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

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Abstract

Since the 1974 Safe Drinking Water Act, the US has spent $2 trillion to provide safe drinking water, yet 10–20 percent of drinking water violates standards. We study trends, causes, and consequences of US drinking water pollution. The analysis uses 230 million readings on 1,800 pollutants over decades that we obtained from 48 states via dozens of Freedom of Information Act and associated requests. We link pollution geographically to administrative Medicare data on older Americans' health outcomes. Three findings emerge. First, US drinking water pollution is declining rapidly. The share of readings exceeding current health standards, for example, fell by half from 2003–2019. Unregulated pollutants declined more slowly. Low-income areas have higher pollution; patterns for Black and Hispanic communities are more complex. Second, loans provided by the Safe Drinking Water Act to cities substantially reduce pollution. These loans could eliminate pollution above health standards for $36 annually per person. Third, these loans significantly reduce mortality rates of older Americans, at a cost of $124,000 per premature death avoided. Although fiscal federalism cautions against federal funding of local public goods with few inter-jurisdictional externalities like drinking water, we estimate enormous net benefits from Safe Drinking Water Act loans.

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1 Introduction

The 1974 US 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 the resulting social welfare consequences and incidence.

Safe drinking water has long been essential to human health. Snow (1855) helped found modern epidemiology and the use of natural experiments by linking contaminated drinking water to cholera in London. Municipal water filtration and disinfection around 1900 dramatically decreased mortality (Cutler and Miller 2005; Anderson, Charles and Rees 2021).

US 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 just one category of drinking water pollution, pathogens, causes 7 million cases of illness and 600,000 emergency department visits a year, though this likely understates the disease burden (APHA 2019; Collier et al. 2021). US industry uses over 33,000 chemicals, many with potential toxicity, but the Safe Drinking Water Act regulates only 90 (USEPA 2019). 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 Biden Administration's top environmental policy priority alongside climate change.

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), but the EPA and independent 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 incomplete and nonrandom reporting, changes in pollution standards, binary measures that may miss changes that occur above or below standards, no information on unregulated pollutants, 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). For example, one influential study finds that federally-reported Safe Drinking Water Act violations doubled between 1982 and 2015 (Allaire, Wu and Lall 2018). This finding 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' health 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 allocates $83 billion for clean water (Farr 2021). The American Society of Civil Engineers (2020) calculates that typical spending on US 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).

Models of fiscal federalism imply 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." Drinking water pollution, unlike air, river, or lake pollution, has few if any inter-jurisdictional externalities.[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 requests, open record requests, and similar inquiries, along with scraping state websites and corresponding with staff from state agencies, we obtained all available data on drinking water pollution concentrations. These data provide 230 million drinking water pollution readings, covering 1,840 different pollutants for 48 states over several decades. We link these to new service territory maps for every available state describing the areas where each drinking water system distributes water. Such maps are important because the US has about 150,000 public water systems—

[1]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.

50 systems per county, on average—of which a third are "community water systems" serving permanent residences. These maps let us link measures of drinking water quality to the demographics of areas served and health outcomes.

Using this information, we match the drinking water data to confidential Medicare administrative data on the health outcomes of all beneficiaries, by zip code. These data cover the near-universe of US adults age 65 and older. Finally, through a federal Freedom of Information Act request, we obtained details on 9,200 subsidized loans to local drinking water systems through the Safe Drinking Water Act.

We have three main findings. First, drinking water pollution declined sharply between 2003 and 2019—the share of readings exceeding current health standards fell by half. Sparser data from before 2003 and standardized values (Z scores$\times$100) also indicate declines. Radioactive particles ("radionuclides") declined the fastest, while organic chemicals like pesticides had low levels in baseline data and flatter trends.[2] We find modest 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 (Gardner 2021; Borusyak, Jaravel and Spiess 2022). A Safe Drinking Water loan decreases the share of waters violating health standards by 10 percent and moderately decreases standardized values. Loans that identify a specifically targeted pollutant decrease the share of concentrations of that pollutant above health standards by 40%. Cost-effectiveness analysis indicates that through these loans, it would cost the average drinking water system \$2.6 million annually (\$2019), or \$36 per person$\times$year, to eliminate readings of regulated pollutants above health standards.

Third, administrative Medicare data indicate that Safe Drinking Water Act loans reduce mortality among older Americans. The average loan decreases mortality rates by half a percent relative to baseline levels, implying a cost of \$124,000 per premature death avoided.

[2] 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.

An age-adjusted estimate of the value of a statistical life implies that these loans have a measured benefit/cost ratio of 19.6. We also estimate a cost of $26,000 per year of life saved due to these loans. The lifetime net benefits of all loans newly provided under the Act each year total $92 billion. These statistics only include benefits due to preventing premature mortality for individuals aged 65 and older. We informally discuss other possible benefits, including health benefits for people under age 65, avoided bottled water and home filter spending, and others, which would yield total benefits larger than we estimate.

In addition to event study graphs, which help assess the extent to which treatment and control communities have parallel trends prior to loan receipt, several additional pieces of evidence support the research design's internal validity and help rule out concern about possible omitted variables bias. First, for loans targeting specific pollutants ex ante, we study effects on targeted versus other pollutants. Second, we control for important potential confounding variables, including Clean Water Act investments, Clean Air Act nonattainment regulations, toxic pollution sources, local income and unemployment, opioid prevalence, health insurance coverage, other federal investments, and baseline federally-reported violations interacted with year fixed effects. Third, we examine whether the health benefits of loans are concentrated among households drinking piped water rather than well water. Fourth, we report falsification tests of the effects of loans on ambient air, river, and lake pollution. Finally, we report synthetic difference-in-differences estimates that effectively match systems on pre-loan trends (Arkhangelsky et al. 2021).

This paper departs from existing research in several ways. It provides the first comprehensive estimate of trends in US 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 Biden Administration recently began adding environmental statistics to the US National Accounts, a process which other countries have already undertaken (DePillis 2023; White House January 2023). The US strategy plans to add surface water pollution and groundwater depletion, among other environmental goods, to the US national accounts by 2028; our work could facilitate 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.[3]

Additionally, we provide the first 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; mandatory letters to customers highlighting drinking water violations decreased federally-reported violations; and drinking water systems use testing frequency strategically to avoid federally-reported violations (Bennear and Olmstead 2008; Bennear, Jessoe and Olmstead 2009; Grooms 2016; Nigra et al. 2017). 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.

Our work builds on recent economic analyses of major US environmental laws (Greenstone 2002; Behrer et al. 2021; Shapiro 2022; Taylor and Druckenmiller 2022). Our work differs from research on the Clean Water Act (Keiser and Shapiro 2019*b*) 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 investments affect health outcomes. Most economic analysis of water pollution and health focuses on earlier decades (Alsan and Goldin 2019; Flynn and Marcus 2021), on developing countries (Kremer et al. 2011; Greenstone and Hanna 2014; Dias, Rocha and Soares 2023), on births and infants (Currie et al. 2013; Hill 2018; Hill and Ma 2022), or on bottled water spending (Graff Zivin, Neidell and Schlenker 2011; Christensen, Keiser and Lade 2023), and largely does not directly analyze the impact of Safe Drinking Water Act interventions on health outcomes. We focus on older Americans for a few reasons—they are especially prone to hos-

[3] 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.

pitalization 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 zip code level data on health outcomes are available from Medicare, whereas zip-code level data on infants or the health of people under age 65 are typically only available for a few states; and Americans over age 65 account for three-fourths all US deaths (Xu et al. 2021).

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 is motivated in part by the concern that minority and low-income communities face higher pollution levels. Commentators often highlight prominent case studies for drinking water, such as in Flint, Michigan, but systematic drinking water 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 2 provides background. Section 3 describes data. Section 4 discusses econometrics. Section 5 discusses pollution levels and trends. Section 6 discusses loans and pollution. Section 7 discusses health. Section 8 concludes.

2 Background

2.1 Drinking Water, Pollution, and Treatment Technologies

Explaining drinking water systems, pollution, and treatment provides useful background. Appendix A discusses details.

We first explain how drinking water reaches households. Ninety percent of US housing units receive drinking water from public water systems, which are primarily what we study. The other ten percent of housing units, largely in rural areas, receive drinking water from private domestic wells, which we do not analyze since they lack drinking water regulation and our data do not cover them.

Public water systems include several components. Intake pipes draw in untreated surface or ground water. Drinking water treatment plants then remove pollution from 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, though they most often fund treatment plants.

We next explain the types of pollution that occur in drinking water systems and how these pollutants affect health. 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 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 originates from natural deposits, lead stems from old household pipes, and nitrate often derives 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.

Research has linked acute or chronic drinking water pollution exposure to many health problems, including gastrointestinal illness, kidney and liver disease, cardiovascular disease, stroke, diabetes, and cancers (Morris 1995; Meliker et al. 2007; Navas-Acien et al. 2008; Lisabeth et al. 2010; D'Ippoliti et al. 2015; Cotruvo 2019; USEPA 2018). 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.

Finally, we explain how public water systems treat these pollutants. General treatment often begins by adding benign chemicals 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 prevent leaching of chemicals like lead from pipes. Finally, pressurizing water in distribution pipes prevents inflow of pollutants through 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 (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.

2.2 The Safe Drinking Water Act

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

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.[4]

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

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. Loans fund capital investments; local governments pay operations and monitoring costs (USEPA 2017).

[4]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.

3 Data

3.1 Drinking Water Data

We obtain all available 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 most data, an observation represents one pollution reading.

Analysis requires choosing years, summary statistics, and pollutants. We analyze trends over the 17-year period from 2003–2019. Sample coverage is limited before 2003, though sensitivity analyses include earlier years. We analyze loans over the period 2009–2019 since the EPA began collecting loan records in 2009 and our Medicare data end in 2019.

Our main estimates use two summary statistics: the share of pollution readings exceeding current health standards and standardized values (Z scores defined within pollutant $\times$ 100). We multiply Z scores by 100 to increase the readability of smaller numbers. 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 current, time-invariant health standards so 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 health standards, "priority" pollutants that Safe Drinking Water loans target, and pollutants without health standards (Appendix Figure 1).[5] 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. Most regressions include system-by-pollutant fixed effects. We restrict some estimates to system-pollutant pairs present for most years. We also emphasize results for the regulated pollutants that are the most widely measured. We further exclude readings with flags identifying

[5]We define priority drinking water pollutants as those that some Safe Drinking Water loans target, have health standards, and routine monitoring. This definition identifies 11 priority pollutants: several disinfection byproducts (bromate, chlorite, haloacetic acids, and trihalomethanes); two inorganic chemicals (arsenic and nitrate); one microorganism (total coliforms); and four radionuclides (gross alpha, gross beta, radium 226+228, and uranium).

repeated or special-purpose readings. We report some results weighted by population. Additionally, we average readings to the system$\times$month then system$\times$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 make this choice of 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 these data represent systems serving over 300 million Americans. 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. Over half the readings represent regulated pollutants. A majority 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 87 percent of pollution readings. The mean pollutant has four readings per system$\times$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 they occur together. Organic and inorganic chemicals have a modest positive association, perhaps because nearby factories contribute to both. "Secondary" pollutants, which affect water's taste or appearance but do not primarily affect health, are correlated with pollutants which affect health. Thus, water which tastes or looks bad is more likely to be unhealthy.

3.2 Who Does Each Drinking Water System Serve?

We obtain information on the exact area each drinking water system serves from the US Community Water Systems Service Boundaries v3.0.0, a dataset that the Environmental Policy Innovation Center (EPIC) created in November 2022. EPIC works with state governments to create and document electronic maps describing precisely where each system distributes water.[6] Prior research has obtained similar information for California, New Jer-

[6] 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.

sey, or Pennsylvania, though has not used national maps (Currie et al. 2013; Hill and Ma 2022; Pace et al. 2022). These data are relevant for our health and inequality estimates only, and 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 79 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.

3.3 Medicare and Other Data

We use individual-level Medicare administrative records on all beneficiaries from years 2009–2019, 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 zip code of residence and date of death, though our data do not report cause of death.[7] The second describes patients' health care utilization, including the number of inpatient hospital stays. The first segment covers all beneficiaries; the second covers the roughly 70% of beneficiaries in traditional fee-for-service Medicare.

We use several other public datasets. The EPA's Safe Drinking Water Information System reports system names, population, and other characteristics. Many environmental and economic data, described in Appendix B.2, provide time-varying controls. The 2010 Census provides block and block group population and demographics. Murray et al. (2021) counts housing units by block group with piped water versus private domestic wells.

[7] We use "zip code" to denote five-digit zip code tabulation areas. These have similar boundaries to zip codes but are standardized nationally by the Census Bureau.

3.4 Safe Drinking Water Act Loans

Through a federal Freedom of Information Act request, we obtain detailed information on Safe Drinking Water loans. The EPA collected these data systemically beginning in 2009, though some records cover earlier years. We analyze 9,200 loans, collectively worth $32 billion (Appendix Table 4). The mean loan provides $3 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, 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, where private wells are more common.

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 are evenly divided across the five groups of pollutants. Essentially no loans target inorganic chemicals other than arsenic and nitrate, or organic chemicals.

Appendix Table 5 describes characteristics of systems receiving loans. Systems serving large populations and with a higher share of readings violating health standards in the year 2006 receive more loans. Black, Hispanic, and low-income communities also receive more loans, which is important for debates about Environmental Justice and loan targeting. 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 densely populated areas. Controlling for population density also somewhat decreases the relative number of loans that Hispanic and low-income communities receive.

4 Empirical Framework

4.1 Trends

We use the following equation to estimate pollution trends:

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

The dependent variable P represents the mean pollution level for pollutant (chemical) c in drinking water system s and year y. It measures 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, and so imply that equation (1) estimates trends within a system and pollutant. 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. The error term ε_{csy} includes other forces affecting drinking water pollution. Regressions in the paper are clustered by drinking water system.

We use the following equation to graph national pollution trends:

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

We plot the year-specific coefficients $\alpha_{2003}, \ldots, \alpha_{2019}$ plus the constant, evaluated at a reference category of μ_{cs}.

4.2 Effects of Safe Drinking Water Loans on Pollution

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

$$P_{csy} = \beta L_{sy} + X'_{csy}\pi + \mu_{cs} + \mu_{gy} + +\mu_{cy} + \varepsilon_{csy} \tag{3}$$

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. We measure the number of loans rather than loan dollars because a large share of loan values are zero (representing system×year observations with no loans) and the rest are approximately lognormal, and since loan values vary with system size and pollution. The controls X_{csy} include the share of readings from each month and, in some specifications, the other controls like nonattainment designations, unemployment, etc. The fixed effects μ_{cs} account for different mean pollution levels in each drinking water system×pollutant. The geographic state-by-year fixed effects μ_{gy} account for different pollution levels over time and space and any time-varying state-specific characteristics of data collection. The pollutant×year fixed effects μ_{cy} allow for differential national trends by chemical.

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

$$\mathbb{E}[L_{sy}\varepsilon_{csy}|X_{csy}, \mu_{cs}, \mu_{gy}, \mu_{cy}] = 0$$

We assess this assumption 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:

$$P_{csy} = \sum_{\tau=-9}^{\tau=10} \beta_\tau 1[L_{s,y+\tau} = 1] + X_{csy}^{'}\pi + \mu_{cs} + \mu_{gy} + \mu_{cy} + \varepsilon_{csy} \tag{4}$$

Here τ represents event time, i.e., years since a system receive a loan, with $\tau = -1$ as the reference period.[8] Equation (4) includes all drinking water systems; those never receiving a loan have event time indicators $1[L_{s,y+\tau} = 1]$ 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 2021; Borusyak, Jaravel and Spiess 2022), which account for treatment in different years, and synthetic differences-in-difference estimates (Arkhangelsky et al. 2021), which construct weighted combination of control water systems to match treatment systems on pollution pre-trends.

Engineering predictions guide our expectations on impact timing. After loan receipt, completing construction can take 1–5 years. 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 that target a specific pollutant, we assess how loans affect targeted versus other pollutants:

$$P_{csy} = \beta^T L_{c'sy} 1[c' = c] + \beta^{NT} L_{c'sy} 1[c' \neq c] + X_{csy}^{'}\pi + \mu_{cs} + \mu_{gy} + \mu_{cy} + \varepsilon_{csy} \tag{5}$$

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

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

arsenic ($c' = arsenic$), this tests how these loans affect arsenic versus 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 $\beta^{NT} \neq 0$.

4.3 Effects of Safe Drinking Water Loans on Health

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

$$lnH_{zy} = \gamma L_{zy} + W_{zy}^{'}\pi + \mu_z + \mu_{gy} + \varepsilon_{gy} \tag{6}$$

Here z represents a five-digit zip code and L_{zy} is cumulative Safe Drinking Water loans for people aged 65 and older in z. We calculate L_{zy} as the population-weighted mean across systems serving z. The dependent variable lnH_{zy} represents the log annual deaths or hospital admissions per 10,000 Medicare beneficiaries. We specify the dependent variable in logs since it is approximately lognormally distributed and rarely zero. The zip code fixed effects μ_z imply that equation (6) exploits variation within zip codes and over time. The time-varying geographic fixed effects μ_{gy} imply this equation also exploits variation across zip codes within a state and year. The controls W_{zy} include nonattainment designations, unemployment, etc. Some estimates are weighted by the over-65 population in each zip code, which efficiently addresses heteroskedasticity and estimates effects for the mean person rather than the mean zip code.

We also estimate event study graphs for health:

$$lnH_{zy} = \sum_{\tau=-9}^{\tau=10} \gamma_\tau 1[L_{z,y+\tau} = 1] + W_{zy}^{'}\beta + \mu_z + \mu_{gy} + \varepsilon_{zy} \tag{7}$$

Cumulative or chronic health effects could take longer than the 3–4 year 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. As with the pollution event study graph, we report heterogeneous difference-in-difference and synthetic difference-in-difference versions of these estimates.

Appendix C.4 discusses the use of loans as an instrument to estimate the concentration-response function between drinking water pollution and older adult mortality. As discussed in that appendix, we interpret these carefully given the setting.

