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WATER WORKS: CAUSES AND CONSEQUENCES OF SAFE DRINKING WATER IN AMERICA

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Water Works: Causes and Consequences of Safe Drinking Water in America
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ABSTRACT

Since the 1974 Safe Drinking Water Act, the U.S. has spent $2 trillion to provide safe drinking water, yet drinking water for 10–20 percent of Americans violates standards. We study trends, causes, and consequences of U.S. drinking water pollution, using 266 million readings on 1,250 pollutants over decades that we obtained from 48 states via dozens of Freedom of Information Act and associated requests. We link pollution to administrative Medicare data on older Americans' health outcomes. Three findings emerge. First, U.S. drinking water pollution has declined rapidly; the share of readings exceeding current health standards fell by half from 2003–2019. Unregulated pollutants declined more slowly. Low-income areas have higher pollution; Black and Hispanic communities have more complex patterns. Second, loans provided by the Safe Drinking Water Act to water systems reduce pollution. At the estimated average loan cost-effectiveness, these loans could eliminate pollution above health standards for $46 annually per person. Third, these loans reduce mortality rates of older Americans. Although fiscal federalism cautions against federal funding of local public goods with few inter-jurisdictional externalities like drinking water, we estimate large benefits from Safe Drinking Water Act loans.

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The 1974 U.S. Safe Drinking Water Act was established to "protect the nation's drinking water from harmful biological and chemical contaminants" (Frederick 1995). This paper describes national trends in drinking water pollution, estimates contributions of the Safe Drinking Water Act to those trends, and assesses effects on mortality and hospitalization rates for older Americans.

Safe drinking water has long been essential to human health. Snow (1855) helped found epidemiology and the use of natural experiments by linking contaminated drinking water to cholera. Municipal water filtration and disinfection around 1900 dramatically improved health (Cutler and Miller 2005; Alsan and Goldin 2019; Cutler and Miller 2022).

U.S. drinking water, however, remains a threat to health. In a typical year, ten to twenty percent of Americans drink water that violates the Safe Drinking Water Act (USEPA 2009; Allaire, Wu and Lall 2018). The Centers for Disease Control and Prevention (CDC) estimate that drinking water pathogens cause 7 million illnesses and 600,000 emergency department visits annually, though this likely understates the disease burden (APHA 2019; Collier et al. 2021). U.S. industry uses over 42,000 chemicals, but the Safe Drinking Water Act regulates only 90 (USEPA 2023). In every Gallup poll since 1990, Americans have rated drinking water pollution as their top environmental concern (Gallup 2018). Drinking water disasters in Flint, Michigan, and Jackson, Mississippi, have galvanized attention to environmental inequality.

The Safe Drinking Water Act has been controversial, however, for two reasons. First is whether it has decreased pollution. No prior analysis has estimated national trends in drinking water pollution concentrations. Many sources analyze drinking water violations reported to the Environmental Protection Agency (EPA). The EPA and researchers have described these data as "very low" quality (USEPA 2000; Bennear and Olmstead 2008; Allaire, Wu and Lall 2018; Josset et al. 2019). Limitations of federally-reported violations data include binary measures that may miss inframarginal changes, lack of information on unregulated pollutants, changes in violations due solely to reforms to pollution standards, incomplete and nonrandom reporting of systems that can confound compliance and failure to report, and governments' potential to strategically and precisely manipulate pollution measurement to avoid federal violations (Bennear, Jessoe and Olmstead 2009; Auffhammer and Kellogg 2011; Zou 2021; Andarge et al. 2025). The monitoring data we compile and analyze help assess at least the first three of these challenges. For example, one influential study finds that federally-reported Safe Drinking Water Act violations doubled between 1982 and 2015 (Allaire, Wu and Lall 2018), which could reflect an increase in drinking water pollution, a tightening of drinking water standards, or an increase in violation reporting.

The second controversy is whether the drinking water investments' benefits exceed their costs. Between 1970 and 2014, public and private sources spent around $2 trillion (in 2017 dollars) to provide clean drinking water (Keiser and Shapiro 2019*a*). The 2021 infrastructure bill allocated $83 billion for clean water (Farr 2021). The American Society of Civil Engineers (2020) calculates that typical spending on U.S. water infrastructure is short of needs required for Safe Drinking Water Act compliance by a factor of three. Between 1998 and 2018, household drinking water bills rose at three times overall inflation, in part due to improving drinking water quality (AWWA 2023). Some households have drinking water connections shut off due to unpaid bills (Miller and Causey 2018; Feinstein, Shimabuku and Pierce 2020). Additionally, fiscal federalism suggests that optimal federal policy would have little involvement in drinking water policy. Oates (2001) described drinking water as "a purely local public good. . . . Both the benefits and also the costs of drinking water standards accrue almost wholly to residents."[1]

To help resolve these debates, we use the most comprehensive records ever compiled on drinking water pollution, including several datasets never previously used in research. This provides the first national description of the pollution in most Americans' drinking water. By submitting dozens of Freedom of Information Act (FOIA) requests and similar inquiries,[2] along with scraping state websites and corresponding with staff from state agencies, we obtained detailed data on drinking water pollution. These data provide 266 million drinking water pollution readings, covering 1,250 different pollutants for 48 states over several decades. We link these to new service territory maps for every available state describing the areas where drinking water systems distribute water. Such maps are important because the U.S. has about 150,000 public water systems—50 systems per county, on average—of which a third are "community water systems" serving permanent residences. These maps let us link

[1]Compared to air, river, or climate pollution, drinking water has few inter-jurisdictional externalities. The famous case of Chicago reversing the direction of the Chicago River around 1900 to obtain cleaner drinking water is renowned because it is unprecedented. Another iconic but unusual case is New York City protecting its watershed in the Hudson Valley and Catskill Mountains, which naturally filters source water, rather than building a more sophisticated treatment plant.

[2]Some state laws are called open record, sunshine, or others, but we generically refer to these as data obtained by FOIA.

drinking water quality to demographics and health.

We match drinking water data to confidential Medicare administrative data on the health outcomes of all beneficiaries. We obtain records on the 9-digit zip code of Medicare beneficiaries, which approximate Census Blocks, provide about 200 times greater geographic resolution than 5-digit zip code, and enable a precise link between health records and water system service territories. The Medicare data cover the near-universe of U.S. adults age 65 and older. We also provide coarser analysis of county×year mortality for other ages' mortality, and for infant health. Finally, through a federal Freedom of Information Act request, we obtained details on 9,200 subsidized loans to water systems through the Safe Drinking Water Act.

We have three main findings. First, the share of drinking water readings exceeding current health standards fell by half between 2003 and 2019. Sparser data from before 2003 and standardized values (z-scores×100) also indicate declines. Radioactive particles ("radionuclides") and disinfection byproducts declined the fastest, while organic chemicals like pesticides had low levels in baseline data and flatter trends.[3] We find slightly smaller declines for pollutants that the Act does not regulate. Poor communities have higher pollution levels; we obtain mixed evidence on relative pollution levels and trends in Black and Hispanic communities.

Second, we find that loans to public drinking water systems through the Safe Drinking Water Act contribute to the decline in water pollution. We report difference-in-differences regressions comparing drinking water pollution concentrations before versus after a system receives a loan, in systems receiving loans in early versus late years, including estimates accounting for treatment in different years (Borusyak, Jaravel and Spiess 2024; Gardner et al. 2024). A Safe Drinking Water loan decreases the share of water readings violating health standards by nearly 10 percent and moderately decreases standardized values. Loans that identify a targeted pollutant decrease the share of concentrations of that pollutant above health standards by 36%. Cost-effectiveness analysis indicates that through these loans, it would cost the average drinking water system \$3.4 million annually (\$2024), or \$46 per person×year, to eliminate readings of regulated pollutants above health standards.

Third, administrative Medicare data indicate that Safe Drinking Water Act loans reduce

[3]Confusingly, "organic food" refers to food produced without pesticides, while "organic chemicals" in science refers to pesticides and other chemicals containing carbon. This paper uses the scientific definition of "organic" as denoting carbon-based molecules, including pesticides and industrial chemicals.

mortality among older Americans. We use a stacked cohort design to track and compare cohorts of individuals who live in water system service territories that receive loans five years before loan receipt against cohorts of all individuals living in territories that never received a loan. We estimate that the first loan a water system receives decreases the mortality rate by half a percent relative to baseline levels. Mortality responds more slowly to loans than pollution does. We also report effects of Safe Drinking Water loans on hospital admissions overall and for two specific sub-groups—admissions for chronic conditions and for conditions related to waterborne infectious disease. We find similar magnitude but less precise estimates for effects of Safe Drinking Water loans on hospitalizations of older Americans as for mortality. Effects on hospital admissions for chronic conditions echo the estimated effects on admissions overall, consistent with the gradual effect of water on mortality that we estimate. We do find evidence that the few loans targeting pathogens significantly decrease pathogen-related hospital admissions. The mortality estimates imply that these investments have modest costs per premature death avoided. County×year analysis of the impact of loans on health at birth and age-specific mortality are less precise, as is analysis of pollution aggregated to the county×year level. We conclude that sub-county data are important to study drinking water pollution, which is perhaps unsurprising since the average U.S. county has 50 separate drinking water systems. We also conclude that our research design lacks sufficient power with county×year data to detect important effects. We informally discuss other possible benefits of Safe Drinking Water loans, including avoided bottled water spending, home filter spending, and others, which would yield total benefits larger than we estimate.

In addition to event study graphs, several additional pieces of evidence support the research design's internal validity. For loans targeting specific pollutants ex ante, we study effects on targeted versus other pollutants. Additionally, we report specifications controlling for important potential confounding variables—Clean Water Act loans for wastewater treatment plants, Clean Air Act ozone and particulates nonattainment regulations, toxic pollution sources, local income and employment, opioid prevalence, health insurance coverage, per capita federal spending, temperature, precipitation, and age. Furthermore, we report falsification tests of the effects of loans on ambient air, river, and lake pollution.

This paper departs from existing research in several ways. It provides the first comprehensive estimate of trends in U.S. drinking water pollution concentrations. This is useful in its own right and because microdata on environmental goods enable macro assessment of their importance (Muller, Mendelsohn and Nordhaus 2011). For example, the U.S. government began adding environmental statistics to the U.S. National Accounts, a process which other countries have already undertaken (DePillis 2023; White House January 2023). The U.S. strategy plans to add surface water pollution and groundwater depletion, among other environmental goods, to the U.S. national accounts; our work could help support the inclusion of drinking water pollution. Existing studies measure trends in violations reported to a federal database, not concentrations, and for subsets of systems (Pennino, Compton and Leibowitz 2017; Allaire, Wu and Lall 2018; McDonald and Jones 2018). Publicly posting our microdata may spur future research on drinking water pollution.[4]

Additionally, we provide the first direct estimate of how Safe Drinking Water Act investments affect drinking water pollution concentrations and the first ex post evaluation of Safe Drinking Water Act loans. Prior work measures how specific features of the Safe Drinking Water Act affect certain outcomes. For example, time series data show that blood arsenic levels declined after the Safe Drinking Water Act regulated arsenic (Nigra et al. 2017). Mandatory letters to customers highlighting drinking water violations decreased federally-reported violations (Bennear and Olmstead 2008). Additionally, drinking water systems use testing frequency strategically to avoid federally-reported violations (Bennear, Jessoe and Olmstead 2009). Several policy papers discuss cost and management of the loans we study, though not their impacts (Beecher and Shanaghan 1998; Pontius 1998; Mullin and Daley 2017). Studying loans' equity has been difficult in existing work because observing the demographics of drinking water systems requires knowing the communities they serve. Following the Foundations for Evidence-Based Policymaking Act of 2018, each federal agency highlights priority areas where better evidence may improve policy; one of the EPA's priorities has been to determine which drinking water policies improve compliance with the Safe Drinking Water Act (USEPA 2022). Our analysis of loans helps answer this question.

We build on recent economic analyses of major U.S. environmental laws (Greenstone 2002; Behrer et al. 2021; Shapiro 2022; Taylor and Druckenmiller 2022; Frank et al. 2025).

[4] An environmental advocacy organization, the Environmental Working Group, has collected drinking water data from states, but the data cover one decade, the data processing is not public, and the microdata are not freely available. No data used in this paper come from the Environmental Working Group. Hughes et al. (2023) compile records of municipal spending on drinking water and system characteristics, though not water quality readings. Austin, Pan and Parthum (2024) use related data to analyze how precipitation affects drinking water quality, though the drinking water pollution concentration data do not appear to be public. Austin, Bardot and El-Khattabi (2025) compare water system territory maps across sources.

Our work differs from research on the Clean Water Act (Keiser and Shapiro 2019*b*; Greenhill et al. 2024; Druckenmiller, Shapiro and Taylor 2026) in several ways. We study a different law, regulating a different environmental good (the tap water people drink, not the rivers where people swim or fish), regulating drinking water treatment, not wastewater treatment, and analyzing health outcomes rather than property values. Pollution levels in rivers and lakes may relate only loosely to pollution levels in drinking water because drinking water systems treat surface water before people drink it and because a majority of drinking water systems draw water from underground aquifers.

We also provide the first direct ex post estimate of how Safe Drinking Water Act expenditures affect health outcomes. Most economic analysis of U.S. drinking water pollution exploits variation in source pollution due to switching water sources or fracking (Hill 2018; Dave and Yang 2022; Hill and Ma 2022; Wang, Chen and Li 2022) or exploits observed variation in drinking water pollution conditional on rich controls (Currie et al. 2013), rather than looking at expenditures due to Safe Drinking Water Act regulation. Marcus (2022) analyzes how coliform violations in North Carolina affect specific health outcomes. Research on drinking water and health typically focuses on earlier decades (Alsan and Goldin 2019; Flynn and Marcus 2025), on developing countries (Kremer et al. 2011; Greenstone and Hanna 2014; Bhalotra et al. 2021; Dias, Rocha and Soares 2023), on births and infants (Currie et al. 2013; Hill 2018; Hill and Ma 2022; DiSalvo and Hill 2024; Baluja et al. 2025; Montoya 2025), or on bottled water spending (Graff Zivin, Neidell and Schlenker 2011; Christensen, Keiser and Lade 2023; Hadachek 2025). The epidemiological studies relating drinking water pollution to adult and older adult mortality are largely observational and use limited samples.[5] We focus on older Americans for a few reasons—they are prone to hospitalization and premature death from drinking contaminated water (Schwartz, Levin and Goldstein 2000; Beaudeau, Schwartz and Levin 2014; Cotruvo 2019); much existing work focuses on infants or bottled water spending; nationally-consistent records with 9-digit zip code data on health outcomes are available from Medicare, whereas geographically refined data on other health outcomes for infants (e.g., birthweight) or others under age 65 are typically only available for a few states; and Americans over age 65 account for three-fourths all U.S. deaths (Xu et al. 2021).

[5] A partial list of drinking water contaminants that epidemiological studies have linked to elderly mortality includes arsenic (Meliker et al. 2007), disinfection byproducts (Mendy 2025), microorganisms (Hoxie et al. 1997), nitrate (Mendy and Thorne 2024), radionuclides (National Research Council 1999), surfactants (Kennedy, Zheng and Huynh 2025), and per- and polyfluoroalkyl substances (Biggeri et al. 2024).

Finally, we contribute to work on environmental inequality by providing the first national analysis of how drinking water pollution concentrations vary by demographics, and of the equality of Safe Drinking Water loans' distribution and impacts. The Environmental Justice movement partly reflects the concern that minority and low-income communities face higher pollution levels. Commentators highlight prominent case studies for drinking water, such as in Flint, Michigan, but systematic evidence is not available (Banzhaf, Ma and Timmins 2019). Several studies correlate federally-reported violations with county-level demographics (e.g., McDonald and Jones 2018; Schaider et al. 2019). Pace et al. (2022) compare concentrations of three drinking water pollutants across demographic groups in California. Partly inspired by these concerns, many laws proposed in Congress, though not passed, would mandate targeting for Safe Drinking Water loans (Tiemann 2018).

The paper proceeds as follows. Section 1 provides background. Section 2 describes data. Section 3 discusses econometrics. Section 4 discusses pollution levels and trends. Section 5 discusses loans and pollution. Section 6 discusses health. Section 7 concludes.

1 Background

1.1 Drinking Water, Pollution, and Treatment Technologies

This section provides background on drinking water systems, pollution, and treatment. Appendix A discusses details.

How drinking water reaches households. Ninety percent of U.S. housing units receive drinking water from public water systems, which are primarily what we study. The other ten percent, largely in rural areas, use private domestic wells, which we do not analyze since they lack Safe Drinking Water Act regulation and our data exclude them.

Public water systems include several components. Intake pipes draw in untreated surface or ground water. Drinking water treatment plants then abate pollution in untreated water. Distribution pipes convey treated water to households and businesses. Storage facilities (e.g., water towers) help maintain water pressure and provide water during emergencies. Loans may fund any of these.

Types of pollution. We organize pollutants into five categories—microorganisms, disinfection byproducts, inorganic chemicals, organic chemicals, and radionuclides. Microorganisms originate in human and animal wastes. Filtration and disinfection decrease their prevalence. Microorganisms like *Cryptosporidium* and *Giardia lamblia* have a shell (an oocyst) that resists traditional disinfection. Systems monitor total coliforms to proxy for all microorganisms. Using chlorine disinfection to kill microorganisms creates harmful compounds called disinfection byproducts, which result from interactions of disinfectants with natural materials like leaf particles.

Inorganic chemicals are molecules that do not contain carbon, which are generally elements of the periodic table. Three are of particular concern: arsenic, lead, and nitrate. Arsenic often originates from natural deposits, lead from old pipes that connect homes to the distribution network (service lines), and nitrate from fertilizer runoff. Organic chemicals like pesticides and industrial solvents come from agricultural runoff or factory discharges. Radionuclides are radioactive particles that arise from natural deposits or nuclear power.

Related Health Conditions. Research has linked acute or chronic drinking water pollution exposure to many health problems, including cancer, cardiovascular disease, dementia, diabetes, gastrointestinal illness, kidney and liver disease, stroke, and others (Morris 1995; Meliker et al. 2007; Navas-Acien et al. 2008; Lisabeth et al. 2010; D'Ippoliti et al. 2015; Bondy and Campbell 2018; USEPA 2018; Cotruvo 2019). Arsenic exposure, for example, has been linked both to contemporaneous stroke mortality and decades-later cancer mortality (Marshall et al. 2007; Rahman et al. 2014; Foster et al. 2019). Due in part to the limited availability of drinking water concentration data, however, we know less about the health impacts of drinking water pollution than air pollution or extreme temperature exposure. The timing between exposure and health impacts varies across these conditions. Some, like end stage renal disease, are chronic but may take several years to appear. Others, like cancer, are chronic but may take many years to occur.

We report effects on an aggregate including all causes of disease and on two subgroups. The first subgroup includes International Classification of Disease (ICD) diagnosis codes that the Centers for Disease Control (CDC) links to infectious waterborne disease including some individual pathogens, e.g., *Pseudomonas* pneumonia or infection by *Vibrio* spp. (Collier et al. 2021). These causes form the basis of the CDC's estimate of 7 million cases of waterborne disease annually (Collier et al. 2021). The second includes chronic illness diagnosis codes, adapted from the Centers for Medicare & Medicaid Services, which clarify mechanisms for the timing of health outcomes in response to improvements in drinking water. As discussed above, water pollution is potentially related to many health conditions, so we focus on these two groups that are both relevant to our setting and have links to water pollution.

Treatment technologies. After filtering larger contaminants from water, general drinking water treatment often begins by adding relatively benign chemicals (e.g., aluminum sulfate) to untreated water, which causes suspended pollution particles to agglomerate. Treatment plants then allow solids to settle and filters remove remaining particles. Disinfectants kill many remaining microorganisms. Corrosion inhibitors like orthophosphates reduce the leaching of metals like lead from pipes. Finally, pressurizing water in distribution pipes prevents backflow, limiting the entry of pollutants into the distribution network. Public water systems thus use both general technologies like filters that affect many of these pollutants, and specific technologies like corrosion inhibitors that primarily affect one category of pollution (e.g., inorganic chemicals like lead and copper in pipes). Our subsequent discussions of how specific interventions affect different pollutants to some extent reflect whether the interventions support general or specific technologies.

1.2 The Safe Drinking Water Act

Congress passed the 1974 Safe Drinking Water Act in response to evidence of high pollution levels in U.S. drinking water. The Act's structure guides our analysis; Appendix A.3 provides further background. The Act determines health standards ("Maximum Contaminant Levels") for regulated pollutants. States may add tighter standards, though we focus on federal standards. Current federal standards cover about 90 pollutants.[6]

Violations of standards are common but cause limited enforcement. The Act requires large systems to notify customers of violations; requiring notifications decreases pollution (Bennear and Olmstead 2008). Systematic violations could increase citizen pressure. Some standards are complex, which may let engineers optimize to avoid formal violations.[7]

The Safe Drinking Water Act also requires monitoring. Larger systems must monitor more frequently and high routine readings can require follow-up tests. Monitoring for most pollutants occurs at treatment plants, though most monitoring for lead is at household taps.

[6]We compiled data on all 50 states' drinking water regulations. Excluding New York, which regulates all organic chemicals, states regulate an average of 2.6 additional pollutants beyond the 90 federally regulated pollutants. Appendix A.3 provides details.

[7]For example, the disinfection byproducts standard applies to the mean within a sampling location of a treatment plant over four quarters. A system that exceeds the standard at different monitoring locations in different quarters has no formal violation.

The 1996 Safe Drinking Water Act Amendments created the Drinking Water State Revolving Loan Fund, which provides subsidized loans to address the "most serious risks to human health" (Tiemann 2018). Loans allocate capital to states based on demonstrated needs. Each state allocates loans according to priority lists describing projects that address the most serious health risks, help ensure compliance, and support systems most in need (see Appendix A.3). Because loans target the highest need projects, loans may have larger effects than other sources of variation in water quality. Loans can fund all types of water capital investments, including treatment, distribution, pumping, storage, and others; local governments pay operations and monitoring costs (USEPA 2017). Subsidies increase loans' attractiveness. For example, one report summarized that these loans had interest rates of 2 to 4 percent in typical years, while a proxy for the relevant market rate was 5.1 to 5.8 percent (USEPA 2003).

An example loan may clarify how they work. The Big Park Water Company provides drinking water to the town of Oak Creek, located in Central Arizona near Sedona. Surrounding groundwater has high arsenic levels, reflecting natural deposits. In 2010, the system received a Safe Drinking Water loan of $415,000 to install arsenic treatment technology. The technology exposes untreated water to a titanium-based granular adsorption material that removes arsenic. The arsenic treatment began operation within a year and won a state "Best Drinking Water Project of the Year" award in 2011, for "project management and commitment to public health protection" (Camp Verde Bugle 2012).

2 Data

2.1 Drinking Water Data

We obtain drinking water data from states via Freedom of Information Act and similar requests, correspondence with government staff, and web scraping; Appendix B.1 provides details. We harmonize these data across states. In many data, an observation represents one pollution reading, though some raw coliforms data represent monthly averages.

Analysis requires choosing years, summary statistics, and pollutants. We analyze trends over the 17-year period from 2003–2019. Drinking water data availability is more limited before 2003, though we show sensitivity analyses beginning in 1992. Some data for year 2019 are incomplete, and we show sensitivity analyses excluding 2019. We analyze loans over the period 2009–2019, since the EPA began requiring collection of loan records in 2009 and our drinking water data end in 2019.

Our main estimates use two summary statistics: the share of pollution readings exceeding current health standards[8] and standardized values (z-scores defined within pollutant $\times$ 100). We multiply z-scores by 100 to increase readability. Sensitivity analyses consider pollution bins, logs, and the share that are positive. Several data characteristics guide these choices. Over half of pollution readings are zero. Positive readings have skewed distributions. Pollutants have different units and unregulated pollutants lack health standards. We analyze time-invariant health standards as of the year 2023 so that results reflect changes in pollution rather than changes in standards, though standards largely did not change in our analysis period.

We emphasize three broad groups of pollutants: pollutants with federal health standards, "priority" pollutants that Safe Drinking Water loans target, and pollutants without federal health standards (Appendix Figure 1).[9] We also highlight six important individual pollutants: arsenic, lead, nitrate, total coliforms, trihalomethanes, and uranium.

We take several steps to address potential sample imbalance and representativeness, in part because the raw data do not represent a random probability sample. Most regressions include system-by-pollutant fixed effects. We restrict some estimates to systems and pollutants monitored in most years. We emphasize results for the regulated pollutants that are the most widely measured. We exclude readings with data flags identifying repeated or special purpose readings, such as in response to natural disasters. We report some results weighted by population; Appendix B.2 explains how we measure population for each water system. Sensitivity analyses control for monitoring and reporting violations from the Safe Drinking Water Information System (SDWIS), where a system fails to conduct required monitoring, and for cases where pollution readings fall below a device's minimum accurate

[8]We do not primarily analyze per- and polyfluoroalkyl substances (PFAS and PFOA) since they became federally regulated in 2024, after our analysis data mostly conclude in 2019, and regulation then was partially rolled back in 2026.

[9]We define priority drinking water pollutants as those that some Safe Drinking Water loans target, have health standards, and routine monitoring. This definition identifies 10 priority pollutants: several disinfection byproducts (bromate, chlorite, haloacetic acids, and trihalomethanes); two inorganic chemicals (arsenic and nitrate); one microorganism (total coliforms); and three radionuclides (gross alpha, radium 226+228, and uranium). Some pollutants, especially per- and polyfluoroalkyl substances (PFAS), perfluorooctane sulfonic acid (PFOS), nickel, and aldicarb have state-specific health standards. Among readings for pollutants we categorize as "unregulated," 8% have state-specific health standards.

detection limit. Additionally, we average readings to the system×month then system×year level, which decreases excess influence from repeated monitoring of high pollution levels. Finally, many results give equal weight to each of the five categories of pollution. We use this weighting to address differential composition of data across pollution categories. For example, organic chemicals have low levels but many chemicals and observations.

Summary Statistics: Pollution

Appendix Table 1 shows that larger states have more data. The mean state monitors 250 pollutants. Most state data begin by the year 2000, some in 1980, and most end between 2019 and 2022.

Appendix Table 2a describes groups of pollutants. Two-thirds of the readings represent regulated pollutants. About two thirds of readings are zero, partly because organic chemicals usually have a value of zero. The number of annual readings grows over time. Community water systems account for 82 percent of pollution readings. The mean pollutant has four and a half readings per system×year and the mean system has 16 years of data.

Correlations between pollutants in Appendix Table 3 show sensible patterns. Disinfectants create disinfection byproducts, so their standardized values have positive correlation. Organic and inorganic chemicals have a modest positive association, perhaps because nearby industry contributes to both. "Secondary" pollutants, which affect water's taste or appearance but do not primarily affect health, are correlated with most pollutants which affect health. Thus, water which tastes or looks bad is more likely to be unhealthy.

2.2 Who Does Each Drinking Water System Serve?

We obtain information on the area each drinking water system serves from the U.S. Community Water Systems Service Boundaries v3.0.0, a dataset that the Environmental Policy Innovation Center (EPIC) created (see Appendix B.3). EPIC works with state governments to create and document electronic maps describing precisely where each system distributes water.[10] Earlier research has obtained similar information for California, New Jersey, or Pennsylvania, though has not used national maps (Currie et al. 2013; Hill and Ma 2022;

[10]Before that release, we had directly obtained or reconstructed these records for most of these states. We found that EPIC's records are extremely similar for states when we both obtained data, but EPIC obtained modestly broader coverage than our direct records.

McDonald et al. 2022; Pace et al. 2022). These data are relevant for our health and inequality estimates only; our estimates of pollution trends or loans' effects on pollution do not use these data. EPIC identifies a system's distribution territory by using state-specific service territory shapefiles, matching a system name with a municipality name then using Census maps of municipal boundaries, or drawing a circle around the centroid of a drinking water system. Our main analysis excludes the third method (circles drawn around system centroids) due to its potential inaccuracy, though sensitivity analyses include it. We link the service territory of each system to demographic and health outcomes by identifying Census blocks where each system distributes water. Blocks are the smallest unit of geography the Census identifies. Our main geographic data cover 86 percent of Americans with piped water. Sensitivity analyses adding EPIC's third method (circles drawn around service territory centroids), cover more Americans. Figure 1, Panel B, shows that these data cover most people in most counties. The South and mid-Atlantic have less coverage, though sensitivity analyses including EPIC's third method cover more of these areas.

2.3 Medicare and Other Data

We use individual-level Medicare administrative records on all beneficiaries from years 2003–2019, covering almost all Americans aged 65 to 100, accessed through the National Bureau of Economic Research. We use two file segments. The first contains patient demographics, including 9-digit zip code of residence and date of death, though our data do not report cause of death. We spatially join each 9-digit zip to the water system serving it using 9-digit zip centroids (Appendix B.4). The second describes patients' health care utilization, including inpatient hospital stays and associated primary diagnoses. The first segment covers all beneficiaries; the second covers the roughly 70% of beneficiaries in traditional fee-for-service Medicare. The Medicare hospital admissions regressions therefore have somewhat smaller sample size than the Medicare mortality regressions.

The Medicare mortality analysis has the strengths of precise geography (9-digit zip code), an individual panel that lets us use a stacked cohort design, and high coverage. The Medicare estimates only cover individuals aged over 65, however, and lack information on cause of death.

We therefore also analyze health at birth, child and infant mortality, and cause of death using administrative, confidential, county×year data, accessed through use agreements with the National Center for Health Statistics. This analysis uses the All-County Natality Files and Detailed Mortality - All County files for the years 2009-2019. These data cover the entire country, but they only record the county rather than zip code, and they lack a panel to follow individuals over time.

We use several other public datasets. The EPA's Safe Drinking Water Information System reports system names and other characteristics. Many environmental and economic data, described in Appendix B.5, provide time-varying controls. The 2010 Census provides block and block group population and demographics.

2.4 Safe Drinking Water Act Loans

Through a Freedom of Information Act request to the U.S. Environmental Protection Agency for "detailed data on all loans made through the Drinking Water State Revolving Fund," we obtained details on 9,200 subsidized loans to local drinking water systems through the Safe Drinking Water Act. We requested data on all loans, all available years, and all variables in the data. The EPA collected these data systemically beginning in 2009, though some records cover earlier years. These loans are collectively worth $36 billion.[11] Loan funds account for about 13 percent of water capital investment nationally.[12] The mean loan provides $4 million and funds a water system serving 74,000 people. Both statistics have a long right tail. In the mean year, 750 loans are given, with more in 2009 due to the American Recovery and Reinvestment Act (Appendix Table 4); hence, some of our estimates control for unemployment, income per capita, and government transfers. Most counties have received loans (Figure 1, Panel A). Loans are less common in the South.

We can identify the pollutant a loan targets for 11 percent of loans, either from a variable listing the targeted pollutant or from free entry text (Appendix Table 4). The 11 percent cover most groups of pollutants, though essentially no loans target organic chemicals, or inorganic chemicals other than arsenic and nitrate.

Appendix Table 5 describes mean characteristics of the county×year controls that some regressions include, separately for systems that do and do not ever receive a loan. Systems

[11]Except where otherwise noted, we deflate all dollar values in the paper to year 2024 equivalents using the GDP deflator.

[12]This statistic represents years 2012 and 2017, the two years when we have loans data and when the Census of Governments reports water capital outlays for all state and local governments. We calculate the ratio of national loan amounts in each year to national capital outlay. The ratio is 12.4 percent in year 2012 and 13.7 percent in year 2017.

with loans are more likely to be in a county with a Clean Water Act loan, less likely to be in counties that are in Clean Air Act nonattainment status, have fewer toxic industrial plants, and are more likely to be urban areas.

Appendix Table 6 summarizes demographics of systems receiving loans. Systems with a higher share of readings violating health standards in the year 2006 receive more loans.[13] Black, and low-income communities also receive more loans, which is important for debates about loan targeting, though Hispanic communities do not. Column (7) shows that conditional on population served, Black communities receive fewer loans. In other words, Black communities receive more loans in part because they are disproportionately in cities and highly populated areas. Controlling for population density also somewhat decreases the relative number of loans that Hispanic and low-income communities receive.

3 Empirical Framework

3.1 Trends

We use the following equation to estimate pollution trends:

$$P_{csy} = \alpha y_y + X'_{sy}\pi + \mu_{cs} + \varepsilon_{csy} \tag{1}$$

The dependent variable P represents the mean pollution level for pollutant (chemical) c in drinking water system s and year y. It measures either the share of (c, s, y) readings above the health standard or their mean standardized value. The coefficient α represents the mean annual trend in drinking water pollution. The fixed effects μ_{cs} adjust for the mean level of each pollutant and drinking water system. The controls X include the share of readings from each calendar month, which address seasonality in drinking water pollution, with July as the reference category; some specifications control for weather. The error term ε_{csy} includes other forces affecting drinking water pollution. Regressions are clustered by water system.

