The effect of lead from drinking water on long-run educational outcomes *

Jiameng Zheng †

February 17, 2022

Abstract

I estimate the long-run impacts on educational outcomes of early childhood exposure to lead through drinking water. Using data on education, on drinking water quality violations and on drinking water lead concentration in Texas, I employ instrumental variables and difference-in-difference strategies. I find that exposure to lead from drinking water in one's year of birth has a significant negative impact on educational achievements, as evidenced by lower scores and pass rates on standardized math and English tests in third grade, and by lower high school graduation rates. Children from African-American households are disproportionately impacted. I find evidence of harm to educational achievement from exposure to lead at levels that are below those currently considered "permissible". My results also suggest that substantial socioeconomic benefits would accrue from eliminating violations of regulations intended to limit lead levels in drinking water. For Texas, this would lead to $241 million to $535 million in increased income.

JEL Codes— I24, J24, Q52, Q53, Q58

*The author acknowledges the support from the Barbara Jordan Professional Development Fund from the University of Texas at Austin, and from the Center for Business and Public Policy, University of Illinois at Urbana-Champaign. I am grateful for helpful feedback from Sheila Olmstead, Raissa Fabregas, Andrew Waxman, Yusuke Kuwayama, Lynn Katz, Tatyana Deryugina, and participants from the SEA 91st annual conference, Camp Resources XXVII, AERE virtual summer conference 2021, SBCA annual conference, WEAI virtual conference, research colloquium at the LBJ School of Public Affairs.

†Address: 515 East Gregory Drive, Champaign, IL 61820; jiamengz@illinois.edu

1 Introduction

Despite more than 30 years of efforts to limit lead exposure and about \$2.0 trillion (measured in 2017 dollars) invested to provide safe drinking water since 1974 (Keiser & Shapiro 2019*b*), nearly 10 million people annually in the United States still drank water from water utilities that violated the Lead and Copper Rule (LCR), the main regulation that governs lead concentration in drinking water (Fedinick 2018). Early childhood exposure to lead has irreversible health and behavioral consequences, as fetuses and young children absorb lead to a greater degree than adults (Hanna-Attisha et al. 2016). Despite the wealth of evidence of the harms of exposure to lead through sources like gasoline and paint, there is little evidence on the long-run causal impact of lead from drinking water. Since ingested lead (from drinking water or paint chips) and inhaled lead (from gasoline or paint dust) are absorbed differently by human body (Agency for Toxic Substances and Disease Registry 2017), there is an important gap in the literature in terms of the potential public health and economic ramifications — especially if long-run returns have been excluded from the benefit-cost analysis of drinking water regulations.

I investigate how early childhood exposure to lead in drinking water affects long-run educational outcomes. I quantify whether and how the impacts of lead exposure through drinking water differ by socioeconomic characteristics such as gender, race and household income levels to discern which groups are most at risk. Thus, this paper provides important information for about the public health and socioeconomic ramification of the regulation and mitigation of lead in drinking water.

Using confidential education data from Texas on educational outcomes for over 2.6 million students and data on lead contamination in drinking water from the U.S. Environmental Protection Agency (EPA), I estimate the causal educational impact of exposure to such contamination during the first year of life. I consider two main educational outcomes: third-grade standardized test results and high school graduation rates, which are the earliest and latest educational outcomes available in my data. I use two identification strategies: an instrumental variables (IVs) strategy to estimate the impact on standardized tests, and a difference-in-difference (DID) strategy to study the impact on high school graduation rate.

A challenge in assessing the long-run impacts of lead exposure through drinking water is controlling for all relevant confounders. Because lead pipes and fixtures exist in homes built before 1986, people who live in older homes and lower-income neighborhoods are likely to be exposed to higher levels of lead through the water they drink. People from minority groups, such as African-Americans and Hispanics are more likely to live in low-income neighborhoods (Osypuk et al. 2009). To address the potential endogeneity problem, I employ IVs strategies by exploiting the exogenous variation of water chemistry that affects lead concentrations in water. Corrosion of lead plumbing materials is the most common source of lead in drinking water. Prior research has shown that surface water trends in chloride affect corrosivity in water distribution systems, which further increase lead concentrations in drinking water (Stets et al. 2018). Thus, I use the following IVs: the exogenous variation in surface water chloride concentration, which affects lead concentrations in finished drinking water; and the exogenous variation of the historical presence of lead pipes. The identifying assumption of the IVs approach is that — after flexibly controlling for many individuals, neighborhood, and climate characteristics — changes in a county's surface water chloride are unrelated to changes in the county's educational outcomes, except through the resulting impact of lead concentrations in drinking water. At the same time, because the IVs approach is constrained by the availability of data on lead concentrations, I also employ a DID strategy using plausibly exogenous variation from the timing of drinking water violations to study the impact of exposure, linking the timing of a violation of the federal regulation with the year of birth.

I find that even a very low level of drinking water lead exposure in a child's birth year has significant negative impacts on third-grade standardized test scores. Specifically, I find that eliminating lead in Texas drinking water could increase average reading scores by 1.5 percent and math scores by 6 percent of a standard deviation. These estimates are in line with standard estimates from the literature using blood lead levels, a more precise physiological measure of lead exposure that is not systematically available at sufficient spatial and inter-temporal scales to allow this kind of analysis. The magnitudes of my estimates are small to medium based on the guidance from Kraft (2020) on the effect size of various educational interventions. The magnitudes are similar to those documented in the existing literature on the causal effects of educational policies, with impacts similar to those found from reducing the student-teacher ratio, or increasing teachers' experience (Krueger 1999). For example, I find that removing lead from drinking water would likely generate educational effects similar to those achieved by having two fewer students in kindergarten classes (Rockoff 2004).

From the DID model, I find that students who experience a new violation in their birth year have a statistically significantly lower probability of graduating high school. Given the income premium of having a high school diploma, such a treatment violation in the birth year may be associated with a 0.6 percent decrease in annual income through the impact on high school graduation alone. For the cohorts in my sample, the benefits in terms of increased income from eliminating such violations in Texas would be around $241 million to $535 million over the lifetime. If 20% of the population during my study period were exposed to such violations, the loss of wages alone could range from $10 billion to $22 billion.

Additionally, I find that children from African-American families are more vulnerable to lead exposure, suggesting that early childhood lead exposure may be one contributing factor of the racial gap in educational achievement in the United States. Specifically, I find that conditional on the same level of lead exposure, African-American students score 2% of a standard deviation lower on reading tests and 1% of a standard deviation less on math tests compared to students from other racial groups. Moreover, African-American students who were exposed to a lead violation in the first year of life are 7% less likely to graduate from high school than students from other racial groups that also experienced such exposure. While I find some mixed evidence on other demographic groups, I find Asian students, Hispanic students and students from families with free and reduced lunch also score less in math tests conditional on the same level of lead exposure.

I make the following contributions to the literature. First, I provide the first evidence of the impacts on elementary school achievement from contemporary exposure to lead from drinking water in the United States. I show that exposure even at the low levels typical of regulated United States water systems may cause damage. Lead in drinking water is an ongoing public health crisis in some cities, with the largest impacts on very young children and pregnant mothers. While the United States has one of the best water supply systems in the world (Columbia Water Center 2016), elevated lead concentrations in drinking water in Flint, Michigan; Newark, New Jersey; and Washington, D.C., are among recent, high-profile occurrences. Most papers that estimate damages from lead exposure focus on airborne lead from gasoline or lead paint dust and paint chips (Billings & Schnepel 2018, Aizer et al. 2018, Aizer & Currie 2019, Hollingsworth & Rudik 2020, Grönqvist et al. 2020). The few studies examine the impact of lead exposure from drinking water are either historical or focus on contemporary effects (Ferrie et al. 2012, Clay et al. 2014, Dave & Yang 2020, Gazze & Heissel 2021, Christensen et al. 2021).

Second, I provide the first evidence that the negative effects of early childhood lead exposure from drinking water persist through longer educational milestones, such as high school graduation. Previous studies have documented lead's impact on children's early cognitive ability, intelligence score (Ferrie et al. 2012), educational outcomes (Reyes 2015*b*, Aizer & Currie 2019), and later crime rate, risky behavior (Reyes 2015*b*) and juvenile delinquency (Aizer & Currie 2019). However, these studies mostly focus on blood lead levels or lead from gasoline. They also look at a fairly short-term impact of lead exposure with a smaller sample. Few studies estimate the long-run impacts of lead exposure, such as the impact on the high school graduation rate (Grönqvist et al. 2020). Using data on millions of children from Texas, I find that the negative impact of lead exposure through the drinking water of one's household during the year of one's birth can persist through high school, some 17 to 18 years after that initial exposure.

Third, this paper contributes to the literature on lead exposure's implications for inequality. Economic and racial inequality can cause poor and minority children to have greater exposure to lead, and prior work suggests that lead may be one cause of continuing disparities in test scores (Aizer & Currie 2019). Studies have shown wide racial and class inequality in lead exposure (Raymond & Brown 2017). While existing research finds that differences in housing conditions and exposures to lead-contaminated house dust contribute strongly to the racial disparity in urban children's blood lead levels (Lanphear et al. 2000), other work reports that such racial disparity persists even after controlling for matters such as neighborhood-level education, poverty, and age of neighborhood housing (Sampson & Winter 2016). Moreover, children from minority and poor neighborhoods are not only disproportionately exposed to lead; they also have less access to mitigating measures such as good nutrition to offset damages caused by lead exposure (Gallicchio et al. 2002, Committee on Environmental Health and others 2005).

As underscored by the recent resurgence of the environmental justice (EJ) literature, better understanding the causes of inequality in lead exposure and its consequences contribute to new approaches and policies for reducing social and economic inequality (Banzhaf et al. 2019).

The rest of the paper proceeds as follows: Section 2 provides a brief introduction of the law governing lead concentrations in drinking water in the United States. Section 3 describes the data used in this paper. Section 4 presents econometric models. Section 5 presents the main results and robustness checks. Section 6 offers a back-of-the-envelope estimation from the benefits of eliminating lead in drinking water, and presents conclusions.

2 The Lead and Copper Rule

The three main historical sources of lead in the United States are lead paint, leaded gasoline, and lead in drinking water (Reyes 2015*a*). The United States EPA (2017) estimates that lead in drinking water contributes to 20% or more of a United States individual's total exposure to lead. Lead in drinking water has larger impacts on very young children and pregnant mothers. For example, infants who consume mostly mixed formula can receive 40% to 60% of contemporaneous lead exposure from drinking water (United States EPA 2017). Also, ingested lead (from drinking water or paint chips) and inhaled lead (from gasoline or paint dust) are absorbed differently by human body (Agency for Toxic Substances and Disease Registry 2017). Thus, though there is evidence on the impacts of lead from gasoline and paint, the impacts of drinking water lead may be different from these.