5 Results: Drinking Water Pollution Levels and Trends

5.1 Levels

We begin by describing spatial patterns in US 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 effects to adjust for potential sampling differences.[9] The map reveals enormous variation across states. For example, Kentucky and Oklahoma have high pollution levels 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 3 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.

We next describe pollution sources and their associations with specific pollutants. These associations 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 6 finds that these associations are positive and many have large magnitudes. For example, counties with arsenic deposits for mining have an additional six percentage points of drinking water violating arsenic standards, or a 170% increase relative to the sample mean.

Finally, we show how drinking water pollution varies by population characteristics. Table

[9]Because pollutants have different probabilities of exceeding health standards, we adjust for pollutant fixed effects to 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.

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 modestly lower pollution, echoing the low pollution levels for cities from the maps. The semi-elasticity of the share of pollution violating standards with respect to log population is -0.08. Mean violation rates are around 2.5 percentage points, so doubling population would represent a 3 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.

Table 1, column (2), shows that Black communities have lower overall pollution than other communities. The sign is surprising, though the magnitude of 0.11, or a 4 percent lower than the baseline mean, is not especially large. Columns (3) and (4) show that low-income communities have significantly higher pollution, while Hispanic communities do not. Conditional on population served, Black and non-Black communities have more similar pollution levels.

Sensitivity analyses in Appendix Table 7 show that the higher overall pollution in low-income communities is robust, but patterns for Black and Hispanic communities are not. 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). Black communities in this estimate have lower pollution, although the difference is statistically insignificant. In Panel A, low-income communities have much higher pollution than high-income communities. Panels B through F consider each category of pollution separately. Patterns differ somewhat by pollutant. Disinfection byproducts are lower in Black communities, though adding population controls in column (5) suggests again that this is primarily because Black communities are more often in cities and have higher population density. Inorganic chemicals are much higher in Hispanic communities, perhaps in part due to agricultural nitrate fertilizers. Microorganisms have high concentrations in Black communities, which is important since microorganisms are the most longstanding and challenging drinking water health problem. Organic chemicals rarely exceed standards anywhere.

5.2 Trends

We first document national trends in overall drinking water pollution, estimated using equation (2). Figure 2 shows that the share of drinking water pollution above standards fell by half in 2003–2019, from 2.6 percent to 1.3 percent. 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.

Table 2 reports corresponding regressions, using equation (1). Panel A, column (1), shows that over a decade, drinking water becomes 1.1 percentage point less likely to violate health standards. Because only 2.9 percent of pollution readings violate standards in the initial year 2003, this represents a rapid decline.[10] This trend estimate is precise, with a t statistic above 45. 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 all pollutants with health standards, which are more rapid for priority pollutants. The magnitude of trends in standardized values, however, is modest. This occurs 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 dot furthest to the right in the figure shows a trend regression where the dependent variable is the share of readings for a system×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

[10]This statistic is slightly above the corresponding share from Figure 2, Panel A, because there we use the residuals plus the constant after partialling out system×pollutant fixed effects and month seasonality.

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. To the extent that these standards identify levels of pollution which affect human health, our estimates suggest that these trends could reflect important positive impacts on human health.

We now turn to examine trends in unregulated pollutants. This analysis uses standardized values rather than readings exceeding health standards, which are undefined for regulated pollutants. Table 2, Panel B, column (4) shows a downward trend in unregulated pollutants that is just over half the trend for regulated pollutants, from column (1), and is statistically significant. 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 8 presents many alternative specifications, which mostly show qualitatively similar results; Appendix C.1 discusses details. These include alternative summary statistics for pollution, a longer sample window, and alternative sample selection rules and weighting. Several sensitivity analyses for organic chemicals and nitrates are flatter and somewhat sensitive to these alternatives, so we interpret trends for these pollutants more cautiously.

Finally, Appendix Table 9 shows trends by demographic group. Pollution is declining slightly faster in Black, Hispanic, and low-income communities. These patterns become smaller and less precise 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.

6 Results: Safe Drinking Water Loans and Pollution

This section analyzes how Safe Drinking Water loans affect overall pollution, specific pollutants, and demographic groups. The event study in Figure 3 analyzes the effect of Safe Drinking Water loans on the percent of readings exceeding health standards, as in equation (4). The blue solid line shows point estimates and the dashed red lines show the 95 percent confidence interval.

Figure 3 shows that loans cause large and sustained decreases in pollution. Each loan decreases the share of pollution above standards by nearly half a percentage point, which is an important decline relative to the baseline rate. In years before a loan, pollution has similar trends in treatment and comparison systems. After a loan, pollution declines, with sensible timing. Pollution changes little in the year of a loan, declines over the next two to five years, and the decline persists through 10 years. This is in line with, though on the early side of, engineering predictions that wastewater treatment construction projects take two to ten years to complete (Keiser and Shapiro 2019*b*).

Table 3 shows corresponding regressions, estimated using equation (3). Panel A finds that each loan decreases the share of water that violates standards nearly a third of a percentage point, or a 10 percent decrease relative to the sample mean violation rate of 3.1 percentage points. For the priority pollutants which loans generally target, column (2) finds that loans decrease the share of readings above standards by half a percentage point. Loans decrease priority more than other pollutants because priority pollutants have higher baseline levels and because loans target priority pollutants.

Loan impacts differ by pollutant. Table 3, columns (3) through (7), shows that loans substantially decrease disinfection byproducts, microorganisms, and radionuclides. Loans cause small decreases in inorganic chemicals and no changes in organic chemicals, partly since organic chemicals hardly ever exceed standards. Panel B shows that a typical loan decreases standardized values by only a small amount, though the estimates are precise. As we discuss below, the smaller impact for standardized values than readings above health standards reflects loans' large impact on the right tail of the pollution distribution but smaller impact elsewhere.

Table 3, Panels C and D, analyzes the 11 percent of loans which identify the specific pollutant a loan targets, following equation (5). We find that a targeted loan primarily and substantially decreases the pollutant it targets. Columns (1) and (2) show that a targeted loan eliminates 40% of violating readings of a targeted pollutant. Columns (3) through (7) show similar patterns across categories of targeted pollution.[11] Panel D shows qualitatively similar results using standardized values.

[11]For microorganisms, we do not find a pollution decrease due to loans, and even find a marginally significant small positive estimate. Microorganism loans target *Cryptosporidium* and *Legionella*, which are difficult to monitor routinely and involve different treatment technologies than total coliforms, which are the microorganism that is typically monitored.

Sensitivity analyses obtain qualitatively similar patterns, including estimates allowing for different treatment years, synthetic difference-in-differences estimates, semi-parametric bin estimates across the distribution of pollution, and others; Appendix Table 10 presents and Appendix C.2 discusses details. We do not find significantly different impacts of loans on pollution between Black, Hispanic, or low-income communities; Appendix C.5 discusses details.

Appendix Table 11 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 meaningfully affect pollution in other media.[12] We estimate regressions analogous to equation (3). Each observation represents a a pollutant$\times$monitor$\times$year, which we link to the population-weighted cumulative number of loans for each county$\times$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 near zero. A few border on statistical significance but have small magnitudes and positive signs (the opposite sign of the loan's impact on drinking water pollution).

6.1 Cost Effectiveness of Safe Drinking Water Loans

Cost effectiveness equals 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 can help choose policies that maximize environmental benefit for given cost, or equivalently, that minimize the cost of achieving a given environmental outcome. We can also compare cost-effectiveness against estimates of the demand for drinking water quality to obtain benefit/cost and social welfare calculations.

Cost-effectiveness and benefit/cost 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.6 discusses regressions of the log of cumulative municipal capital water investment on cumulative Safe Drinking Water loan amounts, estimated using municipal balance

[12] 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.

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 likely imply 20 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 assume is 25 years, following engineering and econometric evidence for similar materials (Keiser and Shapiro 2019*b*). 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.

Table 4, Panel A, shows that the mean loan provides $3.4 million in capital spending. Over a loan's lifetime, operations and maintenance costs almost equal capital costs. Thus, the mean loan costs $6.6 million over its lifetime, or $260,000 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 $2.6 million annually to eliminate readings of all pollutants above health standards. Row 10 shows qthat it would cost $36 annually per person to eliminate pollution levels above health standards. Row 12 calculates that using these Safe Drinking Water loans, it would cost $11 billion annually to eliminate all pollution readings above health standards nationally. Costs to decrease drinking water pollution by one standard deviation are much higher, since loans predominantly affect the right tail of the pollution distribution.

Comparisons help provide a benchmark for these statistics. The average annual US water bill is $185 per person (Bluefield Research 2023; US Census Bureau 2023). Thus, using Safe Drinking Water Act loans to eliminate pollution above standards would increase water bills by 19 percent. Surface water pollution provides another comparison. Using Clean Water Act grants to wastewater treatment plants, it costs $1.5 million annually to make one river-mile safe for fishing (Keiser and Shapiro 2019*b*). Table 4 indicates that it costs 70 percent more ($2.6 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 in environmental economics 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.

7 Effects of Safe Drinking Water Loans on Health

Figure 4 shows an event study graph of how Safe Drinking Water loans affect the log mortality rate of older Americans, as in equation (7). The horizontal axis describes the years since a drinking water system receives a loan. The vertical axis describes the log mortality rate, with the period before loans normalized to the value zero.

Figure 4 shows that Safe Drinking Water loans cause large mortality declines. Before a loan, log mortality rates have parallel trends between recipient and other communities. After a loan, mortality rates steadily decrease in years 0 to 3, decrease faster in years 4 to 5, and still faster in years 6 to 9. The decrease in log mortality rates is 0.005 in most periods, though somewhat more in the final period. This timing of mortality impacts in Figure 4 somewhat echoes the timing of pollution impacts in Figure 3. The decline in pollution is somewhat abrupt, reflecting the completion of construction after a few years, and the decline in mortality is more gradual. Mortality timing may reflect chronic and acute illness, plus cumulative effects of pollution exposure. Appendix Figure 6 shows similar patterns using a heterogeneous difference-in-differences and synthetic difference-in-differences estimator; Appendix C.3 discusses details.

Table 5 shows regression analogs, as in equation (6). Panel A describes unweighted regressions. Panel B weights estimates by the zip code's Medicare population. Column (1) shows a basic estimate with zip code fixed effects and state×year fixed effects. Column (2) adds potential confounding variables, including other environmental policies, local economic conditions, and other forces influencing health. Column (3) restricts the sample to system×years with drinking water data. Column (4) expands the sample to years 1992–2019.

Table 5, column (1), shows that the mean loan decreases the mortality rate in a zip code×year by about half a percent. The unweighted point estimate in Panel A exceeds the population-weighted point estimate in Panel B. Column (2) shows extremely similar effects upon controlling for potential confounding variables, which provides one piece of evidence that such omitted variables do not drive the health results. Systems with drinking water data and the larger time window, in columns (3) and (4), also obtain similar estimates. For the mean system, these estimates imply that each loan presents 2.3 annual deaths per 10,000 population, or 2.1 annual deaths given that the mean system serves 9,300 older Americans. We are unaware of comparable estimates for the older American mortality impact of drinking water pollution to provide a basis for comparison.

Appendix Table 12, columns (5) through (8), examines the inequality of loan effects by demographic group. These estimates interact the cumulative loan variable L from equation (6) with indicators for whether a community is Black, Hispanic, or poor. These estimates find that loans have statistically indistinguishable effects on health in Black, Hispanic, and poor communities. While point estimates suggest that loans provide smaller health benefits in Black, Hispanic, and poor communities, most of the interactions are somewhat imprecise.

Appendix Table 13 reports sensitivity analyses, including interactions with piped versus well water, loans focused on specific pollutants, and a dose-response estimate for the cumulative number of loans, which generally provide qualitatively similar results. Appendix C.3 discusses details.

Appendix Table 14 reports the impact of Safe Drinking Water loans on the log Medicare hospital admission rate, with specification corresponding to equation (6). The main estimate in Panel A, column (1), is close to the corresponding mortality estimate from Table 5, though less precise. Most estimates in Appendix Table 14 are negative but have wide confidence intervals. Hospitalizations, unlike mortality, can depend more on economic conditions, and some other environmental analyses similarly find precise decreases in mortality but less clear changes in hospitalizations (e.g., Deschenes, Greenstone and Shapiro 2018).

Appendix C.4 discusses results from using loans as an instrumental variable to estimate the semi-elasticity of the log mortality rate of older adults with respect to drinking water pollution. We estimate a large concentration-response function. As that appendix discusses, we interpret these results cautiously due to the multi-dimensional nature of pollution and targeting of loans.

7.1 Benefits and Costs

Table 6 finds that these loans generate large benefits relative to their costs. Most entries in that table report values for the mean loan. Several rows report numbers summed over all loans. Panel A summarizes inputs from earlier in the paper. As in the cost-effectiveness analysis, we assume that loan benefits last 25 years.

Table 6, Panel C, aggregates health benefits over a loan's lifetime. Row 9 shows that the mean loan prevents 53 premature deaths over its lifetime. Row 10 uses an age-adjusted value of a statistical life to find that the willingness-to-pay for avoided premature mortality is $129 million per loan. Numbers weighted by population and using the EPA's value of a statistical life are larger. Given the population of older Americans we study, our discussion focuses on the age-adjusted value of a statistical life.

Table 6, Panel F, compares measured benefits and costs of these loans. As discussed below, loans create some benefits this paper does not measure. Row 19 shows our central estimate that loans have a benefit/cost ratio of 19.6. Alternative estimates using the EPA's value of a statistical life, or weighted by population, are larger, and would indicate substantial positive net benefits from these investments.

Given uncertainty over the value of a statistical life, we also describe the loans' cost per premature death avoided, or per life-year saved. These statistics compare mortality against loan project cost, without incorporating the value of a statistical life. Table 6, row 21, shows that through these loans, it costs $124,000 to prevent one premature death. This is far below leading estimates of the value of a statistical life, which is another way of concluding that these loans have large net benefits. Row 23 finds that loans cost $26,000 per life-year saved. Row 24 finds total lifetime net benefits from all 750 loans newly provided in the mean year of $92 billion.

Save Drinking Water loans have high estimated returns relative to other environmental and health investments, though our estimates are in line with some other drinking water numbers. In the mid-1990s, the average medical intervention cost $68,000 per life-year saved (Tengs et al. 1995).[13] Safe Drinking Water loans, at cost of $26,000 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

[13] We deflate monetary values in this section to 2019 dollars using the GDP deflator.

8.3. Our estimated benefit/cost ratio of 19.6 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 estimate of the cost per life×year saved of $26,000 substantially exceeds 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.

Safe Drinking Water loans may create benefits beyond the mortality declines for older Americans that we measure. The costs of adaptation to drinking water pollution would increase benefit/cost ratios 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 Brita-style 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. Loans' mortality benefits likely dwarf at least the bottled water spending they prevent. For example, total national US bottled water spending in 2020 was $36 billion (IBWA 2023). Only a subset of this spending was caused by tap water pollution. The estimated annual mortality benefits of Safe Drinking Water loans in a typical year of $97 billion (Table 6, row 12) exceed all national bottled water spending for all purposes.

Additionally, loans also likely create health benefits for people younger than 65, especially infants. 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 loans is more limited than awareness of prominent drinking water disasters.

Finally, we note that the benefit/cost ratio covaries inversely with the pass-through rate. 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. These funds represent loans that municipalities must repay, not grants where municipalities are only responsible for a portion of costs. Thus, incomplete pass-through may be less likely in this setting than others (see Appendix C.6).

8 Conclusion

The classic economic history of drinking water emphasizes Snow (1855)'s linking it to cholera in the mid-nineteenth century and the beginning of municipal treatment in the early twentieth century (Cutler and Miller 2005). This paper adds a modern chapter to this story—drinking water pollution remains a costly 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. These loans substantially decrease mortality rates of older Americans and have high benefit/cost ratios. More broadly, our compilation of the first national dataset of drinking water pollution concentrations linked to Census blocks may open up additional opportunities to research drinking water pollution.

Our finding of large returns to Safe Drinking Water Act loans would support the additional funding for these loans in the 2021 infrastructure bill. Because loans target pollution cases that systems and states judge to pose the most serious threats to human health, they may represent marginal returns to drinking water investment, and we are cautious to extrapolate our estimates to arbitrary drinking water policies. Nonetheless, our results do suggest encouraging potential for other US drinking water investments to meaningfully increase social welfare—if the marginal return to investment is high, the mean returns may be reasonably positive as well.

We finish with a few broader conclusions. One compares these investments to other major US environmental policies. As discussed earlier, the benefit/cost ratio we estimate for these drinking water investments is similar to or higher than than typical ratios for Clean Air Act regulations, and contrasts more with much smaller benefit/cost ratios for many Clean Water Act investments in improving river and lake water quality (Keiser, Kling and Shapiro 2019). Prevented premature mortality benefits of drinking water and clean air, multiplied by a large estimated value of a statistical life, account for these investments' large estimated net benefits. The measured benefits of Clean Water Act investments focus primarily on recreational (e.g., fishing and boating) rather than health benefits, and so their measured benefit/cost ratios are accordingly lower. Of course, this paper's results do give rise to the question of how investments in cleaning up rivers and lakes affect drinking water quality and health, which we leave for future work.

A second takeaway involves the analysis of fiscal federalism. The large net benefits we estimate from Safe Drinking Water loans challenge the prevailing idea that federal investment in drinking water is inefficient because drinking water is a local public good. Various explanations could account for this discrepancy. These drinking water investments would likely have large benefit/cost ratios regardless of whether local or federal governments fund them. Given the dearth of evidence on drinking water pollution concentrations and Safe Drinking Water Act loans, federal and local governments likely have incomplete information about the returns to these investments. Additionally, some drinking water systems and their customers face credit constraints that make it difficult to fund the capital investments these drinking water improvements require; these subsidized loans help relax those credit constraints.

A third broader point involves our lack of 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 230 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 loans have a precisely-estimated zero effect on their concentrations. Thus, our analysis does not provide a strong empirical basis for the focus on organic chemicals, at least relative to other water pollutants.

