND WATER BUREAU	2012-07-01	Monroe, MI	indirectly tt control	151,944	54,588	0.11	0.11	0.19	0.14	0.25	0.02	0.03	0.07	277.00	0.31	0.09
27	VIRGINIA BEACH, CITY OF	2012-05-01	Currituck, NC	indirectly tt	23,677	57,446	0.10	0.10	0.19	0.13	0.27	0.06	0.03	0.37	90.00	0.42	0.00
28	VIRGINIA BEACH, CITY OF	2012-05-01	Glynn, GA	indirectly tt control	79,628	49,986	0.11	0.15	0.20	0.15	0.24	0.26	0.06	0.23	190.00	0.36	0.14

Table A5: Summary Statistics for Variables Used in the DID Event Study with PN On time

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water sales (2019$)	1,971	3,286	0.8	305	810	2,722	85,523
Log of bottled water sales	6.7	1.4	-0.22	5.7	6.7	7.9	11
Total sales (2019$)	164,846	201,912	2.9	32,363	66,529	238,447	1,814,468
Share of bottled water sales (2019$)	0.012	0.0092	0	0.01	0.01	0.01	0.12
Log Share bottled water sales	-4.6	0.63	-9.7	-5	-4.6	-4.3	-2.1
Controls							
Weekly max temperature	25	9	-11	19	27	32	42
Weekly total precipitation	22	28	0	1.7	11	31	375
County Population	849,615	647,817	10,438	450,201	705,576	936,374	2,699,428
Socio-Demographic Variables							
County Median HH Income ($2012)	54,368	9,070	32,960	46,251	51,582	61,300	71,516
County Share Child Pop.	0.2	0.019	0.15	0.18	0.2	0.2	0.29
County Share Elderly Pop.	0.12	0.027	0.074	0.1	0.11	0.13	0.28
County Share Coll. Degree	0.22	0.036	0.15	0.19	0.23	0.24	0.29
County Share Black	0.18	0.15	0.0025	0.085	0.12	0.23	0.52
County Share Hispanic	0.19	0.19	0.015	0.056	0.11	0.32	0.96
County Share Presid Votes Republican	0.25	0.081	0.095	0.21	0.24	0.31	0.51
Share Rural Pop.	0.097	0.2	0	0.005	0.034	0.095	1
Share Lang. Barrier Pop.	0.22	0.093	0.096	0.17	0.2	0.23	0.51
Share No Fixed Broadband Pop.	0.017	0.023	0	0.002	0.012	0.024	0.42
Share No Broadband or Computer Pop.	0.13	0.048	0.06	0.09	0.11	0.15	0.31
Number of stores in county	89	54	1	43	80	114	193

Table A6: List of Community Water Systems and Violation Events in the Event Study with Public Notification Late

	PWS Name	Violation Type	Violation Category	Compl.period begin	Compl.period end	PN week end	Delay days	County Directly Tt	County Directly Tt Control	County Indirectly Tt	County Indirectly Tt Control
1	WICHITA, CITY OF	Monthly Turbidity Exceed	TT	2010-03-01	2010-03-31	2010-05-08	38	Sedgwick, KS	Hardin, KY	Cowley, KS	Union, OR
2	KENTUCKY-AMERICAN WATER CO	Single Turbidity Exceed	TT	2013-11-01	2013-11-30	2014-02-01	63	Fayette, KY	Knox, TN	Scott, KY	Ottawa, MI
3	SHREVEPORT WATER SYSTEM	Monthly Turbidity Exceed	TT	2018-01-01	2018-01-31	2018-03-24	52	Caddo Parish, LA	Montgomery, AL	Marion, TX	Alpena, MI
4	SCHRIEVER WATER TREATMENT SERVICE AREA	Single Turbidity Exceed	TT	2012-08-01	2012-08-31	2012-10-20	50	Terrebonne Parish, LA	Jackson, GA	Lafourche Parish, LA	Henry, KY
5	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	Single Turbidity Exceed	TT	2007-08-01	2007-08-31	2007-10-13	43	St. Louis, MO	Henrico, VA	St. Louis city, MO	Baltimore city, MD
6	VEOLIA WATER NEW YORK	Monthly Turbidity Exceed	TT	2013-07-01	2013-07-31	2013-08-24	24	Rockland, NY	Montgomery, MD	Putnam, NY	Marin, CA
7	BRUNSWICK COUNTY WATER SYSTEM	Single Turbidity Exceed	TT	2016-10-01	2016-10-31	2016-12-31	61	Brunswick, NC	Benzie, MI	Horry, SC	Otsego, MI
8	ERIE CITY WATER AUTHORITY	Single Turbidity Exceed	TT	2006-08-01	2006-08-31	2006-12-02	93	Erie, PA	Niagara, NY	Chautauqua, NY	Wayne, IN
9	ERIE CITY WATER AUTHORITY	Single Turbidity Exceed	TT	2018-10-01	2018-10-31	2018-12-01	31	Erie, PA	Niagara, NY	Chautauqua, NY	Wapello, IA
10	AQUA PA MAIN SYSTEM	MCL E.Coli (RTCR)	MCL	2017-07-01	2017-07-31	2017-09-02	33	Montgomery, PA	Warren, NJ	Philadelphia, PA	Baltimore city, MD
11	COLUMBIA CITY OF (SC4010001)	Single Turbidity Exceed	TT	2007-05-01	2007-05-31	2007-06-30	30	Richland, SC	Shelby, TN	Lexington, SC	Butler, OH
12	COLUMBIA CITY OF (SC4010001)	Single Turbidity Exceed	TT	2009-10-01	2009-10-31	2009-12-19	49	Richland, SC	Shelby, TN	Kershaw, SC	Gibson, TN
13	COLUMBIA CITY OF (SC4010001)	Single Turbidity Exceed	TT	2015-11-01	2015-11-30	2016-03-05	96	Richland, SC	Shelby, TN	Kershaw, SC	Floyd, GA
14	CITY OF ODESSA	Monthly Turbidity Exceed	TT	2019-10-01	2019-10-31	2020-01-04	65	Ector, TX	Yakima, WA	Ward, TX	Douglas, WA

