Notification Timing and Behavioral Spillovers: Evidence from U.S. Drinking Water Violations*

Raushan Baizakova†

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Abstract

Mandated information disclosure is intended to help households recognize and avoid environmental health risks, but its effects depend on whether warnings arrive on time and reach the people at risk. This paper studies the impact of public notification of acute microbial drinking water violations, which require notice within 24 hours. Using administrative records, I construct the first national measure of recorded notification timing and link it to weekly NielsenIQ bottled water sales for 2,283 U.S. counties from 2006 to 2019. Only about one-fifth of acute violations have a record of on-time notification; the remainder are delayed or have no recorded notification. Separating the recorded notification week from the broader violation window, I find that bottled water sales increase by an additional 31% in the week an on-time notice is recorded, but do not increase when delayed notices are recorded. I also find some evidence of costly information spillovers: bottled water sales rise in an unaffected county after timely notices affecting residents of its neighboring counties. Household purchase-location data provide no evidence that this response reflects affected residents shopping across county lines. Dynamic estimates are consistent with shared local media accelerating responses in adjacent counties, whereas nonadjacent counties show no systematic response even when sharing a local television market or strong social ties to the affected county. The findings show that the effectiveness of right-to-know regulation depends on timely implementation and clearly communicating the geographic scope of risk.

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† *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. This research was supported in part by Lilly Endowment, Inc., through its support for the Indiana University Pervasive Technology Institute.

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. Disclosure requirements are widely used to warn about risks from air and drinking water pollution, toxic releases, and unsafe products, reflecting a broad consensus on the importance of information provision in regulation (Fung, Graham, and Weil 2007; Dranove and Jin 2010; Loewenstein, Sunstein, and Golman 2014). Yet the effectiveness of these policies depends on *when* information reaches the public and *how far* it spreads. Warnings that arrive too late may fail to prompt timely protection, while information that spreads beyond the exposed population may induce precautionary behavior where the underlying hazard is absent (Viscusi 1997; Handel and Schwartzstein 2018; Bordalo, Gennaioli, and Shleifer 2022). These temporal and spatial frictions can leave exposed households insufficiently protected while generating costly avoidance elsewhere.

This paper studies how such informational frictions shape the public response to drinking water quality violations in the U.S. Specifically, I ask how the timing of mandated risk disclosure shapes avoidance behavior in directly affected communities, and whether information about a local violation can change behavior in nearby communities that are not served by the violating water systems. 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 (Hill and Ma 2022; Keiser et al. 2023; DiSalvo and Hill 2024). Federal regulation requires water systems to notify consumers of acute violations within 24 hours, yet government audits have repeatedly documented systematic gaps in compliance (USGAO 1992, 2011; USEPA-OIG 2019). At the same time, because public notices can be communicated through local television and radio, information about a water problem can reach households outside the directly affected service area, raising the prospect of costly behavioral spillovers in commu-

nities that are not themselves at risk.

I use data on all acute microbial violations in U.S. community water systems between 2006 and 2019 from the Environmental Protection Agency's (EPA) Safe Drinking Water Information System (SDWIS). I link each violation to state records from the EPA's Enforcement and Compliance History Online (ECHO) system documenting when state primacy agencies received certification of public notification. This allows me to construct the first national measure of recorded public notification timing for acute violations, classifying each as on-time, late, or having no recorded notification. Using EPA's Community Water System Service Area Boundaries, I allocate each system's served population across the counties covered by its service area. I then merge violations with NielsenIQ Retail Scanner data on bottled water sales from a consistent set of stores, aggregated to a balanced panel of 2,283 counties observed weekly over fourteen years and covering approximately 95% of the U.S. population; bottled water sales serve as a revealed-preference measure of pollution avoidance behavior at the community level. The main panel fixed-effects specification exploits week-to-week variation in acute violations and recorded notification activity within county-years to estimate responses in affected and neighboring counties, controlling for temperature, precipitation, flood events, national weekly shocks, and state-specific seasonality. I enter exposure over the administrative violation window jointly with exposure in the recorded notification week, separating purchasing during the violation from the additional response associated with notification. I complement these estimates with notification-centered event studies, a difference-in-differences estimator robust to heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille 2024), and a stacked difference-in-differences study (Cengiz et al. 2019) of 21 large-system violations.

My measure of recorded notification timing classifies only about one-fifth of acute violations as on-time, while nearly half are delayed and nearly one-third have no recorded notification. The estimates show that these differences in timing matter for consumer avoidance behavior. For an on-time notice covering the entire county, bottled water sales increase by an additional 31% in the week the notice is recorded. Separately accounting for the notification week reduces the estimated increase over the broader violation window from 14.5%

to 9.0%—a 38% reduction—showing that specifications based only on the violation window partly absorb the purchasing response concentrated around timely notification. For violations with delayed notification, sales increase by about 7% over the violation window, and this estimate remains unchanged when notification-week exposure is added; however, sales do not increase when the delayed notice is eventually recorded. The coefficient for violations with no recorded notification is not statistically distinguishable from zero. Event-study estimates reinforce this timing contrast, including under an estimator robust to heterogeneous treatment effects, while a stacked difference-in-differences analysis of large-system events likewise finds a response to on-time but not delayed notification.

I find some evidence that timely notification also changes purchasing behavior beyond the affected county. Controlling for violations and notifications in their own county, counties adjacent to a county in which an on-time notice is recorded increase bottled water purchases by about 15% on average over the notification week and the following two weeks, whereas delayed notices produce no comparable response. The stacked difference-in-differences analysis of large-system events also finds an increase of about 14% in adjacent counties in the notification week. Importantly, I find no evidence that the spillover effect is driven by affected-county residents shopping across county lines. Using NielsenIQ Homescan data, which can identify both a household's county of residence and the county in which its purchases are made, I show that affected-county households increase purchases within their home county during violations with on-time notification but *do not* increase purchases outside it. This evidence weighs against cross-county shopping as the primary explanation for the spillover effects.

To explore how information may reach neighboring communities, I compare adjacent counties that do and do not share the affected county's Nielsen Designated Market Area (DMA), a group of counties served by the same local television market. Dynamic estimates are consistent with shared local media accelerating the response: sales increase in the notification week in adjacent counties within the same DMA, whereas the response in adjacent counties outside the DMA emerges one to two weeks later. Nonadjacent counties show no systematic response even when they share a DMA or have strong social ties to the affected

county, measured using Facebook's Social Connectedness Index (SCI). These patterns suggest that the spillover is geographically localized and that shared local media may accelerate responses in neighboring communities. I also find little evidence that the direct or spillover responses vary systematically across county or household characteristics, including prior experience with drinking water violations.

As a final extension, I examine whether delayed or missing notification is associated with short-run health-related purchasing using sales of over-the-counter gastrointestinal medications. I find that diarrhea-remedy sales increase by 25–40% during the third through fifth weeks after the start of the noncompliance window with no recorded notification. The effects do not appear during or following violations with on-time or delayed notification. Because medication purchases are an indirect proxy for symptoms and I do not observe emergency department visits, hospital admissions, or other clinical outcomes, I interpret this pattern as suggestive evidence of health-related purchasing rather than as evidence of a health effect.

This paper contributes to two strands of literature at the intersection of environmental policy, information economics, and behavioral responses to risk. First, I contribute to the literature on environmental information disclosure and household avoidance behavior. Prior research on the Safe Drinking Water Act examines how disclosure requirements affect regulatory compliance and violation outcomes (Bennear and Olmstead 2008; Baker, Bennear, and Olmstead 2022). Related work examines bottled water purchasing in response to contamination concerns associated with shale-gas development and the Flint water crisis (Wrenn, Klaiber, and Jaenicke 2016; Christensen, Keiser, and Lade 2023). Previous studies on avoidance behavior in response to drinking-water contamination estimate changes in bottled water purchases during the administrative violation period without separately identifying when public notification occurred (Zivin, Neidell, and Schlenker 2011; Allaire et al. 2019). Closest to this paper, Marcus (2022) examines household bottled water purchases during acute coliform violations in North Carolina and finds a 78% increase during the violation month. For acute violations, the analysis in Marcus (2022) uses the statutory requirement of notification within 24 hours to characterize notification as immediate,

rather than using observed notification dates to determine whether and when consumers were notified.[1] I build on this work by constructing a national measure of recorded notification timing for acute microbial violations and showing that the legal requirement does not reliably describe implementation. This enables me to distinguish exposure over the administrative noncompliance window from exposure in the week notification activity is recorded. The distinction matters for measuring avoidance behavior and evaluating notification policy: accounting separately for the notification week reduces the violation-window response by more than one-third and reveals that the largest purchasing response is concentrated in the week timely notification is recorded.

Second, this paper contributes to the literature on behavioral spillovers from risk information. Identifying such spillovers is important for evaluating the full behavioral and economic effects of disclosure policies. Prior work documents that risk information can affect behavior beyond the consumers or products directly targeted by a warning or recall (Shimshack, Ward, and Beatty 2007; Freedman, Kearney, and Lederman 2012), including through shared media markets and social connections (Gallagher 2014; Hu 2022). Drinking-water studies have not, however, examined whether formal public notifications generate avoidance responses in nearby communities outside the affected service area. I provide, to my knowledge, the first national evidence suggesting that timely public notifications of acute microbial violations generate behavioral spillovers. Household purchase-location data provide no evidence that these spillovers are driven by impacted residents crossing county lines to purchase bottled water. From a policy perspective, the findings imply that while timely disclosure is important for alerting affected households to the health risks, it can also induce defensive expenditures beyond the population exposed to the underlying hazard, underscoring the importance of clearly communicating the geographic scope of risk.

To gauge the economic magnitude of these responses, back-of-the-envelope calculations attribute about $0.61 million in additional bottled water sales in directly affected counties

1. Marcus (2022) also studies monthly (non-acute) coliform violations and uses observed public notification distribution dates to compare violations with more and less rapid notification. My analysis focuses on acute microbial violations, for which notification is required within 24 hours.

to timely notification of acute microbial violations between 2006 and 2019, and another $2.18 million to the broader violation-window for both timely and delayed notification. Had delayed notices instead been issued on time, the estimates imply $1.13 million in additional affected-county purchases, assuming they generated the same response as timely notices. Spillover estimates imply approximately $0.53 million in additional purchases following timely notifications in neighboring counties. Together, these findings have two policy implications. First, effective disclosure requires timely implementation so that affected households can take protective action. Second, public notices should clearly identify the affected water systems and service areas so that households in surrounding communities can determine whether a warning applies to their water.

The remainder of the paper proceeds as follows. Section 2 describes the institutional framework governing drinking water regulation and public notification. Section 3 details the data and their construction. Section 4 describes the empirical strategy. Section 5 presents the main results, Section 6 examines mechanisms and robustness, Section 7 extends the analysis to gastrointestinal medication sales, and Section 8 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 covers 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. About 50,000 are community water systems (CWSs), which supply drinking water to the same population year-round and collectively serve nearly 90% of the U.S. population. The remaining systems are non-community systems, including systems serving schools and workplaces as well as transient facilities such as campgrounds and restaurants. Pri-

vate wells, which primarily serve rural households, fall outside SDWA regulation (USEPA 2015b).

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 more than 90 contaminants during the sample period, as well as Maximum Residual Disinfectant Level (MRDL) and Treatment Technique (TT) requirements to ensure public water safety (USEPA 2015a). The EPA also establishes monitoring and reporting requirements specifying the methods and frequency of contaminant testing, and how results are reported to regulators and the public. The enforcement responsibility under the SDWA, known as *primacy*, is delegated to 49 states, territories, and Indian tribes.[2] 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.

Community water systems source their water from groundwater or surface water resources and undertake the treatment and distribution to the served population. They can also buy treated water from other systems. To ensure that their finished water satisfies health-based requirements of the SDWA, systems are required to monitor their water against numerical standards of contaminants and to use specific treatment techniques. Systems report about the quality of their drinking water to their primacy agencies. When the systems' water quality does not satisfy NPDWR requirements, they incur health-based violations.

2.2 Public Notification Rule

Under the SDWA, public water systems are required to inform consumers of health-based water quality violations and certain monitoring and reporting violations. The Public Notifi-

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

cation (PN) Rule ensures consumers have a "right to know" about drinking-water violations and situations that may pose a risk and specifies the content, timing, and delivery channels of required notices, with requirements tiered by severity.

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, using one or more approved delivery methods such as broadcast media, public posting, hand delivery, or another method approved by the primacy agency. 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. Appendix Table A1 maps specific contaminants and rules to required public notification content such as the affected populations, health risks and recommended actions. 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, 2023b; USEPAOIG 2019).[3] Because this study examines immediate consumer responses to acute risks, it focuses on Tier 1 health-based violations.

Content requirements are standardized across notices. The notices 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 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 2023b). This allows states to verify whether a water system complied with the Public Notification Rule following a violation.

While the PN Rule sets out clear delivery requirements, federal oversight has documented persistent gaps between rule and practice. A 1992 Government Accountability Office (GAO) investigation reviewed 167 serious violations and found that public notices were issued in

3. Tier 3 notices may be combined with annual Consumer Confidence Reports and must be provided within one year of the system learning of the violation.

only 68 cases, with more than 70% of those notices delivered weeks or months after the violation occurred (USGAO 1992). The 1996 amendments to the SDWA and the revised PN Rule issued in 2000 sought to address these failures by focusing requirements on acute violations and streamlining the notification process. Subsequent audits, however, indicate that compliance problems have remained widespread. A 2011 GAO report estimated that roughly one quarter of health-based violations and the large majority of monitoring violations were either unreported or inaccurately reported by state primacy agencies, limiting EPA's ability to verify compliance or to confirm that the public had been adequately informed (USGAO 2011). In 2019, the EPA Office of Inspector General reached similar conclusions, finding that several state primacy agencies did not ensure that water systems consistently issued required public notices, particularly for Tier 3 notices (USEPAOIG 2019).

3 Data

The empirical analysis draws on EPA administrative records of drinking water violations at public water systems and states' receipt of public-notification certifications, EPA maps of community water-system service areas, retail scanner data on bottled water sales, and several auxiliary sources used to characterize geographic and informational connections across counties.

3.1 Drinking Water Violations

I use the National Downloads from EPA's Enforcement and Compliance History Online (ECHO) system, which mirrors the Safe Drinking Water Information System (SDWIS) federal database. SDWIS gathers 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. Most states 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.[4] 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-compliance date, I follow USEPA (2013) to find an effective violation end date.

I focus only 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.[5] 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. 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.[6]

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, so SDWIS typically records Tier 1 pathogen violations with noncompliance durations of approximately 30 days (see Appendix Table A2). The SDWIS noncompliance period nevertheless corresponds to the window during which a violation is formally recognized by regulators, and therefore

4. Because the analysis begins with violations recorded in SDWIS, it cannot capture violations absent from the federal records. Such events are absent from both the violation and notification measures, so the estimates apply to recorded acute microbial violations.

5. SDWIS records each violation's public-notification tier, and I keep violations recorded as Tier 1.

6. 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 exclude very small community water systems because they have different monitoring requirements and report irregularly (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.

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.

3.2 CWS Service Area Boundaries

SDWIS records the counties each community water system serves, but it often assigns a system to a single county even when its service area extends into neighboring counties.[7] To measure where the people served by each system live, I use EPA's Community Water System Service Area Boundaries, version 2.1 (USEPA 2025), which link each service area to the 2020 census blocks it covers. I split each system's SDWIS population served across the counties its service area covers, in proportion to the service-area population in each county, ignoring negligible overlaps (Appendix B.0).[8]

3.3 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. States are responsible for recording enforcement actions in the ECHO database.

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 certifica-

7. For example, SDWIS assigns the City of Austin's water system, which serves about 1.1 million people, only to Travis County, Texas, but its service area extends into Williamson County: about 7 percent of the people it serves live there, 14 percent of Williamson County's population. More generally, Austin, Bardot, and El-Khattabi (2024) show that conclusions about disparities in drinking water quality can depend on which service area boundaries are used.

8. Under this assignment, 1,115 of the 54,288 systems operating during 2006–2019 serve more than one county, compared with 144 in SDWIS.

tion to the primacy agency within ten days of issuing a notice to the public when they have a violation. Appendix Figure A1 presents a sample certification form (USEPA 2010). 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*. 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 two conditions. First, the state itself, not a water system, issued a public notification or boil water order on or before the effective violation end date. Second, the state received certification of public notification from the water system on or before the effective violation end date or within eleven days after it, 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*. Appendix Figure A2 displays the distribution of the constructed public notification timing measures at the system level across all violation categories. Among the 5,578 acute microbial violations, 1,184 (21.2%) are classified as on-time, 2,586 (46.4%) as delayed, and 1,808 (32.4%) as having no recorded notification.

Several features in the construction of the timing measure might risk its misclassification. First, it records when the primacy agency learned that the public had been notified, not when the notice reached households; a system that notified promptly but certified late, or did not certify at all, could be classified as late or as never notified. However, under the Public Notification Rule, a system that delivers its certification more than ten days after issuing the notice, or does not deliver one at all, incurs a public notification violation of its own. This disincentivizes systems from delaying or withholding certification when they did issue a public notice. Administrative recording practices may also vary across EPA re-

gions.[9] In addition, independent validation of my constructed timeliness measure against contemporaneous news and web coverage of large acute-pathogen events broadly supports the classification (see Appendix B.1).

Second, SDWIS does not record the exact date of the violation, but the regulatory non-compliance window over which the pathogen rules are evaluated, so the violation length I observe is a month while the actual violation may have lasted days or weeks. As noted above, I conservatively allow eleven days from the end of the violation window for a notice to be classified as on-time, which implies about forty-one days from the start of the window. If the violation occurred in the first week of the window and the state received the certification in the last week, I still classify the notice as on-time although it was in fact delayed.

Taken together, these features can generate classification error in both directions: delayed certification can assign a promptly issued notice to the late or never-recorded category, whereas the use of the end of the regulatory window can assign an actual delayed notice to the on-time category. If such errors are unrelated to short-run purchasing responses, the resulting mixing would tend to attenuate differences across notification regimes, although the direction of bias in any individual coefficient is hard to sign. I therefore interpret the categories as measures of recorded notification timeliness rather than exact statutory compliance. The external validation nevertheless indicates that they capture meaningful differences in the timing of public notices.

3.4 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

9. USEPAOIG (2019) documents gaps in public-notification tracking across EPA regions. Regions 9 and 10 (Pacific Northwest and Southwest) did not consistently track Tier 3 notices, while Region 8 (Mountains and Plains) did not record public-notification violations in some cases. The examples for Regions 9 and 10 concern Tier 3 rather than the Tier 1 events studied here and therefore document general heterogeneity in administrative recording rather than misclassification in this sample specifically.

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 14-year sample period. The resulting balanced panel covers 2,283 counties observed over 730 weeks. 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.

3.5 Spatial and Information Structure

To analyze spillovers, I construct three measures of inter-county connection: geographic adjacency, shared media markets, and social connectedness.

Neighboring Counties (NCs). I define neighboring counties using the 2023 Census County Adjacency file.[10] This file identifies all directly adjacent counties for each focal county and is used to measure geographic spillover exposure.

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. I use Nielsen's crosswalk between counties and DMAs for 2017. Each county belongs to exactly one DMA. The Public Notification Rule identifies broadcast media, including local television, as a delivery method for Tier 1 notices, and EPA guidance recommends broadcast media for large systems when available. I therefore use DMA boundaries as a proxy for counties that may share an information environment (USEPA 2010). 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 distinc-

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

tions are used to construct measures of potential information spillovers through geography and media markets.

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) constructed the SCI based on a snapshot of all Facebook friendships from 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. SCI is widely used as a proxy for real-world social ties, since Facebook serves primarily real-world friend networks and reached about 239 million active users in the U.S. and Canada (Bailey et al. 2018; Hu 2022).

3.6 Weather and Flood Controls

I use county-level historical daily 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 in each county in Celsius degrees and create a categorical variable with ten 5-degree bins ranging from ≤ 0°C to ≥ 40°C. Similarly, I calculate weekly total precipitation in millimeters and create a categorical variable with eight bins from 0 mm to more than 100 mm. I also control for flood-related events using the NOAA Storm Events Database. Floods and heavy rainfall can both contaminate drinking water (Austin, Pan, and Parthum 2024) and shift demand for bottled water directly, so I define an indicator equal to one for any county-week in which NOAA records a flood, flash flood, or heavy rain event in the county.

4 Empirical Strategy

The empirical analysis centers on a balanced panel of 2,283 counties observed weekly from 2006 to 2019. I jointly estimate purchasing patterns during the administrative noncompliance window and in the recorded public-notification week, separately by notification regime. I first examine responses within affected counties and then extend the specification to violations in neighboring counties, distinguishing adjacent counties by whether they share the affected county's media market. Dynamic specifications trace these responses around the recorded notification week. I assess the robustness of the results using the heterogeneity-robust estimator of de Chaisemartin and D'Haultfœuille (2024). Finally, a stacked difference-in-differences event study of 21 violations at large community water systems provides complementary evidence on the timing of the response.

4.1 Own-County Violation and Notification Exposure

I estimate average responses to acute drinking water violations using a fixed-effects framework applied to a balanced panel of 2,283 counties observed weekly from 2006 to 2019. I construct two complementary exposure measures. The *violation-window* measures, V^s_{cyw}, are active during every week of the noncompliance period. They are scaled by the share of days in the week that the system was out of compliance and the share of the county population served by that system, where s indexes the recorded notification regime. Appendix B.2 provides further details. For violations with a recorded public-notification date, I construct a second measure that is active in the week of the corresponding notification-related record. The *notification-week* measure, N^s_{cyw}, is the share of the county population served by systems whose public-notification activity is recorded in that week.

The own-county specification is

$$S_{cyw} = \sum_{s\in\{\text{On-Time,Late,Never}\}} \beta_s V^s_{cyw} + \sum_{s\in\{\text{On-Time,Late}\}} \lambda_s N^s_{cyw} + \delta W_{cyw} + \alpha_{cy} + \mu_{pm} + \tau_{yw} + \varepsilon_{cyw}, \tag{1}$$

where S_{cyw} is the log of weekly bottled water sales in county c, week w and year y. The coefficients β_s capture differences in sales during the administrative noncompliance window under notification regime s, conditional on the notification-week measure. The coefficients λ_s capture the additional change in sales in the recorded notification week for violations classified as on-time or late. There is no notification-week coefficient for violations with no recorded notification because those events have no notification date. As described in Section 3.3, the recorded notification week can fall within or outside the administrative noncompliance window, so the two measures may overlap but are not identical. W_{cyw} is a vector of weather controls (maximum temperature and precipitation bins, and a flood indicator), 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. τ_{yw} denotes year-by-week fixed effects, which absorb national shocks at the weekly level. Standard errors are clustered at the media market (Nielsen Designated Market Area, DMA) level, allowing for correlated regional shocks across counties within the same DMA.

Identification. Identification comes from week-to-week changes in acute pathogen violation exposure and recorded notification activity within county-years, after accounting for primacy-agency-specific seasonality, national weekly shocks, weather, and floods. County-by-year fixed effects absorb persistent differences across communities in baseline purchasing and annual local conditions that may be correlated with notification practices. Entering

the two measures jointly makes the notification-week coefficient conditional on violation-window exposure. Identification could be threatened if an unobserved short-run shock affected bottled water demand and either drinking water quality or recorded notification activity. Acute microbial violations generally reflect unexpected infrastructure or treatment failures rather than conditions tied to weekly fluctuations in consumer demand. For the notification-week coefficient, confounding would require an unobserved demand shock that coincides specifically with the recorded notification week rather than merely with the underlying violation.