The regulation governing lead concentrations in United States drinking water is the Lead and Copper Rule. The rule, established by EPA in response to the 1986 Safe Drinking Water Act amendments, and regulates lead contamination at households' taps. It sets a Maximum Contamination Level Goal for lead of zero, which means there is no safe level of lead in drinking water, and any amount is considered harmful to human health. Unlike many other well-studied regulations under the act, the Lead and Copper Rule is a treatment technique rule, without an enforceable lead level that is allowed in the public water system. The rule specifies a list of treatment, monitoring, and public education guidelines to ensure that water systems provide safe water to their customers; it requires water systems to sample water from taps with a higher chance of having lead in drinking water twice every six months, and to measure the lead concentrations. A series of actions is triggered when the fraction of samples exceeding 15 ppb of lead is found to be greater than 10 percent. Actions include examining source water quality, installing a state designated corrosion control treatment program, public education, and the removal of service lines that contain lead. All the required actions are aimed to reduce the amount of lead leaching into the water from different plumbing materials. If a public water system violates the required monitoring, treatment, and public education guidelines, it triggers a violation of the Lead and Copper Rule. I use the plausibly exogenous timing of these violations to estimate the long-run impact of drinking water lead exposure.

The Lead and Copper Rule is one of the most complicated drinking water regulations for states and drinking water utilities to implement because one must control the corrosivity of treated drinking water as it travels through distribution systems to the consumer's tap (United States EPA 2016). States and public water systems must have expertise and resources to identify the sampling locations and to collect and analyze samples correctly. They also need more resources to identify and install the optimal corrosion control treatments and maintain the effective operation of the treatments. Given the requirements in resources and expertise to comply with rule, small systems that may lack these resources are more likely to have violations. Analysis of data from the EPA's Safe Drinking Water Information System shows that the utilities that violate the rule serve about 3,500 people on average. Roughly 90% of systems that experienced violations serve fewer than 10,000 people, which is the upper threshold for the EPA's definition of small systems(United States EPA 2012).

The Lead and Copper Rule has two main types of violations: monitoring and reporting violations, and treatment technique violations. Monitoring and reporting violations occur when public water systems fail to monitor and report water quality in a timely manner. Such violations occur when entities fail to test both lead concentrations at consumers' taps and water quality parameters, such as pH and alkalinity, in the source water. Treatment technique violations include failing to submit an optimal corrosion control technique study or recommendations, failing to install the required technique on time, failing to meet water quality parameter requirements, failing to replace lead service lines, and/or failing to send out public education materials. [1]

Because the protocols are set to ensure that public water systems minimize lead in drinking water, there are good reasons to believe that violation of these protocols is associated with a potential threat to public health. Even though violations may not indicate the presence of lead in a system's drinking water, they may be correlated with increased lead concentrations. For instance, when a public water system does not report a lead concentration to the appropriate state agency, high lead levels can go unobserved. For example, during the Flint water crisis, the EPA database did not list Flint as having violated the Lead and Copper Rule in 2015; nevertheless, its underlying lead concentration was already high before September 2015 (Olson

[1] It is important to note that having lead concentration over the action level does not trigger a violation. Violations only occur when public systems fail to follow designated treatment techniques and their associated timelines. Under the Safe Drinking Water Act, public water systems can violate drinking water standards through health-based violations, monitoring and reporting violations, or public notice violations (United States EPA 2019*a*). The health-based violations of the Lead and Copper Rule are more serious since they mean that systems fail to follow the treatment technique requirements. However, the non-health-based violations, such as monitoring and reporting violations can also pose threats to drinking water quality (Fedinick et al. 2017). the public may not know about any exceedance in lead concentration levels when a public water system fails to monitor water quality.

& Fedinick 2016). According to a study of 72 Flint households in August 2015, 20% of the samples had lead levels that exceeded the action level (15 ppb), and the 90th percentile was 30 ppb (Masten et al. 2016).

To demonstrate this correlation, consider the coefficients reported in Table 1, which shows results from a logistic regression of violations of the Lead and Copper Rule in 3,010 Texas public water systems from 2006 to 2011; I examine observed lead concentrations as measured in mg/L, controlling for year and county fixed effects. The results indicate that lead concentration is positively associated with a public water system having a lead violation. [2]. Also it is important to note that once in violation, public water systems will not return to compliance status for years. For instance, if a system is in violation of monitoring and reporting lead and copper concentration at consumers' kitchen taps, it needs to meet all monitoring and reporting requirements for two consecutive six-month monitoring periods to be back to compliance (United States EPA 2001). In my data, the average duration of a violation is 1,115 days, more than three years.

violations of the rule and the current rule itself could also pose environmental justice issues. Lead service lines are the most important source of lead from drinking water. But under the current rule, water systems are only accountable for the public portion of the lines' replacement, leaving on average $3,000 dollars to homeowners(United States EPA 2021*b*). Past studies using data from Washington, D.C., have found strong correlation between full replacement of lead service lines and family income and race (Environmental Defense Fund 2020). Moreover, when corrosion control alone is not sufficient, consumers need to take further actions to reduce their exposure to lead, such as installing water filters or switching to bottled water. Consumers' ability to understand and afford these actions poses additional challenges to low income families.

3 Data

I use data from multiple sources. Educational outcome data come from the Texas Education Research Center, which provides linked individual-level education and workforce administrative data. Drinking water quality data comes from the EPA's Safe Drinking Water Information System data, and EPA's National Contaminants Occurrence Database. Surface water quality data is obtained from the Water Quality Portal from the United States Geological Survey (USGS)

[2]Because the Lead and Copper Rule violation status of some counties does not change during the time, adding county and year fixed effects shrinks the sample size.

and the Surface Water Quality Monitoring program of the Texas Commission on Environment Quality. I also use data from other administrative surveys, such as the American Housing Survey, to obtain estimates for population, household income, unemployment rates, poverty levels, and other community characteristics.

3.1 Texas education data

I use administrative data from the Texas Education Research Center for my outcome variables. The data include all students who ever enrolled in public schools in Texas, and cover enrollment, standardized test scores, disciplinary action records, high school graduation status, public secondary school enrollment, and basic demographics such as race, gender, and economic disadvantage status.

To match the inter-temporal availability of lead concentration data, I estimate the impacts using data on two sets of individuals: 1) To estimate the impact of lead exposure, I use information on those born in Texas from 2006 to 2011 for whom I have third-grade standardized test scores (I refer to this group as the IV sample). 2) To estimate the impact of violations, I use information on those born in Texas from 1991 to 2001 who ever enrolled in ninth grade in Texas (I refer to this group as the DID sample). A key limitation is that the data do not identify an individual's date of birth or place of birth. The enrollment data have the year of enrollment, grade of enrollment, and age as of September first in the year that the student began school. I identify the list of individuals who enrolled in early education, prekindergarten, or kindergarten in Texas, and I estimate their year of birth using year of enrollment and age as of September first. I refer to students using their estimated year of birth, so my first cohort is students who were born in 1989. The Texas education data have the county in which a school is located, and I use as a proxy that the county where an individual enrolled in early education, prekindergarten, or kindergarten as her county of birth.

I consider several outcome variables. First, I use scaled reading and math standardized test scores in third grade. I also use flags indicating whether an individual passes the relevant standardized tests, graduates from high school, and enrolls in public university in Texas as binary outcome variables.

Table 2 reports the summary statistics of the IV sample. The IV models use third-grade test scores from more than 1 million students born between 2006 and 2011. The average scaled reading score is 1,431 points with a standard deviation of 173 points. The average scaled math score is 1,465 points with a standard deviation of 174 points. I use the scaled test scores because the scaled scores consider the difficulty level of each individual test question, and they allow me to compare test results from year to year (Texas Education Agency 2015). About 40% of the students born between 2006 and 2011 passed the reading standard in third grade, and 44% of students passed the math standard in third grade. Students enrolled in third grade in Texas are on average eight years old.

Second, I examine two different long-run outcomes of the DID sample: high school graduation and enrollment in Texas public universities for the early cohorts. Panel B of Table 3 reports the summary statistics for the sample used in the DID model. There are about 1.3 million students born in Texas enrolled in Texas high schools from 1991 to 2001. Though 78.4% of these students graduate high school, only 25.8% of these students enrolled in Texas public universities. Of this early cohort sample, 48.9% are females. In the group, 47.6% of these students are Hispanic, 35.4% of are white, and 15% are African-Americans. In all, 38.7% students qualify for free lunch, 8% students qualify for reduced lunch fees, and 7% have other economic disadvantages.

3.2 Water system and drinking water quality data

Data on public water systems and water quality violations come from the Safe Drinking Water Information System from the United States EPA, obtained via Freedom of Information Act (FOIA) request by prior researchers (Baker et al. 2019) and shared with me. The lead concentration data are from the third Six-Year Review pollution occurrence data in the National Contaminant Occurrence Database, also obtained via a FOIA request.

3.2.1 Safe Drinking Water Information System data

Safe Drinking Water Information System provides the public water system identifier, the water system name, number of people served, and dates of the beginning and the ending of each violation. I focus on violations in public community water supply systems in my study. Community water systems are a subgroup of public water systems that supply water to the same population year-round, such as public water utilities providing water to households, comparing to water systems belong to schools, office buildings, hospitals or gas stations. Out of 15,736 public water systems in Texas, 49% (7,713) are community water systems. Using the methods in Baker et al. (2019), I match violations with the data from the EPA for the characteristics of the water systems, such as name of the systems, counties and states served. Given that the Safe Drinking Water Information System data obtained from Baker et al. (2019) has violations through 2014, I use the current Safe Drinking Water Information System database available from the EPA website to update the data to the second quarter of 2020 and estimate the duration of violations.

I focus on violations occur from 2006 to 2011 for the younger cohorts ,and violations between 1991 and 2004 for the older cohorts to measure individuals' early childhood lead exposure. I generate an indicator variable of having a new violation in county c in year t, and link the indicator variable with each individual's birth county and birth year to define early childhood exposure. During the periods of interest, 1,336 new violations happened in community water systems in Texas, affecting 5,675,603 individuals. Figure B1 shows the distribution of violations by year. Most violations happened in 1992, 2010, and 2011. By the second quarter of 2020, 1,236 violators had returned to compliance. The average duration of a violation is 1,115 days, with a standard deviation of 788 days. The average population served by systems that received violations is about 3,700. There is a large variation among counties in terms of the number of violations. On average, each county experienced 60 violations from 1991 to 2011, with a standard deviation of 91. Each public water system had an average of 1.6 violations during the same period.

I include both health-based and non-health-based violations in my count. Among the 1,336 violations recorded, 1,305 involve monitoring and reporting (non-health-based) and 31 are health-based violations. In my sample of the older cohort, 19.5% of students who enrolled in high school were born in counties with new violations recorded in their birth year.

