Testing Above the Limit: Drinking Water Contamination and Test Scores

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Abstract

This paper provides estimates of the contemporaneous effect of drinking water quality violations on students' academic achievement. Using student-level test score data with residential addresses, geographic information on water systems, and drinking water violations from North Carolina, I estimate the within-student impacts of poor water quality on student test scores. Exposure to a bacteria violation during the school year decreases math scores by about 0.038 standard deviations when the public is uninformed. Results suggest that poor water quality may impact retention or comprehension of material throughout the school year.

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The US spent $800 billion, or $15,621 per student, on public elementary and secondary schools in 2018-19 according to the National Center for Education Statistics. Spending these funds efficiently to improve educational outcomes is a key focus of policy makers and requires an understanding of the effective drivers of academic performance. Much of the economics research identifying meaningful inputs into the education production function focuses on factors traditionally thought of as key inputs driving educational outcomes, including school-related inputs, such as class size, tutoring, and teacher quality (Guryan et al., 2023; Chetty et al., 2011; Krueger, 1999), and health-related inputs that are directly linked to education, such as free and reduced price school meals (Ruffini, 2022; Anderson et al., 2018). Far less research has explored how other regulations, even those not directly aimed at education, may still impact educational outcomes.

This paper considers whether regulation of public drinking water supplies may have important spillover benefits to educational outcomes and provides the first causal estimates of the contemporaneous effect of drinking water quality violations on students' academic achievement. By exploiting plausibly exogenous variation in the timing of water quality violations, I estimate the within-student impacts of poor water quality on student test scores using a student fixed effect specification. To do so, I combine student-level test score data with geocoded student residential addresses from the North Carolina Research Data Center with detailed geographic information on community water system service areas and drinking water quality violations.

An estimated 16.4 million cases of acute gastroenteritis are attributed to contamination in community water systems each year in the US (Messner et al., 2006). Yet, more subtle impacts of water contamination likely go unmeasured in traditional health data. For example, symptoms such as nausea and stomach cramps may not be severe enough to warrant a visit to the hospital, but could still meaningfully reduce concentration or comprehension of material during school. As exposure to drinking water quality violations is widespread, it is important to quantify any impacts on student academic achievement. As the Environmental Protection Agency (EPA) is required by law to conduct economic cost-benefit analysis when updating drinking water regulation, failing to quantify the impact on academic outcomes, such as test scores, would mean the current estimates of the damages to human well-being are understated and regulation may be below the social optimum.

This paper finds that drinking water quality violations for coliform bacteria negatively impact student test scores. I focus on violations of the Total Coliform Rule, as this is the most commonly violated drinking water standard and violations have been linked with increased gastrointestinal illness (Marcus, 2022). Consistent with previous work showing that timely public notification allows households to respond to water quality violations by purchasing bottled water (Marcus, 2022), I only find negative impacts of violations when households are not informed immediately and thus are unable to avoid exposure. I find exposure to a violation during the school year decreases math scores by about 0.038 standard deviations. The magnitude of this effect is similar to the effect of about $822 less in school spending per student, an increase in class size of about 4 students, a reduction in teacher quality of about one third of a standard deviation, or a one standard deviation increase in fine particulate matter (Jackson et al., 2021; Ebenstein et al., 2016; Jepsen and Rivkin, 2009; Rivkin et al., 2005). Additional results suggest that effects on test scores persist and are driven to a large degree by reduced retention or comprehension of material presented in the classroom.

This paper makes a number of contributions to the literature. First, this paper adds to a literature measuring the impact of environmental factors on educational outcomes. While existing research has primarily focused on air pollution and heat, I expand this research to consider the contemporaneous effect of drinking water contamination on academic test scores. Research has shown that early exposure to poor air quality in utero and in early childhood harms later-life academic performance (Jacqz, 2022; Hollingsworth et al., 2022; Bharadwaj et al., 2017; Sanders, 2012). Research has also consistently documented a negative impact of contemporaneous exposure to air pollution and heat on academic test scores (Duque and Gilraine, 2022; Heissel et al., 2022; Persico and Venator, 2021; Park et al., 2020; Zivin et al., 2020; Austin et al., 2019; Stafford, 2015). For example, Ebenstein et al. (2016) find that a one standard deviation increase in fine particulate matter during high-stakes exams in Israel reduced student performance by 0.039 standard deviations, which ultimately lowered post-secondary educational attainment and reduced earnings.

However, very limited work has documented the effect of drinking water quality on educational outcomes or test scores. Beach et al. (2016) provide historical evidence that eliminating early life exposure to waterborne diseases in the early 20th century increased later-life earnings and years of education. Work documenting the effect of lead exposure on test scores and later-life outcomes consistently finds significant negative impacts, but typically focuses on channels of exposure other than drinking water, such as through soil, air, or lead paint, or does not distinguish lead exposure through water from other lead sources (Grönqvist et al., 2020; Sorensen et al., 2019; Aizer et al., 2018; Rau et al., 2015).[1] This paper provides new evidence that student test scores can be harmed not only by air pollution and heat, but also through contemporaneous public drinking water contamination.

This paper also contributes to a literature documenting the broader consequences of poor drink-

[1]Very few papers focus specifically on lead in drinking water. From a historical perspective, Ferrie et al. (2012) find prior exposure to water-borne lead among male World War II U.S. Army enlistees was associated with lower intelligence scores. Lu et al. (2022) find an association between lead levels in community drinking water systems and children's academic performances at the school district level. In ongoing research, Zheng (2022) study early life exposure to lead in drinking water on later life test scores and graduation rates.

ing water quality. Much of the existing work studies interventions in low- and middle-income countries (Aggarwal et al., 2024; Bhalotra et al., 2021; Akter, 2019; Cameron et al., 2021; Zhang and Xu, 2016; Brainerd and Menon, 2014; Gamper-Rabindran et al., 2010) or from a historical perspective in the US (Anderson et al., 2022; Beach et al., 2016; Cutler and Miller, 2005; Troesken, 2001). For advanced economies in a modern context, existing evidence is limited (Keiser and Shapiro, 2019), although some work documents negative impacts of poor drinking water quality on health at birth (Hill and Ma, 2022; Currie et al., 2013). Focusing on children and adolescents, Marcus (2022) shows drinking water violations for coliform bacteria negatively impact several measures of health, including emergency room visits for gastrointestinal illness.

However, extreme health measures, such as emergency room visits, are unlikely to capture more subtle effects on health which may have important impacts on human capital accumulation. Even if a child is not sick enough to go to the emergency room or stay home from school, poor water quality throughout the school year may impact concentration during class and comprehension of material, potentially leading to worse test scores. Alternatively, exposure at the time of testing may also negatively impact test performance. Quantifying the effect of water quality on test scores is especially important given that test scores have been shown to impact long-run outcomes, such as income, job stability, and social mobility (Chetty et al., 2014, 2011).

Unfortunately, violations of drinking water standards are a regular occurrence. For example, 11,938 of all public water systems, or about 8 percent, violated health-based standards in 2016 (EPA, 2016).[2] Disadvantaged communities tend to have higher exposure to these water quality violations. This research helps quantify the consequences of failing to maintain public drinking

[2]Health-based standards for microorganisms, disinfectant byproducts, disinfectants, inorganic chemicals, organic chemicals, and radionuclides can be found at https://www.epa.gov/ground-water-and-drinking-water/national-primary-drinking-water-regulations.

water quality standards, which can inform policy decisions aimed at improving water infrastructure and safeguarding the health and academic performance of all students.

1 Background

1.1 Coliform Bacteria

Coliform bacteria are microorganisms that are typically associated with human and animal fecal matter. Because testing for each specific harmful organism individually is generally too expensive and time consuming, the total coliform group of bacteria are often used as "indicator organisms" that potentially harmful fecal bacteria may be present. Within the total coliform group, E. coli is a more specific indicator of fecal contamination and is potentially more harmful than other coliform bacteria.

The presence of coliform bacteria indicates that harmful pathogenic organisms capable of causing a variety of waterborne or water-based diseases (see Table A1) may be present in water. Common symptoms of gastroenteric infections and diseases include nausea, vomiting, diarrhea, and stomach cramps. While severe health impacts may lead to increased visits to the hospital or emergency room, many individuals experience more mild to moderate symptoms that would not be recorded in hospitalization data. Children typically have higher risk of gastrointestinal illness and severe health outcomes from contact with contaminated water than adults (Trtanj et al., 2016).

Contamination of water provided by community drinking water systems can occur in a few different ways. For example, rain can lead to run-off entering the drinking water source, which is especially problematic for systems reliant on surface water rather than groundwater sources. Fecal coliforms are typically present in higher concentrations in surface water, especially in areas with manure run-off (Cox et al., 2005). Contamination can also occur if the water treatment process is ineffective at removing all contamination, or a break in the distribution system allows contaminants to enter the water supply even after treatment. In practice, breaks occur regularly with about 237,000 main breaks per year (Reynolds et al., 2008).

If properly informed, households can avoid exposure to contaminated water by boiling their tap water for at least one minute before drinking or by finding an alternate water source, such as bottled water. Both types of avoidance behavior are costly in terms of inconvenience, time, and money.

1.2 Water Quality Regulation

The US EPA regulates all public drinking water systems through the Safe Drinking Water Act (SDWA), which sets enforceable standards for over 90 different contaminants.[3] About 8 percent of all public drinking water systems in the US violated a health-based drinking water standard and 26 percent violated monitoring and reporting requirements in 2016 (EPA, 2016). Although the SDWA also regulates other types of systems, this study focuses on community water systems, which supply water to the same population year-round.

In this paper, I focus on the most commonly violated health-based drinking water standard, the Total Coliforms Rule (TCR).[4] To be in compliance, each water system was required to take routine samples for total coliform bacteria each month, with larger systems required to sample

[3] Public drinking water systems are defined as having at least 15 service connections or serving at least 25 people per day for 60 days per year.

[4] Although the Revised Total Coliform Rule (RTCR) came into effect in March 2016, this paper focuses on violations prior to these revisions. The RTCR eliminated warnings for "Monthly" coliform violations, but maintained violations for "Acute" coliform (renamed as an "E. coli" violation). The RTCR also introduced new requirements for systems with coliform contamination to initiate assessments to find sanitary defects and take corrective action.

more frequently. Samples were required to be collected at regular time intervals throughout the month at representative sites throughout the distribution system.[5] Samples were then tested for the presence or absence of total coliforms, rather than the amount or concentration of coliforms. For positive tests, repeat samples testing for the presence of fecal coliforms or E. coli were required at additional locations.[6] Even with this relatively coarse measure of exposure, existing research has shown that the presence of coliform bacteria (as measured by TCR violations) in drinking water is sufficiently harmful as to increase hospitalizations for gastrointestinal illness, increase over the counter purchases of stomach remedies, and increase school absences (Marcus, 2022).

Two types of violations could occur: Acute and Monthly. Acute violations required detection of fecal coliforms or E. coli, which are found in large quantities in fecal matter and provide strong evidence that sewage is present. An Acute violation occured when any repeat sample was positive for fecal coliforms or E. coli, or there was a positive total coliform repeat sample following a positive fecal coliform or E. coli routine sample (40 CFR 141.63). Monthly coliform violations occured when a system detected more positive total coliform samples than the allowable monthly limit. For small systems serving less than 33,000 people, a Monthly violation occured if two or more samples tested positive for total coliforms. For larger systems, a Monthly violation occurred when over 5 percent of samples test positive for total coliforms.[7]

[5]Systems were required to provide a sample siting plan which determined sampling locations and was subject to state review and revision. Groundwater systems serving 4,900 or fewer people could collect their samples on the same day.

[6]If a sample tested positive for total coliforms, the system was typically required to take three "repeat" samples: at the same tap, within five service connections upstream, and within five service connections downstream. If the "repeat" samples tested positive for total coliforms, another set of samples must be taken, as before, unless a violation was triggered. In addition, each sample that tested positive for total coliforms must also be tested for the presence of fecal coliforms or E. coli.

[7]Larger systems had some incentive for strategic avoidance of regulatory action. Bennear et al. (2009) find evidence that large systems over-sample to avoid triggering a violation. Although there are no TCR violations for systems serving over 33,000 people in the sample used for this study, violations at some systems may have gone unrecorded and the effects estimated in this study may be understated.