[13]We use the year 2006 as a pre-period, although the loan data begin in 2009, to avoid using the beginning of the Great Recession in 2008 as a pre-period, and since the Recession may produce short-term deviations in variables like the unemployment rate. For this comparison, Appendix Table 6 uses population as reported in SDWIS.

We use the following equation to graph national pollution trends:

$$P_{csy} = \sum_{\tau=2003}^{2019} \alpha_\tau 1[y_y = \tau] + X_{sy}^{'}\pi + \mu_{cs} + \varepsilon_{csy} \tag{2}$$

We plot the year-specific coefficients $\alpha_{2003}, \ldots, \alpha_{2019}$ plus the constant.

3.2 Effects of Safe Drinking Water Loans on Pollution

We use the following equation to estimate how Safe Drinking Water loans affect pollution:

$$P_{csy} = \beta L_{sy} + X_{sy}^{'}\pi + \mu_{cs} + \mu_{cry} + \varepsilon_{csy} \tag{3}$$

We compare pollution P before versus after a loan, across systems receiving loans in different years. The main explanatory variable is the cumulative number of loans L_{sy} received through year y. The parameter β represents the mean effect of a loan on pollution. The controls X_{csy} include the share of readings from each month and, in some specifications, county controls like nonattainment designations, unemployment, etc., listed in Appendix Table 5. The fixed effects μ_{cs} account for different mean pollution levels in each drinking water system×pollutant. The pollutant-by-state-by-year fixed effects μ_{cry} account for different pollution levels over time by state, including any time-varying state-specific characteristics of data collection.

We focus on loan receipt rather than loan value for several reasons. Ninety-five percent of system×year observations have zero cumulative dollars (no loans). The rest are right skewed either in value or value per capita, making estimates using loan value sensitive to the right tail. Analyzing loan value potentially involves different selection and econometric considerations than analysis of loan receipt. For example, the stacked cohort design that we use to compare Medicare health outcomes for cohorts of loan recipients against cohorts initially living in service territories that never received a loan is not well suited to analyzing loan value. Additionally, under common assumptions, regressions involving dollars of loans may combine differential patterns of returns to scale—decreasing returns to abatement, where basic pollution control costs less per unit of pollution removed than sophisticated pollution control; and increasing returns to overall scale, where system cost per unit (e.g., per liter of water) decreases with system scale. We did analyze specifications based on loan value but found that they were sensitive to moderate differences in parametrization, possibly reflecting these concerns.

Equation (3) provides an unbiased estimate of β if loans are orthogonal to the error term, conditional on the other independent variables:

$$\mathbb{E}[L_{sy}\varepsilon_{csy}|X_{sy}, \mu_{cs}, \mu_{cry}] = 0 \tag{4}$$

One possible consideration would be if loans primarily respond to temporary increases in water pollution which would revert to baseline levels over time even in the absence of loans.

We assess assumption (4) in several ways. First, we use the following equation to plot event study graphs of pollution relative to the year when a drinking water system receives a loan:

$$P_{csy} = \sum_{\tau=-9}^{\tau=10} \beta_\tau 1[\mathbb{L}_{s,y-\tau} = 1] + X'_{sy}\pi + \mu_{cs} + \mu_{cry} + \varepsilon_{csy} \tag{5}$$

Here τ represents event time, i.e., years since a system receives a loan, with $\tau = -1$ as the reference period.[14] The variable $\mathbb{L}_{sy}$ represents an indicator for whether system s receives a loan in year y. A system that receives multiple loans can have more than one event time indicator equal one.[15] Equation (5) includes all drinking water systems; those never receiving a loan have event time indicators $1[\mathbb{L}_{s,y+\tau} = 1]$ equal to zero in all time periods. To ease interpretation and limit variability, graphs group event time into two-year bins. We report alternative versions of these graphs using heterogeneous difference-in-difference estimates (Gardner et al. 2024; Borusyak, Jaravel and Spiess 2024), which account for treatment in different years. We also report the Rambachan and Roth (2023) sensitivity tests on parallel trends.

Data and engineering predictions guide our expectations on impact timing. For the subset of loans that report timing, the mean duration of construction is 1.5 years unweighted and 2 years weighted by loan value. Larger projects have longer construction times and may have larger effects on pollution. Engineers estimate that capital investments cleaning up wastewater last for 15–55 years (Keiser and Shapiro 2019*b*).

A second test of internal validity is that for loans targeting a specific pollutant, we assess

[14] We include systems that receive no loans, one loan, or multiple loans. Since no reference category is required here, we normalize graphs so the coefficient for the year before treatment ($\tau = -1$) is zero.

[15] For example, if system s received a loan four years before year y and then another loan two years after year y, that observation would have $1[\mathbb{L}_{s,y-4}] = 1[\mathbb{L}_{s,y+2}] = 1$, and other event time indicators equal to zero.

how loans affect targeted versus other pollutants:

$$P_{csy} = \beta^T L_{c'sy} 1[c' = c] + \beta^{NT} L_{c'sy} 1[c' \neq c] + X'_{sy}\pi + \mu_{cs} + \mu_{cry} + \varepsilon_{csy} \tag{6}$$

Here $L_{c'sy}$ represents the cumulative number of loans that target pollutant c'. The coefficient β^T represents the mean effect of a loan on the pollutant that the loan targets. The coefficient β^{NT} represents the mean effect of a loan on other pollutants. For example, for loans targeting arsenic (c' =arsenic), this tests how these loans affect concentrations of arsenic versus concentrations of other pollutants. Finding a larger value of β^T than β^{NT} suggests loans effectively target pollutants and provide some evidence against omitted variables bias. If pollution control technologies are general and affect many pollutants, however, we could find $\beta^{NT} \neq 0$.

We also report several other tests of the identifying assumption (4), including adding controls for the lagged dependent variable, which help account for mean reversion, and directly testing whether high pollution readings increase probability of loan receipt.

3.3 Effects of Safe Drinking Water Loans on Health

We analyze health effects using a stacked cohort design following a cohort of individuals based on their location five years before loan receipt, echoing approaches in Deryugina and Molitor (2020) and Finkelstein et al. (2025). For each focal year f from 2009 to 2018, we identify two groups of systems: (1) treatment systems that received their first loan in year f, and (2) control systems that never received a loan during our sample period. We then select all Medicare beneficiaries aged 65 and older who resided in each of these systems at baseline, which we define as five years before the focal year (i.e., at $f - 5$). This five-year lag lets us examine pre-treatment mortality trends. We track these beneficiaries annually through 2019. We aggregate outcomes by baseline system of residence s, age a, and event year t. This methodology creates separate treatment and control cohort panels for each focal year, which we stack into a single dataset. In the resulting stacked panel, four dimensions uniquely identify an observation: focal year f, baseline system s, beneficiary age a, and event year t. This design measures the effect of the first loan a system receives; in a minority of cases this precedes additional loans that a system receives. For comparison, Appendix C.2 distinguishes effects of additional subsequent loans to a system on pollution, although this stacked cohort research design does not facilitate that distinction for health.

We then use the following equation to assess how Safe Drinking Water Act loans affect health:

$$H_{fsat} = \gamma L_{st} + W_{vy}^{'}\pi + \mu_{fs} + \mu_{ft} + \mu_{ry} + \varepsilon_{fsat} \tag{7}$$

Here L_{st} indicates whether system s received a loan by year t and H_{fsat} measures annual deaths or hospital admissions per 100 Medicare beneficiaries. The focal-year × system fixed effects μ_{fs} ensure that identification comes from within-system variation over time for each baseline cohort. The focal-year × event-year fixed effects μ_{ft} control for event time shocks common to all systems in a focal-year cohort. Regional (state) × calendar year fixed effects μ_{ry} further restrict comparisons to systems within the same state r and calendar year y. We include county-level time-varying controls W_{vy} for nonattainment designations, unemployment rates, and other potential confounders listed in Appendix Table 5. We weight each observation by the over-65 population, with weights scaled to sum to one within each event year t, which addresses heteroskedasticity and provides estimates for the average beneficiary rather than the average system.

We use this stacked design since it helps address econometric concerns. Like other new differences-in-differences methods, this estimator addresses the concern that differential treatment timing can bias estimates. It also addresses the possibility that loans are correlated with demographic trends. This is important partly since in two-way fixed effects regressions of Medicare demographics on receipt of Safe Drinking Water loans, some specifications indicated that systems receiving loans had trends in local population age. The stacked cohort design shuts down possible changes in demographics of the sample population by fixing the cohort. We also report specifications which control for age fixed effects and add controls for observable county×year characteristics. In addition, we report results which control for the average mortality rate of the water system service territory where a person lives in a given year, regardless of where the person lived in the year before loan receipt.[16] While we cannot use the stacked cohort design to study pollution since migration across systems is not a relevant concept for a system's pollution readings, we do report specifications for pollution regressions that control for the age structure of the population.

[16] Controlling for characteristics of the contemporaneous location has the possibility of being a bad control (Angrist and Pischke 2009), since it could respond to loans.

We also estimate corresponding event study graphs for health:

$$H_{fsat} = \sum_{\tau=-5}^{\tau=10} \gamma_\tau 1[\mathbb{L}_{s,t-\tau} = 1] + W'_{vy}\pi + \mu_{fs} + \mu_{ft} + \mu_{ry} + \varepsilon_{fsat} \tag{8}$$

We plot the γ_τ coefficients against event time to examine pre-trends and post-loan patterns. Cumulative or chronic health effects could take longer than the construction period to appear. In general, pollution may respond more quickly to loans than health does, though acute health impacts of water pollution could track pollution concentrations.

Given the population of older Americans we study, we calculate the willingness to pay for health improvements using an age-adjusted value of a statistical life, following Ashenfelter and Greenstone (2004), Murphy and Topel (2006), Deschenes, Greenstone and Shapiro (2018), Deryugina et al. (2019), and Carleton et al. (2022).

Additionally, we regress measures of infant health and county×year mortality on the number of cumulative drinking water loans. These data use administrative county×year records, which we believe are the only national infant birth certificate data available with county or more detailed geography.[17] Given many available infant health outcomes and associated concerns about multiple hypothesis testing, we follow Kling, Liebman and Katz (2007) and Anderson (2008) in aggregating infant health outcomes into an index of health at birth (Currie, Greenstone and Meckel 2017; Currie, Mueller-Smith and Rossin-Slater 2022; Greenhill 2025), though for reference we report estimates for each component of the index separately.

4 Results: Drinking Water Pollution Levels and Trends

4.1 Levels

This subsection describes spatial patterns of U.S. drinking water pollution. Figure 1, Panel C, shows pollution levels by county, measured as the share of drinking water exceeding health standards. The map includes regulated pollutants and partials out pollutant fixed

[17] Selected research uses infant health records with exact address for a few states that allow research agreements, though not nationally (e.g., Currie et al. (2013); Rossin-Slater (2013); Hill (2018); Dave and Yang (2022)).

effects to adjust for potential sampling differences.[18] The map reveals enormous variation across states. Kentucky and Oklahoma have high pollution levels, for example, while Florida and Oregon have low levels. It also reveals large variation across counties within a state. Large metro areas like Los Angeles and Chicago, for example, have low pollution. This contrasts with air pollution, where urban areas have higher levels. The map also shows spatial clustering, which occurs partly since drinking water systems serve adjacent counties and since determinants of drinking water pollution are spatially correlated.

Appendix Figure 2 shows maps for each pollution category. Many spatial patterns are intuitive. In Panel A, disinfection byproducts are highest east of the 100th meridian, where greater precipitation levels produce more organic materials in water like leaf litter and thus more disinfection byproducts. In Panel B, natural arsenic deposits increase inorganic chemicals in Nevada, and nitrate fertilizer use increases inorganic chemicals in some Midwestern agricultural areas.

Pollution sources and their associations with specific pollutants help explain patterns in the maps, give independent evidence on the quality of the drinking water microdata, and presage some demographic patterns of pollution shown below. We examine several types of pollution which have available data on sources. Appendix Table 7 finds that these associations between pollution sources and related pollutants are positive and many have large magnitudes. For example, counties with arsenic deposits for mining have six percentage points greater probability that drinking water violates arsenic standards, or a 170% increase relative to the sample mean.

Table 1 regresses the share of pollution above health standards on system demographics, which provides a simple way to measure inequality. Columns (5) through (7) also control for log population served and Panel B adds state fixed effects. Column (1) finds that systems serving larger populations have lower pollution, echoing the low pollution levels for cities from the maps, with a semi-elasticity of -0.16. Mean violation rates are around 2.5 percentage points, so doubling population would represent a 4.4 percent pollution decrease relative to the sample mean. Larger systems have better water quality partly because the Safe Drinking Water Act imposes tighter standards on larger systems and because drinking water pollution abatement has increasing returns to scale.

[18]Because pollutants have different probabilities of exceeding health standards, pollutant fixed effects help ensure that the map shows differences in exceedance rates within pollutants, rather than differences in the probability that a given county measures a given pollutant.

Table 1, column (2), shows that Black communities have lower overall pollution than other communities. The sign is surprising and the magnitude of -0.24, or about 10 percent lower than the baseline mean, is moderate. Column (4) shows that low-income communities have significantly higher pollution. Conditional on population served, Black communities have more similar pollution levels. Table 1, Panel B introduces state fixed effects. These largely do not change patterns for Black and low-income communities, though reverse the sign for Hispanic communities.

Sensitivity analyses in Appendix Table 8 show that many of these patterns are fairly robust. Overall, all these estimates do reject the hypothesis of dramatically and systematically higher levels of all pollutants in Black communities. Panel A adds the drinking water systems with less accurate boundaries (EPIC's third methodology that approximates system territory as a circle drawn around the system territory centroid). Panels B through F consider each category of pollution separately. Patterns differ somewhat by pollutant. Disinfection byproducts are lower in Black and Hispanic communities, though adding population controls in column (5) suggests again that the pattern for Black communities primarily reflects their greater concentration in higher population water systems. Inorganic chemicals and radionuclides are higher in Hispanic communities, perhaps in part due to agricultural nitrate fertilizers. Organic chemicals rarely exceed standards anywhere.

4.2 Trends

We estimate national trends in overall drinking water pollution using equation (2). Figure 2 shows that the share of drinking water pollution above standards fell by half in 2003–2019, from 2.5 percent to 1.25 percent. This represents an enormous and previously underappreciated improvement in environmental health. The decline is steady throughout the period. The confidence regions are tight, reflecting the large sample. The figure shows small variability around the trend, though a gradually slowing trend in later years. Appendix Figure 3 shows that each category of pollution declined somewhat steadily over this period, though with some variability around the trends.[19]

Table 2 reports corresponding regressions, using equation (1). Panel A, column (1), shows that over a decade, drinking water becomes 0.9 percentage points less likely to violate health

[19] Panel C suggests that microorganisms increased in 2019, potentially related to incomplete data for this year; we report sensitivity analyses excluding data from this year.

standards. Because only 2.6 percent of pollution readings violate standards in the initial year 2003, this represents a rapid decline. This trend estimate is precise, with a t statistic around 33. Columns (2) and (3) compare priority pollutants to others. Priority pollutants have higher baseline pollution levels than other pollutants and decline faster. We do not interpret the difference between priority and non-priority pollutants as representing causal effects of Safe Drinking Water loans, which focus on priority pollutants, because rapid trends for priority pollutants could represent other forces.

Table 2, Panel B, describes trends in standardized values. Estimates in columns (1) through (3) qualitatively corroborate estimates from Panel A. We find precise downward trends for pollutants with health standards, which are more rapid for priority pollutants. The magnitude of trends in standardized values is modest,[20] perhaps because readings from the right tail of pollution readings are becoming less common, but the moderate values which account for most of the pollution distribution are not.

Appendix Figure 4 shows this change in the distribution of pollution directly. This figure summarizes regressions where the dependent variables are the share of health readings falling into each of a set of bins, defined relative to the health standard. For example, the circle furthest to the right in the figure shows a trend regression where the dependent variable is the share of readings for a system$\times$year where pollution exceeds 200 percent of the health standard for that pollutant. We estimate a separate regression for each bin and estimate a linear trend as in equation (1). We plot the coefficient divided by the sample mean, which can be interpreted as a percent change for each bin.

Appendix Figure 4 shows that the share of readings that are less than 75 percent of health standards has grown, while the share of readings that are more than 75 percent of the health standard has fallen. Readings that are more than 175 percent of the health standard have declined the most rapidly. These trends could reflect important improvements in human health.

Our analysis of trends in unregulated pollutants uses standardized values rather than readings exceeding health standards, since the latter are undefined for unregulated pollutants. In Panel B of Table 2, column (4) shows a downward trend in unregulated pollutants that is about 94 percent of the trend for regulated pollutants and is statistically significant.

[20] We emphasize that standardized values equal 100 times within-pollutant z-scores. Hence, a coefficient of -0.6 in Panel B of Table 2 represents six thousandths of a standard deviation.

The unregulated pollutant sample covers more pollutants and has fewer readings per pollutant. We emphasize two aspects of unregulated pollutants. States regulate some of these other pollutants even though the Safe Drinking Water Act does not. Additionally, other forces could affect unregulated pollutants, such as cleaner source waters.

Appendix Table 9 presents many alternative specifications for these trend estimates, which mostly show qualitatively similar results; Appendix C.1 discusses details. These include alternative summary statistics for pollution, a longer sample window, separating trends for the newer coliform rule, specifying below detectable limit readings as equal to the detection limit, and alternative sample selection rules and weighting. Several sensitivity analyses for nitrates are flatter and somewhat sensitive to these alternatives, so we interpret those trends more cautiously.

Appendix Table 10 shows trends by demographic group. Pollution is declining faster in low-income communities. The pattern is similar when allowing differential trends by population density, in columns (5) through (7), or adding the broader but less precise system service territory maps, in Panel C.

5 Results: Safe Drinking Water Loans and Pollution

5.1 Effects on Pollution

This section analyzes how Safe Drinking Water loans affect drinking water pollution overall, specific pollutants, and pollution for different demographic groups.

The event study in Figure 3 analyzes the effect of Safe Drinking Water loans on the percent of readings exceeding health standards, estimated using equation (5). The blue solid line shows point estimates and the dashed red lines show 95 percent confidence intervals.

Figure 3 shows that loans cause large and sustained decreases in pollution. Each loan decreases the share of pollution exceeding standards by nearly half a percentage point, which is a meaningful decline relative to the baseline rate. In years before a loan, pollution has fairly similar trends in systems receiving loans and comparison systems. In part because the estimate for one period borders on statistical significance, Appendix C.2 discusses many alternative versions, including Rambachan and Roth (2023)'s test for sensitivity to violation of parallel trends, which suggests these estimates are reasonably robust. After a loan, pollution declines, with sensible timing. Pollution changes moderately in the year of a loan and following year, declines over the next two to three years, and the decline persists through 10 years. This is in line with evidence discussed earlier that construction takes a few years to complete.

Table 3 shows corresponding regressions, estimated using equation (3). Panel A finds that each loan decreases the share of water that violates standards by 0.28 percentage points, or a 9 percent decrease relative to the sample mean violation rate of 3.17 percentage points. For the priority pollutants which loans generally target, column (2) finds that loans decrease the share of readings above standards by nearly half a percentage point. Loans decrease priority pollutants more than other pollutants because priority pollutants have higher baseline levels and are a target of loans.

Loan impacts differ by category of pollutant. Table 3, columns (3) through (7), shows that loans substantially decrease disinfection byproducts, microorganisms, and radionuclides. Loans cause no detectable change in organic chemicals overall, partly since organic chemicals rarely exceed standards. Panel B shows that loans decrease standardized pollution values by modest amounts, though the estimates are precise. The smaller impact for standardized values than for readings above health standards reflects loans' large impact on the right tail of the pollution distribution but smaller impact on other parts of the distribution.

Appendix Table 11 analyzes the effects of the first Safe Drinking Water loan each system receives, rather than the cumulative number of loans. This estimate is more similar to the health analysis in the next section. Appendix Table 11 finds similar signs and statistical significance as the estimates for the cumulative number of loans from Table 3, but larger magnitudes. For example, the average loan decreases the standardized value of all pollutants with health standards by 1.54 (0.33), but the first loan decreases the standardized value of pollution by 2.49 (0.56). The first loan has larger effects primarily because some systems receive multiple loans, so in Appendix Table 11, the estimated effect of the first loan also reflects effects of any subsequent loans a system receives.

Appendix Table 12 analyzes the 11 percent of loans which identify the specific pollutant a loan targets, following equation (6). Targeted loans primarily and substantially decrease the pollutant they target. Columns (1) and (2) show that a targeted loan eliminates 36% of violating readings of a targeted pollutant. Columns (3) through (7) show similar patterns across categories of targeted pollution.[21] Panel B shows qualitatively similar results using standardized values.

Sensitivity analyses obtain qualitatively similar patterns, including estimates allowing for different treatment years, semi-parametric bin estimates across the distribution of pollution, and others. Appendix Table 13 presents and Appendix C.2 discusses details, including an additional test which regresses loan receipt on lags and leads of pollution. Appendix Table 14 does not find significantly different impacts of loans on pollution between Black, Hispanic, or low-income communities.

Appendix Table 15 reports a falsification test of how Safe Drinking Water loans affect air and surface water pollution. Because Safe Drinking Water loans target drinking water treatment, they are unlikely to affect pollution in other media substantially.[22] We estimate regressions analogous to equation (3). Each observation represents a pollutant×monitor×year, which we link to the population-weighted cumulative number of loans for each county×year. Columns (7) and (8) show effects on two common surface water pollution indices (Keiser and Shapiro 2019*a*). We find no meaningful effects of drinking water loans on air or surface water pollution. The point estimates are small and centered around zero. The ozone estimates border on statistical significance but have small magnitudes and positive signs (the opposite sign of the loan's impact on drinking water pollution).

5.2 Cost Effectiveness of Safe Drinking Water Loans

Cost effectiveness represents the cost that a loan project requires to reduce pollution by one unit. Equivalently, it represents the cost of supplying environmental quality through Safe Drinking Water loans. Cost effectiveness analysis can help choose policies that maximize environmental benefit for given cost, i.e., that minimize the cost of achieving a given environmental outcome. Analysis can also compare cost-effectiveness against the willingness to pay for drinking water quality.

[21]The microorganism estimate is small and imprecise. Microorganism loans typically target pathogens like *Cryptosporidium* and *Legionella*. These pathogens are difficult to monitor routinely and can involve different treatment technologies than total coliforms, which are the microorganism that is typically monitored.

[22]In principle, because drinking water systems draw in surface or ground water, treat it, and then the used water is returned to surface waters, drinking water treatment's impact on surface water quality is formally ambiguous. In practice, used drinking water accounts for a small share of total surface water, and most surface water pollution comes from household, commercial, and agricultural wastes, so drinking water treatment is unlikely to affect surface water pollution directly.

Cost-effectiveness calculations require assumptions about how a dollar of loans affects municipal capital spending, i.e., the extent of crowd-out or pass-through. Appendix C.4 discusses regressions of the log of cumulative municipal capital water investment on cumulative Safe Drinking Water loan amounts, estimated using municipal balance sheets from the 2009–2019 Census and Annual Survey of Governments. That Appendix estimates that a dollar of loans leads to \$0.78 (0.25) additional spending on municipal water capital, which fails to reject complete pass-through (no crowd-out), though the point estimate would imply about 22 percent crowd-out. Our cost-effectiveness calculations assume complete pass-through, though we discuss alternative assumptions.

Table 4 reports cost-effectiveness estimates. Column (1) describes aggregate values across a loan's lifetime, which we conservatively assume is 25 years.[23] Column (2) provides per-year values. Panel A describes costs. Panel B summarizes environmental impacts from Table 3. Panels C through E describe the cost per unit of environmental impact.

Panel A of Table 4 shows that the mean loan provides \$3.8 million in capital spending. Over a loan's lifetime, operations and maintenance costs almost equal capital costs. Thus, the mean loan costs \$7.4 million over its lifetime, or \$300,000 annually.

Table 4, Panel C, reports the cost to decrease pollution through Safe Drinking Water loans. Row 8 shows that it would cost the mean drinking water system \$3.4 million annually to eliminate readings of all pollutants above health standards. Row 10 shows that it would cost \$46 annually per person to eliminate pollution levels above health standards. Row 12 calculates that using these Safe Drinking Water loans, it would cost \$15 billion annually to eliminate all pollution readings above health standards nationally. Costs to decrease drinking water pollution by one standard deviation are higher, since loans predominantly affect the right tail of the pollution distribution.

Comparisons help provide a benchmark for these statistics. The average annual U.S. water bill is \$215 per person (Appendix B.7). Thus, using Safe Drinking Water Act loans to eliminate pollution above standards would increase water bills by 20 percent. Surface

[23] USEPA (2002) states that water treatment plants have expected useful life of 20 to 50 years before requiring extensive rehabilitation or replacement, and pipes can last 15 to 100 years. The American Society of Civil Engineers (2020) reports that drinking water treatment plants and pumping station concrete structures last 60-70 years, their mechanical and electrical components last 15-25 years, and distribution lines last 60-95 years. An environmental engineering firm describes 40-50 years as the typical wastewater treatment plant life expectancy, and some ex ante analysis of drinking water treatment plant construction assumes life expectancy of 50 years (Hofs et al. 2022; Johnson 2022).

water pollution provides another comparison. Using Clean Water Act grants to wastewater treatment plants, it costs $1.93 million annually ($2024) to make one river-mile safe for fishing (Keiser and Shapiro 2019*b*). Table 4 indicates that it costs 76 percent more ($3.4 million) to make the average drinking water system eliminate pollution above health standards.

The cost-effectiveness statistics in Table 4 require important caveats. They assume each loan has linear and additive effect on pollution. This contrasts with the typical assumption that the marginal cost of abating pollution grows with the amount of pollution reduced. Cost effectiveness numbers scale with the pass-through rate. For example, if Safe Drinking Water loans had a pass-through rate of 50% to municipal capital spending on water, then total costs of a loan project would be 50% lower (since both capital and operations and maintenance costs would be lower). The cost to decrease a unit of pollution would then be half of the values listed in Table 4, i.e., the loans would be more cost-effective than we estimate.

6 Effects of Safe Drinking Water Loans on Health

6.1 Health Impacts

Medicare Mortality

Figure 4 shows an event study graph of how Safe Drinking Water loans affect the mortality rate of older Americans, following equation (8). The horizontal axis describes the years since a drinking water system receives its first loan. The vertical axis describes the Medicare deaths per 100 beneficiaries, with the period before loans normalized to the value zero.

Figure 4 suggests that Safe Drinking Water loans decrease mortality of older Americans. In the five years before a loan, mortality rates have parallel trends between recipient and other communities. The point estimates are near zero and the confidence intervals cover zero. Mortality rates slightly decrease in the three years after a loan, decrease faster in years 4 to 7, and still faster in years 8 and beyond. The implied decrease is about 0.04 deaths per 100 persons on average. Estimates adding age fixed effects are similar (Appendix Figure 6, Panel A).

This timing of mortality impacts in Figure 4 is modestly slower than the timing of pollution impacts in Figure 3. Mortality timing may reflect chronic and acute illness, plus cumulative effects of pollution exposure.

Table 5 shows regression analogs, estimated using equation (7). Column (1) shows the basic estimate. Column (2) adds fixed effects for each age group. Column (3) adds controls for the Medicare year 2003 mortality rate and hospital admission rate in an individual's contemporaneous county of residence. Column (4) adds all the county×year controls listed in Appendix Table 5 (Clean Water Act loans, Clean Air Act nonattainment, etc.). Column (5) analyzes only loans which target microbial pathogens.

Table 5, column (1), shows that the mean Safe Drinking Water loan decreases the mortality rate by 0.036 per hundred Medicare beneficiaries. Given the baseline mortality rate, this represents a decrease of around half a percent relative to baseline levels. This estimate is statistically significant at conventional levels. Adding age fixed effects in column (2) somewhat increases the magnitude, to about 0.045. The column (3) controls for year 2003 health characteristics of the contemporaneous location, or the column (4) county× year controls, do not substantially change the estimates. The estimates with county×year controls have magnitude of 0.038, in the middle of the range of the other estimates, and remain reasonably precise. Column (5) shows a negative but imprecise point estimate for the overall mortality effect of loans that focus on microbial pathogens. The magnitude exceeds the estimate for the average loan, though the standard error is correspondingly larger.

Medicare Hospital Admissions

Appendix Figure 6, Panels B and C, report event study estimates of how a system's first Safe Drinking Water loan affects the number of Medicare hospital admissions per 100 beneficiaries (i.e., the hospital admission rate). Each graph has identical structure to the Medicare mortality event study graph in Figure 4. Compared to non-recipients, in the five years before a loan, recipient systems have parallel hospitalization trends. In the 10 years after receiving a loan, hospitalization rates steadily decrease in recipient systems. On average after a loan, recipient systems have about 0.4 fewer admissions annually per 100 beneficiaries. The confidence intervals are wide and none of the point estimates individually is statistically significant. As with mortality, the estimates with and without age fixed effects are similar.

Panel A of Appendix Table 16 estimates the impact of Safe Drinking Water loans on Medicare hospital admissions per 100 people, with specification corresponding to equation (7). The basic estimate in column (1) implies that each loan decreases hospital admissions per 100 people by 0.45 (0.28). The decrease of half a percent is comparable to the estimated decrease in mortality from Table 5. The admissions estimate, however, is less precise. Adding age fixed effects in column (2), location health controls in column (3), or county×year covariates in column (4), provides similar point estimates.

The event study analyses for mortality show a gradual response of health to drinking water loans, which increases over time. It is informative to understand if this response includes causes of illness that may generate non-immediate responses. Although we lack cause of death in the Medicare mortality data, the cause of admission in the hospitalization data provide one way to understand these results.

Panel D of Appendix Figure 6 therefore presents an event study analysis of hospital admissions for chronic conditions. The similarity of the chronic admissions estimates in Panel D of Appendix Figure 6 to the baseline estimates in Panel B provides one indication that the health response includes conditions that can respond gradually, which may help explain the gradual response of mortality to drinking water loans. Of course, the admissions estimates in Appendix Figure 6 are not especially precise, and results should be interpreted accordingly.

Finally, we consider one group of disease codes which the CDC has particularly linked to drinking water pollution, microbial causes, i.e., waterborne infectious disease. In Appendix Table 16, columns (1) through (4) of Panel C find that the average loan has no impact on hospital admissions for microbial causes. Column (5) finds that loans which target microbial pollution significantly decrease microbial-related hospital admissions. The magnitude of -0.022 is smaller than the estimated effect of loans on all-cause hospital admissions, which makes sense since admissions for microbial causes are far less common than admissions for all causes.

Other Health Outcomes

This subsection discusses results from county×year health records on other ages; Appendix C.5 provides additional details.

Appendix Table 17 presents two-way fixed effects estimates of how Safe Drinking Water loans affect mortality rates by age and by cause, using county×year data. Overall, these estimates using county×year data are imprecise. The point estimates for infants (age 0) and children in Panels B and C are negative but the confidence regions overlap zero. Panels I and J use the same specification to estimate how these loans affect pollution. The imprecise results for pollution when it is aggregated county×year data, which contrasts with the large and precise estimates for pollution with system-by-year data in Table 3, suggest that sub-county geographic detail is important to study drinking water pollution. Partly this is because the average county has over 50 different drinking water systems. Columns (2) and (3) show that the county×year controls from Appendix Table 5, or weighting by population, do not systematically change the findings.

Appendix Table 18 shows the estimated effects of Safe Drinking Water loans on infant health. While the overall estimates for the infant health index are negative, they are generally not statistically distinguishable from zero. Some estimates are positive, others are negative, but most are imprecise.

Although air pollution research has used county×year data (Chay and Greenstone 2003; Isen, Rossin-Slater and Walker 2017), these results suggest that sub-county geographic information is important to study the consequences of drinking water pollution. In part this may be because air pollution mixes in the lower atmosphere of an airshed. In contrast, drinking water pollution generally does not mix across drinking water systems, which have separate pipe networks, and which is a key reason why a water system is the main geographic unit of regulation for the Safe Drinking Water Act.

6.2 Benefits and Costs

Table 6 provides a partial benefit/cost analysis of the Safe Drinking Water loans by comparing estimates of the benefits of older Americans' avoided premature mortality against loan costs. Most entries in Table 6 report values for the mean loan, though several rows report numbers summed over all loans. Panels A and E summarize inputs from earlier in the paper. As earlier, we somewhat conservatively assume that loan benefits last 25 years.

Table 6, Panel C, aggregates the mortality benefits for older Americans over a loan's lifetime. Row 11 calculates that the mean loan prevents 57 premature deaths over the loan's 25 years of assumed benefits. Row 12 uses an age-adjusted value of a statistical life to calculate willingness-to-pay for avoided premature older Americans' mortality of $169 million per loan.