4.2 Neighboring-County Exposure

The preceding specification considers violations occurring within the focal county. I next augment it with parallel measures of violation-window and notification-week exposure originating in geographically adjacent counties. This extension tests whether purchasing responses extend beyond the communities directly served by the violating water system. For each notification regime s, $V_{cyw}^{s,\text{NC}}$ and $N_{cyw}^{s,\text{NC}}$ are population-weighted counterparts of the own-county measures, constructed over all counties adjacent to county c (see details in Appendix B.2). In any week in which a neighboring county shares with county c a water system that has a violation recorded that week, I drop that neighboring county from county c's measures, because residents served by a shared system may be directly exposed to the same violation. The remaining neighboring-county measures therefore capture exposure to violations occurring outside the focal county's own water supply. Adding these measures to Equation 1 gives

$$S_{cyw} = \sum_{s\in\{\text{On-Time,Late,Never}\}} \left(\beta_s V_{cyw}^{s} + \theta_s V_{cyw}^{s,\text{NC}}\right) + \sum_{s\in\{\text{On-Time,Late}\}} \left(\lambda_s N_{cyw}^{s} + \pi_s N_{cyw}^{s,\text{NC}}\right) + \delta W_{cyw} + \alpha_{cy} + \mu_{pm} + \tau_{yw} + \varepsilon_{cyw}. \tag{2}$$

The coefficients θ_s capture the association between focal-county sales and neighboring-

county violation-window exposure under regime s. The coefficients π_s capture the additional association in the week that neighboring-county notification activity is recorded. Both are conditional on the focal county's own violation-window and notification-week exposure.

Dynamic specifications. To examine how purchasing responses evolve around disclosure, I estimate dynamic versions of the own-county and neighboring-county specifications. I replace the notification-week measures with population-weighted event-time exposure measures covering the eight weeks before and after the recorded notification week, constructed separately for on-time and delayed notifications. The own-county specification includes own-county event-time and violation-window measures. The neighboring-county specification includes the corresponding event-time and violation-window measures for adjacent counties while controlling for own-county exposure measures. Both specifications retain the controls and fixed effects from their static versions. The indicator for the week preceding recorded notification, $h = -1$, is omitted. Because weeks outside the eight-week event window remain in the estimation sample with all event-time measures equal to zero, the omitted category pools $h = -1$ with observations outside the event window. The event-time coefficients therefore describe changes around recorded notification relative to this pooled baseline, conditional on violation-window exposure. The pre-notification coefficients provide a diagnostic for whether purchasing was already changing before notification activity was recorded.

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

Event Definition and Sample Construction. As a complement to the national county-level analysis, I examine acute microbial violations in large community water systems (CWSs) for which the affected population is closely aligned with the geography of the retail outcome. I restrict the sample to systems serving at least 100,000 people and to events in which the violating system serves at least 75 percent of the county population. This restriction limits

attenuation arising from assigning system-level violations to county-level retail outcomes.[11]

This selection yields 24 acute violation events, 11 with on-time public notification, 11 followed by delayed notification, and two for which no notification date is recorded. Among delayed events, I retain those for which notification occurred within 100 days of the end of the violation window.[12] The resulting sample contains 21 events, comprising 11 on-time and 10 delayed-notification events. I estimate the event-study specification separately for the two notification regimes. I define the county in which the violating CWS serves at least 75 percent of the population as the "*directly exposed*" county. For each event, I also identify every adjacent county that is observed in the retail data, lies outside the violating system's service area, and had no acute pathogen violation of its own within 12 weeks before or after the event. I refer to these counties as "*indirectly exposed*" counties.[13]

Control Group Construction. For both directly and indirectly exposed counties, I construct control counties using a matching procedure based on socio-demographic characteristics, as in matched-location approaches used in prior work on environmental crises (e.g., Christensen, Keiser, and Lade (2023)). Specifically, I compute a county-level socio-demographic distance using eleven standardized characteristics drawn from the 2008 - 2012 5-year American Community Survey and 2012 Republican vote share, including an ordered population-density-bin measure. For counties i and j, I compute a normalized Euclidean distance over the eleven standardized characteristics; details are in Appendix B.4. For the "*directly exposed*" county, I choose as the control the county closest to it on the socio-demographic distance measure among counties observed in the NielsenIQ Retail Scanner data that are in the same state, outside its media market (DMA), and not adjacent to it,

11. The finest geographic unit at which NielsenIQ Retail Scanner outcomes can be linked reliably in the national sample is the county. An alternative approach, as in Christensen, Keiser, and Lade (2023), is to assign retail outcomes directly to the affected community water system and estimate effects at the water-system level. That approach is well suited to a single large municipal event such as Flint, where the relevant water system and affected retail market are clear. In my setting, one can construct an inferred store-to-CWS assignment by combining EPA CWS service-area boundaries, ZCTA and county geography, Homescan households' ZIP5 locations, and Homescan trips to RMS stores observed at the ZIP3 level. This inference is credible only when the retail market is closely aligned with the water-system service area, such as in large municipal systems served primarily by one dominant CWS. Across the national sample, however, ZIP3 areas often contain multiple water systems, so household-to-store links do not reliably identify the CWS serving each store.

12. This restriction keeps the violation onset within the pre-notification portion of the event window and excludes cases in which the violation and its eventual disclosure are separated by an unusually long interval.

13. A county lies outside the service area if the violating system serves no more than 0.1 percent of its population. There are 78 such counties (41 in on-time and 37 in delayed-notification events).

and that had no acute pathogen violation within 12 weeks before or after the notification week.[14] For each "*indirectly exposed*" county, I choose the county closest to it on the same measure among counties observed in the Retail Scanner data that are in its state, outside both its own DMA and the DMA of the directly exposed county, adjacent to neither county, and without an acute pathogen violation within the same window, in the county itself or in any of its adjacent counties.[15]

Appendix Tables A8 and A11 list the violation events, external validation results and matched control counties for the on-time and delayed-notification samples. Appendix Tables A9 and A12 assess covariate balance for directly and indirectly exposed counties relative to their respective matched controls. Balance is generally close in the delayed-notification sample but less complete in the on-time sample, particularly among indirectly exposed counties. Appendix Section 5.4 discusses the implications of the remaining imbalance for interpreting the event-study estimates.

Event Time and Specification. Event time is defined relative to the public notification week. Let κ_{et} 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:

$$y_{est} = \sum_{\substack{k=-12 \\ k\neq -1}}^{12} \beta_k^D \, \mathbf{1}\{\kappa_{et} = k\} \cdot \mathit{Direct}_{ec} + \sum_{\substack{k=-12 \\ k\neq -1}}^{12} \beta_k^I \, \mathbf{1}\{\kappa_{et} = k\} \cdot \mathit{Indirect}_{ec} + W_{ct}'\delta + \gamma_{es} + \tau_{eyw} + \varepsilon_{est}. \tag{3}$$

Equation (3) 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

14. Same-state controls share the exposed county's primacy agency, which administers the Public Notification Rule, and its seasonal conditions. Excluding media markets and adjacent counties limits the spillover channels through which a violation could affect the control county.

15. For two indirectly exposed counties of the 2009 Portland event (Hood River and Washington, Oregon), all remaining candidates for controls fail the screen only because of violations at very small systems, so for these two I ignore violations at systems serving less than 1 percent of a county's population.

for flexible event-specific fixed effects, following the stacked event-study approach used by Cengiz et al. (2019) and in related applied work such as Butters, Sacks, and Seo (2022). Here, y_{est} is the log of bottled water sales in store s, located in county c, for event e and week t. The sample includes stores with positive bottled water sales in at least 20 of the 25 weeks of the event window. 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 an indirectly exposed county for event e. W_{ct} is a vector of weather controls (maximum temperature and precipitation bins, and a flood indicator). The specification includes event-by-store fixed effects γ_{es}, which absorb store-specific baseline sales within each event, and event-by-year-by-week fixed effects τ_{eyw}, which absorb common time shocks within each event's window. 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. Standard errors are clustered at the county level.

5 Regression Results

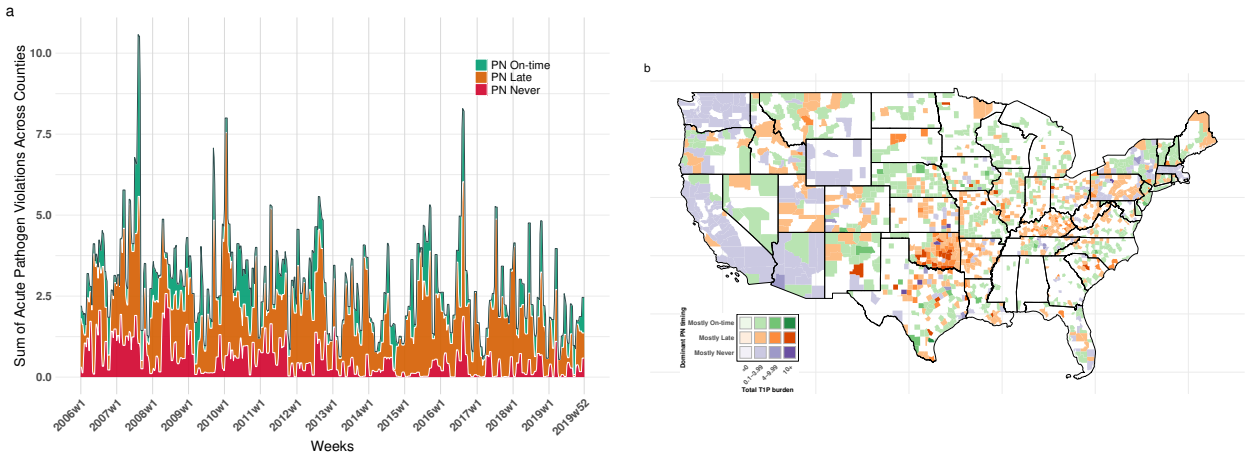
5.1 Descriptive Patterns

This section describes temporal and geographic patterns in acute microbial violations and their recorded public notification. Appendix Table A3 reports summary statistics for the estimation sample. Appendix Table A2 reports CWS-level summary statistics by National Primary Drinking Water Regulation rule and contaminant code. The median recorded noncompliance window is 30 days across the acute microbial violation categories. Turbidity exceedances are the most common, followed by total coliform violations. As described in Appendix B.2, I aggregate CWS-level violations to county-week exposure measures using population weights and the share of days in violation; notification-week exposure is based on the population served by systems whose notification activity is recorded that week.

Panel *a* of Figure 1 plots the weekly sum of county-level acute microbial violation expo-

sure across all counties, disaggregated by recorded notification timing. Violations display seasonality, with the highest incidence during summer months. Aggregate exposure is generally lower after 2017, although violations with delayed notification continue to account for a substantial share. Panel *b* of Figure 1 illustrates cross-sectional variation in violations. The heatmap shows the cumulative violation exposure over the sample period and identifies the predominant public notification timing in each county. Counties with the highest cumulative violation exposure 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, along with Wyoming and Massachusetts, have fewer violations overall but a high share of events for which no notification date is recorded. Because notification status is measured from administrative records, these geographic patterns may reflect regional recording practices as well as differences in notification behavior; Section 3.3 discusses this limitation.

Figure 1: Acute Pathogen Violations by Public Notification Timing Across U.S. Counties



Note: Panel *a* plots, for each week, the sum across counties of the acute pathogen violation exposure measure, disaggregated by public notification timing. Panel *b* maps the cumulative sum of this measure in each county over the sample period and indicates the predominant notification classification. The exposure measure weights each violation by the share of the county population served and the share of days in the week under violation. The figure covers 3,108 counties and 730 weeks.

Table 5.1: The Effects of Acute Pathogen Violations on Bottled Water Sales by Public Notification Timing

	Log bottled water sales				
	(1)	(2)	(3)	(4)	(5)
Own county					
Notification week × On-time		0.3286***	0.2729***	0.2725***	0.2708***
		(0.0718)	(0.0709)	(0.0708)	(0.0702)
Notification week × Late		-0.0326	-0.0294	-0.0295	-0.0271
		(0.0216)	(0.0223)	(0.0222)	(0.0220)
Violation window × On-time	0.1356***		0.0866***	0.0854***	0.0858***
	(0.0286)		(0.0269)	(0.0269)	(0.0270)
Violation window × Late	0.0644***		0.0641***	0.0641***	0.0642***
	(0.0186)		(0.0188)	(0.0188)	(0.0188)
Violation window × Never	0.0669		0.0670	0.0670	0.0671
	(0.0545)		(0.0545)	(0.0545)	(0.0545)
Neighboring counties (total)					
Notification week × On-time					0.1929
					(0.1382)
Notification week × Late					-0.0809*
					(0.0420)
Violation window × On-time				0.0809*	0.0454*
				(0.0433)	(0.0245)
Violation window × Late				0.0503	0.0500
				(0.0437)	(0.0436)
Violation window × Never				0.0277	0.0281
				(0.0925)	(0.0923)
County × Year FE	yes	yes	yes	yes	yes
Primacy Agency × Month FE	yes	yes	yes	yes	yes
Year × Week FE	yes	yes	yes	yes	yes
Clustering	DMA	DMA	DMA	DMA	DMA
Observations	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604
R^2	0.9923	0.9923	0.9923	0.9923	0.9923
Tests of equality (Wald p-value)					
Own: on-time vs late, notification week		p =0.000	p =0.000	p =0.000	p =0.000
Own: on-time vs late, violation window	p =0.040		p =0.507	p =0.532	p =0.526
Own: notification vs violation, on-time			p =0.019	p =0.019	p =0.019
NCs: on-time vs late, notification week					p =0.064
NCs: notification vs violation, on-time					p =0.256

Note: Dependent variable is the log of bottled water sales. Each column is a separate regression. *Notification week* exposure is the share of county residents served by systems whose public notice is recorded that week; *violation window* exposure is the share of residents served by systems in violation, scaled by the share of days in the week out of compliance. *Neighboring counties (total)* is population-weighted exposure across adjacent counties, dropping in any week a neighboring county that shares with the focal county a water system with a violation that week. All columns include categorical controls for precipitation and temperature and a flood indicator. Tests of equality are Wald tests of the linear combination named in the row. Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

5.2 Own-County Responses to Violations and Public Notification

Table 5.1 presents estimates from Equation 1. Column (1) includes only own-county violation-window exposure, column (2) includes only own-county notification-week exposure, and column (3) includes both measures jointly, so each coefficient is conditional on the other exposure measure. Columns (4) and (5), discussed in the next subsection, add the corresponding neighboring-county measures. All specifications include county-by-year, primacy agency-by-month, and year-by-week fixed effects, together with categorical controls for

temperature and precipitation and a flood indicator.

In column (1), bottled water sales increase by 14.5% during violations with on-time notification and by 6.7% during violations with delayed notification; both estimates are statistically significant. Column (2), which includes notification-week exposure alone, implies a 38.9% increase in bottled water sales during an on-time notification week at full exposure and no positive response to delayed notification. When both measures enter jointly in column (3), the on-time violation-window estimate falls from 14.5% to 9.0%—a 38% reduction—while the on-time notification-week estimate falls from 38.9% to 31.4% but remains large and precisely estimated. The build-up therefore shows why the two dates should be separated: when either measure enters alone, it partly captures purchasing changes associated with the other. In the joint specification, the additional notification-week response is more than three times as large as the remaining violation-window response. Evaluated at the mean exposure among notified county-weeks, the notification-week estimate implies an increase of approximately 2%.[16] By contrast, bottled water sales do not increase in the week delayed notification is recorded. This contrast is consistent with delayed notices conveying less actionable information because they are recorded after the acute risk has passed. Adding notification-week exposure leaves the delayed violation-window estimate approximately unchanged at about 6.6%, indicating that the higher sales associated with these events occur during the violation window rather than when the eventual notice is recorded. Violations with no recorded notification are associated with an estimated 6.9% increase during the violation window, but this estimate is not statistically distinguishable from zero.

Wald tests reject equality between the on-time notification-week and violation-window coefficients ($p = 0.019$) and between the on-time and delayed notification-week coefficients ($p < 0.001$). By contrast, I cannot reject equality between the on-time and delayed violation-window coefficients ($p = 0.51$). This could be attributed to the population reacting to observable changes in their drinking water quality during violations. It may also

16. Mean exposure among county-weeks with positive on-time notification exposure is 0.0721. With $\hat{\lambda}_{\text{On-Time}} = 0.2729$ from column (3), the implied effect is $100\left[\exp\left(0.2729 \times 0.0721\right) - 1\right] \approx 2$ percent.

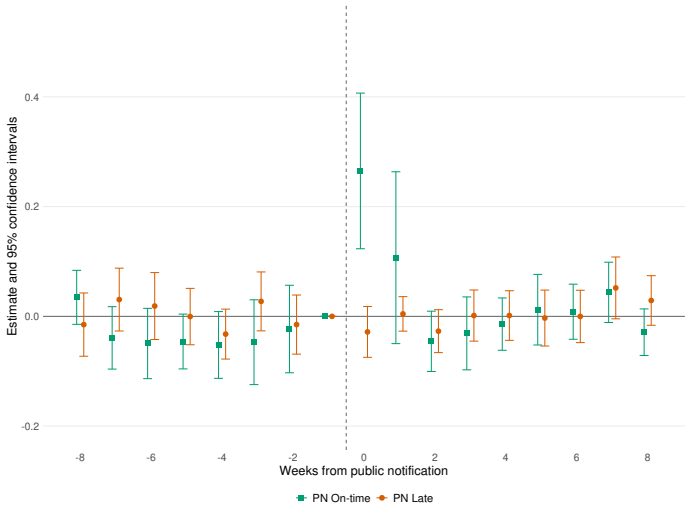
partly reflect notices that reached households on time but were classified as delayed because certification reached the primacy agency later (see discussion in Section 3.3).

Dynamic Estimates. Figure 2 presents the own-county response during the eight weeks before and after recorded public notification. Column 1 of the Appendix Table A6 reports the complete set of underlying coefficient estimates. Event time $h = 0$ denotes the week in which public notification activity is recorded, and the immediately preceding week, $h = -1$, is the omitted period. The notification-event-time and violation-window measures enter jointly, together with the same controls and fixed effects as in Equation 1. The event-time coefficients therefore measure changes in bottled water purchases around recorded notification conditional on exposure during the violation window.

For violations with on-time notification, the Wald test fails to reject the null hypothesis that the pre-notification coefficients are jointly zero ($p = 0.154$). Conditional on violation-window exposure, the notification week event-time coefficient implies an additional increase in bottled water sales of approximately 30% under full county exposure; evaluated at the mean exposure among county-weeks with an on-time notification, the estimate implies an increase of approximately 1.9%. One week after notification, the coefficient declines to 11.28% and is no longer statistically distinguishable from zero, indicating that the response is concentrated in the recorded notification week.

For violations with delayed notification, there is no corresponding increase when notification is recorded. The coefficient at the notification week implies a decrease by 3%, but it is not statistically different from zero. Neither the pre-notification nor post-notification coefficients are jointly different from zero ($p = 0.341$ and $p = 0.379$, respectively). Together, the dynamic estimates show that bottled water purchases increase when notification is recorded on time but do not respond when notification is recorded after the violation.

Figure 2: Dynamic Own-County Responses Around Public Notification, by Notification Timing



Note: Dependent variable is the log of bottled water sales. The figure plots own-county event-time coefficients separately for violations with on-time and delayed public notification. Event time 0 is the week in which public notification activity is recorded, and $h = -1$ is the omitted period. Column (1) of Appendix Table A6 reports its complete set of coefficients. Vertical lines are 95% confidence intervals. Regressions include violation window exposure, categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month, and year×week fixed effects. Standard errors are clustered at the media-market (DMA) level.

Heterogeneity-Robust Estimates. The notification-exposure measure is continuous and non-absorbing and can change repeatedly within a county; its effects may also vary across events and over time. With continuous treatments and heterogeneous effects, linear fixed-effects coefficients can be difficult to interpret (De Chaisemartin and D'Haultfœuille 2020; Callaway, Goodman-Bacon, and Sant'Anna 2024). As a robustness check, I therefore re-estimate the own-county notification response using the estimator of de Chaisemartin and D'Haultfœuille (2024), which accommodates nonbinary, nonabsorbing treatments and allows outcomes to depend on current and lagged exposure. I estimate effects from the notification week through five weeks afterward and six placebo effects, using the same switching counties at every horizon and normalizing estimates to a one-unit increase in exposure.[17] [18] It compares changes in bottled water sales in counties whose notification exposure increases in a given week with counties whose exposure does not change and was at the same

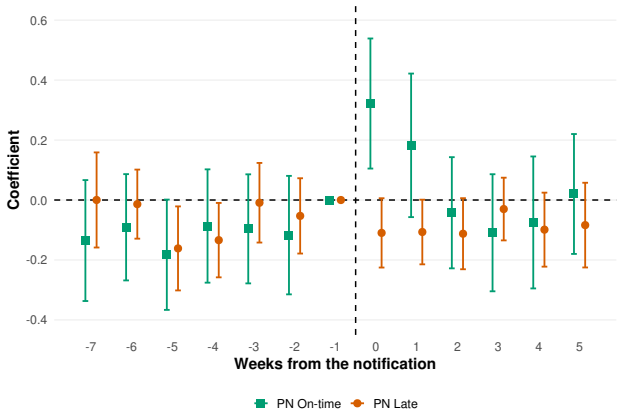
17. In each estimation, treatment is one notification-week exposure measure, and I restrict the switchers to counties whose first change in that measure is an increase from zero.

18. To avoid overlapping event windows, a notification occurring within thirteen weeks of an earlier notification of the same timing in the same county is dropped, keeping the first. Of the 3,313 notifications dated between 2006 and 2019, this removes 479 (140 on-time and 339 late).

level in the preceding week, and aggregates these comparisons using non-negative weights. I include the violation-window exposure and weather and flood controls used in the main specification and cluster standard errors at the media-market level.

Figure 3 plots the coefficients for own county notification week for on-time and late public notices, conditional on violation window exposure, weather, and floods. All percentage changes are full-exposure effects. For on-time notification, the notification-week estimate implies an additional increase in bottled water sales of approximately 38%, an estimate that is statistically significant and is based on 649 switching counties.[19] None of the following five weekly estimates is individually statistically significant, and the six pre-notification placebo estimates are jointly indistinguishable from zero ($p = 0.65$, see Appendix Table A7). For delayed notification, sales decrease by approximately 10% in the notification week, although this estimate is statistically significant only at the 10 percent level.[20] Thus, the heterogeneity-robust estimates reproduce the central pattern: bottled water purchases increase when notification is recorded on time, with no corresponding positive response when notification is delayed.

Figure 3: de Chaisemartin and D'Haultfœuille (2024) Event Study of Avoidance Behavior Following Public Notification of Acute Pathogen Violations, by Notification Timing



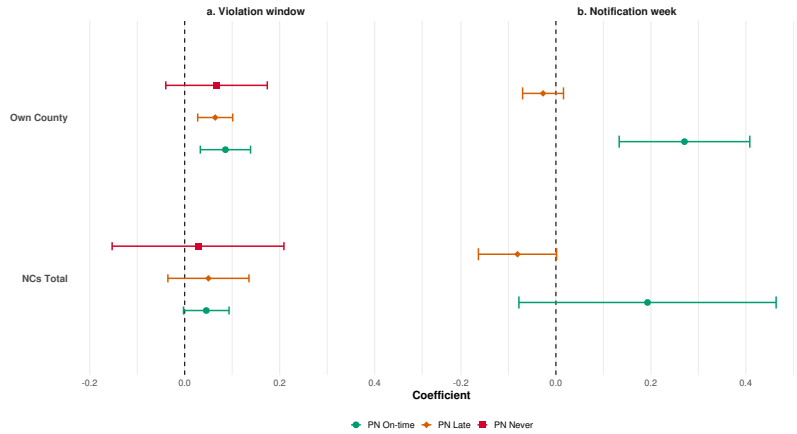
Note: Dependent variable is the log of bottled water sales. *PN* denotes public notification. The figure plots the estimates of de Chaisemartin and D'Haultfœuille (2024) for the own county's notification-week exposure, per unit of exposure, separately for on-time and late public notification. Vertical lines are 95% confidence intervals. Controls include own county's violation weeks exposure, notification-week and violation weeks exposure from neighboring counties, linear maximum temperature, total precipitation, and a flood indicator. Standard errors are clustered at the media market (DMA) level.