Acute and Monthly violations of the TCR had different public notification requirements under the SDWA's Public Notification Rule. Acute coliform violations were classified as Tier 1 and required public notification within 24 hours (through radio, TV, hand delivery, posting, or other methods), whereas Monthly coliform violations were classified as Tier 2 and required notification within 30 days. In practice, public notification can often take even longer than 30 days. Figure 1 shows the distribution of days between the determination date and public notification date for Monthly coliform violations in North Carolina between 2007 and 2015.[8] The figure shows a long right tail with over 20 percent of public notifications occurring more than a year after the determination date. Delayed public notification during Monthly coliform violations limited the ability for individuals to exhibit avoidance behaviors, such as drinking bottled water. Regardless of the tier, all public notifications had to include a description of the violation and contaminant levels, the violation date, potential adverse health risks, a description of the population at risk, whether to seek an alternate water supply, what actions consumers should take, what the system was doing to correct the violation, and when the system expected to return to compliance.[9]

While Acute violations were thought to be more harmful, Marcus (2022) shows that avoidance behaviors, such as increased purchases of bottled water, mitigated the health impacts during Acute violations. On the other hand, Monthly violations did not increase avoidance behavior and led to negative impacts on both direct and indirect measure of health. Protective avoidance behavior during only Acute violations is likely driven by the differences in public notification requirements between Acute (requiring immediate 24-hour public notice) and Monthly (requiring only notifi-

[8]These data come from the North Carolina Department of Environmental Quality. Thanks to Linda Raynor for sharing and assisting in the interpretation of these data.

[9]The notification was also required to include contact information and a statement encouraging individuals to distribute the notice to others served by the water system. If 30 percent or more of the customers were non-English speaking, the system had to provide the notification in the appropriate language(s) or provide additional information on where to get a translated copy or assistance.

cation within 30 days) violations. Appendix B extends these results for bottled water purchases by looking at the responsiveness for households with and without school-aged children, who are the focus of this analysis. Results show that households with school-aged children also increase bottled water purchases in response to Acute coliform violations, but not Monthly coliform violations. These results are consistent with existing work and support the hypothesis that any effects on student tests scores are likely to occur during Monthly violations, rather than Acute violations, due to the differential avoidance behavior in response to public notification.

2 Data

2.1 Water Quality Data

The EPA maintains the Safe Drinking Water Information System (SDWIS), which collects detailed records on all water quality violations in the US. I use data from 2009 to 2015 on health-based maximum contaminant level (MCL) violations and procedural violations, such as testing and reporting violations. I focus on violations of the Total Coliform Rule, which are classified as either Acute violations (requiring notification within 24 hours) or Monthly violations (requiring notification within 30 days). Violations are based on samples collected at regular time intervals throughout the month at representative sites throughout the CWS distribution system.

Public Community Water Supply service areas comes from the North Carolina Center for Geographic Information and Analysis, available via NC OneMap.[10] Figure 2a shows the community water supply system service areas for North Carolina and areas with either Acute or Monthly viola-

[10]Geographic service areas were mapped during 2004-2006 to facilitate planning, siting, and impact analysis. Data are available here: www.nconemap.com.

tions of the Total Coliform Rule. Not all areas of the state are served by community water systems and I exclude students outside community water service areas. Unserved areas tend to be rural and usually supply their own water for domestic use through fresh groundwater wells, which are not regulated under the SDWA.[11]

2.2 School Data

The North Carolina Department of Public Instruction (NCDPI) maintains student-level data from the North Carolina Education Research Data Center (NCERDC). I use end-of-year math and reading test scores for grades 3-8 from 2009 to 2015. These tests aim to assess whether students have met grade-level expectations. I focus primarily on math test scores, as math standardized tests are often thought to better capture learning and are more commonly used in the education literature (Sanders, 2012). I standardize each score by year, grade, and local education agency.[12] Additional demographic characteristics include gender, race, ethnicity, disability status, and indicators for the economically disadvantaged and those with limited English ability. Table 1 provides summary statistics of the full sample and the main analysis sample, and Appendix C discusses the comparability of the analysis sample relative to the full sample.

The student-level data contain a unique code for each student that can be linked over time, allowing for the inclusion of student-level fixed effects. Detailed geocoded addresses allow for a more accurate definition of exposure to poor water quality than exposure based on attendance boundaries. Students are linked to water quality information based on the intersection of their pre-

[11] About 14 percent of the US population supplies their own water for domestic use, primarily through privately owned groundwater wells. There are no federally required monitoring or treatment standards for private domestic wells under the SDWA. Schools-based water systems relying on well water are still regulated under the SDWA as Non-Transient, Non-Community water systems.

[12] All students in North Carolina take the same test conditional on school grade. Grading is done at the local education agency level by the test coordinator who is chosen by the superintendent of the district.

cise home locations and community water supply service areas.[13] I focus on non-moving households, to abstract away from the possibility of endogenous moving behavior. In addition, I use public school location information from NCDPI to separately estimate the effect of water quality at the home and school. Violations at schools are based on water samples taken at the community water system serving the area where the school is located. Because children often live near their school, the same water system may serve children at home and at school. Yet, there are still many children who are served by different CWS systems at home and at school.[14] Because children spend substantial time in both locations, it is useful to consider exposure to violations at both locations.

Additional data come from the Common Core of Data (CCD) Public Elementary/Secondary School Universe Survey Data from 2009 to 2015 and the School Report Card data from 2009 to 2013.[15] These school-year level data allow me to test whether violations coincide with changes in student or school characteristics. These data include information on race/ethnicity, percent eligible for free and reduced price lunch, average daily attendance rate, percent of Adequate Yearly Progress targets met, number of library/media center books per 1000 students, percent of classes taught by high quality teachers (defined as teachers that are fully licensed, have advanced degrees and/or are National Board Certified), percent of classrooms connected to the internet, crimes in school per 1000 students, percent in poverty, one year teacher turnover rate, and teacher tenure

[13] Not all households living within a water supply service area necessarily get their water from the CWS. Some households may supply their own water for domestic use through a privately owned well or through bottled water purchases. However, the vast majority households (and schools) located within the CWS area get their water from the CWS.

[14] Among observations with exposure to a Monthly violation during the school year, about 46 percent experience exposure both at home and school simultaneously, and 54 percent experience exposure at either home or school, but not both. There is less variation within Acute violations during the school year. About 89 percent experience exposure at both home and school, while only 11 percent experience exposure in either home or school, but not both. The correlation coefficients are 0.635 and 0.941 for Monthly and Acute coliform violations during the school year, respectively.

[15] I do not use later years, because variables collected in the School Report Card data changed in 2014.

(specifically, the percent of teachers with 3 or fewer, 4-10, or 11 or more years of experience). Other basic information includes school type (e.g. regular, alternative, vocational), type of school calendar (e.g. traditional, year-round, modified), and school program (e.g. magnet, charter). To explore whether violations have an impact on behavioral outcomes, I also use School Report Card data to test for effects on school-level rates of expulsions and suspensions.

2.3 Weather and Air Pollution Data

It is important to control flexibly for weather, as weather may impact both exposure to contaminated water and test scores. For example, hot weather may increase intake of contaminated tap water and has been shown to impact learning and test scores (Park et al., 2020; Zivin et al., 2020). Daily weather data for each 2.5 by 2.5 mile square in North Carolina come from (Schlenker and Roberts, 2009) and are based on the PRISM weather data set. I calculate measures of total precipitation, average precipitation, and the percent of days with a maximum temperature that falls within 7 temperature bins in degrees Celsius: below 0, 0-5, 5-10, 10-15, 15-20, 20-25, and over 25. I also include controls for 7 precipitation bins in millimeters as a robustness check: 0-1, 1-5, 5-10, 10-15, 15-20, 20-25, and over 25. The main specification includes monthly precipitation and temperature controls for fall, spring, and summer, but the results are robust to including both temperature and precipitation bins separately for each month.

As a robustness check, I include controls for ozone and particulate matter measured at air quality monitors throughout North Carolina, as test scores may be driven by exposure to air pollution (Duque and Gilraine, 2022; Heissel et al., 2022; Persico and Venator, 2021; Austin et al., 2019; Stafford, 2015). I include the percent of days throughout the year within each of five categories to allow for nonlinear effects: 0-25%, 25-50%, 50-75%, 75-100%, and over 100% of the relevant EPA threshold for each criteria pollutant. I use inverse distance weighted measures of air pollution from monitors within 20 miles of a student's residence.

3 Empirical Strategy

The student-level data allows me to define individual-level exposure based on residential and school latitudes and longitudes. I consider exposure separately for Acute and Monthly violations, as they result in different public notification requirements and avoidance response. For each type of violation, I measure exposure as equal to one if a violation occurred within the past school year or equal to one if a violation occurred within the testing window. The school year is defined as months August through April, while the testing window is defined as the month of May.[16] The main specification is as follows,

$$
\begin{aligned}
Y_{i,t} = &\beta_1 Acute\_SchoolYear_{i,t} + \beta_2 Acute\_Testing_{i,t} + \\
&\beta_3 Monthly\_SchoolYear_{i,t} + \beta_4 Monthly\_Testing_{i,t} + \\
&\omega_{i,t} + Grade_i + Year_t + \phi_i + \varepsilon_{i,t}
\end{aligned} \tag{1}
$$

where i indexes individuals and t indexes school years. Outcomes of interest include the end-of-year standardized test scores for grades 3-8. Individual fixed effects, ϕ_i, control for all time-

[16]As of 2013, North Carolina law requires that the public school opening date is no earlier than the Monday closest to August 26th and the end date is no later than the Friday closest to June 11th. From 2005 to 2013, the start date was no earlier than August 25th and the end date was no later than June 10th. Schools with non-traditional calendars, about 6% of schools, were exempt. The End of Grade testing window in North Carolina public schools was the last 22 days of the school year from 2009 to 2012, the last 15 days of the school year in 2013, and the last 10 days of the school year from 2014 to 2015. See General Statute 115C-84.2 and https://www.dpi.nc.gov/images/data/calendar/history-school-calendar/download.

invariant individual, family, and neighborhood characteristics, and standard errors are clustered at the individual level. The specification also includes indicators for grade level and year, as well as time-varying weather controls, $\omega_{i,t}$. The coefficients of interest, β_1 through β_4, capture the impact of exposure to poor water quality during the school year and testing window on an individual's test score. These estimates rely on variation within students across years, rather than variation across students or schools. Estimates would be biased if there are time-varying unobserved factors affecting test scores that impact students in specific areas with water quality violations during the year of violation. Results presented in the robustness section show the estimates are not driven by a broad range of potential confounders, such as changes in employment, procedural violations, other diseases, or air pollution. Violations are also unrelated to school-level changes in student demographics or school characteristics.

4 Results

First, Table 2 documents demographic characteristics of students who have been exposed to any type of coliform water quality violation in the sample. Columns 1 and 2 show mean characteristics for those students unexposed and exposed to a violation at either home or school, respectively, while columns 3-4 are based on exposure at home and columns 5-6 are based on exposure at school. Patterns are similar across both sources of exposure and are consistent with a broader environmental justice literature documenting higher exposure to pollution among disadvantaged communities (Banzhaf et al., 2019). While the average sex and grade level are similar across exposed and unexposed students, economically disadvantaged students are much more likely to be exposed to a water quality violation at both home and school. About 69 percent of students exposed to a violation are economically disadvantaged, as compared to 52 percent for unexposed students when considering exposure at either home or school. Exposed students are also more likely to be Black, by about 6 percentage points. Test scores are also about 4-8 points lower for students exposed to water quality violations.

Next, I explore whether these lower tests scores can be explained by the timing of water quality violations, rather than other student characteristics. Water quality violations may impact student tests scores through two main channels. First, existing research has shown that water quality violations increase absences (Marcus, 2022) and absences decrease test scores (Aucejo and Romano, 2016).[17] Second, even if children are not sick enough to stay home from school, their concentration and comprehension may be impacted. Exposure to poor water quality during different parts of the year may impact test scores through different channels. For example, exposure during the testing window could impact concentration during the test, while exposure during the school year could impact absences or concentration and comprehension of material.

It is also important to consider the potential for poor water quality to impact children through exposure both at home and at school. Children spend significant amounts of time at school and are likely to consume tap water at lunch, during recess, or at other times throughout the school day. While much existing work can only observe pollution exposure at one location, the data used in this study allows us to consider both home and school exposure.

Table 3 shows estimates of equation 1 which includes indicators for grade and year, weather controls, and student fixed effects.[18] Student fixed effects capture all time-invariant student and

[17] In principle, violations may increase both teacher and student absences. Unfortunately, I do not have data on teacher absences or teacher residential locations to be able to test this mechanism directly. While adult health tends to be less sensitive to contaminated water than child health (Trtanj et al., 2016), this channel may also be relevant given evidence that ER visits for gastrointestinal illness at older ages (e.g. 20-39) also increase during violations (Marcus, 2022).