Panel F of Table 6 compares our estimates of measured benefits from older Americans' avoided mortality against measured costs of these loans. Row 21 shows our estimate that loans have a measured benefit/cost ratio of 22.7. Alternative estimates using the EPA's value of a statistical life, or weighted by population, are larger. Under a conservative bound that benefits and operating costs of a loan only last for 10 years, which is the latest outcome we see given the 2009-2019 period, the benefit/cost ratio of loans would be 12.8.

We assume that the loan amount and associated operation and maintenance cost reflects the additional expenditure due to a loan, in line with the pass-through estimates of Appendix C.4. If the effect of loans on total expenditure were smaller, then the benefit/cost ratio would be higher. For example, if each dollar of federal loans leads to only a half dollar of municipal water spending, then the benefit/cost ratio of loans is double what we report. Because these funds represent loans that municipalities must repay, not grants where municipalities are only responsible for a portion of costs, incomplete pass-through may be less likely in this setting than others (see Appendix C.4).

Given uncertainty over the value of a statistical life, we also describe the loans' estimated cost per premature death avoided and per life-year saved. These statistics compare mortality against loan project cost, without incorporating the value of a statistical life. Table 6, row 23, shows that through these loans, it costs \$130,000 to prevent one premature death. This is below standard estimates of the value of a statistical life, which also suggests that these loans have large net benefits. Rows 24–25 find that loans cost \$11,000 to \$27,000 per life-year saved.

To give context, Safe Drinking Water loans have meaningful estimated returns relative to other environmental and health investments, though our estimates are in line with some other numbers for drinking water. In the mid-1990s, the average medical intervention cost \$68,000 per life-year saved (Tengs et al. 1995). Safe Drinking Water loans, at a cost of \$11,000 to \$27,000 per life-year saved, are thus more cost-effective. Our estimated benefit/cost ratio is in the range of some EPA estimates for some drinking water regulations (Cadmus Group 2003), though the EPA estimates the mean recent drinking water regulation to have a lower benefit/cost ratio of 8.3. Our estimated benefit/cost ratio exceeds the ratio of 12.4 the EPA estimates for the mean recent air pollution regulation, though again is in the range of some higher-return air pollution policies. Our estimate far exceeds the benefit/cost ratio of 0.6 that the EPA reports for the average recent surface water quality regulation (i.e., river and lake pollution; see Keiser and Shapiro 2019*a*). Our estimates of the cost per life-year saved substantially exceed Cutler and Miller (2005)'s corresponding estimate of \$670 for drinking water filtration and disinfection in the early twentieth century. This indicates that drinking water treatment was more cost effective in the early 1900s than today, likely in part because the earlier time period involved more basic treatment.

We note that older Americans' mortality represents a large share of the estimated benefits of other environmental regulations, though not all. As one point of reference, for air pollution, the EPA estimates that mortality accounts for 88% of all benefits of the U.S. Clean Air Act that the EPA monetizes, including benefits from recreational demand, residential benefits, land productivity, materials damage, ecology, and morbidity (USEPA (2011), Table 7-1). For $PM_{2.5}$, which accounts for 97% of the EPA's estimated mortality benefits from the Clean Air Act, adults account for 99.8% of mortality benefits. For ground-level ozone air pollution, which accounts for the remaining 3% of the mortality benefits beyond $PM_{2.5}$ that the EPA estimates, the estimates do not separate mortality estimates by age (USEPA 2011, Exhibit 8). Overall, Americans over age 65 account for 75% of all U.S. deaths. For air pollution, at least, older Americans' mortality accounts for a large majority of total estimated health benefits, though the extent to which this conclusion extrapolates to drinking water pollution is unknown.

This discussion of measured benefits and costs requires several important caveats. Safe Drinking Water loans may affect health outcomes beyond those we measure well. We do estimate impacts on mortality rates of Americans younger than 65 and on infants using county×year data, although these estimates are imprecise at this level of aggregation. The costs of adaptation to drinking water pollution increase the net benefits of drinking water quality (Graff Zivin, Neidell and Schlenker 2011; Deschenes, Greenstone and Shapiro 2018; Ito and Zhang 2020; Christensen, Keiser and Lade 2023; Carleton et al. 2022). For example, many Americans use drinking water filters, including pitcher or refrigerator filters, or buy bottled water. While many filters address taste rather than health, filter a limited set of pollutants, or filter a limited amount of a given pollutant, our estimates are net of such adaptation—water pollution could have larger health effects if no such adaptation existed. The mortality benefits that we estimate dwarf at least the bottled water spending they prevent. For example, total national U.S. bottled water spending in 2020 was $36 billion (IBWA 2023). Only a subset of this spending was due to tap water pollution. The estimated annual older Americans' mortality benefits of Safe Drinking Water loans in a typical year (Table 6, row 12) exceed national bottled water spending.

Additionally, loans also likely create health benefits for people younger than 65, especially infants. While we estimate imprecise effects of Safe Drinking Water loans on mortality of Americans younger than 65 in county×year data, we also estimate imprecise effects of these loans on both pollution and older Americans' mortality in county×year data. We therefore interpret these findings mostly as indicating the importance of sub-county data to study drinking water and health, rather than indicating substantive conclusions about health effects for younger ages. Furthermore, loan benefits could also be capitalized into local housing values. Because loan receipt is not always publicized, and because many loans address longstanding pollution problems that are less salient than dramatic episodes like the lead crisis in Flint, Michigan, we conjecture that awareness of drinking water quality improvements due to the loans we study is more limited than awareness of prominent drinking water disasters.

We also note that our comparison of estimated costs and benefits aggregates across all types of pollution and standards. Some categories of pollution likely cost more to eliminate than others. For example, removing lead pipes typically requires excavation and replacement of service lines in many individual homes, whereas addressing disinfection byproducts in some cases only requires re-optimizing the use of disinfectants in the treatment system (Crittenden et al. 2012).

7 Conclusion

The classic economic history of drinking water emphasizes Snow (1855)'s linking cholera to drinking water and early municipal treatment (Cutler and Miller 2005; Alsan and Goldin 2019; Cutler and Miller 2022). This paper adds a modern chapter to this story—drinking water pollution remains a problem, and while it has unequal prevalence across social groups, its prevalence is declining. The Safe Drinking Water Act's loans to cities decrease pollution, and in total we estimate a 50 percent decline in the share of water pollution exceeding health standards between 2003 and 2019. We estimate that these loans decrease mortality rates of older Americans. More broadly, our compilation of national data on drinking water pollution concentrations linked to Census blocks may expand opportunities to research drinking water pollution.

A few areas beyond the scope of this paper may be productive for future research. Early environmental exposures can affect health and other human capital like skills, education, and earnings (Isen, Rossin-Slater and Walker 2017; Almond, Currie and Duque 2018; Marcus 2025). It would be informative to assess how national drinking water pollution exposures affect education and related human capital outcomes, and how other endowments and conditions mediate any such impacts. Similarly, a rapidly emerging body of research on specific settings like Flint, Michigan, fracking, lead service line replacement, discoveries of PFAS in drinking water, leaking underground storage tanks, and others finds that such prominent public changes in drinking water quality affect home values (Boyle et al. 2010; Muehlenbachs, Spiller and Timmins 2015; Guignet, Walsh and Northcutt 2016; Guignet et al. 2018; Theising 2019; Christensen, Keiser and Lade 2023; Marcus and Mueller 2024; Mackay 2025). It would be informative to understand how broad drinking water regulation and other sources of variation in water quality affect housing and land markets.

A second important question is how source water pollution, drinking water pollution, and their regulation interact. Lower pollution levels in rivers and groundwater may produce lower pollution levels in drinking water. The pollutants in source and drinking water could differ. For example, less organic material or microorganisms in source water can cause drinking water disinfection to produce fewer disinfection byproducts and disinfectants in drinking water. Lower source water pollution could also decrease required expenditures on drinking water treatment. Clean Water Act regulation that decreases surface water pollution could produce these impacts and more, including through interactions with Safe Drinking Water Act interventions. Analyses have documented such interactions of source water pollution and either drinking water pollution or health in specific cases (Alsan and Goldin 2019; Austin 2020; Flynn and Marcus 2025).

Third, U.S. and other countries' drinking water policies have a wide range of interventions and analysis of many other policies may provide useful insights for research. To give one example, future work could examine changes in drinking water rules and link them to health and environmental outcomes. This could include the organic chemicals rule changes in the 1980s, disinfection byproduct rule changes in the 1990s, or the arsenic rule change in the 2000s, building on Foster et al. (2019) and Petrusevich et al. (2025).

We finish with a few broader conclusions. One involves fiscal federalism, which argues that local funding of drinking water is optimal because drinking water is a local public good. We estimate meaningful net benefits from Safe Drinking Water loans. Various explanations could account for this discrepancy. These drinking water investments may have similar consequences regardless of whether local or federal governments fund them. Federal and local governments likely have incomplete information about the returns to drinking water investments. Additionally, some drinking water systems and their customers face credit constraints that make it difficult to fund drinking water capital investments; these subsidized loans may help relax those credit constraints. Finally, while the federal government effectively subsidizes these loans, local governments ultimately repay them and choose the nature of the drinking water investments, so one could characterize this setting as local investment in a local public good but with a federal subsidy.

A second broader point involves our limited results for organic chemicals. At least since Rachel Carson's (1962) *Silent Spring*, public concern and policy has focused on pesticides, industrial solvents, and other organic chemicals in drinking water. Organic chemicals account for 55 of the 90 pollutants the Safe Drinking Water Act regulates and around 90 million of our 266 million pollution readings. Yet we find that organic chemicals are the least likely of all types of pollution to violate health standards, essentially no Safe Drinking Water loans target them, and Safe Drinking Water loans have limited effects on organic chemical concentrations. Thus, our analysis does not provide a resounding empirical basis for the focus on organic chemicals, at least relative to other water pollutants.

Finally, much economic research focuses on regulated economic activity, partly because regulation generates data and policies. Analysts sometimes worry that such research does not extrapolate well to unregulated activity. Our finding that regulated pollutants are rapidly decreasing, and that unregulated pollutants are decreasing almost as quickly, suggests this is not a first-order concern in our setting.

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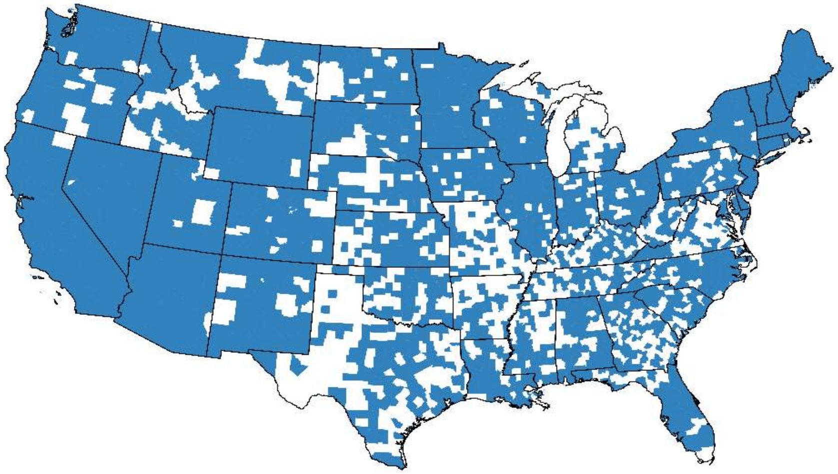
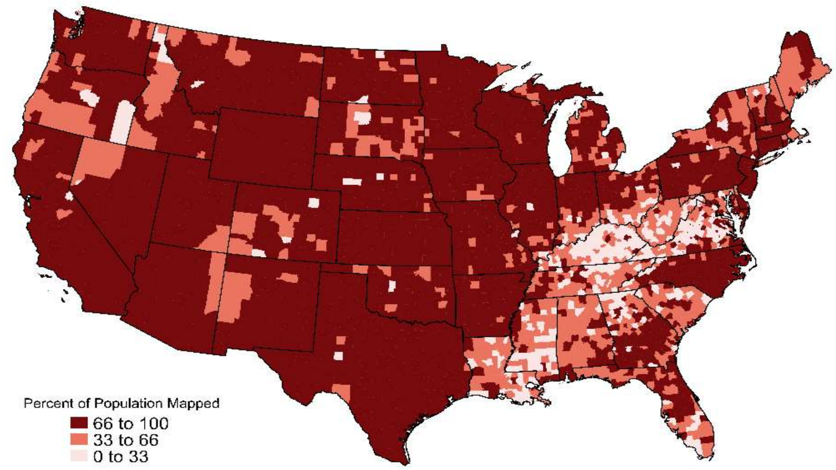
Figure 1: Maps of Drinking Water Data

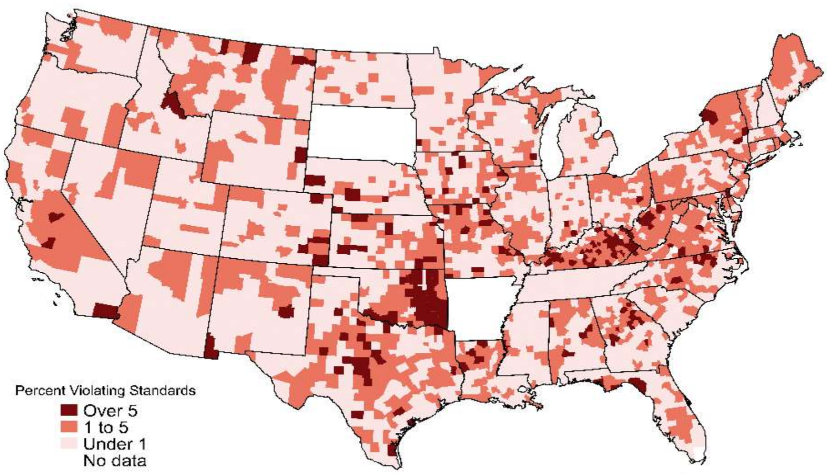
Panel A: Counties receiving Safe Drinking Water loans



Panel B: Percent of population mapped

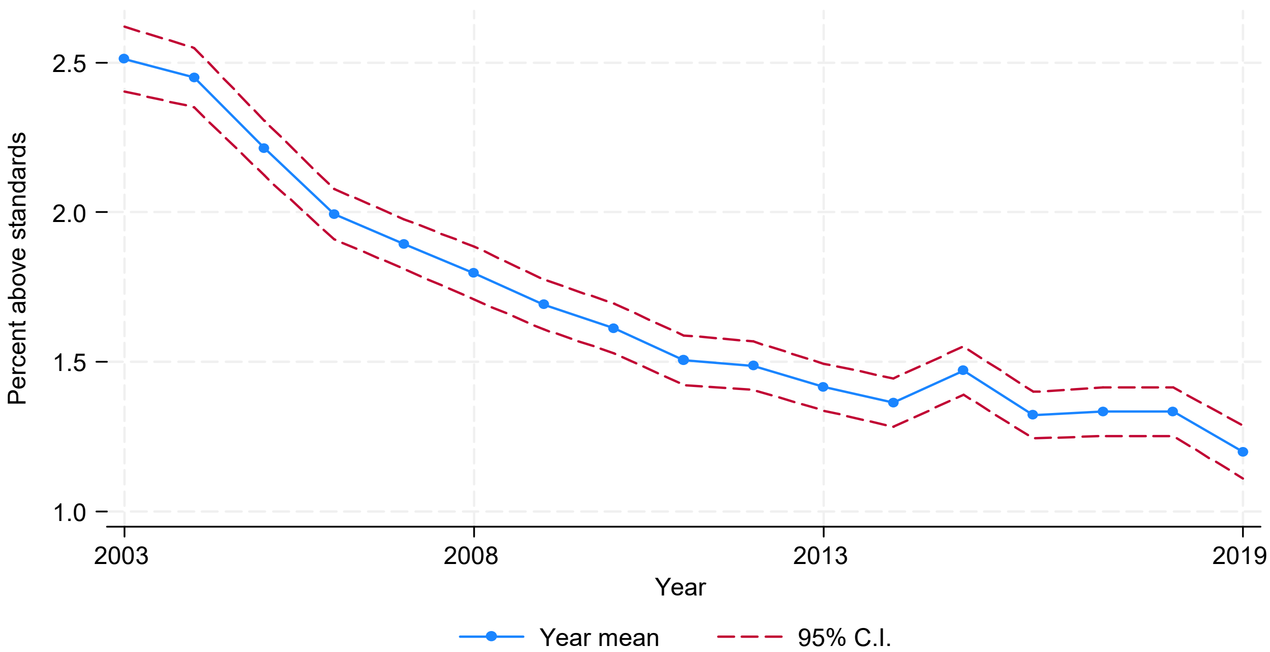


Panel C. Percent of water readings violating health standards, by county



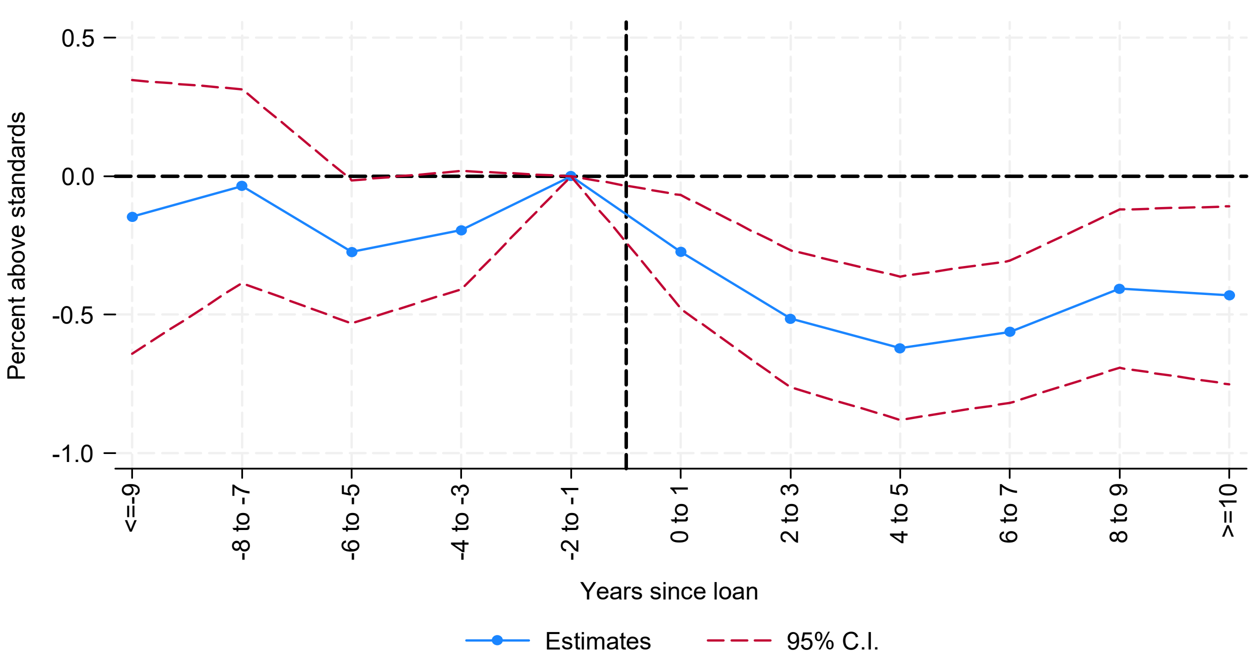
Notes: in Panel A, counties shaded in blue have a drinking water system that receives a loan. In Panel B, the coloring for each county represents the ratio of population with water system service territory mapped to population with piped water. In Panel C, the coloring for each county represents the share of pollution above health standards in years 2009-2019, where an observation is a water system × pollutant × year, and gives equal weight across the five categories of pollution equally and makes weights across systems within a county proportional to population. Arkansas and South Dakota lack pollution data.

Figure 2: Trends in U.S. Drinking Water Pollution



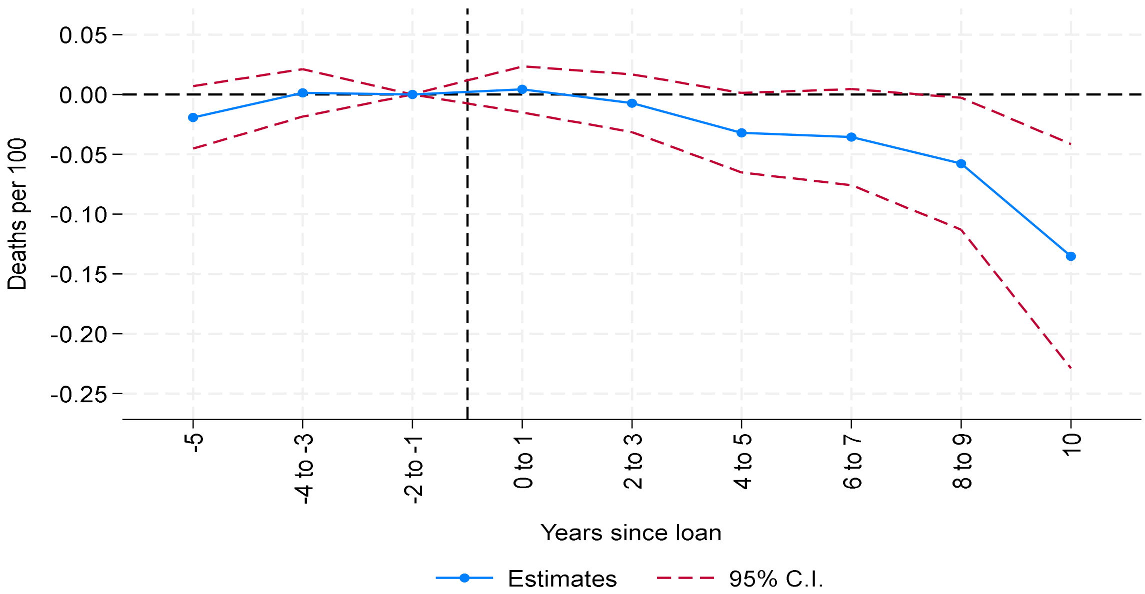
Notes: the graph shows the percent of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. The graph includes pollutants with health standards. Sample includes years 2003-2019. Regressions weight the five categories of pollution equally. Regression includes water system × pollutant fixed effects and controls for the share of readings from each month of the year. Standard errors are clustered by water system.

Figure 3: Effects of Safe Drinking Water Act Loans on Pollution



Notes: the dependent variable is the percent of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. The graph includes pollutants with health standards. Sample includes years 2009-2019. Regressions weight the five categories of pollution equally. Regressions include water system × pollutant, and pollutant × state × year fixed effects, and controls for the share of readings from each month of the year. Standard errors are clustered by water system.

Figure 4: Effects of Safe Drinking Water Loans on Mortality Rate



Notes: the dependent variable is the number of deaths per 100 Medicare beneficiaries aged 65 and older. An observation is a water system × cohort × single-year age bin. This stacked research design fixes a cohort 5 years before a water system receives a loan and compares it to all cohorts that never received a loan. Estimates include years 2009-2019. Regressions are weighted by the relevant population. Standard errors in parentheses are clustered by water system.

Table 1. Drinking Water Pollution Levels, by Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. No additional controls							
Log population served	-0.16***	—	—	—	-0.16***	-0.17***	-0.17***
	(0.02)	—	—	—	(0.02)	(0.02)	(0.02)
Above-median share Black	—	-0.24***	—	—	0.04	—	—
	—	(0.07)	—	—	(0.08)		—
Above-median share Hispanic	—	—	0.11*	—	—	0.24***	—
	—	—	(0.07)	—	—	(0.07)	—
Above-median share Poor	—	—	—	0.40***	—	—	0.47***
	—	—	—	(0.07)	—	—	(0.07)
Panel B. Include state fixed effects							
Log population served	-0.16***	—	—	—	-0.16***	-0.16***	-0.17***
	(0.02)	—	—	—	(0.02)	(0.02)	(0.02)
Above-median share Black	—	-0.31***	—	—	-0.04	—	—
	—	(0.09)	—	—	(0.09)	—	—
Above-median share Hispanic	—	—	-0.20***	—	—	0.00	—
	—	—	(0.07)	—	—	(0.08)	—
Above-median share Poor	—	—	—	0.31***	—	—	0.37***
	—	—	—	(0.07)	—	—	(0.07)
Month controls	X	X	X	X	X	X	X

Note: the dependent variable is the percent of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. Estimates include pollutants with health standards. Sample includes years 2003-2019. Regressions weight the five categories of pollution equally. Sample includes systems with non-missing values of independent variables. N=7,653,485. Month controls are the share of raw pollution readings from each month of the year. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Table 2: U.S. Drinking Water Pollution Trends

	Pollutants with health standards			
	All	Priority	Non-Priority	Unregulated
	(1)	(2)	(3)	(4)
Panel A. Dependent variable: percent violating current health standards				
Year	-0.086***	-0.128***	-0.005***	—
	(0.0026)	(0.0039)	(0.0002)	—
Dep. var. mean, yr. 2003	2.55	3.85	0.17	—
Observations	18,519,148	3,684,068	14,835,080	—
N pollution readings	87,119,587	52,554,106	34,565,481	—
Panel B. Dependent variable: standardized value				
Year	-0.423***	-0.538***	-0.181***	-0.397***
	(0.0145)	(0.0221)	(0.0038)	(0.1208)
Dep. var. mean, yr. 2003	2.92	5.17	-1.19	0.58
Observations	18,519,148	3,684,068	14,835,080	9,392,085
N pollution readings	87,119,587	52,554,106	34,565,481	21,573,426
System × pollutant FE	X	X	X	X
Month controls	X	X	X	X

Notes: the dependent variable is the percent of drinking water pollution readings exceeding current health standards. An observation is a system × pollutant × year. Sample includes years 2003-2019. Regressions weight the five categories of pollution equally. Month controls are the shares of raw pollution readings from each month of the year. Standardized values equal 100 times Z-score, calculated within each pollutant. In Appendix Figure 1, "unregulated" here corresponds to pollutants with no primary health standard, excluding secondary, general quality, and not relevant groups. Standard errors in parentheses are clustered by system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Table 3: Effects of Safe Drinking Water Loans on Drinking Water Pollution

Pollutants:	All with health standard	Priority	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides
			Categories of pollution				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Dependent variable: percent violating current standards							
Loans	-0.282***	-0.469***	-0.420***	-0.021	-0.097**	0.001	-0.733**
	(0.066)	(0.108)	(0.110)	(0.016)	(0.044)	(0.001)	(0.286)
Dependent variable mean	3.17	4.87	4.48	0.75	1.20	0.01	7.05
Observations	12,355,136	2,475,606	565,529	3,134,399	926,045	7,606,327	122,836
Panel B. Dependent variable: standardized value							
Loans	-1.538***	-2.481***	-1.858***	-0.193	-1.422**	-0.021	-4.118***
	(0.325)	(0.528)	(0.653)	(0.151)	(0.723)	(0.056)	(1.246)
Dependent variable mean	9.60	15.99	26.04	-2.67	-8.46	-1.30	15.88
Observations	12,355,136	2,475,606	565,529	3,134,399	926,045	7,606,327	122,836
Fixed effects:							
Pollutant × system	X	X	X	X	X	X	X
Pollutant × state × year	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X

Notes: an observation is a water system × pollutant × year. The table includes pollutants with health standards. Sample includes years 2009-2019. Regressions weight the five categories of pollution equally. Month controls are the shares of raw pollution readings from each month of the year. Loan variable is cumulative. Dependent variable mean represents the mean of the dependent variable for systems receiving loans, in years before a loan is received. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Table 4: Cost Effectiveness of Safe Drinking Water Loans

	Cost over loan lifetime (1)	Cost per year (2)
Panel A. Cost for mean loan ($million)		
1. Capital	$3.84	$0.15
2. Operation & maintenance	$3.60	$0.14
3. Total	$7.43	$0.30
Panel B. Effectiveness of mean loan at reducing pollution		
4. Decrease in readings above standards (pct. points)	0.28	0.28
5. Decrease in pollution (standardized value)	1.54	1.54
Panel C. Cost for mean loan to decrease pollution ($million / unit of pollution)		
6. One pct. point decrease in readings above standards	$26.64	$1.07
7. One unit decrease in pollution standardized value	$4.83	$0.19
8. Eliminate pollution readings above standards	$84.4	$3.4
9. Decrease pollution by one standard deviation	$482.7	$19.3
Panel D. Cost per capita using loans to decrease pollution ($ / person)		
10. Eliminate pollution readings above standards	$1,153.2	$46.1
11. Decrease pollution by one standard deviation	$6,593.2	$263.7
Panel E. National cost to decrease pollution ($billion)		
12. Eliminate readings above standards nationally	$369.0	$14.8
13. Decrease pollution by one standard deviation	$2,109.8	$84.4

Note: capital costs equal loan amount. Annual operation & maintenance costs equal 3.75% of capital investment and assume loan benefits last 25 years, based on Keiser and Shapiro (2019b). Standardized value equals Z-score calculated within pollutant times 100. Costs, impacts, and population are based on Table 4 and Appendix Table 4. Persons in denominator of Panel D includes all ages, not only the population aged 65 and older. National costs in Panel E assume a national population receiving drinking water of 320 million people. All dollar figures are in $2024, deflated using the GDP deflator.

Table 5: Effects of Drinking Water Loans on Mortality Rate of Medicare Beneficiaries

	(1)	(2)	(3)	(4)	(5)
Received loan × post	-0.036**	-0.045**	-0.043**	-0.038***	—
	(0.018)	(0.021)	(0.022)	(0.013)	—
Received microbial loan × post	—	—	—	—	-0.155
	—	—	—	—	(0.134)
Fixed effects:					
System	X	X	X	X	X
State × year	X	X	X	X	X
Age		X	X	X	X
Location health controls			X		
County × year controls				X	
Mean outcome (sample)	6.535	6.535	6.535	6.535	6.476
Mean outcome (baseline)	4.479	4.479	4.479	4.479	4.466
Observations	54,354,288	54,354,288	54,354,272	54,354,288	53,249,516

Notes: the dependent variable is the number of deaths per 100 Medicare beneficiaries 65 and older. Four variables uniquely identify an observation in the underlying data: baseline water system, cohort, calendar year, and single-year age. A cohort represents the year of loan receipt. This stacked research design fixes a cohort five years before a water system receives a loan, and compares it to all systems that never received a loan. Estimates include cohorts from 2009-2019. Regressions are weighted by the relevant Medicare population. Column (3) controls for the year 2003 mortality and hospital admission rates in an individual's contemporaneous county of residence. In column (4), county × year controls are listed in Panel A of Appendix Table 5. They include an indicator for having received a Clean Water Act loan; indicators for ozone and particulate matter nonattainment; number of Toxic Release Inventory plants per county; mean temperature; mean precipitation; income per capita; the employment to population ratio; the number of opioid prescriptions per 100 people; the share of population with health insurance; federal spending per capita; mean age; and the share older than 65. Column (5) only counts loans that contain a flag for targeting microbial pollution. Observations represents the number of water system × cohort × calendar year × age cells in each regression. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 6: Measured Costs and Mortality Benefits of Safe Drinking Water Loans

Panel A. Data inputs	
1. Deaths per 100 persons: impact of loan	-0.036
2. Deaths per 100 persons: sample mean	6.535
3. Deaths per 100 persons: baseline mean	4.479
4. Impact of loan on deaths per 100 Medicare beneficiaries (%)	-0.00551
5. Mean population age ≥65 per loan	9,298
6. Assumed duration of loan benefits (years)	25
7. Age-adjusted VSL ($mn)	$2.94
8. EPA VSL ($mn)	$13.21
Panel B. Benefits per loan ×year	
9. Premature deaths prevented per 100 persons	0.0247
10. Premature deaths prevented	2.294
Panel C. Benefits per loan, totalled across loan's lifetime	
11. Premature deaths prevented	57.355
12. Benefits using age-adjusted VSL ($mn)	$168.6
13. Benefits using EPA VSL ($mn)	$757.7
Panel D. Benefits of all loans provided in a typical year, totalled across loan's lifetime	
14. Benefits using age-adjusted VSL ($bn)	$126.5
15. Benefits using EPA VSL ($bn)	$568.3
Panel E. Loan costs	
16. Federal loan amount ($million)	$3.84
17. Annual state+local operation & maintenance cost ($mn)	$0.14
18. Total state+local operation & maintenance cost ($mn)	$3.60
19. Total costs of a loan ($mn)	$7.43
20. Total costs of all loans provided in a typical year ($bn)	$5.58
Panel F. Measured benefits versus costs	
21. Benefit/cost ratio of loans: age-adjusted VSL	22.7
22. Benefit/cost ratio of loans: EPA VSL	101.9
23. Cost per premature death avoided ($000s)	$130
24. Cost per life-year saved ($000s, all Medicare)	$11
25. Cost per life-year saved ($000s, death within one year)	$27
26. Total net benefits of all loans provided in a typical year: age-adjusted VSL ($bn)	$121
27. Total net benefits of all loans provided in a typical year: EPA VSL ($bn)	$563

Notes: VSL is value of a statistical life, mn are millions, bn are billions. Currency values are in 2024 dollars, deflated using the GDP deflator. Population values refer to individuals aged 65 and older. EPA VSL is discussed in Carleton et al. (2022). Age-adjusted VSL is deflated value from Deschenes, Greenstone, and Shapiro (2018), which is age-adjusted from Ashenfelter and Greenstone (2004), using age adjustments from Murphy and Topel (2006, p. 888). Life-year saved statistics assume 11.36 years of life expectancy for mean Medicare beneficiary, and 4.80 for deaths within one year estimated using a Cox-Lasso model, from Deryugina et al. (2019), Figure 5. Loans provided in a typical year are from Appendix Table 4, column (1). Mortality impact is from column (1) of Table 5.