19. Mean exposure is 0.0721, so the estimate implies about a 2.3% increase at the mean dose.
20. The six post-notification estimates are jointly indistinguishable from zero ($p = 0.38$), as are the placebo estimates ($p = 0.11$).

5.3 Spillovers to Neighboring Counties

Columns (4) and (5) of Table 5.1 present estimates from Equation 2, where column (4) introduces exposure to neighboring counties' violation window and Column (5) adds exposure to neighboring counties' notification week, while controlling for exposure from own county. Exposure to neighboring counties' violation period with timely notification is associated with an 8.4% increase in bottled water sales in the focal county. Adding neighboring-county notification-week exposure reduces the violation-window estimate to 4.6% — approximately half its previous magnitude. Exposure to neighboring counties' public notification week implies an additional 21.3% increase but is not statistically distinguishable from zero (see Figure 4). These point estimates suggest that part of the neighboring-county response is concentrated around timely disclosure rather than distributed evenly over the broader violation window, although the notification-week and violation-window coefficients are not statistically distinguishable from each other ($p = 0.256$).

Figure 4: Own-County and Neighboring-County Responses by Public Notification Timing



Note: Dependent variable is the log of bottled water sales. Both panels plot coefficients from a single regression (column (5) of Table 5.1) in which the violation-window and notification-week exposure measures enter jointly. Horizontal lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Standard errors are clustered at the media market (DMA) level. *NCs* denotes neighboring counties.

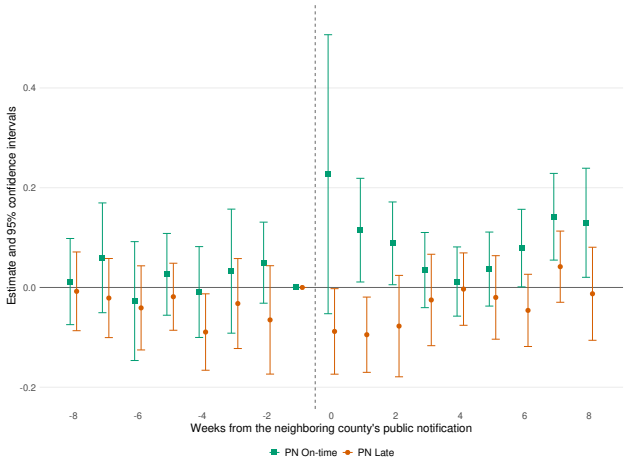
The notification-week contrast also follows the own-county pattern. For violations with delayed notification, the neighboring-county violation-window estimate remains approximately unchanged at about 5.1% when notification-week exposure is added, while sales do not increase when the delayed notice is recorded. The difference between the timely-

and delayed-notification-week coefficients is statistically significant at the 10% level. Violations with no recorded notification produce a small neighboring-county estimate that is statistically indistinguishable from zero.

Dynamic Estimates. Figure 5 examines the neighboring-county response dynamically, with event time defined by the week in which notification activity is recorded for a violation in adjacent counties (see Appendix Table A6.) The Wald test does not reject that the pre-notification coefficients are jointly zero ($p = 0.275$). Conditional on neighboring-county violation-window exposure, the notification-week estimate implies an additional 25.5% increase under full exposure (not statistically significant, $p = 0.112$), and the estimates remain positive during the following two weeks. Averaged over the notification week and the following two weeks, the increase is about 15.4% (statistically significant at the 1% level). The timely-notification coefficients become positive again near the end of the event window, following several estimates close to zero, so I do not interpret this later movement as persistence of the initial response.

The delayed-notification series does not show the same increase at the recorded notification week. Its coefficients are negative around the notice and jointly different from zero afterward ($p = 0.025$), but the decline begins before the notification week. Taken together, the static and dynamic estimates suggest that timely public notification changes bottled-water purchasing beyond the county in which the violation occurs. The individual neighboring-county estimates are less precise than the own-county estimates, but the concentration of the response after timely notification, its absence beforehand, and the lack of a comparable change following delayed notification support interpreting it as a behavioral spillover.

Figure 5: Dynamic Neighboring-County Responses Around Public Notification, by Notification Timing



Note: Dependent variable is the log of bottled water sales. The figure plots event-time coefficients for neighboring counties, separately for violations with on-time and delayed public notification. Event time 0 is the week in which the neighboring county's public notification activity is recorded, and $h = -1$ is the omitted period. Vertical lines are 95% confidence intervals. Regressions include own-county violation-window and notification-week exposure, neighboring counties' violation-window exposure, and categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month, and year×week fixed effects. Standard errors are clustered at the media-market (DMA) level.

As a heterogeneity-robust check, I also apply the estimator of de Chaisemartin and D'Haultfœuille (2024) to total neighboring-county exposure. Column 3 of the Appendix Table A7 presents the results. The notification-week estimate for timely notices implies an increase of approximately 24%, and all six post-notification point estimates are positive, and five are individually significant at the 10 percent level, but they are jointly indistinguishable from zero ($p = 0.53$).[21]

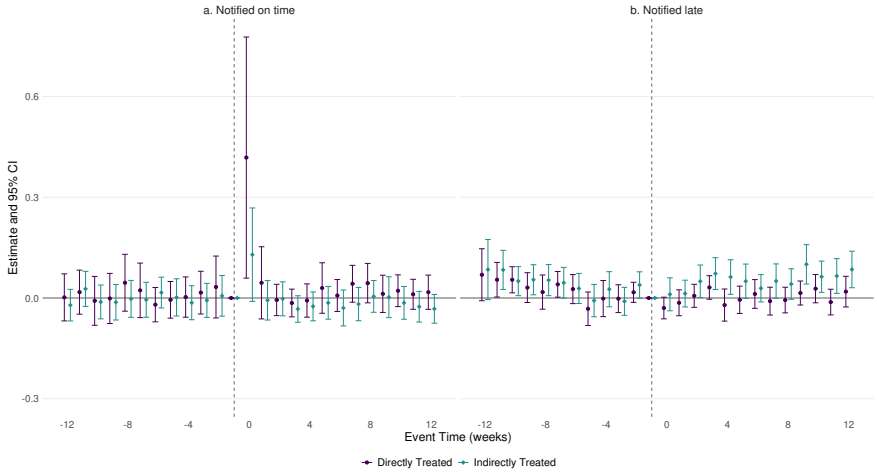
5.4 Evidence from Matched Events

I next examine the stacked difference-in-difference event-study (Cengiz et al. 2019) estimates for 21 large-system violations, comprising eleven events with on-time notification and ten with delayed notification. Events are restricted to acute microbial violations at public water systems serving at least 100,000 people and where systems serve at least

21. Neighboring-county exposure is considerably more diffuse than own-county exposure. Timely neighboring-county notification reaches 1,637 counties over the sample period, leaving 646 counties that are never exposed, compared with 1,627 never-exposed counties in the own-county analysis. Mean positive exposure is also lower for neighboring counties, at 0.0143 compared with 0.0721 for the own county.

75% of the county population. Appendix Tables A8 and A11 list the event characteristics. Appendix Tables A10 and A13 report summary statistics for the two samples at the store-week level. Figure 6 presents the estimates from Equation 3 for directly and indirectly exposed (adjacent) counties relative to their matched controls. The specification includes weather controls, a flood indicator, and event-by-store and event-by-year-by-week fixed effects. For events with on-time notification, the directly exposed counties exhibit no clear pre-notification trend. Relative to stores in their matched control counties, bottled water sales at stores in directly exposed counties increase by approximately 52% in the notification week (statistically significant at the 5 percent level) and return to baseline afterward. Stores in indirectly exposed neighboring counties show an increase of approximately 14% relative to their controls in the same week (statistically significant at the 10 percent level). In the delayed-notification sample, neither directly nor indirectly exposed counties exhibit a positive response when notification is recorded.[22]

Figure 6: Stacked Difference-in-Differences Event Study from Cengiz et al. (2019) of Avoidance Behavior and Spillover Effects, by Public Notification Timing



Note: Dependent variable is the log of bottled water sales. The left panel covers the eleven acute pathogen violation events with on-time public notification and the right panel the ten events with late public notification. 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 matched control counties. Event time 0 denotes the week of public notification; the reference week -1 is omitted. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature, a flood indicator, and event×store and event×year×week fixed effects. Standard errors are clustered at the county level. Observations: 73,452 in panel *a* and 44,584 in panel *b*.

22. Results are robust to using the log of bottled water's share of total store sales as an outcome, which normalizes bottled water sales by total sales across all store products (Appendix Figure A3).

Appendix Section C.1 examines covariate balance and the sensitivity of the estimates to individual events. The on-time estimates are particularly sensitive to the October 2018 Austin event: without it, the stacked event-study estimates for directly and indirectly exposed counties fall from 52% to 17.9% and from 14% to 3.7%, respectively, and are no longer statistically significant. This sensitivity is consistent with heterogeneity in the scale, duration, and salience of the events: the Austin event involved a state-issued boil-water order covering all customers (about 1.1 million people) for seven days. By contrast, the national-panel dynamic estimates change little when the Austin event is excluded. The own-county notification-week response falls from about 30% to 26% and remains statistically significant. The neighboring-county coefficient for the notification week falls from 25.5% to 20.2%, but the average spillover over the notification week and the following two weeks remains positive and statistically significant, at about 14% (15% with Austin) (Appendix Section C.2).

6 Mechanisms and Robustness

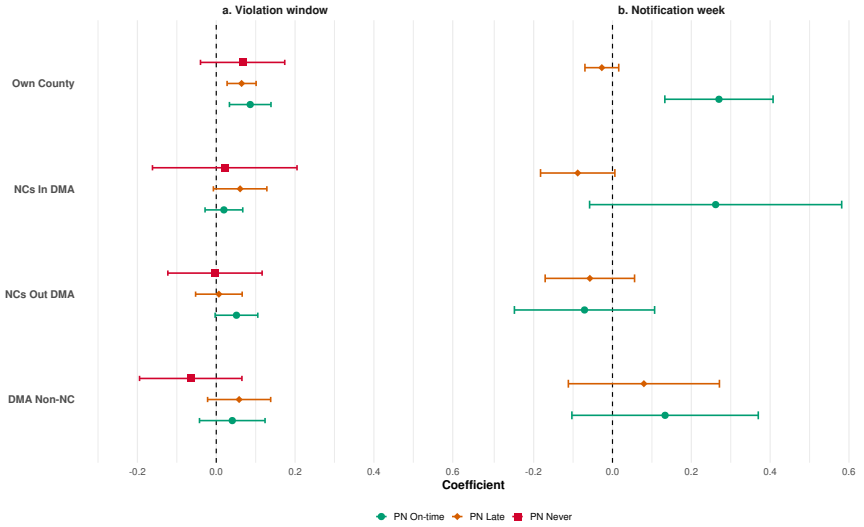
6.1 Media-Market Connectivity and Geographic Reach

I next examine whether neighboring-county responses differ according to media-market overlap. Because television and radio are among the recommended methods for disseminating Tier 1 public notices, counties within the same Designated Market Area (DMA) are more likely to share local broadcast coverage. I divide spillover exposure in the national county-week panel into three categories: adjacent counties within the affected county's DMA, adjacent counties outside its DMA, and non-adjacent counties within the same DMA. The last category helps distinguish the role of shared media coverage from geographic proximity. All three exposure measures enter the regression jointly, together with own-county exposure, so each estimate is conditional on exposure from the other geographic categories.

Figure 7 presents the average effects during the violation window and in the notifica-

tion week for neighboring counties. The violation-window estimates do not exhibit a consistent pattern across geographic categories. In the notification week, the coefficient for timely exposure from adjacent counties within the same DMA implies an additional increase in bottled water sales of approximately 30% under full exposure (not statistically significant, $p = 0.109$), conditional on violation-window exposure.[23] The estimates for adjacent counties outside the DMA (-6.9%) and non-adjacent counties within the DMA (14.3%) are smaller and also statistically indistinguishable from zero, but the estimate for adjacent counties within the DMA is significantly larger than that for adjacent counties outside it (p=0.020). None of the three geographic categories exhibits a statistically significant positive response when a delayed notification is recorded. Appendix Table A5 reports the underlying estimates across alternative fixed effects and clustering choices.

Figure 7: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing



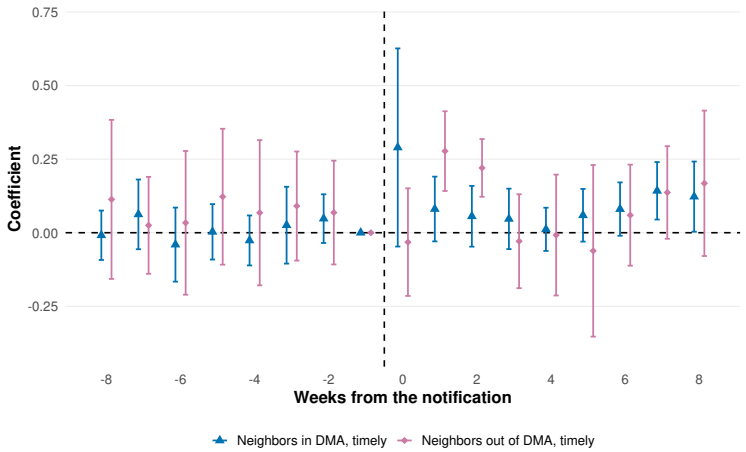
Note: Dependent variable is the log of bottled water sales. Figure plots coefficients from a single regression in which the violation-window and notification-week exposure measures enter jointly for each of the four geographies (column (9) of Appendix Table A5). Horizontal lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Standard errors are clustered at the media market (DMA) level. *NCs In DMA* (*Out DMA*) refers to adjacent counties that share (do not share) the same Designated Market Area as the violation county.

The dynamic estimates in Figure 8 reveal an additional difference in timing. For adjacent counties within the same DMA, bottled water sales increase by approximately 34% in the

23. Among county-weeks with timely notification exposure from an adjacent county in the same DMA mean exposure is 0.016. Evaluated at this mean, the estimate implies increases of approximately 0.4%.

notification week (statistically significant at the 10 percent level) and by about 8% one week later (not statistically significant). Adjacent counties outside the DMA show no response in the notification week, but sales increase by approximately 32% one week later and 25% two weeks later (both statistically significant at the 1 percent level) before returning to baseline. Wald tests for within DMA and outside DMA do not reject that pre-notification estimates are jointly zero $p = 0.256$ and $p = 0.764$ (see Appendix Table A6). Non-adjacent counties within the same DMA show no systematic response; none of their post-notification estimates is individually significant, and their pre-notification estimates are jointly different from zero (p<0.001).

Figure 8: Dynamic Spillover Responses Around On-Time Public Notification, by Media-Market Overlap



Note: Dependent variable is the log of bottled water sales. *PN* denotes public notification. Figure plots event time coefficients for on-time notification exposure from adjacent counties inside and outside the violating county's Designated Market Area (DMA). Event time 0 is the week the public notice is recorded; the indicator for week -1 is omitted. Vertical lines are 95% confidence intervals. Regressions include own county violation window and notification week exposure, neighboring counties' violation-window exposure terms, categorical controls for precipitation and temperature and a flood indicator. Fixed effects: county×year, primacy agency×month and year×week. Standard errors are clustered at the media market (DMA) level.

Taken together, these estimates suggest that geographic proximity is important for the reach of the spillover, while media-market overlap may affect its timing. The immediate response among neighbors within the same DMA is consistent with information traveling through shared local media. Because DMA membership is only a proxy for exposure to local information, these patterns do not identify a specific transmission channel. Corresponding heterogeneity-robust estimates are imprecise and do not produce a consistent

pattern across the geographic categories (Appendix Table A7). I therefore interpret the results as suggestive evidence that shared media markets might accelerate spillovers among neighboring counties.

6.2 Distinguishing Spillovers from Cross-County Shopping

An increase in bottled water sales in an unaffected county during a neighboring county's violation can come from two groups of shoppers: the county's own residents or residents of the affected county who cross the county line to buy water. Store-level NielsenIQ Retail Scanner data record only where a purchase is made, so they cannot separate the two explanations. To analyze these possible mechanisms, I use the NielsenIQ Homescan panel, which records each household's county of residence and, for purchases at retailers matched to the Retail Scanner panel, the county of the store.[24] Appendix B.3 describes the Homescan data and sample construction.

I classify each such trip as made inside or outside the household's home county by comparing the store's county with the household's, and I aggregate bottled water spending to the household-month level as purchases are too sparse at the household-week level. This gives three outcomes for each household-month: total bottled water spending across all trips, spending at stores in the home county, and spending at stores outside it. Only trips with an identified store county enter the location-specific outcomes; they account for 27.9% of panel spending, 23.3% at stores in the home county and 4.6% outside it. Household-months without such a trip enter both location-specific outcomes as zero, so all three regressions use the same household-month sample.

For each outcome I estimate a household-month regression analogous to Equation (2), with the log of spending plus one as the dependent variable, reflecting the large share of zero-purchase months. Because the panel is monthly, exposure is measured over the violation window rather than the notification week, and each violation is classified by its

24. Relative to the long-running-store Retail Scanner sample, Homescan has thinner and less stable coverage within counties because relatively few households participate in each county and panel tenure varies. I therefore use it as complementary evidence on purchaser residence and purchase location rather than as a substitute for the weekly retail estimates.

recorded notification timing as on-time, late, or never notified. I distinguish four exposure geographies: the household's own county, adjacent counties in the same DMA, adjacent counties in a different DMA, and non-adjacent counties in the same DMA, with the spillover exposures defined as in Section 4.2. Regressions include the weather controls, a flood indicator, and household, county-by-year, primacy-agency-by-month, and year-by-month fixed effects, with standard errors clustered by DMA.[25] Appendix Table A15 reports summary statistics for the sample.

Table 6.1 reports the results. Column (1) shows that own-county exposure during violations with on-time notification is associated with approximately 8.7% higher total monthly bottled water purchases, although the estimate is not statistically distinguishable from zero. If the retail spillover were driven by affected-county residents crossing county lines to purchase bottled water, however, an own-county violation should increase their purchases outside their county. Columns (2) and (3) do not show this pattern. Own-county exposure during violations with on-time notification is associated with approximately 4.7% higher purchases at stores within the household's county (statistically significant at 10% level), whereas the estimated change outside the county is approximately -0.3% and statistically indistinguishable from zero. Thus, among purchases whose location can be identified, there is no evidence that affected-county residents shift bottled water purchases across county lines.

The table also shows that residents of adjacent counties within the same DMA increase their purchases outside their own county by approximately 3.5% when their neighboring counties have violations classified as having on-time notification while their own counties are in compliance (statistically significant at 5% level). This represents a different flow of shoppers: neighboring-county residents purchasing outside their county, rather than affected-county residents crossing into it. Taken together, the Homescan results provide no evidence for the specific alternative in which affected-county residents generate the retail spillover by shopping across the county line.

25. Appendix Table A16 reports the total-purchase estimates under alternative fixed effects and clustering choices.

Table 6.1: Household Bottled Water Purchases During Violation Windows, by Store Location and Recorded Notification Regime

	All purchases (1)	Purchases in home county (2)	Purchases outside home county (3)
Own county			
On-time notification	0.0837	0.0463*	-0.0027
	(0.0661)	(0.0237)	(0.0051)
Late notification	0.0467*	0.0156	0.0039
	(0.0263)	(0.0137)	(0.0064)
Never notified	0.0654	0.0268	0.0090
	(0.0507)	(0.0481)	(0.0091)
Neighboring counties, in DMA			
On-time notification	0.0194	-0.0076	0.0345**
	(0.0580)	(0.0210)	(0.0146)
Late notification	0.0725**	0.0025	0.0080
	(0.0317)	(0.0179)	(0.0098)
Never notified	0.0571	0.0112	0.0046
	(0.0527)	(0.0342)	(0.0215)
Neighboring counties, out of DMA			
On-time notification	-0.0096	0.0120	-0.0127
	(0.0641)	(0.0295)	(0.0176)
Late notification	-0.0526*	0.0155	-0.0180
	(0.0312)	(0.0250)	(0.0182)
Never notified	0.0298	-0.0015	-0.0040
	(0.1042)	(0.0461)	(0.0217)
DMA counties, non-neighboring			
On-time notification	0.1814**	-0.0036	-0.0011
	(0.0757)	(0.0332)	(0.0212)
Late notification	-0.0031	0.0709	-0.0212
	(0.0824)	(0.0508)	(0.0162)
Never notified	0.0036	-0.0137	0.0105
	(0.0994)	(0.0748)	(0.0190)
Share of panel spending, by store location	100.0%	23.3%	4.6%
Household FE	yes	yes	yes
County × Year FE	yes	yes	yes
State × Month FE	yes	yes	yes
Year × Month FE	yes	yes	yes
Clustering	DMA	DMA	DMA
Observations	7,520,489	7,520,489	7,520,489

Note: NielsenIQ Homescan household-by-month panel. Column (1) is the log of (all bottled water purchases + 1); column (2) the log of (purchases made at stores in the household's own county + 1); column (3) the log of (purchases made at stores outside it + 1). Columns (2) and (3) use only the 28% of spending that can be matched to a store county; the sample of household-months is the same in all columns. Exposure is measured over the violation window. Regressions include categorical controls for precipitation and temperature, a flood indicator, and household, county×year, primacy agency×month and year×month fixed effects. Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

6.3 Alternative Information Channels

I next test whether information travels through cross-county connections other than geographic adjacency or shared media markets. Social ties may transmit warnings and draw attention to risk through interpersonal communication, including across geographically distant places (Hu 2022). Information may also circulate disproportionately within similar groups because of homophily, the tendency of individuals to be associated with others sim-

ilar to themselves (Halberstam and Knight 2016). Bailey et al. (2018) finds that counties similar in income, education and religiosity have higher levels of Facebook friendships. To test whether avoidance behavior following notification of violations spreads through social ties, I construct a measure of exposure to violations and notifications in a county's five most socially connected counties, using the Facebook Social Connectedness Index (SCI) from Bailey et al. (2018). To test for a channel based on socio-demographic similarity, I construct an exposure variable using each county's five most similar counties, based on a standardized distance measure combining eleven socio-demographic characteristics, including income, education, and racial composition. Appendix B.5 provides additional details on the construction of the two measures. The socially connected peer set excludes both adjacent counties and counties in the same DMA, while the socio-demographically similar set excludes adjacent counties.

Table 6.2 adds these exposure measures one at a time to the own-county specification, which includes the affected county's exposure in both the notification week and the violation window (column 1). Column (2) adds exposure to the recorded notification week in socially connected peers, column (3) adds exposure to the recorded notification week in socio-demographically similar peers, and column (4) includes both channels jointly for both timely and delayed notification. Column (5) also adds exposure to the notification week and the violation window in neighboring counties.

The results provide no evidence that bottled water sales in a focal county respond to timely recorded notifications of acute microbial violations in either the most socially connected or the most socio-demographically similar non-adjacent peer counties. In column (5), the estimates correspond to changes of approximately -2.4% for the most socially connected counties and -0.3% for the most socio-demographically similar counties, and both are statistically indistinguishable from zero. In the same regression, the point estimates correspond to increases of approximately 21% in adjacent counties and 31% in the affected county.[26] Although the adjacent-county estimate is substantially larger than the alternative-

26. The only statistically significant alternative-peer estimate is a 3.6% increase associated with delayed notification of violations in socio-demographically similar counties. Because it has no corresponding notification-week response in the affected or adjacent counties and does not appear for timely notification, I treat it as an isolated result rather than evidence of a socio-demographic-similarity channel.

peer estimates, these differences are imprecisely estimated. Together with the preceding spatial results, these estimates are consistent with spillovers being geographically localized.