Finally, much economic research focuses on regulated economic activity, in part because regulation generates data and policies. While regulated activity is important, it may be unrepresentative. Our finding that regulated pollutants are rapidly decreasing, but that unregulated pollutants are decreasing much more slowly, highlights the general challenge that regulated economic activity can provide an unrepresentative picture of all economic activity.

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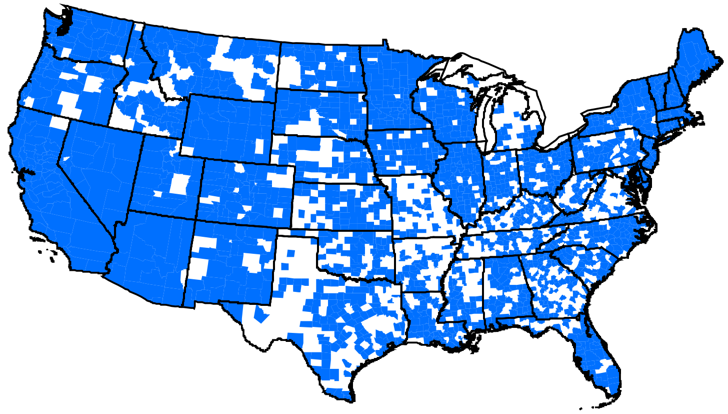
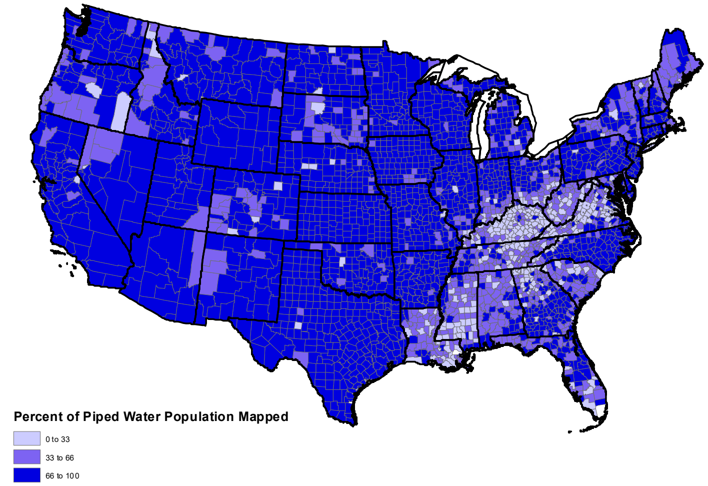
Figure 1: Maps of Drinking Water Data

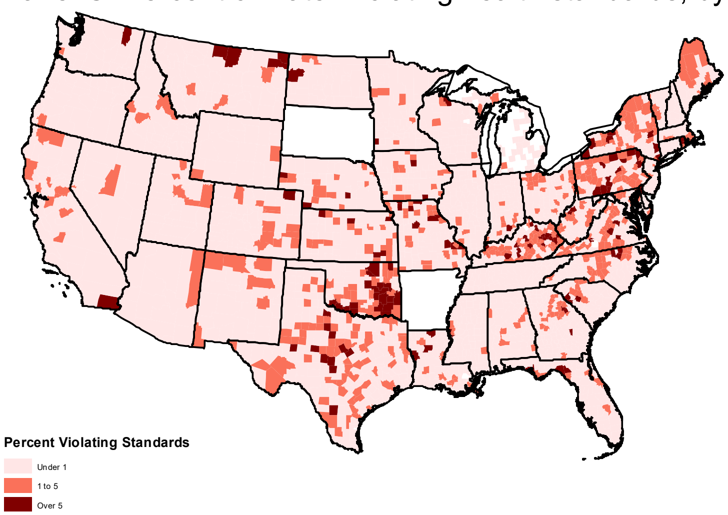
Panel A: Counties receiving Safe Drinking Water loans



Panel B: Percent of Population Mapped

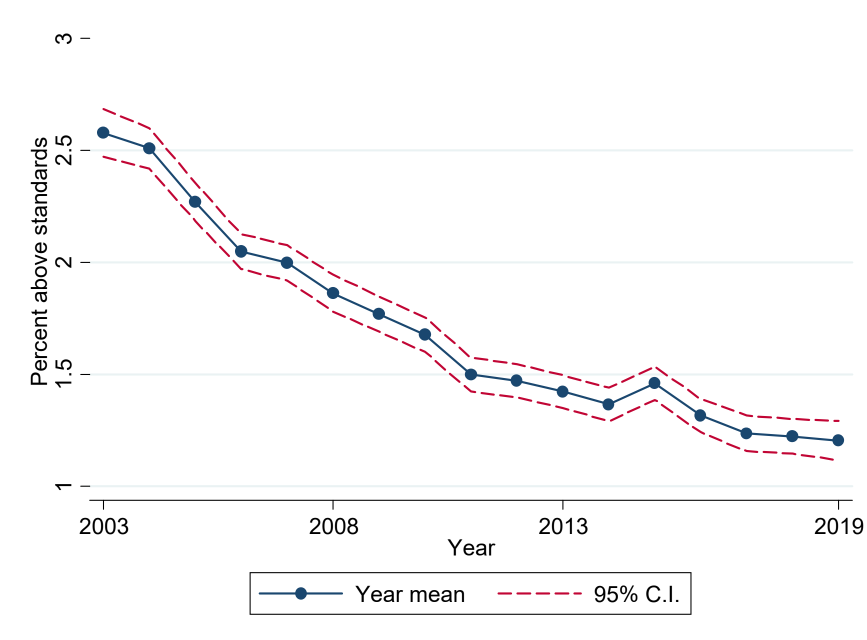


Panel C. Percent of water violating health standards, by county



Notes: in Panel A, counties shaded in blue have a drinking water system that receives a loan. In Panel B, each county shows the ratio of population with drinking water distribution mapped divided by population with piped water. Panel C shows the share of pollution above health standards in years 2009-2019. It partialls out pollutant fixed effects from system × pollutant × year data, then averages residuals plus the constant within each county. Averages weight the five categories of pollution equally and are proportional to population. Areas in white lack pollution data.

Figure 2: Trends in US Drinking Water Pollution

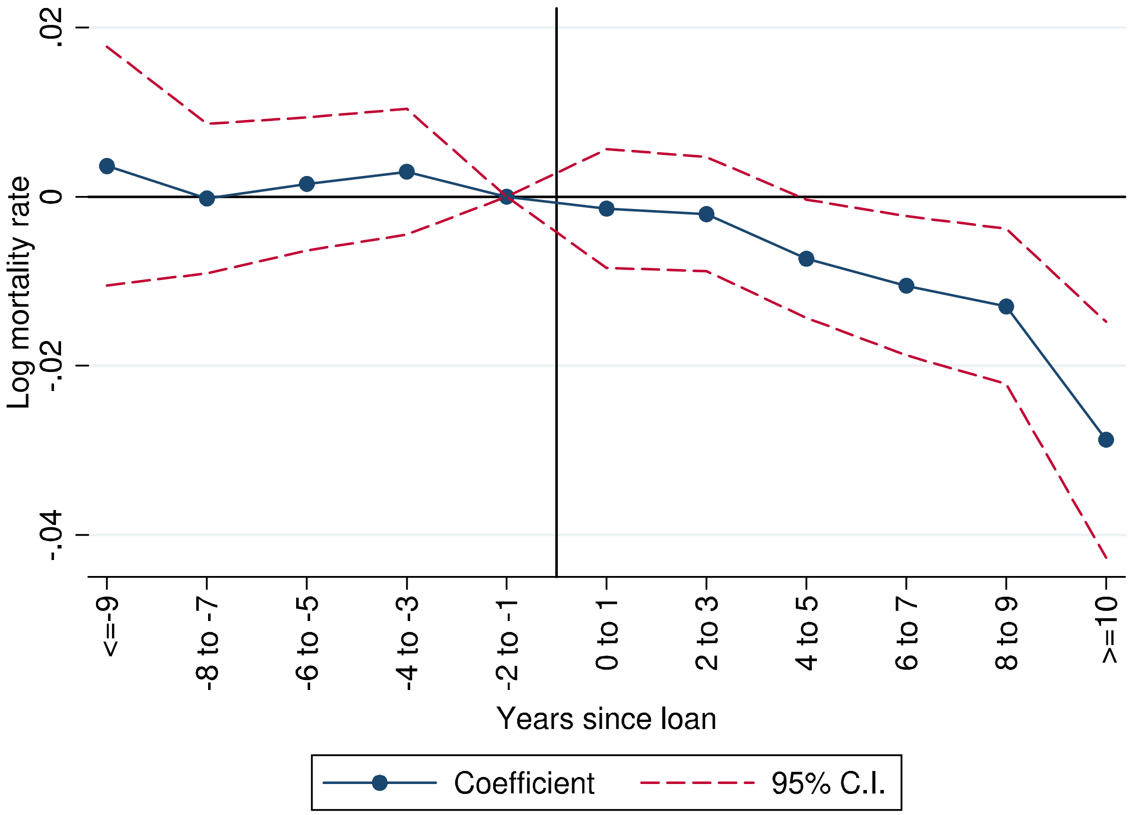


Notes: graph shows percent of drinking water exceeding current health standards, years 2003-2019. Graph includes pollutants with health standards. Each observation is a drinking water system × pollutant × year. Regression includes drinking water system × pollutant fixed effects and controls for the share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

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

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

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



Notes: the dependent variable is the log number of deaths among Medicare beneficiaries per 10,000 Medicare beneficiaries 65 and older in the zip code × year. Standard errors are clustered by drinking 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	-0.08***	—	—	—	-0.08***	-0.09***	-0.09***
	(0.02)	—	—	—	(0.02)	(0.02)	(0.02)
Above-median share Black	—	-0.11*	—	—	0.03	—	—
	—	(0.06)	—	—	(0.07)		—
Above-median share Hispanic	—	—	0.07	—	—	0.14**	—
	—	—	(0.06)	—	—	(0.06)	—
Above-median share Poor	—	—	—	0.39***	—	—	0.43***
	—	—	—	(0.06)	—	—	(0.06)
Panel B. Include state fixed effects							
Log population served	-0.08***	—	—	—	-0.08***	-0.08***	-0.09***
	(0.02)	—	—	—	(0.02)	(0.02)	(0.02)
Above-median share Black	—	-0.17**	—	—	-0.03	—	—
	—	(0.08)	—	—	(0.08)	—	—
Above-median share Hispanic	—	—	-0.16**	—	—	-0.06	—
	—	—	(0.07)	—	—	(0.07)	—
Above-median share Poor	—	—	—	0.32***	—	—	0.36***
	—	—	—	(0.07)	—	—	(0.07)
Month controls	X	X	X	X	X	X	X
N	7,770,693	7,770,693	7,770,693	7,770,693	7,770,693	7,770,693	7,770,693

Note: dependent variable is the percent of drinking water pollution readings above health standards. Each observation represents mean pollution for a drinking water system × pollutant × year. Regressions weight the five categories of pollution equally. Sample includes years 2003-2019. Sample includes systems with non-missing values of independent variables. Standard errors are clustered by drinking water system. Asterisks are shown for difference and indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Table 2: US 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	-0.114***	-0.178***	-0.005***	—
	(0.0025)	(0.0039)	(0.0002)	—
Dep. var. mean, yr. 2003	2.91	4.61	0.18	
Observations	18,172,145	3,678,875	14,493,270	—
N pollution readings	79,052,447	45,383,507	33,668,940	—
Panel B. Dependent variable: standardized value				
Year	-0.637***	-0.810***	-0.280***	-0.350**
	(0.0142)	(0.0217)	(0.0063)	(0.1372)
Dep. var. mean, yr. 2003	4.39	7.19	-0.33	0.47
Observations	18,302,776	3,678,875	14,493,270	11,427,311
N pollution readings	80,332,828	45,383,507	33,668,940	28,006,210
System × pollutant FE	X	X	X	X
Month controls	X	X	X	X

Notes: Each observation represents mean pollution for a drinking water system × pollutant × year. Regressions weight the five categories of pollution equally. Sample includes years 2003-2019. Month controls are the share of raw pollution readings from each month of the calendar 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 are clustered by drinking water 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

			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. All loans. Dependent variable: percent violating current standards							
Loans	-0.304***	-0.506***	-0.400***	-0.022	-0.212*	0.000	-0.769***
	(0.064)	(0.107)	(0.108)	(0.016)	(0.115)	(0.001)	(0.296)
Depend. var. mean	3.05	4.82	4.45	0.76	1.56	0.01	6.92
Observations	12,123,195	2,479,101	562,388	3,117,976	943,854	7,378,552	120,417
Panel B. All loans. Dependent variable: standardized value							
Loans	-1.514***	-2.399***	-1.672***	-0.211	-0.163	-0.027	-3.680***
	(0.314)	(0.520)	(0.640)	(0.155)	(0.549)	(0.076)	(1.194)
Depend. var. mean	9.05	15.64	25.35	-2.67	-12.61	-1.77	15.27
Observations	12,203,461	2,502,291	562,388	3,117,976	1,000,930	7,378,552	143,608
Panel C: Loans targeting one pollutant. Dependent variable: percent violating current standards							
Targeted loans *	-10.707***	-10.707***	-5.526***	-17.486***	1.118*	—	-14.666***
targeted pollutant	(1.308)	(1.299)	(1.136)	(2.163)	(0.636)	—	(2.375)
Targeted loans *	0.268	0.659*	0.375	0.072	-0.118	—	1.061
non-targeted pollutant	(0.181)	(0.377)	(0.453)	(0.069)	(0.253)	—	(0.880)
Depend. var. mean	27.49	27.49	15.23	50.44	1.44	—	39.93
Observations	12,123,195	2,479,101	45,451	94,938	100,642	—	21,789
Panel D: Loans targeting one pollutant. Dependent variable: standardized value							
Targeted loans *	-42.432***	-41.671***	-24.741***	-60.659***	8.644*	—	-51.350***
targeted pollutant	(6.301)	(6.385)	(5.726)	(9.607)	(4.862)	—	(11.506)
Targeted loans *	0.083	1.429	3.107	-0.442	0.855	—	-0.858
non-targeted pollutant	(0.792)	(1.724)	(2.654)	(0.806)	(1.530)	—	(3.556)
Depend. var. mean	138.86	142.40	109.43	266.00	-12.81	—	174.63
Observations	12,123,195	2,502,291	562,388	3,117,976	1,000,930	—	143,608
Fixed effects:							
Pollutant × system	X	X	X	X	X	X	X
Pollutant × year	X	X	X	X	X	X	X
State × year	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X

Notes: Sample includes years 2009-2019. Loans variables are cumulative. An observation represents mean pollution for a drinking water system × pollutant × year. Depend. var. mean represents the mean of the dependent variable for systems receiving loans, in years before a loan is received. Regressions weight the five categories of pollution equally. Targeted in Panels C and D indicates that a loan targets the pollutant that an observation represents. For Panels C and D, Appendix Table 4 shows the share of loans targeting each pollutant. Standard errors clustered by drinking water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 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	$3.38	$0.14
2. Operation & maintenance	$3.17	$0.13
3. Total	$6.55	$0.26
Panel B. Effectiveness of mean loan at reducing pollution		
4. Decrease in readings above standards (pct. points)	0.30	0.30
5. Decrease in pollution (standardized value)	1.51	1.51
Panel C. Cost for mean loan to decrease pollution ($million / unit of pollution)		
6. One pct. point decrease in readings above standards	$21.55	$0.86
7. One unit decrease in pollution standardized value	$4.33	$0.17
8. Eliminate pollution readings above standards	$65.8	$2.6
9. Decrease pollution by one standard deviation	$432.7	$17.3
Panel D. Cost per capita using loans to decrease pollution ($ / person)		
10. Eliminate pollution readings above standards	$899.1	$36.0
11. Decrease pollution by one standard deviation	$5,909.8	$236.4
Panel E. National cost to decrease pollution ($billion)		
12. Eliminate readings above standards nationally	$269.7	$10.8
13. Decrease pollution by one standard deviation	$1,772.9	$70.9

Note: capital costs equal loan amount. Annual operation & maintenance costs equal 3.75% of capital investment and loan benefits last 25 years, based on Keiser & Shapiro (2019b). Standardized value equals Z-score calculated within pollutant times 100. Costs, impacts, and population 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 300 million people. All dollars figures are in $2019, deflated using the GDP deflator.