Table A7: Socio-Demographic Characteristics for Directly Exposed Counties and their Controls in the DID Event Study with PN Late

	PWS Name	Compl.period begin	County	role	Population	Median HH Income ($2012)	Unemployment Rate	Share HH Below Poverty Rate	Share Child Pop.	Share Elderly Pop.	Share Coll. Degree	Share Black	Share Hispanic	Share Vacant Houses	Population Density	Share Presid Votes Republican	SD Distance
1	AQUA PA MAIN SYSTEM	2017-07-01	Montgomery, PA	directly tt	799,886	78,984	0.07	0.06	0.19	0.15	0.16	0.09	0.04	0.05	1,656.00	0.30	0.00
2	AQUA PA MAIN SYSTEM	2017-07-01	Warren, NJ	directly tt control	108,488	73,056	0.08	0.07	0.19	0.14	0.17	0.04	0.07	0.08	304.00	0.33	0.06
3	BRUNSWICK COUNTY WATER SYSTEM	2016-10-01	Brunswick, NC	directly tt	107,925	46,490	0.13	0.14	0.16	0.22	0.23	0.11	0.05	0.39	127.00	0.41	0.00
4	BRUNSWICK COUNTY WATER SYSTEM	2016-10-01	Benzie, MI	directly tt control	17,554	47,491	0.11	0.11	0.17	0.21	0.23	0.00	0.02	0.38	55.00	0.37	0.07
5	CITY OF ODESSA	2019-10-01	Ector, TX	directly tt	138,193	50,851	0.06	0.15	0.25	0.10	0.25	0.04	0.53	0.08	154.00	0.28	0.00
6	CITY OF ODESSA	2019-10-01	Yakima, WA	directly tt control	242,454	44,256	0.11	0.18	0.25	0.12	0.22	0.01	0.45	0.07	56.00	0.30	0.12
7	COLUMBIA CITY OF (SC4010001)	2007-05-01	Richland, SC	directly tt	384,596	48,420	0.10	0.16	0.19	0.10	0.23	0.46	0.05	0.11	508.00	0.19	0.00
8	COLUMBIA CITY OF (SC4010001)	2007-05-01	Shelby, TN	directly tt control	929,437	46,251	0.11	0.18	0.22	0.10	0.24	0.52	0.06	0.14	1,218.00	0.21	0.06
9	COLUMBIA CITY OF (SC4010001)	2009-10-01	Richland, SC	directly tt	384,596	48,420	0.10	0.16	0.19	0.10	0.23	0.46	0.05	0.11	508.00	0.19	0.00
10	COLUMBIA CITY OF (SC4010001)	2009-10-01	Shelby, TN	directly tt control	929,437	46,251	0.11	0.18	0.22	0.10	0.24	0.52	0.06	0.14	1,218.00	0.21	0.06
11	COLUMBIA CITY OF (SC4010001)	2015-11-01	Richland, SC	directly tt	384,596	48,420	0.10	0.16	0.19	0.10	0.23	0.46	0.05	0.11	508.00	0.19	0.00
12	COLUMBIA CITY OF (SC4010001)	2015-11-01	Shelby, TN	directly tt control	929,437	46,251	0.11	0.18	0.22	0.10	0.24	0.52	0.06	0.14	1,218.00	0.21	0.06
13	ERIE CITY WATER AUTHORITY	2006-08-01	Erie, PA	directly tt	280,181	45,249	0.09	0.16	0.18	0.15	0.17	0.07	0.03	0.09	351.00	0.23	0.00
14	ERIE CITY WATER AUTHORITY	2006-08-01	Niagara, NY	directly tt control	215,869	47,736	0.08	0.14	0.17	0.16	0.20	0.07	0.02	0.11	413.00	0.23	0.05
15	ERIE CITY WATER AUTHORITY	2018-10-01	Erie, PA	directly tt	280,181	45,249	0.09	0.16	0.18	0.15	0.17	0.07	0.03	0.09	351.00	0.23	0.00
16	ERIE CITY WATER AUTHORITY	2018-10-01	Niagara, NY	directly tt control	215,869	47,736	0.08	0.14	0.17	0.16	0.20	0.07	0.02	0.11	413.00	0.23	0.05
17	KENTUCKY-AMERICAN WATER CO	2013-11-01	Fayette, KY	directly tt	296,766	48,779	0.08	0.17	0.18	0.11	0.21	0.14	0.07	0.09	1,046.00	0.28	0.00
18	KENTUCKY-AMERICAN WATER CO	2013-11-01	Knox, TN	directly tt control	433,207	47,270	0.06	0.14	0.18	0.13	0.21	0.09	0.03	0.07	852.00	0.33	0.06
19	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2007-08-01	St. Louis, MO	directly tt	999,147	58,485	0.08	0.10	0.19	0.15	0.22	0.23	0.03	0.08	1,968.00	0.31	0.00
20	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2007-08-01	Henrico, VA	directly tt control	307,576	61,300	0.08	0.09	0.20	0.12	0.21	0.29	0.05	0.07	1,316.00	0.33	0.05
21	SCHRIEVER WATER TREATMENT SERVICE AREA	2012-08-01	Terrebonne Parish, LA	directly tt	111,666	49,545	0.07	0.15	0.22	0.11	0.17	0.18	0.04	0.11	91.00	0.37	0.00
22	SCHRIEVER WATER TREATMENT SERVICE AREA	2012-08-01	Jackson, GA	directly tt control	60,268	53,393	0.08	0.14	0.22	0.12	0.20	0.07	0.06	0.11	177.00	0.45	0.07
23	SHREVEPORT WATER SYSTEM	2018-01-01	Caddo Parish, LA	directly tt	254,970	40,497	0.09	0.18	0.20	0.14	0.23	0.47	0.02	0.12	290.00	0.28	0.00
24	SHREVEPORT WATER SYSTEM	2018-01-01	Montgomery, AL	directly tt control	229,376	44,401	0.09	0.18	0.20	0.12	0.22	0.55	0.03	0.13	292.00	0.23	0.04
25	VEOLIA WATER NEW YORK	2013-07-01	Rockland, NY	directly tt	312,011	86,020	0.07	0.09	0.23	0.14	0.16	0.12	0.16	0.05	1,798.00	0.26	0.00
26	VEOLIA WATER NEW YORK	2013-07-01	Montgomery, MD	directly tt control	974,824	96,985	0.06	0.06	0.20	0.12	0.15	0.17	0.17	0.05	1,984.00	0.21	0.10
27	WICHITA, CITY OF	2010-03-01	Sedgwick, KS	directly tt	497,062	49,885	0.09	0.14	0.23	0.12	0.26	0.09	0.13	0.09	498.00	0.31	0.00
28	WICHITA, CITY OF	2010-03-01	Hardin, KY	directly tt control	104,513	49,257	0.09	0.13	0.21	0.11	0.25	0.12	0.05	0.11	168.00	0.31	0.05