[18] Table A2 in the appendix builds up to this fully specified model for both math and reading test scores. Without

family characteristics, such as race/ethnicity, household income, and parental education, such that estimates are based off within-student comparisons in test scores across years rather than comparisons across students. Columns 1-2 in Table 3 show the results for home exposure to violations during the school-year and during the testing window, and columns 3-4 show the results for school exposure.

I start by focusing on water quality at students' homes in column 1. There is no statistically significant impact of exposure to an Acute coliform violation at any time on math scores. This is perhaps not surprising given previous work and additional evidence in Appendix B showing that households avoid exposure through purchasing bottled water during Acute coliform violations, which require immediate public notification (Marcus, 2022). On the other hand, there is a larger impact of poor water quality on test scores during Monthly violations, when households are not required to be informed immediately. Exposure to a Monthly coliform violation during the school year decreases math scores by about 0.038 standard deviations in column 1.[19] While the coefficient for exposure during the testing window is negative, it is not statistically significant. As actual test dates are unobserved and there are relatively few violations during the testing window, I may lack power to detect an effect of exposure during testing. In addition, health-related absences on the test day are not observed. If the students most impacted by the poor water quality are absent on the test day, the effect on test scores may be understated. When considering exposure based on

accounting for student ability by controlling for student fixed effects, estimates are sensitive to the inclusion of demographics and weather controls. However, when student fixed effects are included, the estimates are much more stable and show a negative impact on math scores for Monthly coliform violations during the school year. This can be seen in column 5 which includes additional weather controls and across a variety of robustness tests shown in Figure 4 and described in section 4.2. While I find no significant impact on reading test scores, this is consistent with some existing research on environmental exposures, which often finds smaller effects on reading than math scores (Duque and Gilraine, 2022; Jacqz, 2022; Hollingsworth et al., 2022). In the remainder of the results, I focus on math tests scores.

[19]The effect of a Monthly coliform violation during the school year remains statistically significant even after correcting for multiple hypothesis testing. Table A3 shows that the sharpened q-value is 0.051, the Westfall-Young p-value is 0.050, and the Romono-Wolf p-value is 0.0099.

school location rather than students' residential location in column 3, the estimates are similar in magnitude and direction for both Acute and Monthly violations. Only Monthly violations during the school year have a statistically significant negative effect on test scores. Appendix D explores the interactive effect of exposure at home and school simultaneously.

The magnitude of the effect of exposure to a Monthly violation during the school year is well within the range of the effects of other environmental factors on student test scores. Table 4 compares the estimated effect to other studies quantifying the impact of air pollution on math scores. The estimates on water quality are similar to the effect of attending schools downwind of a highway or a 1 standard deviation increase in carbon monoxide exposure during the third trimester (Heissel et al., 2022; Bharadwaj et al., 2017). The estimates are smaller than the effects of indoor air quality improvement projects or airborne lead emissions (Stafford, 2015; Hollingsworth et al., 2022).

While existing research has shown that exposure to Monthly coliform violations also increases school absences, the effect on test scores cannot be entirely explained by an increase in absences. Aucejo and Romano (2016) find that it takes about 10 additional absent days to decrease math scores by 0.055 standard deviations. Marcus (2022) finds exposure to a Monthly coliform violation in North Carolina increases absences by about 0.4 days, which would be expected to decrease math scores by about 0.0022, or only about 6 percent of the estimated effect on test scores.[20] Instead, it is likely that these effects on test scores are driven in large part through the impact of Monthly coliform violations on concentration and/or comprehension of material while in the classroom.

[20] In Table A4, I also show that including absences as a control does not have a large impact on the estimated effect of violations on test scores. Although absences have a statistically significant negative impact on student test scores, as expected, there is little change in the magnitude or significance of the other point estimates, suggesting that increased absences are not driving the main effects. However, it is important to acknowledge that this is a "bad control" given that absences are an endogeneous outcome of the treatment.

Next, I explore whether the physical effects of poor water quality on children's health and cognitive ability appear to be either long-lasting or short-lived. If impacts of poor water quality are long-lasting, effects that degrade health in one period may ultimately impact cognition and test scores in both current and future periods. In this case, one might expect to see violations in the summer months having a delayed impact on test scores in the next school year. Alternatively, the impacts of poor water quality on health may be more short-lived. During the poor water quality episode, cognition and concentration may decrease, but suppose the effects are temporary. In this case, violations in the summer months are unlikely to have an impact on student test scores, because school was not in session and the students did not miss learning any material while they were feeling ill. When violations happen during the school year, students may fall behind or miss out on key learning goals due to the consequences of poor water quality on their health, cognition, and ability to concentrate. Table 6 shows that violations occurring either at home or at school during the summer months have no statistically significant impact on test scores and the coefficients are small in magnitude. These results suggest that the physical effects of these violations may be temporary.

Even if these physical effects are short-lived, the impact of exposure to poor water quality on learning may still have long-lasting effects due to the fact that learning goals tend to be cumulative. For example, falling behind or doing poorly in one year may leave students further behind in future years and lower test scores have been linked to worse later-life outcomes, such as earnings. However, it is uncertain whether the test score impact of exposure to a Monthly coliform violation during the school year would persist into future years. In columns 2 and 4 of Table 3, I include lagged exposure to a Monthly coliform violation during the previous school year. The negative impact of both home and school exposure on math scores seems to persist. The coefficients on lagged exposure are statistically significant and the magnitude of the effect is almost the same magnitude as exposure in the current year. These results suggest that the effect of Monthly coliform violations on test scores may impact later life outcomes.[21]

4.1 Additional Results and Heterogeneity

First, I leverage information on the timing of public notification to explore whether the effects are driven by Monthly coliform violations for which the public was not notified immediately. Unlike Acute coliform violations which require public notice within 24 hours, the water system is only required to notify the public within 30 days for Monthly coliform violations. Figure 1 shows the variation in public notification timing for Monthly coliform violations. Table 7 shows results separately for Monthly coliform violations during the school year during which the public was notified either within one day or later. As expected, the negative effects on math test scores are driven by violations where public notification was delayed beyond one day. Effects for Monthly coliform violations where the public was notified within one day, similar to Acute violations, are slightly smaller in magnitude and statistically insignificant. Although confidence intervals are too wide to statistically distinguish between these effects, it is reassuring that the main results are driven by Monthly coliform violations with delayed public notification. This is consistent with the findings in Marcus (2022) showing that bottled water purchases were higher during violations with immediate public notification, whereas over-the-counter stomach remedy purchases were elevated during Monthly violations with delayed public notification.

[21] Given this evidence that the effects on math scores persist, I also estimate specifications that capture the intensity of exposure and cumulative exposure. Table A5 shows very similar results when exposure is defined as the number of months in violation in the past school year or the number of cumulative months of exposure since first observed. In this setting, most exposed children are exposed to only one month of poor water quality so these results are very similar to the baseline specification.

Next, I explore heterogeneity in the effects across student demographic characteristics. As documented in Table 2, disadvantaged students are much more likely to be exposed to water quality violations overall. Consistent with the broader environmental justice literature, students exposed to a TCR violation are significantly more likely to be Black and more likely to be economically disadvantaged. Yet, conditional on exposure to a violation, it is unclear whether additional heterogeneity in effects may exist across demographic groups. Differences may arise due to different propensities to consume contaminated tap water across individuals or differences in sensitivity to poor water quality conditional on exposure. For example, Hispanics and economically disadvantaged children tend to consume less tap water (Drewnowski et al., 2013). However, without individual information on the amount of tap water actually consumed, I am unable to distinguish between heterogeneity in effects due to differences in the amount of contaminated tap water ingested from differences due to sensitivity conditional on amount ingested.

Figure A1a and Table A6 report the results after interacting key demographics with exposure to Monthly coliform violations during the school year. Point estimates are consistently negative across a variety of groups, but in most cases effects across different sub-groups are statistically indistinguishable. Point estimates are very similar for males and females and by grade level. In a few cases point estimates are larger among populations that tend to consume more tap water, including non-Hispanic students and students who are not economically disadvantaged (Drewnowski et al., 2013). However, I lack sufficient power in this setting to draw strong conclusions from these results across demographic groups.

Next, I explore heterogeneity in the effects across different types of community drinking water systems. Figure A1b and Table A7 report the results after interacting system characteristics with exposure to Monthly coliform violations during the school year. System characteristics include water source, whether the system has violated the TCR more than once, ownership type, and size.[22] Although results appear to be driven by surface water systems, repeat offenders, publicly owned water supply systems and larger systems, these differences are not statistically distinguishable and should be interpreted with caution. It is perhaps not surprising that the estimates show only a statistically significant impact for water systems supplied by surface waters. This is consistent with sampling data which reports higher concentrations of fecal coliform in surface water as compared with groundwater, especially where run-off from manure is likely (Cox et al., 2005).

Finally, it is possible that water quality violations may have an impact on student behavioral problems, possibly through an incapacitation effect. To test this, I use school-level data on expulsions and suspensions. Outcomes are measured as the number of expulsions or suspensions per 100 students. Long suspensions are over 10 days and short suspensions are 10 days or less. Exposure to violations is measured as the percent of students in the school exposed at their residential location during the school year or the testing window. All specifications include school and year fixed effects and controls for weather. The results in Table A8 show there is no strong evidence of an impact of these violations on expulsions or suspensions.

4.2 Robustness

In order for the results to measure the impact of water quality violations on student test scores, it must be that there are no time-varying unobserved factors affecting test scores that impact students in specific areas with water quality violations during the year of violation. I provide support for this assumption in Figures 3 and 4.

[22] I define repeat offenders as water systems with more than one violation of the TCR since 1990 and non-repeat offenders as systems that violate the TCR for the first time.

First, Figure 3 tests whether monthly coliform violations during the school year are systematically correlated with changes in student demographics or school characteristics, including race/ethnicity, poverty, crime, school resources, teacher quality, and school quality. The variable of interest is measured as the percent of students at the school exposed to a monthly coliform violation at their residential location. All specifications include school fixed effects and controls for year and weather. Corresponding regression results are included in Table A9. Across all outcomes, there is no systematic pattern and no statistically significant relationship between violations and changes in student or school characteristics. This provides support for the assumption that violations are unrelated to other time-varying factors that impact student test scores.

Next, Figure 4 and Table A10 show the robustness of the main results to a variety of alternative specifications. The baseline regression model is included in column 1 for reference, and all specifications include individual fixed effects, grade and year indicators, and weather controls. First, it is important that other drivers of test scores do not change systematically with violations. For example, it would be problematic if violations were correlated with a decline in family income or changes in the composition of peers at school. In columns 2 and 3, I show the robustness of the results to adding additional controls for the county-month employment rate as a proxy for family income and controls for student demographic characteristics at the school level, respectively.[23]

Another concern may be that not all health-based violations are reported in the data. For example, measurement error will be introduced if water systems do not fulfill the sampling requirements necessary to detect violations of the Total Coliform Rule. To account for this possibility, Column 4 adds additional controls for water systems that have any monitoring and reporting violations. The

[23] Employment rates at the county-school year level come from the Bureau of Labor Statistics' Local Area Unemployment Statistics data. Demographic characteristics at the school-year level come from the Common Core Data and include percent white, percent black, percent Hispanic, and percent free or reduced price lunch.

main coefficient remains very similar to the baseline specification with these additional controls.

Next, it may be important to account for other time-varying health factors that could impact student test scores. In particular, rates of influenza and asthma tend to be relatively high for the students in the sample in grades 3 to 8. Column 5 includes controls for the prevalence of other common diseases affecting children by controlling for the number of emergency room visits for influenza and asthma.[24] Next, column 6 adds controls for air pollution, as air pollution has been shown to impact test scores (Duque and Gilraine, 2022; Heissel et al., 2022; Persico and Venator, 2021; Austin et al., 2019; Ebenstein et al., 2016; Stafford, 2015). Ozone and particulate matter are included as the percent of days within each of five categories to allow for nonlinear effects: 0-25%, 25-50%, 50-75%, 75-100%, and over 100% of the relevant EPA threshold. The results remain significant and very similar to the baseline specification.

Next, I show the results are robust to dropping schools that may be outliers in the data. To account for the possibility that schools in and around the biggest cities in North Carolina, Charlotte and Raleigh, represent outliers, I drop Mecklenburg and Wake county schools in column 7. In addition, it is possible that some schools close in response to water quality violations, which could reduce learning through a different mechanism. I obtain data on unplanned school closures and show the results are robust to dropping the two schools that experienced a closure in response to water quality violations in column 8.[25]

Measurement error in the timing of the school year or testing window may also be a concern. Therefore, columns 9-11 introduce restrictions that focus on schools most likely to adhere to the

[24] I use data from the Cecil G. Sheps Center for Health Services Research at the University of North Carolina on the number of ER admissions at the zip code level for influenza and pneumonia (ICD-9 codes: 480-488) and asthma (ICD-9 code: 493) per person.