Table 5: Effects of Drinking Water Loans on Log Mortality Rate

	(1)	(2)	(3)	(4)
Panel A: Unweighted				
Cumulative loans	-0.0059***	-0.0053***	-0.0058***	-0.0044*
	(0.0014)	(0.0014)	(0.0014)	(0.0022)
Observations	259,254	257,681	232,334	653,903
Mortality rate mean	429.7	432.1	429.9	470.0
Panel B: Weighted by population				
Cumulative loans	-0.0023**	-0.0019*	-0.0021**	-0.0034***
	(0.0010)	(0.0011)	(0.0010)	(0.0013)
Observations	259,254	257,681	232,334	653,903
Mortality rate mean	412.7	416.2	413.3	452.2
Fixed effects:				
Zip code	X	X	X	X
State × year	X	X	X	X
County controls		X		
With drinking water data			X	
Years 1992-2019				X

Notes: each observation is a zip code × year. Columns (1)-(3) include years 2009-2019. Mortality rate is deaths per 10,000 Medicare population. Dependent variable is log mortality rate. Main explanatory variable is the cumulative number of drinking water loans a system has received. County controls include cumulative 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; personal income per capita; unemployment rate; opioid dispensing rate per 100 people; federally-reported violations in years 2006-2008 interacted with year fixed effects; percent of population with health insurance; inverse hyperbolic sine of federal assistance and contracts. "With drinking water data" restricts the sample to drinking water systems and years for which we have drinking water pollution microdata. Standard errors clustered by drinking water system. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

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

Panel A. Data inputs	
1. Impact of loan on log mortality rate	-0.00525
2. Mean annual mortality rate	432.1
3. Mean population per loan	9,298
4. Assumed duration of loan benefits (years)	25
5. Age-adjusted VSL ($mn)	$2.4
6. EPA VSL ($mn)	$10.95
Panel B. Benefits per loan × year	
7. Premature deaths prevented per 10,000 population	2.3
8. Premature deaths prevented	2.1
Panel C. Benefits per loan, totalled across loan's lifetime	
9. Premature deaths prevented	52.7
10. Benefits using age-adjusted VSL ($mn)	$128.7
11. Benefits using EPA VSL ($mn)	$577.4
Panel D. Benefits of all loans provided in a typical year, totalled across loan's lifetime	
12. Benefits using age-adjusted VSL ($bn)	$96.5
13. Benefits using EPA VSL ($bn)	$433.1
Panel E. Loan costs	
14. Federal loan amount ($million)	$3.4
15. Annual state+local operation & maintenance cost ($mn)	$0.1
16. Total state+local operation & maintenance cost ($mn)	$3.2
17. Total costs of a loan ($mn)	$6.6
18. Total costs of all loans provided in a typical year ($bn)	$4.9
Panel F. Measured benefits versus costs	
19. Benefit/cost ratio of loans: age-adjusted VSL	19.6
20. Benefit/cost ratio of loans: EPA VSL	88.1
21. Cost per premature death avoided ($000s)	$124
22. Cost per life-year saved ($000s, all Medicare)	$11
23. Cost per life-year saved ($000s, death within one year)	$26
24. Total net benefits of all loans provided in a typical year: age-adjusted VSL ($bn)	$92
25. Total net benefits of all loans provided in a typical year: EPA VSL ($bn)	$428

Notes: VSL is value of a statistical life, mn are millions, bn are billions. Currency values are in 2019 dollars, deflated using the GDP deflator. Population values refer to individuals aged 65 and older. Mortality rate is deaths per 10,000 population. 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 Table 5, Panel A, column (2).

Online Appendix

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

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

Table of Contents

A Background: Additional Details

A.1 US Public Water Systems

Section 2.1 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*d*). Local governments like town water boards or local water districts own and operate most public water systems. A minority of public water systems have private owners, like apartments or campgrounds.

A single public water system can have multiple treatment plants. We analyze systems rather than individual treatment plants both because most data define a 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 US public water systems into three types. About 50,000 are community water systems, which serve year-round housing units. About 80,000 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 20,000 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*d*). Some public water systems procure water from other systems, which does not directly affect our analysis.

Section 1 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 2.1 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, a byproduct of disinfectants we measure separately, and microorganisms, a pollutant that disinfectants decrease, rather than disinfectants themselves. Finally, disinfectants have relatively few observations.

Section 3.1 of the main text describes reasons for the summary statistics we analyze; here we mention a few others. The share of readings above standards focuses on the margin where pollution is believed to affect health and is 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 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 include 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. Because a majority of pollution readings are zero, taking the log of pollution would exclude most of the sample, and the inverse hyperbolic sine is scale-dependent.

Section 1 of the main text notes limitations from analyzing federally-reported violations rater 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. Failure to use treatment technique might not produce elevated measured pollution concentrations but still violates the SDWA. Second, some systems fail to record specific pollutants when the SDWA requires it. Such monitoring violations violate the Act, although they by definition do not produce elevated pollution readings. Monitoring violations could in general be inferred from raw pollution concentrations data by using information on timing, frequency, and requirements of monitoring.

A.3 Safe Drinking Water Act Policies and Pollutants

This section discusses policies and pollutants under the Safe Drinking Water Act.

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 August 13, 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 implements also rules and other 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*b*).

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 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 serving over 10,000 population. 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. We interpret this rule as a health standard for an individual reading of zero.

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 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 implemented a more stringent Revised Lead and Copper Rule in 2021. Finally, the year 2000 Radionuclides Rule increased radionuclides monitoring requirements and regulated uranium.

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*e*). Apart from loans, the SDwA leaves funding and enforcement largely to states (Tiemann 2018; USEPA 2022).

Safe Drinking Water Act Pollutants

The Safe Drinking Water Act has health standards for 88 to 97 pollutants. The National Primary Drinking Water Regulations (USEPA 2009) list 88 contaminants. 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, fecal coliforms and *E. coli* are together considered 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, which makes their data unrepresentative. We also do not analyze acrylamide, *Cryptosporidium*, epichlorohydrin, enteric viruses, heterotrophic bacteria, *Legionella*, mercury, trichloroethylene, or enteric viruses, for which we have little or no data, and in several cases where regulations stipulate a treatment technique rather than a maximum contaminant level or action level. Most data record gross beta in pCi/L, but the MCL is in mrem/year, and converting between these units requires data on the underlying emitters which we do not typically have, so we also do not analyze gross beta.

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 individual regulations but are part of broader groups that have health standards. It also excludes broader groups that include a regulated pollutant and others.

One ongoing dispute with the SDWA is the set of pollutants it covers. States can regulate more pollutants than the EPA, and epidemiological research suggests health damages from several unregulated pollutants. Additionally, EPA has a Contaminant Consideration List of pollutants it seeks to understand better and may consider regulating in the future. Many states monitor these pollutants, though they are not yet federally regulated. For example, a controversy has arisen over per- and polyfluoroalkyl substances (PFAS), popularly known as "forever chemicals," which occur in many communities' drinking water systems. The EPA after much debate has recently chosen to regulate PFAS in drinking water.

This paper analyzes the SDWA, but it is informative to compare its pollutants against those of the Clean Water Act. For example, one of the most important pollutants in rivers and lakes for the Clean Water Act is dissolved oxygen. Oxygen is practically never measured in drinking water. The difference is partly because the Clean Water Act protects fish and other aquatic life, while the SDWA focuses 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 the Freedom of Information Act, open record request, direct request to government staff, or similar; and for 25 states through web scraping or downloading.

Not all jurisdictions have data available on all pollutants. For example, Panel A of Appendix Figure 3 shows that in addition to Arkansas and South Dakota, we lack data from Tennessee and Minnesota on disinfection byproducts. Panel C shows that we lack data from Tennessee on total coliforms. Massachusetts and California staff indicated they do not have comprehensive electronic records of total coliforms data available. Additionally, for several states we only have data on community water systems.

We impose several sample selection rules. We drop 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, and we report sensitivity analyses restricted to the readings identified as routine. Additionally, we exclude 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 where the relationship to health may not be monotone. Some examples include alkalinity, hardness, temperature, and flow rate. We also exclude chemicals with less than 1,000 observations each nationally.

In addition, we impose several data cleaning rules. We winsorize pollution readings at the 99.5th percentile or two times the health standard, whichever is greater, and Z scores at +/- 10. Although we define the mean and standard deviation for calculating Z scores with data at the system$\times$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. 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$\times$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. We have the most data on total coliforms. Arsenic is the most likely to violate standards, followed by TTHM and uranium.

Appendix Figure 2 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 County×Year Controls

We obtain county×year control variables from many sources. Safe Drinking Water loans and Clean Water Act loans are separate and affect different plants (wastewater treatment versus drinking water plants). We do collect data on nearby Clean Water Act loans and some estimates control for them. 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, which in 1987 succeeded the Clean Water construction grants program analyzed in Keiser and Shapiro (2019*b*). We count the cumulative number of wastewater treatment loans provided for each county×year. We use the EPA's Green Book 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 inverse hyperbolic sine of the number of active Toxic Release Inventory (TRI) plants. We use the number of plants, rather than reported emissions, given challenges with accurate TRI reporting (Currie et al. 2015); and we use the inverse hyperbolic sine given the large number of zeros and then skewed distribution. Additionally, we count the total number of drinking water violations reported to SDWIS in the years 2006-2008, and interact this baseline violation count with year fixed effects, which may help adjust for mean reversion.

We also include several economic controls. We control for per capita personal income from the Regional Economic Accounts of the Bureau of Economic Analysis, and we control for the local unemployment rate. Additionally, we include two measures of federal assistance and federal contracts, from USA Spending.

We include a few health controls. From the Centers for Disease Control, we use data on the number of opioid prescriptions per 100 persons in each county×year. We also use measures of the share of people who lack health insurance, from the Census Bureau's Small

Area Health Insurance Estimates program.

B.3 Other Data

We use a few additional general data sources. 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 11 correlates loans with air and water pollution data, using air pollution data from the EPA's Air Quality System and water pollution data from the Water Quality Portal.

Appendix Table 6 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 material in source waters. Columns (2) and (7) use data from the Mineral Resources Data System of the US 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 number of lead service lines per 100,000 population compiled by the Natural Resources Defense Council (NRDC). Column (4) uses estimates of the pounds of nitrogen from fertilizer and manure in each county in the year 2012, from the US Department of Agriculture, divided by county area, which are likely to affect nitrate in drinking water. Column (5) counts the total pounds of release of regulated chemicals to water by plants reporting in the Toxic Release Inventory, and calculate the log of these releases per mile of county area. 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.

C Results: Sensitivity and Additional Analyses

C.1 Trends

Appendix Table 8 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. Row (1) includes all regulated pollutants and weights equally across the five categories of pollution. Columns (2) through (7) show the five categories of regulated pollution, limited to pollutants with health standards. Columns (7) through (9) show three pollutants of particular interest—arsenic, lead, and nitrate. Columns (10) and (11) show standardized values for regulated and for non-regulated pollutants.

Appendix Table 8 rows have the following structure. Row 1 re-states the main estimates from Table 2, Panel A. In row 2, the dependent variable is the standardized value (Z score times 100). Row 3 restricts the sample to only community water systems. Row 4 limits the sample 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 population a drinking water system serves. Row 7 does not weight equally across the five different types of pollution.

Rows 8-12 of Appendix Table 8 use the unaggregated data, so that an observation represents an individual reading of a specific pollutant, system, date, and time. Row 8 estimates the main results at this unit of observation. Row 9 adds untreated source water to the sample. Row 10 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 11 specifies the dependent variable as the log of the raw pollution reading. Row 12 specifies the dependent variable as an indicator for being strictly positive.

Almost all of these Appendix Table 8 estimates show that regulated drinking water pollutants are declining, and most have similar magnitude to the main estimates. One interesting pattern here is that several estimates for nitrates obtain positive signs, indicating that the trend estimate for nitrates is not robust, while estimates for other pollutants are more systematically negative. Notably, estimates of national trends in nitrogen pollution concentrations in rivers and lakes are also somewhat flat (Keiser and Shapiro 2019*b*), and increasing nitrogen fertilizer use for agriculture is one typical explanation. In the time period we study, US corn acreage expanded, partly driven by policy incentives for corn-based ethanol, and corn intensively uses nitrogen fertilizer. 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.

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

Appendix Table 10 shows sensitivity analyses of how Safe Drinking Water loans affect drinking water pollution. Each row describes a different specification; each column describes a different set of pollutants. Row 1 repeats the main estimates from Table 3. Row 1, column (10) shows that drinking water loans substantially decrease standardized values of regulated pollutants; the point estimate in column (11) shows that loans somewhat decrease non-regulated pollutants, though the point estimate is not statistically distinguishable from zero.

Rows 2 through 7 of Appendix Table 10 show impacts of Safe Drinking Water loans using other specifications and samples. In row 2, the dependent variable is the standardized value rather than the percent of readings above standards. Row 3 restricts the sample to community water systems, and Row 4 restricts the sample to system×pollutants present in at least eight years of the sample. Row 5 expands the time window to begin in the year 1992. Row 6 weights the sample by the population each drinking water system serves. Row 7 does not apply weights across pollutants.

Rows 8 through 12 use the non-aggregated microdata, so an observation represents an individual water pollution reading on a particular site and day. Row 8 provides the basic estimate at this level of disaggregation. Row 9 adds in data on untreated water data to the sample. Row 10 adds fixed effects for each sample point. Row 11 uses the log of pollution as the dependent variable, which excludes observations with zero pollution. Row 12 uses an indicator for positive pollution as the dependent variable.

Rows 1-12 use sensitivity analyses that we also use for estimating trends in Appendix Table 8, while Rows 13-15 incorporate other alternatives specific to loans. Row 13 adds the various county×year and associated controls for the Clean Air Act, Clean Water Act, etc. Row 14 uses as an explanatory variable whether a system receives any loan (equivalently, it only counts the first loan a system receives). Row 15 shows a dose-response function for how one, two, or three or more loans affect pollution.

The alternative estimates in Appendix Table 10 are generally in line with the main results, but we comment on a few of the more interesting estimates. The estimates using a somewhat balanced panel are generally larger in absolute magnitude than the estimates with the full sample, while the unweighted estimates are smaller, since they put more weight on the large sample of organic chemicals, which rarely exceed health standards. 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, from -0.30 (0.06) in the main estimate in Row 1 to -0.31 (0.06) in Row 13. The dose-response type estimate in Row 15 shows that additional loans decrease pollution; this is primarily driven by disinfection byproducts and microorganisms.

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 2021), which is one case of more general heterogeneous difference in difference estimators (Borusyak, Jaravel and Spiess 2022).[1] We estimate standard errors using 200 bootstrap replications. Panel A also shows comparable two-way fixed effects (TWFE) estimates using the same sample and specification. The results with both the heterogeneous difference-in-difference estimate and TWFE 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.

We also report an event study using synthetic differences-in-differences (Arkhangelsky et al. 2021). Applying this estimator requires changing the data setup in several ways. We begin the sample in 2008 rather than 2009, so the estimate can include systems receiving loans in 2009, since this estimator cannot accommodate always-treated units. We also recode loans as an absorbing state, so that loan receipt is binary (thus ignoring when a system receives a second, third, or additional loan). Additionally, since this estimator is not designed to weight across pollutants, we estimate treatment effects separately by pollutant, then average. We also weight event study indicators evenly across the different treatment years. Using this adjusted sample, we report results using both this estimator and TWFE on the same sample and data for comparison. As with the heterogeneous difference in difference estimator, we use 200 bootstrap replications to estimate standard errors.

Appendix Figure 5, Panel B, shows event study indicators using both TWFE and synthetic differences in differences, on the same sample. The patterns of impacts are similar. Both estimators find somewhat flat pre-trends in years before a loan is received. Both also find gradual decreases in the 2 to 5 years after a loan is received. Point estimates remain negative out to ten years, though precision and magnitude decrease in the later years, which are identified by fewer observations.

Appendix Figure 5, Panel C, 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

[1] Among the various heterogeneous difference-in-difference estimators, we use Gardner (2021) since it requires the fewest changes to the basic setup of the estimate in the main text to accommodate the estimator's assumptions and since it executes relatively quickly in our large samples.

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.

C.3 Effects of Safe Drinking Water Loans on Health and Benefit/Cost Analysis

Appendix Table 13 shows sensitivity analyses for mortality. Row 1 re-states estimates from the main text. Row 2 interacts the loans indicator with a measure of the share of a zip code that receives water from public water systems, which the SDWA regulates and may benefit from loans, rather than private wells. The point estimates indicate that all the estimated treatment effect comes from areas with public water systems, and none from wells, though the estimates are imprecise. Row 3 shows that each cumulative loan further decreases mortality rates, so we observe a loan-mortality dose-response function. Rows 4 through 9 use the 11 percent of loans that identify the pollutant each loan targets, and estimates separate regressions analyzing how loans targeting arsenic (row 4), coliforms (row 5), Disinfectants or disinfection byproducts (row 6), microbial causes (row 7), nitrates (row 8), or radionuclides (row 9) affect health. Most of these point estimates are negative, and the magnitude is the largest for arsenic, although given the small sample sizes of these loans, all these estimates are imprecise. Ultimately, this setting lacks the statistical power to determine which of these investments most affects mortality rates.[2]

Appendix Figure 6 shows alternative event study graphs. Panel A uses an estimator accomodating heterogeneous treatment timing, from Gardner (2021). Panel B uses synthetic difference-in-differences Arkhangelsky et al. (2021). In both cases, we also show TWFE estimates using the same sample, controls, and weighting. In both Panels, the TWFE and alternative estimators imply qualitatively similar results. The Gardner and TWFE are estremely similar, though Gardner shows very slightly larger treatment effects in post years. The synthetic difference-in-differences estimator effectively normalizes pre-intervention treatment effects to zero, and then obtains somewhat larger post treatment effects, though the year-by-year pattern is broadly similar to the TWFE estimates.

The benefit/cost analysis considers two estimates of the value of a statistical life, both in 2019 dollars: an age-adjusted value of $2.4 million, based on several papers (Ashenfelter and Greenstone 2004; Murphy and Topel 2006; Deschenes, Greenstone and Shapiro 2018),

[2]We also investigated separating loans by whether a public water system had elevated rates of a specific pollutant in 2006–8. Loans with high levels of any specific pollutant decreased mortality by similar amounts.

and a value of $10.95 million, which the Environmental Protection Agency uses in regulatory impact assessments (Carleton et al. 2022);[3]

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.

C.4 Instrumental Variables Estimates of Pollution and Health

Methodology

Environmental threats to health, such as air and river pollution, are routinely correlated with weather, income, and population density. The correlation of drinking water quality with such confounding variables is plausibly important though empirically unknown, which can make it difficult to separately establish the health effects of drinking water pollution from effects of other potential confounding variables.

Thus, we report instrumental variables regressions which use the cumulative number of loans to a drinking water system as an instrument for drinking water pollution, to measure the effect of pollution on health. The structural equation is as follows:

$$lnH_{zy} = \eta P_{czy} + W'_{zy}\pi + \mu_z + \mu_{gy} + \varepsilon_{gy} \tag{C–1}$$

The parameter η represents the pollution-mortality concentration response function, i.e., the semi-elasticity of the mortality rate with respect to mean pollution concentrations. The first stage resembles equation (3), but with data aggregated from system s to zip code z:

$$P_{czy} = \beta L_{zy} + W'_{czy}\pi + \mu_{cz} + \mu_{gy} + \varepsilon_{czy} \tag{C–2}$$

We also report a version where we discretize L_{zy} to have indicators for whether a system receives 1, 2, 3, etc. loans. We additionally report limited information maximum likelihood estimates, which are mean-unbiased with many weak instruments.