Table A8: Socio-Demographic Characteristics for Indirectly Exposed Counties and their Controls in the DID Event Study with PN Late

	PWS Name	Compl.period begin	County	role	Population	Median HH Income ($2012)	Unemployment Rate	Share HH Below Poverty Rate	Share Child Pop.	Share Elderly Pop.	Share Coll. Degree	Share Black	Share Hispanic	Share Vacant Houses	Population Density	Share Presid Votes Republican	SD Distance
1	AQUA PA MAIN SYSTEM	2017-07-01	Philadelphia, PA	indirectly tt	1,525,811	37,016	0.14	0.24	0.19	0.12	0.17	0.43	0.12	0.13	11,378.00	0.09	0.00
2	AQUA PA MAIN SYSTEM	2017-07-01	Baltimore city, MD	indirectly tt control	620,644	40,803	0.14	0.22	0.18	0.12	0.20	0.64	0.04	0.19	7,668.00	0.06	0.10
3	BRUNSWICK COUNTY WATER SYSTEM	2016-10-01	Horry, SC	indirectly tt	270,943	42,183	0.11	0.16	0.17	0.17	0.23	0.14	0.06	0.39	239.00	0.35	0.00
4	BRUNSWICK COUNTY WATER SYSTEM	2016-10-01	Otsego, MI	indirectly tt control	24,175	47,140	0.12	0.11	0.18	0.17	0.25	0.00	0.01	0.34	47.00	0.38	0.11
5	CITY OF ODESSA	2019-10-01	Ward, TX	indirectly tt	10,705	40,222	0.05	0.20	0.23	0.14	0.22	0.05	0.48	0.16	13.00	0.32	0.00
6	CITY OF ODESSA	2019-10-01	Douglas, WA	indirectly tt control	38,369	52,285	0.09	0.13	0.22	0.14	0.24	0.00	0.28	0.12	21.00	0.40	0.15
7	COLUMBIA CITY OF (SC4010001)	2007-05-01	Lexington, SC	indirectly tt	262,424	53,644	0.09	0.12	0.20	0.12	0.23	0.14	0.05	0.09	375.00	0.40	0.00
8	COLUMBIA CITY OF (SC4010001)	2007-05-01	Butler, OH	indirectly tt control	368,029	56,253	0.09	0.13	0.21	0.12	0.20	0.07	0.04	0.09	788.00	0.39	0.05
9	COLUMBIA CITY OF (SC4010001)	2009-10-01	Kershaw, SC	indirectly tt	61,583	44,068	0.12	0.16	0.20	0.14	0.22	0.25	0.04	0.13	85.00	0.36	0.00
10	COLUMBIA CITY OF (SC4010001)	2009-10-01	Gibson, TN	indirectly tt control	49,594	36,981	0.13	0.18	0.20	0.17	0.23	0.19	0.02	0.12	82.00	0.35	0.05
11	COLUMBIA CITY OF (SC4010001)	2015-11-01	Kershaw, SC	indirectly tt	61,583	44,068	0.12	0.16	0.20	0.14	0.22	0.25	0.04	0.13	85.00	0.36	0.00
12	COLUMBIA CITY OF (SC4010001)	2015-11-01	Floyd, GA	indirectly tt control	96,204	41,442	0.12	0.19	0.20	0.14	0.21	0.14	0.09	0.14	189.00	0.33	0.06
13	ERIE CITY WATER AUTHORITY	2006-08-01	Chautauqua, NY	indirectly tt	134,599	41,975	0.08	0.18	0.18	0.17	0.19	0.02	0.06	0.18	127.00	0.23	0.00
14	ERIE CITY WATER AUTHORITY	2006-08-01	Wayne, IN	indirectly tt control	68,797	39,131	0.12	0.18	0.19	0.16	0.20	0.03	0.03	0.10	171.00	0.27	0.07
15	ERIE CITY WATER AUTHORITY	2018-10-01	Chautauqua, NY	indirectly tt	134,599	41,975	0.08	0.18	0.18	0.17	0.19	0.02	0.06	0.18	127.00	0.23	0.00
16	ERIE CITY WATER AUTHORITY	2018-10-01	Wapello, IA	indirectly tt control	35,449	41,088	0.09	0.18	0.19	0.16	0.21	0.01	0.09	0.09	82.00	0.26	0.06
17	KENTUCKY-AMERICAN WATER CO	2013-11-01	Scott, KY	indirectly tt	47,211	60,553	0.09	0.14	0.23	0.09	0.23	0.06	0.04	0.08	168.00	0.38	0.00
18	KENTUCKY-AMERICAN WATER CO	2013-11-01	Ottawa, MI	indirectly tt control	264,835	55,760	0.09	0.10	0.21	0.12	0.22	0.01	0.09	0.08	470.00	0.47	0.08