[25] Unplanned school closure data was generously provided by CDC/DGMQ/CI-ICU. Please consult Wong et al. (2014) for data collection and methods.

standard public school schedule. Columns 9-11 limit the sample to regular schools (excludes alternative education, exceptional children, and vocational education), regular programs (excludes cooperative innovative high schools, early college schools, magnet schools, etc.), and schools with traditional calendars (excludes modified calendars and year-round calendars), respectively.

Although the main estimates already control for temperature and precipitation, columns 12 and 13 include even more flexible weather controls to account for non-linearities and additional variation throughout the year. Column 12 includes seven flexible bins for precipitation, and column 13 includes temperature and precipitation bins separately for each month. The results remain statistically significant and similar in magnitude to the baseline specification.

The main results include year fixed effects to account for yearly shocks impacting all students in the state. However, it may also be possible for regional or local shocks, such as a hurricane or influenza outbreak, to impact the test scores of all students in a given region. Any correlation between regional shocks and violations may bias the estimates. To test the robustness of my results to time-varying regional shocks, columns 14 and 15 include region-by-year fixed effects. Regions are defined as either NCDEQ regions in column 14, or the Coastal Plains, Piedmont, and Mountains geographic regions in column 15. Columns 16 and 17 control for even more granular time-varying geographic shocks by including county-by-year and LEA-by-year fixed effects. Across all specifications, the coefficients and standard errors remain very similar.

To ensure that the effects on test scores are driven by coliform bacteria rather than other types of health-based drinking water quality violations, Table A11 includes controls for other types of health-based drinking water violations. The main coefficients are robust to these controls.[26]

[26]Columns 2 and 4 of Table A11 include controls for the number of months of other types of health-based violations, including radionuclides, disinfectants and disinfection by-products, synthetic organic compounds (SOCs), and volatile organic chemicals (VOCs). The main results are not sensitive to these controls. However, I hesitate to put too much emphasis on the magnitude of the coefficients on other types of violations, because this research design is not well

While the main results cluster standard errors at the individual level to account for correlation in the standard errors across time for the same student and because treatment effects are not expected to be uniform within a CWS, Table A12 in the appendix shows that the results are robust to clustering at alternate levels, such as at the community water system level, the school level, the school-grade level, and the CWS-school level. To further address potential concerns related to heterogeneity in cluster size, I also follow recommendations in MacKinnon et al. (2023) to report wild cluster restricted bootstrapped p-values, which also support the main findings.

Finally, Table 5 provides additional placebo tests. Water quality violations occurring in the future should be unrelated to current test scores. The results in Columns 1 and 4 of Table 5 replicate the baseline specification for violations based on both home and school exposure. Columns 2 and 5 include violations one year in the future and columns 3 and 6 include violations two years in the future. It is reassuring that these placebo violations are statistically insignificant, as expected.

5 Discussion & Conclusion

This paper quantifies the impact of drinking water violations for coliform bacteria on student test scores. Results show that violations only harm student test scores when the public is not required to be notified immediately. I find Monthly violations during the school year decrease math test scores by 0.038 standard deviations. This effect persists and cannot be explained by student absences alone, suggesting that poor water quality impacts comprehension or retention of material presented in the classroom. However, timely notification of the public helps mitigate the negative impacts from exposure.

suited to capture the effects of other contaminants that have more infrequent and complicated sampling requirements.

The magnitude of this effect is very similar to the effect of air pollution on math test scores. For example, attending schools downwind of a highway reduces math test scores by 0.040 standard deviations (Heissel et al., 2022). However, indoor air quality improvements, such as mold remediation, tend to have larger effects on test scores (Stafford, 2015). Compared to other policy levers to improve student test scores, exposure to a monthly coliform bacteria violation is equivalent to about $822 less in school spending per student, an increase in class size of about 4 students, or a reduction in teacher quality of about one third of a standard deviation (Jackson et al., 2021; Jepsen and Rivkin, 2009; Rivkin et al., 2005).

Using estimates from Chetty et al. (2014), the 0.038 standard deviation decrease in test scores from poor water quality that I estimate is associated with a 0.44 percent decrease in lifetime earnings. As the present value of expected future earnings at age 12 is $618,705 (2020 dollars) (Chetty et al., 2014), a 0.44 percent decrease in lifetime earnings is about $2,722. This effect on earnings is large relative to the cost of avoiding exposure to coliform bacteria violations through purchasing bottled water. Marcus (2022) finds that when households are informed immediately of coliform bacteria violations, bottled water purchases increase by 78 percent and households avoid harmful impacts on health. Estimates from Marcus (2022) suggest that if responsiveness to Monthly coliform violations yielded similar avoidance behavior, bottled water spending would have been about $365,000 higher from 2007 to 2015 in North Carolina.[27] Over the same time frame, lost lifetime earnings from the effect of exposure on test scores would be about $241 million in North Carolina.[28]

These findings provide evidence that clean drinking water is yet another important input into

[27] Note that this calculation was based on population estimates from the 2010 census. Since estimates for bottled water purchases were at the household level, this will overstate cost estimates.

[28] Based on an estimated 88,726 school-aged children exposed to a monthly coliform bacteria violation between 2007 and 2015 in North Carolina.

the education production function. By estimating the effect on student tests scores, this paper quantifies an important measure of the subtle, but costly, harms of exposure to poor drinking water. These estimates contribute to an overall calculation of the damages of poor water quality on human well-being, providing needed information to policymakers as they seek to set safe drinking water regulations at the social optimum.

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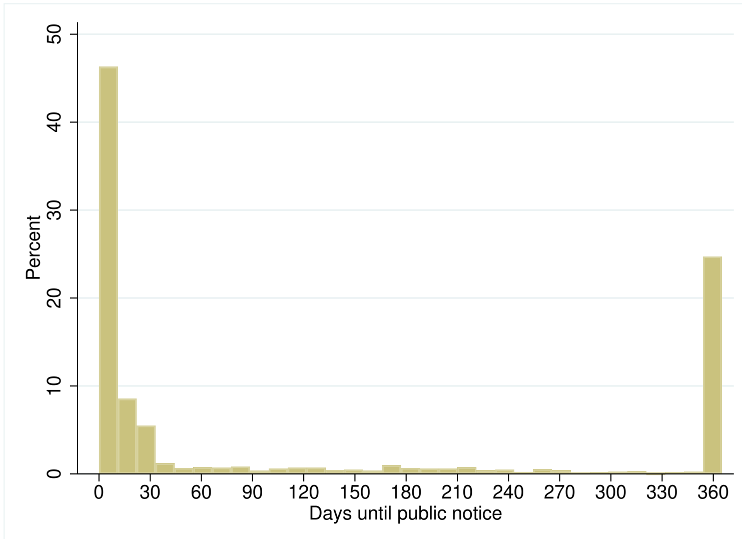
6 Figures

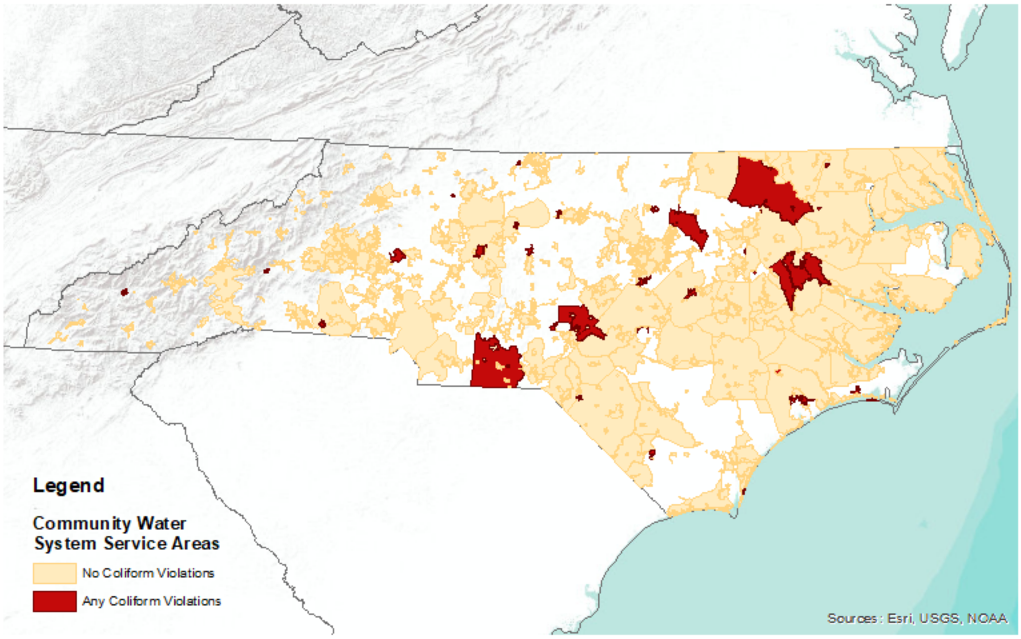
Figure 1: Days Until Public Notification: Monthly Coliform



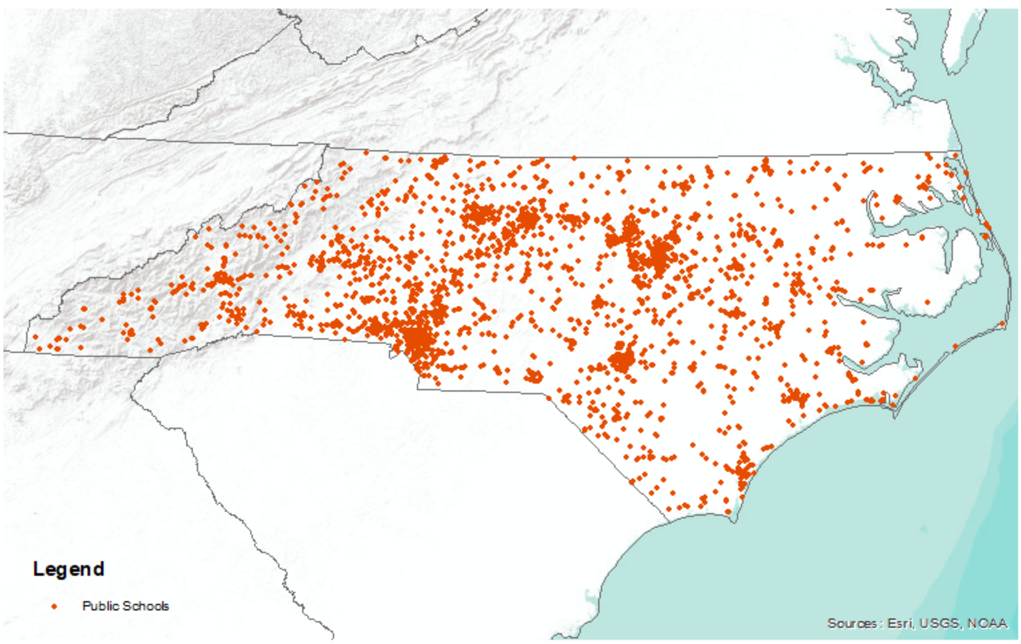
Source: NCERDC.

Notes: Figure plots days between the determination date and public notification date for Monthly coliform violations in North Carolina between 2007 and 2015. The final bin includes notifications that occurred 365 or more days from the time of the violation.