Table 6.2: Spillover Effects at the Notification Week Across Geographic Adjacency, Social Connectedness, and Socio-Demographic Similarity

	Log bottled water sales				
	(1)	(2)	(3)	(4)	(5)
Own county					
Notification week × On-time	0.2729***	0.2734***	0.2729***	0.2734***	0.2713***
	(0.0709)	(0.0709)	(0.0708)	(0.0709)	(0.0702)
Notification week × Late	-0.0294	-0.0294	-0.0292	-0.0292	-0.0270
	(0.0223)	(0.0223)	(0.0222)	(0.0223)	(0.0220)
Violation window × On-time	0.0866***	0.0867***	0.0867***	0.0867***	0.0859***
	(0.0269)	(0.0269)	(0.0269)	(0.0269)	(0.0270)
Violation window × Late	0.0641***	0.0641***	0.0641***	0.0642***	0.0643***
	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)
Violation window × Never	0.0670	0.0670	0.0670	0.0670	0.0670
	(0.0545)	(0.0545)	(0.0545)	(0.0545)	(0.0545)
Neighboring counties (total)					
Notification week × On-time					0.1935
					(0.1382)
Notification week × Late					-0.0808*
					(0.0420)
Violation window × On-time					0.0455*
					(0.0245)
Violation window × Late					0.0500
					(0.0436)
Violation window × Never					0.0282
					(0.0923)
Most socially connected peers, not adjacent, different DMA					
Notification week × On-time		-0.0237		-0.0238	-0.0245
		(0.0189)		(0.0188)	(0.0189)
Notification week × Late		0.0029		0.0014	0.0016
		(0.0109)		(0.0108)	(0.0109)
Demographically closest peers, not adjacent					
Notification week × On-time			-0.0031	-0.0025	-0.0029
			(0.0125)	(0.0124)	(0.0125)
Notification week × Late			0.0353***	0.0353***	0.0353***
			(0.0106)	(0.0105)	(0.0105)
County × Year FE	yes	yes	yes	yes	yes
Primacy Agency × Month FE	yes	yes	yes	yes	yes
Year × Week FE	yes	yes	yes	yes	yes
Clustering	DMA	DMA	DMA	DMA	DMA
Observations	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604
R^2	0.9923	0.9923	0.9923	0.9923	0.9923
Tests of equality (Wald p-value)					
Neighboring vs socially connected, on-time	—	—	—	—	p =0.130
Neighboring vs demographically closest, on-time	—	—	—	—	p =0.155

Note: Dependent variable is the log of bottled water sales. Column (1) is the own-county specification; columns (2) and (3) add each non-adjacent peer set separately, column (4) adds both, and column (5) adds neighboring-county exposure. Peer exposures are population-weighted averages over the peer set. *Most socially connected* peers are the five counties with the highest Social Connectedness Index (SCI) to a focal county that are neither adjacent nor in the same Designated Market Area (DMA); *demographically closest* peers are the five closest on the socio-demographic distance metric that are not adjacent. All columns include categorical controls for precipitation and temperature and a flood indicator. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

6.4 Heterogeneity Analysis

I next examine whether avoidance behavior and spillover responses differ across county characteristics, relationships between neighboring counties, and household characteristics. Table 6.3 interacts exposure to the timely recorded notification week following violations with indicators for whether each county is above or below the national median for income, education, demographic composition, political composition, broadband access, and rural status. The table reports estimates separately for the affected county and the three neighboring-county categories, together with tests of equality of coefficients across the two groups.

Estimated avoidance behavior in directly affected counties is similar across nearly all characteristics, although it is larger in counties with a below-median Republican vote share. Responses do not otherwise differ systematically by income, education, racial or age composition, language barriers, broadband access, or rural status. The differences among the spillover estimates occur across different characteristics and geographic cells and do not form a consistent pattern. Overall, the county-level results suggest that the direct response to timely notification is broad-based rather than concentrated in particular types of counties.[27]

The previous subsection finds no evidence that spillovers operate through social ties or socio-demographic similarity. I also examine whether these relationships moderate the response among geographic neighbors. Appendix Table A19 interacts exposure to timely recorded notifications in neighboring counties with indicators for social connectedness, socio-demographic similarity, and recent own-county violation experience.[28] Estimates imply that spillover responses do not differ systematically by any of them.

27. Appendix Table A17 examines heterogeneity in the household-level Homescan estimates. Six equality tests reject at the 5% level: households with elderly members exhibit a larger response during violations in their own county, while households with children, nonwhite and Black households, and households with cable television exhibit a larger response to violations in adjacent counties within the same DMA, and non-rural households to violations in non-adjacent counties of the same DMA. But these contrasts do not form a consistent pattern across geographic categories.

28. The social connectedness indicator equals one if the population-weighted mean SCI between the focal county and its geographic neighbors exceeds the state-level median. Socio-demographic similarity is based on whether the mean normalized distance to neighboring counties is below the national median. Recent experience equals one if the focal county had an acute microbial violation during the current week or the preceding two years.

Table 6.3: Heterogeneity in Avoidance Behavior and Spillover Effects Across Socio-Demographic Characteristics

	Notification-Week 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 Median HH Income	0.248**	0.191	-0.484*	0.084
	(0.103)	(0.153)	(0.265)	(0.106)
Above Median Median HH Income	0.319***	0.420**	-0.037	0.177
	(0.099)	(0.186)	(0.100)	(0.163)
p(diff)	p=0.642	p=0.067	p=0.126	p=0.600
Below Median Coll. Degree	0.287***	0.251	-0.390*	0.138
	(0.101)	(0.206)	(0.219)	(0.150)
Above Median Coll. Degree	0.257***	0.300**	-0.025	0.155
	(0.098)	(0.131)	(0.103)	(0.144)
p(diff)	p=0.832	p=0.748	p=0.143	p=0.918
Below Median Child Pop.	0.242***	0.147	0.478*	0.133
	(0.087)	(0.101)	(0.288)	(0.153)
Above Median Child Pop.	0.291***	0.325	-0.167	0.162
	(0.098)	(0.203)	(0.102)	(0.122)
p(diff)	p=0.697	p=0.234	p=0.037	p=0.838
Below Median Elderly Pop.	0.229**	0.330*	-0.198***	0.112
	(0.095)	(0.190)	(0.075)	(0.139)
Above Median Elderly Pop.	0.359***	0.102	0.328	0.189
	(0.083)	(0.169)	(0.201)	(0.149)
p(diff)	p=0.277	p=0.213	p=0.025	p=0.591
Below Median Hispanic Pop.	0.299***	-0.007	0.266	-0.126
	(0.071)	(0.155)	(0.290)	(0.154)
Above Median Hispanic Pop.	0.252**	0.360*	-0.146	0.267**
	(0.111)	(0.191)	(0.097)	(0.128)
p(diff)	p=0.719	p=0.145	p=0.182	p=0.032
Below Median Black Pop.	0.247***	0.308	-0.021	0.148
	(0.084)	(0.229)	(0.113)	(0.136)
Above Median Black Pop.	0.287***	0.229	-0.236	0.143
	(0.108)	(0.159)	(0.189)	(0.147)
p(diff)	p=0.783	p=0.721	p=0.349	p=0.972
Below Median Republican	0.359***	0.309	-0.109	0.297**
	(0.094)	(0.200)	(0.093)	(0.145)
Above Median Republican	0.120	0.179	0.130	-0.117
	(0.077)	(0.145)	(0.316)	(0.111)
p(diff)	p=0.043	p=0.492	p=0.473	p=0.010
Below Median Lang. Barrier Pop.	0.271***	0.015	0.076	0.105
	(0.059)	(0.099)	(0.273)	(0.151)
Above Median Lang. Barrier Pop.	0.273**	0.419**	-0.093	0.165
	(0.115)	(0.204)	(0.095)	(0.154)
p(diff)	p=0.987	p=0.084	p=0.563	p=0.767
Below Median Fixed Broadband Access	0.285***	0.134	-0.044	0.144
	(0.092)	(0.177)	(0.113)	(0.096)
Above Median Fixed Broadband Access	0.268***	0.311	-0.117	0.147
	(0.090)	(0.201)	(0.119)	(0.187)
p(diff)	p=0.892	p=0.511	p=0.618	p=0.987
Below Median Broadband and Computer Access	0.262***	0.512**	-0.059	0.191
	(0.091)	(0.222)	(0.098)	(0.172)
Above Median Broadband and Computer Access	0.277***	0.098	-0.223	0.082
	(0.092)	(0.098)	(0.212)	(0.123)
p(diff)	p=0.904	p=0.028	p=0.483	p=0.586
Below Median Rural	0.206*	0.253	-0.296**	-0.169
	(0.114)	(0.209)	(0.115)	(0.147)
Above Median Rural	0.349***	0.286*	-0.009	0.192
	(0.073)	(0.145)	(0.102)	(0.132)
p(diff)	p=0.271	p=0.823	p=0.102	p=0.051

Note: The table reports coefficients from interactions between the notification-week 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, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Standard errors (in parentheses) are clustered at the media market (DMA) level. Number of observations: 1,649,604. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

7 Extension: Gastrointestinal Medication Sales

When households consume tap water during acute microbial violations without boiling it, they might develop gastrointestinal symptoms. If delayed or absent notification of a violation event limits avoidance behavior, continued exposure may therefore increase purchases of over-the-counter (OTC) gastrointestinal medications (Marcus 2022). I examine this possibility using county-week sales of diarrhea remedies, oral rehydration solutions, and antacids (see Appendix Section B.6 for details of data construction).

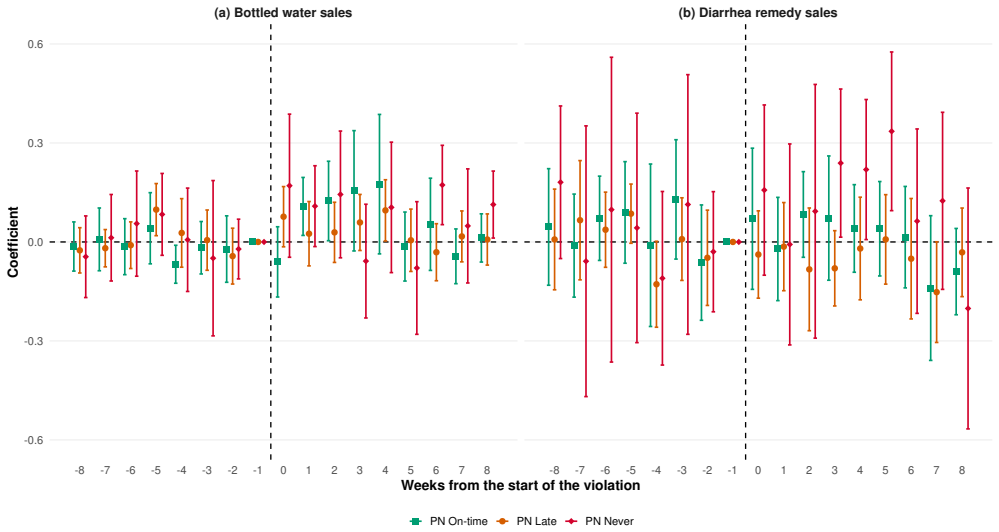
Figure 9 plots the event-study coefficients for bottled-water and OTC diarrhea-remedy sales during the eight weeks before and after the beginning of the violation window in affected counties, separately for the three recorded notification regimes.[29] Both specifications control for own-county on-time and delayed notification-week exposure. Panel *a* shows positive bottled-water sales coefficients of approximately 11–19% during the first four weeks after the start of violations classified as having on-time notification. Thus, some purchasing remains associated with the broader violation window, but these estimates are smaller than the approximately 31% additional response in the recorded notification week. Panel *b* shows no corresponding pattern in diarrhea-remedy sales following violations with on-time or delayed notification. For violations without a recorded notice, however, diarrhea-remedy sales increase by approximately 27%, 25%, and 40% three, four, and five weeks after the violation begins. A Wald test fails to reject the null hypothesis that the pre-violation coefficients are jointly zero ($p = 0.730$) (see Appendix Table A20). Purchases of diarrhea remedies are an indirect proxy for gastrointestinal symptoms rather than a direct measure of illness. I therefore interpret the concentration of the response weeks after violations without recorded notification as suggestive evidence of a health-related response.[30] The pattern is consistent with Marcus (2022), who finds increased purchases of gastrointestinal

29. Appendix Table A21 provides complementary estimates separating sales during the violation window from sales in each of the four weeks after it ends. Aggregate sales across all three gastrointestinal-medication categories do not increase systematically under any notification regime. Diarrhea-remedy sales increase by approximately 55% in the first week after the end of a violation with no recorded notification; diarrhea remedies account for about 11% of the medication basket, and the corresponding estimate for aggregate gastrointestinal-medication sales is 5.9%. Oral-rehydration-solution sales increase after violations with timely notification, whereas antacid sales show no comparable response.

30. Because the recorded violation start denotes the beginning of an administrative noncompliance period rather than the exact onset of contamination or exposure, the event-time pattern cannot be mapped directly to a biological incubation period.

medications during months of non-acute pathogen violations with delayed notice.

Figure 9: Event Study of Bottled Water and Diarrhea Remedy Sales Around the Violation Start, by Notification Timing



Note: Dependent variables are the log of bottled water sales (panel a) and the log of over-the-counter diarrhea remedy sales (panel b). Both panels plot event-study coefficients for the eight weeks before and after the start of the violation, with the indicator for the week before the violation ($h = -1$) omitted. Vertical lines are 95% confidence intervals. Regressions include own-county notification-week exposure for on-time and delayed notices, categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Standard errors are clustered at the media market (DMA) level.

8 Discussion and Conclusion

This paper examines how the timing of public notification shapes avoidance behavior following acute microbial drinking water violations and whether the response extends beyond the affected community. The measure of recorded notification timing used in the paper classifies only about one-fifth of acute violations as on-time, while nearly half are delayed and nearly one-third have no recorded notification. In affected counties, the estimates imply a 31% increase in bottled water sales in the week an on-time notice is recorded, whereas no detectable increase occurs when delayed notices are eventually recorded. I also find some evidence of spillovers: the corresponding notification-week increase in neighboring counties is about 25%. Dynamic estimates suggest that the response occurs immediately among adjacent counties within the same media market and later among adjacent counties outside

it, while delayed notices produce no comparable increase. Household purchase-location data provide no evidence that this response is driven by affected residents shopping across county lines.

To gauge the economic magnitude of these effects, back-of-the-envelope calculations attribute about $0.61 million in additional bottled water sales in directly affected counties to timely notification of acute microbial violations between 2006 and 2019, and another $2.18 million to exposure over the broader violation-window with timely or delayed notification (see Appendix Table A22).[31] Had delayed notices instead been issued on time, the estimates imply $1.13 million in additional affected-county purchases, assuming they generated the same response as timely notices. Spillover estimates imply approximately $0.53 million in additional purchases following timely notifications in neighboring counties.[32] These calculations exclude other avoidance responses, such as boiling water, as well as any health consequences.

These findings have two policy implications. First, effective disclosure requires timely implementation so that affected households can take protective action. More broadly, reliance on household avoidance shifts the immediate cost of protection to consumers, which may impose a greater burden on lower-income households. Second, public notices should clearly identify the affected water systems and service areas so that households in surrounding communities can determine whether a warning applies to their water. Future research could examine how notification timing translates into health and economic outcomes beyond short-run avoidance behavior. Taken together, the results contribute to a more nuanced understanding of the role and limits of information-based environmental policy.

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

32. Because this calculation excludes later responses among neighboring counties, it captures only part of total spillover expenditure.

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A Public Notification Rule: Additional Details

EPA established its first public notification (PN) rules in 1976 and revisions were made in 1987. The 1996 amendments to the SDWA called on EPA to change the regulation to focus on notifying during acute, serious violations and making the PN process less burdensome for systems. These changes were implemented in the revised PN rule issued in 2000. Subsequent National Primary Drinking Water Regulations amended some of the public-notification requirements. EPA issued PN guidance to water systems and states in 2010 and 2023 (USEPA 2010, 2023b).

Although the PN rule was last revised 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 these channels as a main delivery method (USEPA 2010). The 2023 update of the PN Handbook adds that large systems should use email, websites, and social media platforms in addition to traditional methods; however, it doesn't apply to this analysis as the sample covers the pre-2023 period (USEPA 2023a).

During the violation period some systems might provide free or discounted bottled water to the affected population (Christensen, Keiser, and Lade 2023). The PN Rule suggests following up with the public or providing "problem corrected" notices via radio, television, public posting, or personal delivery 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). The PN Handbook provides suggestions on how to prevent overreactions to a public notice. It discusses the role of public education and working with experts such as local healthcare professionals, university researchers, or advocacy group leaders.

B Data and Measurement Details

B.0 Assignment of Community Water Systems to Counties

I use EPA's Community Water System (CWS) Service Area Boundaries (SAB), version 2.1 (USEPA 2025), to identify the counties served by each system. EPA classifies boundaries as *System Sourced*, based on GIS boundaries supplied by states or systems, or *Modeled*, estimated using decision tree and random forest models to assign each census block to a CWS based on multiple factors, such as block imperviousness, distance to public water intake and housing unit density measures. EPA reviews submitted boundaries for completeness and validates its modeled boundaries against state data, reporting high predictive performance (USEPA 2024). Among the 42,305 systems for which I use SAB assignments, 24,642 (58.2 percent) have system-sourced boundaries and 17,663 (41.8 percent) have modeled boundaries.

SAB data also record the identifier and population of each census block in a CWS boundary, which enables a detailed crosswalk between CWSs and counties. For each system–county pair, I sum the building-weighted population of the census blocks inside the service-area boundary. I retain the system's principal county, the county holding the largest share of the system's service-area population, and any other county in which the population inside the boundary is at least 1 percent of the county's population, which excludes negligible boundary intersections. Dividing each retained county's population inside the boundary by the system's total over its retained counties gives the share of system i's service-area population that lives in county c, s_{ic}. I use these shares to split each system's population served across counties (Appendix B.2). Systems absent from version 2.1, or whose retained SAB counties include none of their SDWIS counties, keep their SDWIS counties, and their population served is split across those counties in proportion to county population. This procedure assigns 1,115 of the 54,288 systems operating at some point during 2006–2019 to multiple counties.

B.1 Validation of Recorded Public Notification Timing

Because the on-time, late, and never-notified classification depends on state recording of public-notification-related enforcement actions, I cross-check the classification against external sources for acute microbial violations at community water systems serving at least 100,000 people. There were 74 such events between 2006 and 2019. For each event, I conduct two searches: a general web search and a query in Access World News (NewsBank), using the system name, county, state, contaminant category (*coliform* or *turbidity*), and violation month and year. Access World News is a full-text database of articles from thousands of U.S. local newspapers and broadcast transcripts and provides more systematic coverage of smaller local outlets and earlier sample years than a general web search. For each event, I record whether any source confirms the violation and, when one does, whether coverage appears during the noncompliance period or within the ten-day certification window, versus only after that window has closed.

The searches broadly support the SDWIS-based classification. Of the 29 on-time PN events, 16 have contemporaneous coverage, 13 have no media mentions, and none have coverage that appears only after the certification window. Among the 31 late PN events, 10 have only post-window coverage (consistent with delayed public visibility), 4 have during-window coverage and 17 have no external mentions. In the group of the 14 never-notified events, 11 have no mentions, 2 have during-window coverage, and 1 has only post-window coverage. The asymmetry is informative: no on-time PN event has only post-window coverage, while 10 of 31 late events do.[33] This pattern suggests that the administrative classification captures meaningful variation in the timeliness of public notices.

33. Appendix Tables A8 and A11 report the event-level evidence for the 21 large-system violations used in the stacked difference-in-differences analysis, including the external validation outcome and administrative notification record. For on-time events, the table also reports the documented notice date, scope, and advisory duration when available.

B.2 County-Level Violation and Notification Exposure Measures

This section provides construction details for the county-level violation-window and notification-week exposure measures used in the empirical analysis.

Own-County Exposure Measures. SDWIS data provide violation information at the community water system level. Since NielsenIQ Retail Scanner data identify only the county in which the store is located, I aggregate violations and recorded notification measures to the county level. Counties may be served by multiple community water systems (CWSs), so I weight each system by the share of the county population it serves. Let $P_{ic} = s_{ic}P_i^{SDWIS}$ denote the population served by system i in county c, where P_i^{SDWIS} is the system's population served recorded in SDWIS and s_{ic} is the share of the system's service-area population that lives in county c (Appendix B.0), and let P_c denote the total population of county c from the 2015–2019 American Community Survey. I weight system i in county c by the PWS-to-county population ratio P_{ic}/P_c, capped at one.[34]

To construct the violation exposure measure, 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 $V_{cyw}^{\text{On-time}} = \sum_{i \in I_c} \left(\frac{k_{i,cyw}}{7} \cdot \frac{P_{ic}}{P_c} \cdot \mathbf{1}\{\text{on-time}\} \right)$, with analogous definitions for V_{cyw}^{Late} and V_{cyw}^{Never}.

To construct the recorded notification exposure measure, let $n_{i,cyw}$ equal one if the earliest recorded public notification for an acute-pathogen violation at CWS i serving county c falls in week w of year y, and zero otherwise. The on-time notification-week exposure is $N_{cyw}^{\text{On-time}} = \sum_{i \in I_c} \left(n_{i,cyw} \cdot \frac{P_{ic}}{P_c} \cdot \mathbf{1}\{\text{on-time}\} \right)$, with an analogous definition for N_{cyw}^{Late}. Violations with no recorded notification have no notification date and therefore no notification-week measure.

Neighboring-County Exposure Measures. To quantify potential behavioral spillovers, I construct measures of each county's exposure to violations and recorded notifications in

34. For systems that keep their SDWIS counties, s_{ic} is county c's share of the total population of those counties.

neighboring counties. Let $N(c)$ denote the set of neighboring counties. To account for the possibility that water systems serve multiple counties, let d_{cjyw} equal one if county c and neighboring county j are served by a common water system that has a health-based violation recorded in week w of year y, and zero otherwise.

I define county c's exposure to violations in neighboring counties as: $V_{cyw}^{s,\text{NC}} = \sum_{j \in N(c)} V_{jyw}^{s} \cdot \frac{P_j \, (1 - d_{cjyw})}{\sum_{k \in N(c)} P_k \, (1 - d_{ckyw})}$, with each recorded notification regime $s \in \{\text{On-time}, \text{Late}, \text{Never}\}$. Similarly, I define county c's exposure to recorded notification in neighboring counties as $N_{cyw}^{s,\text{NC}} = \sum_{j \in N(c)} N_{jyw}^{s} \cdot \frac{P_j \, (1 - d_{cjyw})}{\sum_{k \in N(c)} P_k \, (1 - d_{ckyw})}$, for $s \in \{\text{On-time}, \text{Late}\}$. These measures capture the population-weighted intensity of acute-pathogen violations and their recorded notifications in counties adjacent to county c, with each neighboring county's exposure weighted by its population share among adjacent counties.

B.3 NielsenIQ Homescan (HMS) Data

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. The household files report each panelist's county of residence and ZIP code, along with detailed demographic characteristics. For each transaction, the data report the purchase date, UPC, quantity and expenditure. For purchases made at retailers that can be matched to the Retail Scanner data, store identifiers also allow me to identify the county in which the purchase occurred.

Households remain in the panel for at least one calendar year, though panel tenure varies: approximately 35% appear in the data for only a single year, while about 20% remain for at least seven years. Because prices are self-reported for purchases made outside RMS-covered stores, measurement error could be 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. 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. Appendix Figure A5 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.

For the household-level heterogeneity analysis, I use Homescan information on household income, educational attainment, the presence of children ages 0–18 or elderly household members, race and ethnicity, internet access, and cable television.

B.4 County Characteristics and Socio-Demographic Similarity

I use county-level sociodemographic variables from the 2008–2012 5-year American Community Survey for my heterogeneity analyses. I focus on household median income and composition of the population for factors such as college degree, children, elderly, Black, Hispanic, and nonwhite.[35] I use the share of votes for the Republican presidential candidate in 2012 from the National Neighborhood Data Archive (NaNDA).

I employ county-level data on high-speed internet and computer access provided by Census and the National Telecommunications and Information Administration (NTIA) administered under the Digital Equity Act (DEA) 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.[36] In addition, I use other variables such as whether the population is rural and the estimate of the population with language barriers.[37] [38]

35. For children, I use the share of the population between ages 0–10.

36. This was the only available year. I assume county-level internet access between 2006–2019 is highly correlated with the 2021 measure.