19	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2007-08-01	St. Louis city, MO	indirectly tt	318,527	34,384	0.14	0.24	0.18	0.11	0.22	0.49	0.03	0.20	5,145.00	0.10	0.00
20	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	2007-08-01	Baltimore city, MD	indirectly tt control	620,644	40,803	0.14	0.22	0.18	0.12	0.20	0.64	0.04	0.19	7,668.00	0.06	0.08
21	SCHRIEVER WATER TREATMENT SERVICE AREA	2012-08-01	Lafourche Parish, LA	indirectly tt	96,453	50,574	0.06	0.15	0.20	0.13	0.15	0.13	0.04	0.09	90.00	0.40	0.00
22	SCHRIEVER WATER TREATMENT SERVICE AREA	2012-08-01	Henry, KY	indirectly tt control	15,428	43,083	0.09	0.18	0.20	0.14	0.17	0.03	0.03	0.10	54.00	0.34	0.09
23	SHREVEPORT WATER SYSTEM	2018-01-01	Marion, TX	indirectly tt	10,544	32,226	0.09	0.24	0.16	0.22	0.25	0.24	0.03	0.26	28.00	0.32	0.00
24	SHREVEPORT WATER SYSTEM	2018-01-01	Alpena, MI	indirectly tt control	29,602	38,900	0.11	0.17	0.17	0.20	0.26	0.01	0.01	0.18	52.00	0.31	0.14
25	VEOLIA WATER NEW YORK	2013-07-01	Putnam, NY	indirectly tt	99,702	95,259	0.07	0.05	0.19	0.12	0.19	0.02	0.12	0.08	433.00	0.29	0.00
26	VEOLIA WATER NEW YORK	2013-07-01	Marin, CA	indirectly tt control	252,759	90,962	0.07	0.07	0.17	0.17	0.19	0.03	0.15	0.07	486.00	0.18	0.10
27	WICHITA, CITY OF	2010-03-01	Cowley, KS	indirectly tt	36,259	41,905	0.08	0.16	0.20	0.16	0.27	0.03	0.09	0.14	32.00	0.30	0.00
28	WICHITA, CITY OF	2010-03-01	Union, OR	indirectly tt control	25,670	41,784	0.08	0.18	0.18	0.17	0.26	0.00	0.04	0.10	13.00	0.39	0.08

Table A9: Summary Statistics for Variables Used in the DID Event Study with PN Late

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water sales (2019$)	1,559	2,635	0.31	203	512	1,867	60,166
Log of bottled water sales	6.4	1.5	-1.2	5.3	6.2	7.5	11
Total sales (2019$)	128,450	176,870	90	24,383	43,171	163,537	2,114,520
Share of bottled water sales (2019$)	0.012	0.0084	0	0.01	0.01	0.01	0.09
Log Share bottled water sales	-4.7	0.65	-9.8	-5	-4.6	-4.3	-2.4
Controls							
Weekly max temperature	25	8.7	-7.5	19	27	32	44
Weekly total precipitation	23	27	0	3.4	15	33	265
County Population	644,372	409,615	10,017	308,174	609,032	936,374	1,579,075
Socio-Demographic Variables							
County Median HH Income ($2012)	50,419	13,442	32,226	44,401	46,251	49,885	96,985
County Share Child Pop.	0.2	0.018	0.16	0.18	0.19	0.22	0.25
County Share Elderly Pop.	0.12	0.023	0.093	0.1	0.12	0.14	0.22
County Share Coll. Degree	0.21	0.029	0.15	0.2	0.22	0.24	0.27
County Share Black	0.32	0.2	0.0014	0.11	0.43	0.52	0.64
County Share Hispanic	0.069	0.068	0.011	0.041	0.056	0.06	0.53
County Share Presid Votes Republican	0.23	0.091	0.061	0.21	0.21	0.31	0.47
Share Rural Pop.	0.15	0.23	0	0.027	0.034	0.14	1
Share Lang. Barrier Pop.	0.2	0.051	0.1	0.15	0.21	0.22	0.34
Share No Fixed Broadband Pop.	0.018	0.023	0	0.009	0.012	0.018	0.4
Share No Broadband or Computer Pop.	0.17	0.052	0.052	0.13	0.17	0.22	0.3
Number of stores in county	94	64	1	46	67	166	194