Online Appendix

Water Works: Causes and Consequences of Safe Drinking Water in America

David A. Keiser, Bhashkar Mazumder,
David Molitor, and Joseph S. Shapiro

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D Appendix Figures and Tables **D-1**

A Background: Additional Details

A.1 U.S. Public Water Systems

Section 1.1 of the main text contrasts public water systems and private wells. Formally, a public water system "provides water for human consumption through pipes or other constructed conveyances to at least 15 service connections or serves an average of at least 25 people for at least 60 days a year" (USEPA 2023*g*). Local governments like town water boards or local water districts own and operate many public water systems. Many water systems are public though a minority, including but not limited to apartments or campgrounds, have private owners.

A single public water system can have multiple treatment plants. We analyze water systems rather than individual treatment plants both because most data define a water system as the unit of observation and because one water system may mix water from multiple treatment plants before the water reaches customers.

The EPA categorizes the roughly 150,000 U.S. public water systems into three types.[1] About 50,000 are community water systems, which serve year-round housing units. About 20,000 are non-transient non-community water systems, which serve at least 25 of the same people at least six months per year. This category includes schools, factories, offices, and hospitals. About 80,000 are transient non-community water systems, which provide water to places like gas stations or campgrounds where a person does not spend sustained amounts of time (USEPA 2023*g*). Some public water systems procure water from other systems, which does not directly affect our analysis.

The introduction of the main text mentions rapid price increases for household water bills. These increases reflect stricter requirements which mandate systems to spend more; shrinking populations in some older cities like Detroit, which force drinking water systems to pay for legacy fixed capital costs; and potentially increased pumping costs to lift groundwater from depleted underground aquifers.

A.2 Drinking Water Pollution Categories and Measurement

Section 1.1 of the main text describes five categories of pollution that we analyze. We do not focus on a possible sixth category, disinfectants, for several reasons. Disinfectants do not have maximum contaminant level health standards, but instead Maximum Residual Disinfectant Levels (MRDLs). Additionally, disinfectants rarely exceed MRDLs. Most health concerns focus on disinfection byproducts, which we measure separately, and microorganisms, a pollutant that disinfectants decrease, rather than disinfectants themselves. Finally, we have relatively few observations on disinfectants.

Section 2.1 of the main text describes reasons for the summary statistics we do and do not analyze; here we mention a few others. For many pollutants, the share of readings above standards focuses on the margin where pollution is believed to affect health. It is also less sensitive to whether a reading is coded as zero or at the minimum detection level, and thus also less sensitive to changes in minimum detection levels over time and space. It relies on

[1] Water systems, especially small systems, regularly open and close. Our entire sample has 171,000 public water systems, but only about 150,000 are active in a given year

a binary classification that can miss inframarginal changes, however, and is undefined for pollutants without health standards. Standardized values allow interpretation in terms of common units (standard deviations$\times$100) and cover pollutants without health standards, though do not directly account for the large share of zeros, and may not focus on the most health-relevant part of the pollution distribution. Bins can reveal nonlinear patterns and suggest strategic changes in pollution. We focus on these statistics rather than the log or inverse hyperbolic sine of pollution because a majority of pollution readings are zero, so taking the log of pollution would exclude most of the sample; and because the inverse hyperbolic sine is scale-dependent (Mullahy and Norton 2022).

The introduction of the main text notes limitations from analyzing federally-reported violations rather than pollution concentrations. It is also worth noting some of the information that violations data routinely record and that analysis of raw readings can miss. First, some pollutants have treatment technique rather than concentration requirements. For example, because it is prohibitively costly to test for each individual microorganism like *Cryptosporidium*, systems must expose water to disinfectants with a certain concentration and duration rather than meet a limit for *Cryptosporidium* concentrations (since *Cryptosporidium* is not routinely tested). Failure to use a required treatment technique might not produce elevated measured pollution concentrations but may still violate the SDWA. Second, some systems fail to record specific pollutants when the SDWA requires it. Such monitoring violations violate the SDWA, although they by definition do not produce elevated pollution readings. Monitoring violations could in principle be inferred from raw pollution concentrations data by using information on timing, frequency, and requirements of monitoring. Of course, analysts can always use the monitoring violations data from SDWIS in conjunction with the sampling data, as we do in a sensitivity analysis.

Appendix Figure 1 shows groups of drinking water pollutants which we define. Here we list the main types of pollutants for two of the groupings that require some judgment to construct. "General quality" includes variations of the following: acidity; additional chemicals; aggressive index; alkalinity; calcium carbonate; carbon; chemical oxygen demand; conductivity; corrosion; counting errors; digestion; field parameters; filtration; flow; hardness; Langelier index; minerals; nitric acid; oxidation reduction potential; ozone; pH; plant material; pumping level; quality assurance; run time; saturation; scale forming; sodium; specific conductance; specific ultraviolet absorbance; stability index; temperature; and water depth. "Part of regulated" includes variations of the following: alachlor; alpha emitters; beta emitters; bromoacetic acid; bromodichloromethane; bromoform; chloroacetic acid; chloroform; chromium-6; coliform; radium 226; radium 228; coliphage; cryptosporidium; dibromoacetic acid; dibromochloromethane; dichloroacetic acid; disinfectant residuals; E. coli; enterococcus; fecal coliforms; giardia; heterotrophic plate count; lead/copper; nitrate/nitrite; PCBs; pesticides; LT2ESWtR; radon; sediment; secondary organic chemicals; total organic carbon; total metals; trichloroacetic acid; tritium; turbidity; uranium; virus inactivation; and VOCs.

A.3 Safe Drinking Water Act Policies and Pollutants

Safe Drinking Water Act Rules and Other Policies

Our measure of which readings exceed health standards primarily examines maximum contaminant level (MCL) standards, with some exceptions. Lead and copper have "action levels" based on feasibility, rather than MCLs based on health (Pupovac 2016). Regulations for microorganisms, lead, and copper provide a binary indicator for whether more than a specified percent of readings exceed a standard, which we formalize by measuring the continuous share of readings exceeding the standard. The Safe Drinking Water Act also describes Maximum Contaminant Goals (MCLGs), which are not a standard and which we do not analyze. MCLGs are the level of pollution below which regulators expect no health risk, allowing for a margin of safety. MCLs are near MCLGs, but also consider costs and available treatment technology. While we refer to MCLs as health standards, we note that they reflect these cost and feasibility considerations in addition to health objectives.

The EPA also implements other rules and policies under the Safe Drinking Water Act. In the period we study, these rules largely do not change the numerical standard for most pollutants, but instead change monitoring or treatment requirements, or change the systems that a rule covers (USEPA 2023*d*).

Several rules target pathogens. Surface water treatment rules, which apply to systems using surface water or groundwater under the direct influence of surface water, increase filtration and disinfection requirements in order to treat pathogens including *Legionella*, *Giardia lamblia*, and *Cryptosporidium*. The 1989 Surface Water Treatment Rule requires surface water systems to filter and disinfect water, and set health standards for viruses, bacteria, and *Giardia lamblia*. It also set treatment technique requirements. The 1998 Interim Enhanced Surface Water Treatment Rule applied to surface water systems with a service population over 10,000. It set a treatment technique requirement for systems using filtration, required watershed protection for systems without filtration, increased filtration requirements, and required covers on new finished water reservoirs. The 2002 Long Term 1 Enhanced Surface Water Treatment Rule set similar requirements but for smaller systems. The Long Term 2 Enhanced Surface Water Treatment Rule added *Cryptosporidium* treatment requirements to some systems at high risk. The 2006 Ground Water Rule also targeted microorganisms. For systems using groundwater, it required additional monitoring for systems with positive total coliforms readings, and additional monitoring to ensure that installed treatment technology could remove almost all viruses.

Separate rules target total coliforms. The 1990 Total Coliform Rule set a health standard for total coliforms, which also applies to readings of fecal coliforms or *E. coli*. Positive samples require additional testing and can result in a boil water notice. The Total Coliform rule also increased monitoring requirements. The Revised Total Coliform Rule, which became effective in 2016, set a health standard for *E. coli*, imposed a treatment technique requirement for total coliform, and expanded requirements for non-community water systems. These rules set a standard that no more than 5 percent of total coliform readings can exceed zero for an individual reading. For an individual reading, we interpret this rule as a health standard of zero. The 2016 Revised Total Coliform Rule changed several monitoring requirements—systems detecting a positive total coliform reading had to complete repeated *E. coli* readings within 24 hours; it allowed small systems using groundwater and serving $\leq$ 1,000 people to monitor less frequently if they met water quality and violation criteria; it required systems serving $\leq 4,100$ people to collect somewhat fewer additional total coliform readings in the month after a positive reading; and it modified monitoring for seasonal systems that only operate during part of the year (Federal Register 2013). Panel C of Appendix Figure 3 shows an increase in microorganism readings after the Revised Total Coliform Rule takes effect in 2016, which could be related to these requirements.

Other rules regulate disinfectants and disinfection byproducts. The 1998 Stage 1 Disinfectants and Disinfection Byproducts rule applies to systems that use disinfectants. It increased monitoring requirements for TTHM and HAA5. The Stage 2 Disinfectants and Disinfection Byproducts Rule applied the health standard to each monitoring site in a distribution system, and targets monitoring to where high levels of these pollutants are likely to occur.

A few rules regulate other chemicals. The 2001 Arsenic Rule tightened the health standard for arsenic and increased monitoring requirements. This built on Phase II through Phase V rules implemented in the early 1990s that regulated additional organic and inorganic chemicals. The 1991 Lead and Copper Rule requires monitoring for lead and copper, and then mandates information and treatment actions if high lead concentrations are detected. The EPA added modest revisions to the rule in 2000, 2004, and 2007, and then required more stringent monitoring, remediation, and expansive service line replacements in 2021 and 2024. Finally, the year 2000 Radionuclides Rule increased radionuclides monitoring requirements and regulated uranium.

Congress passed several complementary acts during our sample period. Some targeted lead in drinking water, including the 2011 Reduction of Lead in Drinking Water Act and the Community Fire Safety Act of 2013. The Drinking Water Protection Act of 2015 focused on algal toxins. The National Defense Authorization Act of 2019 provided funding for the monitoring of PFAS and other emerging contaminants. Finally, a few policies provided funding for technical and infrastructure improvements targeted mainly at small and disadvantaged communities, including the Grassroots Rural and Small Community Water Systems Assistance Act of 2015, Water Infrastructure Improvements for the Nation Act of 2016, and America's Water Infrastructure Act of 2018 (Congressional Research Service 2021).

The SDWA's Public Testing Rule requires all public water systems to notify customers of violations. Research finds that these notifications increase bottled water expenditures, which represent one form of avoidance investment (Graff Zivin, Neidell and Schlenker 2011; Marcus 2022). The timing of required notifications varies by pollutant and violation type. For example, detecting *E. coli* or violating health standards for nitrate requires notification within 24 hours, exceeding health standards for disinfection byproducts requires notification within 30 days, and failure to monitor certain pollutants requires notification within a year (USEPA 2009*b*). To the extent that these notifications increase avoidance investments (e.g., bottled water consumption) and thereby decrease direct health impacts, we might expect more such avoidance responses for pollutants that require notification within a day, like microorganisms and nitrate violations, than for other pollutants that do not require notifications within a day.

Some rules mandate minimum monitoring frequencies for pollutants, which can depend on system characteristics. USEPA (2023*e*) and USEPA (2023*h*) summarize many requirements.

For example, the required number of total coliform, lead, and copper readings increases with system population served; required arsenic readings depend whether water is sourced from a surface or ground water source; and the required number of disinfection byproduct readings depends on system population served, number of treatment plants, number of entry points into the distribution system, and whether surface or ground water supplies the system.

In addition to loans, standards, and rules, the Safe Drinking Water Act regulates pollution around some water sources, including wells drilled for injecting fluids underground, and the SDWA restricts development around drinking water source aquifers. Loans can support investments for source water protection (USEPA 2023*i*). Apart from loans, the SDWA leaves funding and enforcement largely to states (Tiemann 2018; USEPA 2022*b*).

Safe Drinking Water Loans

Receiving a Safe Drinking Water Loan requires a standardized application process which differs by state. Several states have attempted to streamline this process. For example, Colorado in 2012 decreased the major steps required for loan receipt from 14 to 10, and Pennsylvania's switch to a fully digital application process allowed loan funding within 6 months (USEPA 2022*a*).

While the details of receiving a Safe Drinking Water Loan differs across states, a typical process is as follows. A water system submits an application to the state loan coordinator providing details on the system, community, need for improvement, costs, and schedule. State staff score and rank proposals for annual "Project Priority Lists." States have flexibility in developing scoring criteria, as long as projects fit within the broader goals of the SDWA to protect public health. Some common criteria listed by states include protecting public health, addressing water supply and conservation issues, mitigating infrastructure and safety hazards, and addressing water security concerns. Other criteria for ranking can include whether a project is "ready to proceed." Some states release and discuss project priority lists in public meetings. States send a document (an "Intended Use Plan") to the EPA describing anticipated use of federal loan funds, including this priority list. That document provides the federal justification for a state to receive its annual loan resources. States typically exhaust resources available that year from the loan pool to fund highly scored projects (Florida Department of Environmental Protection 2023; Minnesota Department of Health 2023; Vermont Agency of Natural Resources 2023).[2]

While a small minority of loans are related to disasters, most loan funds address medium- to long-run, chronic drinking water concerns. Some states do set aside a small share of SDWA loan funds to help water systems prepare for natural and human-caused disasters (USEPA 2021). Other loans help communities improve or rebuild water systems in years after such disasters. We are not aware of emergency use of SDWA loans as a short-term response to disasters; the Federal Emergency Management Agency rather than SDWA primarily addresses such needs. The SDWA does have investments under Section 1442(b), separate from the loans we study, which provide technical assistance and grants in response to emergencies (Humphreys 2021).

[2]We spent considerable effort collecting these priority lists but were able to obtain priority lists for less than 1% of the relevant population.

We can also compare the loans data in our primary analysis to microdata from the Census of Governments to describe relative investment sizes. Conducted in years ending in 2 and 7, the Census of Governments obtains essentially a balance sheet from every state government, local government, and special district in the U.S. The Census of Governments includes a field where governments report total spending for water capital investment. We compare these values against the water loan microdata.

This comparison shows that drinking water loans fund relatively large projects, though for a small minority of systems. In 2012, 10,600 governments reported strictly positive water investment, but only 753 public water systems received SDWA loans, a ratio of 7 percent. In 2017, this ratio was 8 percent. We interpret this as an upper bound on the proportion of the governments which make water investments that receive SDWA loans, since some public water systems represent apartment complexes, schools, or other non-government entities, and hence do not appear in the Census of Governments.

Appendix Figure 7 shows the distributions of all governments' capital spending on water and of the value of SDWA loans, separately for 2012 and 2017. Loans fund relatively large investments, although the support of government spending and loans is similar. For example, in 2017, the mean loan amount was $5.2 million (2024 dollars) and the mean government with water investment spent $2.6 million. The comparison is similar in the year 2012.

Within a drinking water system and time period, loans could decrease pollution pre- and post-treatment. Loans could affect pollution before water reaches a treatment plant by investing in source water protection, closing some intake facilities, or adding others (e.g., closing a well where intake pollution concentrations are high or opening one where they are not), or otherwise changing the water source used. Loans can affect pollution during or after water reaches a treatment plant by improving treatment, distribution, or other infrastructure components. We report one sensitivity analysis using only pre-treatment data.

Pollutants

The Safe Drinking Water Act has health standards for 88 to 97 pollutants. The National Primary Drinking Water Regulations (USEPA 2009*a*) list 88 contaminants. The total ranges up to 97 because three are groups—HAA5 equals the total of five haloacetic acids, TTHM equals the total of four trihalomethanes, and Radium 226+228 combines two. In addition, the SDWA groups fecal coliforms and *E. coli* together as one contaminant.

We exclude several pollutants from most analysis. We exclude fecal coliforms and *E. coli*, since they are primarily monitored when readings detect total coliforms (USEPA 2013*a*,*b*), which makes their data systematically unrepresentative (i.e., many of the *E. coli* readings are non-missing only because the system detected total coliforms). We also do not analyze several regulated pollutants – acrylamide, *Cryptosporidium*, epichlorohydrin, enteric viruses, heterotrophic bacteria, *Legionella*, mercury, trichloroethylene, or enteric viruses – since we have little or no data for them, and in several cases regulations stipulate a treatment technique rather than a maximum contaminant level or action level. We also do not analyze gross beta. Since most data record gross beta in pCi/L, but the MCL is in mrem/year. Converting between these units requires data on the underlying emitters, which we do not typically have.

Several parts of the main text analyze unregulated pollutants. This set of unregulated pollutants excludes components of TTHM, HAA5, and radium 226+228 measured individually, since they do not have regulations as individual pollutants but they are part of broader groups that do have health standards. Our analysis of unregulated pollutants also excludes broader groups that include a regulated pollutant and others.

All but 8 states report "total coliforms," an important pollutant, as a binary presence indicator. Therefore, we transform all "total coliforms" to match. Data scraped from some websites report a small number of total coliform readings which data managers rejected. We exclude these observations from the analysis sample.

We clean names of pollutants using chemical synonyms and names following the nomenclature of the International Union of Pure and Applied Chemistry (IUPAC), a standardized naming system for organic and inorganic compounds, listed at the National Library of Medicine National Center for Biotechnology Information (NIH 2023). For example, ethylene dibromide is sometimes listed as 1,2-Dibromoethane, but the two names refer to the same chemical. We assign chemical groupings for unregulated pollutants based on a list of known drinking water disinfectants (WA DOH 2004), a list of 622 disinfectant by-products from EPA's CompTox dashboard (Richardson 2019), and a chemical's molecular formula.

States can regulate more pollutants than the EPA, and epidemiological research suggests health damages from several pollutants that the SDWA does not regulate. Additionally, the EPA has a Contaminant Consideration List of pollutants it seeks to understand better and may consider regulating in the future. Some states monitor some of these pollutants, though they are not yet federally regulated. For example, per- and polyfluoroalkyl substances (PFAS) ("forever chemicals") occur in many communities' drinking water systems. The EPA in 2024 regulated PFAS in drinking water, though in 2025 substantially deferred enforcement of this regulation. To understand state-specific drinking water regulations, we gather information on drinking water standards that individual states enforce. We obtain this information from state government documents, including state codes and regulations, annual compliance reports, and governmental websites. In practice, a limited number of states regulate additional pollutants, particularly California, Michigan, New Jersey and New York. Aldicarb and nickel most often have state regulations, and were previously covered by federal regulations until 1992 and 1995, respectively (USEPA 2023*c*). More states have regulated per- and polyfluorinated substances (PFAS) in recent years. Of 82 million individual pollution readings of pollutants in our micro data that lack federal regulations, 8% have state-enforced health standards.

This paper analyzes the SDWA, but the pollutants it focuses on differ somewhat from the pollutants that the Clean Water Act focuses on. For example, one of the most important measures of water quality in rivers and lakes for the Clean Water Act is dissolved oxygen. Oxygen is rarely measured in drinking water. The difference is partly because the Clean Water Act emphasizes protection of fish and other aquatic life, while the SDWA focuses more directly on protecting human health.

B Data: Details

B.1 Drinking Water Data

Our drinking water data sources vary by state. For 23 states, we gather data via Freedom of Information Act or related requests, direct requests to government staff, or similar; and for 25 states through web scraping or downloading.[3] We define the different states' data to have the same variable definitions and database structure. After this cleaning, the scraped and non-scraped data are reasonably comparable, though have some remaining differences. For example, the scraped data typically include only systems that are currently active, whereas the open request data typically include systems that are currently inactive but were active during part of our analysis years. SDWIS does identify years when systems are active.

Not all jurisdictions have data available on all pollutants and systems. For example, Panel A of Appendix Figure 2 shows that in addition to Arkansas and South Dakota (and Washington, DC), we lack data from Tennessee and Minnesota on disinfection byproducts. Panel C shows that we lack data on total coliforms for six states: California, Hawaii, Massachusetts, New Hampshire, Nevada, and Tennessee. Additionally, Alabama, which reports both pre- and post-treatment coliform readings, and Nebraska, which has separate coliform filtration, treatment, and monitoring requirements for systems served by ground versus surface water, are excluded from our sample. In Minnesota, the total number of coliform readings drops from around 85,000 per year to 15,000 per year in 2017, so we only analyze coliform data in Minnesota prior to 2016. Most states provide information on all types of water systems, but for six states – Illinois, Maine, Michigan, New Jersey, Rhode Island, and West Virginia – we lack information on non-community water systems. Some states have partial-year data for certain types of pollutants in the year 2019, and we exclude these pollutant×state×year cells from the main analysis sample.

The drinking water sample size grows somewhat steadily in most years, due to population growth and expanding investment in treatment and monitoring (Appendix Figure 8). For several states, the available data ends partway through 2019 (Appendix Table 1). Due to the incomplete drinking water data sample for that year, we report sensitivity analyses that exclude pollution readings from 2019.

Our analysis sample imposes several sample selection rules. We exclude pollution readings that are negative, which are rare. To exclude additional readings completed after a high initial reading, our main analysis excludes readings identified as special purpose, repeat, or untreated. Additionally, our main sample excludes readings identified as raw (i.e., untreated), which reflect pollution in the source water rather than the treated water that households drink. In analyzing unregulated pollutants, we exclude general water pollution measures such as alkalinity, hardness, temperature, and flow rate, where the relationship to health may not be monotone. We also exclude chemicals with less than 1,000 observations each nationally.

For a few states, we obtained drinking water data both through a FOIA request and from scraping data on the internet. Correspondence with state administrators indicates that they

[3] We scrape or otherwise download data for Alabama, Alaska, California, Colorado, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Missouri, Montana, Mississippi, North Carolina, Nebraska, New Mexico, Ohio, Oklahoma, South Carolina, Wisconsin, and Wyoming.

fulfilled some FOIA requests by compiling information posted on associated websites (e.g., Drinking Water Watch). We do not expect the data collection type (FOIA request versus web scraping) to be the dominant driver of differences between states' data.

Nebraska is one state where we have data from both a FOIA and web scraping, and where the FOIA data has different format than the scraped data. Nebraska's data can therefore provide source of information about potential differences between data from FOIA versus web scraping. One possibility is that FOIA and web-scraped data have different patterns of updating or review. We find no evidence of this possibility in the Nebraska data, as results for a system×pollutant×day are numerically equivalent between the FOIA and the web-scraped data in more than 99.9% of observations. A second possibility is that states may switch from paper to electronic readings at some point. If values of zero have different systematic patterns of recording in electronic versus paper records, this switch could produce a time-series discontinuity in the share of readings that are zero. We examine the share of zeros over time within each system×pollutant, and observe no discontinuous shifts. A third possibility is that FOIA and web-scraped data cover different sets of systems. Because our FOIA request to Nebraska covered only Community Water Systems but the scraped data cover all system types, Nebraska's scraped data do cover substantially more systems than the FOIA data, though the additional systems in the scraped data are essentially all non-Community Water Systems.

These drinking water microdata provide a potentially valuable resource alongside the federally-reported violations data. For example, many scholars use air pollution microdata, not only binary air pollution violations like nonattainment designations. The monitoring microdata record inframarginal changes in pollution for systems that remain above or that remain below federal standards. Additionally, the monitoring microdata provide records of around 1,170 unregulated pollutants. Because the microdata record nearly the full distribution of values whereas the federally-reported violations data record certain moments of these values,[4] the microdata can provide additional ways to understand settings where governments may engage in strategic behaviors like oversampling coliforms (Bennear, Jessoe and Olmstead 2009).

Minimum Detection Limits

Drinking water analysis uses two concepts to describe the lowest pollution levels a lab can accurately measure—the minimum reporting level (MRL) and the method detection level (MDL). Informally, the MRL represents the lowest concentration at which a laboratory can accurately report the concentration, while the MDL represents the lowest concentration at which a laboratory can accurately distinguish a reading from zero.

Formally, the MDL represents the smallest concentration of a pollutant that can be reliably distinguished from blank samples with 99% confidence (USEPA 2016). The MDL is a laboratory-specific value influenced by the measurement method, the instrumentation used, and the expertise of the lab technician. The MRL equals the minimum concentration at which a pollutant can be reported with confidence as a quantitative value. The MRL is sometimes derived from the MDL. For instance, some laboratories use measurement methods

[4]We say "nearly" the full distribution partly because many systems for coliforms record the share of readings that are positive, but do not always record the exact values of each positive reading.

that define the MRL as three or five times the MDL, and regardless the MRL generally exceeds the MDL. Analysts can use the MDL and MRL to learn about the accuracy of a reading. When a pollutant reading exceeds the MRL, analysts typically conclude that the measurement is accurate and precise.

If a reading falls between the MDL and the MRL, it means the concentration of the pollutant lies within this range, but the exact value may be less accurate. The MDL and MRL can vary across pollutants due to differences in measurement methods, and they can change over time with measurement techniques and lab expertise.

For some radionuclides, California reports the Minimum Detectable Activity (MDA) at 95% confidence as a separate observation. Radioactive materials require different measurement methods, as radionuclides are unstable and emit radiation. When calculating the MDA, a lab measures radiation in order to detect and quantify the presence of radioactive materials. The MDA depends on the instrument and technique used for analysis (Department of Energy Office of Health, Safety, and Security 2008).[5] In all states, radionuclides are measured based on their radioactivity. USEPA (2023*a*) provides more information on approved measurement methods for radionuclides and other pollutants.

All states report a "detection limit" for each observation and some report the "level type" indicating if the reported detection limit is the MRL or MDL. We match MDA observations from California with actual readings by system×sample location×pollutant×date, if we have one matching MDA reading. For example, we give a radium reading an MDA value if California also reports a "radiumMDA95" reading with the same system, sample point location, and date. We treat all reported results less than the MRL (or MDL if MRL is not available) as zero and construct a Below Detectable Limit indicator to identify them. In our sample, 560 unregulated pollutants are always non-detects, and 233 unregulated pollutants are always reported at a detectable level. No regulated pollutants are always, or never, below detectable level. We do not examine detection limits for coliforms, and do not undertake sensitivity analyses of detection limits for coliforms, because coliform readings and detection limits are often in non-comparable units (readings are often reported as the share of readings in a system×month or ×year that are non-zero, while limits are reported as the minimum possible value that can be rejected as non-zero).

The raw drinking water data uses various different units. We scale all results possible to the MCL unit of measurement. For unregulated pollutants, we scale results to the modal unit. For analysis of aggregated data (e.g., system×year), we impute the MCL unit of measurement or modal unit for observations with missing units. This imputation assumes that readings with missing units match MCL units. This assumption is relatively unimportant for our analysis of the share of readings exceeding health standards since nearly all (>99%) readings with missing units are below detectable level. Finally, we exclude readings measured in non-comparable units, which represent less than 1% of readings from pollutants we analyze.

The EPA's Total Coliform Rule mandates monthly testing for public water systems. At the same time, some states have incomplete coliform data. To address this gap, our baseline analysis abstracts from deliberate non-reporting, and assigns a zero reading for

[5] The MDA equals $L_D/(Y \cdot \epsilon \cdot T)$, where Y is the radiation yield, ϵ is the detection efficiency of the instruments (determined before analysis), T is the counting time per sample, and L_D is the limit of detection. The term L_D is an analog of MDL for radionuclides, and is a function of the baseline level of radiation a detector picks up from its surroundings (Knoll 2010, Department of Defense 2000)

system×months lacking coliform data. The Revised Total Coliform Rule, implemented in 2016, let systems using ground water and serving less than 1,000 people monitor less often. We do not impute readings for these system×years. To account for potential changes in reporting behavior due to the Revised Total Coliform Rule, Appendix Tables 9 and 13 report estimates that treat coliform readings under these rules as different pollutants.

Only 0.7% of readings list a detection limit that is not in comparable units to or exceeds health standards. This is important because it implies that when pollution concentrations exceed standards, lab detection thresholds are sufficient to detect the exceedance. EPA typically requires detection limits to fall below health standards (USEPA 1999), although this may not be universally enforced. Most of the 0.7% fall into two categories—readings where the detection limit has missing units or units that cannot be scaled to comparable units for health standards; or organic chemicals with low health standards that report a detection limit slightly above standards. Two organic chemicals with low health standards (1,2-dibromo-3-chloropropane and ethylene dibromide, with health standards of 0.0002 and 0.00005 mg/l, respectively), account for more than 70% of readings with a detection limit that exceeds health standards.

We scale detection limits to comparable units, similar to pollution readings. Disinfection byproducts have a disproportionate number of pollution readings with missing detection limit units. To address this, we take advantage of the fact that over 99.9% of disinfection byproduct pollutant readings are measured using "mg/l" or "ug/l," two units with different orders of magnitude. We calculate the 99.5th percentile of all observations with a non-missing detection limit measured in "mg/l," and impute "mg/l" as the detection limit unit for all observations with a detection limit below this threshold, and "ug/l" otherwise.

Other Drinking Water Data Cleaning

We also use several other data cleaning rules. We winsorize pollution readings at the 99.5th percentile or two times the health standard, whichever is greater, z-scores at +/− 10, and detection limits at the 99.5th percentile. Although we define the mean and standard deviation for calculating z-scores across systems and within pollutants (using data at the system×pollutant level in the full sample), standardized means in most tables do not exactly equal zero due to weighting and analysis of sub-samples. Some zeros reflect a true reading of zero, while others reflect a non-zero reading below a monitor's minimum accurately detectable level. For comparability, we treat all these values as zero.

In most of the unprocessed data, one observation represents a single pollution reading. As we noted earlier, some total coliform readings are recorded as the number of readings in a month that did not detect total coliforms. We interpret these multiple total coliform readings in a system×month as effectively separate observations.

Appendix Table 2a, columns (5) through (9), describes the five categories of pollution. Organic chemicals have the second-largest sample but exceed standards the least. Reasons for the low levels of organic chemicals are unclear and could include that treatment of these chemicals has been effective; standards are set at somewhat high levels, making violations rare; and these chemicals may only reach high levels for a few systems. Radionuclides have the least data.

Appendix Table 2b summarizes data on six important individual pollutants. Among these, we have the most data on total coliforms. Arsenic is the most likely to violate standards, followed by uranium and TTHM.

Appendix Figure 9 shows histograms describing the distributions of six pollutants. Our data on total coliforms report binary measurements (any concentration detected versus none). The other pollutants have skewed distributions, with over half of readings at or near zero.

B.2 Other Data

We use a few additional data sources beyond those discussed in the main text. We use the EPA's Safe Drinking Water Information System to identify a public water system's population served and other basic characteristics. Appendix Table 15 correlates loans with air and water pollution data, using air pollution data from the EPA's Air Quality System (USEPA 2020) and water pollution data from the Water Quality Portal (National Water Quality Monitoring Council 2025). A few results compare against the share of population that has piped (rather than well) water, from Murray et al. (2021).

We estimate some results that use population weights, especially for health. In Medicare data, we observe the number of Medicare beneficiaries whose 9-digit zip code is within the service territory of each water system that has EPIC maps. We use these Medicare population data as the relevant weight in Medicare estimates. In the final analysis sample of the Medicare data, the median (water system $\times$ cohort year $\times$ calendar year $\times$ single year of age bin) cell has five Medicare beneficiaries, and 56.8% of these cells have zero deaths, which is one reason we analyze mortality rates in levels rather than logs. In county$\times$year health estimates, we use either the county population from the population census or the number of births in a county$\times$year as reported in our administrative birth data. SDWIS also reports an estimate of population for essentially all water systems in our data, which may have measurement error though may also be relevant to population-based Safe Drinking Act requirements like monitoring frequency. For the subset of systems with EPIC Tier 1 and Tier 2 maps, we estimate population by summing the population from each Census block within a system's service territory, as reported in the 2010 Population Census. A regression of this Census-based measure of population on the SDWIS measure of population in logs with robust standard errors obtains a coefficient of 0.976 (0.004). Given this relationship, for the fewer pollution estimates that weight by population, we use the SDWIS population values since these are available for all systems, and not only for systems with EPIC maps.