3.2.2 National Contaminants Occurrence Data

The lead concentration data come from the third six-year review of pollution occurrence data from National Contaminants Occurrence Database. The EPA is required to review each National Primary Drinking Water Regulation at least once every six years. During this review process, EPA analyzes compliance monitoring data from public water supplies for regulated drinking water contaminants, and it publishes the results. The National Contaminants Occurrence data collected for the review process provide information on the public water system ID, lead concentration, detection limit, and the date of testing. I use the date of testing to merge with a cohort's birth year. I use the geographic area data from the Safe Drinking Water Information System to define the counties served by the public water systems.

The average lead concentration in Texas from 2006 to 2011 is 1.87 ppb with a standard deviation of 1.7. Figure 1 shows the temporal and spatial variation in lead concentrations. As Panel (a) of Figure 1 shows, the lead concentration in Texas remains fairly constant over time with a small decrease in 2009. Panel (b) shows that lead concentration varies largely across counties. The counties with higher lead concentrations are mostly in central and eastern Texas, corresponding to the state's population distribution.

3.3 Surface water quality data

Surface water quality data come from Kuwayama et al. (2020). Chloride and sulfate concentration in surface waters was collected from multiple publicly available data sources: 1) the Water Quality Portal, a platform that provides water quality data from the National Water Information System of the USGS; the EPA STOrage and RETrieval Data Warehouse; and the United States Department of Agriculture's Sustaining The Earth's Watershed-Agricultural Research Database System. Additional data are collected from the Surface Water Quality Monitoring Information System provided by Texas Commission on Environment Quality.

Surface water quality observations are obtained at the monitoring station level. I obtain the watershed boundary database from the Texas Natural Resources Information System, which is derived from the 1:24,000 USGS National Hydrography Dataset (Texas Natural Resources Information System 2014). I define the chloride level of a watershed in a given year by calculating the average chloride concentration of all water quality monitoring stations located within the watershed, using ArcGIS. I obtain the county boundary shapefile from the United States Census Bureau (United States Census Bureau 2020) and, and I use ArcGIS to estimate the area of overlap between a county and a watershed. I then estimate the average concentration of chloride of a county in a given year weighted by the area of overlap.

There is large variation in the chloride concentration across counties and over time in Texas. The weighted average chloride level is 190.7 mg/L in Texas surface water with a standard deviation of 473.4 mg/L. Figure 2 shows the temporal and spatial variation of surface water chloride concentrations in Texas. Figure 2a shows the year fixed effect plus a constant from regressions that control for county fixed effects following Keiser & Shapiro (2019*a*). As it is shown in Figure 2a, the average chloride concentration increases from 2006 to 2011. Figure 2b shows the spatial distribution of surface water chloride concentration by county. chloride concentrations tend to be higher in northwestern and southeastern Texas.

As a robustness check, I calculate the Chloride-Sulfate Mass Ratio (CSMR) as the simple ratio of chloride to sulfate in mass units. The average ratio in Texas is 1.7, suggesting a potentially high corrosivity of surface water (Belitz et al. 2016).

3.4 Lead pipes data

Data on the presence of lead pipes and cities' historical water characteristics are from Clay et al. (2014). The authors collect information on cities' use of lead pipes from the Manual of American Water-Works (Baker 1897). Clay et al. (2014) collect data on 172 large and medium United States cities in 1900. When I match city-level lead data to the county in which each city is located, only have five counties in Texas have information on lead pipes' presence in 1900: Galveston, Harris, Jefferson, McLennan, and Tarrant counties. Figure B3 shows the location of these counties within the state. Those without lead pipes present in 1900 are shaded yellow, and those with lead pipes are shaded pink. I also map the top 11 big cities by population in Texas in 2019 with red circles. As shown in the figure, the historical presence of lead pipes is not strongly correlated with the current levels of urbanization.

Following Clay et al. (2014a), I use a categorical indicator of the presence of lead pipes. It is coded as one if the city has pipes made only with lead or a mix of lead and non-lead service pipes. Table 2 shows that 2% of the people in the younger sample in my study were born in counties with a historical presence of lead pipes.

3.5 Additional controls

I control for neighborhood characteristics, which include the county-year unemployment rate, median household income, poverty rate, and population. Unemployment and population data come from the Bureau of Labor Statistic's Local Area Unemployment Statistics. Income and poverty estimates come from the Census Bureau's Small Area Income and Poverty Estimates program.

Summary statistics from tables 2 and 3 show that the average unemployment rates for the younger cohorts and older cohorts are about 6.5% and 7.3% respectively. The average poverty rate is 17.9% for the younger cohort and 19.5% for the older cohorts. The median household income for the younger cohorts is $48,757, and the median income for the older cohort is $31,427. The average county population is 1,591,577 for the younger cohort, and 1,011,788 for the older cohort.

I also include a list of weather control variables because the weather may affect the amount of water people drink and, thus, play a role in the amount of lead they consume, which in turn could affect educational outcomes. There is also evidence that temperature change over time affects the biochemical attributes of rivers (Ouellet et al. 2020). Weather data are from Schlenker & Roberts (2009), obtained from Schlenker's website, which provides daily minimum and maximum temperatures and total precipitation on a 2.5 × 2.5 mile grid for the United States from 1900 to 2019. Using this information, I estimate county-year average maximum temperature and precipitation in counties.

4 Empirical Strategy

I identify the effect of early childhood exposure to lead from drinking water on school-aged and young adult outcomes by exploiting variation in the magnitude and timing of exposure among individuals born in two time frames: between 1992 and 2001, and between 2006 and 2011. The amount of lead exposure experienced by an individual depends on the year and county of birth. The identifying assumption is that after flexibly controlling for many observable and unobservable potential confounders, changes in a county's drinking water lead concentration in the birth year affect the educational outcome of individuals born in the particular county.

4.1 Baseline Econometric Model

Following Isen et al. (2017), my baseline econometric model is an OLS regression:

$$Outcome^{a}_{ict} = \beta_0 + \beta_1 logLead_{ct} + \mathbf{X}_i\theta + \mathbf{N}_{ct}\psi + \gamma_c + \alpha_t + \varepsilon_{ict} \tag{1}$$

Because I only have lead concentration data from 2006 to 2011, I use the baseline OLS regression to examine the impact of lead on on the short-term outcomes of individuals born during this period. $Outcome^{a}_{ict}$ is the scaled third-grade reading or math score, or a categorical variable indicating whether the child failed, passed with the standard scores, or passed with above-standard scores in one of these tests. $logLead_{ct}$ is the log transformation of average lead concentration from drinking water of an individual's birth county in the year of his or her birth. Because the response function for lead is a "hockey-stick shape" and unlikely to be linear, I use log-transformed lead in my analysis (Grönqvist et al. 2020). $\mathbf{X}_i$ is a vector of individual characteristics including gender, race and economic disadvantage status. $\mathbf{N}_{ct}$ is a vector of county-level, time-varying characteristics, including median income, the percentage of residents with income below the poverty line and the unemployment rate. γ_c is a birth-county fixed effect that controls for time-invariant, unobserved characteristics that could affect third-grade standardized test scores for individuals born in a particular county. α_t is a birth-year fixed effect that controls for time-varying birth-outcome determinants that are common to all individuals born in Texas a given year. By using these fixed effects, I am comparing individuals born within the same county in different years. $\hat{\beta}_1$ is the coefficient of interest and measures the effect that an increase in the lead concentration in drinking water in the birth year later has on third-grade test scores.

The OLS model assumes that the unobserved determinants of test scores should not covary with changes in lead exposure conditional on the covariates. However, this assumption can be violated if there exist any unobserved determinants that also change with lead exposure over time by county. For instance, neighborhoods with higher level of lead may be in older cities and have higher population densities. If unobservable factors change differently over time between old and newer cities, or between urban and rural areas, the OLS model coefficient estimates are likely to be biased.

Moreover, people from certain racial groups and economically disadvantaged families are more likely to be exposed to higher levels of lead from drinking water (Banzhaf et al. 2019, Marcus 2020). Though I use birth-county fixed effects to capture time-invariant characteristics, this identification strategy may still suffer from omitted variable bias. Locations with different levels of lead may also have different underlying conditions such as average income or crime rates. People with different backgrounds or preferences for clean water might sort into locations that have varying levels of lead concentration (Deschenes & Meng 2018). To address concerns about endogenous lead exposure, I use the three identification strategies: the plausibly exogenous variation from chloride levels in surface water, the presence of lead pipes in 1900 (Clay et al. 2014, Stets et al. 2018), and the exogenous timing of violations.

To analyze the endogenous exposure to lead, I use the directed acylic graph (DAG) (Figure A1) to explain my identification strategy (See Appendix A). I control for family income, race and ethnicity, neighborhood income, population, and poverty to remove bias. Also, I use exogenous variation in surface water chemistry, the presence of historical lead pipes, and the timing of lead violations to discern a causal relationship between drinking water lead exposure and educational outcomes.

4.2 Instrumental variables models

Prior research has shown that surface water trends in chloride affect corrosivity in water distribution systems, further affecting drinking water quality (Stets et al. 2018). I use two different instruments that exploit this fact: the level of chloride in source water in an individual's birth county year, and the interaction of surface water chloride and the presence of lead pipes in an individual's birth county in 1900. Surface water chloride level is a valid instrument for the following reasons: First, chloride is strongly related to elevated lead concentration in the drinking water. Past studies have found that high chloride concentration promotes galvanic corrosion of lead service lines and lead solder in water distribution systems (American Water Works Association 1996, Edwards & Triantafyllidou 2007, Willison & Boyer 2012, DeSantis et al. 2018), a water chemistry issue that played a role in the ongoing crisis in Flint. [3] Similarly, in Washington, D.C., from 2004 to 2006, where the city's water system switched from free chlorine to chloramine as a disinfectant, the failure to control corrosion caused elevated lead levels (Edwards et al. 2009).

Second, surface water chloride concentrations strongly correlate with chloride levels in finished drinking water. chloride is a naturally occurring ion and mostly exists in the form of sodium chloride in water. There are no federal or state primary health-based drinking water standards for chloride; there is only an advisory standard for aesthetic purposes (e.g., taste)

[3] When the water authority in Flint switched its water source from Lake Huron to water from the Flint River, the high level of chloride in Flint river was not properly treated to optimize corrosion control; Flint water was found to have lead concentrations of over 5,000 ppb, more than 400 times the action level of 15 ppb (Pieper et al. 2017, 2018, Torrice 2020).