Table A10: Spillover Effects to Non-Neighboring Counties with High Social and Demographic Connectivity

	Log Sales BW		
	(1)	(2)	(3)
County Acute Pathogens – PN on time	0.1380***	0.1377***	0.1380***
	(0.0264)	(0.0264)	(0.0264)
County Acute Pathogens – PN late	0.0558***	0.0557***	0.0558***
	(0.0187)	(0.0187)	(0.0187)
SD Close Acute Pathogens – PN on time	-0.0536		
	(0.0386)		
SD Close Acute Pathogens – PN late	0.0561*		
	(0.0322)		
Top SCI Acute Pathogens – PN on time		0.0386	
		(0.0293)	
Top SCI Acute Pathogens – PN late		0.0336*	
		(0.0191)	
Bottom SCI Acute Pathogens – PN on time			-0.0282
			(0.0198)
Bottom SCI Acute Pathogens – PN late			0.0014
			(0.0412)
Temp Max Control	Yes	Yes	Yes
Total Precip. Control	Yes	Yes	Yes
R^2	0.99193	0.99193	0.99193
Observations	1,649,604	1,649,604	1,649,604
County–Year fixed effects	✓	✓	✓
State-Month fixed effects	✓	✓	✓
Year–Month fixed effects	✓	✓	✓

Note: Clustered (County) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. The estimates capture spillover effects originating from the acute pathogen violations in the top 5 and bottom 5 connected counties based on the Social Connectedness Index (SCI) and the top 5 counties on Socio-Demographic (SD) Closeness. These groups exclude all geographic neighbors and same-DMA counties.

Table A11: Heterogeneity in Spillover Responses by Social Connectivity, Socio-Demographic Similarity, and Prior Experience

	Exposure: NC Total (On-time)
Row	NC total (On-time)
Below-median SCI (NCs) × NC Acute PN on-time	0.083** (0.032)
Above-median SCI (NCs) × NC Acute PN on-time	0.145* (0.064)
p(diff)	p=0.382
Below-median SD-close × NC Acute PN on-time	0.130*** (0.032)
Above-median SD-close × NC Acute PN on-time	0.000 (0.051)
p(diff)	p=0.030
0 past-2y own Acute × NC Acute PN on-time	0.102** (0.033)
1 past-2y own Acute × NC Acute PN on-time	0.032 (0.066)
p(diff)	p=0.369

Note: Each group of rows represents a separate regression interacting the spillover treatment with the specified heterogeneity variable. $p(diff)$ reports the p-value from a test of equality between the coefficients of the two subgroups. All regressions include controls for precipitation and temperature, as well as county×year, state×month, and year×month fixed effects. The dependent variable is the log of bottled water sales. Clustered (County) standard errors are reported in parentheses. Number of observations: 1,649,604. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A12: The Role of Social Connectedness in Moderating Spillover Effects Across Neighbor Categories

	Exposure: NC / DMA On-Time Tier 1 Pathogens
Row	T1P PN On-time
Below-median SCI to NCs in DMA × NCs (in DMA) PN on-time	0.087** (0.029)
Above-median SCI to NCs in DMA × NCs (in DMA) PN on-time	0.016 (0.060)
p(diff)	p=0.284
Below-median SCI to NCs out of DMA × NCs (out DMA) PN on-time	0.046 (0.041)
Above-median SCI to NCs out of DMA × NCs (out DMA) PN on-time	0.066 (0.055)
p(diff)	p=0.761
Below-median SCI to DMA non-NCs × DMA (non-NC) PN on-time	0.091 (0.071)
Above-median SCI to DMA non-NCs × DMA (non-NC) PN on-time	0.052 (0.049)
p(diff)	p=0.651

Note: Each group of rows represents a separate regression interacting the spillover treatment with binary indicators for above/below median Social Connectedness Index (SCI). $p(diff)$ reports the p-value from a test of equality between the coefficients of the two subgroups. All regressions include controls for precipitation and temperature, as well as county×year, state×month, and year×month fixed effects. The dependent variable is the log of bottled water sales. Clustered (County) standard errors are reported in parentheses. Number of observations: 1,649,604. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A13: Spillover Effects on First- and Second-Degree Neighbors by Media Market and Notification Timing