Appendix Table 7 combines several datasets in order to correlate drinking water pollution with its source causes. Column (1) uses our drinking water microdata, and averages mean total organic carbon in mg/L within each county, pooling years 2003-2019. Disinfection byproducts form when disinfectants like chlorine interact with organic carbon material in source waters. Columns (2) and (7) use data from the Mineral Resources Data System of the U.S. Geological Survey on whether the primary minerals in any mineral property in a given county include arsenic or uranium. Column (3) uses state data on the log number of lead service lines per 100,000 population, compiled by the Natural Resources Defense Council (NRDC). Column (4) uses estimates of the log pounds of nitrogen from fertilizer and manure in each county in the year 2012, from the U.S. Department of Agriculture, divided by county area, which are likely to affect nitrate in drinking water. Column (5) includes an indicator for whether the county has a plant in the Toxic Inventory that releases regulated toxic chemicals to water. Column (6) measures the log of the total kilograms of regulated pesticides used in a county in the year 2010, retrieved from the US Geological Survey Pesticide National Synthesis project, divided by county area. We average the high and low pesticide estimates.

B.3 SimpleLab/EPIC Data

We utilize Water System Service Boundaries data developed by SimpleLab and EPIC (2022). These data map water system boundaries for U.S. community water systems. They describe three "Tiers" of descending match quality. Tier 1 systems have explicit water system boundaries from electronic maps (shapefiles) that states provided. For Tier 2 systems, a matching algorithm identifies a system one-to-one with an electronic map from the Census Bureau describing a town or city boundary. Tier 3 systems utilize the best available system centroid and draw a circle around the centroid using a statistical model trained on Tier 1 systems to estimate the radius. Our main analysis excludes Tier 3 systems due to their less accurate territory map, though sensitivity analyses include them.

We identify approximately 99,000 recently-active SDWIS systems not covered by the SimpleLab/EPIC data, including about 1,000 community water systems. Out of these missing community water systems, 88 do not have a listed centroid in the EPA's Enforcement and Compliance History Online (ECHO) data, the primary source of facility information used by SimpleLab/EPIC. Among them, 685 system centroids are based on the state, county, place, or zip code. These numbers may include centroids that were not available when the SimpleLab/EPIC dataset was constructed, since ECHO is regularly updated. Community water systems may also be absent if they serve fewer than 25 people or have fewer than 15 service connections. The relative lack of piped-water coverage in the mid-Atlantic and South shown in Figure 1B partially reflects Tier 3 systems. For example, Tier 1 and 2 account for only 26% of SDWIS community water systems in Louisiana, but all tiers cover 86%. Additionally, these areas may have less accurate estimates of private well prevalence (Murray et al. 2021), or systems with low-quality centroids may be unable to be matched due to multiple 'counties', 'cities', and 'places' with similar names in the same state.

Because we combine shapefiles of water system service territories (EPIC's "Tier 1") for states where they are available and estimates of those territories based on municipal boundaries (EPIC's "Tier 2") for states without service territory shapefiles, we sought to compare the accuracy of the two methods. For the states with water system shapefiles, we defined system service territories based on municipal boundaries. We then assigned Census Blocks to water systems based the two different methods. In other words, for each Block, we assigned a water system once using the service territory shapefile; and then a second time based on linking the system name to municipal boundaries. This comparison found that the two methods (using reported service territories versus linking systems to municipal boundaries) produce extremely similar results, and assign Census Blocks to the same water system in the vast majority of cases.

The EPIC service territory maps have good though not perfect coverage and accuracy. EPIC's Tier 1 systems, which have service territory maps that provide the highest spatial accuracy, serve the largest share of community water system customers nationally. Thirty-five states plus Washington, DC, have Tier 1 maps covering a nontrivial share of community water system customers. This is a greater number of states than the 24 states that McDonald et al. (2022) identify as having maps. Tiers 1 and 2 together comprise a majority of community water system customers in all states except Alaska, Delaware, Hawaii, Maine, and Nebraska.

B.4 Spatially Linking Water Systems to Other Data

We link drinking water service territories to other datasets in two steps. First, we link Census Blocks and water systems. We obtain the latitude and longitude of the centroid of each Census Block from the Census Bureau, via the National Historical Geographic Information System (NHGIS). Using the water system service territory maps, we link each of these Census Block centroids with the water system(s) serving that Census Block.

Second, we obtain Medicare data at the 9-digit zip code (ZIP+4) level and aggregate it to the level of a public water system. We gather information on the coordinates of 9-digit zip code centroids from Zip-Codes.com (2015) and GeoLytics, Inc. (2016). We then overlay these centroids on shapefiles of public water systems from EPIC. Our main results only consider Tier 1 or 2 shapefiles. If a zip code centroid is within multiple public water systems, we first keep only Tier 1 shapefiles, then match the 9-digit zip code to the system with centroid nearest to its own. If the distance is the same, we exclude the 9-digit zip code to maximize accuracy. Finally, if the 9-digit zip code centroid exists in both sources but the sources match to different public water systems, we keep the match from zipcodes.com due to its larger coverage and more recent year.

B.5 County×Year Controls

We obtain county×year control variables from many sources. Because some of these records have missing data for a small number of observations, we recode these missing values to zero and include a flag for missing values.

We include several variables relevant to other environmental policies and damages. Safe Drinking Water loans and Clean Water Act loans are separate and affect different plants (wastewater treatment versus drinking water plants). We collect data on Clean Water Act loans by county. We filed a Freedom of Information Act request to the EPA to obtain records of each loan provided for wastewater treatment as part of the Clean Water State Revolving Fund (USEPA 2019*a*), which in 1987 succeeded the Clean Water construction grants program analyzed in Keiser and Shapiro (2019*b*). In these data, 99% of counties have zero or one loan, so we specify an indicator for ever having received at least one Clean Water Act loan. We use the EPA's Green Book (USEPA 2019*b*) to define whether each county is in Clean Air Act nonattainment status for ozone or particulate matter in each year. We define partial, whole, and all levels (moderate, severe, extreme, etc.) of nonattainment as equivalent. In each county×year, we include a control for the number of active Toxic Release Inventory (TRI) plants, measured from USEPA (2019*c*). We use the number of plants, rather than reported emissions, given challenges with accurate TRI reporting (Currie et al. 2015).

We use weather from the daily Global Historical Climatology Network (GHCNd) (National Centers for Environmental Information 2023). We calculate temperature and precipitation for each county×day as the inverse distance-weighted average of all monitors within a

20-mile radius of the county centroid. To account for missing observations, we only consider counties with at least 3 non-missing values in each month of the year. We define and control for temperature and precipitation bins spanning the support of these variables aggregated to the county×year level. For example, one bin counts the number of observations in a county×year that have mean daily temperature (defined as the mean of the daily maximum and minimum) between 60 and 70 F; a second bin counts the number of observations with mean daily temperature between 70 and 80 F; etc.

We also include several economic controls. We control for personal income per capita from the Regional Economic Accounts of the BEA (2021), and we control for the local employment rate. Additionally, we control for federal spending per capita in each county×year (US Census Bureau 2021*b*; USASpending.gov 2025), which requires several steps to calculate. We obtain federal spending data for calendar years 2004-2008 from the Consolidated Federal Funds Report (CFFR), and for calendar years 2009-2020 from USAspending. We separate the CFFR reports for New York City into the five boroughs based on the share of federal spending across boroughs in USAspending. Both series report for the year 2009, and we splice all years of CFFR by the same proportion so that national reported spending in the two sources matches in 2009. We calculate values for calendar years as a weighted average of the corresponding fiscal years, which are what the raw data report. To enhance comparability between the two series, we combine CFFR reports from four categories: direct loans, direct pay not for individuals, grants, and guaranteed loans. From USAspending, we combine block grants, formula grants, project grants, cooperative agreements, direct payment for specified use, direct loans, or guaranteed/insured loans. Also in USAspending, we measure spending according to the amount of the federal government's obligation that each database entry represents.

We include a few health and demographic controls. From the Centers for Disease Control, we use data on the number of opioid prescriptions per 100 persons in each county×year (CDC 2025). We also use measures of the share of people who lack health insurance, from the Census Bureau's Small Area Health Insurance Estimates program (US Census Bureau 2021*a*). Finally, we control for mean age in each county×year, and the share of population aged 65 and over, using data from the National Cancer Institute (2025).

B.6 Health Data by Cause

We classify hospital admissions for chronic causes using lists of the International Classification of Disease (ICD10) diagnosis codes used in Medicare's Beneficiary Summary File chronic conditions flags. ICD10 diagnosis codes are similar but not identical to ICD10 cause of death codes; we believe no concordance exists between the two, partly because they lack a one-to-one, one-to-many, or other deterministic relationship. We also believe that no listing of "chronic" ICD10 cause of death files exists. To translate ICD10 chronic diagnosis codes to ICD10 chronic cause of death codes, we queried a large language model, ChatGPT-5 Thinking, "Attached is Stata code defining chronic ICD10 diagnosis codes, based on Medicare BSF chronic conditions. Please write a list (not code) of ICD10 cause of death codes that corresponds as closely to the attached diagnosis codes as possible" (OpenAI 2025). We manually checked the results for quality.

B.7 Average Water Bill

Industry estimates place the average monthly U.S. drinking water bill at approximately $50 per household (Bluefield Research 2025). This is consistent with recent academic evidence showing that, combining fixed and volumetric charges, the average household drinking water bill was $44 per month in 2023 (Teodoro and Thiele 2024). Using these sources to characterize current costs, we take a representative monthly household bill of $47. With an average household size of 2.6 persons, this implies an annual per-capita drinking water expenditure of approximately $215 (US Census Bureau 2023*b*).

C Results: Sensitivity and Additional Analyses

C.1 Trends

Appendix Table 9 shows sensitivity analyses for estimates of trends in drinking water pollution, corresponding to equation (1). Except where otherwise noted, the dependent variable is the share of readings in a system×pollutant×year that exceed health standards. Column (1) includes all regulated pollutants and weights equally across the five categories of pollution. Column (2) measures the standardized value (Z score times 100). Columns (3) through (7) show the five categories of regulated pollution, limited to pollutants with health standards. Columns (8) through (10) show three pollutants of particular interest—arsenic, lead, and nitrate. Column (11) shows standardized values for non-regulated pollutants.

The rows of Appendix Table 9 report various sensitivity analyses. Row 1 re-states the main estimates from Table 2, Panel A. In row 2, the dependent variable is the standardized value. Row 3 restricts the sample to only community water systems. Row 4 limits the analysis to system×pollutant pairs present in at least 12 years of the 2003-2019 window. Row 5 expands the sample to the period from 1992 to 2019. Row 6 weights each observation by the log population a drinking water system serves. Row 7 does not weight equally across the five different types of pollution. Row 8 excludes data from the year 2019, since that year has incomplete pollution records. Row 9 gives coliform readings under the Revised Total Coliform Rule a separate fixed effect than coliform readings under prior rules.

Rows 10–15 of Appendix Table 9 use the unaggregated data, so that an observation represents an individual reading of a specific pollutant, system, date, and time. Row 10 estimates the main results at this unit of observation. Row 11 adds untreated source water to the sample. Row 12 includes fixed effects for each system×pollutant×location within a drinking water system (e.g., some systems might monitor pollution at 20 different locations, and have a sample point identification code for each of the 20). Row 13 sets all observations with a flag for reading below the detectable level to have a reading equal to the detection limit. We omit the microorganism estimates for this specification since their health standard is effectively zero. Row 14 specifies the dependent variable as the log of the raw pollution reading. Row 15 specifies the dependent variable as an indicator for being strictly positive.

Rows 16–19 of Appendix Table 9 include additional controls and subsamples. Row 16 adds the county×year controls from Panel A of Appendix Table 5: Clean Water Act loans for wastewater treatment plants, Clean Air Act ozone and particulates nonattainment regulations, toxic pollution sources, local income and employment, opioid prevalence, health insurance coverage, per capita federal spending, temperature, precipitation, and age. Rows

17-18 restrict to systems in urban versus non-urban areas, and row 19 restricts to small systems (defined as serving $\leq$3,300 customers, following EPA's definition).

The majority of these Appendix Table 9 estimates show that regulated drinking water pollutants overall and individually are declining. The magnitudes are centered around the main estimates, though some specifications show larger or smaller trends. Row 4 finds larger trends in a semi-balanced panel, which could be because systems that monitor more extensively also invest more extensively to treat pollution. Row 7 shows that trends not weighted across pollutants are flatter, which in part occurs because organic chemicals have large samples and fairly flat trends. Rows 18–19 show that rural systems have steeper downward trends, though smaller systems generally do not.

Each panel of Appendix Figure 3 graphs trends for a separate type of pollutant. These pollutant-specific graphs generally trend downward, though with more variability than the pooled results from Figure 2. Disinfection byproducts, inorganic chemicals, and radionuclides have the most systematic downward trends. Microorganisms have a smaller downward trend, with a modest though statistically insignificant jump in 2017–2019, potentially related to the Revised Total Coliform Rule and limited data in 2019. Organic chemicals have the lowest level, echoing the descriptive pattern that few organic chemical readings exceed standards.

While our measurement of trends in drinking water pollution is new, since existing work carefully measures trends in mortality rates over this period (Curtin and Spencer 2021), we do not separately report national overall mortality trends here. Although the mean age of the U.S. population is rising, age-adjusted mortality declined steadily through 2010, then the trend slowed somewhat through 2019. Mortality rates in urban areas have declined somewhat faster than in rural areas. Our analysis exploits variation in loan timing within this period when overall mortality rates had flattened.

C.2 Effects of Safe Drinking Water Loans on Drinking Water Pollution

Appendix Table 13 shows sensitivity analyses of how Safe Drinking Water loans affect drinking water pollution. Each row describes a different specification; each column describes a different pollutant. Many of the rows echo sensitivity analyses from trends in Table 9. Row 1 repeats the main estimates from Table 3.

Rows 2–16 of Appendix Table 13 repeat estimates from the trends sensitivity analysis of Table 9, though add a specification that controls for SDWIS monitoring and reporting violations.

Rows 17–24 use additional specifications for analyzing loans. Row 17 adds the county$\times$year controls listed in Appendix Table 5, Panel A (Clean Air Act, Clean Water Act, etc.). In row 18, the independent variable measures only the first loan given to each system. Row 19 separately controls for the first, second, or third-or-more loans a system receives. Row 20 adds a control for the lagged dependent variable (i.e., pollution). Rows 21–23 consider three systems grouped by size: urban, rural, and small (defined as serving $\leq$3,300 customers, following EPA's definition).

The majority of the alternative estimates in Appendix Table 13 are in line with the main results, but we comment on a few interesting estimates. The estimates using a somewhat balanced panel are generally larger in absolute magnitude than the estimates with the full sample. The unweighted estimates are smaller, since they disproportionately represent organic chemicals, which are widely measured but rarely exceed health standards. Controlling for monitoring and reporting violations slightly increases estimates in absolute value. Separating coliform estimates by rule attenuates the coliform estimates, though as mentioned earlier, the recent coliform rules generally focus on chlorine-resistant microbes like *Legionella* but the coliform readings focus on total coliforms, which are less responsive to the reforms the recent rules target. We find no effect of loans on pollution in the pre-treatment surface or underground water sources that systems use, which is a weak falsification test (since systems in principle could change water sources). Logs and binary indicators have the same signs but variable magnitudes, and their precision varies across groups of pollutants. Adding the county×year and associated controls hardly changes estimates. Controlling for the lagged dependent variable obtains results that are typically similar to the main numbers, so estimates allowing for mean reversion in pollution still find large effects of loans on pollution. Estimates for lead vary in sign and significance. Rural and small systems have larger estimated treatment effects on some pollutants and on our measures overall than our baseline estimates for all systems, though we find smaller or less precise estimates for other pollutants like microorganisms.

One interesting finding in Appendix Table 13, row 19, is that additional loans to a system decrease some pollutants. Disinfection byproducts clearly decrease with additional loans. Microorganisms also decrease, though the relationship is less precise. Point estimates for inorganic chemicals, organic chemicals, radionuclides, and the specific chemicals we separate (arsenic, nitrate, and lead) have less clear evidence on impacts of loans beyond the first. Only 0.68% of systems receive two loans and 0.42% of systems receive three or more loans, so the sample sizes for studying multiple loans are limited.

Mechanisms for the effects of multiple loans in Appendix Table 13, row 19, may be complex. For surface water pollution investments, three projects that one system receives sometimes have the first fund create a facility plan, the second fund detailed engineering schematics, and the third fund construction (Keiser and Shapiro 2019*b*), though this may be less typical for drinking water investments. Another possible explanation is that Safe Drinking Water Act rules for disinfection byproducts and microorganisms have changed more than rules for some other categories of pollution (Appendix A.3), so the additional loans may seek to meet tighter goals for these groups of pollutants but have less clear effects for others. An additional possible story is that systems receiving two or more loans serve larger populations than systems receiving a single loan, and loans to larger population systems may benefit from returns to scale or differential treatment technologies. Because the stacked cohort research design we use for health examines the effect of the first loan a system receives, it does not distinguish effects of the first, second, or third loan.

We considered implementing matching or synthetic differences-in-differences versions of these estimates. The stacked cohort research design we use for health, and the high-dimensional fixed effects we use for pollution regressions, are not ideally suited to these approaches, so we do not implement them.

Appendix Figure 5 shows additional graphs analyzing how Safe Drinking Water loans affect pollution. Panel A reports results from a difference-in-difference estimator accommodating heterogeneous event timing (Gardner et al. 2024), which is one case of more general heterogeneous difference in difference estimators (Borusyak, Jaravel and Spiess 2024). We estimate standard errors using 200 bootstrap replications. Panel A also shows comparable two-way fixed effects estimates using the same sample and specification. The results with both the heterogeneous difference-in-difference estimate and two-way fixed effects are similar to those of the main text. The Gardner estimate has slightly flatter outcomes in the pre-period, and slightly larger impacts in the post-period, but the coefficients on each event study have overlapping confidence intervals between the two estimators.

Appendix Figure 5, Panel B, shows effects of loans on bins summarizing the distribution of regulated pollutants. We estimate versions of equation (3), but where the dependent variable measures the share of readings that fall in a given pollution bin (e.g., 175 to 200 percent of the health standard). This graph shows that loans especially decrease pollution above health standards. We find no statistically significant effects on the prevalence of readings below 75 percent of the health standard. Loans appear to decrease violations, but not to decrease pollution further below health standards.

We also evaluate the robustness of our main pollution estimates to potential violations of the parallel trends assumption. The event study graph in Figure 3 does not show substantial departures from parallel trends, though the pre-period outcomes do vary. Panel A of Appendix Figure 10 reports the smoothness restriction from Rambachan and Roth (2023), which evaluates how allowing bounded changes in the slope or curvature of potential outcomes between pre- and post-periods affects conclusions. The value for $M = 0$ on the horizontal axis represents a scenario where we assume that years after receiving a loan follow a linear extrapolation from observed outcomes in the years before receiving a loan. This linear extrapolation of pre-trends gives similar results to the original estimate, which is shown in the left-most part of the graph. The values for $M \geq 0.01$ show that allowing bounded deviations from a linear extrapolation of pre-trends yields only minor changes in inference. Only for $M = 0.05$ does the confidence interval include zero. Panel B shows the relative magnitude restriction from Rambachan and Roth (2023). This sensitivity analysis yields a breakdown value beyond $\overline{M} = 0.1$. Both panels indicate that our estimates are reasonably robust to this concern.

As an additional test of the identifying assumption (4), we regress an indicator for loan receipt on lags and leads of pollution:

$$1[\mathbb{L}_{sy} = 1] = \sum_{\tau=-9}^{\tau=9} \beta_\tau P_{cs,y-\tau} + \mu_{cs} + \mu_{cry} + \epsilon_{csy} \tag{C–1}$$

Here $1[\mathbb{L}_{sy} = 1]$ represents an indicator for whether system s received a loan in year y and $P_{cs,y+\tau}$ represents the share of chemical c readings above health standards τ years after year y. The regression includes pollutant-by-system fixed effects μ_{cs} and pollutan-by-state-by-year fixed effects μ_{cry}.

Estimates of equation (C–1) (not shown for space) suggest a few patterns. Pollution in years before a loan does not predict loan receipt. The point estimates and confidence regions are near zero, vary in their sign, and none are statistically significant. Pollution in a given year does negatively predict loan receipt 6 to 7 years earlier. This occurs because a loan decreases subsequent pollution, as shown in the main text.

C.3 Effects of Safe Drinking Water Loans on Health and Comparisons of Costs and Benefits

The benefit/cost analysis considers two estimates of the value of a statistical life, both in 2024 dollars: an age-adjusted value of $2.94 million, based on several papers (Ashenfelter and Greenstone 2004; Murphy and Topel 2006; Deschenes, Greenstone and Shapiro 2018), and a value of $13.21 million, which the Environmental Protection Agency has used in regulatory impact assessments.[6]

Since capital costs of these investments come from low-interest loans, which are repaid, and operating and maintenance costs come from household water user fees (e.g., charges on monthly utility bills), we do not separately discuss fiscal externalities through the government budget.

An important question we leave for future work is whether regulated pollutants harm health at concentrations below health standards. This setting is not ideally suited to answer this question, for several reasons. The most plausible approach to this question in our setting would be a model with several endogenous pollution variables, corresponding to measures of whether pollution falls in different ranges relative to the health standard. Appendix Figure 5 shows an example of such bins. One would then need multiple instrumental variables for this model to be identified. It is statistically possible to use the count of whether a system has received one; two; three; etc. loans as distinct instrumental variables. Alternatively, one could interact the cumulative number of loans with other system characteristics. In practice, these approaches do not generally provide strong or valid instruments. Additionally, our general caveats about the use of instrumental variables in this paper would apply more strongly to such a model.

C.4 Loans and Municipal Water Spending: Rates and Pass-Through

This appendix section evaluates how Safe Drinking Water loans affect municipal water spending and drinking water rates. The pass-through rate of drinking water loans to municipal spending influences cost-effectiveness and benefit-cost calculations.

A dollar of Safe Drinking Water loans could increase a drinking water system's spending on drinking water capital by a dollar if loans are completely passed through to spending, which would imply no crowding in or crowding out. By contrast, a dollar of loans could lead to more or less than a dollar of municipal spending. Existing research finds either complete pass-through of federal to local water spending, or some degree of crowding out (Keiser and Shapiro 2019*b*; Flynn and Smith 2022).

To estimate pass-through, we use microdata from the Annual Survey of Governments and Census of Governments for years 2009-2019, obtained from the U.S. Census Bureau (US Census Bureau 2023*a*,*c*). We restrict the sample to a balanced panel of 1,962 governments that can readily be uniquely identified within a county (e.g., if a county has two governments with names similar to "Johnstown," we exclude these governments from the sample, since in this case we cannot reliably match the government spending to the loan data). We clean

[6] This number is similar in magnitude to several value of a statistical life estimates used in USEPA regulatory impact assessments over the past decade; it is also similar to estimates from more recent economic analyses (Carleton et al. 2022; USEPA 2023*b*,*f*).

government names to have similar formatting, then join the drinking water loan data to the government spending data, requiring an exact match on government name and county.

We estimate pass-through from a regression of the log of cumulative municipal capital investment on the log of cumulative Safe Drinking Water loan amounts:

$$lnC_{sy} = \beta lnL_{sy} + \mu_s + \mu_{ry} + \varepsilon_{sy}$$

Here s represents a drinking water system (equivalently, a local government), y is a year, and μ_{ry} are regional state-by-year fixed effects.

We summarize these regressions here. We estimate an elasticity of cumulative water capital with respect to cumulative Safe Drinking Water loans of β =0.16 (0.05). Evaluated at the sample mean values of capital and loans, this implies that a dollar of loans leads to \$0.78 (0.25) additional spending on municipal water capital. This point estimate implies less-than complete pass-through, although fails to reject the hypothesis of complete pass-through. The estimated elasticity excludes many system-year observations with zero capital or loan spending. Thus, we also estimate this elasticity in levels, from a regression of C_{sy} on L_{sy}. Cumulative spending is approximately lognormally distributed, so the regression in levels is strongly influenced by the extreme right tail.[7] It obtains a pass-through rate of \$2.93 (0.34), implying that a dollar of loans leads to nearly three dollars in additional municipal capital investment, which would imply substantial crowding in.[8]

The main text primarily assumes a pass-through rate of one, which is slightly higher than but within the 95 percent confidence interval of the point estimates. The main text also discusses the effects of an alternative pass-through rate of 0.5. Because cost-effectiveness and benefit-cost statistics scale with the pass-through rate, these alternatives or others are straightforward to calculate.

We also estimate a relationship like equation (C.4), but where the dependent variable represents a water system's revenues, which clarifies how loans affect water rates. Because a system must repay a loan plus incur associated operating and maintenance costs, loans are likely to increase water rates. We estimate an elasticity of system revenues with respect to cumulative loan amounts of 0.022 (0.010), or an estimate in levels of 0.38 (0.07). Either would suggest that loans increase water rates.

Increases in water rates due to loans could provide a mechanism for loans to affect health. If higher rates lead to less water use for drinking, or possibly other purposes like hand washing, this channel could decrease health. While studies have estimated meaningful residential water demand elasticities (Espey, Espey and Shaw 1997; Olmstead, Hanemann and Stavins 2007), it is more difficult to discern which water uses respond most to prices. We conjecture that water consumption and potential associated dehydration responds less to prices than other uses, though we are unaware of any evidence to test this conjecture. We also believe that decreased water consumption due to the higher water rates that a loan brings

[7]Several measures indicate the skewness of the cumulative capital spending data. The mean spending level is 12.5 times greater than the median. The spending data in levels has skewness of 18.6, while in logs it has skewness of -0.45. The top 1% of spending accounts for 36.0 percent of the total in levels.

[8]The municipal spending data include a series of reported water utility construction spending, which is listed separately from total water utility capital outlay. The two series are similar (in cumulative logs, the pairwise correlation is 0.95).

would, if it had any health impact, tend to worsen health outcomes. This would suggest that health improvements associated with a Safe Drinking Water loan could if anything be larger if loans did not increase water rates.

C.5 County×Year Estimates for Pollution and Health

Appendix Table 17 uses county×year data on health outcomes and pollution to estimate

$$H_{cy} = \beta L_{cy} + X'_{cy}\pi + \mu_c + \mu_{ry} + \epsilon_{cy} \tag{C–2}$$

Here H represents the average health or pollution outcome in county c and year y, L_{cy} is the cumulative number of loans received by the average person in this county×year, and X_{cy} includes county×year controls from Panel A of Appendix Table 5: Clean Water Act loans for wastewater treatment plants, Clean Air Act ozone and particulates nonattainment regulations, toxic pollution sources, local income and employment, opioid prevalence, health insurance coverage, per capita federal spending, temperature, precipitation, and age. Here μ_c are county fixed effects and μ_{ry} are regional state-by-year fixed effects. We report results with and without the controls X_{cy}, and also report versions weighted by population of the relevant age group or, for infant health, births.

Appendix Table 17 finds that county×year data yield imprecise estimates of how Safe Drinking Water loans affect mortality and pollution. Column (1) of Panel A finds that each additional loan changes the all-age mortality rate for the average county× year by -0.006 (0.0032). Adding controls in column (2) reverses the sign, while also weighting by population obtains a larger negative point estimate. The main text estimates that each loan decreases the mortality rate for older Americans by about half a percentage point, which is within the high end of the confidence intervals in the richest county×year estimates from column (3).

Panels B through F of Appendix Table 17 estimate generally negative but imprecise effects of loans on age group-specific mortality in county×year data. For infants (Panel B) and young children (Panel C), the point estimates are large and negative, but standard errors are wide.

Panel G of Appendix Table 17 estimates effects of loans on the all-age mortality rate for chronic ICD cause of death codes. This is analogous to the main text estimate for chronic hospital admissions, except here for mortality. The main point estimate is negative but imprecise.

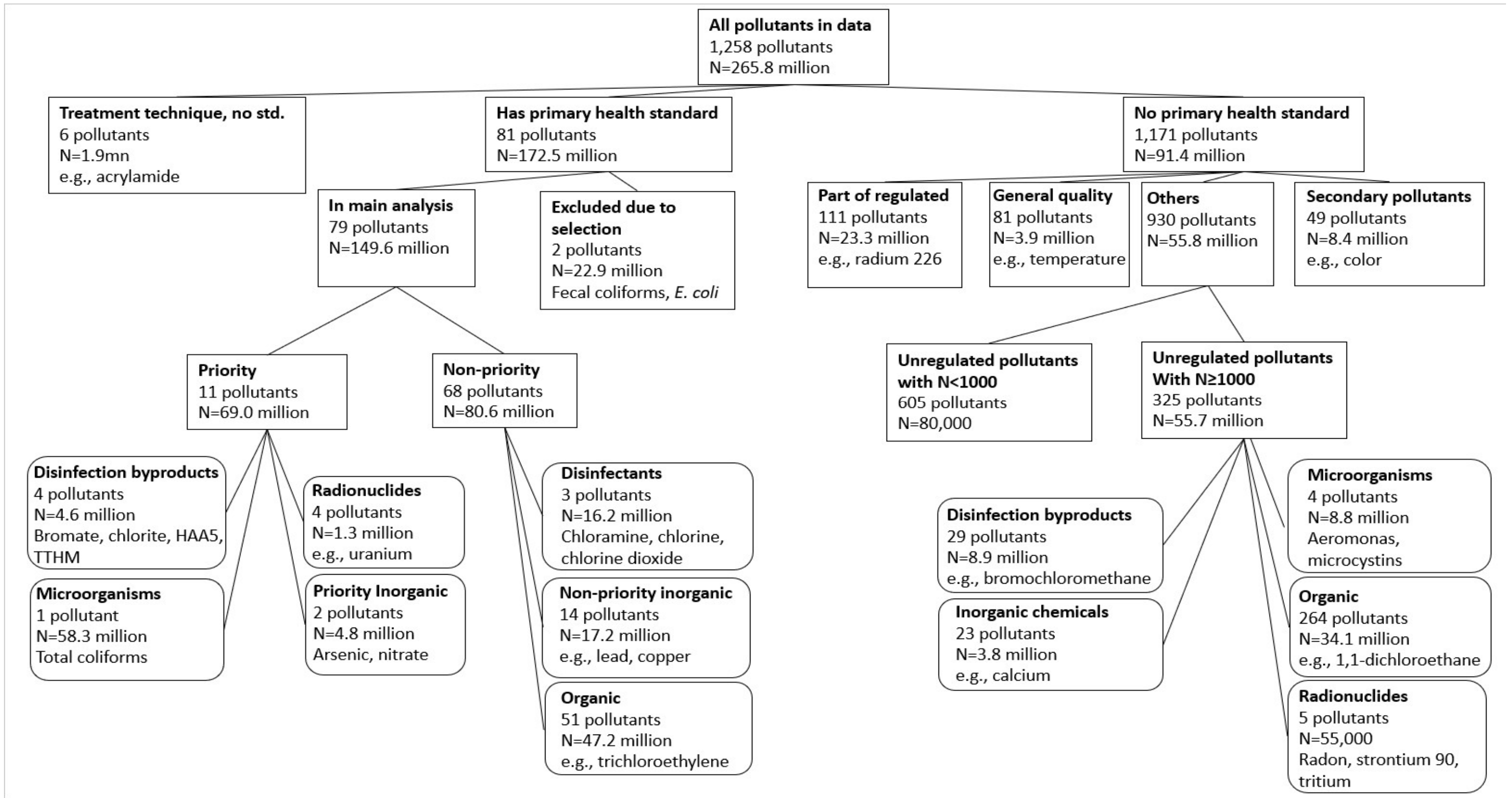
Panel H of Appendix Table 17 considers how the small subset of loans that target microbial pollution problems affect the mortality rate from ICD10 codes that the Centers for Disease Control explicitly links to microbial drinking water problems (Collier et al. 2021). The regressions estimate small and generally statistically insignificant changes in microbial-related causes of death when estimated with these county×year data.

The final two panels of Appendix Table 17 examine how Safe Drinking Water loans affect pollution. Panel I examines all pollutants with health standards and Panel J examines priority pollutants. These estimates use county×year data, following equation (C–2). Most resulting estimates are negative but imprecise, and are much less clear than the system×year data in Table 3. These estimates also suggest that county×year data with this research design lack statistical power to detect effects on important outcomes.

Appendix Table 18 estimates effects of Safe Drinking Water loans on infant health, using equation (C–2). We focus on the infant health index in Panel A, which aggregates over the outcomes listed in Panels B through H. The unweighted estimates in columns (1) and (2) have moderate negative values. The estimate weighted by the number of births in column (3) has far smaller standard errors, obtains a more modest negative estimate, and borders on statistical significance. The individual components of the index in Panels C through H vary in sign, magnitude, and significance. Overall, these infant health data echo the Appendix Table 17 estimates in suggesting that this county×year analysis of drinking water lacks sufficient statistical power to detect economically meaningful impacts on important outcomes.