(United States EPA 2003). Though it is possible that people drink less water if the water is too salty from a high level of chloride, the average level of chloride in my data is lower than the standard that the EPA identifies as a concentration sufficient to likely cause a salty taste in drinking water (New Hampshire Department of Environmental Services 2010). Moreover, typical drinking water treatment techniques, such as alkalinity or pH adjustments, do not remove chloride, and drinking water treatment plants do not desalinate; therefore, high chloride concentrations should be conserved even after treatment (Stets et al. 2018). It is important to note that I am using the surface water chloride concentration because finished drinking water chloride sources are not available.

Third, chloride is not likely to be correlated with educational outcomes other than by affecting lead concentrations. Chloride is an essential nutrient for human health. But, based on tap water consumption of 2 L/day, water would typically contribute only 2.5% to 5% of the dietary salt goal (United States EPA 2003). Because the intake of chloride from drinking water is only a small portion compared to other pathways, it is not likely to affect human health or educational outcomes.

The identifying assumption is that after controlling for individual and neighborhood characteristics and fixed effects, changes in surface water chloride of a county are unrelated to the changes in education outcomes of people born there except through the changes in drinking water lead concentration. One threat to my identification is that the change in the chloride across counties over the years could relate to factors that would affect education outcomes that my models do not control for. For example, anthropogenic sources of chloride include but are not limited to the use of fertilizers and irrigation in agricultural fields, road salts, and wastewater discharge or runoff from urban areas (Panno et al. 2006, Steele & Aitkenhead-Peterson 2011). As a result, the change in surface water chloride could be correlated with the change in the degree of urbanization, which may be correlated with educational outcomes later in life. However, I believe this is less of a concern given that chloride concentrations in source water are also increased by the use of irrigation and fertilizers in agricultural fields. Using data on surface water quality from 1982 to 2012, Stets et al. (2020) find that freshwaters are being salinized rapidly in all kinds of landscapes in the United States. Moreover, one major source of chloride in the United States is from the use of road salts for melting snow, which is less common in Texas. But because of the threat to identification, I use this instrument as a robustness check.

I use the interaction of birth-year surface chloride levels and the presence of lead pipes in 1900 as my preferred instrumental variable. For each individual, I use the data from Clay et al. (2014) on lead pipes to determine if that individual's water system historically had lead pipes. While Clay et al. (2014) data only have information on the presence of lead pipes in only 172 large and medium-sized cities, I geocode the cities to the counties of location. I emphasize that my instrument is not the *presence* of lead pipes but the *interaction* of surface water chloride and the historical presence of lead pipes. While the temporal and spatial variations in chloride levels may be affected by the changes in the degree of urbanization and agricultural activity over time and across counties, the presence of lead pipes in 1900 is correlated with the presence of lead pipes in later years, but is less likely to be correlated with the urbanization and agricultural activities of counties during my sample period. The identifying assumption is that chloride levels in surface water are more predictive of lead concentration changes in areas where there is a historical presence of lead pipes.

The first-stage regression in the two-stage least square (2SLS) estimator is as follows:

$$Lead_{ict} = \alpha_0 + \alpha_1 Z_{ict} + \mathbf{X}_i\theta + \mathbf{X}_{ct}\psi + \gamma_c + \eta_t + \varepsilon_{ict} \tag{2}$$

where $Lead_{ict}$ indicates the lead concentrations in drinking water. In the preferred IV, I use the concentration of drinking water lead in a county c and year t when an individual i was born as the dependent variable and use the interaction of surface water chloride and lead pipes as the Z_{ict}. I regress lead on the interaction of weighted average chloride concentration of surface water and the historical presence of lead pipes in an individual's birth county and birth year. For the weighted average chloride concentration, I first calculate the average chloride level of a watershed at a given year. Then I estimate the average chloride concentration of a county using the overlapping area between a county and a watershed as weights. In my robustness check, I use an indicator of lead concentration exceeding the regulation action level in a county c and year t when an individual i was born as my dependent variable.

In the second stage, I use the predicted indicator of lead from equation (2) in the place of actual lead concentration.

$$Outcome_{ict} = \delta_0 + \delta_1 \widehat{Lead}_{ict} + \mathbf{X}_i\theta + \mathbf{N}_{ct}\psi + \gamma_c + \eta_t + \varepsilon_{ict} \tag{3}$$

The coefficient of interest in equation (3) is δ_1, which measures the effect on third-grade standardized tests that stem from lead concentrations in an individual's birth county in the year of her birth. The IV in robustness check measures the effect on the same tests that stem from an individual living in a county that, at the time of her birth, had lead concentrations that exceeded the level that required safe drinking water actions.

4.3 Using rule violations to examine long-run outcomes

While the IV approach can solve potential endogeneity problems, it is constrained by the availability of lead concentration data, so I cannot use it to study the effect of lead on long-run outcomes, such as the high school graduation rate. Thus, for longer-run outcomes, I use plausibly exogenous variation from the timing of water quality violations (Currie et al. 2013, Marcus 2020), and I employ a fixed-effects model to estimate impacts of childhood lead exposure from drinking water on individuals in Texas. I explore the effect of lead violations on individual outcomes using the following specification:

$$Outcome_{ct} = \beta_0 + \beta_1 LCR_{ict} + \mathbf{X}_i\theta + \mathbf{N}_{ct}\psi + \gamma_c + \eta_t + \varepsilon_{ict} \tag{4}$$

where the outcome is the high school graduation rate and rate of Texas public universities. LCR_{ct} measures if the cohort experiences a new lead violation in their birth county c in the birth year t. Similar to Equation 1, I also control for individual characteristics, county-of-birth fixed effects, and year-of-birth fixed effects. With the fixed effects, I compare children born in counties without a new lead violation to children born exposed to a new lead violation. β_1 is the coefficient of interest, which measures the effects of exposure to violations on the outcome of interest. Standard errors are clustered by county.

One key advantage of this approach is that it allows me to use data for all the cohorts from 1992 to 2011, and to examine the impact of lead on long-run outcomes, such as high school graduation. The assumption for this specification is that the variation in lead violation exposure is "as good as random." The assumption is likely to hold with the county fixed effects for the cross-sectional difference between counties that might be related to violations and the educational outcomes of children. For instance, individuals born in poor counties with worse public schools may also have a higher probability of exposure to violations since the water systems that serve their homes may have less funding to test lead concentrations in a timely manner. However, in the presence of time-varying unobservable confounders, my estimate will be biased. For example, violations may happen because a water system's funding is reduced during the financial crisis, which could also affect the children's health and educational outcomes. If this is the case, I may overestimate the impacts of lead violations.

Thus, I use a DID estimator for this specification. As mentioned before, the Lead and Copper Rule is a treatment technique rule. All the technical requirements in the rule are designed to reduce the likelihood of lead exposure in drinking water. From the IV models, I estimate the impacts of lead from drinking water. The DID estimator with this specification evaluates the effectiveness of the policy that aims to reduce lead levels from drinking water.

5 Results

5.1 OLS results

Table 4 shows OLS estimates from equation (1), where panel A presents results using the scaled standardized test scores and panel B presents results where the outcome variable is an indicator of whether an individual meets the standard. I add control variables from left to right. Columns 1 to 5 show the OLS estimates of the impact of lead concentration on reading scores, and columns 6 to 10 show the estimated impacts on math scores. Columns 1 and 6 include only birth county and birth year fixed effects. Columns 2 and 7 show the results of adding individual controls, including gender, race, and economic disadvantage status. Columns 3 and 8 add controls for additional neighborhood characteristics, such as median household income, unemployment rate, and the poverty rate of the birth county in the birth year. I add county-by-year-level average maximum temperature and precipitation in columns 4 and 9. Columns 5 and 10 are robustness checks by including birth-county-by-birth-year trends.

Columns 1 to 5 in panel A of table 4 suggest that the lead concentration in the year of birth reduces third-grade reading scores. The estimated coefficients on log(lead) are fairly consistent as more control variables are added [4]. Because I do not have controls that have been found highly predictive of child outcomes, such as maternal education, birth order, birth weight, or maternal

[4] I also checked the asinh transformation of lead as a robustness check and it did not change the main results (Table available upon request)

education, the consistent magnitude of coefficients shows similar results with the past literature and suggests that a set of basic control variables may be sufficient to control for confounding bias (Aizer & Currie 2019). The coefficient in column 1, -2.335, implies that a 1% increase in lead concentrations in drinking water decreases the third-grade standardized reading scores by 0.023 points. This change seems small. But recall that the mean lead concentration in Texas (1.856 ppb) is well below the action level (15 ppb). Even so, the findings show that if the average lead concentration in Texas were to increase to the 15 ppb threshold to trigger regulatory action, the mean reading scores in Texas would decrease by 16.7 points (719 times 0.023), or 1.16 percent of the average reading score. Past studies have found that a mean increase in blood lead levels of 10 μ g/dL is associated with a decline of average third and fourth-grade English Language Arts scores by 2.6 percentage points in Massachusetts (Reyes 2015*b*) and a decline in third-grade reading scores by 0.335 points in Rhode Island (Aizer et al. 2018). Because my study uses lead concentrations in drinking water, not blood lead levels, it is hard to compare these two measures. However, the fact that I find a statistically significant negative impact at levels that are two orders of magnitude smaller than the threshold that compels federal action is notable.

Columns 1-5 in panel B suggest mixed results for the impact on third-grade math scores of birth-year exposure to lead in drinking water. The estimated lead coefficients are of the expected signs but only weakly significant when I include birth-county fixed effects, birth-year fixed effects, and individual controls; the estimated lead coefficients are insignificant in the other specifications. Estimated coefficients are also smaller than those in the reading models. If we interpret the insignificant column 1 coefficient, a one percent increase in the drinking water lead concentration is associated with a decrease in third-grade math scores of 0.012 points. The smaller impact on math scores is consistent with the epidemiological literature, which suggests that lead has a stronger relationship with verbal functioning (Bellinger et al. 1992, CDC 2004).

Panels C and D of table 4 show the regression results using Equation (1) where the dependent variable is an indicator variable set equal to one for individuals that meet Texas standards for reading and math. Because the dependent variable is an indicator, I use linear probability models. Results are consistent with those from panel A. Exposure to lead in drinking water in the birth year reduces the probability of passing reading tests; the finding is robust to controlling for various confounding factors. Impacts on the likelihood of passing the third-grade math test are not robust, and there is one counter-intuitive, positive and weakly significant coefficient in column 5 of panel D.

5.2 Instrumental variables results

Table 5 shows the first-stage results from using the instrumental variables. Panel A reports the first stage using the interaction between chloride and the historical presence of lead pipes as the instrument for lead concentrations in drinking water. Panel B reports the first stage of chloride as an instrument for exceeding the federal action level of lead regulation. . Columns 1-5 are estimated using equation (2), where I add control variables as one moves across columns.