Figure 2: Water System and School Locations in North Carolina



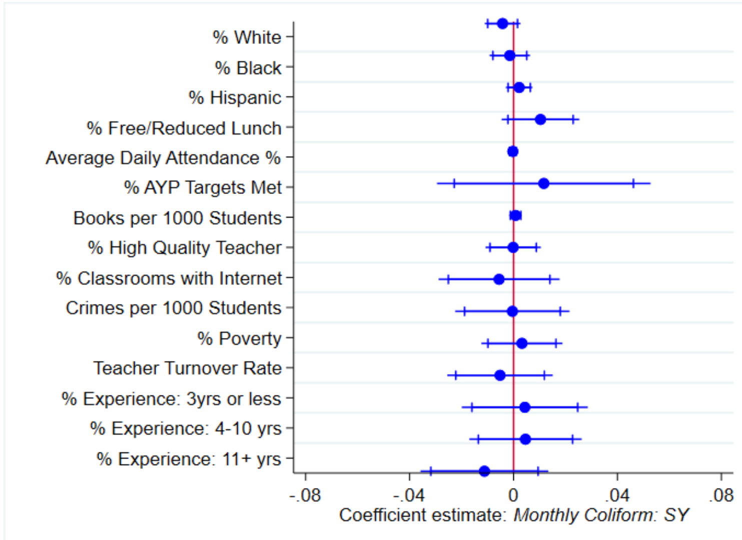
(a) Community Water System Service Areas and Violations



(b) Public Schools

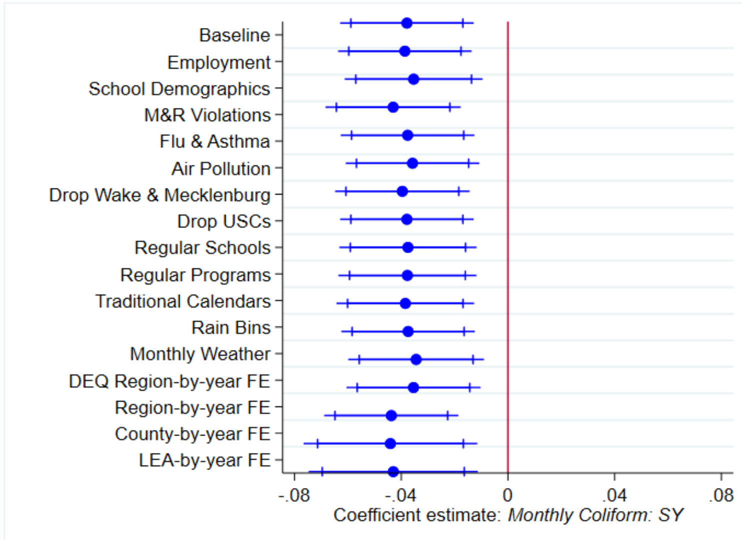
Source: NC OneMap, SDWIS, and NCDPI.
Notes: Panel a plots Public Community Water Supply service areas from the North Carolina Center for Geographic Information and Analysis, available via NC OneMap. Maximum contaminant violations of the Total Coliform Rule come from the Safe Drinking Water Information System (SDWIS). Panel b plots public school location information from North Carolina Department of Public Instruction (NCDPI).

Figure 3: Exogeneity of Violations



Source: NCERDC school-year level data.
Notes: The figure reports results for the effect of monthly coliform violations during the school year on student demographic and school characteristics. See Table A9 for the associated regression results. The variable of interest is measured as the percent of students at the school exposed to a monthly coliform violation at their residential location. All specifications include school fixed effects and controls for year and weather. Standard errors are clustered at the school level. Outcomes include percent white, percent black, percent Hispanic, percent receiving free or reduced price lunch, average daily attendance percent, percent of Adequate Yearly Progress targets met, number of library/media center books per 1000 students, percent of classes taught by high-quality teachers (defined as teachers that are fully licensed, have advanced degrees and/or are National Board Certified), percent of classrooms connected to the internet, crimes in school per 1000 students, percent in poverty, one year teacher turnover rate, percent of teachers with 3 years or less experience, percent of teachers with 4-10 years of experience, and percent of teachers with 11 or more years of experience.

Figure 4: Robustness of the Effect on Math Scores



Source: NCERDC student-year level data.

Notes: The figure reports the robustness of the baseline results, where the outcome is standardized student math scores for grades 3-8. See Table A10 for the associated regression results. All specifications include individual fixed effects and controls for grade, year, and weather. The Baseline specification replicates the main model from the paper. The Employment, M&R Violations, and Flu & Asthma specifications include controls for the employment rate, monitoring and reporting violations, and influenza and asthma ER admissions, respectively. The Air Pollution specification includes controls for OZ and PM10 as the percent of days within each of five categories to allow for nonlinear effects: 0-25%, 25-50%, 50-75%, 75-100%, and over 100% of the relevant EPA threshold. The Drop Wake & Mecklenburg specification excludes Wake and Mecklenburg county schools. The Drop USCs specification excludes schools with water-related unplanned school closures. The Regular Schools, Regular Programs, and Traditional Calendars specifications limit the sample to regular schools, regular programs, and schools with traditional calendars, respectively. The Rain Bins specification includes controls for 7 precipitation bins and the Monthly Weather specification includes temperature and precipitation bins separately for each month. The DEQ Region-by-year FE adds region-by-year fixed effects, where regions are based on North Carolina's Department of Environmental Quality. The Region-by-year FE includes region-by-year fixed effects, where regions are the coastal plains, piedmont, and mountain regions. The County-by-year FE and LEA-by-year FE specifications add county-year and LEA-year fixed effects, respectively. Standard errors are clustered at the individual level.

7 Tables

Table 1: Summary Statistics

	Full sample		Analysis Sample	
	mean	count	mean	count
	(1)	(2)	(3)	(4)
Math Score	384	1,726,319	388	558,336
Read Score	381	1,716,698	385	554,204
Grade	5.51	1,807,027	5.47	558,336
Absent %	.0401	1,792,257	.0341	556,553
Male	.51	1,793,526	.507	556,688
White	.454	1,793,525	.508	556,688
Black	.315	1,793,525	.258	556,688
Hispanic	.147	1,793,525	.152	556,688
Other Race	.0842	1,793,525	.0815	556,688
Disability	.153	1,660,343	.101	558,334
Econ. Disadvantaged	.631	1,660,344	.52	558,336
Limited English	.124	1,660,349	.123	558,336

Source: NCERDC student-year level data.
Notes: The table reports the mean, standard deviation, minimum value, maximum value, and number of observations for each variable used in the main estimation sample. The sample includes individuals served by community water systems in grades 3-8.

Table 2: Student Characteristics by Exposure to Coliform Violations

	Either location		Home		School	
	Unexposed	Exposed	Unexposed	Exposed	Unexposed	Exposed
	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.507	0.508	0.507	0.509	0.507	0.507
Grade	5.467	5.455	5.467	5.387**	5.467	5.553**
Econ. Disadvantaged	0.519	0.685***	0.520	0.682***	0.520	0.691***
White	0.508	0.509	0.508	0.500	0.508	0.521
Black	0.258	0.315***	0.258	0.336***	0.258	0.306***
Hispanic	0.152	0.130***	0.152	0.118***	0.152	0.125***
Other Race	0.082	0.047***	0.082	0.047***	0.082	0.048***
Disabled	0.101	0.098	0.101	0.097	0.101	0.098
Limited English	0.123	0.105**	0.123	0.093***	0.123	0.099***
Math score	387.574	383.221***	387.585	379.670***	387.552	386.131
Read score	384.649	380.268***	384.660	376.616***	384.626	383.231
N	554,602	3,734	555,510	2,826	555,665	2,671

Source: NCERDC student-year level data.

Notes: Exposure is measured as any exposure to a violation of the Total Coliform Rule, including both Acute and Monthly violations. Columns 1 and 2 define exposure using either a violation at home or at school, while columns 3-4 and 5-6 define exposure based on violations at home and at school, respectively. Mean demographic characteristics are reported. Stars indicate the p-value associated with a test of the equality of means between exposed and unexposed student characteristics. The sample includes individuals served by community water systems in grades 3-8.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 3: Effect on Student-level Math Scores

	Home Exposure		School Exposure	
	(1)	(2)	(3)	(4)
Acute Col: SY	0.00939	0.0195	0.0378	0.0114
	(0.0778)	(0.0875)	(0.0649)	(0.0688)
Acute Col: Testing	0.0181		0.0638	
	(0.0323)		(0.0393)	
Monthly Col: SY	-0.0379**	-0.0394*	-0.0274*	-0.0392*
	(0.0128)	(0.0159)	(0.0124)	(0.0158)
Monthly Col: Testing	-0.0198	0.0192	-0.00777	0.0237
	(0.0437)	(0.0518)	(0.0300)	(0.0371)
Monthly Col: Last SY		-0.0335*		-0.0399*
		(0.0168)		(0.0165)
Observations	558,336	337,611	521,206	302,333
R-squared	0.874	0.883	0.878	0.886

Source: NCERDC student-year level data.

Notes: Outcomes include standardized student math scores for grades 3-8. Columns 1-2 report results for exposure measured at the student's residential location, while columns 3-4 report results for exposure measured at the school location. All regressions include student and year fixed effects, and controls for grade and weather. Weather controls include separate measures for the summer, school year, and testing window. Columns 2 and 4 control for lagged exposure to a monthly coliform violation during the previous school year. Standard errors are clustered at the individual level.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table 4: Comparison to Other Environmental Impacts on Math Test Scores

Citation	Treatment	Effect on Math Score
Stafford (2015)	Average mold remediation renovation at school	0.15 sd
Hollingsworth et al. (2022)	Distance-adjusted 10kg lifetime lead emissions by third grade	0.095 sd
Stafford (2015)	Average ventilation improvement project at school	0.07 sd
Sanders (2012)	1 sd of mean TSP in child's year of birth	0.056 sd
Sorensen et al. (2019)	1 percentage point in lead poisoning in early childhood	0.045 sd
Heissel et al. (2022)	Attending schools downwind of highway	0.040 sd
Marcus (2024)	*Drinking water quality violation for monthly coliform bacteria during the school year*	*0.038 sd*
Bharadwaj et al. (2017)	1 sd of CO in third trimester	0.034 sd
Persico and Venator (2021)	Attending schools within 1 mile of TRI site	0.025 sd
Jacqz (2022)	1 sd of airborne toxicity in the school catchment area at birth	0.024 sd
Duque and Gilraine (2022)	1 million megawatt hours of coal-fired power production within 10km	0.020 sd

Source: See citations.
Notes: Table reports the effect of various environmental exposures on student test scores for math, measured in standard deviations (sd). Note that Heissel et al. (2022) reports estimates for combined math and reading scores and Jacqz (2022) report estimates for third grade math proficiency. TSP stands for total suspended particulates, CO stands for carbon monoxide, and TRI stands for Toxic Release Inventory.

Table 5: Future Violations as a Placebo Test

	Home Exposure			School Exposure		
	Violation	+ 1	+ 2	Violation	+ 1	+ 2
	(1)	(2)	(3)	(4)	(5)	(6)
Acute Col: SY	0.00939	0.103	0.141	0.0378	-0.0806	-0.0216
	(0.0778)	(0.0870)	(0.115)	(0.0649)	(0.0642)	(0.0883)
Monthly Col: SY	-0.0379**	0.0180	-0.00102	-0.0274*	0.0168	-0.00937
	(0.0128)	(0.0141)	(0.0172)	(0.0124)	(0.0127)	(0.0141)
Monthly Col: Testing	-0.0198	0.0566	-0.122	-0.00777	0.0274	0.0752
	(0.0437)	(0.0546)	(0.160)	(0.0300)	(0.0344)	(0.157)
Observations	558,336	391,564	278,203	521,206	360,159	258,089
R-squared	0.874	0.880	0.885	0.878	0.883	0.887

Source: NCERDC student-year level data

Notes: The outcome is standardized student math scores for grades 3-8. All specifications include individual fixed effects and indicators for grade and year, and weather controls. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Columns 1-3 report results based on exposure at each student's residential location, while columns 4-6 are based on exposure at school. Columns 2 and 5 include violations one year in the future and columns 3 and 6 include violations two years in the future. Standard errors are clustered at the individual level.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 6: Summer Violations

	Home Exposure		School Exposure	
	(1)	(2)	(3)	(4)
Monthly Col: Summer	0.00503	0.00671	-0.00871	-0.00804
	(0.0108)	(0.0107)	(0.0124)	(0.0124)
Monthly Col: SY		-0.0385**		-0.0273*
		(0.0128)		(0.0124)
Monthly Col: Testing		-0.0205		-0.00821
		(0.0437)		(0.0300)
Observations	558,336	558,336	521,206	521,206
R-squared	0.874	0.874	0.878	0.878

Source: NCERDC student-year level data

Notes: The outcome is standardized student math scores for grades 3-8. All specifications include individual fixed effects and indicators for grade and year, and weather controls. "Summer" measures violations during the summer months, "SY" measures violations during the school year, and "Testing" measures violations during the testing window. Columns 1-2 report results based on exposure at each student's residential location, while columns 3-4 are based on exposure at school. Standard errors are clustered at the individual level.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 7: Effects by public notification timing

	Home Exposure		School Exposure	
	(1)	(2)	(3)	(4)
Acute Col: SY	0.00939	0.00932	0.0378	0.0377
	(0.0778)	(0.0778)	(0.0649)	(0.0649)
Acute Col: Testing	0.0181	0.0182	0.0638	0.0601
	(0.0323)	(0.0323)	(0.0393)	(0.0392)
Monthly Col: SY	-0.0379**		-0.0274*	
	(0.0128)		(0.0124)	
Monthly Col: SY $\times$ Notice $\leq$ 1 Day		-0.0288		-0.0242
		(0.0467)		(0.0727)
Monthly Col: SY $\times$ Notice $>$ 1 Day		-0.0377**		-0.0335*
		(0.0133)		(0.0161)
Monthly Col: Testing	-0.0198	-0.0198	-0.00777	-0.00778
	(0.0437)	(0.0437)	(0.0300)	(0.0300)
Observations	558,336	558,290	521,206	521,160
R-squared	0.874	0.874	0.878	0.878

Source: NCERDC student-year level data.