D Appendix Figures and Tables

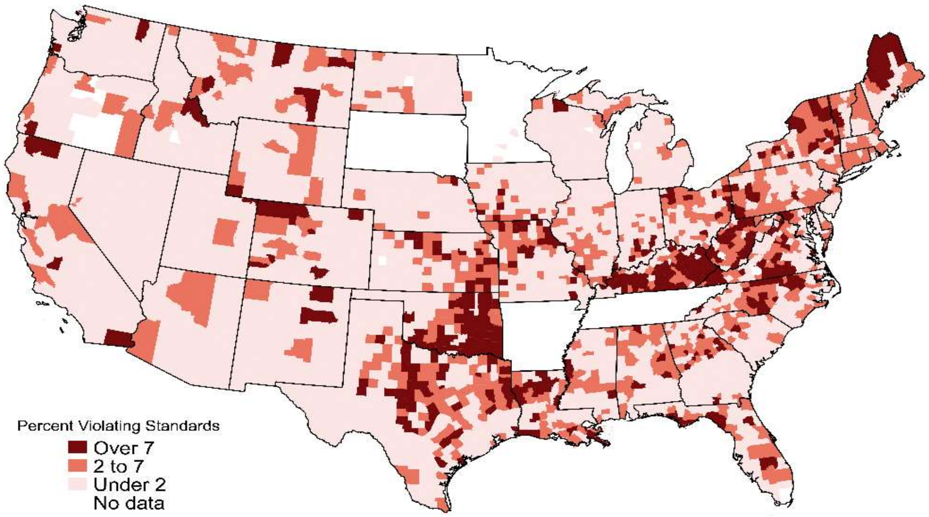
Appendix Figure 1: Categories of Drinking Water Pollution



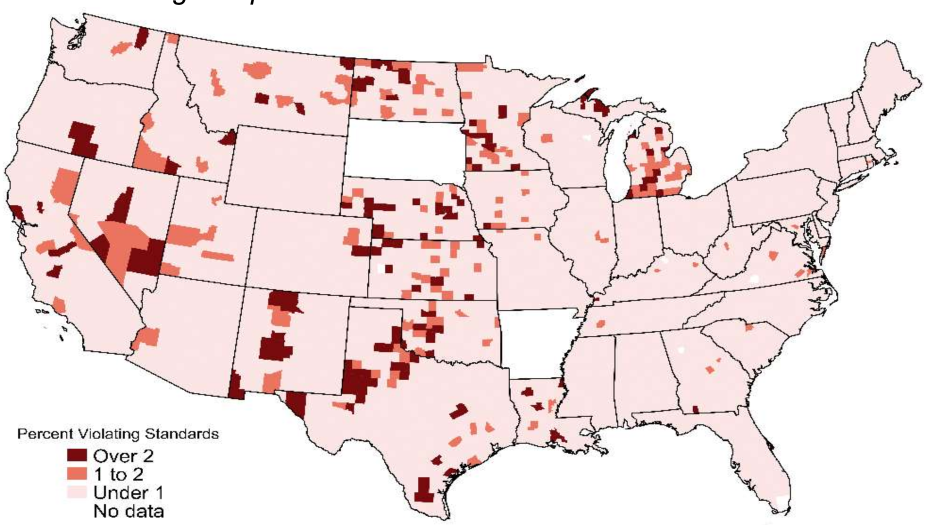
Note: square boxes denote a general group of pollution, boxes with rounded edges identify the five categories of pollution. N represents the number of distinct pollution readings in the national data. Statistics include all readings, pollutants, and years, before applying the exclusion criteria to construct the analysis sample that are used in most tables and figures. Statistics exclude California Minimum Detectable Activity (MDA) readings that the raw data organize as separate observations. "Treatment technique, no std." includes acrylamide, epichlorohydrin, enteric viruses, heterotrophic bacteria, Legionella, and turbidity, which have treatment technique requirements but no health standard. Appendix A.3 explains exclusion of fecal coliforms and *E. coli* from main analysis due to selection. Section 3.1 of the main text defines ``priority'' pollutants as those that some loans target. "Part of regulated" includes pollutants that are a part of a regulated pollutant (e.g., this group includes radium 226, which some systems report separately, although only the pair radium 226+228 has a health standard), or a non-comparable way of measuring a regulated pollutant (e.g., the SDWA regulates the dissolved component of the pollutant, but a system also reports the suspended quantity of the pollutant); or where a regulated pollutant is otherwise closely tied to a regulated pollutant. "General quality" includes generic water quality measures like temperature, measures like "counting errors" which do not directly measure pollution, and measures which have a non-monotone relationship to pollution. "Secondary pollutants" includes pollutants with National Secondary Drinking Water Regulations, which have primarily cosmetic or aesthetic effects.

Appendix Figure 2: Percent of Readings Violating Health Standards, by County and Pollutant

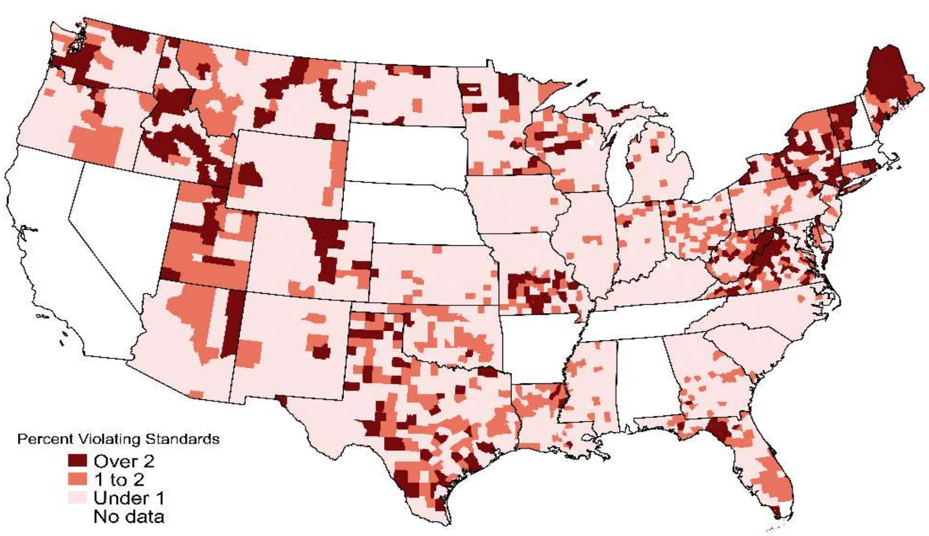
Panel A. Disinfection byproducts



Panel B. Inorganic pollutants



Panel C. Microorganisms (Total coliforms)



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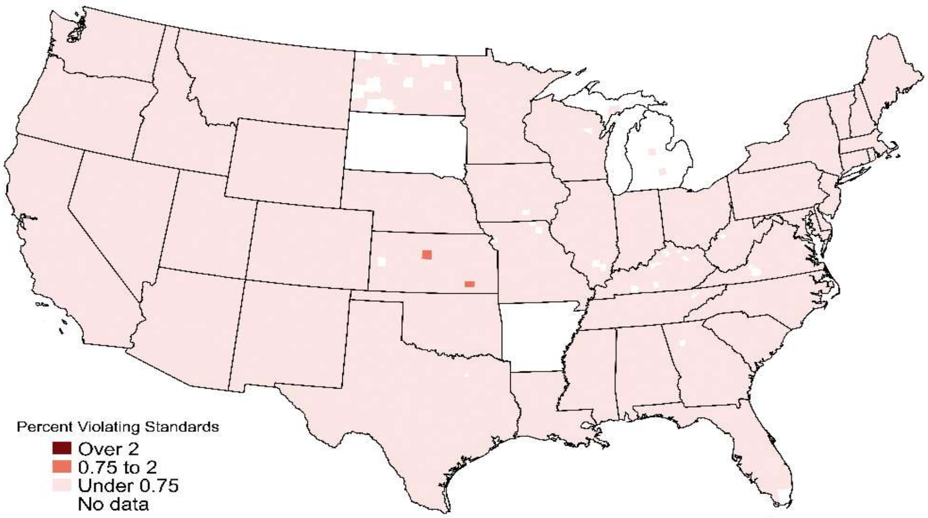
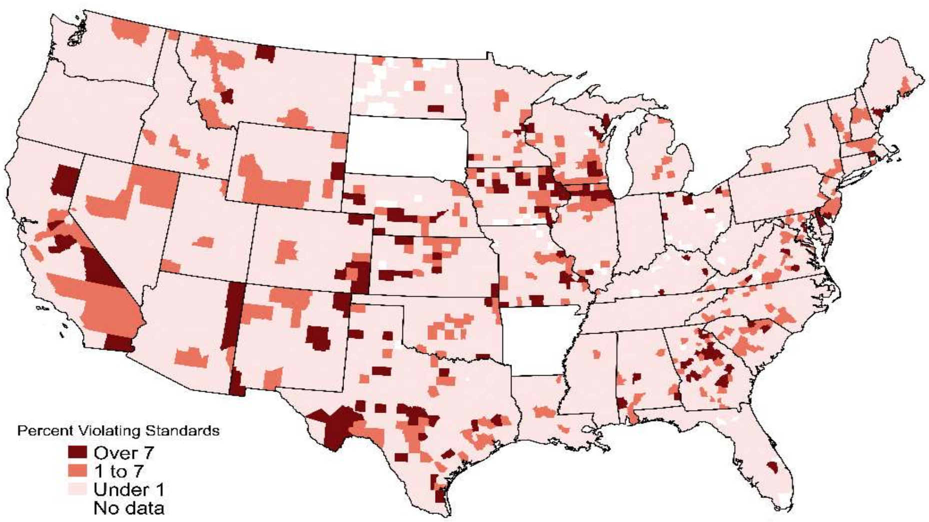
Appendix Figure 2: Percent of Readings Violating Health Standards, by County and Pollutant (Ctd.)

Panel D. Organic Chemicals



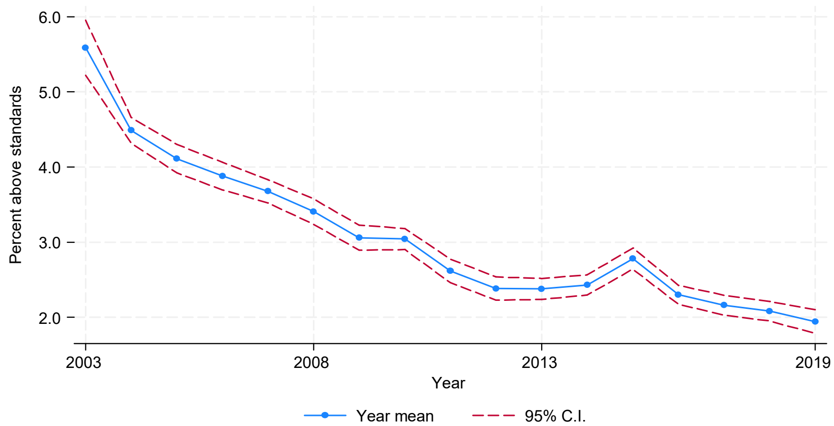
Panel E. Radionuclides



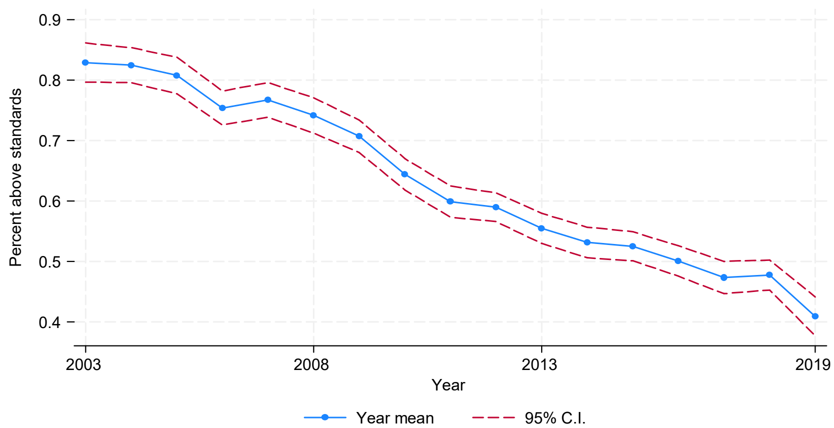
Notes: maps show the percent of drinking water pollution readings exceeding current health standards in each county. Sample includes years 2009-2019. Areas in white lack data.

Appendix Figure 3: Trends in U.S. Drinking Water Pollution, by Pollutant Categories

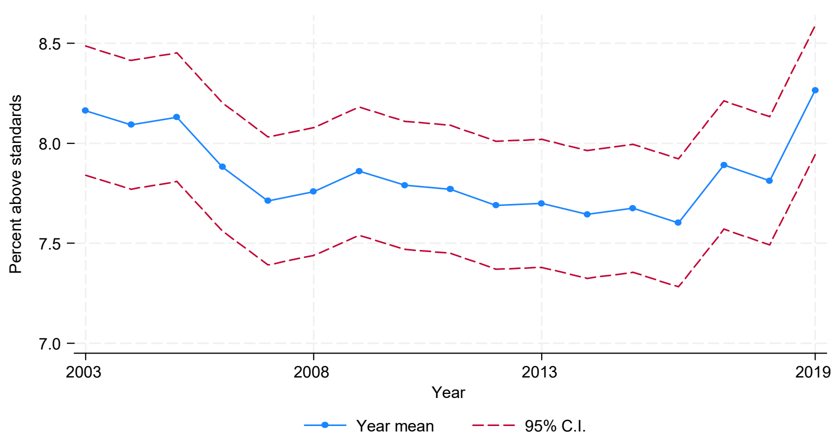
Panel A. Disinfection byproducts



Panel B. Inorganic pollutants



Panel C. Microorganisms (Total coliforms)



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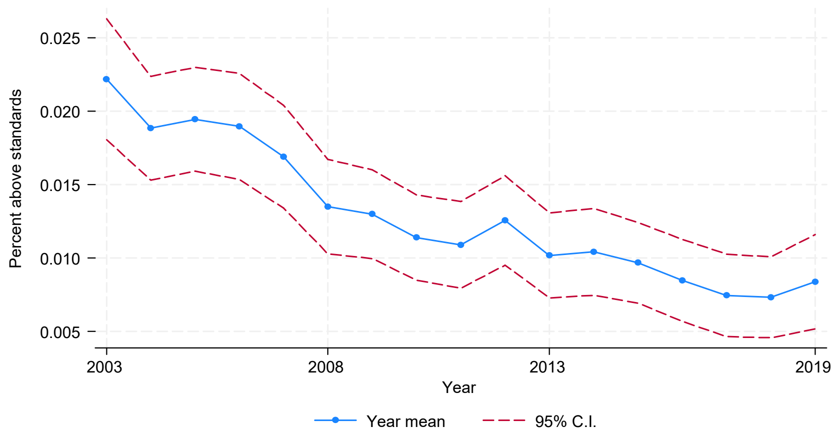
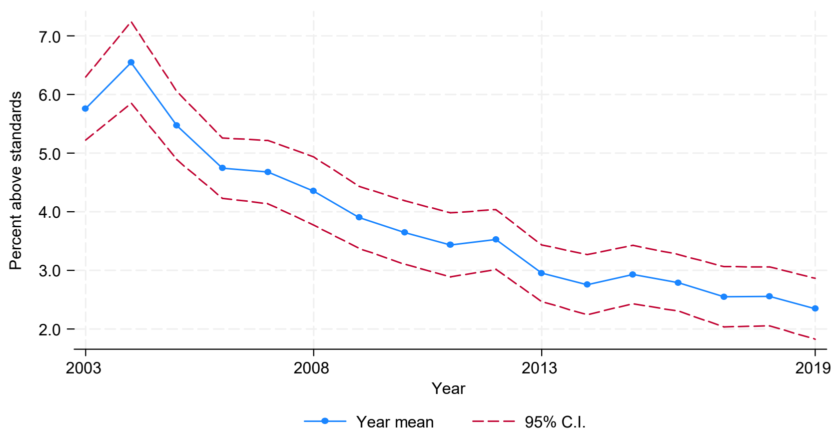
Appendix Figure 3: Trends in U.S. Drinking Water Pollution, by Pollutant Categories

Panel D. Organic Chemicals

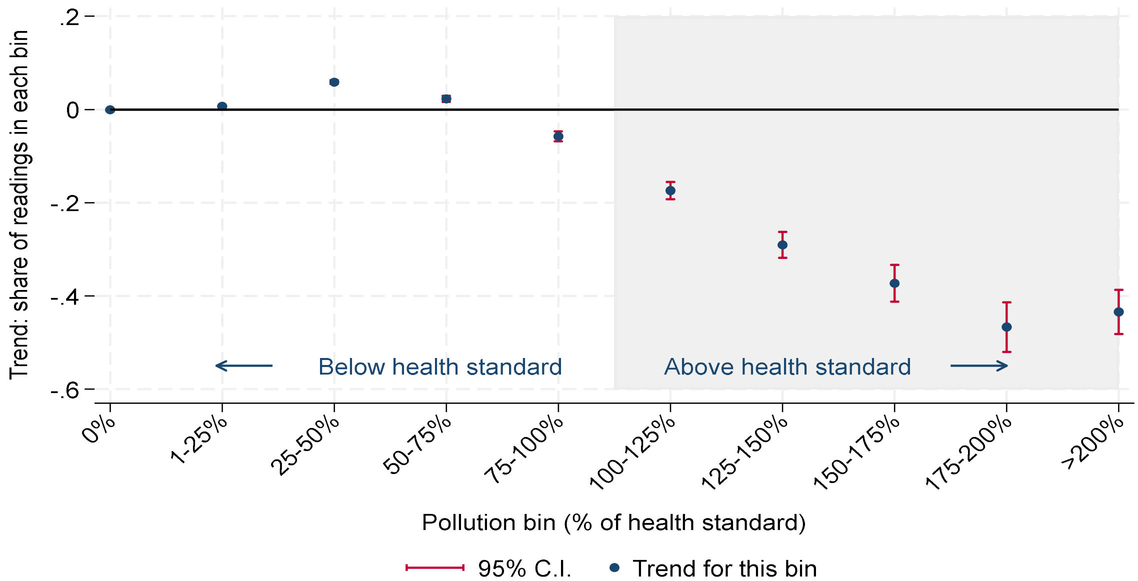


Panel E. Radionuclides



Notes: each graph shows the percent of drinking water pollution readings exceeding current health standards, by year. An observation represents a water system × pollutant × year. The graph includes pollutants with health standards. Sample includes years 2003-2019. Regression includes water system × pollutant fixed effects and controls for the share of readings from each month of the year. Standard errors are clustered by water system.

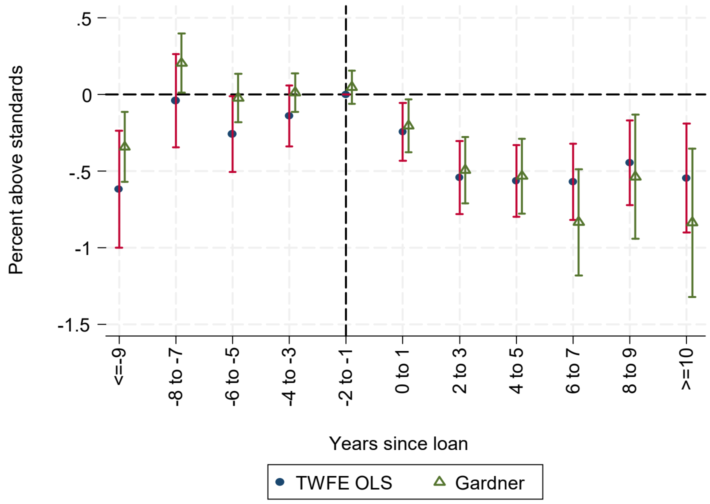
Appendix Figure 4: Trends in U.S. Drinking Water Pollution, Semi-Parametric Bin Estimates



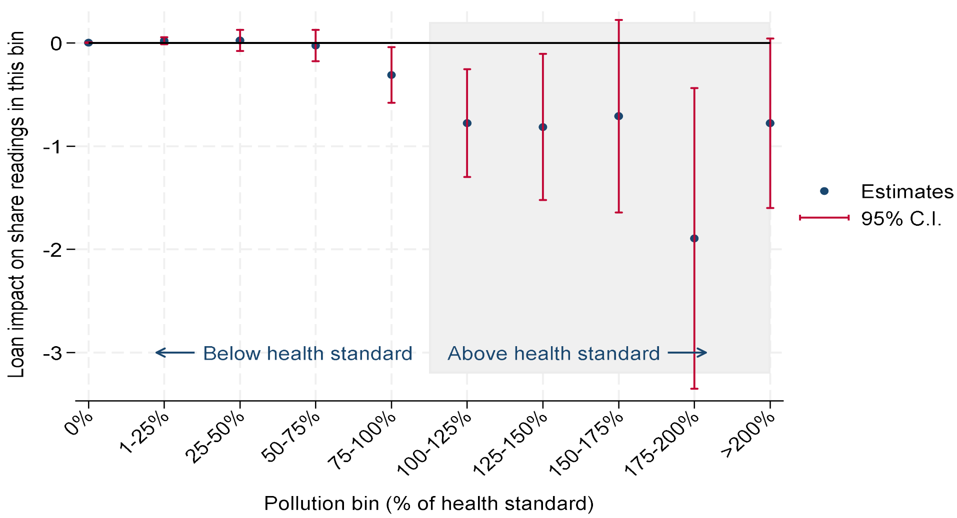
Note: figure shows estimates from ten separate regressions. In each regression, the dependent variable is the share of drinking water pollution readings that equal a certain proportion of the current health standard. An observation is a water system × pollutant × year. The sample includes the years 2003-2019. The graph includes pollutants with health standards. Regressions weight the five categories of pollution equally. Each regression controls for water system × pollutant fixed effects and the shares of raw pollution readings from each month of the year. The graph shows the regression coefficient for a bin divided by the dependent variable mean for the bin, so points in the graph can be interpreted as the trend in percent relative to the overall share of readings in the bin. For example, in the right-most estimate, the dependent variable equals the share of readings that are over 200 percent of the current health standard. Standard errors are clustered by water system.

Appendix Figure 5: Effects of Safe Drinking Water Loans on Pollution, Alternative Estimates

Panel A. Heterogeneous treatment timing



Panel B. Semi-parametric bin estimates across the distribution of pollution



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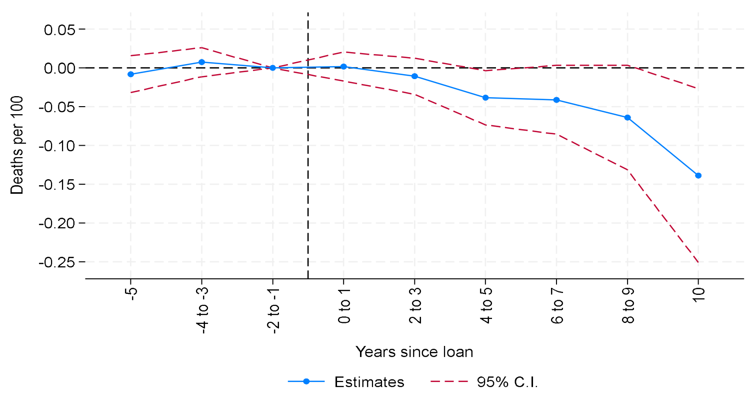
Appendix Figure 5: Effects of Safe Drinking Water Loans on Pollution, Alternative Estimates (Continued)

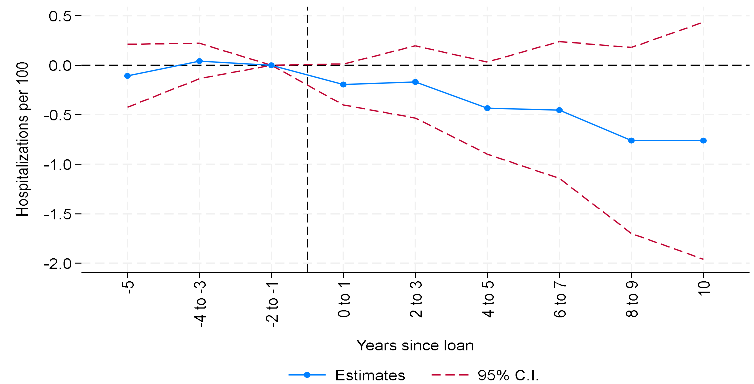
Note: In Panel A, the dependent variable is the percent of drinking water pollution readings exceeding current health standards. In Panel B, the dependent variable is the share of drinking water pollution readings that equal a certain proportion of the current health standard. An observation is a water system × pollutant × year. The graph includes pollutants with health standards. Samples include years 2009-2019. Regressions weight the five categories of pollution equally. Panel A shows the estimate of Gardner et al. (2024), with standard errors estimated using 200 bootstrap samples. Panel A also shows two-way fixed effects (TWFE) estimate using same sample and comparable methodology. In Panel B, bins are defined in terms of percent of the health standard (1-25% of the health standard, 25-50%, etc.). Figure shows regression coefficients divided by share of overall sample in the indicated bin. TWFE regressions include water system × pollutant and pollutant × state × year fixed effects and controls for the share of readings from each month. Panel A treats loans as an absorbing state, i.e., it measures whether a water system has received any loans.

Appendix Figure 6: Effects of Safe Drinking Water Loans on Mortality and Hospital Admission Rates, Sensitivity Analyses

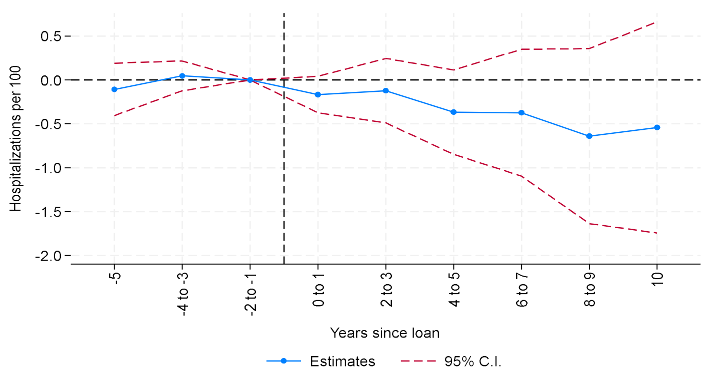
Panel A. Mortality Rate, Controlling for Age Fixed Effects



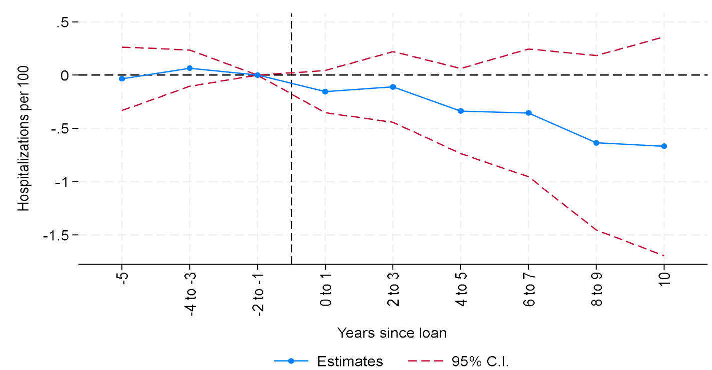
Panel B. Hospital Admission Rate, Baseline Specification



Panel C. Hospital Admission Rate, Controlling for Age Fixed Effects

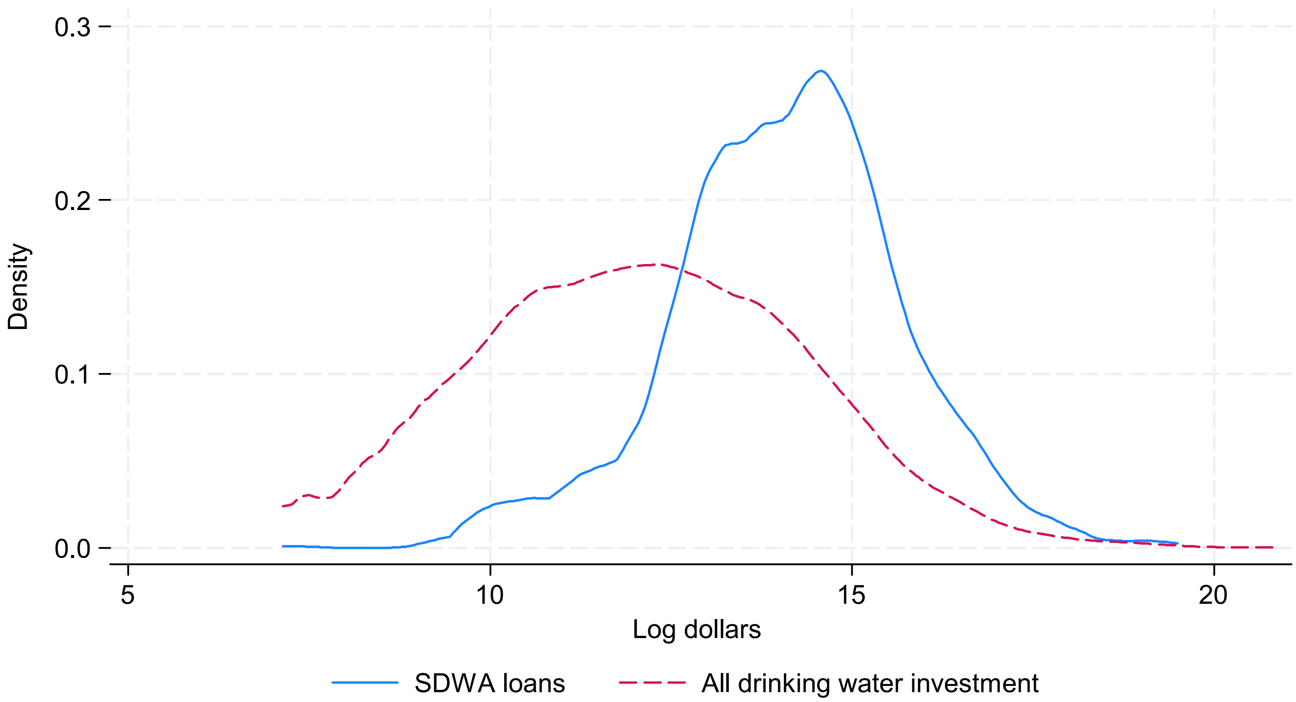


Panel D. Hospital Admission Rates for Chronic Conditions, Baseline Specification



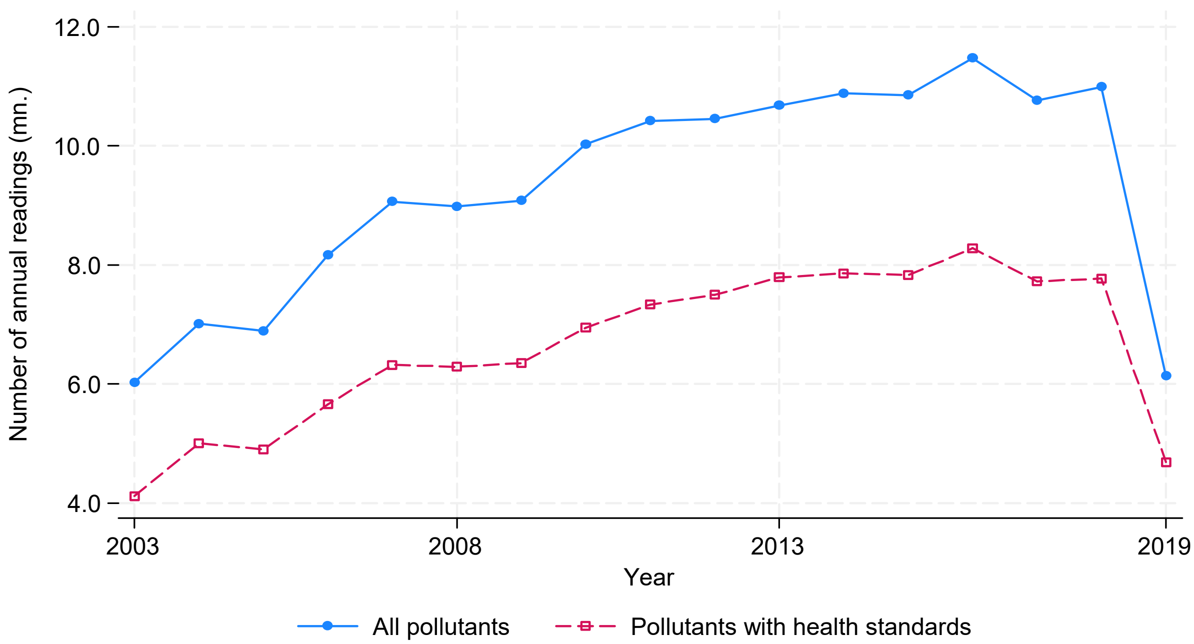
Notes: in Panel A, the dependent variable is the number of deaths per 100 Medicare beneficiaries aged 65 and older. In Panels B–D, the dependent variable is the number of hospital admissions per 100 Medicare beneficiaries aged 65 and older. An observation is a water system × cohort × calendar year × single-year age bin. This stacked research design fixes a cohort 5 years before a water system receives a loan, and compares it to all cohorts that never received a loan. Estimates include years 2009-2019. Regressions are weighted by the relevant population. Standard errors in parentheses are clustered by water system.