37. Variable "rural" is based on the definition of "rural area" from DEA.

38. 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

Socio-Demographic Similarity Measure (SD-Close). I construct a socio-demographic similarity measure across counties to match control counties in the stacked difference-in-difference design (see Section 4.3) and in regressions with alternative information channels (Section 6.3). I build a standardized Euclidean distance between counties based on eleven characteristics.[39] Specifically, for county pairs i and j, let X_{ik} denote the value of the k-th standardized characteristic. The raw distance is $D_{ij} = \sqrt{\sum_{k=1}^{11}(X_{ik} - X_{jk})^2}$, and is normalized to the unit interval: $D_{ij}^{\text{norm}} = \frac{D_{ij} - \min_{(i',j')} D_{i'j'}}{\max_{(i',j')} D_{i'j'} - \min_{(i',j')} D_{i'j'}}$.

B.5 Non-Geographic Peer Exposure Measures

This section defines the alternative exposure measures used in Section 6.3 to test whether spillover responses operate through non-geographic channels.

Social Connectedness Exposure (Top 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.2. The notification-week counterpart $N_{cyw}^{s,\text{TopSCI}}$ is built with the same weights.

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} (defined in Appendix B.4), excluding counties that share a border with c. 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, with the notification-week counterpart defined analogously.

Statistics. (US Census Bureau, National Telecommunications and Information Administration, and Department of Commerce 2023)

39. They include: 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.

B.6 NielsenIQ Gastrointestinal Medication Sales

Following Marcus (2022), who uses purchases of over-the-counter stomach remedies as an indirect measure of gastrointestinal health, I construct an analogous measure from Nielsen Retail Scanner data on three product categories: diarrhea remedies, electrolyte oral rehydration solutions (ORS), and antacids. Diarrhea remedies and antacids are taken directly from the corresponding NielsenIQ product modules. 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.[40] The total GI medication outcome is the sum of expenditures across all three categories.

C Event Influence and Sensitivity

C.1 Matched-Event Balance and Sensitivity

Appendix Tables A9 and A12 compare the characteristics of the exposed and matched control counties. Balance is generally closer in the delayed-notification sample. In the on-time sample, most differences are modest, but the directly exposed counties have a higher college-educated share (by 1.6 percentage points) and a lower Republican vote share (by 3.8 percentage points) than their controls, and the indirectly exposed counties have higher median income and population density than their controls.

Given the small number of events, Appendix Figure A4 examines sensitivity to individual events by re-estimating the notification-week response after omitting each event in turn. The implied timely notification-week estimate for directly affected counties remains

40. I include liquids, powders, freezer pops, and strips. 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).

between approximately 43% and 63%, and the estimate for indirectly affected counties between about 9% and 28%, when any event other than Austin is omitted. Omitting the October 2018 Austin event reduces the direct estimate from approximately 52% to 17.9% and the indirect estimate from 14% to 3.7%. By contrast, the delayed-notification estimates for both directly and indirectly affected counties remain near zero when any single event is omitted. Appendix Table A8 shows that the Austin episode was unusually intensive: the system served approximately 1.1 million people, 1.04 million of them in Travis County, and the state-issued boil-water order covered all customers and remained in effect for seven days. By comparison, the other documented advisories with known duration lasted two or three days, and several applied to only part of the system. Austin's influence is therefore consistent with heterogeneity in the scale, duration, and salience of notification events.

C.2 National Panel Sensitivity

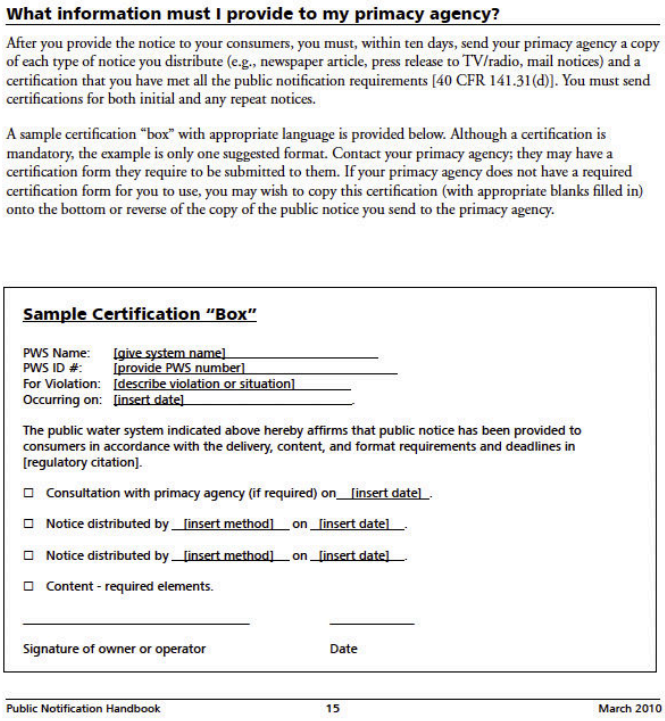
The national-panel estimates draw on many more notifications, but the October 2018 Austin event is also part of that sample. Appendix Table A14 reestimates the event-time specifications of Appendix Table A6 without it: the Austin notices are removed from all exposure measures, and the counties exposed to the event are dropped around the notice week.[41] The own-county estimates change little: the event-study coefficient for the notification week implies an increase of approximately 26% (30% with Austin). For neighboring counties, the notification-week coefficients are smaller and not statistically significant, both for all neighbors (20.2% compared with 25.5%) and for neighbors within the same DMA (26.8% compared with 34%, which is significant at the 10 percent level with Austin). Averaged over the notification week and the following two weeks, however, the spillover remains at about 14% (15% with Austin) and statistically significant, both for all neighbors and for neighbors within the same DMA. The joint test of the pre-notification coefficients for all neighbors has $p = 0.09$, compared with $p = 0.28$ with Austin.[42]

41. The removed notices are those recorded in the week of October 27, 2018 by the City of Austin system (Travis and Williamson counties) and by the smaller West Travis County Public Utility Agency (about 28,000 people in Travis and Hays counties), which had the same turbidity violation in the same month. This drops sixteen counties from eight weeks before to eight weeks after the notice week (170 county-weeks): the three counties these systems serve, their neighbors, and the other counties of the Austin media market.

42. The static notification-week estimates show the same pattern. Excluding the Austin event, the own-county estimate is 26.6% (31.1% with Austin), while the estimates for all neighbors and for neighbors within the same DMA fall to 15.3% (21.3%) and 22.5% (30%) and are not statistically significant.

D Appendix Figures

Figure A1: Sample Public Notification Certification Form



What information must I provide to my primacy agency?

After you provide the notice to your consumers, you must, within ten days, send your primacy agency a copy of each type of notice you distribute (e.g., newspaper article, press release to TV/radio, mail notices) and a certification that you have met all the public notification requirements [40 CFR 141.31(d)]. You must send certifications for both initial and any repeat notices.

A sample certification "box" with appropriate language is provided below. Although a certification is mandatory, the example is only one suggested format. Contact your primacy agency; they may have a certification form they require to be submitted to them. If your primacy agency does not have a required certification form for you to use, you may wish to copy this certification (with appropriate blanks filled in) onto the bottom or reverse of the copy of the public notice you send to the primacy agency.

Sample Certification "Box"

PWS Name: [give system name]
PWS ID #: [provide PWS number]
For Violation: [describe violation or situation]
Occurring on: [insert date].

The public water system indicated above hereby affirms that public notice has been provided to consumers in accordance with the delivery, content, and format requirements and deadlines in [regulatory citation].

☐ Consultation with primacy agency (if required) on [insert date].

☐ Notice distributed by [insert method] on [insert date].

☐ Notice distributed by [insert method] on [insert date].

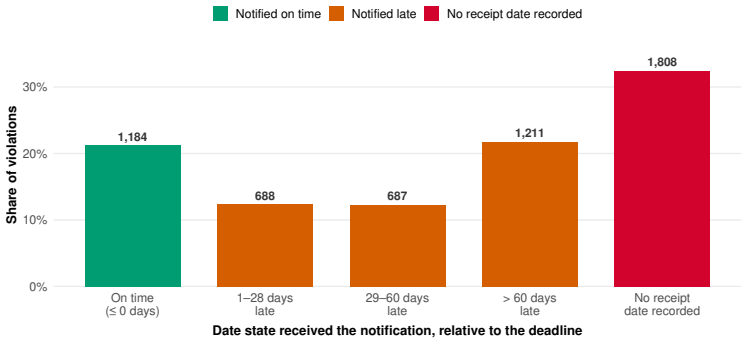
☐ Content - required elements.

Signature of owner or operator Date

Public Notification Handbook 15 March 2010

Note: Sample certification form reproduced from the EPA's revised public notification handbook (USEPA 2010). A system that issues a public notice must certify to the state primacy agency, within ten days, that the notice was issued and that it met the content and delivery requirements of the Public Notification Rule. For system-issued notices, I use the primacy agency's recorded certification-receipt date; for notices or boil-water orders issued by the primacy agency, I use the issue date.

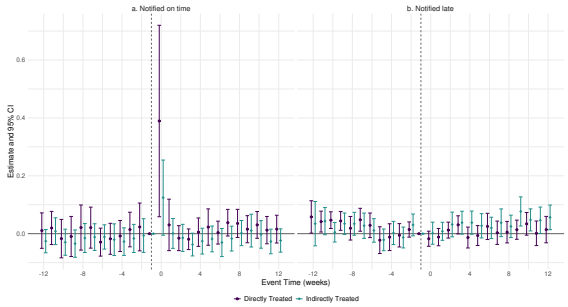
Figure A2: Distribution of Recorded Public Notification Timing



Note: The figure plots the distribution of the difference in days between the date the state received the public notification certification from a system and the notification deadline, for the 5,578 acute pathogen violations, measured at the system by violation category level. The deadline is the end of the non-compliance period plus one day to account for the required notification window plus the ten days a system has to certify to the state.

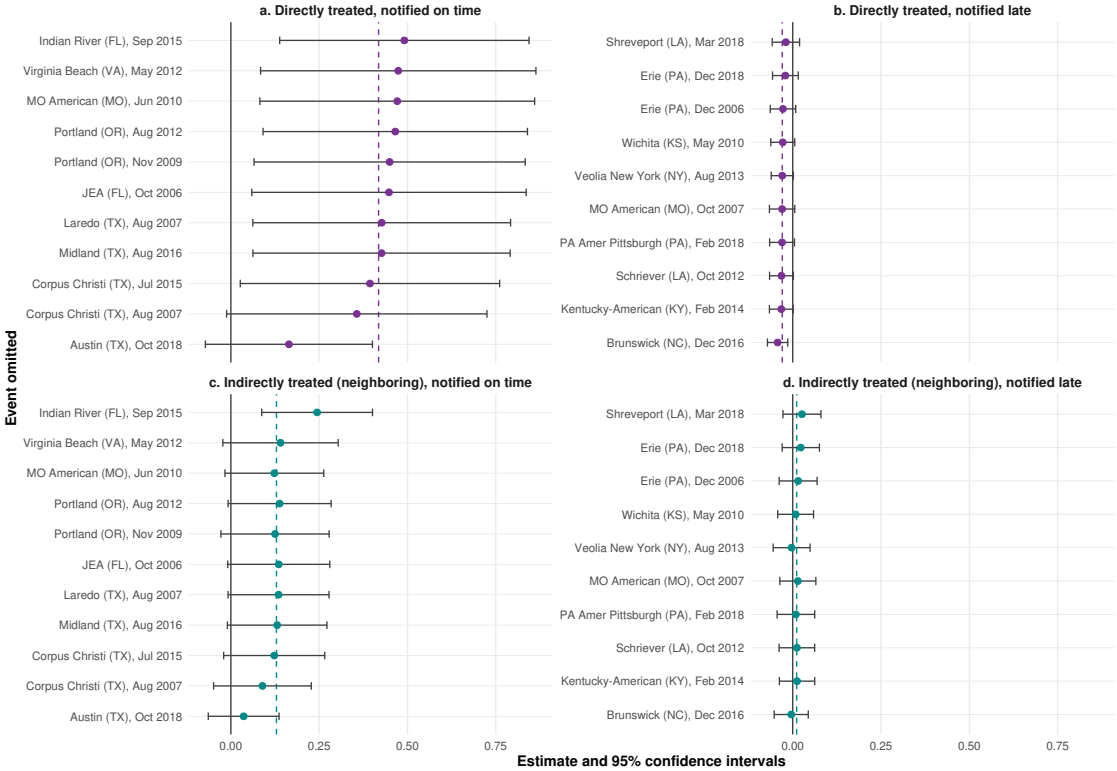
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Figure A3: Stacked Difference-in-Differences of Avoidance Behavior and Spillover Effects (Log Bottled Water Share), by Notification Timing



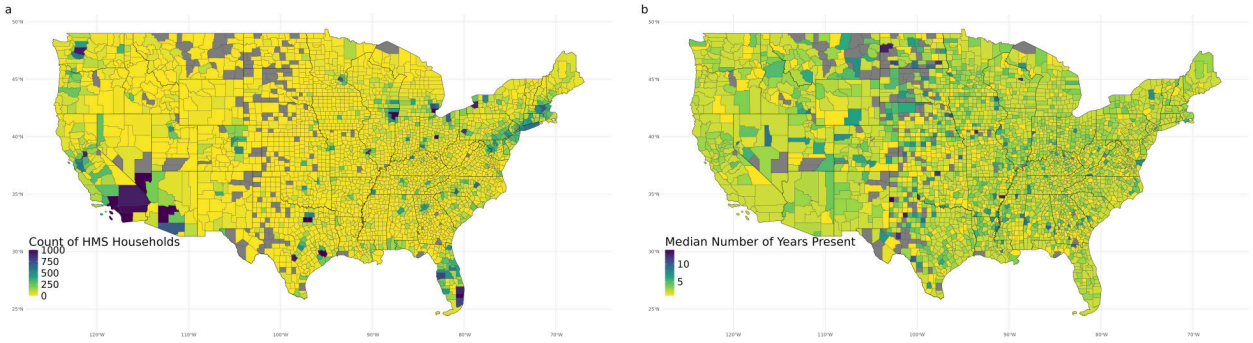
Note: Dependent variable is the log of the share of bottled water sales in total store sales, which normalizes bottled-water sales by total store sales. The figure plots the event-study coefficients estimating the differential change in sales for stores in directly affected counties (purple circles) and indirectly affected (neighboring) counties (teal diamonds) relative to matched control counties. Event time 0 denotes the week of public notification; the reference week -1 is omitted. Vertical lines are 95% confidence intervals. Regressions include categorical controls for precipitation and temperature, a flood indicator, and event×store and event×year×week fixed effects. Standard errors are clustered at the county level. Observations: 73,452 in panel *a* and 44,584 in panel *b*.

Figure A4: Leave-One-Out Sensitivity of the Stacked Difference-in-Differences Notification-Week Estimates



Note: Dependent variable is the log of bottled water sales. Each row omits one of the eleven on-time (panels *a* and *c*) or ten late (panels *b* and *d*) events and re-estimates the notification-week coefficient; panels *a* and *b* report the coefficient for directly affected counties and panels *c* and *d* the coefficient for indirectly affected (neighboring) counties, from the same regressions. The dashed line is the full-sample estimate for that panel and horizontal lines are 95% confidence intervals. Standard errors are clustered at the county level. The corresponding full-sample regressions observations: 73,452 in panels *a* and *c*, and 44,584 in panels *b* and *d*.

Figure A5: Households' Spatial Distribution in the NielsenIQ Homescan Data



(a) Households per county

(b) Median years in panel

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: 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 Disinfectant 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	do not drink the water; use bottled water or another source

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 A2: 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 A3: 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
Violation-window exposure, by public notification timing							
Own County Acute Pathogens — PN on time	0.00023	0.0099	0	0	0	0	1
Own County Acute Pathogens — PN late	0.00051	0.015	0	0	0	0	1
Own County Acute Pathogens — PN never	0.00016	0.008	0	0	0	0	0.99
Violation-window spillover exposure							
NCs (In-DMA) Acute Pathogens — PN on time	0.00024	0.0081	0	0	0	0	0.96
NCs (In-DMA) Acute Pathogens — PN late	0.00045	0.0097	0	0	0	0	0.95
NCs (In-DMA) Acute Pathogens — PN never	0.00013	0.0047	0	0	0	0	0.8
NCs (Out-DMA) Acute Pathogens — PN on time	0.00015	0.0062	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN late	0.00045	0.011	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN never	0.00011	0.0045	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	0.0075	0	0	0	0	1
DMA Non-NC Acute Pathogens — PN never	0.00014	0.0038	0	0	0	0	0.68
Notification-anchored exposure (week of the notice)							
Own County — notification week, on time	0.000054	0.005	0	0	0	0	1
Own County — notification week, late	0.0001	0.0068	0	0	0	0	1
Notification-anchored spillover exposure							
NCs (In-DMA) — notification week, on time	0.000045	0.0036	0	0	0	0	0.83
NCs (In-DMA) — notification week, late	0.000069	0.0039	0	0	0	0	0.83
NCs (Out-DMA) — notification week, on time	0.000013	0.0017	0	0	0	0	0.81
NCs (Out-DMA) — notification week, late	0.000027	0.002	0	0	0	0	0.6
DMA Non-NC — notification week, on time	0.000044	0.0026	0	0	0	0	0.55
DMA Non-NC — notification week, late	0.000059	0.0026	0	0	0	0	0.39
Total number of neighboring counties (NCs)	6	1.3	1	5	6	7	14
Weekly max temperature	24	9.6	-20	18	26	31	49
Weekly total precipitation	20	25	0	2.5	12	29	963
Flood or heavy rain in the county (week)	0.033	0.18	0	0	0	0	1
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. Violation-window exposure is the share of county residents served by systems in violation, scaled by the share of days in the week out of compliance; notification-week exposure is the share of county residents served by systems whose public notice is recorded that week. *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 A4: Own-County and Neighboring-County Coefficients Under Alternative Fixed Effects and Clustering

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own county									
Notification week × On-time	0.2937***	0.2920***	0.2750***	0.2640***	0.2593***	0.2708***	0.2708***	0.2708***	0.2708***
	(0.0677)	(0.0678)	(0.0689)	(0.0678)	(0.0680)	(0.0691)	(0.0697)	(0.0779)	(0.0702)
Notification week × Late	0.0199	0.0210	-0.0264	-0.0231	-0.0300	-0.0271	-0.0271	-0.0271	-0.0271
	(0.0321)	(0.0314)	(0.0214)	(0.0213)	(0.0206)	(0.0202)	(0.0201)	(0.0187)	(0.0220)
Violation window × On-time	0.1502***	0.1478***	0.0852***	0.0937***	0.0917***	0.0858***	0.0858***	0.0858***	0.0858***
	(0.0444)	(0.0435)	(0.0261)	(0.0261)	(0.0253)	(0.0252)	(0.0257)	(0.0297)	(0.0270)
Violation window × Late	0.1152***	0.1134***	0.0709***	0.0674***	0.0660***	0.0642***	0.0642***	0.0642***	0.0642***
	(0.0363)	(0.0359)	(0.0207)	(0.0207)	(0.0196)	(0.0193)	(0.0193)	(0.0181)	(0.0188)
Violation window × Never	-0.1060	-0.1012	0.0656	0.0616	0.0699	0.0671	0.0671	0.0671	0.0671
	(0.1086)	(0.1071)	(0.0494)	(0.0497)	(0.0479)	(0.0476)	(0.0472)	(0.0628)	(0.0545)
Neighboring counties (total)									
Notification week × On-time	0.2061**	0.1966**	0.2092**	0.1832**	0.1644*	0.1929**	0.1929	0.1929	0.1929
	(0.0870)	(0.0864)	(0.0842)	(0.0833)	(0.0842)	(0.0842)	(0.1342)	(0.1466)	(0.1382)
Notification week × Late	0.0012	-0.0161	-0.0625**	-0.0492	-0.0806**	-0.0809**	-0.0809*	-0.0809	-0.0809*
	(0.0537)	(0.0540)	(0.0317)	(0.0312)	(0.0313)	(0.0319)	(0.0419)	(0.0542)	(0.0420)
Violation window × On-time	0.0080	0.0012	0.0493*	0.0700**	0.0632**	0.0454*	0.0454	0.0454*	0.0454*
	(0.0925)	(0.0933)	(0.0274)	(0.0273)	(0.0266)	(0.0264)	(0.0284)	(0.0252)	(0.0245)
Violation window × Late	0.1796**	0.1572**	0.0791*	0.0798*	0.0586	0.0500	0.0500	0.0500	0.0500
	(0.0778)	(0.0769)	(0.0427)	(0.0420)	(0.0404)	(0.0401)	(0.0443)	(0.0383)	(0.0436)
Violation window × Never	-0.2983*	-0.2836	0.0083	0.0167	0.0356	0.0281	0.0281	0.0281	0.0281
	(0.1743)	(0.1724)	(0.0840)	(0.0784)	(0.0758)	(0.0761)	(0.0860)	(0.0869)	(0.0923)
Observations	1,649,605	1,649,605	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604
R^2	0.974	0.974	0.992	0.992	0.992	0.992	0.992	0.992	0.992
County FE	yes	yes							
Year FE	yes								
Week FE	yes		yes						
County × Year FE			yes	yes	yes	yes	yes	yes	yes
Primacy Agency × Month FE				yes	yes	yes	yes	yes	yes
Year × Month FE					yes				
Year × Week FE		yes				yes	yes	yes	yes
Clustering	County	County	County	County	County	County	County + week	Primacy agency	DMA
Tests of equality (Wald p-value)									
Own: on-time vs late, notification week	p =0.000	p =0.000	p =0.000	p =0.000	p =0.000	p =0.000	p =0.000	p =0.001	p =0.000
Own: notification vs violation, on-time	p =0.087	p =0.083	p =0.014	p =0.025	p =0.027	p =0.016	p =0.017	p =0.048	p =0.019
NCs: on-time vs late, notification week	p =0.045	p =0.037	p =0.003	p =0.009	p =0.007	p =0.002	p =0.052	p =0.111	p =0.064

Note: Dependent variable is the log of bottled water sales. All columns include categorical controls for precipitation and temperature and a flood indicator. Standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A5: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing Under Alternative Fixed Effects and Clustering