Results

We discuss these estimates cautiously in part due to the multi-dimensional and potentially nonlinear effects of drinking water pollution. Loans decrease many types of pollution, in-

[3]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 focused on drinking water (Carleton et al. 2022; USEPA 2023*a*,*c*).

cluding measured and unregulated pollutants, and plausibly also decrease concentrations of pollutants that are both unmeasured and unregulated. It is difficult for one or several endogenous variables to provide a complete summary of how loans affect many pollutants, and to summarize all aspects of the pollutants' effect on health. Additionally, loans target the most serious health risks, while instrumental variable regressions extrapolate these estimates to arbitrary changes in pollution. Loans could reflect local knowledge about which treatment technologies, pollutants, or parts of a pollutant's distribution are especially relevant to health. Finally, these estimates aggregated to the zip code×year level have somewhat weak instruments, though we discuss multi-valued loan instruments and limited information maximum likelihood (LIML) estimates, which give qualitatively similar results.

Appendix Table 15 reports instrumental variable estimates of the mortality-pollution concentration-response function, i.e., the semi-elasticity of mortality rates of older Americans with respect to drinking water pollution. Panel A, reports first-stage regressions of the zip code's mean percent of pollution exceeding health standards on the cumulative number of loans a system has received, corresponding to equation (C–2). These are similar to the pollution regressions from Table 3, except aggregated to zip code and restricted to the instrumental variables sample. Panel B reports reduced-form regressions of log mortality rates on cumulative loans, which resemble (6) except again use zip code rather than drinking water system, and the Appendix Table 15 sample. Panel C reports the structural equation corresponding to equation (C–1). Panel D reports LIML estimates using multi-valued loan instruments, which are mean-unbiased in the presence of weak instruments. Panel E shows ordinary least squares regressions of mortality on pollution, which provide a comparison. Columns (1)-(3) are unweighted; columns (4)-(6) are weighted by population. Within a given column, the four panels use the same sample.

The first stage estimates in Appendix Table 15, Panel A, shows that loans decrease pollution. The point estimate is moderately larger than the corresponding value in Table 3, but is less precise given the smaller sample and aggregate geography. The first-stage F statistic, the square of the t statistic, is 7.5, which suggests these are weak instruments, which we revisit below. The first-stage estimate remains between -0.45 and -0.5 with the richer controls of columns (4) through (6), but precision increases.

The reduced-form estimates in Appendix Table 15, Panel B, show that loans decrease log mortality rates for older Americans, echoing Table 5. The unweighted estimates are about -0.0056, indicating that each loan decreases the mortality rate by around half a percentage point. As in the main text, the population-weighted estimates are smaller.

Instrumental variables estimates in Appendix Table 15, Panel C, show large effects of drinking water pollution on mortality. Columns (1) through (3) indicate that a 1 percentage point increase in the share of drinking water pollution violating health standards increases mortality rates by a bit under one percentage point. As a point of reference, Table 3 shows that in the mean drinking water system receiving loans, 3.1 percent of water violates health standards. Weighting by population, in columns (4) through (6), obtains a smaller elasticity.

We interpret the difference between weighted and unweighted elasticities cautiously given the confidence intervals. Nonetheless, one possible explanation would be that more populated areas have fewer co-morbidities or better access to adaptation opportunities like bottled water or home filters (Rosinger, Patel and Weaks 2022).

Given the somewhat weak instruments, Panel D shows LIML estimates. The unweighted LIML estimates are somewhat smaller than the exactly-identified IV estimates in Panel C, but the weighted LIML estimates are slightly larger than the corresponding IV estimates in Panel C. Overall, the broad similarity of LIML and exactly-identified IV suggests that weak instruments do not account for the large semi-elasticities found in Appendix Table 15.

Ordinary least squares regressions in Appendix Table 15, Panel E, show positive and statistically significant semi-elasticities of log mortality rates with respect to pollution. The OLS magnitude is far below the instrumental variables magnitude. Measurement error is one important explanation for these smaller least squares estimates. Water pollution varies across systems, years, and pollutants, and our aggregate measure of pollution at the zip code level above standards may crudely proxy the true pollution aggregate that is most relevant to health. If economic activity increases drinking water pollution but decreases mortality rates, then omitted variables bias in the least squares regressions would also bias these parameter estimates towards zero. For reference, ordinary least squares regressions of infant mortality on particulate matter air pollution can obtain the wrong sign and magnitude (Chay and Greenstone 2003). Thus, these least squares estimates for drinking water are slightly more stable than some analogous estimates for air pollution, as they have the expected sign and are precise.

C.5 Equity of Loans

Appendix Table 12 finds insignificantly different effects of loans on drinking water pollution across demographic groups. Columns (1) through (4) estimate versions of equation (3) but where we add interaction terms of the cumulative loans variable with the share of the community that is black, Hispanic, or has income below the poverty line. Panel A shows unweighted estimates; Panel B shows estimates weighted by population. No interaction terms are statistically different from zero. The point estimates weighted by population suggest that loans decrease mortality relatively less in black and low-income communities, but are imprecise.

C.6 Pass-Through of Loans to Municipal Water Spending

This Appendix section evaluates how loans affect municipal water spending. The pass-through rate of drinking water loans to municipal spending is part of the cost-effectiveness and benefit-cost calculations from the main text.

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 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 US Census Bureau. 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 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:

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

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

Because we estimate relatively few regressions, we summarize them 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}. The levels regression is heavily influenced by a few large cities with skewed capital and loan values. It obtains a pass-through rate of \$2.93

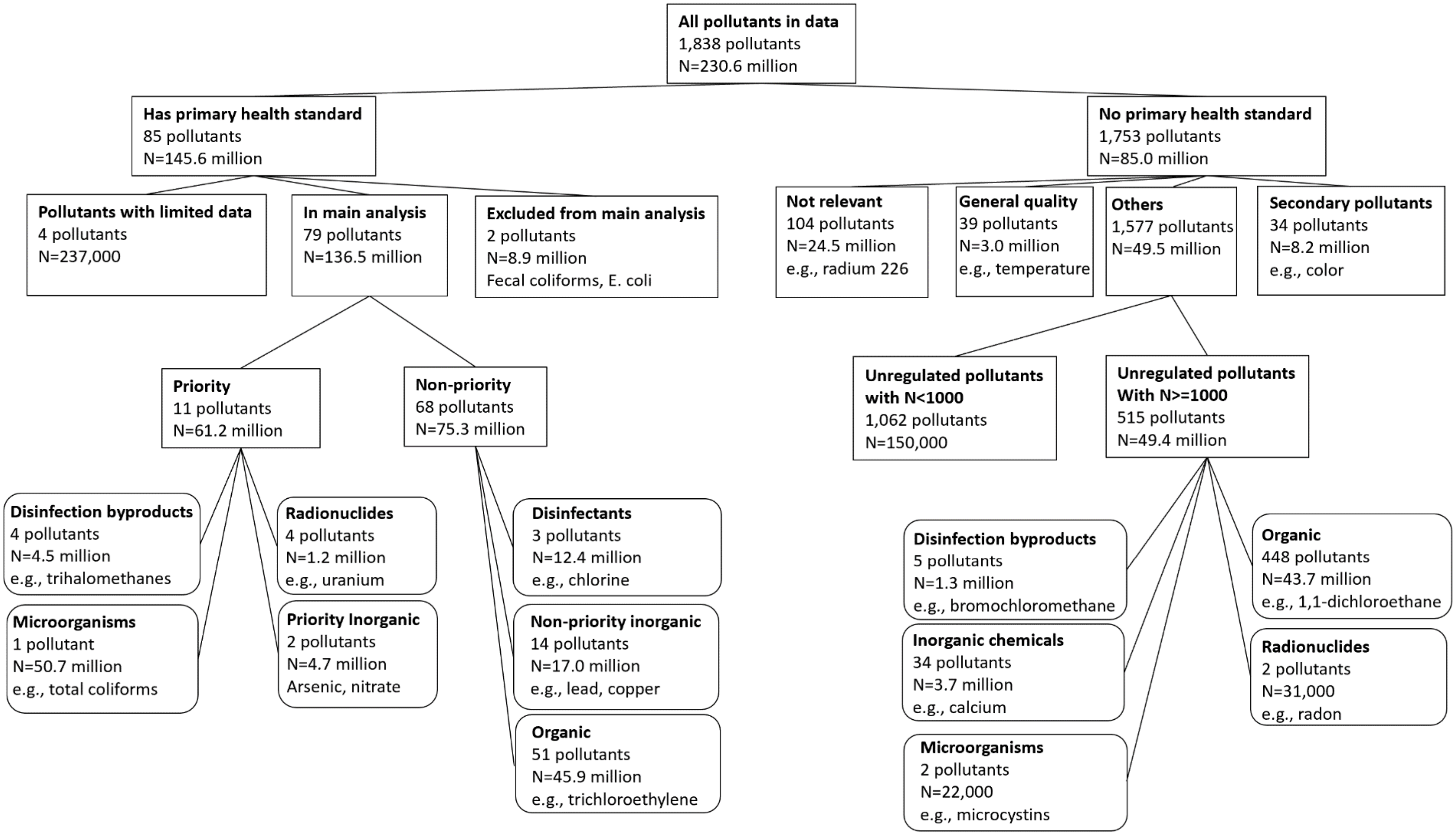
(0.34), implying that a dollar of loans leads to nearly three dollars in additional municipal capital investment, which would imply substantial crowding in.[4]

The main text mainly 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 mentions sensitivity analyses considering a pass-through rate of 0.5. Because cost-effectiveness and benefit-cost statistics scale linearly with the pass-through rate, these alternatives or others are straightforward to calculate.

[4]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).

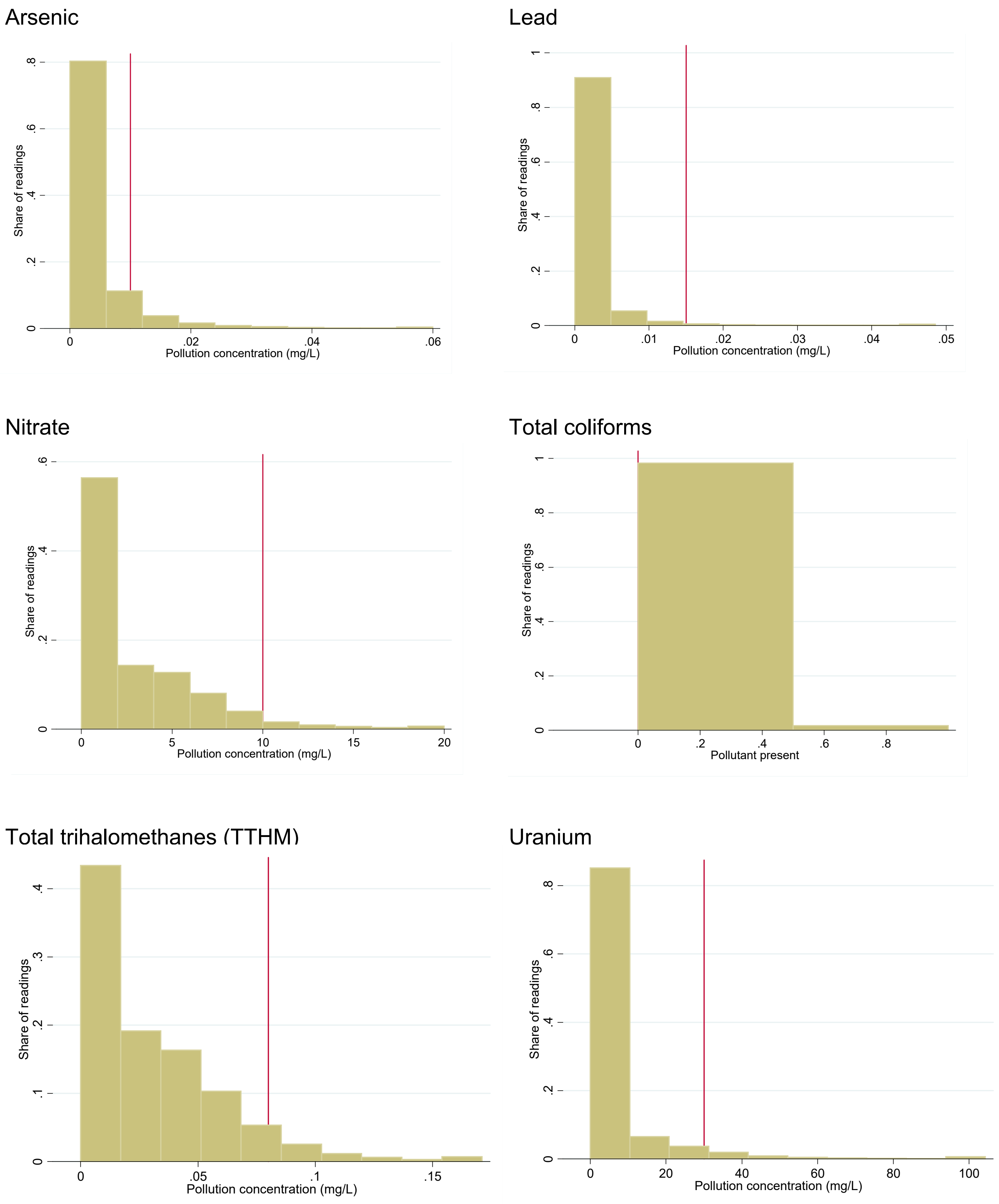
D Appendix Figures and Tables

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.

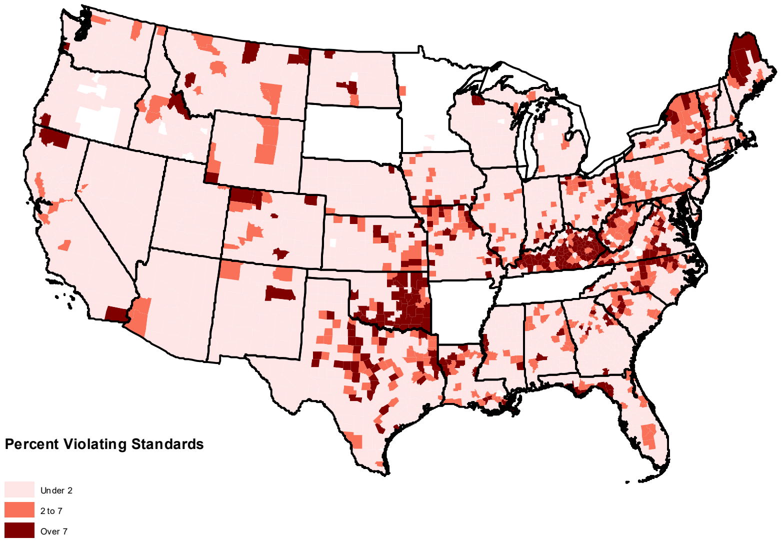
Appendix Figure 2: Histograms, Levels of Selected Individual Pollutants



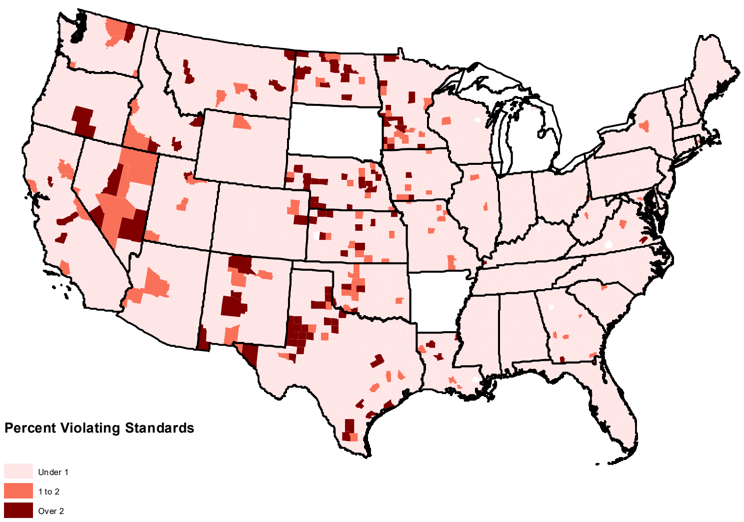
Notes: graphs use 2003-2019 raw readings data. Vertical line in each graph shows health standard.