Appendix Figure 7: Value of Safe Drinking Water Loans and Annual Government Water Investment



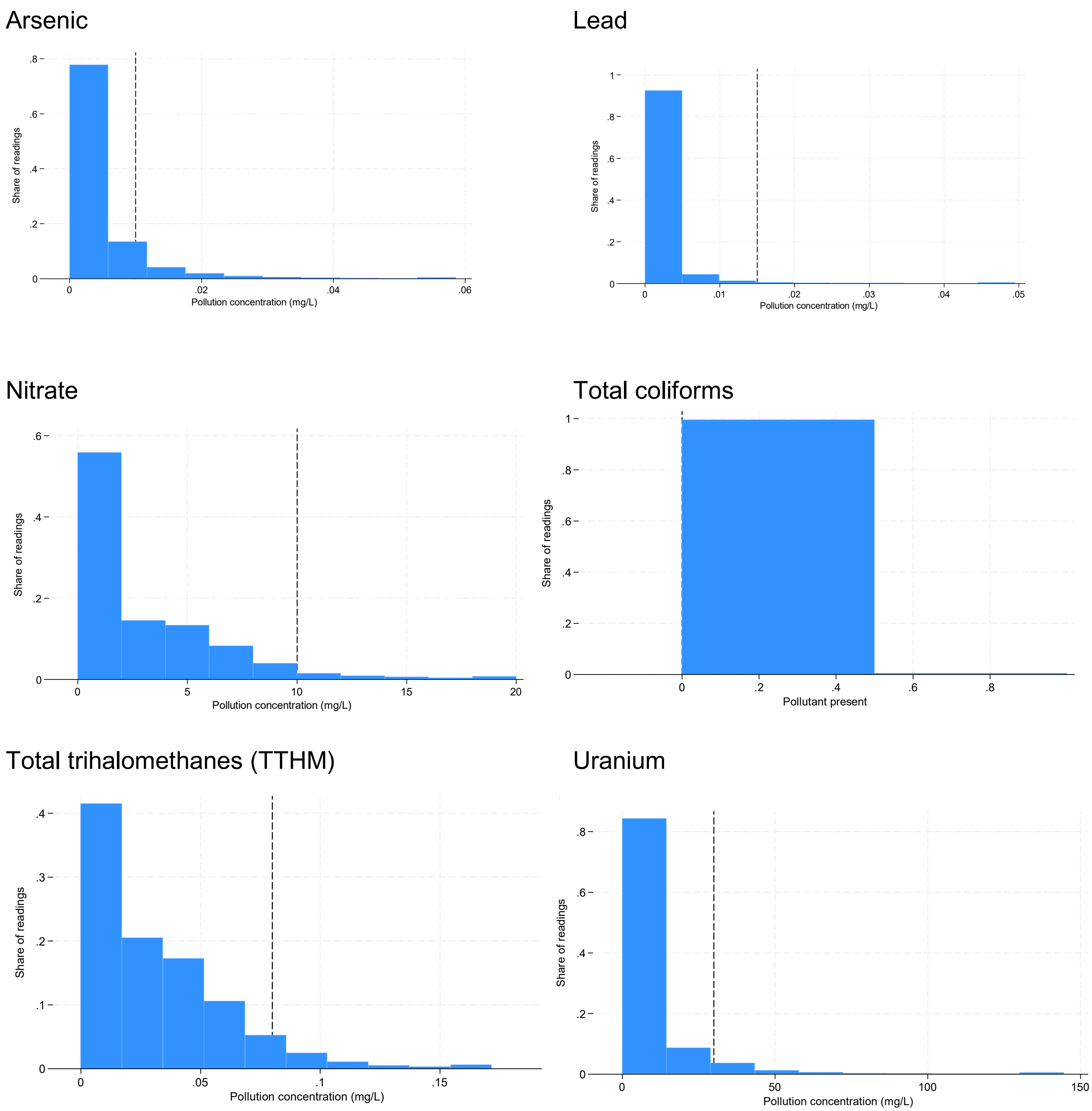
Notes: SDWA is Safe Drinking Water Act. The data pools years 2012 and 2017, the two years when we have data on both loans and the Census of Governments. The graph excludes observations with zero spending. The graph shows kernel density plots. Dollars are deflated to \$2024 using the GDP deflator. In the solid line, each observation is a water system × year. In the dashed line, each observation is a government × year. Government drinking water investment represents capital investment in water reported in the Census of Governments. The Census includes all levels of government, including special districts.

Appendix Figure 8. Number of Pollution Readings, By Year



Note: Graph shows total number of millions of pollution readings in each year from pollution microdata. Number of readings increases each year due to larger number of pollutants and readings per pollutant. Number of readings declines in 2019 due to partial-year data available for some states in that year.

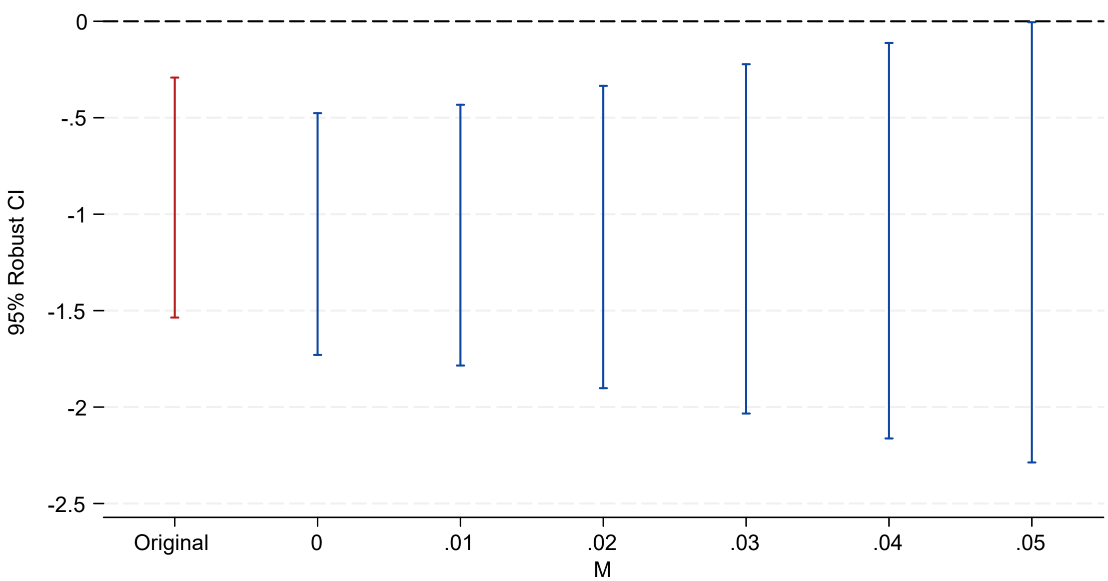
Appendix Figure 9: Histograms for Concentrations of Selected Individual Pollutants



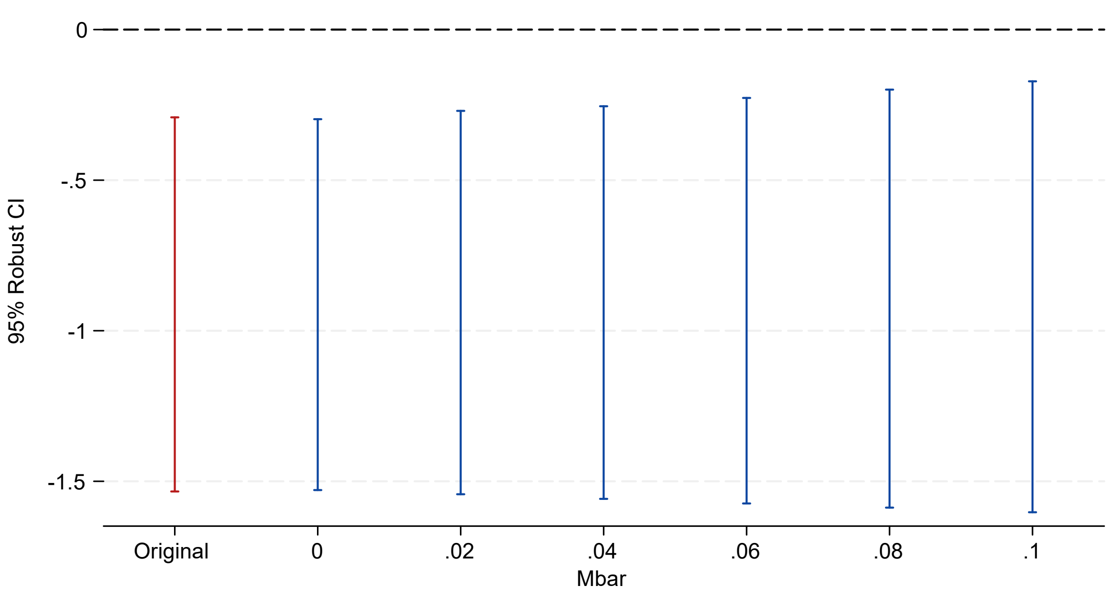
Notes: An observation is an individual pollution reading. Sample includes years 2003-2019. Vertical line in each graph shows health standard.

Appendix Figure 10: Effects of Safe Drinking Water Loans on Pollution, Sensitivity to Violations of Parallel Trends Assumption

Panel A. Smoothness restriction



Panel B. Magnitude restriction



Notes: The y-axis displays the 95% robust confidence interval (CI) of the estimate in Figure 2 when testing for violations of the parallel trends assumption. Panel A shows the CI when imposing that the slope of the pre-trend can change by no more than M across consecutive periods. Panel B shows the CI when imposing that the post-treatment violation of parallel trends is no more than Mbar larger than the largest violation of parallel trends in the pre-treatment period. Both tests consider the average effect across all post-treatment periods, using methods from Rambachan and Roth (2023).

Appendix Table 1: States with Drinking Water Pollution Data

State	Full sample			Years 2003-2019			Years 2009-2019				
	Readings (1)	Systems (2)	Pollutants (3)	Readings (4)	Systems (5)	Pollutants (6)	Readings (7)	Systems (8)	Pollutants (9)	First year (10)	Last year (11)
Panel A. National											
National	265,762,500	171,234	1,258	200,967,800	145,337	1,127	143,581,300	132,135	1,013	1974	2022
Panel B. By state											
Alabama	2,135,438	592	236	1,633,602	590	209	1,209,452	590	187	1984	2022
Alaska	851,000	1,329	258	596,079	1,292	251	384,910	1,272	184	1980	2021
Arizona	5,706,098	1,477	225	3,075,501	1,288	162	1,899,474	1,287	151	1980	2022
Arkansas	—	—	—	—	—	—	—	—	—	—	—
California	36,538,570	11,585	506	24,420,360	9,533	453	16,302,910	8,691	422	1974	2019
Colorado	2,892,273	2,875	201	2,487,863	2,829	200	1,769,251	2,575	185	2000	2020
Connecticut	6,437,663	3,154	302	6,251,911	3,154	295	4,203,594	2,544	224	2002	2019
Delaware	1,103,083	739	285	898,838	661	280	273,295	528	247	1992	2020
Florida	28,653,080	7,427	127	28,653,080	7,427	127	21,885,660	6,282	111	2004	2018
Georgia	6,601,702	3,167	251	5,365,423	2,919	189	3,425,345	2,639	173	1985	2022
Hawaii	239,854	137	51	204,278	136	51	204,278	136	51	2011	2021
Idaho	1,428,712	1,994	244	807,587	1,965	204	524,988	1,963	192	1974	2021
Illinois	10,439,420	1,870	442	6,581,331	1,849	375	4,263,274	1,811	351	1980	2022
Indiana	3,563,824	4,521	142	2,876,015	4,416	131	1,880,739	4,366	112	1980	2022
Iowa	3,583,864	3,326	242	1,922,456	2,333	205	1,313,815	2,110	186	1976	2021
Kansas	2,882,617	1,135	314	1,877,639	1,123	288	1,309,259	1,055	278	1985	2022
Kentucky	1,747,846	432	140	1,247,708	429	138	867,184	429	114	1992	2021
Louisiana	4,532,494	1,260	254	3,176,694	1,236	234	2,309,566	1,235	197	1991	2021
Maine	864,388	436	240	716,235	426	238	463,523	397	234	1993	2019
Maryland	3,692,933	3,868	200	2,368,944	3,711	192	1,480,247	3,387	190	1985	2022
Massachusetts	2,016,279	2,279	197	1,765,268	1,987	192	1,425,877	1,822	190	1978	2019
Michigan	1,612,185	1,501	161	983,265	1,492	79	967,790	1,479	79	2004	2022
Minnesota	7,191,757	11,863	350	4,055,421	9,465	311	2,478,500	7,945	270	1988	2021
Mississippi	2,443,139	1,228	131	2,086,445	1,211	128	1,309,219	1,195	127	1992	2021
Missouri	5,270,367	2,726	332	3,616,074	2,677	330	2,416,929	2,674	325	1985	2022
Montana	3,104,597	2,197	319	1,943,483	2,147	314	1,375,243	2,143	307	1974	2022
Nebraska	3,202,067	2,156	192	1,959,303	1,726	171	1,266,592	1,545	168	1974	2021
Nevada	1,611,767	247	385	1,039,292	235	359	719,311	207	345	1985	2021
New Hampshire	1,041,574	2,745	295	1,041,572	2,745	295	1,027,876	2,745	295	2000	2017
New Jersey	6,277,224	576	283	4,307,036	576	278	3,004,191	576	273	1981	2019

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Appendix Table 1: States with Drinking Water Pollution Data (Continued)

State	Full sample			2003-2019			2009-2019				
	Readings	Systems	Pollutants	Readings	Systems	Pollutants	Readings	Systems	Pollutants	First year	Last year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
New Mexico	2,741,615	1,615	305	1,478,955	1,413	288	854,498	1,271	189	1989	2022
New York	5,343,404	2,281	376	5,272,968	2,281	375	4,893,024	2,278	371	1982	2019
North Carolina	10,534,650	2,881	168	6,350,495	2,444	168	4,202,060	2,193	161	1980	2022
North Dakota	234,325	395	169	170,266	395	138	142,888	395	137	1990	2020
Ohio	4,866,613	6,154	250	4,429,050	6,154	242	3,349,602	5,768	224	2000	2018
Oklahoma	3,456,222	2,215	221	2,737,265	2,084	219	1,952,275	1,898	181	1981	2022
Oregon	1,068,499	954	143	956,773	948	143	325,137	906	86	1993	2011
Pennsylvania	23,352,310	15,271	249	19,157,920	12,363	231	15,449,680	10,742	220	1980	2019
Rhode Island	782,815	93	278	448,860	91	255	306,409	91	239	1986	2020
South Dakota	—	—	—	—	—	—	—	—		—	—
South Carolina	2,634,163	1,372	159	2,267,564	1,337	151	1,550,552	1,334	149	2000	2022
Tennessee	280,245	706	117	212,923	693	112	138,705	693	112	2000	2021
Texas	16,360,650	9,085	498	16,150,740	8,703	498	13,727,200	8,226	442	1992	2019
Utah	4,016,689	500	234	2,074,543	497	231	1,112,302	494	221	1980	2020
Vermont	1,108,127	469	380	770,898	468	369	545,859	450	360	1985	2020
Virginia	4,171,598	4,017	365	4,136,054	4,007	365	2,763,907	3,466	351	1977	2019
Washington	14,868,900	19,873	304	9,464,225	14,103	260	5,795,754	11,766	232	1975	2019
West Virginia	1,077,522	441	289	986,632	440	285	679,954	439	244	1986	2020
Wisconsin	10,163,820	23,310	300	5,302,642	14,587	236	3,352,053	13,347	230	1974	2022
Wyoming	1,034,498	762	196	640,340	752	185	477,172	751	178	1979	2022

Notes: Table includes all pollutants and systems.

Appendix Table 2a: Descriptive Statistics on Pollution Data, by Category of Pollutant

		Regulated pollutants		Non-	Categories of regulated pollution				
	All	All	Priority	regulated pollutants	Disinfection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Numbers of readings									
N readings	265,762,500	172,467,000	68,970,620	93,295,490	4,589,572	21,944,440	83,175,960	47,220,790	1,322,097
N sys. × year × pollutants	57,687,560	30,834,440	5,389,257	26,853,120	959,660	8,108,597	2,848,023	18,469,570	471,537
N sys. × years	2,733,810	2,639,310	2,561,682	1,769,205	532,652	1,880,958	1,952,990	686,748	257,725
N sys.	171,234	166,130	163,804	145,995	61,438	153,624	139,155	74,952	51,718
N pollutants	1,258	80	11	1,177	4	16	9	53	4
Panel B. Share outside thresholds									
Percent above health std	3.040	3.040	4.560	—	5.04	1.91	0.87	0.24	6.41
Share equal to zero	0.66	0.69	0.51	0.78	0.22	0.59	0.95	0.98	0.46
Panel C. Share by time period									
Pre-1993	0.09	0.04	0.02	0.05	0.02	0.04	0.01	0.05	0.06
1993-1997	0.09	0.10	0.07	0.10	0.03	0.11	0.05	0.12	0.07
1998-2002	0.11	0.12	0.12	0.13	0.05	0.13	0.10	0.13	0.12
2003-2007	0.17	0.18	0.19	0.18	0.19	0.19	0.16	0.18	0.26
2008-2012	0.20	0.21	0.24	0.20	0.23	0.20	0.24	0.20	0.19
2013-2019	0.30	0.32	0.31	0.32	0.42	0.30	0.37	0.28	0.26
Panel D. Share by system type									
Community water sys.	0.82	0.81	0.77	0.88	0.95	0.81	0.61	0.87	0.96
School	0.016	0.017	0.016	0.02	0.01	0.03	0.02	0.02	0.01

Notes: "All" statistics weight the five categories of pollution equally. This table imposes several restrictions applied to construct the analysis sample.

Appendix Table 2b: Descriptive Statistics on Pollution Data, by Pollutant

	Arsenic (1)	Lead (2)	Nitrate (3)	Total coliforms (4)	Trihalo-methanes (TTHM) (5)	Uranium (6)
Panel A. Numbers of readings						
N readings	1,204,958	3,972,313	3,567,629	58,286,370	2,508,423	270,732
N sys. × year × pollutants	508,182	487,641	1,619,566	1,830,312	529,669	78,747
N sys. × years	508,182	487,641	1,619,566	1,830,312	529,669	78,747
N sys.	76,362	73,578	130,220	122,647	61,345	26,873
N pollutants	1	1	1	1	1	1
Panel B. Other summary statistics						
Percent above health std.	9.41	2.09	3.76	0.87	6.28	6.88
Mean reading (mg/L or pCi/L)	0.003	0.002	2.48	0.01	0.03	8.18
Health standard	0.010	0.015	10.00	0.00	0.08	30.00
Share equal to zero	0.60	0.67	0.30	0.98	0.23	0.42
Panel C. Share by time period						
Pre-1993	0.06	0.03	0.03	0.01	0.03	0.02
1993-1997	0.08	0.11	0.10	0.07	0.05	0.03
1998-2002	0.10	0.11	0.13	0.13	0.08	0.06
2003-2007	0.17	0.17	0.20	0.19	0.18	0.27
2008-2012	0.22	0.20	0.22	0.25	0.22	0.24
2013-2017	0.33	0.33	0.29	0.29	0.39	0.34
Panel D. Share by system type						
Community water system	0.84	0.88	0.65	0.45	0.96	0.95
School	0.03	0.03	0.02	0.03	0.01	0.01

Appendix Table 3: Pairwise Correlations Between Pollutants

	Dis-infectants (1)	Disinfection byproducts (2)	Inorganic chemicals (3)	Microorganisms (4)	Organic chemicals (5)	Radio-nuclides (6)	Secondary (taste) (7)
Panel A. Percent above health standard, pollution categories							
Disinfectants	1.00	—	—	—	—	—	—
Disinfection byproducts	0.00	1.00	—	—	—	—	—
Inorganic chemicals	0.00	0.00	1.00	—	—	—	—
Microorganisms	0.02	0.02	0.00	1.00	—	—	—
Organic chemicals	0.00	0.00	0.05	0.00	1.00	—	—
Radionuclides	-0.01	-0.02	0.12	0.01	0.04	1.00	—
Panel B. Standardized values, pollution categories							
Disinfectants	1.00	—	—	—	—	—	—
Disinfection byproducts	0.12	1.00	—	—	—	—	—
Inorganic chemicals	-0.03	-0.07	1.00	—	—	—	—
Microorganisms	-0.02	0.00	0.00	1.00	—	—	—
Organic chemicals	0.01	0.05	0.08	0.00	1.00	—	—
Radionuclides	-0.07	-0.13	0.14	0.00	0.04	1.00	—
Secondary (taste)	0.03	0.00	0.09	0.01	0.02	0.10	1.00

Note: an observation is a system × pollutant × year. (Continued next page)

Appendix Table 3 (ctd.): Pairwise Correlations Between Pollutants

	Arsenic (1)	Lead (2)	Nitrate (3)	Total Coliforms (4)	Trihalo-methanes (5)	Uranium (6)
Panel C. Percent above health standard, individual pollutants						
Arsenic	1.00	—	—	—	—	—
Lead	0.01	1.00	—	—	—	—
Nitrate	0.07	0.00	1.00	—	—	—
Total coliforms	0.02	0.02	0.00	1.00	—	—
Trihalomethanes	-0.02	0.01	0.00	0.01	1.00	—
Uranium	0.27	0.01	0.15	0.02	0.00	1.00
Panel D. Standardized values, individual pollutants						
Arsenic	1.00	—	—	—	—	—
Lead	0.00	1.00	—	—	—	—
Nitrate	0.09	0.04	1.00	—	—	—
Total coliforms	0.01	0.02	0.01	1.00	—	—
Trihalomethanes	-0.11	-0.01	-0.12	-0.01	1.00	—
Uranium	0.32	0.02	0.30	0.02	-0.09	1.00

Note: These correlations analyze the share of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. Sample includes years 2009-2019. Standardized values equal the Z-score calculated within each pollutant, times 100.

Appendix Table 4: Description of Safe Drinking Water Loans

	Years 2009-2019		All years	
	(1)		(2)	
Panel A. Overall summary statistics				
Total number of loans	8,251		9,217	
Total loan amount (million $)	31,656		36,002	
Mean loan amount (million $/loan)	3.84		3.92	
Mean population served per loan	73,211		74,223	
Mean population age ≥ 65 served per loan	9,298		9,426	
Panel B. Share of loans listing targeted pollutant:	Share	Count	Share	Count
Arsenic	0.03	246	0.03	290
Coliform	0.01	115	0.01	122
Disinfectants, disinfection byproducts	0.03	249	0.03	259
Microbial	0.02	148	0.02	163
Nitrate	0.01	107	0.01	115
Radionuclides	0.01	122	0.01	126
No listed targeted pollutant	0.89	7,356	0.89	8,236
Panel C. Share of loans by year				
<2009	0.00	0	0.10	934
2009	0.16	1,302	0.14	1,302
2010	0.09	722	0.08	722
2011	0.08	620	0.07	620
2012	0.09	758	0.08	758
2013	0.10	798	0.09	798
2014	0.09	766	0.08	766
2015	0.09	719	0.08	719
2016	0.09	746	0.08	746
2017	0.09	770	0.08	770
>2017	0.10	819	0.09	819

Notes: dollar figures are deflated using the GDP deflator. Population age 65 and over multiplies population per loan from SDWIS by the share of US in 2010 that was 65 years and over (12.7%).

Appendix Table 5: Characteristics of Systems With and Without Safe Drinking Water Loans

	Systems with loans (1)	Systems without loans (2)
Panel A. County × year controls		
County has Clean Water Act loan (through 2009)	0.45	0.41
	(0.50)	(0.49)
Ozone nonattainment	0.18	0.21
	(0.38)	(0.41)
Particulate matter nonattainment	0.15	0.17
	(0.36)	(0.38)
Toxic release inventory plants (#/county)	16.05	20.99
	(40.83)	(49.94)
Temperature (F)	52.30	52.26
	(8.60)	(9.59)
Precipitation (in)	0.11	0.11
	(0.05)	(0.04)
Income per capita	34,545.12	35,914.75
	(8,032.75)	(9,200.80)
Employment to population ratio	0.52	0.53
	(0.14)	(0.13)
Opioid dispensing rate (prescriptions per 100 ppl)	83.28	79.27
	(44.18)	(34.90)
Health insurance (% uncovered)	16.60	16.04
	(5.66)	(5.91)
Federal spending per capita ($)	3,638.17	3,614.33
	(8,365.78)	(8,903.53)
Age	38.60	38.59
	(3.11)	(3.55)
Share older than 65	0.15	0.15
	(0.04)	(0.04)
Panel B. System characteristics		
Share urban	0.52	0.41
	(0.47)	(0.47)

Notes: table shows mean values. Standard deviations are in parentheses. An observation is a water system. Data represent the year 2009. Monetary values are in 2024 dollars, deflated using the GDP deflator. Table considers all water systems with drinking water data in 2009. Water systems with loans includes all water systems that received at least one loan in 2009-2019.

Appendix Table 6. Characteristics of Systems Receiving Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. No fixed effects										
Log population served	0.077***	—	—	—	—	0.077***	0.086***	0.079***	0.075***	0.086***
	(0.003)	—	—	—	—	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above-median share violating	—	0.054***	—	—	—	0.058***	—	—	—	0.054***
health standards in 2006	—	(0.009)	—	—	—	(0.009)	—	—	—	(0.009)
Above-median share Black	—	—	0.051***	—	—	—	-0.084***	—	—	-0.082***
	—	—	(0.008)	—	—	—	(0.008)		—	(0.008)
Above-median share Hispanic	—	—	—	-0.002	—	—	—	-0.050***	—	-0.038***
	—	—	—	(0.008)	—	—	—	(0.007)	—	(0.008)
Above-median share Poor	—	—	—	—	0.091***	—	—	—	0.061***	0.062***
	—	—	—	—	(0.008)	—	—	—	(0.007)	(0.007)
Panel B. Include State Fixed Effects										
Log population served	0.075***	—	—	—	—	0.075***	0.079***	0.075***	0.074***	0.077***
	(0.003)	—	—	—	—	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above-median share violating	—	0.068***	—	—	—	0.070***	—	—	—	0.064***
health standards in 2006	—	(0.009)	—	—	—	(0.009)	—	—	—	(0.009)
Above-median share Black	—	—	0.076***	—	—	—	-0.043***	—	—	-0.045***
	—	—	(0.009)	—	—	—	(0.008)	—	—	(0.008)
Above-median share Hispanic	—	—	—	0.088***	—	—	—	0.006	—	0.013
	—	—	—	(0.010)	—	—	—	(0.009)	—	(0.009)
Above-median share Poor	—	—	—	—	0.109***	—	—	—	0.091***	0.088***
	—	—	—	—	(0.008)	—	—	—	(0.008)	(0.008)

Note: the dependent variable is the cumulative number of Safe Drinking Water loans a water system receives by the year 2019. An observation is a water system. Sample includes systems with non-missing values of independent variables. All regressions have N=23,224. Robust standard errors are in parentheses.

Appendix Table 7: Pollution Sources and Levels

Pollution category	Disinfection byproducts	Inorganic chemicals			Organic chemicals		
		Arsenic	Lead	Nitrate	Synthetic	Pesticides	Uranium
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total organic carbon	2.277***	—	—	—	—	—	—
	(0.381)	—	—	—	—	—	—
Arsenic deposits	—	6.200***	—	—	—	—	—
	—	(1.557)	—	—	—	—	—
Log lead service	—	—	0.162***	—	—	—	—
lines	—	—	(0.028)	—	—	—	—
Log nitrogen from	—	—	—	0.343***	—	—	—
fertilizer & manure	—	—	—	(0.052)	—	—	—
TRI source	—	—	—	—	0.007*	—	—
	—	—	—	—	(0.004)	—	—
Log pesticide	—	—	—	—	—	0.012***	—
application	—	—	—	—	—	(0.003)	—
Uranium deposits	—	—	—	—	—	—	1.738**
	—	—	—	—	—	—	(0.775)
N	556,951	402,254	411,007	1,397,250	16,687,842	1,518,172	289,968
Dependent var. mean	3.96	3.65	1.62	1.00	0.02	0.16	4.16

Notes: The dependent variable is the percent of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. Sample includes all available years in 2003-2019. Each independent variable measures one potential cause of drinking water pollution. See text for data sources. Total organic carbon is county mean from drinking water data. Arsenic and uranium deposits are indicators for whether a county has deposits of the minerals. Lead service lines is log lines per capita. Nitrogen and pesticide are in log pounds per land area. TRI is an indicator for whether a county has a Toxic Release Inventory plant that emits a regulated water pollutant. Standard errors in parentheses are clustered by county. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 8: Inequality in U.S. Drinking Water Pollution Levels, Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Include service territories imputed as a circle							
Log population served	-0.082***	—	—	—	-0.077***	-0.091***	-0.092***
	(0.012)	—	—	—	(0.013)	(0.013)	(0.012)
Above-median share …							
Black	—	-0.168***	—	—	-0.056	—	—
	—	(0.056)	—	—	(0.059)	—	—
Hispanic	—	—	0.119**	—	—	0.190***	—
	—	—	(0.054)	—	—	(0.058)	—
Poor	—	—	—	0.321***	—	—	0.360***
	—	—	—	(0.055)	—	—	(0.055)
Panel B. Disinfection byproducts							
Log population served	-0.712***	—	—	—	-0.720***	-0.634***	-0.740***
	(0.036)	—	—	—	(0.037)	(0.036)	(0.036)
Above-median share …							
Black	—	-0.931***	—	—	0.080	—	—
	—	(0.133)	—	—	(0.135)	—	—
Hispanic	—	—	-1.839***	—	—	-1.391***	—
	—	—	(0.128)	—	—	(0.126)	—
Poor	—	—	—	1.583***	—	—	1.731***
	—	—	—	(0.120)	—	—	(0.117)
Panel C. Inorganic chemicals							
Log population served	-0.121***	—	—	—	-0.117***	-0.135***	-0.123***
	(0.007)	—	—	—	(0.009)	(0.008)	(0.007)
Above-median share …							
Black	—	-0.240***	—	—	-0.036	—	—
	—	(0.028)	—	—	(0.035)	—	—
Hispanic	—	—	0.240***	—	—	0.334***	—
	—	—	(0.027)	—	—	(0.030)	—
Poor	—	—	—	-0.008	—	—	0.062**
	—	—	—	(0.028)	—	—	(0.028)
Panel D. Microorganisms							
Log population served	-0.128***	—	—	—	-0.117***	-0.138***	-0.130***
	(0.010)	—	—	—	(0.011)	(0.010)	(0.010)
Above-median share …							
Black	—	-0.266***	—	—	-0.095**	—	—
	—	(0.033)	—	—	(0.037)	—	—
Hispanic	—	—	0.120***	—	—	0.209***	—
	—	—	(0.033)	—	—	(0.033)	—
Poor	—	—	—	0.045	—	—	0.092***
	—	—	—	(0.033)	—	—	(0.033)

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Appendix Table 8: Inequality in U.S. Drinking Water Pollution Levels, Sensitivity (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel E. Organic chemicals							
Log population served	0.002***	—	—	—	0.002***	0.001***	0.001***
	(0.000)	—	—	—	(0.000)	(0.000)	(0.000)
Above-median share …							
Black	—	0.002	—	—	-0.001	—	—
	—	(0.001)	—	—	(0.001)	—	—
Hispanic	—	—	0.003**	—	—	0.002	—
	—	—	(0.001)	—	—	(0.001)	—
Poor	—	—	—	0.002	—	—	0.001
	—	—	—	(0.001)	—	—	(0.002)
Panel F. Radionuclides							
Log population served	-0.525***	—	—	—	-0.543***	-0.606***	-0.532***
	(0.068)	—	—	—	(0.074)	(0.073)	(0.069)
Above-median share …							
Black	—	-0.795***	—	—	0.170	—	—
	—	(0.305)	—	—	(0.328)	—	—
Hispanic	—	—	1.273***	—	—	1.750***	—
	—	—	(0.285)	—	—	(0.303)	—
Poor	—	—	—	0.064	—	—	0.287
	—	—	—	(0.299)	—	—	(0.297)
Month controls	X	X	X	X	X	X	X

Notes: The dependent variable is the percent of pollution readings exceeding current health standards. Each observation represents a water system × pollutant × year. The table includes pollutants with health standards. Sample includes years 2003-2019. Regressions weight the five categories of pollution equally. Month controls are the share of raw pollution readings from each month of the year. Demographics describe each system, using time-invariant demographic data from year 2010 Census, aggregated from block data. Standards refer to current primary health standards. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 9: Trends in U.S. Drinking Water Pollution, Sensitivity