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Own county									
Notification week × On-time	0.2932***	0.2915***	0.2743***	0.2634***	0.2586***	0.2701***	0.2701***	0.2701***	0.2701***
	(0.0677)	(0.0677)	(0.0689)	(0.0678)	(0.0680)	(0.0691)	(0.0696)	(0.0777)	(0.0701)
Notification week × Late	0.0215	0.0225	-0.0261	-0.0231	-0.0301	-0.0270	-0.0270	-0.0270	-0.0270
	(0.0320)	(0.0313)	(0.0213)	(0.0213)	(0.0206)	(0.0201)	(0.0201)	(0.0187)	(0.0219)
Violation window × On-time	0.1517***	0.1492***	0.0855***	0.0942***	0.0921***	0.0862***	0.0862***	0.0862***	0.0862***
	(0.0445)	(0.0436)	(0.0261)	(0.0261)	(0.0253)	(0.0252)	(0.0257)	(0.0296)	(0.0269)
Violation window × Late	0.1149***	0.1132***	0.0709***	0.0675***	0.0661***	0.0643***	0.0643***	0.0643***	0.0643***
	(0.0363)	(0.0359)	(0.0207)	(0.0207)	(0.0196)	(0.0192)	(0.0193)	(0.0181)	(0.0188)
Violation window × Never	-0.1056	-0.1009	0.0655	0.0615	0.0698	0.0669	0.0669	0.0669	0.0669
	(0.1087)	(0.1072)	(0.0494)	(0.0497)	(0.0479)	(0.0476)	(0.0472)	(0.0628)	(0.0545)
Neighboring counties, in DMA									
Notification week × On-time	0.2451**	0.2385**	0.2647***	0.2413**	0.2316**	0.2617***	0.2617	0.2617	0.2617
	(0.1002)	(0.0977)	(0.1003)	(0.0996)	(0.0989)	(0.0984)	(0.1597)	(0.2015)	(0.1632)
Notification week × Late	-0.0880	-0.1003*	-0.0762**	-0.0572	-0.0820**	-0.0883**	-0.0883*	-0.0883	-0.0883*
	(0.0550)	(0.0557)	(0.0388)	(0.0377)	(0.0379)	(0.0389)	(0.0474)	(0.0593)	(0.0481)
Violation window × On-time	0.0893	0.0878	0.0239	0.0353	0.0330	0.0194	0.0194	0.0194	0.0194
	(0.0679)	(0.0690)	(0.0251)	(0.0251)	(0.0244)	(0.0241)	(0.0252)	(0.0244)	(0.0244)
Violation window × Late	0.1018*	0.0935	0.0781**	0.0720**	0.0649**	0.0606**	0.0606*	0.0606**	0.0606*
	(0.0582)	(0.0575)	(0.0320)	(0.0320)	(0.0304)	(0.0303)	(0.0325)	(0.0290)	(0.0346)
Violation window × Never	-0.2563	-0.2419	0.0095	0.0070	0.0257	0.0216	0.0216	0.0216	0.0216
	(0.1639)	(0.1612)	(0.0784)	(0.0745)	(0.0715)	(0.0713)	(0.0831)	(0.0770)	(0.0936)
Neighboring counties, out of DMA									
Notification week × On-time	-0.2683	-0.3046*	-0.0111	-0.0129	-0.0821	-0.0710	-0.0710	-0.0710	-0.0710
	(0.1733)	(0.1821)	(0.0906)	(0.0906)	(0.0881)	(0.0884)	(0.0680)	(0.0748)	(0.0907)
Notification week × Late	0.2229*	0.1986	-0.0300	-0.0380	-0.0774	-0.0574	-0.0574	-0.0574	-0.0574
	(0.1328)	(0.1348)	(0.0560)	(0.0566)	(0.0556)	(0.0559)	(0.0687)	(0.0588)	(0.0579)
Violation window × On-time	-0.0298	-0.0341	0.0554*	0.0628*	0.0592*	0.0513	0.0513	0.0513**	0.0513*
	(0.1263)	(0.1274)	(0.0328)	(0.0322)	(0.0326)	(0.0318)	(0.0336)	(0.0250)	(0.0276)
Violation window × Late	0.1306*	0.1233	0.0135	0.0185	0.0120	0.0067	0.0067	0.0067	0.0067
	(0.0765)	(0.0771)	(0.0325)	(0.0303)	(0.0315)	(0.0309)	(0.0318)	(0.0305)	(0.0301)
Violation window × Never	-0.2893**	-0.2842**	-0.0053	-0.0036	-0.0000	-0.0032	-0.0032	-0.0032	-0.0032
	(0.1245)	(0.1239)	(0.0639)	(0.0566)	(0.0533)	(0.0548)	(0.0574)	(0.0724)	(0.0610)
DMA counties, non-neighboring									
Notification week × On-time	0.0907	0.0729	0.1492*	0.1139	0.0847	0.1334	0.1334	0.1334	0.1334
	(0.0865)	(0.0849)	(0.0840)	(0.0857)	(0.0863)	(0.0833)	(0.1082)	(0.1061)	(0.1206)
Notification week × Late	0.2594**	0.2071*	0.1407**	0.1815***	0.1110*	0.0797	0.0797	0.0797	0.0797
	(0.1054)	(0.1058)	(0.0689)	(0.0671)	(0.0663)	(0.0693)	(0.1060)	(0.0919)	(0.0978)
Violation window × On-time	0.0174	0.0175	0.0593	0.0566	0.0622	0.0406	0.0406	0.0406	0.0406
	(0.0979)	(0.1002)	(0.0391)	(0.0400)	(0.0392)	(0.0393)	(0.0445)	(0.0482)	(0.0424)
Violation window × Late	0.2065**	0.1823*	0.0781**	0.0911***	0.0697**	0.0581*	0.0581	0.0581	0.0581
	(0.0965)	(0.0956)	(0.0339)	(0.0345)	(0.0319)	(0.0317)	(0.0380)	(0.0458)	(0.0408)
Violation window × Never	-0.1728	-0.1698	-0.0423	-0.0633	-0.0539	-0.0647	-0.0647	-0.0647	-0.0647
	(0.1351)	(0.1340)	(0.0641)	(0.0583)	(0.0609)	(0.0619)	(0.0787)	(0.0797)	(0.0663)
Observations	1,649,605	1,649,605	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604	1,649,604
R^2	0.974	0.974	0.992	0.992	0.992	0.992	0.992	0.992	0.992
County FE	yes	yes							
Year FE	yes								
Week FE	yes		yes						
County × Year FE			yes	yes	yes	yes	yes	yes	yes
Primacy Agency × Month FE				yes	yes	yes	yes	yes	yes
Year × Month FE					yes				
Year × Week FE		yes				yes	yes	yes	yes
Clustering	County	County	County	County	County	County	County + week	Primacy agency	DMA
Tests of equality (Wald p-value)									
NCs: in DMA vs out of DMA, notification week	p =0.011	p =0.009	p =0.042	p =0.060	p =0.018	p =0.012	p =0.050	p =0.063	p =0.020
NCs: in DMA vs out of DMA, violation window	p =0.389	p =0.384	p =0.443	p =0.498	p =0.519	p =0.424	p =0.419	p =0.344	p =0.366
NCs in DMA: on-time vs late, notification week	p =0.003	p =0.002	p =0.002	p =0.005	p =0.003	p =0.001	p =0.036	p =0.112	p =0.044
NCs out of DMA: on-time vs late, notification week	p =0.029	p =0.032	p =0.856	p =0.812	p =0.964	p =0.895	p =0.886	p =0.900	p =0.897
DMA non-neighboring vs NCs in DMA, notification week	p =0.258	p =0.215	p =0.388	p =0.344	p =0.276	p =0.331	p =0.234	p =0.350	p =0.292

Note: Dependent variable is the log of bottled water sales. All columns include categorical controls for precipitation and temperature and a flood indicator. 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 A6: Violation-Window and Notification Event-Time Coefficients by Specification

	Log bottled water sales				
	Group 1	Group 2	Group 3		
	(1) Own county	(2) NCs total	(3) NCs in DMA	(4) NCs out of DMA	(5) Non-adjacent in DMA
Panel A. Violation window, by notification regime					
PN on time	0.0942***	0.0164	0.0018	0.0305	0.0115
	(0.0260)	(0.0280)	(0.0250)	(0.0320)	(0.0629)
PN late	0.0637***	0.0587	0.0630*	0.0111	0.0661*
	(0.0185)	(0.0407)	(0.0341)	(0.0279)	(0.0387)
PN never	0.0669	0.0289	0.0217	-0.0022	-0.0657
	(0.0544)	(0.0917)	(0.0930)	(0.0603)	(0.0665)
Mean exposure, on time	0.0581	0.0118	0.0174	0.0211	0.0053
Mean exposure, late	0.1035	0.0188	0.0260	0.0477	0.0080
Panel B. Notification week, event time					
PN on-time					
$h = -8$	0.0346	0.0118	-0.0086	0.1132	0.0667
	(0.0251)	(0.0441)	(0.0428)	(0.1378)	(0.0951)
$h = -7$	-0.0392	0.0595	0.0623	0.0251	0.1965**
	(0.0290)	(0.0561)	(0.0604)	(0.0840)	(0.1002)
$h = -6$	-0.0495	-0.0273	-0.0404	0.0336	-0.0102
	(0.0327)	(0.0608)	(0.0642)	(0.1246)	(0.0804)
$h = -5$	-0.0458*	0.0263	0.0031	0.1223	-0.1477
	(0.0255)	(0.0418)	(0.0481)	(0.1178)	(0.0984)
$h = -4$	-0.0521*	-0.0091	-0.0262	0.0678	0.0369
	(0.0310)	(0.0465)	(0.0433)	(0.1258)	(0.0796)
$h = -3$	-0.0471	0.0327	0.0256	0.0907	0.0524
	(0.0394)	(0.0634)	(0.0666)	(0.0945)	(0.1458)
$h = -2$	-0.0231	0.0497	0.0479	0.0684	0.0485
	(0.0407)	(0.0415)	(0.0422)	(0.0899)	(0.0903)
$h = -1$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$h = 0$	0.2651***	0.2270	0.2896*	-0.0320	0.1521
	(0.0724)	(0.1427)	(0.1717)	(0.0932)	(0.1317)
$h = 1$	0.1069	0.1149**	0.0806	0.2773***	0.0721
	(0.0799)	(0.0530)	(0.0561)	(0.0691)	(0.0800)
$h = 2$	-0.0455	0.0885**	0.0558	0.2202***	0.0849
	(0.0280)	(0.0423)	(0.0526)	(0.0500)	(0.0532)
$h = 3$	-0.0310	0.0349	0.0470	-0.0288	-0.0630
	(0.0339)	(0.0384)	(0.0524)	(0.0814)	(0.0518)
$h = 4$	-0.0141	0.0119	0.0116	-0.0079	0.0569
	(0.0243)	(0.0354)	(0.0374)	(0.1048)	(0.0606)
$h = 5$	0.0122	0.0369	0.0593	-0.0614	-0.0891
	(0.0328)	(0.0379)	(0.0457)	(0.1487)	(0.0933)
$h = 6$	0.0085	0.0790**	0.0803*	0.0597	0.0450
	(0.0256)	(0.0397)	(0.0463)	(0.0876)	(0.0727)
$h = 7$	0.0437	0.1418***	0.1424***	0.1367*	0.1084
	(0.0280)	(0.0443)	(0.0498)	(0.0803)	(0.1857)
$h = 8$	-0.0289	0.1297**	0.1226**	0.1678	-0.1481
	(0.0217)	(0.0558)	(0.0608)	(0.1260)	(0.1112)
Mean exposure	0.0721	0.0143	0.0160	0.0107	0.0043
PN late					
$h = -8$	-0.0150	-0.0077	0.0180	-0.1074	0.0635
	(0.0294)	(0.0403)	(0.0482)	(0.0707)	(0.1084)
$h = -7$	0.0306	-0.0212	-0.0353	0.0183	-0.1138
	(0.0292)	(0.0405)	(0.0416)	(0.1015)	(0.1160)
$h = -6$	0.0188	-0.0409	-0.0277	-0.0842	-0.0062
	(0.0311)	(0.0430)	(0.0480)	(0.0795)	(0.0876)
$h = -5$	-0.0004	-0.0186	-0.0486	0.0853	-0.0591
	(0.0262)	(0.0343)	(0.0342)	(0.0862)	(0.0834)
$h = -4$	-0.0323	-0.0893**	-0.1061**	-0.0509	-0.0396
	(0.0232)	(0.0391)	(0.0464)	(0.0771)	(0.0562)
$h = -3$	0.0273	-0.0322	-0.0770	0.0887	0.1430
	(0.0274)	(0.0460)	(0.0565)	(0.0873)	(0.0996)
$h = -2$	-0.0150	-0.0650	-0.0476	-0.1292*	0.1428
	(0.0275)	(0.0554)	(0.0598)	(0.0696)	(0.1030)
$h = -1$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$h = 0$	-0.0283	-0.0881**	-0.0996*	-0.0713	0.0849
	(0.0236)	(0.0437)	(0.0516)	(0.0600)	(0.1002)
$h = 1$	0.0045	-0.0947**	-0.1025**	-0.0843	0.1276
	(0.0161)	(0.0385)	(0.0446)	(0.0573)	(0.0847)
$h = 2$	-0.0270	-0.0774	-0.0532	-0.1454*	0.0002
	(0.0200)	(0.0519)	(0.0627)	(0.0773)	(0.0999)
$h = 3$	0.0015	-0.0250	-0.0724	0.1071*	0.0375
	(0.0238)	(0.0468)	(0.0603)	(0.0577)	(0.0824)
$h = 4$	0.0015	-0.0033	-0.0032	-0.0251	0.0953
	(0.0231)	(0.0370)	(0.0475)	(0.0538)	(0.1005)
$h = 5$	-0.0031	-0.0200	-0.0493	0.0595	0.0631
	(0.0260)	(0.0427)	(0.0530)	(0.0795)	(0.0654)
$h = 6$	-0.0001	-0.0459	-0.0391	-0.0735	0.0880
	(0.0243)	(0.0369)	(0.0433)	(0.0620)	(0.0982)
$h = 7$	0.0519*	0.0417	0.0116	0.1153	0.0234
	(0.0287)	(0.0364)	(0.0369)	(0.0712)	(0.1128)
$h = 8$	0.0290	-0.0126	-0.0603	0.1037	0.0166
	(0.0231)	(0.0476)	(0.0443)	(0.1122)	(0.0883)
Mean exposure	0.1234	0.0226	0.0228	0.0218	0.0059
Own-county terms	Reported	Control	Control	Control	Control
Joint tests of the event-time path (Wald χ^2, p-value)					
Pre-notification ($h = -8$ to -2), PN on-time	p =0.154	p =0.275	p =0.256	p =0.764	p =0.000
Pre-notification ($h = -8$ to -2), PN late	p =0.341	p =0.189	p =0.019	p =0.008	p =0.062
Notification onward ($h = 0$ to $+8$), PN on-time	p =0.000	p =0.022	p =0.126	p =0.000	p =0.000
Notification onward ($h = 0$ to $+8$), PN late	p =0.379	p =0.025	p =0.067	p =0.063	p =0.325
Observations	1,649,604	1,649,604		1,649,604	

Note: Dependent variable is the log of bottled water sales. The columns come from three separate regressions: (1) own county alone; (2) adding neighbors as a single total; (3)–(5) splitting neighbors by media market and adding non-adjacent same-market counties. Own county is reported in column (1) and is included as a control in the other specifications. Panel A reports the violation-window coefficients by notification regime; Panel B the event-time coefficients around the notification week, with the indicator for $h = -1$ omitted. *Mean exposure* is the average of the exposure measure where it is positive; coefficients are full-exposure effects. Regressions include categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A7: de Chaisemartin and D'Haultfœuille (2024) Estimates by Geography and Notification Timing, All Horizons

	Own county		NCs total		NCs in DMA		NCs out of DMA		Non-adjacent in DMA	
	(1) PN on-time	(2) PN late	(3) PN on-time	(4) PN late	(5) PN on-time	(6) PN late	(7) PN on-time	(8) PN late	(9) PN on-time	(10) PN late
Placebos, weeks before the notice										
$h = -7$	-0.135	0.000	0.403	0.273	0.200	0.170	0.422	0.822	-0.687	3.034*
	(0.103)	(0.081)	(0.337)	(0.284)	(0.358)	(0.269)	(0.633)	(0.543)	(1.305)	(1.675)
$h = -6$	-0.091	-0.014	0.214	-0.154	-0.069	-0.078	0.557	-0.032	-1.520	3.258**
	(0.090)	(0.059)	(0.313)	(0.297)	(0.356)	(0.262)	(0.620)	(0.470)	(1.185)	(1.415)
$h = -5$	-0.183*	-0.161**	0.355	-0.143	-0.133	-0.471*	0.674	0.584	-1.476	2.229
	(0.094)	(0.071)	(0.305)	(0.274)	(0.349)	(0.282)	(0.567)	(0.484)	(1.246)	(1.525)
$h = -4$	-0.087	-0.134**	0.227	0.119	0.077	-0.250	0.875	0.758	-1.672	4.411***
	(0.096)	(0.063)	(0.280)	(0.277)	(0.353)	(0.304)	(0.595)	(0.516)	(1.184)	(1.553)
$h = -3$	-0.096	-0.009	0.471	0.412	0.186	0.098	0.753	1.135**	-0.902	3.411***
	(0.093)	(0.068)	(0.313)	(0.269)	(0.344)	(0.257)	(0.531)	(0.458)	(1.034)	(1.320)
$h = -2$	-0.117	-0.053	0.237	0.106	0.323	0.057	-0.292	0.097	-0.292	1.611
	(0.101)	(0.064)	(0.257)	(0.311)	(0.300)	(0.302)	(0.485)	(0.461)	(1.040)	(1.481)
Effects, from the notification week										
$h = 0$	0.322***	-0.110*	0.218	-0.060	-0.144	-0.334	0.713*	0.193	-0.150	0.469
	(0.111)	(0.059)	(0.254)	(0.259)	(0.317)	(0.278)	(0.409)	(0.435)	(0.799)	(1.512)
$h = 1$	0.182	-0.107*	0.490*	0.196	0.120	-0.048	0.933*	0.460	-0.309	2.478
	(0.122)	(0.055)	(0.288)	(0.309)	(0.359)	(0.275)	(0.491)	(0.425)	(0.991)	(1.512)
$h = 2$	-0.042	-0.112*	0.481*	-0.038	0.035	-0.210	1.036**	0.647	0.166	-0.899
	(0.095)	(0.060)	(0.284)	(0.279)	(0.357)	(0.266)	(0.473)	(0.503)	(0.979)	(1.759)
$h = 3$	-0.109	-0.030	0.564*	0.002	-0.015	-0.029	1.306**	0.482	0.709	0.224
	(0.100)	(0.053)	(0.303)	(0.295)	(0.314)	(0.323)	(0.570)	(0.500)	(0.828)	(1.565)
$h = 4$	-0.075	-0.099	0.536*	0.180	0.134	-0.268	0.414	0.633	0.737	0.872
	(0.112)	(0.063)	(0.283)	(0.299)	(0.328)	(0.265)	(0.509)	(0.538)	(0.980)	(1.627)
$h = 5$	0.020	-0.084	0.628*	0.030	0.178	-0.204	1.220**	0.548	1.209	-0.739
	(0.102)	(0.072)	(0.334)	(0.266)	(0.351)	(0.302)	(0.572)	(0.488)	(1.244)	(1.461)
Controls										
Violation weeks										
Own county, PN on-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Own county, PN late	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Own county, PN never	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NCs total, PN on-time	—	—	Yes	Yes	—	—	—	—	—	—
NCs total, PN late	—	—	Yes	Yes	—	—	—	—	—	—
NCs total, PN never	—	—	Yes	Yes	—	—	—	—	—	—
NCs in DMA, PN on-time	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
NCs in DMA, PN late	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
NCs in DMA, PN never	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
NCs out of DMA, PN on-time	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
NCs out of DMA, PN late	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
NCs out of DMA, PN never	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
Non-adjacent in DMA, PN on-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-adjacent in DMA, PN late	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-adjacent in DMA, PN never	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Notification week										
Own county, PN on-time		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Own county, PN late	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NCs total, PN on-time	—	—		Yes	—	—	—	—	—	—
NCs total, PN late	—	—	Yes		—	—	—	—	—	—
NCs in DMA, PN on-time	Yes	Yes	—	—		Yes	Yes	Yes	Yes	Yes
NCs in DMA, PN late	Yes	Yes	—	—	Yes		Yes	Yes	Yes	Yes
NCs out of DMA, PN on-time	Yes	Yes	—	—	Yes	Yes		Yes	Yes	Yes
NCs out of DMA, PN late	Yes	Yes	—	—	Yes	Yes	Yes		Yes	Yes
Non-adjacent in DMA, PN on-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes
Non-adjacent in DMA, PN late	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Weather										
Maximum temperature (linear)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total precipitation (linear)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood or heavy rain	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Joint effects (p)	0.015	0.385	0.530	0.954	0.948	0.794	0.199	0.902	0.854	0.192
Joint placebos (p)	0.649	0.115	0.804	0.067	0.753	0.410	0.476	0.092	0.705	0.081
Switchers	649	549	1,614	1,508	1,326	1,236	759	739	1,860	1,768
Observations	746,555	692,943	445,591	479,345	517,693	536,399	524,498	528,459	247,649	274,923
Mean exposure	0.0721	0.1234	0.0143	0.0226	0.0160	0.0228	0.0107	0.0218	0.0043	0.0059

Note: Dependent variable is the log of bottled water sales. *PN* denotes public notification and *NCs* neighboring counties; *NCs in DMA* (*out of DMA*) are adjacent counties that share (do not share) the violation county's Designated Market Area, and *non-adjacent in DMA* are non-adjacent counties within the same market. In the controls block, *Yes* marks a term included as a control, a blank marks the term the column estimates, and a dash marks a term absent from that specification. Each column is a separate estimation with the estimator of de Chaisemartin and D'Haultfœuille (2024). Estimates are normalized so that coefficients are per unit of exposure and are clustered at the media market. *Switchers* is the number of county-weeks whose exposure changed and which the estimator therefore uses. *mean exposure* is the average of the exposure measure across county-weeks where it is positive. *Joint effects* is the p-value for the null that the effects at all six post-notification horizons are zero. *Joint placebos* is the p-value for the null that the six pre-notification placebo estimates are zero. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Table A8: List of Community Water Systems and Violation Events in the Stacked Difference-in-Differences Event Study with Public Notification On-Time

	PWS Name	Pop. served (000s)	Share of county served	Violation Type	Compl.period begin	Compl.period end	PN week end	External evidence	Notice scope	Notice date	Advisory days	PN record	County Directly Tt	County Directly Tt Control	County Indirectly Tt	County Indirectly Tt Control
1	CITY OF AUSTIN WATER & WASTEWATER (2 notices)	1,040	0.85	Single Turbidity Exceed	2018-10-01	2018-10-31	2018-10-27	Contemporaneous	All customers	2018-10-22	7	State BWO	Travis, TX	Dallas, TX	Bastrop, TX; Caldwell, TX	Victoria, TX; Atascosa, TX
2	CITY OF CORPUS CHRISTI	318	0.88	MCL Violation, Acute (TCR)	2007-08-01	2007-08-31	2007-08-18	Contemporaneous	All customers	2007-08-14	3	State BWO	Nueces, TX	Bexar, TX	Aransas, TX; Jim Wells, TX; Kleberg, TX; San Patricio, TX	Henderson, TX; Val Verde, TX; Frio, TX; Victoria, TX
3	CITY OF CORPUS CHRISTI	318	0.88	MCL Violation, Acute (TCR)	2015-07-01	2015-07-31	2015-07-25	Contemporaneous	All customers	2015-07-23	3	State BWO	Nueces, TX	Bexar, TX	Aransas, TX; Jim Wells, TX; Kleberg, TX; San Patricio, TX	Bosque, TX; Val Verde, TX; Frio, TX; Victoria, TX
4	CITY OF LAREDO	260	0.95	MCL Violation, Acute (TCR)	2007-07-01	2007-07-31	2007-08-04	Contemporaneous	All customers	2007-07-20	2	Certification received	Webb, TX	Hidalgo, TX	Dimmit, TX; Duval, TX; Jim Hogg, TX; La Salle, TX; Maverick, TX; Zapata, TX	Presidio, TX; Reeves, TX; Frio, TX; Pecos, TX; Starr, TX; Zavala, TX
5	CITY OF MIDLAND WATER PURIFICATION PLANT	142	0.85	Monthly Turbidity Exceed	2016-07-01	2016-07-31	2016-08-06	Contemporaneous	No advisory	Unknown	–	Certification received	Midland, TX	Guadalupe, TX	Andrews, TX; Ector, TX	Moore, TX; San Patricio, TX
6	INDIAN RIVER COUNTY UTILITIES (2 WTPS)	127	0.82	MCL Violation, E. coli (RTCR)	2015-08-01	2015-08-31	2015-09-05	Post-window (CCR)	Part of system	2015-08-28	3	Certification received	Indian River, FL	Marion, FL	Brevard, FL; Okeechobee, FL; Osceola, FL; St. Lucie, FL	Pasco, FL; DeSoto, FL; Hillsborough, FL; Polk, FL
7	JEA MAJOR GRID	748	0.80	MCL Violation, Acute (TCR)	2006-10-01	2006-10-31	2006-10-21	None located	–	–	–	Certification received	Duval, FL	Escambia, FL	Baker, FL; Nassau, FL	Lafayette, FL; Okaloosa, FL
8	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	993	1.00	Single Turbidity Exceed	2010-06-01	2010-06-30	2010-06-05	Contemporaneous	Part of system	2010-06-02	Unknown	Certification received	St. Louis, MO	Cole, MO	Franklin, MO; Madison, IL; Monroe, IL; St. Clair, IL	Newton, MO; Peoria, IL; Effingham, IL; Kankakee, IL
9	PORTLAND WATER BUREAU	666	0.83	MCL Violation, Acute (TCR)	2009-11-01	2009-11-30	2009-11-28	Contemporaneous	Part of system (about 50,000)	2009-11-28	2	Certification received	Multnomah, OR	Benton, OR	Clark, WA; Columbia, OR; Hood River, OR; Washington, OR	Pierce, WA; Umatilla, OR; Deschutes, OR; Jackson, OR
10	PORTLAND WATER BUREAU	666	0.83	MCL Violation, Acute (TCR)	2012-07-01	2012-07-31	2012-08-04	Contemporaneous	Part of system (about 135,000)	2012-07-21	2	Certification received	Multnomah, OR	Benton, OR	Clackamas, OR; Clark, WA; Columbia, OR; Hood River, OR; Washington, OR	Deschutes, OR; Walla Walla, WA; Lane, OR; Umatilla, OR; Malheur, OR
11	VIRGINIA BEACH, CITY OF	438	0.97	MCL Violation, Acute (TCR)	2012-05-01	2012-05-31	2012-05-26	Contemporaneous	No advisory	2012-05-25	–	Certification received	Virginia Beach city, VA	Chesterfield, VA	Chesapeake city, VA; Currituck, NC; Hampton city, VA; Northampton, VA	Henrico, VA; Carteret, NC; Prince George, VA; Mecklenburg, VA

Note: The table lists the violation events used in the stacked DID sample at community water systems serving at least 100,000 people and at least 75% of the host county population. *PWS Name* is the violating system; *Pop. served* is the population the system serves in the host county, in thousands, and *Share of county served* the ratio of that population to the host county's population. *Compl.period begin* and *Compl.period end* report the regulatory noncompliance period; *PN week end* is the Saturday ending the week containing the recorded public-notification date. *External evidence* records whether a general web search or Access World News (NewsBank) finds coverage of the violation during the noncompliance period or certification window (Contemporaneous) or only after that window (Post-window only). Post-window (CCR) marks events that neither search found but that appear in the utility's annual Consumer Confidence Report, published the following year; None located means neither search found the event and no Consumer Confidence Report on file mentions it. *Notice scope* records whether the documented boil-water advisory applied to all of the system's customers or only to part of its service area; No advisory marks a documented notice that did not ask customers to boil water. *Notice date* is the day the documented notice or advisory was issued; *Advisory days* is the number of calendar days the advisory was in effect; *PN record* is the SDWIS state action type: Certification received (the state received the system's public-notification certification) or State BWO (a state-issued boil-water order). *County Directly Tt* is the system's host county and *County Indirectly Tt* lists the adjacent counties outside the system's service area with no acute pathogen violation within 12 weeks of the notification week; *County Directly Tt Control* and *County Indirectly Tt Control* are their matched controls, listed in the same order.