	Log Sales BW					
	(1)	(2)	(3)	(4)	(5)	(6)
Own County Acute Pathogens — PN on time	0.1380***	0.1376***	0.1372***	0.1373***	0.1374***	0.1373***
	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)
Own County Acute Pathogens — PN late	0.0561***	0.0561***	0.0562***	0.0563***	0.0563***	0.0563***
	(0.0187)	(0.0188)	(0.0188)	(0.0187)	(0.0187)	(0.0187)
Own County Acute Pathogens — PN never	0.0660	0.0660	0.0661	0.0660	0.0660	0.0660
	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)
NCs (In-DMA) Acute Pathogens — PN on time		0.0707***	0.0703***	0.0685**	0.0704***	0.0704***
		(0.0268)	(0.0269)	(0.0270)	(0.0270)	(0.0270)
NCs (In-DMA) Acute Pathogens — PN late		0.0731***	0.0731***	0.0719***	0.0711***	0.0712***
		(0.0255)	(0.0255)	(0.0255)	(0.0256)	(0.0256)
NCs (In-DMA) Acute Pathogens — PN never		0.0151	0.0151	0.0149	0.0149	0.0150
		(0.0571)	(0.0571)	(0.0571)	(0.0571)	(0.0571)
NCs (Out-DMA) Acute Pathogens — PN on time			0.0534*	0.0537*	0.0538*	0.0533*
			(0.0323)	(0.0323)	(0.0323)	(0.0323)
NCs (Out-DMA) Acute Pathogens — PN late			0.0233	0.0233	0.0232	0.0231
			(0.0322)	(0.0322)	(0.0322)	(0.0322)
NCs (Out-DMA) Acute Pathogens — PN never			-0.0114	-0.0113	-0.0112	-0.0112
			(0.0519)	(0.0518)	(0.0518)	(0.0518)
DMA Non-NC Acute Pathogens — PN on time				0.0732*	0.1182**	0.1182**
				(0.0441)	(0.0585)	(0.0585)
DMA Non-NC Acute Pathogens — PN late				0.0665**	0.0479	0.0481
				(0.0311)	(0.0421)	(0.0421)
DMA Non-NC Acute Pathogens — PN never				-0.0505	-0.0287	-0.0283
				(0.0605)	(0.0791)	(0.0791)
NC2 (In-DMA) Acute Pathogens — PN on time					-0.0786	-0.0785
					(0.0631)	(0.0631)
NC2 (In-DMA) Acute Pathogens — PN late					0.0395	0.0395
					(0.0557)	(0.0557)
NC2 (In-DMA) Acute Pathogens — PN never					-0.0485	-0.0485
					(0.1002)	(0.1002)
NC2 (Out-DMA) Acute Pathogens — PN on time						0.0644
						(0.0412)
NC2 (Out-DMA) Acute Pathogens — PN late						0.0477
						(0.0537)
NC2 (Out-DMA) Acute Pathogens — PN never						0.0767
						(0.0824)
Temp Max Control	Yes	Yes	Yes	Yes	Yes	Yes
Total Precip. Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.99193	0.99193	0.99193	0.99193	0.99193	0.99193
Observations	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604
County–Year fixed effects	✓	✓	✓	✓	✓	✓
State-Month fixed effects	✓	✓	✓	✓	✓	✓
Year–Month fixed effects	✓	✓	✓	✓	✓	✓

Note: The table reports coefficients from a fixed effects regression estimating spillovers onto first- and second-degree neighbors. Columns add controls and neighbor definitions progressively; Column (6) represents the full specification. Clustered (County) standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *NCs* denotes first-degree neighboring counties; *NCs2* denotes second-degree neighboring counties. *In DMA* (*Out DMA*) refers to counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Table A14: Effects of Acute Pathogen Violations on Gastrointestinal Medication Sales by Product Category

	Log Sales GI Meds (1)	Log Sales Diarrhea (2)	Log Sales Electrolytes ORS (3)	Log Sales Antacid (4)
County Acute pathogens – PN on time (t)	0.0003	0.0794	0.0692	-0.0137
	(0.0219)	(0.0541)	(0.0627)	(0.0232)
County Acute pathogens – PN on time (t-1)	-0.0505*	-0.1464*	-0.1607*	-0.0250
	(0.0291)	(0.0866)	(0.0896)	(0.0297)
County Acute pathogens – PN on time (t-2)	0.0446	0.0764	0.0426	0.0383
	(0.0289)	(0.0716)	(0.0904)	(0.0288)
County Acute pathogens – PN on time (t-3)	-0.0108	0.0713	-0.0439	-0.0226
	(0.0326)	(0.0664)	(0.0829)	(0.0365)
County Acute pathogens – PN on time (t-4)	-0.0292	-0.0905*	0.1038*	-0.0288
	(0.0296)	(0.0529)	(0.0604)	(0.0319)
County Acute pathogens – PN late (t)	0.0159	-0.0045	-0.0190	0.0127
	(0.0215)	(0.0557)	(0.0635)	(0.0220)
County Acute pathogens – PN late (t-1)	-0.0340	0.0027	0.0043	-0.0350
	(0.0262)	(0.0636)	(0.0842)	(0.0283)
County Acute pathogens – PN late (t-2)	0.0085	0.0041	0.0024	0.0097
	(0.0308)	(0.0669)	(0.0669)	(0.0336)
County Acute pathogens – PN late (t-3)	0.0580*	-0.0215	0.0466	0.0617*
	(0.0338)	(0.0609)	(0.0743)	(0.0373)
County Acute pathogens – PN late (t-4)	-0.0316	0.0333	-0.0546	-0.0324
	(0.0208)	(0.0376)	(0.0596)	(0.0235)
County Acute pathogens – PN never (t)	-0.0908**	-0.0519	-0.1048	-0.0618
	(0.0447)	(0.0840)	(0.0871)	(0.0489)
County Acute pathogens – PN never (t-1)	0.1153**	-0.0304	0.1393	0.0944**
	(0.0475)	(0.1598)	(0.1300)	(0.0470)
County Acute pathogens – PN never (t-2)	-0.1001*	0.1095	0.0196	-0.1182**
	(0.0599)	(0.1854)	(0.1615)	(0.0568)
County Acute pathogens – PN never (t-3)	0.0447	0.1916	-0.2635*	0.0739
	(0.0739)	(0.1391)	(0.1552)	(0.0714)
County Acute pathogens – PN never (t-4)	0.0186	-0.1439**	0.1936*	0.0185
	(0.0634)	(0.0726)	(0.1052)	(0.0680)
Temp Max Control	Yes	Yes	Yes	Yes
Total Precip. Control	Yes	Yes	Yes	Yes
R^2	0.98870	0.95644	0.93423	0.98705
Observations	1,641,685	1,589,643	1,434,595	1,641,614
County–Year fixed effects	✓	✓	✓	✓
State-Month fixed effects	✓	✓	✓	✓
Year–Month fixed effects	✓	✓	✓	✓