The first-stage estimates using the my preferred instruments are in panel A of Table 5. The interaction of source water chloride and historical lead pipes are all positive and significant, suggesting an association between surface water chloride and lead pipes with the drinking water lead concentration. The coefficient in column 4 suggests that, holding individual and neighborhood characteristics constant, in cities with lead pipes in 1900, the lead concentration in drinking water increases by 0.0015 ppb (0.08% of the average lead concentration) for each 1 mg/L (0.5% of average chloride level) rise in the source water chloride concentration.

Similar to the first-stage results for my preferred instrument, the coefficients in panel B are also all positive and significant. The coefficient on mean chloride level in column 4 suggests that holding individual characteristics, neighborhood characteristics, and weather constant, results in a 0.0002 percentage point increase in the probability that a one-unit increase in surface water chloride concentrations occurred in one's birth county in one's birth year.

I also report the first-stage F statistics and the Sanderson-Windmeijer (SW) first-stage under-identification test in Table 5.The F statistics for the my preferred IV is well above 10, suggesting that the instrument is unlikely to be a weak instrument(Stock & Yogo 2005). The F statistics are lower than 10 for using chloride as an IV, suggesting that this instrument could be a weak instrument. The SW chi-square underidentification tests suggest that both instruments are relevant. The overidentification test of both instruments (Hansens J statistics) is zero, suggesting both models are just identified.

Table 6 presents regression results using the interaction of surface water chloride concentrations and lead pipes. The coefficients I present here are 2SLS estimates. Panel A of Table 6 shows estimates of lead impact on third-grade reading scores with additional controls added across the columns. Panel B reports the impacts of drinking water lead concentration on math scores.

In all the specifications, the average lead concentration has a negative and statistically significant impact on third-grade standardized test scores in both subjects, except for column 4 of panel A. Contrary to previous findings, the impact of lead seems to be larger for math scores than for reading scores. Column 5 reports the effect of lead on third-grade reading scores, controlling for individual and neighborhood characteristics, and a birth-county-by-year trends. The coefficient suggests that a one ppb increase in average lead concentration is associated with a 3.911 point decrease in third-grade reading scores. If the average lead concentration in drinking water were to increase to 15 ppb, a 13 ppb raise from the current average lead concentration in Texas, the associated decrease in third-grade reading scores would be 50.8 points, 3.6 percent of the average reading scores. The magnitudes of the IV estimates are similar to those from the OLS estimates. Column 5 of Panel B shows the equivalent estimates of lead impact on third-grade math scores. A one ppb increase in the drinking water lead concentration is associated with a 5.198 point decrease in math scores. If the average lead concentration increase to 15 ppb, the average third-grade math scores would decrease by 4.6 percentage points.

Panels C and D of Table 6 present IV results using the indicator for whether an individual meets the reading and math standards, using the second instrument (chloride $\times$ lead pipes). Since these dependent variables are dummy variables, the models reported here are linear probability models. I report results for reading standards in panel C and results for math standards in panel D. Coefficients suggest that higher lead concentrations in the drinking water in the year of one's birth has robust, significant negative impacts on students' probability of passing third-grade reading and math standards. The coefficient in column 4 of panel C suggests that a one ppb increase in average lead concentration leads to a decrease in the probability of meeting the third-grade reading standard by 0.8 percent, holding all else constant. From column 4 of panel D, a one ppb increase in lead concentration is associated with a 1.74% decrease in the probability of passing the math standardized test. The coefficients on the lead are negative but insignificant in columns 5 of both panels. This result may be caused by the fact that my data include only five counties with lead pipes; as a result data, the birth-county-by-year trend absorbs a lot of variation.

Given the robustness of the results, the IV strategy using the interaction of surface chloride concentration and presence of lead pipes may be the preferred approach to estimate the impact of lead in drinking water. However, it is important to note that the sample size is significantly smaller than the OLS sample as it includes only data for locations that had lead pipes in 1900. In Texas, this information is available for only five counties. Even though I find consistent negative impacts of lead in drinking water on academic performance, the IV sample may not be representative of the impact of lead statewide. For these reasons, in the next section, I use the fixed effect model to examine the long-run effect of lead — an approach I plan to apply to the whole United States in the future.

5.3 Long-run impacts of lead violations

The results presented so far are based on the availability of lead concentration data and the IVs. However, given that I only have lead concentration data from 2006 to 2011, I cannot estimate the long-run impacts of lead exposure with these strategies because children born in that time frame have not yet graduated from high school. Since the lead violations have plausibly exogenous timing, I use a DID design to exploit changes in lead violation status across counties to examine this long-run question. With the DID design, I compare the difference in outcomes between cohorts born in counties with and without violations.

The key assumption underlying this identification strategy is that, absent differences in violations, treatment and control counties would have the same trends in high school graduation rates. To test the validation of the parallel trends assumption, I regress the high school graduation on the interaction of violation status in one's birth year and in the years since the lead violation initially occurred, including birth-county and birth-year fixed effects. The estimates of the event study nonparametrically identify treatment effect over time and also test the parallel-trend assumption. Figure B4 shows the coefficient for the interaction term with one year before the violation as the reference year. In the pre-period, the coefficients of violation are small and insignificant, suggesting that the parallel-trends assumption holds. The treatment is negative and statistically significant in periods T+1 and T+2, suggesting that a violation that persists for two years has negative impacts on high school graduation rate. It is important to note that the coefficients of years T-8 to T-6 and T+4 to T+6 have large standard errors. This is because the majority of violations happened in 1992 and lasted for an average three years; as a result, the coefficients for the years before T-6 and after T+4 are less precisely estimated.

I estimate the DID model using the cohort born between 1990 and 2001 enrolled in a Texas public school in ninth grade. Table 7 presents the regression results with Equation (4). Panel A shows results from estimating the impacts on high school graduation that stem from the presence of lead in drinking water. Panel B shows results for public university enrollment in Texas.

Results in panel A suggest that a lead violation in the birth year has a significant and robust negative impact on the high school graduation rate. Column 4 suggests that, holding all else constant, students experiencing a lead violation in the year of their birth are 0.6 percent less likely to graduate high school. By contrast, panel B results suggest that, a violation in one's birth year does not have an impact on public university enrollment in Texas. It is also important to note that the Texas education data only have information on an individual's enrollment in public universities in Texas. Therefore, a child who enrolls in a private university in Texas, or any university outside of the state is not included in these data. Another factor concerns the Top Ten Percent rule used in the state, which guarantees entrance to a Texas public university to all those who graduate in the top 10 percent of their high school class. This rule may also attenuate my coefficient on public university enrollment. My estimate may be an underestimate of the true effect of early exposure to drinking water lead treatment violation on college enrollment.

It is important to note that I only include those who were born with a new violation in their birth county in my main DID sample. Given that the average violation in Texas lasts about three years, and that water systems are required to notify the public about the violation, parents of individuals who were born in the second or third year of a violation may be aware of the potentially high level of lead in their drinking water, and they may take avoidance actions. In panel C of Table 7, I use the sample of people who are born with any year of a lead violation. The coefficients in panel C are smaller and less robust, consistent with potential mitigation methods may be taken for the cohorts born in counties that had existing violations in that year.

5.4 Heterogeneity in impacts of lead exposure

I examine the heterogeneous effects of lead exposure by individual demographics, such as gender and race, using regressions for my preferred IV strategy and the DID strategy. I include an interaction term of my key treatment variables with indicators for race, gender, and economic status. Since the models contain interaction terms between instrument/treatment and the group-specific dummy variable, I also include the group dummy variables in the regressions, so the effect on each group is the sum of these two coefficients. Figure 3 reports the regression coefficients on the interaction term of treatment variable and an indicator of race, gender and economic background groups from 30 separate regressions.

The dependent variables are third-grade reading scores, math scores and high school graduation rates. Figure 3a uses the IV sample, and 3b uses the DID sample. Figure 3a reports estimates from reduced-form models that include additional interaction terms between the second instrument and a group-specific dummy variable. I also report the group-specific dummy variable and the instrument variables separately in the regression models. Figure 3b reports estimates from the DID model with the additional interaction term of the lead violation exposure at birth and the group dummy, a group-specific dummy and lead violation status at birth. I also include birth-year fixed effects, birth-county fixed effects, and control for individual characteristics, neighborhood characteristics, and weather. Table B2 presents the coefficients in the regression tables.

From the Figure 3a, the interaction coefficient is significantly negative for female students in both third-grade reading and math scores, suggesting that female students' third-grade standardized test scores may be more vulnerable to lead exposure. However, Figure 3b suggests that there do not seem to be heterogeneous impacts on high school graduation rates by gender.

Similarly, Figure 3a also suggests that there may be significant heterogeneous treatment effects on later educational outcomes across different racial groups. White, African-American, Asian, and Hispanic students are disproportionately impacted by lead exposure in the year of birth, as indicated by both third-grade reading and math scores. However, the only persistent negative educational impact of drinking water exposure (measured by high school graduation rates) surfaces among African-American students (Figure 3b).

Figure 3 further shows that children born to families with economic disadvantages are also disproportionately affected by exposure to lead in their drinking water during the year of their birth. But the negative impact seems also to fade out when they graduate from high school. These results provide suggestive evidence that early pollution exposure may fade out in the long-run, possibly as the result of interventions (such as improved nutrition) (Jacob et al. 2010, Chetty, Hendren & Katz 2016).

Among all the 30 regressions, I find persistent negative impacts of lead exposure at birth on long-run educational achievement in African-American students. Coefficients from Table B2 shows that, conditioning on lead exposure, African-American students achieve 2% and 1% of a standard deviation lower scores on third-grade reading and math, respectively. They are also 7.4% less likely to graduate from high school.

5.5 Robustness checks

In this section, I explore the robustness of my results to a variety of additional tests and specifications.

5.6 Using surface chloride concentration as an instrument

Table 8 reports second-stage results from the chloride-only IV models. Since the F statistics from the first stage are weak, rather than using the 2SLS, I use the limited information maximum likelihood (LIML) estimator, which is more robust to weak instruments (Stock et al. 2002). The LIML results of my preferred instrument are identical to the 2SLS results (see Table B1). I partial out the fixed effects and controls since the covariance matrix of orthogonality conditions is not of full rank, and the overidentification tests are infeasible when clustering standard errors (Baum et al. 2007).

Panel A presents the effects of lead concentrations exceeding the federal regulatory level on third-grade scaled reading scores, and panel B present the effects on scaled math scores. Panels C and D also present effects of exceeding federal lead regulatory levels on meeting reading and math standards. Across panels, there is a consistent significant and negative impact on third-grade reading test results of lead exposure in drinking water in one's birth year. The coefficient in column 4 of panel A suggests that after controlling for individual, neighborhood, and weather characteristics, having a lead concentration in drinking water over 15 ppb is associated with an 18.3-point decrease in third-grade reading scores.