Table A9: Socio-Demographic Balance for Directly and Indirectly Exposed Counties and Their Matched Controls, Stacked Difference-in-Differences Sample – On-Time Public Notification Events

	Directly Exposed					Indirectly Exposed				
Variable	Treated Mean	Control Mean	Mean Pair Difference	p-value	Norm. Diff.	Treated Mean	Control Mean	Mean Pair Difference	p-value	Norm. Diff.
Median HH Income ($2012)	51,729	50,293	1,436	0.328	0.153	48,514	44,918	3,596	0.006	0.365
Pop. Density Bin (1–9)	7.273	7.091	0.182	0.676	0.177	5.537	4.805	0.732	0.002	0.409
Share Coll. Degree	0.240	0.224	0.016	0.008	0.672	0.230	0.228	0.002	0.717	0.046
Share Child Pop.	0.203	0.202	0.001	0.806	0.035	0.209	0.206	0.003	0.223	0.120
Share Elderly Pop.	0.124	0.126	-0.002	0.712	-0.043	0.139	0.145	-0.006	0.148	-0.168
Share Black	0.105	0.103	0.002	0.926	0.022	0.069	0.068	0.001	0.860	0.013
Share Hispanic	0.307	0.291	0.016	0.080	0.055	0.348	0.345	0.003	0.845	0.009
Share Vacant Houses	0.108	0.109	-0.002	0.863	-0.038	0.167	0.165	0.002	0.834	0.024
Unemployment Rate	0.086	0.087	-0.000	0.941	-0.019	0.093	0.094	-0.001	0.722	-0.061
Share HH Below Poverty	0.147	0.164	-0.017	0.052	-0.279	0.158	0.170	-0.013	0.046	-0.194
Republican Vote Share 2012	0.250	0.287	-0.038	0.046	-0.358	0.273	0.291	-0.018	0.021	-0.172
Mean SD Distance	0.000	0.086	-0.086	$<$0.001	-4.082	0.000	0.112	-0.112	$<$0.001	-3.022

Note: The table reports mean socio-demographic characteristics for directly and indirectly exposed counties and their matched control counties. *Mean Pair Difference* is the average $(\text{Treated}_i - \text{Control}_i)$ across pairs; p is the p-value of a paired t-test across the pairs, and *ND* is the normalized difference in means. *Pop. Density Bin (1–9)* is the ordered population-density bin used in the matching procedure.

Table A10: Summary Statistics for Variables Used in the Stacked Difference-in-Differences Event Study with PN On-Time

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water sales (2019$)	1,639	2,207	0.012	268	737	2,375	46,670
Log of bottled water sales	6.6	1.3	-4.4	5.6	6.6	7.8	11
Total sales (2019$)	136,887	172,464	141	28,370	54,767	201,799	1,696,891
Share of bottled water sales (2019$)	0.013	0.0093	0	0.01	0.01	0.01	0.12
Log Share bottled water sales	-4.5	0.58	-13	-4.9	-4.5	-4.2	-2.1
Controls							
Weekly max temperature	29	7.4	-2.1	25	31	34	42
Weekly total precipitation	27	31	0	3.3	18	40	262
Flood or heavy rain in the county (week)	0.099	0.3	0	0	0	0	1
County Population	949,976	823,236	5,231	327,535	686,218	1,422,278	2,606,868
Socio-Demographic Variables							
County Median HH Income ($2012)	52,503	8,311	24,653	49,099	49,450	58,485	72,363
County Share Child Pop.	0.2	0.025	0.14	0.19	0.2	0.23	0.29
County Share Elderly Pop.	0.12	0.038	0.074	0.1	0.11	0.13	0.28
County Share Coll. Degree	0.24	0.031	0.12	0.2	0.24	0.26	0.3
County Share Black	0.14	0.11	0.0009	0.058	0.1	0.22	0.51
County Share Hispanic	0.24	0.22	0.014	0.071	0.12	0.38	0.98
County Share Presid Votes Republican	0.27	0.076	0.056	0.22	0.27	0.32	0.53
Share Rural Pop.	0.15	0.25	0	0.004	0.047	0.1	1
Share Lang. Barrier Pop.	0.22	0.088	0.1	0.15	0.19	0.29	0.57
Share No Fixed Broadband Pop.	0.02	0.042	0	0.001	0.005	0.026	0.69
Share No Broadband or Computer Pop.	0.14	0.059	0.069	0.093	0.13	0.16	0.43
Number of stores in county	112	108	1	44	80	131	374

Note: Summary statistics for the stacked event-study sample with on-time public notification, at the store–event–week level. The sample window is ± 12 weeks around the public notification week for 11 acute microbial Tier 1 violation events at community water systems serving at least 100,000 people.

Table A11: List of Community Water Systems and Violation Events in the Stacked Difference-in-Differences Event Study with Public Notification Delayed

	PWS Name	Pop. served (000s)	Share of county served	Violation Type	Compl.period begin	Compl.period end	PN week end	Delay days	External evidence	PN record	County Directly Tt	County Directly Tt Control	County Indirectly Tt	County Indirectly Tt Control
1	BRUNSWICK COUNTY WATER SYSTEM	137	1.00	Single Turbidity Exceed	2016-10-01	2016-10-31	2016-12-31	61	Post-window (CCR)	Certification received	Brunswick, NC	Carteret, NC	Columbus, NC; Horry, SC; New Hanover, NC	Lenoir, NC; Beaufort, SC; Buncombe, NC
2	ERIE CITY WATER AUTHORITY	220	0.80	Single Turbidity Exceed ; Monthly Turbidity Exceed	2006-08-01	2006-08-31	2006-12-02	93	Post-window only	Certification received	Erie, PA	Lackawanna, PA	Ashtabula, OH; Chautauqua, NY; Crawford, PA; Warren, PA	Hocking, OH; Fulton, NY; Clarion, PA; Susquehanna, PA
3	ERIE CITY WATER AUTHORITY	220	0.80	Single Turbidity Exceed	2018-10-01	2018-10-31	2018-12-01	31	Post-window (CCR)	Certification received	Erie, PA	Lackawanna, PA	Ashtabula, OH; Warren, PA	Hocking, OH; Huntingdon, PA
4	KENTUCKY-AMERICAN WATER CO	266	0.83	Single Turbidity Exceed	2013-11-01	2013-11-30	2014-02-01	63	Post-window (CCR)	Certification received	Fayette, KY	Warren, KY	Madison, KY	Union, KY
5	MO AMERICAN ST LOUIS ST CHARLES COUNTIES	993	1.00	Single Turbidity Exceed	2007-08-01	2007-08-31	2007-10-13	43	Post-window (CCR)	Certification received	St. Louis, MO	Clay, MO	Franklin, MO; Monroe, IL; St. Clair, IL	Cape Girardeau, MO; Piatt, IL; Peoria, IL
6	PA AMER WATER CO-PITTSBURGH	191	0.92	Single Turbidity Exceed	2017-11-01	2017-11-30	2018-02-17	79	Contemporaneous	Certification received	Washington, PA	Montour, PA	Beaver, PA; Fayette, PA; Greene, PA; Hancock, WV; Marshall, WV; Ohio, WV	Lycoming, PA; Northumberland, PA; Columbia, PA; Taylor, WV; Kanawha, WV; Marion, WV
7	SCHRIEVER WATER TREATMENT SERVICE AREA	100	0.90	Single Turbidity Exceed	2012-08-01	2012-08-31	2012-10-20	50	Contemporaneous	Certification received	Terrebonne Parish, LA	Vermilion Parish, LA	Assumption Parish, LA; St. Mary Parish, LA	Richland Parish, LA; Calcasieu Parish, LA
8	SHREVEPORT WATER SYSTEM	198	0.81	Monthly Turbidity Exceed	2018-01-01	2018-01-31	2018-03-24	52	None located	Certification received	Caddo Parish, LA	East Baton Rouge Parish, LA	Cass, TX; De Soto Parish, LA; Harrison, TX; Marion, TX; Miller, AR; Panola, TX; Red River Parish, LA	Lamar, TX; Richland Parish, LA; Grayson, TX; Houston, TX; Union, AR; Freestone, TX; Catahoula Parish, LA
9	VEOLIA WATER NEW YORK	270	0.83	Monthly Turbidity Exceed	2013-07-01	2013-07-31	2013-08-24	24	None located	Certification received	Rockland, NY	Saratoga, NY	Bergen, NJ; Passaic, NJ; Putnam, NY; Westchester, NY	Burlington, NJ; Cumberland, NJ; Schenectady, NY; Onondaga, NY
10	WICHITA, CITY OF	396	0.77	Monthly Turbidity Exceed	2010-03-01	2010-03-31	2010-05-08	38	Contemporaneous	Certification received	Sedgwick, KS	Shawnee, KS	Butler, KS; Cowley, KS; Harvey, KS; Reno, KS; Sumner, KS	Pottawatomie, KS; Labette, KS; Bourbon, KS; Clay, KS; Crawford, KS

Note: The table lists the violation events used in the stacked DID sample at community water systems serving at least 100,000 people and at least 75% of the host county population. *PWS Name* is the violating system; *Pop. served* is the population the system serves in the host county, in thousands, and *Share of county served* the ratio of that population to the host county's population. *Compl.period begin* and *Compl.period end* report the regulatory noncompliance period; *PN week end* is the Saturday ending the week containing the recorded public-notification date. *Delay days* is the number of days from the end of the regulatory noncompliance period to that Saturday. *External evidence* records whether a general web search or Access World News (NewsBank) finds coverage of the violation during the noncompliance period or certification window (Contemporaneous) or only after that window (Post-window only). Post-window (CCR) marks events that neither search found but that appear in the utility's annual Consumer Confidence Report, published the following year; None located means neither search found the event and no Consumer Confidence Report on file mentions it. *PN record* is the state action type. *County Directly Tt* is the system's host county and *County Indirectly Tt* lists the adjacent counties outside the system's service area with no acute pathogen violation within 12 weeks of the notification week; *County Directly Tt Control* and *County Indirectly Tt Control* are their matched controls, listed in the same order.

Table A12: Socio-Demographic Balance for Directly and Indirectly Exposed Counties and Their Matched Controls, Stacked Difference-in-Differences Sample – Delayed Public Notification Events

	Directly Exposed					Indirectly Exposed				
Variable	Treated Mean	Control Mean	Mean Pair Difference	p-value	Norm. Diff.	Treated Mean	Control Mean	Mean Pair Difference	p-value	Norm. Diff.
Median HH Income ($2012)	52,352	50,070	2,282	0.318	0.215	47,764	45,166	2,597	0.086	0.225
Pop. Density Bin (1–9)	7.100	6.800	0.300	0.193	0.360	5.757	5.459	0.297	0.047	0.209
Share Coll. Degree	0.199	0.200	-0.002	0.754	-0.048	0.211	0.205	0.006	0.084	0.140
Share Child Pop.	0.194	0.187	0.007	0.321	0.281	0.188	0.187	0.001	0.492	0.068
Share Elderly Pop.	0.144	0.148	-0.004	0.655	-0.113	0.157	0.159	-0.002	0.522	-0.081
Share Black	0.153	0.097	0.056	0.008	0.433	0.113	0.114	-0.000	0.970	-0.003
Share Hispanic	0.057	0.045	0.012	0.432	0.312	0.056	0.044	0.012	0.121	0.200
Share Vacant Houses	0.119	0.129	-0.010	0.229	-0.100	0.148	0.150	-0.003	0.682	-0.038
Unemployment Rate	0.086	0.076	0.010	0.065	0.643	0.087	0.082	0.005	0.129	0.202
Share HH Below Poverty	0.138	0.131	0.008	0.191	0.227	0.151	0.154	-0.003	0.520	-0.068
Republican Vote Share 2012	0.300	0.319	-0.020	0.135	-0.265	0.318	0.320	-0.002	0.775	-0.030
Mean SD Distance	0.000	0.076	-0.076	$<$0.001	-3.108	0.000	0.075	-0.075	$<$0.001	-2.627

Note: The table reports mean socio-demographic characteristics for directly and indirectly exposed counties and their matched control counties in the delayed public notification event-study sample (10 matched pairs for directly and 37 for indirectly exposed counties). *Mean Pair Difference* is the average $(\text{Treated}_i - \text{Control}_i)$ across pairs; p is the p-value of a paired t-test across the pairs, and *ND* is the normalized difference in means. *Pop. Density Bin (1–9)* is the ordered population-density bin used in the matching procedure.

Table A13: Summary Statistics for Variables Used in the Stacked Difference-in-Differences Event Study with PN Delayed

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Dependent variable							
Bottled water sales (2019$)	1,669	3,786	1.1	178	418	1,738	92,785
Log of bottled water sales	6.3	1.5	0.093	5.2	6	7.5	11
Total sales (2019$)	120,929	190,543	742	21,297	37,006	136,323	2,687,627
Share of bottled water sales (2019$)	0.012	0.0073	0	0.01	0.01	0.01	0.07
Log Share bottled water sales	-4.6	0.62	-10	-4.9	-4.6	-4.2	-2.7
Controls							
Weekly max temperature	23	8.8	-7.2	18	25	30	41
Weekly total precipitation	24	27	0	4.6	16	35	331
Flood or heavy rain in the county (week)	0.061	0.24	0	0	0	0	1
County Population	352,017	292,146	8,082	151,906	245,831	445,702	996,919
Socio-Demographic Variables							
County Median HH Income ($2012)	52,454	13,223	32,226	44,247	48,274	56,581	95,259
County Share Child Pop.	0.19	0.017	0.15	0.18	0.19	0.2	0.24
County Share Elderly Pop.	0.15	0.024	0.11	0.13	0.15	0.16	0.22
County Share Coll. Degree	0.2	0.035	0.13	0.17	0.21	0.23	0.3
County Share Black	0.16	0.14	0.0023	0.056	0.13	0.23	0.47
County Share Hispanic	0.069	0.073	0.0057	0.025	0.041	0.067	0.37
County Share Presid Votes Republican	0.29	0.057	0.19	0.24	0.28	0.32	0.47
Share Rural Pop.	0.34	0.35	0	0.059	0.16	0.61	1
Share Lang. Barrier Pop.	0.18	0.05	0.075	0.14	0.16	0.2	0.34
Share No Fixed Broadband Pop.	0.046	0.082	0	0.001	0.013	0.052	0.74
Share No Broadband or Computer Pop.	0.15	0.061	0.052	0.12	0.14	0.18	0.5
Number of stores in county	52	40	1	20	45	77	145

Note: Summary statistics for the stacked event-study sample with late public notification, at the store–event–week level. The sample window is ± 12 weeks around the public notification week for 10 acute microbial Tier 1 violation events at community water systems serving at least 100,000 people.

Table A14: Violation-Window and Notification Event-Time Coefficients by Specification, Excluding the Austin Event

	Log bottled water sales				
	Group 1	Group 2	Group 3		
	(1) Own county	(2) NCs total	(3) NCs in DMA	(4) NCs out of DMA	(5) Non-adjacent in DMA
Panel A. Violation window, by notification regime					
PN on time	0.0894***	0.0109	-0.0015	0.0310	0.0075
	(0.0256)	(0.0298)	(0.0259)	(0.0321)	(0.0639)
PN late	0.0636***	0.0590	0.0632*	0.0111	0.0659*
	(0.0185)	(0.0407)	(0.0341)	(0.0279)	(0.0387)
PN never	0.0670	0.0289	0.0217	-0.0021	-0.0657
	(0.0544)	(0.0917)	(0.0929)	(0.0603)	(0.0665)
Mean exposure, on time	0.0575	0.0116	0.0170	0.0210	0.0053
Mean exposure, late	0.1036	0.0189	0.0260	0.0478	0.0080
Panel B. Notification week, event time					
PN on-time					
$h = -8$	0.0366	0.0263	0.0073	0.1136	0.0679
	(0.0255)	(0.0459)	(0.0461)	(0.1378)	(0.0977)
$h = -7$	-0.0377	0.0882*	0.0974*	0.0268	0.2179**
	(0.0297)	(0.0503)	(0.0528)	(0.0838)	(0.0983)
$h = -6$	-0.0445	0.0090	0.0011	0.0385	0.0111
	(0.0332)	(0.0505)	(0.0513)	(0.1243)	(0.0793)
$h = -5$	-0.0436*	0.0381	0.0147	0.1199	-0.1477
	(0.0258)	(0.0431)	(0.0503)	(0.1203)	(0.1011)
$h = -4$	-0.0525*	0.0055	-0.0111	0.0648	0.0368
	(0.0315)	(0.0510)	(0.0477)	(0.1266)	(0.0820)
$h = -3$	-0.0449	0.0372	0.0284	0.0912	0.0516
	(0.0398)	(0.0652)	(0.0693)	(0.0945)	(0.1497)
$h = -2$	-0.0181	0.0716*	0.0710*	0.0709	0.0526
	(0.0409)	(0.0409)	(0.0396)	(0.0908)	(0.0927)
$h = -1$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$h = 0$	0.2303***	0.1836	0.2376	-0.0373	0.1500
	(0.0646)	(0.1486)	(0.1800)	(0.0927)	(0.1342)
$h = 1$	0.0991	0.1157**	0.0787	0.2764***	0.0636
	(0.0812)	(0.0559)	(0.0595)	(0.0689)	(0.0814)
$h = 2$	-0.0431	0.1018**	0.0681	0.2235***	0.0876
	(0.0286)	(0.0450)	(0.0581)	(0.0499)	(0.0546)
$h = 3$	-0.0306	0.0355	0.0492	-0.0281	-0.0677
	(0.0345)	(0.0411)	(0.0569)	(0.0802)	(0.0530)
$h = 4$	-0.0141	0.0195	0.0213	-0.0082	0.0473
	(0.0247)	(0.0385)	(0.0407)	(0.1049)	(0.0615)
$h = 5$	0.0114	0.0375	0.0623	-0.0619	-0.0982
	(0.0334)	(0.0408)	(0.0499)	(0.1485)	(0.0956)
$h = 6$	0.0061	0.0877**	0.0916*	0.0597	0.0448
	(0.0260)	(0.0421)	(0.0492)	(0.0870)	(0.0749)
$h = 7$	0.0431	0.1500***	0.1531***	0.1377*	0.1024
	(0.0286)	(0.0469)	(0.0538)	(0.0803)	(0.1904)
$h = 8$	-0.0333	0.1293**	0.1222*	0.1638	-0.1572
	(0.0216)	(0.0599)	(0.0665)	(0.1267)	(0.1146)
Mean exposure	0.0714	0.0141	0.0156	0.0106	0.0042
PN late					
$h = -8$	-0.0150	-0.0079	0.0180	-0.1075	0.0638
	(0.0294)	(0.0403)	(0.0481)	(0.0707)	(0.1083)
$h = -7$	0.0305	-0.0217	-0.0355	0.0180	-0.1124
	(0.0292)	(0.0405)	(0.0416)	(0.1015)	(0.1155)
$h = -6$	0.0187	-0.0414	-0.0279	-0.0846	-0.0058
	(0.0311)	(0.0431)	(0.0481)	(0.0795)	(0.0875)
$h = -5$	-0.0005	-0.0186	-0.0486	0.0855	-0.0591
	(0.0262)	(0.0342)	(0.0342)	(0.0862)	(0.0834)
$h = -4$	-0.0324	-0.0894**	-0.1060**	-0.0506	-0.0394
	(0.0232)	(0.0391)	(0.0464)	(0.0771)	(0.0563)
$h = -3$	0.0273	-0.0321	-0.0767	0.0887	0.1431
	(0.0274)	(0.0460)	(0.0565)	(0.0873)	(0.0996)
$h = -2$	-0.0151	-0.0650	-0.0474	-0.1293*	0.1430
	(0.0275)	(0.0555)	(0.0598)	(0.0697)	(0.1030)
$h = -1$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$h = 0$	-0.0282	-0.0874**	-0.0992*	-0.0712	0.0851
	(0.0236)	(0.0437)	(0.0516)	(0.0600)	(0.1002)
$h = 1$	0.0046	-0.0940**	-0.1017**	-0.0841	0.1279
	(0.0161)	(0.0383)	(0.0443)	(0.0573)	(0.0847)
$h = 2$	-0.0270	-0.0773	-0.0530	-0.1454*	0.0004
	(0.0200)	(0.0519)	(0.0628)	(0.0773)	(0.0999)
$h = 3$	0.0015	-0.0251	-0.0724	0.1072*	0.0376
	(0.0238)	(0.0468)	(0.0603)	(0.0577)	(0.0825)
$h = 4$	0.0014	-0.0033	-0.0032	-0.0249	0.0954
	(0.0231)	(0.0370)	(0.0475)	(0.0538)	(0.1005)
$h = 5$	-0.0032	-0.0200	-0.0493	0.0597	0.0630
	(0.0260)	(0.0427)	(0.0530)	(0.0795)	(0.0655)
$h = 6$	-0.0002	-0.0460	-0.0392	-0.0735	0.0877
	(0.0243)	(0.0370)	(0.0433)	(0.0620)	(0.0982)
$h = 7$	0.0518*	0.0415	0.0114	0.1152	0.0229
	(0.0288)	(0.0364)	(0.0369)	(0.0711)	(0.1127)
$h = 8$	0.0289	-0.0123	-0.0600	0.1040	0.0163
	(0.0231)	(0.0476)	(0.0443)	(0.1121)	(0.0882)
Mean exposure	0.1235	0.0226	0.0228	0.0218	0.0060
Own-county terms	Reported	Control	Control	Control	Control
Joint tests of the event-time path (Wald χ^2, p-value)					
Pre-notification ($h = -8$ to -2), PN on-time	p =0.164	p =0.087	p =0.099	p =0.762	p =0.000
Pre-notification ($h = -8$ to -2), PN late	p =0.343	p =0.189	p =0.019	p =0.008	p =0.064
Notification onward ($h = 0$ to $+8$), PN on-time	p =0.000	p =0.040	p =0.227	p =0.000	p =0.000
Notification onward ($h = 0$ to $+8$), PN late	p =0.380	p =0.026	p =0.067	p =0.063	p =0.327
Observations	1,649,434	1,649,434		1,649,485	