Note: The table reports coefficients from a distributed lag model estimating the dynamic response of medication sales. (t) denotes the week the violation began; (t-k) corresponds to the variable "Lag k," representing the effect k weeks after the violation start. Column (1) uses total GI medication sales; Columns (2)–(4) disaggregate by category. Clustered (County) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A15: Estimated Aggregate Economic Costs of Acute Pathogen Violations (Bottled Water Sales)

Exposure	beta	Full exposure effect (perc. change sales)	Change in BW sales per fully exposed county-week (usd)	Full-exposure county-week equivalents	Total change in BW sales, 2006–2019 (mill. usd)
Own county: Acute PN on-time	0.1373	14.72	3491.05	376.10	1.3129843
Own county: Acute PN late	0.0563	5.79	1372.80	816.33	1.1206590
Neighbors in DMA: Acute PN on-time	0.0686	7.10	1682.86	440.79	0.7417878
Neighbors in DMA: Acute PN late	0.0719	7.45	1767.15	810.30	1.4319262

Note: The table calculates the total excess expenditure on bottled water attributed to acute pathogen violations. *Beta* is the regression coefficient from the preferred specification. *Full exposure effect* is calculated as $(\exp(\beta) - 1) \times 100$. *Full-exposure county-week equivalents* is the sum of the exposure variable across the sample period. *Total change in sales* is the product of the percentage increase, mean weekly sales ($23,717), and the total exposure equivalents.

Table A16: Estimated Foregone Avoidance Expenditures due to Delayed Public Notification

Scenario	Log difference ($\beta_{hi} - \beta_{lo}$)	Full exposure effect (perc. change in sales)	Change in BW sales per fully exposed county-week (usd)	Exposure under low-timing regime (full-exposure equivalents)	Total change in BW sales if high-timing regime (mill. usd)
Own County: On-time vs Late	0.0811	8.4427	2002	816.33	1.6345725
Own County: On-time vs Never	0.0713	7.3912	1753	264.28	0.4632735

Note: The table estimates the additional bottled water expenditures that would have occurred if *Late* or *Never* notified violations had instead been notified *On-Time*. *Log difference* represents the difference in coefficients ($\beta_{OnTime} - \beta_{Late/Never}$). *Total change* estimates the additional sales generated by shifting the exposure from the low-information regime (Late/Never) to the high-information regime (On-Time).

Table A17: Estimated Public Health Costs of Non-Notified Violations (GI Medication Sales)

Exposure	beta	Full exposure effect (perc. change sales)	Change in OTC GI Meds sales per fully exposed county-week (usd)	Full-exposure county-week equivalents	Total change in OTC GI Meds sales, 2006–2019 (usd)
Lag 1 Own county: Acute PN never	0.1153	12.22	952.62	66.07	62939.56

Note: The table estimates the excess expenditure on GI medications associated with "Never Notified" violations. The calculation relies on the Lag 1 coefficient, which captures the increase in sales one week following the violation start. *Full-exposure county-week equivalents* are estimated by dividing the total number of *Never Notified* violation-weeks by 4, approximating the number of unique violation events based on an average monthly compliance period. *Total change* is the product of the Lag 1 percentage increase, mean weekly sales ($7,797), and the estimated number of events.

Table A18: Summary Statistics for Key Variables in the Homescan Sample (2006-2019)