Appendix Figure 3: Percent of Readings Violating Health Standards, by County and Pollutant

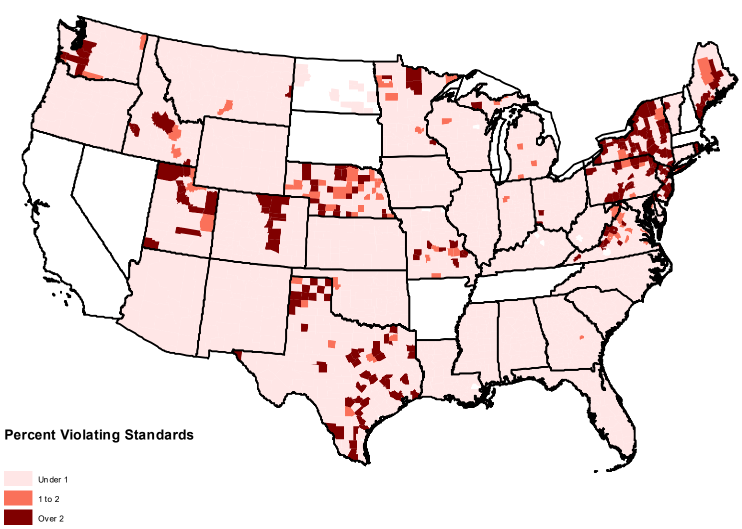
Panel A. Disinfection byproducts



Panel B. Inorganic pollutants



Panel C. Microorganisms (Total coliforms)



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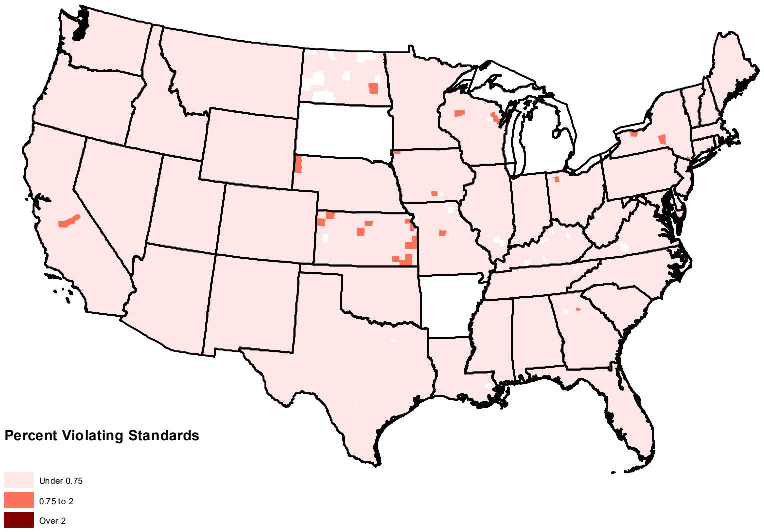
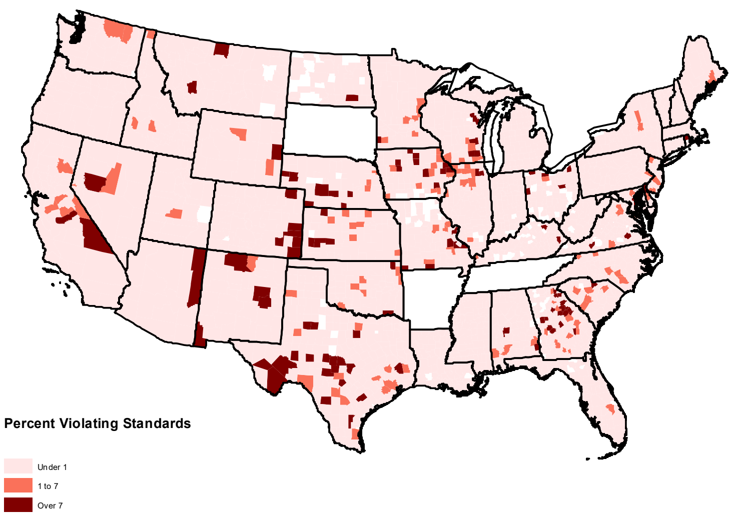
Appendix Figure 3: Percent of Readings Violating Health Standards, by County and Pollutant (Ctd.)

Panel D. Organic Chemicals

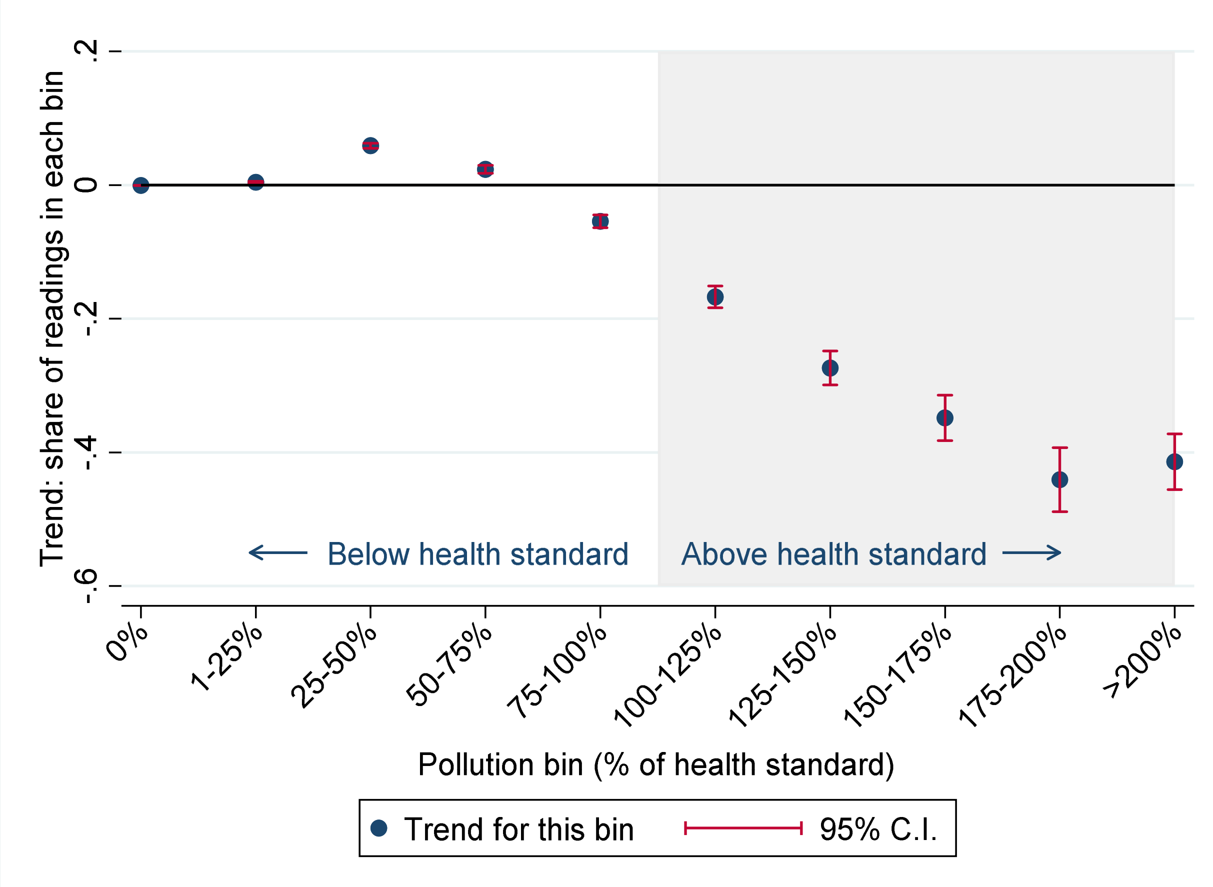


Panel E. Radionuclides



Notes: data are from the years 2009-2019. Areas in white lack data.

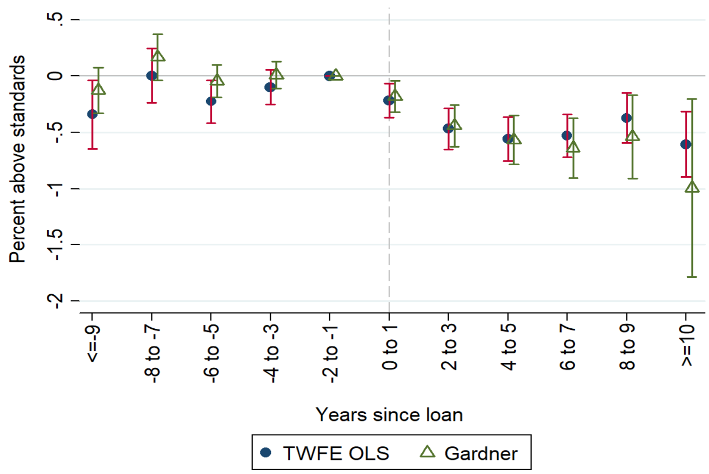
Appendix Figure 4: Trends in US Drinking Water Pollution, Semi-Parametric Bin Estimates



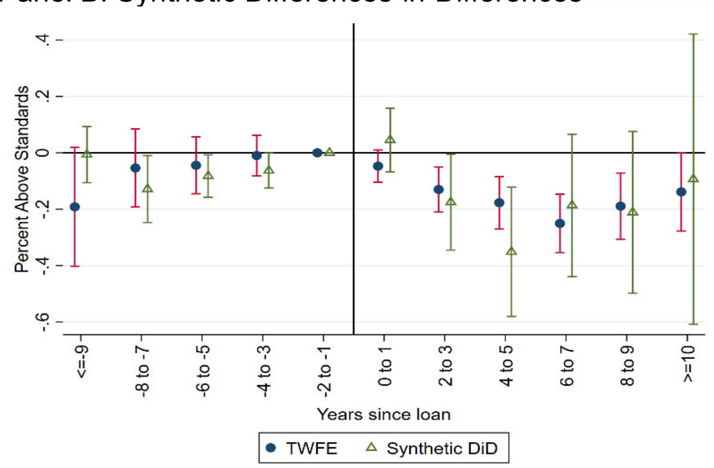
Note: figure shows estimates from ten separate regressions. In each, the dependent variable is the share of pollution readings in a drinking water system × pollutant that equal a certain proportion of the current health standard. The graph shows the regression coefficient for a bin divided by the dependent variable mean for the bean, so points in the graph can be intepreted 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.

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

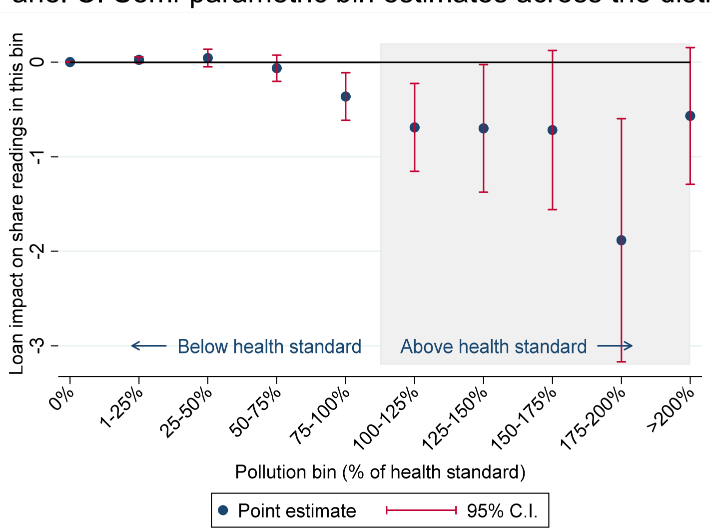
Panel A. Heterogeneous treatment timing



Panel B. Synthetic Differences-in-Differences



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



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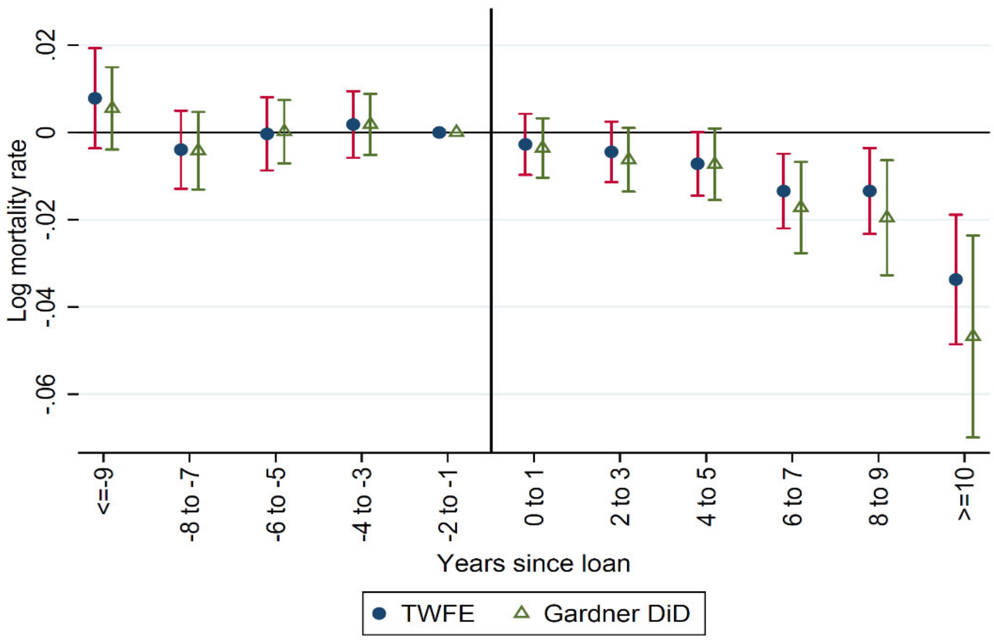
Appendix Figure 5: Effects of Safe Drinking Water Loans on Pollution, Alternative Estimates (Continued)

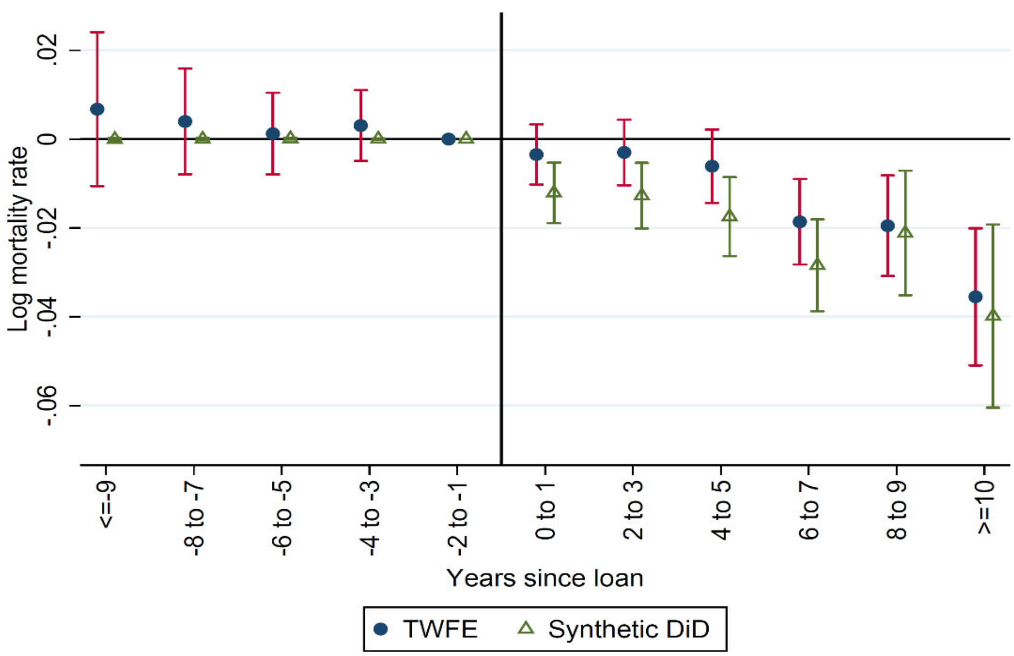
Note: Panel A shows the estimate of Gardner (2021), with standard errors estimated using 200 bootstrap samples. Panel A also shows two-way fixed effects (TWFE) estimate using same sample and comparable methodology. Panel B shows the estimator of Arkhangelsky et al. (2021), with standard errors estimated using 200 bootstrap samples. Panel B also shows TWFE estimate using same sample and comparable methodology. In Panel C, 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. Panels A and C samples include years 2009-2019, while Panel B sample includes years 2008-2019. TWFE regressions include system × pollutant, pollutant × year, and state × year fixed effects and controls for the share of readings from each month. Panels A and C weight the five categories of pollution equally, while Panel B is estimated separately for each pollutant then pooled. Standard errors are clustered by drinking water system. Panel A and B estimates treat loans as an absorbing state, i.e., they measure whether a system has received any loans. See text for additional details.

Appendix Figure 6: Effects of Safe Drinking Water Loans on Log Mortality Rates, Alternative Estimates

Panel A. Heterogeneous treatment timing



Panel B. Synthetic Differences-in-Differences



Notes: Panel A implements the heterogeneous differences in differences estimate of Gardner (2021) and Panel B implements Arkhangelsky et al. (2021). Each panel uses 200 bootstrap draws to estimate standard errors and reports two-way fixed effect (TWFE) estimates using the same sample and assumptions. See notes to Appendix Figure 5 for additional details.

Appendix Table 1: States with Drinking Water Pollution Data

State	Readings (1)	Systems (2)	Pollutants (3)	First year (4)	Last year (5)
Panel A. National					
National	*230,576,900*	*168,291*	*1,838*	*1974*	*2022*
Panel B. By state					
Alabama	3,521,035	594	239	1984	2022
Alaska	838,277	1,329	264	1980	2021
Arizona	4,026,448	1,364	227	1990	2022
Arkansas	—	—	—	—	—
California	36,650,010	11,585	532	1974	2019
Colorado	2,746,908	2,875	202	2000	2020
Connecticut	6,203,540	3,154	308	2002	2019
Delaware	1,048,575	739	290	1992	2020
Florida	7,773,607	7,427	130	2004	2018
Georgia	6,476,386	3,167	252	1985	2022
Hawaii	239,858	137	51	2011	2021
Idaho	1,421,996	1,994	247	1974	2021
Illinois	10,430,640	1,870	454	1980	2022
Indiana	3,153,689	4,521	142	1980	2022
Iowa	3,187,774	1,469	246	1980	2021
Kansas	2,866,430	1,135	322	1985	2022
Kentucky	1,749,503	432	140	1992	2021
Louisiana	4,502,076	1,260	254	1991	2021
Maine	830,281	436	243	1993	2019
Maryland	3,285,959	3,868	204	1985	2022
Massachusetts	2,019,027	2,285	200	1978	2019
Michigan	1,600,507	1,501	163	2004	2022
Minnesota	5,464,413	11,864	356	1988	2021
Mississippi	2,427,074	1,228	132	1992	2021
Missouri	5,227,835	2,726	340	1985	2022
Montana	2,999,623	2,197	327	1974	2022
Nebraska	3,787,527	2,158	201	1974	2021
Nevada	1,611,996	247	394	1985	2021
New Hampshire	1,034,819	2,740	386	2000	2017
New Jersey	6,282,194	576	288	1981	2019
New Mexico	2,690,984	1,615	307	1989	2022
New York	5,252,772	2,281	387	1982	2019
North Carolina	10,070,690	2,881	168	1980	2022
North Dakota	230,759	395	169	1990	2020
Ohio	4,511,281	6,153	254	2000	2018
Oklahoma	3,122,883	1,240	223	1981	2022
Oregon	1,048,562	954	144	1993	2011
Pennsylvania	22,217,500	15,269	251	1980	2019
Rhode Island	771,057	93	284	1986	2020
South Dakota	—	—	—	—	—
South Carolina	2,544,311	1,372	160	2000	2022
Tennessee	280,321	706	128	2000	2021
Texas	16,235,130	9,085	517	1992	2019
Utah	3,981,903	500	238	1980	2020
Vermont	1,102,293	469	389	1985	2020
Virginia	4,075,639	4,017	374	1977	2019
Washington	9,740,486	19,872	315	1975	2019
West Virginia	1,066,288	441	295	1986	2020
Wisconsin	7,254,215	23,310	302	1974	2022
Wyoming	971,800	762	197	1979	2022

Notes: Table includes all pollutants and systems.