5.6.1 Including median house age as control

A common pathway of lead entering into children's bodies is through lead paint and the contaminated dust and soils it generates (Lanphear & Roghmann 1997, Jacobs et al. 2002). Though lead paint was banned in 1978, older homes are more likely to still have lead paint and lead pipes. To control for the potential presence of lead paint, I include the median home age in the birth county in the birth year as an additional control variable in the IV strategy and report the coefficients in Table 9.

Column 1 of Table 9 reports the first-stage result using the interaction of surface water chloride concentration and the historical presence of lead pipes as an instrument. Columns 2 and 3 show results for third-grade reading scores, and columns 4 and 5 report results for math. All coefficients are estimated with birth-year fixed effects, birth-county fixed effects, and controls for individual characteristics, neighborhood characteristics, and weather.

Columns 2 and 4 show results consistent with previous results indicating that lead exposure during one's first year of life significantly reduces third-grade reading and math scores. Relative to the baseline results without median home age controls, the effect of drinking water lead on third-grade scores is slightly larger.

5.6.2 Including county trends

To address the concern that broad trends at the county level might be influencing my results, columns 5 of tables 8, 6 and 7 report additional results including county-by-year trends. The results are of the same sign and similar magnitude to the main results.

5.6.3 Controlling for water system size

Violations are more likely to happen in small public water systems. People born in households served by small these small systems may differ from people born in households served by larger systems in unobservable ways. As a robustness check, I estimate the IV model using the interaction between chloride concentration and lead pipes, and controlling for the sum of the population served by public water systems and the number of small and very small systems in a county. Table 10 reports the results, where columns 1 and 2 control for the population served by public water systems, and columns 3 and 4 control for the number of small and very small systems. Columns 1 and 3 are results from specification 4, while columns 2 and 4 add birth-county-by-birth-year trends. Comparing the coefficient estimates in Table 10 to those in Table 7 shows that controlling for the size of the systems has little effect on the educational impact of violations in one's birth year.

5.6.4 Using the Chloride-Sulfate Mass Ratio (CSMR)

The last robustness check uses the chloride-sulfate mass ratio instead of chloride as an instrument. While high chloride can promote solubility of lead in drinking water, sulfate may inhibit corrosion of lead-bearing materials both in isolation and in galvanic connections to copper(Edwards & Triantafyllidou 2007). Environmental engineering experiments and utilities' practical experience have shown that this ratio may also be an important indicator to control lead leaching into potable water (Edwards & Triantafyllidou 2007). In tables 12 and 13, I report results from a set of IV models using this alternative instrument, interacted with the historical presence of lead pipes.

In the first stage (Table 11), the ratio has a consistently positive impact on lead concentration and indicator of exceeding lead regulatory level. The F statistics on the ratio suggest that the interaction of the ratio and lead pipes is a strong instrument, but the ratio alone, like chloride is a weak instrument.

Table 12 reports results using the interaction of the chloride-sulfate mass ratio and the historical presence of lead pipes as an instrument. Table 13 reports 2nd stage results using the ratio alone as an alternative instrument. Panels A and C report results on reading, and panels B and D report the results on math. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level characteristics as controls. Column 3 includes neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 weather control variables. Column 5 also include birth-county-by-birth-year trends. Similar to the results using chloride as an instrument, lead concentration exposure in one's birth year has consistent negative and significant impacts on third-grade standardized tests results.

6 Discussion and Conclusions

This study investigates the educational impacts of drinking water lead exposure in early childhood. Using education and water data from Texas over a period from 1991 to 2011, I exploit variation in lead concentrations. I examine both changes in surface water chloride concentration, which affects treated drinking water chemistry, and the historical presence of lead pipes. I also exploit the plausibly exogenous timing of Lead and Copper Rule violations of measures intended to limit exposure to lead by comparing the outcomes of children living in locations that experienced lead-related water violations in their birth year, with the outcomes of those who did not experience this.

My results provide empirical evidence that lead exposure through drinking water in the birth year has significant negative impacts that last into adulthood — even when exposure is well below the federal action level set for lead in drinking water under provisions of the Safe Drinking Water Act. Specifically, I find that a 1-ppb increase in lead concentration in drinking water is associated with a 4-points decrease in reading scores and 5.2-point decrease in math scores in the third grade. Given the average concentration of lead reported is about 2 ppb, eliminating lead in Texas could increase average reading scores by 52 points (30 percent of a standard deviation) and math scores by 65 points (37 percent of a standard deviation). These are relatively modest gains given that the average scores of both tests are around 1,400, but the magnitude is actually bigger than the estimates derived by using blood lead levels in the existing literature (Aizer & Currie 2019). Eliminating lead in drinking water is also associated with an increase in the probability of passing reading tests (0.8%) and math tests (1.7%) in third grade. These estimates are also consistent with the existing literature using blood lead levels in both economics and epidemiology (Aizer & Currie 2019). Importantly, the effects that I estimated occur even at locations and times when the lead concentrations in drinking water were, on average, quite low and below the levels considered "permissible" under the current regulation.

The findings also suggest that violations of the federal measures that regulate lead in drinking water that occur during a student's year of birth lead to a lower probability of graduating from high school. Results suggest that being born in a county with a new lead-related drinking water violation is associated with a 0.6% decrease in the probability of graduating from high school. A high school drop-out's weekly income is $606 — $143 less than the weekly average income of those who have high school diplomas (United States Bureau of Labor Statistics 2019). Thus, a lead violation that affects drinking water in the first year of life may be associated with a $45 decrease (a 0.14% decrease) in average annual income through its impact on high school graduation. For the older cohort in my sample, the benefits in terms of increased income that would result from having eliminated such violations would be around $12 million annually in Texas. My estimates are smaller than the only existing study of the long-term impact of lead, which suggests reducing childhood blood lead levels from 10 $\mu g/dL$ to 5 $\mu g/dL$ in the United States would have a benefit of around $198 million annually (Grönqvist et al. 2020). However, it is important to note that my study uses violations that are associated with very low levels of lead concentrations. Given the 1.85 ppb in lead, concentrations in my student represent only about 4% of the 5 $\mu g/dL$ reduction mentioned in Grönqvist et al. (2020); despite these smaller concentrations that are the source of lead exposure, my findings show that eliminating such violations would confer sizeable economic benefits.

If the $45 annual income loss persists over the life cycle, an individual's lifetime wage loss alone from the occurence of such violations during the first year of life is about $900 [5]. However, recognizing that an individual's wage is unlikely to be constant through the life cycle, Carnevale et al. (2011) estimate that during their working lives workers with a high school diploma on average earn $331,000 more than those who do not have a diploma. Exposure to a violation of the federal Lead and Copper Rule during the first year of life, thus suggests a present discounted value of lifetime earnings of about $2,000. Given that 20% of individuals in my sample are exposed to new violations during the year of birth, the loss in lifetime earnings ranges from around $241 million to $535 million in Texas. While I do not have an accurate estimate of how many people were exposed to violations during the first year of life during the 1991 to 2004 period, one can generalize from my estimates by assuming that the rate of the population exposed in Texas is the same as that of the rest of the country. The average number of births in the United States is around 4 million per year; thus, roughly 56 million people were born during the 1991 to 2004 period. If 20% of them (11.2 million) were exposed to a new lead violation during that first year of life, the annual loss of income would be about $504 million. The loss in lifetime earnings would be around $10 billion to $22 billion.

My estimates are higher than those calculated to estimate the economic benefits for children from the current regulations as estimated by the EPA. The findings of this paper thus support long-term revision of the Lead and Copper Rule and its economic ramifications. In the long-run revision of the rule under consideration, the EPA estimates the economic benefit of changes by simulating the impact on blood levels, and calculating how much IQ would change as a result of ensuring reductions in lead concentrations in the blood. The EPA then calculates the monetary value of IQ lost as the result of lead exposure. According the EPA estimate, the benefits of current rule is around $220 per child annually (United States EPA 2019*b*). My analysis suggests that reducing the number of violations through more investment and better enforcement can lead to even higher economic benefits per child.

[5] I assume an individual can work from 18 to 78 and use a discount rate of 5%.

I also find that female children and children from African-American families and families with economic disadvantages are more vulnerable to lead exposure, in line with the existing literature (Chetty, Hendren, Lin, Majerovitz & Scuderi 2016, Heckman & Karapakula 2019, Grönqvist et al. 2020). The findings suggest that early childhood lead exposure may be one contributing factor to the racial-achievement gaps in the United States.

President Joe Biden's infrastructure bill includes $15 billion to replace lead pipes and service lines across the country. A back-of-the-envelope calculation based on the EPA's estimate of average replacement costs per line ($4,700) and on the assumption of 6 million to 10 million lead service lines across the country, suggests the costs could range from $28 billion to $47 billion (Campbell & Wessel 2021). The benefit from an increase in lifetime earnings alone would potentially cover the cost of replacing all lead pipes in the United States. Since this is just one slice of potential benefits from eliminating lead from drinking water, the total benefits, including benefits such as reduced crime rates, are likely much larger.

This study provides the first empirical evidence that early childhood exposure to lead from drinking water well below levels that trigger regulatory action has a significant impact on educational outcomes. Though my investigation of five Texas counties which have relatively low lead concentrations may not provide a comprehensive estimate of wider impacts across the country, the approach used in this paper can be employed across a broader geographic area. This is a direction for my future research.

Affiliation: Center for Business and Public Policy, Gies College of Business, University of Illinois at Urbana-Champaign

A Appendix A: DAG figure

To analyze the endogenous exposure to lead, I use the directed acylic graph (DAG) (Figure A1) to explain my identification strategy. DAG is a graphic presentation of the causal effects using nodes and arrows (Cunningham 2021). Nodes represent random variables created by some data-generating process and arrows represent a causal effect between two random variables moving in the direction of the arrow. In Figure A1, I have a list of variables including: drinking water lead exposure at birth, educational outcomes, lead pipes, water treatment, source water chemistry, geology, neighborhood characteristics (public funding, neighborhood resources, urbanization), and individual characteristics (family income, race and ethnicity). These variables are connected by arrows representing the causal relationship among them.