Notes: Outcomes include standardized student math scores for grades 3-8. Exposure is measured at the student's residential location in columns 1-2 and at the school location in columns 3-4. All regressions include controls for grade, year, and weather. Weather controls include separate measures for the summer, school year, and testing window. Columns 1 and 3 show the baseline results. Columns 2 and 4 interact Monthly coliform violations during the school year with an indicator for whether the public was notified within one day or later. I exclude the few observations with more than one Monthly coliform violation within the same school year that differ in public notification timing.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Online Appendix

A Additional Tables and Figures

Table A1: Agents of Waterborne or Water-based Disease

Bacteria	Protozoa	Viruses
Vibrio cholerae	*Giardia lamblia*	Norovirus
Salmonella spp.	*Cryptosporidium parvum*	Sapprovirus
Shigella spp.	*Entamoeba histolitica*	Poliovirus
Toigenic *Escherichia coli*	*Cyclospora cayetanensis*	Coxsackievirus
Campylobacter spp.	*Isospora belli*	Echovirus
Yersinia enterocolitica	Microsporidia	Paraechovirus
Legionella	*Ballantidium coli*	Enteroviruses 69-91
Helicobacter pylori	*Toxoplasma gondii*	Reovirus
	Naegleria fowleri	Adenovirus
		Hepatitis A & E
		Rotavirus
		Astrovirus
		Picobirnavirus
		Coronavirus

Source: Reynolds et al. (2008)

Table A2: Student-level Math and Reading and the Impact of Water Quality Violations

	(1)	(2)	(3)	(4)	(5)
Panel A. Math					
Acute Col: SY	-0.585***	-0.391***	-0.333***	0.0161	0.00939
	(0.0979)	(0.0996)	(0.0998)	(0.0771)	(0.0778)
Acute Col: Testing	-0.00979	0.125**	0.120*	0.0247	0.0181
	(0.0493)	(0.0473)	(0.0483)	(0.0324)	(0.0323)
Monthly Col: SY	-0.0450**	0.0542**	0.0308+	-0.0355**	-0.0379**
	(0.0158)	(0.0177)	(0.0181)	(0.0126)	(0.0128)
Monthly Col: Testing	-0.176*	-0.0850	-0.192**	-0.00894	-0.0198
	(0.0703)	(0.0603)	(0.0694)	(0.0387)	(0.0437)
Observations	720,815	646,324	631,091	572,206	558,336
R-squared	0.001	0.240	0.246	0.874	0.874
Panel B. Read					
Acute Col: SY	-0.544***	-0.370**	-0.311**	-0.0373	-0.0413
	(0.118)	(0.116)	(0.117)	(0.0716)	(0.0725)
Acute Col: Testing	0.00275	0.118**	0.120**	0.0303	0.0299
	(0.0481)	(0.0454)	(0.0464)	(0.0344)	(0.0352)
Monthly Col: SY	-0.0392*	0.0569***	0.0372*	0.00567	0.00805
	(0.0159)	(0.0169)	(0.0173)	(0.0129)	(0.0132)
Monthly Col: Testing	-0.104	-0.0361	-0.155*	0.0356	0.0170
	(0.0648)	(0.0539)	(0.0630)	(0.0414)	(0.0454)
Observations	717,048	643,805	628,620	569,115	555,297
R-squared	0.000	0.264	0.269	0.864	0.864
Grade	yes	yes	yes	yes	yes
Year	yes	yes	yes	yes	yes
Demographics		yes	yes		
Weather			yes		yes
Student FE				yes	yes
Cluster SE				yes	yes

Source: NCERDC student-year level data.
Notes: Panels a and b report results for student math and reading scores for grades 3-8, which are standardized by year, grade, and local education agency. All specifications include indicators for grade and year. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Columns 2 and 3 include demographic controls, including gender, birth month, race/ethnicity, disability status, economically disadvantaged status, and limited English status. Columns 3 and 5 add weather controls, including separate measures for the summer, school year, and testing window. Columns 4 and 5 include individual fixed effects for each student and cluster standard errors at the student level.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table A3: Adjusting for Multiple Hypothesis Testing

	Home Exposure		School Exposure	
	Math	Read	Math	Read
	(1)	(2)	(3)	(4)
Acute Col: SY	0.00939	-0.0413	0.0378	-0.0196
P-value	(0.0778)	(0.0725)	(0.0649)	(0.0531)
Sharpened Q-value	[1.00]	[1.00]	[1.00]	[1.00]
Westfall-Young P-value	{1.00}	{1.00}	{1.00}	{1.00}
Romano-Wolf P-value	{1.00}	{0.990}	{1.00}	{1.00}
Acute Col: Testing	0.0181	0.0299	0.0638	0.0254
P-value	(0.0323)	(0.0352)	(0.0393)	(0.0392)
Sharpened Q-value	[1.00]	[1.00]	[0.960]	[1.00]
Westfall-Young P-value	{1.00}	{1.00}	{0.720}	{1.00}
Romano-Wolf P-value	{1.00}	{0.970}	{0.346}	{1.00}
Monthly Col: SY	-0.0379**	0.00805	-0.0274*	0.00278
P-value	(0.0128)	(0.0132)	(0.0124)	(0.0127)
Sharpened Q-value	[0.051]	[1.00]	[0.261]	[1.00]
Westfall-Young P-value	{0.050}	{1.00}	{0.380}	{1.00}
Romano-Wolf P-value	{0.0099}	{1.00}	{0.0495}	{1.00}
Monthly Col: Testing	-0.0198	0.0170	-0.00777	0.00572
P-value	(0.0437)	(0.0454)	(0.0300)	(0.0311)
Sharpened Q-value	[1.00]	[1.00]	[1.00]	[1.00]
Westfall-Young P-value	{1.00}	{1.00}	{1.00}	{1.00}
Romano-Wolf P-value	{1.00}	{1.00}	{1.00}	{1.00}

Source: NCERDC student-year level data.
Notes: Outcomes include standardized student math and reading scores for grades 3-8. Exposure is measured at the student's residential location in columns 1-2 and at the school location in columns 3-4. All regressions include student and year fixed effects, and controls for grade and weather. Weather controls include separate measures for the summer, school year, and testing window. Standard errors are clustered at the student level. P-values are reported in parentheses. Sharpened False Discover Rate q-values from Anderson (2008) are reported in square brackets. Westfall-Young and Romano-Wolf stepdown adjusted p-values based on 100 bootstrap replications are reported in curly brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A4: Controlling for School Absences

	Home Exposure		School Exposure	
	(1)	(2)	(3)	(4)
Acute Col: SY	0.00939	0.0103	0.0378	0.0387
	(0.0778)	(0.0784)	(0.0649)	(0.0648)
Acute Col: Testing	0.0181	0.0187	0.0638	0.0601
	(0.0323)	(0.0326)	(0.0393)	(0.0395)
Monthly Col: SY	-0.0379**	-0.0379**	-0.0274*	-0.0275*
	(0.0128)	(0.0127)	(0.0124)	(0.0124)
Monthly Col: Testing	-0.0198	-0.0129	-0.00777	-0.000920
	(0.0437)	(0.0439)	(0.0300)	(0.0300)
Pct Absent		-1.243***		-1.214***
		(0.0325)		(0.0339)
Observations	558,336	555,937	521,206	519,114
R-squared	0.874	0.875	0.878	0.878

Source: NCERDC student-year level data.

Notes: Student math scores for grades 3-8 are standardized by year, grade, and local education agency. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Columns 2 and 4 control for the percent of days a student was absent. Standard errors clustered at the individual level are shown in parenthesis.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

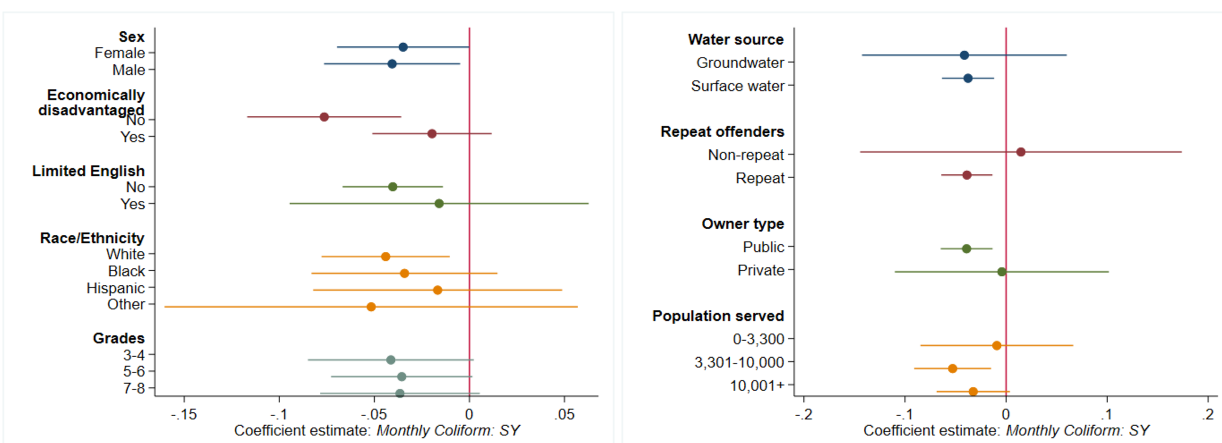
Table A5: Cumulative Exposure

	Home Exposure			School Exposure		
	Baseline	Num Months	Cumulative	Baseline	Num Months	Cumulative
	(1)	(2)	(3)	(4)	(5)	(6)
Acute Col: SY	0.00939	0.00938		0.0378	0.0378	
	(0.0778)	(0.0778)		(0.0649)	(0.0649)	
Acute Col: Testing	0.0181	0.0182		0.0638	0.0636	
	(0.0323)	(0.0323)		(0.0393)	(0.0393)	
Monthly Col: SY	-0.0379**	-0.0375**		-0.0274*	-0.0263*	
	(0.0128)	(0.0126)		(0.0124)	(0.0118)	
Monthly Col: Testing	-0.0198	-0.0198		-0.00777	-0.00777	
	(0.0437)	(0.0437)		(0.0300)	(0.0300)	
Cumulative Acute Col			-0.133*			-0.0342
			(0.0674)			(0.0623)
Cumulative Monthly Col			-0.0312*			-0.0291**
			(0.0124)			(0.0109)
Observations	558,336	558,336	974,518	521,206	521,206	974,518
R-squared	0.874	0.874	0.871	0.878	0.878	0.871

Source: NCERDC student-year level data.
Notes: Outcomes include standardized student math scores for grades 3-8. Exposure is measured at the student's residential location in columns 1-3 and at the school location in columns 4-6. All regressions include controls for grade, year, and weather. Weather controls include separate measures for the summer, school year, and testing window. Columns 1 and 4 show the baseline results. Columns 2 and 5 measure exposure as the number of months of exposure during either the school year or testing window. Columns 3 and 6 define exposure as the number of months of cumulative exposure to a violations since they were first observed in the data.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure A1: Heterogeneity in the Effect on Math Scores



(a) By Demographics (b) By System Characteristics

Source: NCERDC student-year level data.
Notes: Outcome is standardized student math scores for grades 3-8. All specifications include individual fixed effects and controls for grade, year, and weather. Results in panel a interact Monthly coliform violations during the school year with student demographic characteristics, including gender, whether they are economically disadvantaged, whether they have limited English ability, race/ethnicity, and grade level. Results in panel b interact Monthly coliform violations during the school year with community water system characteristics, including water source, whether the system has had multiple violations, type of ownership, and size. Standard errors are clustered at the individual level.