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

		Regulated pollutants			Categories of regulated pollution				
	All	All	Priority	Unregulated pollutants	Disinfection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
N readings	230,576,900	145,339,390	61,172,410	83,520,310	4,545,660	21,737,960	61,286,950	45,915,720	1,210,190
N sys. × year × pollutants	57,196,410	29,952,390	5,356,117	27,055,920	952,969	8,065,994	2,552,846	17,978,060	451,104
N sys. × years	2,678,375	2,602,520	2,549,859	1,717,807	529,373	1,857,983	1,932,230	685,237	251,930
N sys.	168,291	163,200	161,568	140,595	60,485	150,994	136,148	74,501	50,463
N pollutants	1,838	80	11	1,749	4	16	9	53	4
Percent above health std.	1.614	1.614	3.144	—	5.05	1.91	2.58	0.25	6.11
Share equal to zero	0.82	0.87	0.83	0.75	0.21	0.59	0.95	0.98	0.47
Share by time period									
Pre-1993	0.04	0.03	0.01	0.05	0.02	0.04	0.01	0.05	0.06
1993-1997	0.09	0.08	0.04	0.10	0.03	0.11	0.03	0.12	0.07
1998-2002	0.11	0.10	0.09	0.13	0.05	0.12	0.07	0.13	0.12
2003-2007	0.17	0.17	0.17	0.18	0.19	0.19	0.14	0.18	0.26
2008-2012	0.21	0.22	0.24	0.20	0.23	0.20	0.24	0.20	0.19
2013-2019	0.34	0.35	0.39	0.31	0.43	0.30	0.43	0.28	0.26
Share by system type									
Community water sys.	0.87	0.85	0.84	0.90	0.95	0.82	0.84	0.87	0.96
School	0.017	0.018	0.012	0.02	0.01	0.03	0.01	0.02	0.01

Notes: "systems" refers to drinking water systems. "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)
N readings	1,193,143	3,952,215	3,518,972	50,704,450	2,481,685	181,912
N system × year × pollutants	507,432	487,366	1,598,421	1,846,191	524,794	65,688
N system × years	507,432	487,366	1,598,421	1,846,191	524,794	65,688
N system	75,923	73,084	127,540	123,498	60,355	24,045
N chemicals	1	1	1	1	1	1
Percent above health std.	9.41	2.10	3.77	2.58	6.30	4.73
Mean reading (mg/L or pCi/L)	0.003	0.002	2.49	0.02	0.03	5.37
Health standard	0.010	0.015	10.00	0.00	0.08	30.00
Share equal to zero	0.59	0.65	0.29	0.97	0.22	0.51
Share by time period						
Pre-1993	0.07	0.03	0.03	0.01	0.03	0.00
1993-1997	0.08	0.11	0.10	0.03	0.05	0.01
1998-2002	0.11	0.11	0.13	0.09	0.08	0.03
2003-2007	0.17	0.17	0.20	0.16	0.18	0.28
2008-2012	0.22	0.20	0.22	0.25	0.22	0.26
2013-2017	0.33	0.33	0.29	0.40	0.39	0.35
Share by system type						
Community water system	0.84	0.89	0.65	0.84	0.96	0.96
School	0.03	0.03	0.02	0.01	0.01	0.01

Appendix Table 3: Pairwise Correlations Between Pollutants

	Dis-infectants (1)	Disinfection byproducts (2)	Inorganic chemicals (3)	Micro-organisms (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	0.00	0.00	1.00	—	—	—
Organic chemicals	0.00	0.00	0.05	0.00	1.00	—	—
Radionuclides	-0.01	-0.02	0.11	-0.01	0.05	1.00	—
Panel B. Standardized values, pollution categories							
Disinfectants	1.00	—	—	—	—	—	—
Disinfection byproducts	0.22	1.00	—	—	—	—	—
Inorganic chemicals	-0.10	-0.07	1.00	—	—	—	—
Microorganisms	-0.01	0.01	0.01	1.00	—	—	—
Organic chemicals	0.04	0.06	0.07	0.00	1.00	—	—
Radionuclides	-0.06	-0.12	0.16	0.00	0.04	1.00	—
Secondary (taste)	0.06	0.01	0.09	0.10	0.00	0.11	1.00

Note: each observation in this analysis is a system × pollutant × year.

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

	Arsenic (1)	Lead (2)	Nitrate (3)	Trihalomethanes (4)	Total coliforms (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	—	—	—
Trihalomethanes	0.01	0.01	0.00	1.00	—	—
Total coliforms	-0.02	0.01	0.00	0.00	1.00	—
Uranium	0.24	0.02	0.14	0.01	0.01	1.00
Panel D. Standardized values, individual pollutants						
Arsenic	1.00	—	—	—	—	—
Lead	0.00	1.00	—	—	—	—
Nitrate	0.09	0.04	1.00	—	—	—
Trihalomethanes	0.00	0.02	0.02	1.00	—	—
Total coliforms	-0.11	-0.01	-0.12	0.00	1.00	—
Uranium	0.31	0.05	0.30	0.01	-0.07	1.00

Note: each observation in this analysis is a system × pollutant × year. 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)	
Total number of loans	8,251		9,217	
Total loan amount ($2019 millions)	27,896		31,735	
Mean loan amount (million $/loan)	3.38		3.46	
Mean population served per loan (SDWIS)	73,211		74,223	
Mean population age ≥ 65 served per loan	9,298		9,426	
Share of loans listing targeted pollutant:	Share	Count	Share	Count
Arsenic	0.03	246	0.03	290
Coliform	0.02	130	0.01	138
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	7,342	0.89	8,222
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 multiples 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 Receiving Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. No fixed effects										
Log population served	0.077***	—	—	—	—	0.078***	0.086***	0.079***	0.075***	0.086***
	(0.003)	—	—	—	—	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above-median share violating	—	0.055***	—	—	—	0.065***	—	—	—	0.060***
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***	—	-0.037***
	—	—	—	(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***	—	—	—	—	0.076***	0.080***	0.075***	0.074***	0.078***
	(0.003)	—	—	—	—	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above-median share violating	—	0.065***	—	—	—	0.069***	—	—	—	0.063***
health standards in 2006	—	(0.009)	—	—	—	(0.009)	—	—	—	(0.009)
Above-median share Black	—	—	0.076***	—	—	—	-0.043***	—	—	-0.046***
	—	—	(0.009)	—	—	—	(0.008)	—	—	(0.008)
Above-median share Hispanic	—	—	—	0.088***	—	—	—	0.007	—	0.013
	—	—	—	(0.010)	—	—	—	(0.009)	—	(0.009)
Above-median share Poor	—	—	—	—	0.109***	—	—	—	0.091***	0.088***
	—	—	—	—	(0.008)	—	—	—	(0.008)	(0.008)
N	23,272	23,272	23,272	23,272	23,272	23,272	23,272	23,272	23,272	23,272

Note: dependent variable is cumulative number of loans received by year 2019. Each observation represents one drinking water system. Sample includes systems with non-missing values of independent variables. All regressions have N=23,272.

Appendix Table 6: 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	2.280***	—	—	—	—	—	—
	(0.400)	—	—	—	—	—	—
Arsenic deposits	—	6.238***	—	—	—	—	—
	—	(1.558)	—	—	—	—	—
Log lead service lines	—	—	0.183***	—	—	—	—
	—	—	(0.029)	—	—	—	—
Nitrogen from	—	—	—	0.349***	—	—	—
fertilizer and manure	—	—	—	(0.053)	—	—	—
TRI emissions	—	—	—	—	0.005	—	—
	—	—	—	—	(0.004)	—	—
Pesticide application	—	—	—	—	—	0.012***	—
	—	—	—	—	—	(0.004)	—
Uranium deposits	—	—	—	—	—	—	1.106*
	—	—	—	—	—	—	(0.623)
N	542,322	401,868	411,520	1,378,394	16,221,588	1,400,419	279,150
Dependent var. mean	4.02	3.62	1.63	0.99	0.02	0.18	4.04

Notes: Each observation is a system × pollutant × year representing the share of drinking water pollution readings above health standards. Data pool available years in 2003-2019. See text for data sources. Total organic carbon is county mean. Arsenic and uranium deposits are indicators for whether a county has deposits of the minerals. Lead service lines is 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 clustered by county. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 7: Inequality in U.S. Drinking Water Pollution Levels, Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Include service territories imputed as a circle							
Log population served	-0.016	—	—	—	-0.011	-0.021*	-0.025**
	(0.011)	—	—	—	(0.012)	(0.012)	(0.011)
Above-median share Black	—	-0.074	—	—	-0.058	—	—
	—	(0.051)	—	—	(0.055)	—	—
Above-median share Hispanic	—	—	0.080	—	—	0.097*	—
	—	—	(0.049)	—	—	(0.052)	—
Above-median share Poor	—	—	—	0.321***	—	—	0.332***
	—	—	—	(0.050)	—	—	(0.050)
Panel B. Disinfection byproducts							
Log population served	-0.733***	—	—	—	-0.745***	-0.655***	-0.761***
	(0.037)	—	—	—	(0.038)	(0.037)	(0.037)
Above-median share Black	—	-0.917***	—	—	0.119	—	—
	—	(0.136)	—	—	(0.138)	—	—
Above-median share Hispanic	—	—	-1.829***	—	—	-1.364***	—
	—	—	(0.130)	—	—	(0.128)	—
Above-median share Poor	—	—	—	1.574***	—	—	1.728***
	—	—	—	(0.122)	—	—	(0.119)
Panel C. Inorganic chemicals							
Log population served	-0.121***	—	—	—	-0.118***	-0.136***	-0.123***
	(0.007)	—	—	—	(0.009)	(0.008)	(0.007)
Above-median share Black	—	-0.236***	—	—	-0.031	—	—
	—	(0.029)	—	—	(0.035)	—	—
Above-median share Hispanic	—	—	0.244***	—	—	0.340***	—
	—	—	(0.027)	—	—	(0.030)	—
Above-median share Poor	—	—	—	-0.006	—	—	0.065**
	—	—	—	(0.028)	—	—	(0.028)
Panel D. Microorganisms							
Log population served	0.286***	—	—	—	0.305***	0.261***	0.292***
	(0.034)	—	—	—	(0.035)	(0.033)	(0.034)
Above-median share Black	—	0.279***	—	—	-0.172***	—	—
	—	(0.061)	—	—	(0.053)	—	—
Above-median share Hispanic	—	—	0.687***	—	—	0.519***	—
	—	—	(0.064)	—	—	(0.054)	—
Above-median share Poor	—	—	—	-0.084	—	—	-0.201***
	—	—	—	(0.061)	—	—	(0.060)

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Appendix Table 7: Inequality in U.S. Drinking Water Pollution Levels, Sensitivity Analysis (Ctd.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel E. Organic chemicals							
Log population served	0.001***	—	—	—	0.001***	0.001***	0.001***
	(0.000)	—	—	—	(0.000)	(0.000)	(0.000)
Above-median share Black	—	0.001	—	—	-0.001	—	—
	—	(0.001)	—	—	(0.001)	—	—
Above-median share Hispanic	—	—	0.002	—	—	0.001	—
	—	—	(0.001)	—	—	(0.001)	—
Above-median share Poor	—	—	—	0.003***	—	—	0.003**
	—	—	—	(0.001)	—	—	(0.001)
Panel F. Radionuclides							
Log population served	-0.462***	—	—	—	-0.480***	-0.532***	-0.466***
	(0.066)	—	—	—	(0.072)	(0.071)	(0.067)
Above-median share Black	—	-0.666**	—	—	0.167	—	—
	—	(0.295)	—	—	(0.321)	—	—
Above-median share Hispanic	—	—	1.058***	—	—	1.472***	—
	—	—	(0.279)	—	—	(0.295)	—
Above-median share Poor	—	—	—	-0.019	—	—	0.170
	—	—	—	(0.289)	—	—	(0.288)
Month controls	X	X	X	X	X	X	X

Notes: Demographics describe each drinking water system, using time-invariant demographic data from year 2010 Census, aggregated from block data. FE stands for fixed effects. Each observation underlying the analysis represents mean pollution for a drinking water system × pollutant × year. Sample includes systems in years 2003-2019. Standards refer to current primary health standards. Month controls are the share of raw pollution readings from each month of the calendar year. Standard errors clustered by drinking water system. Asterisks are shown for difference and indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 8: Trends in US Drinking Water Pollution, Sensitivity and Heterogeneity

		Regulated Pollution Categories					Individual pollutants			Standardized value	
	Regulated	Disinfection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Lead	Nitrate	Regulated	Non-regulated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1. Main estimates	-0.114***	-0.175***	-0.026***	-0.155***	-0.001***	-0.233***	-0.258***	-0.053***	-0.011***	-0.638***	—
	(0.002)	(0.006)	(0.001)	(0.003)	(0.000)	(0.013)	(0.009)	(0.003)	(0.002)	(0.014)	—
<u>Other</u>											
2. Standardized value	-0.638***	-0.192***	-0.372***	-1.160***	-0.182***	-1.323***	-0.966***	-1.202***	-0.072***	-0.638***	-0.350**
	(0.014)	(0.034)	(0.008)	(0.025)	(0.007)	(0.063)	(0.042)	(0.034)	(0.018)	(0.014)	(0.137)
3. Only CWS	-0.098***	-0.184***	-0.026***	-0.051***	-0.001***	-0.237***	-0.243***	-0.044***	-0.005*	-0.511***	—
	(0.003)	(0.006)	(0.001)	(0.003)	(0.000)	(0.013)	(0.010)	(0.003)	(0.002)	(0.015)	—
4. Semi-balanced panel	-0.306***	-0.303***	-0.048***	-0.039***	-0.001***	-1.267***	-0.841***	-0.094***	-0.010***	-1.473***	—
	(0.015)	(0.010)	(0.002)	(0.002)	(0.000)	(0.077)	(0.031)	(0.009)	(0.002)	(0.082)	—
5. Years 1992-2019	-0.105***	-0.202***	-0.027***	-0.154***	-0.002***	-0.208***	-0.202***	-0.065***	-0.022***	-0.664***	—
	(0.002)	(0.007)	(0.001)	(0.003)	(0.000)	(0.011)	(0.006)	(0.002)	(0.002)	(0.012)	—
6. Weight by population	-0.101***	-0.135***	-0.011***	-0.581***	-0.001**	-0.117***	-0.103***	-0.016	0.001	-0.494***	—
	(0.009)	(0.019)	(0.002)	(0.089)	(0.000)	(0.024)	(0.019)	(0.010)	(0.004)	(0.067)	—
7. Unweighted	-0.032***	-0.164***	-0.026***	-0.151***	-0.001***	-0.225***	-0.259***	-0.054***	-0.011***	-0.338***	—
	(0.000)	(0.005)	(0.001)	(0.003)	(0.000)	(0.013)	(0.009)	(0.003)	(0.002)	(0.006)	—
<u>Non-aggregated data</u>											
8. Basic non-aggregated	-0.148***	-0.268***	-0.063***	-0.071***	0.000	-0.398***	-0.600***	-0.066***	-0.028***	-0.625***	—
	(0.006)	(0.009)	(0.003)	(0.003)	(0.002)	(0.032)	(0.028)	(0.004)	(0.010)	(0.024)	—
9. Include raw water	-0.134***	-0.253***	-0.065***	-0.082***	-0.004**	-0.304***	-0.576***	-0.065***	-0.047**	-0.533***	—
	(0.005)	(0.009)	(0.004)	(0.004)	(0.002)	(0.029)	(0.030)	(0.004)	(0.020)	(0.024)	—
10. Sample point FE	-0.107***	-0.278***	-0.045***	-0.027***	-0.001***	-0.338***	-0.378***	-0.063***	0.002	-0.568***	—
	(0.006)	(0.013)	(0.002)	(0.002)	(0.000)	(0.032)	(0.022)	(0.004)	(0.008)	(0.024)	—
11. Log	-0.579***	0.002	-1.126***	—	-0.796	-1.201***	-2.587***	-1.811***	0.092	-0.625***	—
	(0.046)	(0.061)	(0.035)	—	(0.514)	(0.132)	(0.164)	(0.067)	(0.067)	(0.024)	—

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Appendix Table 8: Trends in US Drinking Water Pollution, Sensitivity Analysis (Continued)

	Regulated Pollution Categories						Individual pollutants			Standardized value	
	Regulated	Disinfection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Lead	Nitrate	Regulated	Non-regulated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(8)	(10)	(11)
12. Indicator:	-0.042***	0.425***	-0.065***	-0.067***	-0.052***	-0.570***	0.026	-0.642***	-0.084***	-0.625***	—
positive	(0.007)	(0.016)	(0.007)	(0.003)	(0.007)	(0.036)	(0.035)	(0.021)	(0.015)	(0.024)	—
Fixed effects:											
System × pollutant	X	X	X	X	X	X	X	X	X	X	X
Month controls	X	X	X	X	X	X	X	X	X	X	X

Notes: Each observation is a drinking water system × pollutant × year. Basic sample weights the five categories of pollution equally, and includes years 2003-2019. Dependent variables are multiplied by 100. Standard errors clustered by drinking water system. Except where otherwise noted, dependent variable is percent of readings violating current health standards. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 9. Drinking Water Pollution Trends, by Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. No additional controls							
Year	-0.03**	-0.10***	-0.10***	-0.10***	-0.04***	-0.03**	-0.03**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Year * …							
Log population served	-0.01***	—	—	—	-0.01***	-0.01***	-0.01***
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	-0.02***	—	—	-0.01	—	—
	—	(0.01)	—	—	(0.01)		—
Above-median share Hispanic	—	—	-0.03***	—	—	-0.02***	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	-0.02**	—	—	-0.01
	—	—	—	(0.01)	—	—	(0.01)
Panel B. Include state×year linear time trends							
Year * …							
Log population served	-0.01***	—	—	—	-0.01***	-0.01***	-0.01***
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	-0.02***	—	—	-0.01	—	—
	—	(0.01)	—	—	(0.01)	—	—
Above-median share Hispanic	—	—	-0.02**	—	—	-0.01	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	-0.02***	—	—	-0.02***
	—	—	—	(0.01)	—	—	(0.01)
Panel C. Include "Tier 3" geography links							
Year	-0.05***	-0.09***	-0.09***	-0.10***	-0.05***	-0.04***	-0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Year * …							
Log population served	-0.01***	—	—	—	-0.01***	-0.01***	-0.01***
	(0.00)	—	—	—	(0.00)	(0.00)	(0.00)
Above-median share Black	—	-0.01**	—	—	0.00	—	—
	—	(0.01)	—	—	(0.01)	—	—
Above-median share Hispanic	—	—	-0.03***	—	—	-0.02***	—
	—	—	(0.01)	—	—	(0.01)	—
Above-median share Poor	—	—	—	0.00	—	—	0.00
	—	—	—	(0.01)	—	—	(0.01)
Month controls	X	X	X	X	X	X	X
N	7,670,661	7,670,661	7,670,661	7,670,661	7,670,661	7,670,661	7,670,661

Note: dependent variable is share of drinking water pollution readings above health standards. Each observation represents mean pollution for a drinking water system × pollutant × year. Regressions weight the five categories of pollution equally. Sample includes years 2003-2019. Sample includes systems with non-missing values of independent variables. Standard errors are clustered by drinking water system. Panel C adds systems where EPIC determines service territory by drawing a circle around the system centroid. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), or 0.10 (*).