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water Purchases (2019$)	3.4	7	0	0	0	4.2	412
Bottled Water Purchases (gallons)	0.78	1.1	0	0	0	1.7	6
Log (BW Purchases+1)	2.2	4.7	0	0	0	3	222
Direct Violation Exposure by Public Notification Timing							
Own County Acute Pathogens — any PN timing	0.00085	0.019	0	0	0	0	1
Own County Acute Pathogens — PN on time	0.00027	0.011	0	0	0	0	0.95
Own County Acute Pathogens — PN late	0.00038	0.013	0	0	0	0	1
Own County Acute Pathogens — PN never	0.0002	0.0083	0	0	0	0	0.88
Spillover Exposure							
NCs (all) Acute Pathogens — any PN timing	0.00072	0.011	0	0	0	0	0.8
NCs (all) Acute Pathogens — PN on time	0.00022	0.007	0	0	0	0	0.8
NCs (all) Acute Pathogens — PN late	0.00032	0.007	0	0	0	0	0.7
NCs (all) Acute Pathogens — PN never	0.00017	0.0045	0	0	0	0	0.78
NCs (In-DMA) Acute Pathogens — PN on time	0.00022	0.0077	0	0	0	0	0.96
NCs (In-DMA) Acute Pathogens — PN late	0.00032	0.008	0	0	0	0	0.92
NCs (In-DMA) Acute Pathogens — PN never	0.00015	0.0048	0	0	0	0	0.78
NCs (Out-DMA) Acute Pathogens — PN on time	0.000081	0.0042	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN late	0.00019	0.0066	0	0	0	0	0.92
NCs (Out-DMA) Acute Pathogens — PN never	0.00011	0.0037	0	0	0	0	0.62
DMA Non-NC Acute Pathogens — PN on time	0.00021	0.0044	0	0	0	0	0.68
DMA Non-NC Acute Pathogens — PN late	0.00038	0.0054	0	0	0	0	0.86
DMA Non-NC Acute Pathogens — PN never	0.00015	0.0037	0	0	0	0	0.66
Total number of neighboring counties (NCs)	5.9	1.5	1	5	6	7	14
Number of NCs in DMA	4.6	1.9	0	3	5	6	11
Number of NCs out of DMA	1.4	1.5	0	0	1	2	9
Controls							
Weekly max temperature	27	8	-8	22	29	33	49
Weekly total precipitation	87	66	0	40	76	119	1,169
Household Socio-Demographic Variables							
HH Income Below $50k	0.43	0.49	0	0	0	1	1
HH Some College	0.82	0.38	0	1	1	1	1
HH Has Children	0.26	0.44	0	0	0	1	1
HH Has Elderly	0.26	0.44	0	0	0	1	1
HH White	0.81	0.39	0	1	1	1	1
HH Black	0.11	0.31	0	0	0	0	1
HH Asian	0.031	0.17	0	0	0	0	1
HH Hispanic Origin	0.064	0.24	0	0	0	0	1
HH Has Internet	0.91	0.29	0	1	1	1	1
HH Has Cable TV	0.73	0.44	0	0	1	1	1
County Socio-Demographic Variables							
County Population	967,084	1,646,410	395	123,804	410,463	973,977	10,081,570
County Median HH Income ($2012)	55,037	13,698	19,624	45,603	52,806	61,038	122,844
County Share Child Pop.	0.2	0.025	0.03	0.18	0.2	0.21	0.31
County Share Elderly Pop.	0.13	0.037	0.041	0.11	0.13	0.15	0.45
County Share Coll. Degree	0.22	0.035	0.064	0.19	0.21	0.24	0.37
County Share Black	0.12	0.12	0	0.032	0.085	0.18	0.86
County Share Hispanic	0.14	0.14	0	0.038	0.082	0.2	0.98
County Share Presid Votes Republican	0.29	0.09	0.034	0.23	0.29	0.35	0.82
Share Rural Pop.	0.29	0.36	0	0.02	0.1	0.48	1
Share Lang. Barrier Pop.	0.00053	0.023	0	0	0	0	1
Share No Fixed Broadband Pop.	0.0052	0.072	0	0	0	0	1
Share No Broadband or Computer Pop.	0.00046	0.022	0	0	0	0	1

Note: Number of counties in the sample is 2,956. *Neighboring Counties In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

Table A19: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing (NielsenIQ Homescan Analysis)

	Log Purchases 1			
	(1)	(2)	(3)	(4)
Own County Acute Pathogens — PN on time	0.0860	0.0862	0.0862	0.0866
	(0.0629)	(0.0628)	(0.0628)	(0.0628)
Own County Acute Pathogens — PN late	0.0434*	0.0435*	0.0435*	0.0435*
	(0.0259)	(0.0259)	(0.0259)	(0.0259)
Own County Acute Pathogens — PN never	0.0666	0.0670	0.0670	0.0671
	(0.0494)	(0.0494)	(0.0493)	(0.0493)
NCs (In-DMA) Acute Pathogens — PN on time		0.0396	0.0397	0.0326
		(0.0465)	(0.0465)	(0.0461)
NCs (In-DMA) Acute Pathogens — PN late		0.0242	0.0242	0.0242
		(0.0329)	(0.0329)	(0.0331)
NCs (In-DMA) Acute Pathogens — PN never		0.0410	0.0415	0.0418
		(0.0545)	(0.0543)	(0.0544)
NCs (Out-DMA) Acute Pathogens — PN on time			-0.0189	-0.0183
			(0.0589)	(0.0589)
NCs (Out-DMA) Acute Pathogens — PN late			-0.0660*	-0.0661*
			(0.0374)	(0.0374)
NCs (Out-DMA) Acute Pathogens — PN never			0.0128	0.0129
			(0.0973)	(0.0973)
DMA Non-NC Acute Pathogens — PN on time				0.1797***
				(0.0641)
DMA Non-NC Acute Pathogens — PN late				0.0018
				(0.0729)
DMA Non-NC Acute Pathogens — PN never				0.0074
				(0.0781)
Temp Max Control	Yes	Yes	Yes	Yes
Total Precip. Control	Yes	Yes	Yes	Yes
R^2	0.35375	0.35375	0.35375	0.35375
Observations	7,520,489	7,520,489	7,520,489	7,520,489
Household fixed effects	✓	✓	✓	✓
County–Year fixed effects	✓	✓	✓	✓
State–Month fixed effects	✓	✓	✓	✓
Year–Month fixed effects	✓	✓	✓	✓

Note: The table reports coefficients from a fixed effects regression estimating spillover effects from the household-level panel. Clustered (County) standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Neighboring Counties In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county. *DMA non-Neighboring* refers to non-adjacent counties within the same DMA.

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