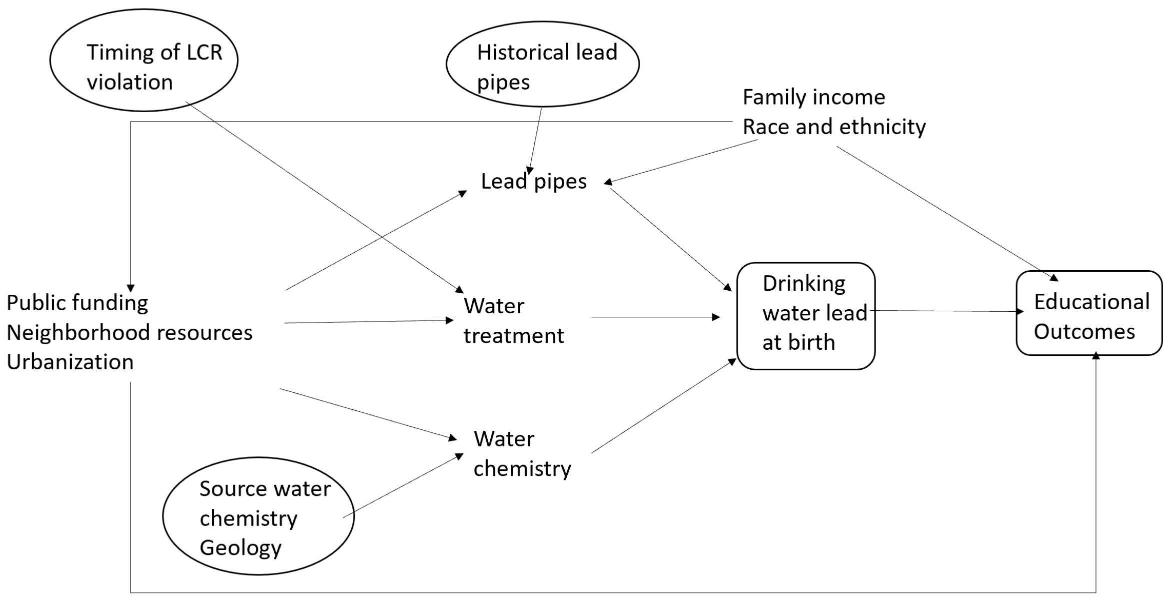


Figure A1: DAG of drinking lead impacts

Notes: Figure shows the DAG of drinking water lead impact on educational outcomes.

There are a list of direct and indirect paths between drinking water lead exposure and later educational outcomes:

1. Drinking water lead at birth $\longrightarrow$ Educational outcome (direct path 1)

2. Drinking water lead at birth $\longleftarrow$ Lead pipes $\longleftarrow$ Family income, race and ethnicity $\longrightarrow$ Educational outcomes (backdoor path 1)

3. Drinking water lead at birth $\longleftarrow$ Lead pipes $\longleftarrow$ Neighborhood characteristics (public

funding, resources and urbanization) $\longleftarrow$ Family income, race and ethnicity $\longrightarrow$ Educational outcomes (backdoor path 2)

4. Drinking water lead at birth $\longleftarrow$ Water treatment $\longleftarrow$ Neighborhood characteristics (public funding, resources and urbanization) $\longleftarrow$ Family income, race and ethnicity $\longrightarrow$ Educational outcomes (backdoor path 3)

5. Drinking water lead at birth $\longleftarrow$ Water chemistry $\longleftarrow$ Urbanization $\longleftarrow$ Family income, race and ethnicity $\longrightarrow$ Educational outcomes (backdoor path 4)

6. Source water chemistry and geology $\longrightarrow$ Water chemistry $\longrightarrow$ Drinking water lead at birth $\longrightarrow$ Educational outcomes (direct path 2)

There are six paths between drinking water lead exposure at birth and later educational outcomes. The first path is the direct causal relationship between drinking water lead exposure at birth and educational outcomes. Paths 2 through 5 are backdoor paths, which means that the correlations between lead exposure and educational outcomes are driven solely by fluctuations in variables such as family income and neighborhood resources. Path 6 is another direct path from drinking water lead exposure to educational outcomes. This is different from the first direct path because this path is driven by changes in source water chemistry and geology, which are unrelated to backdoor variables.

Lead enters drinking water when water corrodes pipes and fixtures that contain lead (United States EPA 2021*a*). There are three crucial parts to the process. First, there need to be plumbing materials containing lead, such as pipes, solders, or fixtures. Second, water utilities are required to implement optimal corrosion control techniques, such as adjusting pH or adding orthophosphate to make lead-phosphate scale in pipes. But these approaches may not always be useful and could have unintended consequences given the complexity of water chemistry in pipes and new findings from environmental engineering research (Pelley 2018). Moreover, water utilities need to test for drinking water lead concentration. Failing to meet the monitoring schedule at the water utility level could cause lead pollution to go undiscovered. Third, water corrodes lead pipes when drinking water is acidic or contains disinfectant, inorganic carbon, iron, manganese, and aluminum compounds, or other components that promote the corrosion of scale in lead pipes and cause a release of lead particles. While water utilities alter the water chemistry, factors such as temperature and weather may influence the chemistry of drinking water even after utilities implement corrosion control techniques. (Roy & Edwards 2019).

The backdoor paths in Figure A1 show the complex relationship between various socioeconomic variables and the factors affecting drinking water lead exposure. Backdoor path 1 shows that an individual's family background, such as parents' income, race, and ethnicity, affects the probability of being born in a house with lead pipes. As mentioned before, replacing lead pipes could be expensive to many low-income residents even with federal and state funding programs. For example, the Trenton (New Jersey) Water Works Lead Service Line Replacement Program limits homeowner expenses to $1,000 by covering the rest of the cost for replacement, which typically runs between $3,000 and $7,000 (Santucci & Scully 2020). Family income could also affect students' educational outcomes by investment in students' education and productivity.

Backdoor path 2 suggests that on top of backdoor path 1 relationships, family income, race, and ethnicity could also sort people to live in certain neighborhoods. While the Lead and Copper Rule requires the lead service line replacement rate, it is up to communities and utilities to make plans for this replacement. Wealthy neighborhoods may have more resources to replace lead pipes. There are also better schools in those neighborhoods that would lead to better student educational outcomes. Backdoor path 3 and backdoor path 4 show a similar story. Water districts and communities with more funding and resources could implement better corrosion control techniques. Urbanization, though, can also influence drinking water chemistry and lead to a higher level of lead from drinking water.

Since there are four *open* backdoor paths, I control for family income, race and ethnicity, neighborhood income, population, and poverty to remove bias. Also, I use exogenous variation in surface water chemistry, the presence of historical lead pipes, and the timing of violations to discern a causal relationship between drinking water lead exposure and educational outcomes.

B Appendix B: Tables and Discussion

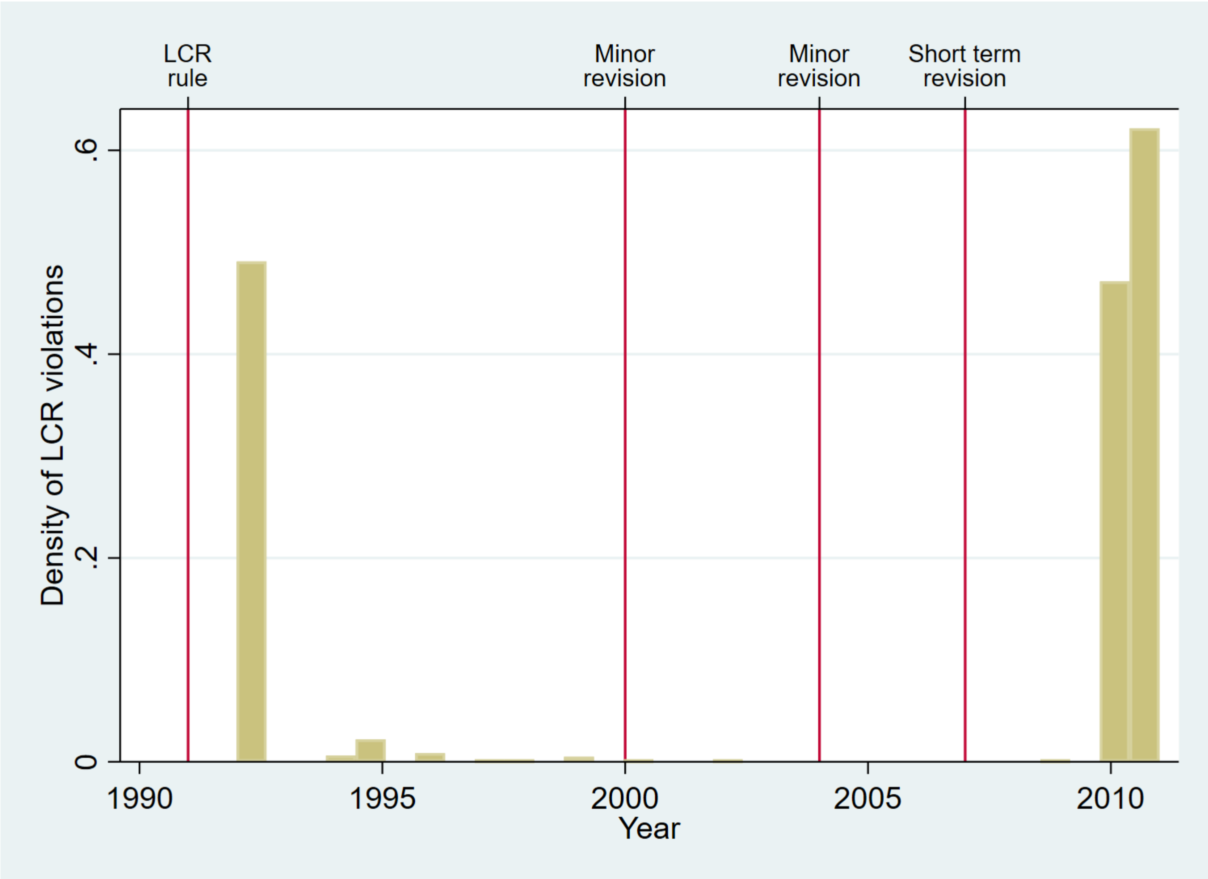


Figure B1: Number of lead violations by year, 1992-2011

Notes: Figure shows the distribution of lead violations by year. The red lines show years when changes happen to the Lead and Copper Rule (LCR).