Table A6: Heterogeneity by Demographics

	(1)	(2)	(3)	(4)	(5)
Monthly Col: Testing	-0.0144	-0.0200	-0.0198	-0.0145	-0.0198
	(0.0442)	(0.0438)	(0.0437)	(0.0442)	(0.0437)
Female $\times$ Monthly Col: SY	-0.0349*				
	(0.0177)				
Male $\times$ Monthly Col: SY	-0.0407*				
	(0.0183)				
Non-Disadvantaged $\times$ Monthly Col: SY		-0.0764***			
		(0.0207)			
Disadvantaged $\times$ Monthly Col: SY		-0.0197			
		(0.0160)			
Non-Limited English $\times$ Monthly Col: SY			-0.0403**		
			(0.0135)		
Limited English $\times$ Monthly Col: SY			-0.0159		
			(0.0401)		
White $\times$ Monthly Col: SY				-0.0440*	
				(0.0172)	
Black $\times$ Monthly Col: SY				-0.0341	
				(0.0250)	
Hispanic $\times$ Monthly Col: SY				-0.0167	
				(0.0334)	
Other Race $\times$ Monthly Col: SY				-0.0517	
				(0.0554)	
Grades 3-4 $\times$ Monthly Col: SY					-0.0413^{+}
					(0.0223)
Grades 5-6 $\times$ Monthly Col: SY					-0.0356^{+}
					(0.0190)
Grades 7-8 $\times$ Monthly Col: SY					-0.0365^{+}
					(0.0214)
Observations	556,116	558,336	558,336	556,116	558,336
R-squared	0.874	0.874	0.874	0.874	0.874

Source: NCERDC student-year level data.

Notes: Student math scores for grades 3-8 are standardized by year, grade, and local education agency. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Results interact Monthly coliform violations during the school year with student demographic characteristics, including gender, whether they are economically disadvantaged, whether they have limited English ability, race/ethnicity, and grade level. Standard errors clustered at the individual level are shown in parenthesis.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A7: Heterogeneity by System Characteristics

	(1)	(2)	(3)	(4)
Monthly Col: Testing	-0.0200	-0.0198	-0.0199	-0.0200
	(0.0437)	(0.0437)	(0.0437)	(0.0438)
Groundwater × Monthly Col: SY	-0.0412			
	(0.0517)			
Surface Water × Monthly Col: SY	-0.0376**			
	(0.0132)			
Non-Repeat × Monthly Col: SY		0.0147		
		(0.0812)		
Repeat × Monthly Col: SY		-0.0388**		
		(0.0129)		
Public × Monthly Col: SY			-0.0391**	
			(0.0131)	
Private × Monthly Col: SY			-0.00419	
			(0.0540)	
Pop. served: 0-3,300 × Monthly Col: SY				-0.00914
				(0.0386)
Pop. served: 3,301-10,000 × Monthly Col: SY				-0.0529**
				(0.0194)
Pop. served: 10,001+ × Monthly Col: SY				-0.0325^{+}
				(0.0185)
Observations	553,739	558,336	558,336	558,336
R-squared	0.874	0.874	0.874	0.874

Source: NCERDC student-year level data.
Notes: Student math scores for grades 3-8 are standardized by year, grade, and local education agency. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Results interact Monthly coliform violations during the school year with community water system characteristics, including water source, whether the system has had multiple violations, type of ownership, and size. Standard errors clustered at the individual level are shown in parenthesis.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A8: Expulsions and Suspensions

	Expelled (1)	Suspensions: Long (2)	Suspensions: Short (3)
Monthly Col: SY	-0.000675	-0.0637	-0.0474
	(0.000841)	(0.0724)	(2.401)
Monthly Col: Testing	0.00367^{+}	0.641	-4.447
	(0.00203)	(0.590)	(9.499)
Observations	9,318	9,318	9,318
R-squared	0.245	0.677	0.902

Source: NCERDC school-year level data

Notes: Outcomes are the number of expulsions or suspensions per 100 students. Long suspensions are over 10 days and short suspensions are 10 days or less. Exposure to violations is measured as the percent of students in the school exposed during the school year (SY) or the testing window (Testing). All specifications include school fixed effects, indicators for year, and weather controls. Standard errors clustered at the school level are shown in parenthesis.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A9: Exogeneity of Monthly Coliform Violations

	% White	% Black	% Hisp	% Free/Red Lunch	Avg Daily Attendance %	% AYP Targets Met	Books per 1000 Students	% High Qual Teacher	% Classrooms w/ Internet	Crimes per 1000 Students	% Poverty	Teacher Turnover	% Experience: 3yrs or less	% Experience: 4-10 yrs	% Experience: 11+ yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Monthly Col: SY	-0.00421	-0.00143	0.00217	0.0104	-0.000276	0.0117	0.000776	-0.000134	-0.00556	-0.000428	0.00324	-0.00519	0.00435	0.00459	-0.0112
	(0.00349)	(0.00396)	(0.00260)	(0.00762)	(0.000805)	(0.0209)	(0.00122)	(0.00543)	(0.0119)	(0.0112)	(0.00796)	(0.0104)	(0.0124)	(0.0110)	(0.0125)
Monthly Col: Testing	-0.0194	0.0220	0.00593	0.00372	-0.00633+	0.114	-0.000431	0.0198	-0.00179	-0.0525	-0.00101	-0.0157	0.0263+	-0.00147	-0.0218
	(0.0191)	(0.0144)	(0.00679)	(0.0239)	(0.00363)	(0.0801)	(0.00141)	(0.0149)	(0.00323)	(0.0373)	(0.00638)	(0.0233)	(0.0160)	(0.00955)	(0.0148)
Observations	13,377	13,377	13,377	12,887	9,377	9,350	9,299	9,357	9,287	9,377	9,263	9,085	9,277	9,277	9,277
R-squared	0.989	0.986	0.969	0.900	0.935	0.612	0.347	0.674	0.440	0.719	0.949	0.484	0.729	0.664	0.829

Source: NCERDC and CCD school-year level data.

Notes: Outcomes include percent white, percent black, percent Hispanic, percent receiving free or reduced price lunch, average daily attendance percent, percent of Adequate Yearly Progress targets met, number of library/media center books per 1000 students, percent of classes taught by high quality teachers (defined as teachers that are fully licensed, have advanced degrees and/or are National Board Certified), percent of classrooms connected to the internet, crimes in school per 1000 students, percent in poverty, one year teacher turnover rate, percent of teachers with 3 years or less experience, percent of teachers with 4-10 years experience, and percent of teachers with 11 or more years experience. All specifications include school fixed effects, indicators for year, and weather controls. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Standard errors clustered at the school level are shown in parenthesis.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table A10: Robustness of the Effect on Student-level Math Scores

	Baseline	Employment rate	School Demographics	MR Violations	Flu and Asthma	Air Pollution	Drop Wake & Mecklenburg	Drop USCs	Regular Schools	Regular Programs	Traditional Calendars	Rain Bins	Monthly Weather	DEQ-Region -by-year FE	Region -by-year FE	County -by-year FE	LEA -by-year FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Monthly Col: SY	-0.0379**	-0.0387**	-0.0354**	-0.0431***	-0.0376**	-0.0358**	-0.0396**	-0.0379**	-0.0375**	-0.0377**	-0.0385**	-0.0374**	-0.0344**	-0.0354**	-0.0437***	-0.0441**	-0.0430**
	(0.0128)	(0.0128)	(0.0132)	(0.0129)	(0.0128)	(0.0128)	(0.0129)	(0.0128)	(0.0131)	(0.0132)	(0.0132)	(0.0128)	(0.0130)	(0.0128)	(0.0128)	(0.0166)	(0.0162)
Monthly Col: Testing	-0.0198	-0.0222	-0.0183	-0.0227	-0.0177	-0.0294	-0.0101	-0.0198	-0.0201	-0.0234	-0.0176	-0.0126	-0.0383	-0.00795	-0.00669	-0.0773	0.0232
	(0.0437)	(0.0437)	(0.0437)	(0.0438)	(0.0438)	(0.0438)	(0.0437)	(0.0437)	(0.0438)	(0.0444)	(0.0438)	(0.0438)	(0.0450)	(0.0444)	(0.0438)	(0.0881)	(0.0995)
Observations	558,336	558,264	522,210	558,336	557,824	558,336	367,777	558,336	544,945	475,568	507,367	558,336	558,336	557,824	557,824	557,817	558,254
R-squared	0.874	0.874	0.875	0.874	0.874	0.874	0.866	0.874	0.874	0.875	0.875	0.874	0.874	0.874	0.874	0.875	0.875

Source: NCERDC student-year level data.

Notes: Student math scores for grades 3-8 are standardized by year, grade, and local education agency. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Weather controls include separate measures for the summer, school year, and testing window. Exposure is based on violations at each student's residential location. "SY" measures violations during the school year and "Testing" measures violations during the testing window. Columns 2-5 include controls for the employment rate, school-level demographics, monitoring and reporting violations, and influenza and asthma ER admissions. Column 6 includes controls for OZ and PM10 as the percent of days within each of five categories to allow for nonlinear effects: 0-25%, 25-50%, 50-75%, 75-100%, and over 100% of the relevant EPA threshold. Columns 7 and 8 drop Wake and Mecklenburg county schools and schools with water-related unplanned school closures. Columns 9-11 limit the sample to regular schools, regular programs, and schools with traditional calendars, respectively. Column 12 adds controls for 7 precipitation bins and column 13 includes temperature and precipitation bins separately for each month. Columns 14 and 15 add region-by-year fixed effects, where regions are based on North Carolina's Department of Environmental Quality in column 14 and the coastal plains, piedmont, and mountain regions in column 15. Columns 16 and 17 add county-by-year and LEA-by-year fixed effects, respectively. Standard errors clustered at the individual level are shown in parentheses.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table A11: Robustness to Controlling for Other Violations

	Home Exposure		School Exposure	
	(1)	(2)	(3)	(4)
Acute Col: SY	0.00939	0.00911	0.0378	0.0368
	(0.0778)	(0.0778)	(0.0649)	(0.0649)
Acute Col: Testing	0.0181	0.0186	0.0638	0.0652+
	(0.0323)	(0.0323)	(0.0393)	(0.0393)
Monthly Col: SY	-0.0379**	-0.0368**	-0.0274*	-0.0235+
	(0.0128)	(0.0128)	(0.0124)	(0.0124)
Monthly Col: Testing	-0.0198	-0.0198	-0.00777	-0.00793
	(0.0437)	(0.0437)	(0.0300)	(0.0300)
Radionuclides		-0.00444		3.06e-05
		(0.00393)		(0.00430)
Disinfect		0.000704		0.00262***
		(0.000598)		(0.000622)
SOCs		-0.0137*		-0.0147**
		(0.00552)		(0.00483)
VOCs		0.000509		0.00268
		(0.00342)		(0.00502)
Observations	558,336	558,336	521,206	521,206
R-squared	0.874	0.874	0.878	0.878

Source: NCERDC student-year level data.

Notes: Outcomes include standardized student math scores for grades 3-8. Exposure is measured at the student's residential location in columns 1-2 and at the school location in columns 3-4. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Weather controls include separate measures for the summer, school year, and testing window. Columns 2 and 4 include controls for the number of months of other types of health-based violations in the past year, including radionuclides, disinfectants and disinfection by-products, synthetic organic compounds (SOCs), and volatile organic chemicals (VOCs).

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table A12: Robustness to Clustering

	Baseline (1)	CWS (2)	School (3)	School-Grd (4)	CWS-School (5)
Monthly Col: SY	-0.0379**	-0.0379^{+}	-0.0379*	-0.0379*	-0.0379*
	(0.0128)	(0.0194)	(0.0179)	(0.0163)	(0.0180)
	[0.00340]	[0.0933]	[0.0271]	[0.0221]	[0.0277]
Monthly Col: Testing	-0.0198	-0.0198	-0.0198	-0.0198	-0.0198
	(0.0437)	(0.0198)	(0.0262)	(0.0246)	(0.0262)
	[0.651]	[0.302]	[0.515]	[0.354]	[0.519]
Observations	558,336	558,336	558,336	558,336	558,336
R-squared	0.874	0.874	0.874	0.874	0.874

Source: NCERDC student-year level data.