Appendix Table 10: Effects of Safe Drinking Water Loans on Pollution, Sensitivity and Heterogeneity

	Regulated Pollution Categories						Individual pollutants			Standardized value	
	Regulated	Dis-infection byproducts	Inorganic chemicals	Micro-organisms	Organic chemicals	Radio-nuclides	Arsenic	Nitrate	Lead	Regulated	Non-regulated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1. Main estimates	-0.30***	-0.40***	-0.02	-0.21*	0.00	-0.78***	-0.31*	-0.08*	0.09	-1.53***	-0.73
	(0.06)	(0.11)	(0.02)	(0.12)	(0.00)	(0.30)	(0.16)	(0.05)	(0.06)	(0.32)	(0.65)
Other											
2. Standardized value	-1.53***	-1.70***	-0.20	-0.03	-0.03	-3.73***	-0.86	-0.19	1.42*	-1.53***	-0.73
	(0.32)	(0.65)	(0.16)	(0.60)	(0.08)	(1.22)	(0.76)	(0.41)	(0.84)	(0.32)	(0.65)
3. Only CWS	-0.27***	-0.38***	-0.02	-0.47***	0.00	-0.81***	-0.32**	-0.08*	0.05	-1.32***	—
	(0.05)	(0.11)	(0.02)	(0.11)	(0.00)	(0.30)	(0.16)	(0.05)	(0.06)	(0.27)	—
4. Semi-balanced panel	-0.45**	-0.32***	0.10***	-0.38***	0.00	-1.60*	0.47**	-0.10*	0.24**	-2.00**	—
	(0.19)	(0.12)	(0.03)	(0.11)	(0.00)	(0.82)	(0.23)	(0.05)	(0.11)	(0.83)	—
5. Years 1992-2019	-0.28***	-0.53***	0.02	-0.29**	0.00	-0.31	-0.09	0.01	0.06	-1.79***	—
	(0.05)	(0.13)	(0.01)	(0.11)	(0.00)	(0.22)	(0.16)	(0.04)	(0.05)	(0.31)	—
6. Weight by population	-0.14***	-0.18	0.01	-2.91*	0.00	0.00	0.14**	-0.02	0.05	-0.52**	—
	(0.05)	(0.12)	(0.01)	(1.64)	(0.00)	(0.17)	(0.06)	(0.03)	(0.06)	(0.22)	—
7. Unweighted	-0.07***	-0.40***	-0.02	-0.21*	0.00	-0.77***	-0.31*	-0.08*	0.09	-0.39***	—
	(0.01)	(0.11)	(0.02)	(0.11)	(0.00)	(0.30)	(0.16)	(0.05)	(0.06)	(0.08)	—
Non-aggregated data											
8. Basic non-aggregated	-0.16**	-0.19	0.06	-0.05	-0.02	-1.34**	0.22	-0.08	0.23	-0.75	—
	(0.07)	(0.13)	(0.04)	(0.05)	(0.02)	(0.52)	(0.40)	(0.10)	(0.16)	(0.48)	—
9. Include raw water	-0.13**	-0.15	0.02	-0.09	-0.05***	-1.08**	0.20	-0.14	0.21	-0.58*	—
	(0.06)	(0.10)	(0.05)	(0.06)	(0.02)	(0.51)	(0.37)	(0.20)	(0.15)	(0.32)	—
10. Sample point FE	-0.22***	-0.29*	0.08	0.02	-0.01	-1.79***	-0.40	0.00	0.39*	-1.15**	—
	(0.07)	(0.17)	(0.05)	(0.02)	(0.00)	(0.50)	(0.25)	(0.11)	(0.21)	(0.58)	—

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Appendix Table 10: Effects of Safe Drinking Water Loans on Pollution, Sensitivity Analyses (Continued)

		Regulated Pollution Categories					Individual pollutants			Standardized value	
	Regulated	infection	chemicals	organisms	chemicals	nuclides	Arsenic	Nitrate	Lead	Regulated	regulated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
11. Log	-1.98**	-1.73	0.27	—	-5.95***	-5.64***	1.73	0.44	2.47	—	—
	(0.90)	(1.38)	(0.46)	—	(1.56)	(1.55)	(2.16)	(0.54)	(1.55)	—	—
12. Indicator:	-0.09	0.09	-0.47***	-0.07	-0.39*	0.06	-1.99**	-0.36*	-0.37	—	—
positive	(0.10)	(0.15)	(0.15)	(0.05)	(0.23)	(0.53)	(0.89)	(0.20)	(0.39)	—	—
<u>Estimates specific to loans</u>											
13. Other controls	-0.31***	-0.41***	-0.02	-0.21*	0.00	-0.78***	-0.31*	-0.08	0.08	-1.56***	—
	(0.06)	(0.11)	(0.02)	(0.12)	(0.00)	(0.30)	(0.17)	(0.05)	(0.06)	(0.32)	—
14. First loan	-0.53***	-0.64***	-0.10***	-0.01	0.00	-1.52***	-0.86***	-0.17*	-0.05	-2.30***	—
	(0.11)	(0.18)	(0.03)	(0.12)	(0.00)	(0.49)	(0.33)	(0.10)	(0.10)	(0.55)	—
15. Loan #1	-0.50***	-0.60***	-0.10***	0.06	0.00	-1.47***	-0.79**	-0.17*	-0.11	-2.11***	—
	(0.11)	(0.18)	(0.03)	(0.11)	(0.00)	(0.51)	(0.33)	(0.10)	(0.11)	(0.57)	—
Loan #2	-0.73***	-0.86***	-0.11*	-0.43*	0.00	-1.94***	-1.48***	-0.18	0.29*	-3.31***	—
	(0.17)	(0.30)	(0.06)	(0.24)	(0.00)	(0.69)	(0.56)	(0.15)	(0.15)	(0.81)	—
Loan #3 or more	-0.82***	-1.34***	0.03	-1.11*	0.01	-1.36	-0.29	-0.13	0.59**	-4.70***	—
	(0.26)	(0.45)	(0.05)	(0.63)	(0.01)	(1.24)	(0.55)	(0.10)	(0.29)	(1.38)	—
Fixed effects:											
Pollutant × system	X	X	X	X	X	X	X	X	X	X	X
Pollutant × year	X	X	X	X	X	X	X	X	X	X	X
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

Notes: Each observation is a system × pollutant × year. Disinfectant and radionuclide readings are all below the associated health standards (MCL). Sample includes years 2009-2019 for all pollutants with health standards.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. Other controls includes air pollution ozone nonattainment, air pollution particulate matter nonattainment, cumulative Clean Water Act revolving loans, number of Toxic Release Inventory plants emitting water pollution, log income per capita, and the employment rate. Standard errors clustered by drinking water system. Except where otherwise indicated, dependent variable is percent of water violating standards. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 11: Falsification Test: Effects of Safe Drinking Water Act Loans on Air, River, and Lake

	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	0.0001*	-0.0429	-0.0231	-32.8829	0.6041*	-1.343	0.0036	-0.0008
	(0.0001)	(0.0277)	(0.0427)	(21.0866)	(0.3333)	(1.0380)	(0.0028)	(0.0036)
Y mean	0.04	8.63	1.64	597.92	24.00	28.62	0.24	0.47
Observations	46,745	48,896	144,964	234,686	2,781,116	520,388	3,675,366	3,675,366
Panel B. Standardized values								
Loans	0.0168*	-0.0161	-0.0114	-0.015	0.0190*	-0.0149	—	—
	(0.0098)	(0.0104)	(0.0211)	(0.0096)	(0.0105)	(0.0115)	—	—
Y mean	0.0000	0.0000	0.036	0.016	0.025	-0.005	—	—
Observations	46,745	48,896	144,964	234,686	2,781,116	520,388	—	—
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: Each observation is a pollutant × monitor × year, which we link to the population-weighted cumulative number of loans for each county × year. Data covers years 2009-2019. Loans variables are cumulative. All variables are measured in physical units. Not fishable and not swimmable are defined as in Keiser and Shapiro (2019b). Standard errors are clustered by county. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 12: Inequality and Impacts of Safe Drinking Water Loan Loans on Pollution and Health

	Pollution				Health			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Unweighted								
Cumulative loans	-0.210	-0.527**	-0.210	-0.097	-0.0101***	-0.00863***	-0.00998***	-0.00573**
	(0.163)	(0.209)	(0.163)	(0.189)	(0.00212)	(0.00228)	(0.00218)	(0.00292)
Cumulative loans * Black	0.228	0.252	0.228	-0.231	0.00699	0.00900	0.00772	-0.00884
	(0.387)	(0.549)	(0.387)	(0.415)	(0.00654)	(0.00686)	(0.00697)	(0.00688)
Cumulative loans * Hispanic	0.025	-0.132	0.025	0.089	0.00745	0.00608	0.00696	-0.000791
	(0.541)	(0.717)	(0.541)	(0.579)	(0.00477)	(0.00522)	(0.00521)	(0.00516)
Cumulative loans * Poverty	-0.194	0.658	-0.194	-0.225	0.0103	0.00434	0.00996	0.0168
	(0.962)	(1.275)	(0.962)	(1.000)	(0.0132)	(0.0158)	(0.0144)	(0.0130)
Observations	862,710	762,771	862,710	142,426	259,190	234,165	232,282	653,741
Panel B: Weighted by population								
Cumulative loans	-0.035	-0.224	-0.035	-0.314	-0.00754***	-0.00690***	-0.00784***	-0.00611***
	(0.204)	(0.279)	(0.204)	(0.229)	(0.00170)	(0.00138)	(0.00183)	(0.00188)
Cumulative loans * Black	0.029	-0.016	0.029	0.431	0.0119*	0.0131**	0.0130*	0.00942
	(0.528)	(0.750)	(0.528)	(0.448)	(0.00703)	(0.00659)	(0.00681)	(0.00707)
Cumulative loans * Hispanic	-0.603	-0.703	-0.603	0.322	0.00439	0.00393	0.00367	0.00318
	(0.930)	(1.144)	(0.930)	(0.959)	(0.00442)	(0.00453)	(0.00452)	(0.00452)
Cumulative loans * Poverty	0.901	2.029	0.901	0.239	0.0140*	0.0107	0.0167**	0.0171**
	(1.816)	(2.262)	(1.816)	(1.754)	(0.00737)	(0.00664)	(0.00791)	(0.00770)
Observations	862,710	762,771	862,710	142,426	259,190	234,165	232,282	216,751
System × pollutant FE	X	X	X	X				
Month controls	X	X	X	X				
Zip code FE					X	X	X	X
State × year FE	X	X	X	X	X	X	X	X
County controls		X				X		
With drinking water data			X				X	
Years 1993-2019				X				X

Notes: In columns (1) through (4), the dependent variable is the percent of readings in a system × pollutant × year that violate health standards. Demographics are time-invariant, from year 2010 Census Block data. Statistics weight the five categories of pollution equally.

Appendix Table 13: Effects of Drinking Water Loans on Log Mortality Rates: Sensitivity and Heterogeneity

	(1)	(2)
1. Main estimates	-0.0059***	-0.0023**
	(0.0014)	(0.0010)
Alternatives		
2. Piped water interaction	-0.0105	-0.0021
	(0.0078)	(0.0039)
Main estimate	0.0042	-0.0002
	(0.0077)	(0.0039)
3. Loan# 1	-0.0022	0.0030
	(0.0042)	(0.0028)
loan #2	-0.0102*	-0.0045
	(0.0056)	(0.0040)
loan #3 or more	-0.0263***	-0.0110**
	(0.0058)	(0.0044)
By pollutant a loan targets		
4. Arsenic	-0.0235	0.0147
	(0.0223)	(0.0246)
5. Coliforms	-0.0006	-0.0077
	(0.0120)	(0.0056)
6. Disinfectants, disinfection byproducts	-0.0044	0.0008
	(0.0040)	(0.0021)
7. Microbial	-0.0058	-0.0011
	(0.0040)	(0.0015)
8. Nitrates	0.0234	0.0381**
	(0.0268)	(0.0186)
9. Radionuclides	-0.0097	-0.0018
	(0.0198)	(0.0096)
Weighted		X

Note: Standard errors clustered by drinking water system. Estimates include zip code fixed effects, state-by-year fixed effects, and log system population interacted with year fixed effects. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 14: Effects of Drinking Water Loans on Log Hospital Admissions Rate

	(1)	(2)	(3)	(4)
Panel A: Unweighted				
Cumulative loans	-0.0048*	-0.0042	-0.0046	0.0031
	(0.0027)	(0.0026)	(0.0029)	(0.0040)
Observations	263,576	261,969	236,201	665,990
Panel B: Weighted by population				
Cumulative loans	-0.0007	0.0000	-0.0005	0.0020
	(0.0026)	(0.0025)	(0.0026)	(0.0035)
Observations	263,576	261,969	236,201	665,990
Fixed effets:				
Zip code	X	X	X	X
State × year	X	X	X	X
County controls		X		
With drinking water data			X	
Years 1993-2019				X

Notes: each observation is a zip code×year. Columns (1)-(3) include years 2009-2019. Dependent variable is log of hospital admissions per 10,000 Medicare population. Main explanatory variable is the cumulative number of drinking water loans a system has received. "County controls" include county-year controls for the following: cumulative 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; personal income per capita; unemployment rate; SDWIS violations in years 2006-2008; opioid dispensing rate per 100 people (plus missing indicator); percent of population with health insurance; inverse hyperbolic sine of federal assistance and contracts. Standard errors clustered by drinking water system. "With drinking water data" restricts the sample to drinking water systems and years for which we have drinking water pollution microdata. Standard errors clustered by drinking water system. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 15: Instrumental Variables Estimates of Drinking Water Pollution and Mortality Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage estimates for pollution above health standards						
Cumulative loans	-0.608***	-0.551**	-0.469**	-0.491***	-0.436**	-0.439**
	(0.222)	(0.223)	(0.202)	(0.174)	(0.193)	(0.171)
Observations	725,682	662,998	256,878	725,682	662,998	256,878
Panel B: Reduced-form regression of log mortality rate on cumulative loans						
Cumulative loans	-0.00559***	-0.00532***	-0.00290*	-0.00200*	-0.00189*	-0.00116
	(0.00141)	(0.00140)	(0.00166)	(0.00106)	(0.00112)	(0.00128)
Observations	725,682	662,998	256,878	725,682	662,998	256,878
Panel C: Instrumental variables estimates: effect of drinking water pollution above standards on log mortality rate						
Pollution above health standards	0.00920**	0.00966**	0.0161*	0.00406	0.00433	0.0158**
	(0.00406)	(0.00439)	(0.00845)	(0.00270)	(0.00307)	(0.00659)
Observations	725,682	662,998	256,878	725,682	662,998	534,176
First stage R-K F statistic	7.5	6.1	5.4	7.9	5.1	6.6
Panel D: LIML Instrumental variables estimates: effect of drinking water pollution above standards on log mortality rate						
Pollution above health standards	0.00764**	0.00734**	0.00562	0.00476*	0.00514*	0.00451
	(0.00323)	(0.00334)	(0.00390)	(0.00264)	(0.00303)	(0.00358)
Observations	725,682	662,998	256,878	725,682	662,998	256,878
Panel E: Ordinary least squares regression of log mortality rate on pollution above health standards						
Pollution above health standards	0.000121***	0.000115***	0.000144***	0.0000680***	0.0000683***	0.0000787***
	(0.0000397)	(0.0000406)	(0.0000506)	(0.0000219)	(0.0000210)	(0.0000261)
Observations	725,682	662,998	256,878	725,682	662,998	256,878
Fixed effects:						
Zip code	X	X	X	X	X	X
State × year	X	X	X	X	X	X
County controls		X			X	
Years 1992-2019			X			X
Weighted by population				X	X	X

Notes: each observation is a zip code × year. Data include years 2009-2019 except where otherwise noted. Mortality rate is deaths per 10,000 Medicare population; dependent variable is log mortality rate. Cumulative loans equals the cumulative number of drinking water loans a system has received. Log population is log of mean system population, averaged across systems in a zip code with weight equal to the system's over-65 population. County controls include cumulative 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; personal income per capita; unemployment rate; federally-reported violations in years 2006-2008 interacted with year fixed effects; opioid dispensing rate per 100 people (plus missing indicator); percent of population with health insurance; inverse hyperbolic sine of federal assistance and contracts. LIML uses count indicators for cumulative number of loans (1; 2; 3; etc.) as instruments for pollution. Standard errors clustered by drinking water system. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

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