	All regulated pollutants		Regulated Pollution Categories					Individual pollutants			
	Above standards (1)	Standardized value (2)	Disinfection byproducts (3)	Inorganic chemicals (4)	Micro-organisms (5)	Organic chemicals (6)	Radio-nuclides (7)	Arsenic (8)	Lead (9)	Nitrate (10)	Non-regulated (standard-ized) (11)
1. Main estimates	-0.086***	-0.423***	-0.177***	-0.027***	-0.005***	-0.001***	-0.235***	-0.259***	-0.054***	-0.012***	—
	(0.003)	(0.014)	(0.006)	(0.001)	(0.002)	(0.000)	(0.013)	(0.009)	(0.003)	(0.002)	—
<u>Other</u>											
2. Standardized value	—	-0.423***	-0.215***	-0.325***	-0.110***	-0.065***	-1.279***	-0.964***	-1.214***	-0.106***	-0.397***
	—	(0.014)	(0.034)	(0.008)	(0.025)	(0.003)	(0.068)	(0.042)	(0.035)	(0.018)	(0.121)
3. Only community water systems	-0.090***	-0.462***	-0.185***	-0.026***	-0.007***	-0.001***	-0.239***	-0.242***	-0.044***	-0.004*	—
	(0.003)	(0.015)	(0.006)	(0.001)	(0.002)	(0.000)	(0.014)	(0.010)	(0.003)	(0.002)	—
4. Semi-balanced panel	-0.322***	-1.454***	-0.307***	-0.049***	0.006***	-0.001***	-1.246***	-0.842***	-0.095***	-0.011***	—
	(0.017)	(0.083)	(0.010)	(0.002)	(0.002)	(0.000)	(0.076)	(0.031)	(0.009)	(0.002)	—
5. Years 1992-2019	-0.082***	-0.538***	-0.201***	-0.033***	-0.028***	-0.002***	-0.206***	-0.201***	-0.066***	-0.023***	—
	(0.002)	(0.012)	(0.007)	(0.001)	(0.001)	(0.000)	(0.011)	(0.006)	(0.002)	(0.002)	—
6. Weight by log population	-0.077***	-0.479***	-0.136***	-0.012***	-0.132***	-0.001**	-0.112***	-0.104***	-0.015	0.001	—
	(0.007)	(0.066)	(0.019)	(0.002)	(0.021)	(0.000)	(0.022)	(0.019)	(0.010)	(0.004)	—
7. Unweighted	-0.019***	-0.175***	-0.165***	-0.027***	-0.001	-0.001***	-0.225***	-0.260***	-0.055***	-0.012***	—
	(0.000)	(0.004)	(0.005)	(0.001)	(0.002)	(0.000)	(0.013)	(0.009)	(0.003)	(0.002)	—
8. Exclude year 2019	-0.089***	-0.438***	-0.183***	-0.027***	-0.023***	-0.001***	-0.248***	-0.269***	-0.059***	-0.011***	—
	(0.003)	(0.015)	(0.006)	(0.001)	(0.002)	(0.000)	(0.014)	(0.009)	(0.003)	(0.002)	—
9. Separate coliform rules	—	—	—	—	-0.023***	—	—	—	—	—	—
	—	—	—	—	(0.002)	—	—	—	—	—	—
<u>Non-aggregated data</u>											
10. Basic non-aggregated	-0.137***	-0.534***	-0.275***	-0.064***	-0.011***	0.000	-0.391***	-0.627***	-0.067***	-0.023**	—
	(0.006)	(0.025)	(0.010)	(0.003)	(0.001)	(0.002)	(0.033)	(0.030)	(0.004)	(0.010)	—
11. Include raw water	-0.121***	-0.448***	-0.258***	-0.066***	-0.011***	-0.004**	-0.303***	-0.607***	-0.065***	-0.043**	—
	(0.006)	(0.024)	(0.010)	(0.004)	(0.001)	(0.002)	(0.030)	(0.032)	(0.003)	(0.020)	—

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Appendix Table 9: Trends in U.S. Drinking Water Pollution, Sensitivity (Continued)

	All regulated pollutants		Regulated Pollution Categories					Individual pollutants			
	Above standards (1)	Standardized value (2)	Disinfection byproducts (3)	Inorganic chemicals (4)	Micro-organisms (5)	Organic chemicals (6)	Radio-nuclides (7)	Arsenic (8)	Lead (9)	Nitrate (10)	Non-regulated (standardized) (11)
12. Sample point FE	-0.132***	-0.634***	-0.290***	-0.046***	—	-0.001***	-0.323***	-0.396***	-0.065***	0.003	—
	(0.008)	(0.032)	(0.014)	(0.002)	—	(0.000)	(0.031)	(0.023)	(0.004)	(0.008)	—
13. BDL = detection limit	—	-0.534***	-0.261***	-0.075***	—	-0.056***	-0.391***	-0.644***	-0.067***	-0.023**	—
	—	(0.025)	(0.010)	(0.003)	—	(0.003)	(0.033)	(0.030)	(0.004)	(0.010)	—
14. Log	-0.594***	—	0.001	-1.087***	-1.325***	-0.967*	-1.248***	-2.681***	-1.887***	0.117	—
	(0.052)	—	(0.064)	(0.036)	(0.084)	(0.530)	(0.161)	(0.166)	(0.073)	(0.071)	—
15. Indicator: positive	-0.029***	-0.534***	0.402***	-0.072***	-0.023***	-0.026***	-0.537***	0.033	-0.597***	-0.149***	—
	(0.008)	(0.025)	(0.019)	(0.008)	(0.002)	(0.006)	(0.041)	(0.036)	(0.021)	(0.015)	—
Additional specifications											
16. County×year controls	-0.113***	-0.513***	-0.306***	-0.023***	0.026***	-0.001***	-0.152***	-0.238***	-0.031***	-0.008	—
	(0.008)	(0.045)	(0.019)	(0.003)	(0.005)	(0.000)	(0.040)	(0.026)	(0.009)	(0.008)	—
17. Urban	-0.089***	-0.492***	-0.158***	-0.025***	-0.040***	-0.001***	-0.225***	-0.253***	-0.030***	-0.002	—
	(0.004)	(0.025)	(0.009)	(0.001)	(0.004)	(0.000)	(0.022)	(0.016)	(0.005)	(0.004)	—
18. Rural	-0.105***	-0.540***	-0.269***	-0.036***	-0.005*	-0.001***	-0.212***	-0.333***	-0.040***	-0.011**	—
	(0.005)	(0.029)	(0.014)	(0.002)	(0.003)	(0.000)	(0.025)	(0.021)	(0.005)	(0.006)	—
19. Small	-0.089***	-0.428***	-0.189***	-0.028***	-0.002	-0.001***	-0.238***	-0.275***	-0.058***	-0.012***	—
	(0.003)	(0.016)	(0.007)	(0.001)	(0.002)	(0.000)	(0.015)	(0.009)	(0.003)	(0.002)	—
Fixed effects:											
System × pollutant	X		X	X	X	X	X	X	X	X	X
Month controls	X		X	X	X	X	X	X	X	X	X

Notes: This table estimates trends in drinking water pollution, as in Table 2. In columns (1) and (3)-(10), the dependent variable is the percent of drinking water pollution readings exceeding current health standards. In columns (2) and (11), the dependent variable is the Z score calculated within pollutant, times 100. An observation is a water system × pollutant × year. Sample includes years 2003-2019. Unless otherwise noted, regressions weight the five categories of pollution equally. Month controls are shares of raw pollution readings from each month of the year. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 10. Drinking Water Pollution Trends, by Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. No additional controls							
Year	-0.09***	-0.09***	-0.09***	-0.08***	-0.09***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Year * …							
Log population served	0.00	—	—	—	0.00	0.00	0.00
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	-0.01	—	—	0.00	—	—
	—	(0.01)	—	—	(0.01)		—
Above-median share Hispanic	—	—	-0.01	—	—	-0.01	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	-0.03***	—	—	-0.03***
	—	—	—	(0.01)	—	—	(0.01)
Panel B. Include state ×year linear time trends							
Year * …							
Log population served	0.00	—	—	—	0.00	0.00	0.00
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	-0.01	—	—	0.00	—	—
	—	(0.01)	—	—	(0.01)	—	—
Above-median share Hispanic	—	—	-0.01	—	—	0.00	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	-0.02***	—	—	-0.02***
	—	—	—	(0.01)	—	—	(0.01)
Panel C. Include "Tier 3" geography links							
Year	-0.08***	-0.09***	-0.08***	-0.09***	-0.08***	-0.08***	-0.07***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Year * …							
Log population served	0.00	—	—	—	0.00	0.00	0.00
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	0.00	—	—	0.00	—	—
	—	(0.01)	—	—	(0.01)	—	—
Above-median share Hispanic	—	—	-0.01**	—	—	-0.01**	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	-0.01**	—	—	-0.01**
	—	—	—	(0.01)	—	—	(0.01)
System × pollutant FE	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X
N	7,751,580	7,751,580	7,751,580	7,751,580	7,751,580	7,751,580	7,751,580

Note: the dependent variable is the percent of drinking water pollution readings exceeding current health standards. An observation is a water system × pollutant × year. Table includes pollutants with health standards. Sample includes years 2003-2019. Regressions weight the five categories of pollution equally. Month controls are shares of raw pollution from each month of the year. Sample includes water systems with non-missing values of independent variables. Panel C adds water systems where EPIC determines service territory by drawing a circle around the system centroid, and includes state fixed effects. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 11: Effects of First Safe Drinking Water Loan on Drinking Water Pollution

			Categories of pollution				
Pollutants	All with health standard	Priority	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Dependent variable: percent violating current standards							
Any loans	-0.531***	-0.841***	-0.668***	-0.088***	-0.119**	-0.002	-1.471***
	(0.114)	(0.179)	(0.177)	(0.032)	(0.059)	(0.003)	(0.484)
Dependent variable mean	3.17	4.87	4.48	0.75	1.20	0.01	7.05
Observations	12,355,136	2,475,606	565,529	3,134,399	926,045	7,606,327	122,836
Panel B. Dependent variable: standardized value							
Any loans	-2.487***	-3.830***	-2.548**	-0.463*	-1.695*	-0.086	-7.090***
	(0.556)	(0.870)	(0.997)	(0.280)	(0.961)	(0.092)	(2.190)
Dependent variable mean	9.60	15.99	26.04	-2.67	-8.46	-1.30	15.88
Observations	12,355,136	2,475,606	565,529	3,134,399	926,045	7,606,327	122,836
Fixed effects:							
Pollutant × system	X	X	X	X	X	X	X
Pollutant × state × year	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X

Notes: an observation is a water system × pollutant × year. The graph includes pollutants with health standards. Sample includes years 2009-2019. Regressions weight the five categories of pollution equally. Month controls are the shares of raw pollution readings from each month of the year. Dependent variable mean represents the mean of the dependent variable for water systems receiving loans, in years before a loan is received. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 12: Effects of Safe Drinking Water Loans on Drinking Water Pollution, Targeted Loans

			Categories of pollution				
Pollutants	All with health standard	Priority	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Loans targeting one pollutant. Dependent variable: percent violating current standards							
Targeted loans *	-10.140***	-10.121***	-5.772***	-16.331***	-0.739	—	-13.483***
targeted pollutant	(1.367)	(1.368)	(1.153)	(2.155)	(0.629)	—	(2.419)
Targeted loans *	0.321*	0.679*	0.347	0.093	-0.079	—	1.186
non-targeted pollutant	(0.189)	(0.386)	(0.463)	(0.063)	(0.188)	—	(0.860)
Dependent variable mean	28.32	28.32	15.46	51.45	3.27	—	39.27
Observations	12,834,744	2,475,606	45,727	98,897	100,750	—	21,788
Panel B: Loans targeting one pollutant. Dependent variable: standardized value							
Targeted loans *	-41.380***	-41.109***	-26.880***	-55.878***	-11.965	—	-52.590***
targeted pollutant	(6.531)	(6.569)	(5.865)	(9.626)	(10.403)	—	(11.664)
Targeted loans *	0.514	1.757	2.415	-0.066	-1.165	—	1.923
non-targeted pollutant	(0.824)	(1.598)	(2.710)	(0.868)	(3.109)	—	(3.347)
Dependent variable mean	142.77	142.77	110.67	268.97	25.84	—	169.68
Observations	12,834,744	2,475,606	565,529	3,263,168	926,045	—	122,836
Fixed effects:							
Targeted pollutant × system	X	X	X	X	X	X	X
Targeted pollutant × state × year	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X

Notes: An observation is a water system × pollutant × year. The graph includes pollutants with health standards. Sample includes years 2009-2019. Regressions weight the five categories of pollution equally. Month controls are the shares of raw pollution readings from each month of the year. Loans variables are cumulative. Dependent variable mean represents the mean of the dependent variable for water systems receiving loans, in years before a loan is received. Targeted indicates that a loan targets the pollutant that an observation represents. Appendix Table 4 shows the share of loans targeting each pollutant. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 13: Effects of Safe Drinking Water Loans on Pollution, Sensitivity

	All regulated pollutants		Regulated categories (% > std)					Individual pollutants (% > std)			Non-regulated (standardized)
	Above standards	Standardized value	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Nitrate	Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1. Main estimates	-0.282***	-1.538***	-0.421***	-0.020	-0.086*	0.001	-0.755***	-0.301*	-0.086*	0.097	—
	(0.066)	(0.325)	(0.113)	(0.016)	(0.044)	(0.001)	(0.290)	(0.163)	(0.051)	(0.062)	—
Other											
2. Standardized	—	-1.538***	-1.882***	-0.185	-1.236*	-0.021	-4.201***	-0.825	-0.136	1.718**	-1.782
value	—	(0.325)	(0.664)	(0.152)	(0.724)	(0.056)	(1.271)	(0.763)	(0.411)	(0.847)	(1.775)
3. Only CWS	-0.234***	-1.325***	-0.399***	-0.025	-0.072*	0.000	-0.780***	-0.321**	-0.083*	0.064	—
	(0.054)	(0.286)	(0.114)	(0.016)	(0.044)	(0.001)	(0.290)	(0.161)	(0.048)	(0.061)	—
4. Semi-	-0.488**	-2.631***	-0.345***	0.059**	-0.120***	0.003	-1.585**	0.448*	-0.100*	0.237**	—
balanced panel	(0.194)	(0.817)	(0.126)	(0.024)	(0.044)	(0.002)	(0.758)	(0.230)	(0.053)	(0.109)	—
5. Years	-0.224***	-1.507***	-0.514***	0.018	-0.117**	0.000	-0.374*	-0.091	0.022	0.071	—
1992-2019	(0.055)	(0.297)	(0.127)	(0.014)	(0.052)	(0.002)	(0.217)	(0.161)	(0.038)	(0.049)	—
6. Weight by log	-0.233***	-1.454***	-0.359***	0.00	-0.106**	0.00	-0.609**	-0.10	-0.06	0.09	—
population	(0.059)	(0.294)	(0.100)	(0.012)	(0.043)	(0.001)	(0.263)	(0.122)	(0.037)	(0.060)	—
7. Unweighted	-0.040***	-0.267***	-0.420***	-0.021	-0.097**	0.001	-0.733**	-0.308*	-0.084*	0.097	—
	(0.008)	(0.071)	(0.110)	(0.016)	(0.044)	(0.001)	(0.286)	(0.163)	(0.050)	(0.062)	—
8. Exclude year 2019	-0.266***	-1.372***	-0.367***	-0.022	-0.016	0.001	-0.779**	-0.335**	-0.080	0.087	—
	(0.071)	(0.351)	(0.121)	(0.015)	(0.047)	(0.002)	(0.311)	(0.170)	(0.049)	(0.062)	—
9. Ctrl for monitoring/	-0.324***	-1.597***	-0.485***	-0.017	-0.047	0.000	-0.887***	-0.328*	-0.055	0.129*	—
reporting violations	(0.073)	(0.360)	(0.126)	(0.018)	(0.049)	(0.002)	(0.312)	(0.181)	(0.053)	(0.070)	—

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Appendix Table 13: Effects of Safe Drinking Water Loans on Pollution, Sensitivity (Continued)

	All regulated pollutants		Regulated categories (% > std)					Individual pollutants (% > std)			Non-regulated (standardized)
	Above standards	Standardized value	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Nitrate	Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(9)	(10)	(11)
10. Separate coliform	—	—	—	—	-0.019	—	—	—	—	—	—
rules	—	—	—	—	(0.049)	—	—	—	—	—	—
<u>Non-aggregated data</u>											
11. Basic	-0.245***	-1.356***	-0.180	0.074*	-0.149***	-0.034	-1.191**	0.210	-0.074	0.215	—
non-aggregated	(0.091)	(0.495)	(0.130)	(0.043)	(0.034)	(0.034)	(0.508)	(0.408)	(0.098)	(0.158)	—
12. Pre-treatment	-0.013	-0.345	-0.005	-0.142	—	0.017	0.068	0.555	-0.425	-0.020	—
pollution readings	(0.042)	(0.257)	(0.007)	(0.182)	—	(0.069)	(0.556)	(0.430)	(0.521)	(0.051)	—
13. Sample point FE	-0.340***	-1.992***	-0.274	0.078	—	-0.006	-1.655***	-0.434*	-0.006	0.409*	—
	(0.101)	(0.635)	(0.185)	(0.053)	—	(0.007)	(0.508)	(0.262)	(0.104)	(0.219)	—
14. BDL = detection	-0.241***	—	-0.199	0.070	-0.014	-0.022	-1.191**	0.172	-0.074	0.215	—
limit	(0.092)	—	(0.129)	(0.045)	(0.143)	(0.040)	(0.508)	(0.411)	(0.098)	(0.158)	—
15. Log	-2.046***	—	-1.920	0.795	-8.517***	-6.044***	-5.115***	1.813	1.037*	2.295	—
	(0.774)	—	(1.463)	(0.519)	(3.080)	(1.581)	(1.748)	(2.091)	(0.611)	(1.521)	—
16. Indicator:	-0.286**	—	-0.098	-0.407***	-0.014	-0.382*	-0.511	-2.011**	-0.331**	-0.304	—
positive	(0.120)	—	(0.167)	(0.147)	(0.143)	(0.224)	(0.224)	(0.988)	(0.167)	(0.406)	—
<u>Estimates specific to loans</u>											
17. County×year	-0.282***	-1.547***	-0.424***	-0.020	-0.086*	0.001	-0.768***	-0.294*	-0.084*	0.094	—
controls	(0.066)	(0.324)	(0.113)	(0.016)	(0.044)	(0.001)	(0.290)	(0.162)	(0.051)	(0.062)	—
18. First loan	-0.531***	-2.487***	-0.668***	-0.089***	-0.105*	-0.002	-1.497***	-0.858***	-0.181*	-0.034	—
	(0.114)	(0.556)	(0.180)	(0.032)	(0.059)	(0.003)	(0.488)	(0.330)	(0.099)	(0.104)	—

Appendix Table 13: Effects of Safe Drinking Water Loans on Pollution, Sensitivity (Continued)

	All regulated pollutants		Regulated categories (% > std)					Individual pollutants (% > std)			Non-regulated (standardized)
	Above standards	Standardized value	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Nitrate	Lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
19. Loan #1	-0.509***	-2.395***	-0.624***	-0.090***	-0.097	-0.002	-1.449***	-0.794**	-0.182*	-0.088	—
	(0.117)	(0.570)	(0.184)	(0.032)	(0.059)	(0.003)	(0.498)	(0.333)	(0.102)	(0.107)	—
Loan #2	-0.677***	-2.827***	-0.900***	-0.101*	-0.127	0.000	-1.865***	-1.460***	-0.176	0.286*	—
	(0.166)	(0.803)	(0.307)	(0.056)	(0.107)	(0.003)	(0.670)	(0.562)	(0.154)	(0.154)	—
Loan #3 or more	-0.734***	-4.868***	-1.467***	0.024	-0.364*	0.012	-1.509	-0.274	-0.135	0.641**	—
	(0.283)	(1.428)	(0.464)	(0.051)	(0.200)	(0.008)	(1.210)	(0.547)	(0.100)	(0.290)	—
20. Control for lagged	-0.297***	-1.712***	-0.330***	0.004	-0.090**	0.003	-1.537**	0.015	-0.085*	0.225**	—
dependent variable	(0.079)	(0.404)	(0.121)	(0.020)	(0.045)	(0.002)	(0.619)	(0.183)	(0.048)	(0.111)	—
21. Urban	-0.173***	-1.330***	-0.323**	0.008	-0.091	0.000	-0.542	0.129	-0.037	-0.052	—
	(0.066)	(0.349)	(0.147)	(0.013)	(0.059)	(0.002)	(0.344)	(0.134)	(0.040)	(0.077)	—
22. Rural	-0.419***	-1.580**	-0.265	-0.191***	-0.073	-0.001	-1.800**	-2.054***	-0.251	0.137	—
	(0.140)	(0.708)	(0.270)	(0.065)	(0.085)	(0.003)	(0.712)	(0.608)	(0.168)	(0.143)	—
23. Small	-0.578***	-2.208***	-0.958***	-0.165***	-0.021	-0.003	-1.202**	-1.798***	-0.175	0.090	—
	(0.149)	(0.721)	(0.291)	(0.048)	(0.071)	(0.003)	(0.573)	(0.459)	(0.116)	(0.122)	—
24. Cumulative loan dollars per person											
Bottom tercile	-0.103	-1.058	-0.211	0.039	-0.052	0.004	-0.324	0.529	0.122**	-0.252	—
	(0.127)	(0.703)	(0.235)	(0.040)	(0.094)	(0.005)	(0.527)	(0.340)	(0.059)	(0.162)	—
Middle tercile	-0.104	-0.189	0.040	0.105*	0.085	-0.003	-0.770	0.328	0.174**	-0.163	—
	(0.155)	(0.739)	(0.243)	(0.054)	(0.077)	(0.004)	(0.614)	(0.438)	(0.086)	(0.186)	—
Top tercile	-0.707***	-3.090***	-0.665*	-0.002	0.262**	0.001	-2.196**	-1.719***	-0.195	-0.069	—
	(0.232)	(1.108)	(0.353)	(0.082)	(0.107)	(0.006)	(0.878)	(0.665)	(0.192)	(0.184)	—
Fixed effects:											
Pollutant × system	X	X	X	X	X	X	X	X	X	X	X
Pollutant × state × year	X	X	X	X	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X	X	X	X	X

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Notes: This table estimates effects of loans on pollution, as in Table 3. In columns (1) and (3)-(10), the dependent variable is the percent of drinking water pollution readings exceeding current health standards. In columns (2) and (11), the dependent variable is the Z score calculated within pollutant times 100. An observation is a water system × pollutant × year. Sample includes years 2009-2019. Columns (1), (2), and (11) weight the five categories of pollution equally. Month controls are the share of readings from each month of the year. Disinfectant and radionuclide readings are all below the associated health standards (MCL). Statistics weight the five categories of pollution equally. "Years since grant trend" equals the year an observation represents minus the first year any system in an observation's county received a loan. County × year controls listed in Appendix Table 5: an indicator for receipt of Clean Water Act revolving fund loans; Clean Air Act nonattainment status for ozone and particulate matter; inverse hyperbolic sine of the number of Toxic Release Inventory plants; log personal income per capita; employment rate; inverse hyperbolic sine of opioid dispensing rate per 100 people (plus missing indicator); percent of population with health insurance; log of federal spending per capita; temperature and precipitation bins, mean age, and share aged 66 and older. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 14: Inequality and Impacts of Safe Drinking Water Loans on Pollution

	(1)	(2)
Panel A: Unweighted		
Cumulative loans	-0.505***	-0.512***
	(0.196)	(0.196)
Cumulative loans * Black	0.335	0.299
	(0.533)	(0.531)
Cumulative loans * Hispanic	0.434	0.435
	(0.593)	(0.592)
Cumulative loans * Poverty	0.462	0.543
	(1.162)	(1.161)
Observations	853,292	849,748
Panel B: Weighted by population		
Cumulative loans	-0.357**	-0.392**
	(0.178)	(0.180)
Cumulative loans * Black	0.424	0.439
	(0.456)	(0.455)
Cumulative loans * Hispanic	0.048	0.121
	(0.338)	(0.366)
Cumulative loans * Poverty	0.756	0.917
	(0.874)	(0.899)
Observations	852,660	849,116
Pollutant × system FE	X	X
Pollutant × state × year FE	X	X
Month controls	X	X
County × year controls		X

Notes: The dependent variable is the percent of drinking water readings exceeding current health standards. An observation represents a water system × pollutant × year. Regressions weight the five categories of pollution equally. Month controls are shares of raw pollution readings from each month of the calendar year. County × year controls include an indicator for receipt of Clean Water Act revolving fund loans; Clean Air Act nonattainment status for ozone and particulate matter; inverse hyperbolic sine of the number of Toxic Release Inventory plants; log personal income per capita; employment rate; federally-reported violations in years 2006-2008 interacted with year fixed effects; inverse hyperbolic sine of opioid dispensing rate per 100 people (plus missing indicator); percent of population with health insurance; inverse hyperbolic sine of federal assistance and contracts; and precipitation and temperature bins. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 15: Falsification Test: Effects of Safe Drinking Water Act Loans on Air, River, and Lake Pollution

	Air pollution		River and lake pollution					
Pollutants	Ozone	$PM_{2.5}$	BOD	Fecal coliform	Oxygen deficit	TSS	Not fishable	Not swimmable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Levels								
Loans	0.0002*	0.0122	-0.0034	-13.1489	0.03	-0.9279	-0.003	-0.0019
	(0.0001)	(0.0370)	(0.0979)	(9.5853)	(0.2194)	(0.8908)	(0.0020)	(0.0029)
Dep. var. mean	0.04	8.63	3.45	355.64	23.00	40.05	0.21	0.44
Observations	46,745	48,896	152,980	824,942	4,878,404	1,198,694	7,163,997	7,163,997
Panel B. Standardized values								
Loans	0.0299*	0.0046	-0.0005	-0.0084	0.001	-0.0075	—	—
	(0.0153)	(0.0139)	(0.0134)	(0.0061)	(0.0072)	(0.0072)	—	—
Dep. var. mean	0.0000	0.0000	0.008	-0.002	0.009	-0.007	—	—
Observations	46,745	48,896	152,980	824,942	4,878,404	1,198,694	—	—
Fixed effects:								
Pollutant × monitor	X	X	X	X	X	X	X	X
Pollutant × year	X	X	X	X	X	X	X	X
State × year	X	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X	X

Notes: $PM_{2.5}$ is particulate matter smaller than 2.5 micrometers; BOD is biochemical oxygen demand; TSS is total suspended solids. In columns (1) and (2), the dependent variable is the air pollution concentration. In columns (7) and (8), the dependent variable is the share of water pollution readings that exceed fishable or swimmable standards. An observation is a pollutant × monitor × year, which we link to the population-weighted cumulative number of loans for each county × year. Sample includes years 2009-2019. Month controls are the shares of raw pollution readings from each month of the year. Loans variables are cumulative. All pollution variables are measured in physical units. Not fishable and not swimmable are defined as in Keiser and Shapiro (2019b). Standard errors in parentheses are clustered by county. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 16: Effects of Drinking Water Loans on Hospital Admissions Rate of Medicare Beneficiaries

	(1)	(2)	(3)	(4)	(5)
Panel A. Admissions for all causes					
Received loan × post	-0.45	-0.36	-0.36	-0.39	—
	(0.28)	(0.29)	(0.29)	(0.27)	—
Received microbial loan × post	—	—	—	—	-0.44
	—	—	—	—	(1.80)
Panel B. Admissions for chronic conditions					
Received loan × post	-0.39	-0.30	-0.30	-0.33	—
	(0.24)	(0.25)	(0.25)	(0.23)	—
Received microbial loan × post	—	—	—	—	-0.059
	—	—	—	—	(1.70)
Panel C. Admissions for microbial conditions					
Received loan × post	-0.0001	0.0002	0.0001	0.0001	—
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	—
Received microbial loan × post	—	—	—	—	-0.022***
	—	—	—	—	(0.0065)
Fixed effects:					
System	X	X	X	X	X
State × year	X	X	X	X	X
Age		X	X	X	X
Location health controls			X		
County × year controls				X	

Notes: the dependent variable is the number of hospital admissions per 100 Medicare beneficiaries 65 and older. Four variables uniquely identify an observation in the underlying data: baseline water system, cohort, calendar year, and single-year age. A cohort represents the year of loan receipt. This stacked research design fixes a cohort 5 years before a water system receives a loan, and compares it to all systems that never received a loan. Estimates include cohorts from 2009-2019. Regressions are weighted by the relevant population. Column (3) controls for the year 2003 mortality and hospital admission rates in an individual's current county of residence. In column (4), county × year controls are listed in the main text (they include an indicator for receipt of Clean Water Act revolving fund loans; Clean Air Act nonattainment status for ozone and particulate matter, and many other environmental, economic, and demographic variables). Column (5) only counts loans that contain a flag for targeting microbial pollution. Columns (1) through (4) include 51.3 million observations, and column (5) includes 50.2 million observations. Standard errors in parentheses are clustered by water system. Asterisks indicate p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 17: Effects of Safe Drinking Water Loans on Mortality and Pollution, County × Year Estimates

	(1)	(2)	(3)
Panel A: All age mortality rate			
Cumulative loans	-0.0006	0.0007	-0.0010
	(0.0032)	(0.0031)	(0.0012)
Panel B: Age 0 mortality rate			
Cumulative loans	-0.0022	-0.0015	-0.0076
	(0.0146)	(0.0146)	(0.0053)
Panel C: Age 1-4 mortality rate			
Cumulative loans	-0.0023	-0.0025	-0.0004
	(0.0016)	(0.0016)	(0.0003)
Panel D: Age 5-17 mortality rate			
Cumulative loans	0.0000	-0.0001	-0.0001
	(0.0011)	(0.0011)	(0.0002)
Panel E: Age 18-64 mortality rate			
Cumulative loans	-0.0019	-0.0011	0.0012
	(0.0022)	(0.0022)	(0.0008)
Panel F: Age ≥65 mortality rate			
Cumulative loans	-0.0083	0.0044	0.0009
	(0.0155)	(0.0152)	(0.0116)
Panel G: All age chronic mortality rate			
Cumulative loans	-0.0001	0.0004	-0.0013
	(0.0024)	(0.0023)	(0.0011)
Panel H: All age microbial mortality rate			
Cumulative microbial loans	0.0003	0.0003	0.0000
	(0.0002)	(0.0002)	(0.0000)
Panel I: All pollutants: violating current health standards (%)			
Cumulative loans	-0.0109	-0.0111	-0.0043
	(0.0201)	(0.0200)	(0.0179)
Panel J: Priority pollutants: violating current health standards (%)			
Cumulative loans	-0.0747	-0.0752	0.0952
	(0.0608)	(0.0606)	(0.0605)
County FE	X	X	X
State × year FE	X	X	X
County × year characteristics		X	X
Weighted by population			X

Notes: Each observation represents a county × year. Regressions include years 2009-2019. Mortality rate equals deaths per 100 population of the indicated age. County × year characteristics are listed in the main text.

Appendix Table 18: Effects of Drinking Water Loans on Infant Health, County × Year Data

	(1)	(2)	(3)
Panel A: Infant health index			
Cumulative loans	-0.0810	-0.0700	-0.034*
	(0.078)	(0.077)	(0.021)
Panel B: Birth weight			
Cumulative loans	-0.1160	-0.0870	0.053**
	(0.079)	(0.083)	(0.021)
Panel C: 1[high birth weight]			
Cumulative loans	-0.0200	-0.0110	0.0120
	(0.070)	(0.068)	(0.018)
Panel D: 1[Non-preterm birth]			
Cumulative loans	0.0660	0.0660	-0.0230
	(0.152)	(0.150)	(0.023)
Panel E: 5-minute apgar			
Cumulative loans	-0.1060	-0.1160	0.0000
	(0.125)	(0.126)	(0.038)
Panel F: Gestational age			
	0.0430	0.0490	0.108***
	(0.149)	(0.147)	(0.034)
Panel G: Non-abnormal birth			
Cumulative loans	-0.1540	-0.1220	-0.157**
	(0.095)	(0.100)	(0.063)
Panel H: No congenital anomaly			
Cumulative loans	-0.1740	-0.1630	-0.0170
	(0.112)	(0.116)	(0.018)
County FE	X	X	X
State × year FE	X	X	X
County × year characteristics		X	X
Weighted by births			X

Notes: Each observation represents a county × year. Regressions include years 2009-2019. Infant health index aggregates over the other infant health measures. Panels B through H are in z-scores. County × year characteristics are defined in main text. All measures are transformed so that more positive values indicate better outcomes.

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