Note: Same specifications as Appendix Table A6, estimated without the October 2018 Austin event. The Austin notices are removed from all exposure measures, and the sixteen counties of the Austin media market (DMA) are dropped from eight weeks before to eight weeks after the notice week (170 county-weeks). Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A15: 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
Log (BW Purchases+1)	0.78	1.1	0	0	0	1.7	6
Bottled Water Purchases (gallons)	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	0.0079	0	0	0	0	0.88
Spillover Exposure							
NCs (all) Acute Pathogens — any PN timing	0.00064	0.0093	0	0	0	0	0.8
NCs (all) Acute Pathogens — PN on time	0.00019	0.0059	0	0	0	0	0.8
NCs (all) Acute Pathogens — PN late	0.00029	0.0058	0	0	0	0	0.7
NCs (all) Acute Pathogens — PN never	0.00016	0.0043	0	0	0	0	0.78
NCs (In-DMA) Acute Pathogens — PN on time	0.00019	0.0063	0	0	0	0	0.96
NCs (In-DMA) Acute Pathogens — PN late	0.00028	0.0067	0	0	0	0	0.92
NCs (In-DMA) Acute Pathogens — PN never	0.00014	0.0044	0	0	0	0	0.78
NCs (Out-DMA) Acute Pathogens — PN on time	0.000085	0.0043	0	0	0	0	0.95
NCs (Out-DMA) Acute Pathogens — PN late	0.00019	0.0065	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	0.0043	0	0	0	0	0.68
DMA Non-NC Acute Pathogens — PN late	0.00038	0.0053	0	0	0	0	0.86
DMA Non-NC Acute Pathogens — PN never	0.00016	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
Flood or heavy rain in the county (month)	0.16	0.37	0	0	0	0	1
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.	0.2	0.076	0.049	0.14	0.18	0.24	0.58
Share No Fixed Broadband Pop.	0.04	0.078	0	0.005	0.014	0.037	1
Share No Broadband or Computer Pop.	0.13	0.055	0.025	0.098	0.13	0.16	0.65

Note: The sample includes 165,082 households in 2,956 counties. Number of observations: 7,751,568 household-months. *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 A16: Spillover Effects of Acute Pathogen Violations by Media Market Connectivity and Notification Timing Under Alternative Fixed Effects and Clustering (NielsenIQ Homescan Analysis)

	Log (bottled water purchases + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Own county						
On-time notification	0.0833	0.0837	0.0837	0.0837	0.0837	0.0837
	(0.0632)	(0.0626)	(0.0633)	(0.0659)	(0.0784)	(0.0661)
Late notification	0.0428*	0.0467**	0.0467*	0.0467*	0.0467**	0.0467*
	(0.0228)	(0.0236)	(0.0239)	(0.0250)	(0.0220)	(0.0263)
Never notified	0.0295	0.0654	0.0654	0.0654	0.0654	0.0654
	(0.0714)	(0.0534)	(0.0540)	(0.0523)	(0.0578)	(0.0507)
Neighboring counties, in DMA						
On-time notification	0.0228	0.0194	0.0194	0.0194	0.0194	0.0194
	(0.0558)	(0.0573)	(0.0580)	(0.0548)	(0.0492)	(0.0580)
Late notification	0.0812**	0.0725*	0.0725*	0.0725**	0.0725	0.0725**
	(0.0404)	(0.0373)	(0.0377)	(0.0299)	(0.0434)	(0.0317)
Never notified	-0.0056	0.0571	0.0571	0.0571	0.0571	0.0571
	(0.0568)	(0.0570)	(0.0576)	(0.0539)	(0.0586)	(0.0527)
Neighboring counties, out of DMA						
On-time notification	0.0156	-0.0096	-0.0096	-0.0096	-0.0096	-0.0096
	(0.0673)	(0.0572)	(0.0578)	(0.0573)	(0.0516)	(0.0641)
Late notification	-0.0536	-0.0526	-0.0526	-0.0526*	-0.0526*	-0.0526*
	(0.0368)	(0.0362)	(0.0366)	(0.0281)	(0.0306)	(0.0312)
Never notified	0.0137	0.0298	0.0298	0.0298	0.0298	0.0298
	(0.1023)	(0.0984)	(0.0995)	(0.1057)	(0.0829)	(0.1042)
DMA counties, non-neighboring						
On-time notification	0.2152***	0.1814***	0.1814***	0.1814***	0.1814***	0.1814**
	(0.0751)	(0.0652)	(0.0659)	(0.0684)	(0.0598)	(0.0757)
Late notification	0.0125	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031
	(0.0733)	(0.0735)	(0.0743)	(0.0803)	(0.0858)	(0.0824)
Never notified	-0.0326	0.0036	0.0036	0.0036	0.0036	0.0036
	(0.0870)	(0.0762)	(0.0770)	(0.0791)	(0.1068)	(0.0994)
Observations	7,520,499	7,520,499	7,520,489	7,520,489	7,520,489	7,520,489
Household FE			yes	yes	yes	yes
County × Year FE	yes	yes	yes	yes	yes	yes
State × Month FE		yes	yes	yes	yes	yes
Year × Month FE	yes	yes	yes	yes	yes	yes
Clustering	County	County	County	County + month	State	DMA

Note: The dependent variable is the log of (bottled water purchases + 1). Exposure is measured over the violation window. Regressions include categorical controls for precipitation and temperature and a flood indicator. 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 A17: Heterogeneity in Household-Level Responses to Acute Pathogen Violations (NielsenIQ Homescan Analysis)

	Exposure Specification			
Row	Own (On-time)	NC in DMA (On-time)	NC out of DMA (On-time)	DMA non-NC (On-time)
HH Above 50K Income	0.074 (0.071)	0.021 (0.079)	0.041 (0.085)	0.250** (0.118)
HH Below 50K Income	0.097 (0.072)	0.026 (0.083)	-0.068 (0.088)	0.109 (0.094)
p(diff)	p=0.651	p=0.959	p=0.351	p=0.357
HH No Some College	0.062 (0.076)	-0.021 (0.121)	0.080 (0.199)	0.082 (0.156)
HH Some College	0.087 (0.074)	0.031 (0.071)	-0.036 (0.072)	0.206** (0.088)
p(diff)	p=0.780	p=0.728	p=0.602	p=0.500
HH No Children	0.082 (0.080)	-0.047 (0.064)	0.027 (0.081)	0.118 (0.091)
HH Has Children	0.088 (0.059)	0.186** (0.084)	-0.124 (0.162)	0.394** (0.186)
p(diff)	p=0.939	p=0.004	p=0.451	p=0.202
HH No Elderly	0.046 (0.067)	0.046 (0.069)	-0.070 (0.079)	0.212** (0.099)
HH Has Elderly	0.190** (0.088)	-0.051 (0.091)	0.131 (0.124)	0.111 (0.144)
p(diff)	p=0.043	p=0.352	p=0.200	p=0.585
HH Not White	0.035 (0.109)	0.279*** (0.086)	-0.005 (0.130)	0.430*** (0.151)
HH White	0.094 (0.069)	-0.028 (0.065)	-0.010 (0.067)	0.142* (0.080)
p(diff)	p=0.580	p=0.003	p=0.971	p=0.059
HH Not Black	0.100 (0.071)	-0.003 (0.059)	-0.030 (0.062)	0.158** (0.081)
HH Black	-0.054 (0.097)	0.353*** (0.136)	0.232 (0.238)	0.447** (0.210)
p(diff)	p=0.172	p=0.013	p=0.250	p=0.193
HH Not Hispanic	0.076 (0.062)	0.012 (0.058)	-0.017 (0.064)	0.174** (0.075)
HH Hispanic	0.167 (0.124)	0.148 (0.184)	0.116 (0.161)	0.303 (0.297)
p(diff)	p=0.304	p=0.455	p=0.385	p=0.661
HH No Internet	0.050 (0.113)	-0.053 (0.180)	0.254 (0.193)	-0.180 (0.225)
HH Has Internet	0.086 (0.071)	0.030 (0.061)	-0.032 (0.063)	0.217** (0.088)
p(diff)	p=0.787	p=0.651	p=0.114	p=0.139
HH No Cable TV	0.121 (0.076)	-0.093 (0.072)	0.076 (0.173)	0.175 (0.124)
HH Has Cable TV	0.068 (0.072)	0.071 (0.068)	-0.025 (0.063)	0.185** (0.092)
p(diff)	p=0.415	p=0.045	p=0.555	p=0.950
Below Median Republican	0.073 (0.074)	-0.005 (0.060)	-0.112 (0.095)	0.193** (0.080)
Above Median Republican	0.144 (0.089)	0.135 (0.133)	0.050 (0.064)	0.156 (0.115)
p(diff)	p=0.519	p=0.337	p=0.114	p=0.730
Non-Rural	0.084 (0.070)	0.026 (0.066)	0.011 (0.063)	0.255*** (0.077)
Rural	0.067 (0.092)	0.012 (0.109)	-0.135 (0.183)	-0.026 (0.119)
p(diff)	p=0.872	p=0.906	p=0.430	p=0.031

Note: Each pair of rows reports the coefficient on timely-notified acute pathogen exposure for households on either side of the indicated split, estimated jointly within a single regression, with $p(diff)$ testing their equality. Splits are panelist attributes from the NielsenIQ Consumer Panel except the final two, which are county characteristics. Columns correspond to the four exposure measures: own county, neighboring counties within the media market, neighboring counties outside it, and non-adjacent counties within the media market. The dependent variable is the log of (bottled water purchases + 1). Regressions include categorical controls for precipitation and temperature, a flood indicator, and household, county×year, primacy agency×month and year×month fixed effects. Standard errors are clustered at Designated Media Market (DMA) level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A18: Summary Statistics for Robustness Checks in the National Sample

Variable	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
GI Medications sales (2019$)	7797	23033	0	484	1558	5642	631251
Log GI Medications sales	7.347	1.878	-0.1054	6.182	7.351	8.638	13.36
Diarrhea Medications sales (2019$)	866.2	2639	0.01	48.57	164.4	610.5	149328
Antacids sales (2019$)	6446	18300	0.34	409.6	1321	4761	454616
Electrolytes ORS sales (2019$)	587.1	2573	0.01018	30.94	94.65	333.4	132152
Top SCI — notification week, on time	0.0002275	0.009592	0	0	0	0	1
Top SCI — notification week, late	0.0005643	0.01565	0	0	0	0	1
SD Close — notification week, on time	0.0002435	0.01016	0	0	0	0	1
SD Close — notification week, late	0.000519	0.01484	0	0	0	0	1
Above Median SD Close to NCs	0.516	0.4997	0	0	1	1	1
Below median HH income	0.4757	0.4994	0	0	0	1	1
Above median child share	0.5265	0.4993	0	0	1	1	1
Above median elderly share	0.4179	0.4932	0	0	0	1	1
Below median college degree	0.5269	0.4993	0	0	1	1	1
Above median Black share	0.5607	0.4963	0	0	1	1	1
Above median Hispanic share	0.5361	0.4987	0	0	1	1	1
Above median Republican vote share	0.4376	0.4961	0	0	0	1	1
Above median SCI to NCs	0.4174	0.4931	0	0	0	1	1
Own-county acute violation in current week or past 2 years	0.14	0.347	0	0	0	0	1

Note: Number of counties in the sample is 2,283. *Top SCI* refers to the top 5 connected counties based on the Social Connectedness Index (SCI), excluding all geographic neighbors and same-DMA counties. *SD Close* refers to the 5 closest counties based on Socio-Demographic (SD) Closeness, excluding geographic neighbors.

Table A19: Heterogeneity in Spillover Responses at the Notification Week 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	0.251 (0.174)
Above-median SCI (NCs) × NC Acute PN on-time	0.139 (0.162)
p(diff)	p=0.616
Below-median SD-close (NCs) × NC Acute PN on-time	0.330* (0.171)
Above-median SD-close (NCs) × NC Acute PN on-time	-0.023 (0.138)
p(diff)	p=0.104
Below-median past-2y own Acute × NC Acute PN on-time	0.240 (0.169)
Above-median past-2y own Acute × NC Acute PN on-time	0.151 (0.132)
p(diff)	p=0.682

Note: Each group of rows represents a separate regression interacting neighboring-county exposure at the notification week with a binary indicator for the specified characteristic (above or below the median). $p(diff)$ reports the p-value from a test of equality between the coefficients of the two subgroups. The social connectedness indicator equals one if the population-weighted mean Social Connectedness Index (SCI) between a county and its geographic neighbors exceeds the median across counties in its state. All regressions include controls for precipitation and temperature and a flood indicator, as well as county×year, primacy agency×month, and year×week fixed effects. The dependent variable is the log of bottled water sales. Standard errors (in parentheses) are clustered at Designated Media Market (DMA) level. Number of observations: 1,649,604. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A20: Event-Study Coefficients for Bottled Water and Diarrhea Remedy Sales Around the Violation Start, by Notification Timing

	Group 1 Log bottled water sales			Group 2 Log diarrhea remedy sales		
	On-time (1)	Late (2)	Never (3)	On-time (4)	Late (5)	Never (6)
$h = -8$	-0.0138	-0.0254	-0.0448	0.0455	0.0076	0.1809
	(0.0380)	(0.0350)	(0.0631)	(0.0901)	(0.0778)	(0.1180)
$h = -7$	0.0078	-0.0190	0.0128	-0.0111	0.0659	-0.0584
	(0.0485)	(0.0288)	(0.0669)	(0.0797)	(0.0922)	(0.2093)
$h = -6$	-0.0143	-0.0098	0.0556	0.0717	0.0371	0.0979
	(0.0433)	(0.0360)	(0.0813)	(0.0652)	(0.0581)	(0.2357)
$h = -5$	0.0415	0.0980**	0.0836	0.0895	0.0857*	0.0426
	(0.0550)	(0.0403)	(0.0633)	(0.0785)	(0.0458)	(0.1774)
$h = -4$	-0.0676**	0.0274	0.0066	-0.0100	-0.1282*	-0.1101
	(0.0294)	(0.0530)	(0.0799)	(0.1256)	(0.0664)	(0.1342)
$h = -3$	-0.0176	0.0055	-0.0493	0.1290	0.0086	0.1136
	(0.0405)	(0.0466)	(0.1201)	(0.0923)	(0.0639)	(0.2008)
$h = -2$	-0.0215	-0.0429	-0.0215	-0.0626	-0.0480	-0.0296
	(0.0514)	(0.0432)	(0.0462)	(0.0892)	(0.0737)	(0.0929)
$h = -1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$h = 0$	-0.0604	0.0765	0.1705	0.0703	-0.0381	0.1572
	(0.0543)	(0.0466)	(0.1107)	(0.1092)	(0.0675)	(0.1316)
$h = 1$	0.1077**	0.0250	0.1085*	-0.0213	-0.0142	-0.0075
	(0.0448)	(0.0497)	(0.0625)	(0.0798)	(0.0681)	(0.1554)
$h = 2$	0.1242**	0.0291	0.1440	0.0833	-0.0830	0.0930
	(0.0614)	(0.0465)	(0.0980)	(0.0662)	(0.0949)	(0.1962)
$h = 3$	0.1550*	0.0591	-0.0580	0.0723	-0.0799	0.2390**
	(0.0930)	(0.0433)	(0.0879)	(0.0961)	(0.0582)	(0.1146)
$h = 4$	0.1752	0.0958**	0.1048	0.0409	-0.0199	0.2194**
	(0.1078)	(0.0473)	(0.1009)	(0.0677)	(0.0793)	(0.1083)
$h = 5$	-0.0140	0.0051	-0.0789	0.0400	0.0078	0.3353***
	(0.0534)	(0.0482)	(0.1026)	(0.0730)	(0.0692)	(0.1227)
$h = 6$	0.0535	-0.0311	0.1727***	0.0145	-0.0508	0.0630
	(0.0713)	(0.0441)	(0.0613)	(0.0784)	(0.0931)	(0.1426)
$h = 7$	-0.0435	0.0168	0.0486	-0.1397	-0.1521*	0.1246
	(0.0423)	(0.0394)	(0.0882)	(0.1119)	(0.0778)	(0.1369)
$h = 8$	0.0122	0.0074	0.1133**	-0.0899	-0.0315	-0.2016
	(0.0373)	(0.0396)	(0.0518)	(0.0667)	(0.0685)	(0.1863)
Own-county notification-week exposure						
Notification week × On-time		0.2691***			0.0227	
		(0.0694)			(0.0520)	
Notification week × Late		-0.0311			0.0020	
		(0.0211)			(0.0509)	
County × Year FE	yes	yes	yes	yes	yes	yes
Primacy Agency × Month FE	yes	yes	yes	yes	yes	yes
Year × Week FE	yes	yes	yes	yes	yes	yes
Clustering	DMA	DMA	DMA	DMA	DMA	DMA
Observations	1,649,604	1,649,604	1,649,604	1,598,018	1,598,018	1,598,018
Joint tests (Wald p-value)						
All pre-period weeks ($h = -8$ to -2)	0.153	0.010	0.158	0.629	0.183	0.730
All post-period weeks ($h = 0$ to 8)	<0.001	0.112	<0.001	0.124	0.474	0.004

Note: The columns come from two regressions: Group 1 (columns (1)–(3)) for bottled water and Group 2 (columns (4)–(6)) for diarrhea remedies; within each, the on-time, late and never-notified event-time coefficients are estimated jointly. Event time h is measured in weeks from the start of the violation, with the indicator for $h = -1$ omitted. Joint tests report Wald p-values for the hypothesis that all listed coefficients equal zero. Regressions include categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A21: Effects of Acute Pathogen Violations on Gastrointestinal Medication Sales by Product Category

Dependent Variables:	Log Sales GI Meds	Log Sales Diarrhea	Log Sales Electrolytes ORS	Log Sales Antacid
Model:	(1)	(2)	(3)	(4)
Variables				
County Acute pathogens – PN on time (during)	-0.0160	0.0200	-0.0465	-0.0153
	(0.0170)	(0.0314)	(0.0477)	(0.0186)
County Acute pathogens – PN on time (after 1)	-0.0191	-0.0184	-0.1271	-0.0220
	(0.0410)	(0.0881)	(0.1040)	(0.0429)
County Acute pathogens – PN on time (after 2)	-0.0538	-0.0391	0.1302	-0.0635
	(0.0434)	(0.0705)	(0.0830)	(0.0514)
County Acute pathogens – PN on time (after 3)	-0.0300	-0.0248	0.2249***	-0.0502
	(0.0399)	(0.0916)	(0.0756)	(0.0384)
County Acute pathogens – PN on time (after 4)	-0.0125	-0.0749	0.0476	-0.0107
	(0.0319)	(0.0874)	(0.0891)	(0.0345)
County Acute pathogens – PN late (during)	0.0006	-0.0092	-0.0019	-0.0005
	(0.0138)	(0.0319)	(0.0335)	(0.0137)
County Acute pathogens – PN late (after 1)	-0.0193	0.0207	-0.0919	-0.0121
	(0.0385)	(0.0597)	(0.1010)	(0.0407)
County Acute pathogens – PN late (after 2)	-0.0081	-0.0024	0.0156	-0.0146
	(0.0368)	(0.0752)	(0.0774)	(0.0406)
County Acute pathogens – PN late (after 3)	-0.0032	-0.0448	-0.0653	0.0165
	(0.0333)	(0.0697)	(0.0792)	(0.0331)
County Acute pathogens – PN late (after 4)	-0.0548*	-0.0201	-0.1132	-0.0471
	(0.0307)	(0.0471)	(0.0838)	(0.0324)
County Acute pathogens – PN never (during)	-0.0273	0.0558	-0.0380	-0.0166
	(0.0221)	(0.0410)	(0.0612)	(0.0262)
County Acute pathogens – PN never (after 1)	0.0574	0.4413***	0.1338	0.0449
	(0.0399)	(0.1128)	(0.1788)	(0.0431)
County Acute pathogens – PN never (after 2)	-0.0027	0.1673	-0.0556	-0.0060
	(0.0660)	(0.1295)	(0.1740)	(0.0674)
County Acute pathogens – PN never (after 3)	0.0843	0.0043	0.1632	0.0752
	(0.0578)	(0.2143)	(0.2427)	(0.0594)
County Acute pathogens – PN never (after 4)	0.0311	-0.1697	0.2977	0.0341
	(0.0965)	(0.1619)	(0.2140)	(0.1166)
County Acute pathogens – PN on time (notification week)	0.0208	0.0347	0.0201	0.0105
	(0.0265)	(0.0525)	(0.0745)	(0.0326)
County Acute pathogens – PN late (notification week)	-0.0093	-0.0021	0.0093	-0.0197
	(0.0214)	(0.0500)	(0.0469)	(0.0231)
Fixed-effects				
County–Year	Yes	Yes	Yes	Yes
State–Month	Yes	Yes	Yes	Yes
Year–Week	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,650,343	1,598,018	1,441,602	1,650,271

Note: *During* is the exposure over the weeks the violation was in effect; *after* k is the exposure at the last week of the violation carried forward k weeks, so that the during and after terms do not overlap. Column (1) uses total GI medication sales; Columns (2)–(4) disaggregate by category. Regressions include categorical controls for precipitation and temperature, a flood indicator, and county×year, primacy agency×month and year×week fixed effects. Clustered (DMA) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A22: Estimated Avoidance Expenditure Attributable to Acute Pathogen Violations and Their Recorded Public Notification (Bottled Water Sales)

	β	Full-exposure effect (%)	Change in sales per fully exposed unit ($)	Full-exposure equivalents	Total change, 2006–19 ($m)
Panel A. At the notification week (equivalents are fully exposed notification events)					
Own county, timely notice	0.2651***	30.35	7,198	90.6	0.607
Neighboring counties, timely notice	0.2270	25.49	6,045	95.8	0.530
Panel B. During the violation window (equivalents are fully exposed county-weeks)					
Own county, timely notice	0.0942***	9.88	2,343	383.0	0.873
Own county, delayed notice	0.0637***	6.58	1,559	853.4	1.307
Panel C. Counterfactual: delayed notices issued on time					
Own county, notification week	0.2651	30.35	7,198	169.3	1.133

Note: The table calculates the excess expenditure on bottled water attributed to acute pathogen violations. *Beta* is the regression coefficient from Table A6 (columns (1) and (2); notification week at $h = 0$). *Full-exposure effect* is calculated as $(\exp(\beta) - 1) \times 100$. *Change in sales per fully exposed unit* applies that percentage to mean weekly bottled water sales in the sample ($23,717). *Full-exposure equivalents* is the sum of the exposure variable over the estimation sample: fully exposed notification events in Panel A and fully exposed county-weeks in Panel B. *Total change* adds up each exposed county-week's own effect, evaluated at that county-week's own exposure and priced at mean weekly sales. Panel C applies the timely-notice coefficient to the delayed events' exposure, setting the response to delayed notification to zero and holding purchases during the violation window fixed. Amounts are in 2019 dollars and cover sampled NielsenIQ stores only. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Appendix References

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