Notes: Outcomes include standardized student math scores for grades 3-8. Exposure is measured at the student's residential location. All specifications include individual fixed effects, indicators for grade and year, and weather controls. Weather controls include separate measures for the summer, school year, and testing window. Column 1 replicates the baseline results where standard errors are clustered at the student level. In columns 2-5, standard errors are clustered at the community water system level, the school level, the school-grade level, and the CWS-school level, respectively. Wild cluster restricted bootstrapped p-values based on 9999 replications are reported in brackets.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

B Bottled Water Results

One way in which households might avoid exposure to contaminated drinking water is through switching to an alternate drinking source, such as bottled water. Using the NielsenIQ household panel survey data recording grocery purchases, one can observe changes in bottled water purchases in response to TCR violations.[29] The household-level consumer panel data from 2004 to 2015 include information about purchases made by a panel of households from all retail outlets. Bottled water sales each month record total dollar sales before coupons. I follow Marcus (2022) to show that Acute coliform violations (requiring immediate 24-hour public notice) increase bottled water purchases, whereas Monthly coliform violations (requiring only notification within 30 days) have no detectable impact on bottled water purchases. Specifically, I estimate the following specification,

$$Water_{h,z,m,y} = \alpha_1 Acute_{z,m,y} + \alpha_2 Monthly_{z,m,y} + X_{h,z,m,y} + \eta_h + \zeta_z \times \mu_m + \zeta_z \times \psi_y + \psi_y \times \mu_m + \epsilon_{h,z,m,y} \tag{2}$$

where h indexes household, z indexes zip code, m indexes month, and y indexes year. Exposure to Acute and Monthly coliform violations are measured as the percentage of the zip code exposed to a violation in each month. Bottled water purchases are measured as the inverse hyperbolic sine of total dollar sales. The specification includes household (η_h), year-month ($\psi_y \times \mu_m$), zip code-

[29]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.

year ($\zeta_z \times \psi_y$), and zip code-month ($\zeta_z \times \mu_m$) fixed effects. Controls in $X_{h,z,m,y}$ include a vector of weather controls, household size, and employment from the Local Area Unemployment Statistics. Standard errors are clustered at the zip code level.

Column (1) of Table B1 below replicates the estimates from Marcus (2022) and shows that Acute coliform violations have a statistically significant positive effect on bottled water purchases during the month of the violation. However, the coefficient on Monthly coliform violations is statistically insignificant. These results support the claim that households can and do respond to immediate notification during Acute violations by avoiding exposure to contaminated drinking water through purchasing bottled water. On the other hand, Monthly coliform violations have no detectable impact on bottled water purchases, suggesting little avoidance response when public notification is delayed. (See Marcus (2022) for more details and robustness tests.)

Column (2) of Table B1 extends these results to look specifically at the effect for households with school-aged children, who are the subject of this paper's analysis. Here, I interact each of the two TCR violations, Acute and Monthly, with indicators for households with and without school-aged children. Although splitting the sample reduces power to detect effects in these smaller subgroups, there are still statistically significant increases in bottled water purchases during Acute coliform violations for both households with and without school aged children. The magnitude of the estimated effect is even larger for school-aged children, but with wide confidence intervals the effects are not statistically significantly different (p-value of 0.17).

Finally, Figure B1 shows these effects graphically. Estimated effects are shown for the actual violation month at time zero, and for placebo violations two months before and after the actual violation. Note that violations in the data almost always last one month before returning to compliance. Any pre-existing trends in bottled water purchases should show up in the months before the violation, while long-lasting effects on avoidance may show up in months after the violation. Figure B1 shows results for households with and without school-aged children. Both figures show a statistically significant increase in bottled water purchases at the time of the violation for Acute coliform violations only. There is no detectable increase in purchases during Monthly coliform violations. There are also no significant effects for months before or after either type of violation. Figure B1 highlights that both households with and without school-aged children increase purchases of bottled water during Acute but not Monthly coliform violations.

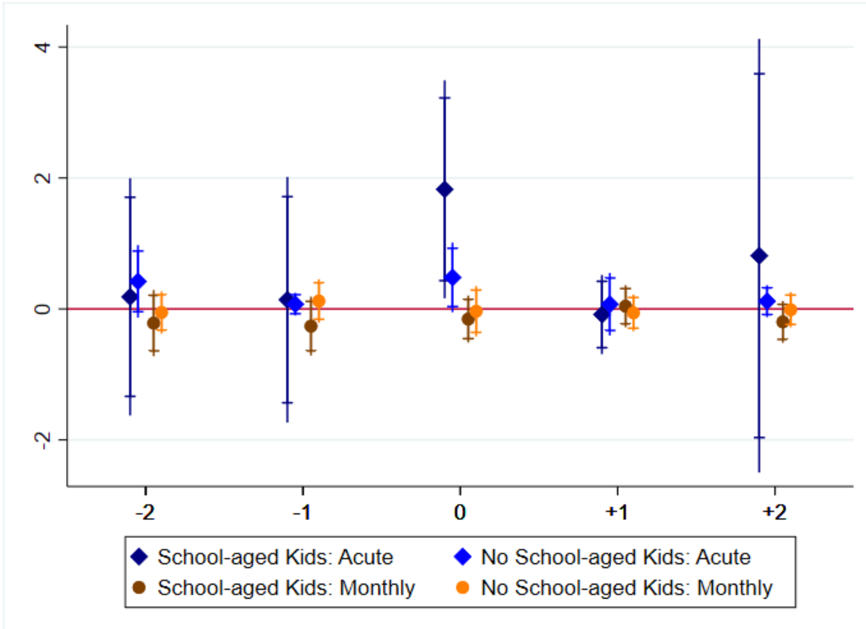
These results provide direct evidence of avoidance behaviors in response to Acute but not Monthly coliform violations and that these behaviors also hold for households with school-aged children. So I hypothesize that any negative impacts on test scores will arise through Monthly, rather than Acute violations.

Table B1: Effect of violations on household avoidance

	Bottled Water	
	(1)	(2)
Pct Acute Col	0.577*	
	(0.259)	
Pct Acute Col × School-age Kids		1.751^{+}
		(0.974)
Pct Acute Col × No School-age Kids		0.418^{+}
		(0.248)
Pct Monthly Col	-0.0525	
	(0.151)	
Pct Monthly Col × School-age Kids		-0.111
		(0.193)
Pct Monthly Col × No School-age Kids		-0.0258
		(0.187)
Observations	245,632	245,632
R-squared	0.382	0.382
Household FE	yes	yes
Year-month FE	yes	yes
Zip-yr FE	yes	yes
Zip-month FE	yes	yes

Notes: The outcome is bottled water purchases, measured as the inverse hyperbolic sine of total dollar sales. Exposure to Acute and Monthly violations is measured as the percentage of the zip code of residence exposed to a violation in a given month. Regressions include household, year-month, zip code-year, and zip code-month fixed effects, as well as controls for weather, employment rate, and household size. Standard errors clustered at the zip code level are shown in parenthesis.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure B1: Effect of violations on avoidance: by presence of school-aged children



Notes: The outcome is bottled water purchases, measured as the inverse hyperbolic sine of total dollar sales. Estimated effects are shown for the violation month at time zero, and for placebo violations two months before and after the actual violation. Coefficients are shown for the effects of Acute and Monthly violations for both households with and without school-aged children. Regressions include household, year-month, zip code-year, and zip code-month fixed effects, as well as controls for weather, employment rate, and household size. Standard errors are clustered at the zip code level.

C Comparability of Analysis Sample to Full Sample

Table C1 provides information on how the analysis sample compares to the full sample of students. Columns 1-2 show characteristics of the full sample. Columns 3-8 sequentially add the necessary data restrictions for the main analysis. Columns 9-10 show characteristics for the final analysis sample used in the main results. Restricting to non-movers reduces the sample from about 1.73 million to 1.27 million. The sample size drops to about 626,000 and then 612,000 from restricting to observations with non-missing water quality and weather data, respectively. Limiting to the final analysis sample, which requires multiple observations per student, reduces the sample to 558,336 observations in column 10.

The characteristics of the analysis sample in column 9 are generally similar to the full sample characteristics in column 1. The analysis sample is similar in terms of average test scores, grade, gender, and percent with limited English. If anything, the analysis sample is slightly more advantaged with slight differences showing a lower absence rate, higher percent white, lower disability, and lower percent economically disadvantaged. Because of these small differences, the reader should keep in mind that the local average treatment effects estimated here may not generalize to the full population of students.

Table C1: Sample Restrictions and Comparability of the Analysis Sample

	Full sample		Non-movers		Non-missing violations		Non-missing weather		Analysis Sample	
	mean	count	mean	count	mean	count	mean	count	mean	count
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Math Score	384	1,726,319	385	1,268,630	385	625,967	385	612,359	388	558,336
Grade	5.51	1,807,027	5.48	1,319,008	5.45	648,055	5.45	633,908	5.47	558,336
Absent %	.0401	1,792,257	.0374	1,310,412	.0362	644,261	.0361	630,190	.0341	556,553
Male	.51	1,793,526	.513	1,311,254	.511	644,408	.511	630,333	.507	556,688
White	.454	1,793,525	.519	1,311,253	.488	644,408	.485	630,333	.508	556,688
Black	.315	1,793,525	.259	1,311,253	.28	644,408	.283	630,333	.258	556,688
Hispanic	.147	1,793,525	.135	1,311,253	.15	644,408	.151	630,333	.152	556,688
Other Race	.0842	1,793,525	.0869	1,311,253	.081	644,408	.0813	630,333	.0815	556,688
Disability	.153	1,660,343	.141	1,172,360	.129	583,297	.129	570,308	.101	558,334
Econ. Disadvantaged	.631	1,660,344	.544	1,172,363	.529	583,300	.53	570,311	.52	558,336
Limited English	.124	1,660,349	.113	1,172,367	.125	583,300	.126	570,311	.123	558,336
Non-movers			X	X	X	X	X	X	X	X
Non-missing violations					X	X	X	X	X	X
Non-missing weather							X	X	X	X

D Home and School Exposure

In this section, I explore the joint role of home- and school-based violations in more depth. Because children often live near their school, the same water system may serve children at home and at school. Yet, there are still many children who are served by different CWS systems at home and at school. Among observations with exposure to a Monthly violation during the school year, about 46 percent experience exposure both at home and school simultaneously, and 54 percent experience exposure at either home or school, but not both. There is less variation within Acute violations during the school year. About 89 percent experience exposure at both home and school, while only 11 percent experience exposure in either home or school, but not both. The correlation coefficients are 0.635 and 0.941 for Monthly and Acute coliform violations during the school year, respectively.

Table D1 below replicates the main results in columns (1) and (2) based on home and school exposure, respectively. Column (3) includes home and school exposure measures in the same equation. Estimates for Acute coliform exposure are highly correlated (0.941) and therefore difficult to interpret. Given the high correlation, it is not surprising that there are significant and opposite signed coefficients for Acute coliform violations during the school year at home and at school. The estimates for Monthly coliform violations during the school year are more sensible given the lower degree of correlation between exposure at home and at school (0.635). Both coefficients are negative, but the estimates appear to be driven by home exposure to Monthly coliform violations occurring during the school year. Finally, column (4) considers whether the effects are larger when students experience exposure at both home and school simultaneously. Effects are negative for Monthly coliform exposure during the school year at school only, at home only, and at both home and school simultaneously. The coefficients for exposure at home only and at both home and school are statistically significant. While the point estimate for home exposure is the largest in magnitude, these three coefficients are not statistically distinguishable.

Table D1: Jointly Estimating Home and School Exposure

	(1)	(2)	(3)	(4)
Home Exp. Acute Coliform: SY	0.00939		0.321***	0.321***
	(0.0778)		(0.0796)	(0.0796)
Home Exp. Acute Coliform: Testing	0.0181		0.0437	0.0434
	(0.0323)		(0.0411)	(0.0411)
Home Exp. Monthly Coliform: SY	-0.0379**		-0.0335^{+}	
	(0.0128)		(0.0187)	
Home Exp. Monthly Coliform: Testing	-0.0198		-0.185	-0.186
	(0.0437)		(0.219)	(0.220)
School Exp. Acute Coliform: SY		0.0378	-0.304***	-0.304***
		(0.0649)	(0.0535)	(0.0535)
School Exp. Acute Coliform: Testing		0.0638	0.0372	0.0370
		(0.0393)	(0.0492)	(0.0492)
School Exp. Monthly Coliform: SY		-0.0274*	-0.00426	
		(0.0124)	(0.0172)	
School Exp. Monthly Coliform: Testing		-0.00777	0.121	0.122
		(0.0300)	(0.214)	(0.215)
School Exp. Only Monthly Coliform: SY				-0.0105
				(0.0205)
Home Exp. Only Monthly Coliform: SY				-0.0462^{+}
				(0.0273)
Home and School Exp. Monthly Coliform: SY				-0.0343*
				(0.0157)
Observations	558,336	521,206	481,203	481,203
R-squared	0.874	0.878	0.877	0.877

Source: NCERDC student-year level data.

Notes: Outcomes include standardized student math scores for grades 3-8. All regressions include student and year fixed effects, and controls for grade and weather. Weather controls include separate measures for the summer, school year, and testing window. Standard errors are clustered at the individual level.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1