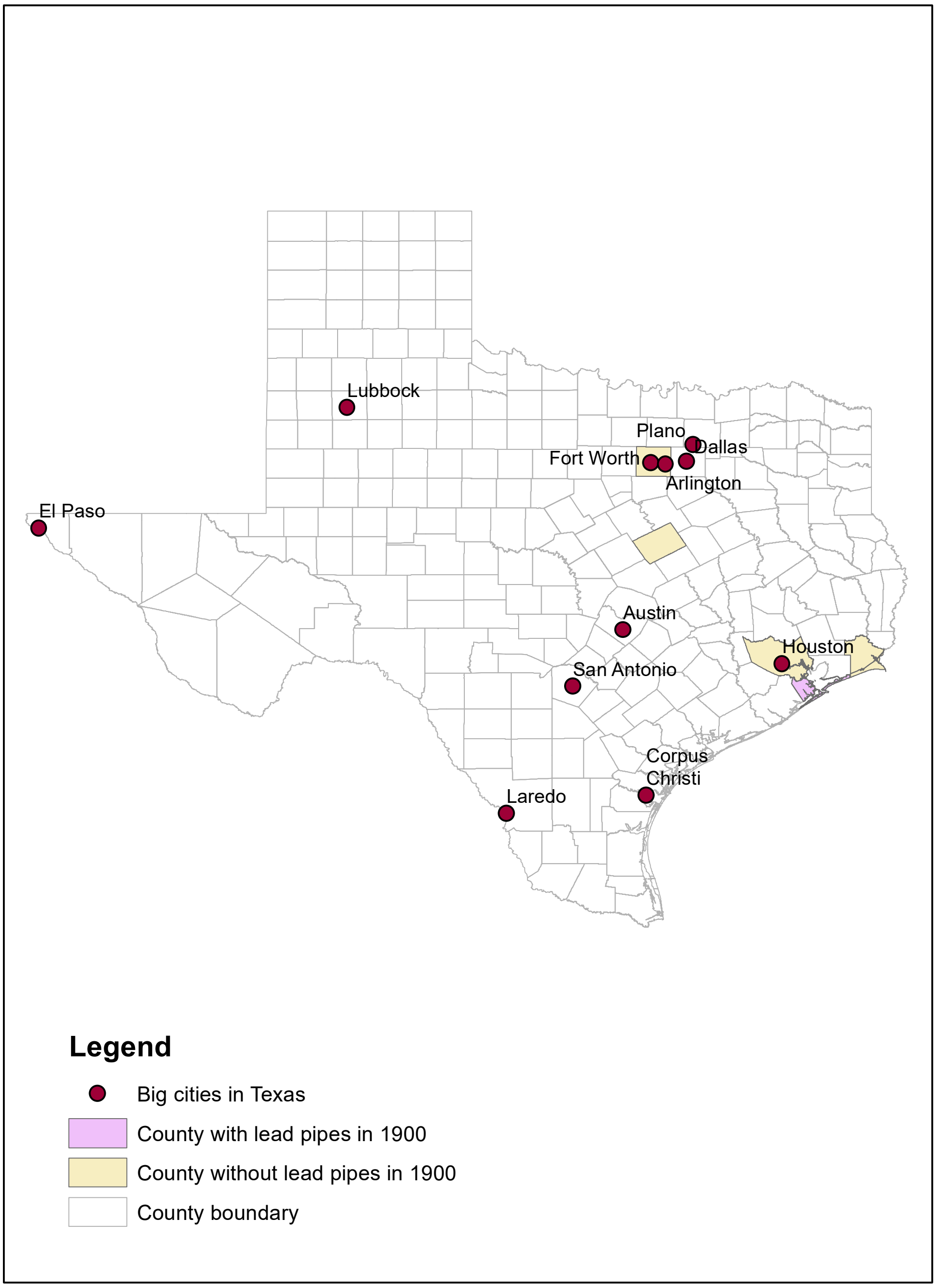


Figure B3: Texas counties with information on lead pipes in 1900.

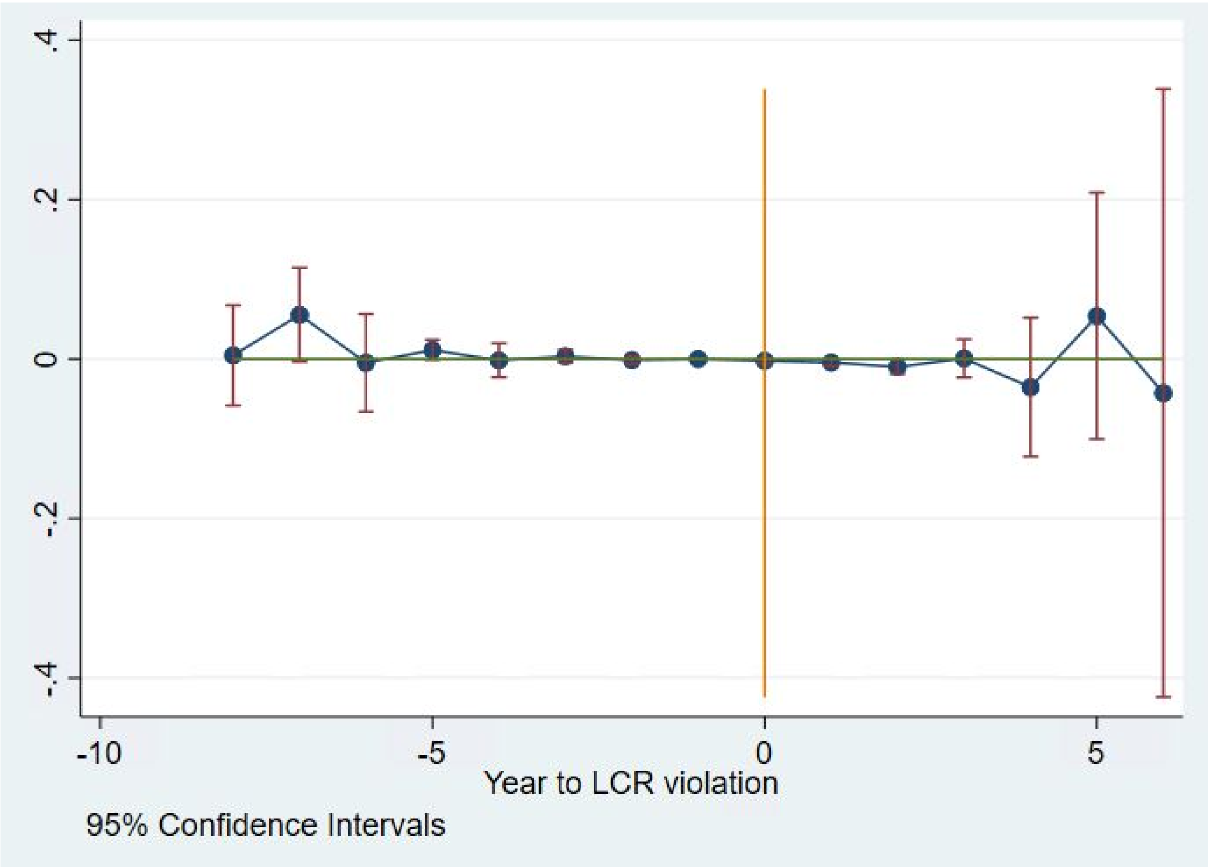


Figure B4: The estimated treatment effects by event time

Notes: Figure presents estimated trends in high school graduation rate using the sample from the primary analyses plus years “T-8” to “T+6” to better map out the pre-treatment periods and treatment response. I regress the high school graduation rate with an interaction of Lead and Copper Rule (LCR) violation status and time dummies for all periods before and after treatment. Blue connected dots show the coefficient and red dashed lines show the 95% confidence interval, with the year before a violation as the reference year. I calculate robust, individual level standard errors.

Table B1: IV estimates of lead impact using LIML

	(1)	(2)	(3)	(4)	(5)
	A: Reading scores				
Chloride * pipes	-0.910***	-2.192***	-2.304***	-1.453	-3.911**
	(0.061)	(0.039)	(0.121)	(0.886)	(1.956)
	B: Math scores				
Chloride * pipes	-2.416***	-3.537***	-4.093***	-5.637***	-5.198***
	(0.095)	(0.040)	(0.063)	(0.520)	(2.345)
	C: Meet reading standard				
Chloride * pipes	-0.001***	-0.005***	-0.006***	-0.006***	-0.0137***
	(0.0003)	(0.00008)	(0.0005)	(0.0009)	(0.005)
	D: Meet math standard				
Chloride * pipes	-0.007***	-0.010***	-0.011***	-0.0174***	-0.0127***
	(0.0002)	(0.00005)	(0.0002)	(0.001)	(0.00287)
Observations	361,106	361,024	361,106	361,106	361,106
First stage F statistics	3,748.53	3,860.22	1,761.13	529.17	30.86
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

This table reports the LIML estimates of the effects of lead exposure using my preferred instrument. Panels A and B report results on standardized test scores, and panels C and D report results on meeting the standards. Column 1 shows the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level characteristics as controls. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 also includes weather control variables. Column 5 has birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: The effect of lead exposure on third-grade scores and high school graduation rate by gender, race and economic status

	(1) Male	(2) Female	(3) White	(4) African American	(5) Asian	(6) Hispanic	(7) Native American	(8) Free lunch	(9) Reduced lunch	(10) Other disadvantages
Panel A:third-grade reading										
Instrument	-0.003***	0.001*	0.003**	0.001*	0.00009	-0.0004	-0.0003	0.006***	-0.0001	-0.001*
	(0.0003)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0008)	(0.0006)	(0.0004)	(0.0003)	(0.0003)
Second instrument * group	0.005***	-0.005***	-0.010***	-0.014**	-0.004***	0.0008	0.008**	-0.014***	-0.006***	0.010***
	(0.0003)	(0.0003)	(0.001)	(0.003)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)
R2	0.0814	0.0814	0.0689	0.0678	0.07	0.0647	0.0633	0.073	0.0621	0.063
Panel B:third-grade math										
Instrument	-0.010***	-0.006***	-0.004*	-0.007***	-0.007***	-0.006***	-0.007***	-0.004***	-0.007***	-0.008***
	(0.0005)	(0.0007)	(0.001)	(0.0004)	(0.0005)	(0.0008)	(0.0006)	(0.0003)	(0.0004)	(0.0004)
Instrument * group	0.004***	-0.004***	-0.009**	-0.008*	-0.008***	-0.004**	0.018**	-0.009***	-0.011***	-0.0087***
	(0.0005)	(0.0005)	(0.002)	(0.002)	(0.0002)	(0.001)	(0.004)	(0.001)	(0.0002)	(0.001)
R2	0.0851	0.0851	0.0592	0.0696	0.0685	0.0554	0.0554	0.0794	0.071	0.0714
N	361024	361024	361024	361024	361024	361024	361024	361024	361024	361024
Panel C:High school graduate										
Lead violation	-0.037*	-0.040**	-0.058***	-0.021	-0.039***	-0.031**	-0.038***	-0.033**	-0.037***	-0.034**
	(0.020)	(0.025)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.016)	(0.014)	(0.014)
Lead violation * group	-0.003	0.003	0.063***	-0.074***	0.059	-0.018	-0.054	-0.010	-0.018	-0.070
	(0.026)	(0.015)	(0.019)	(0.016)	(0.052)	(0.017)	(0.113)	(0.016)	(0.019)	(0.043)
R2	0.050	0.050	0.047	0.047	0.049	0.047	0.047	0.047	0.047	0.047
N	1341714	1341714	1341714	1341714	1341741	1341741	1341741	1341741	1341741	1341741
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients from 30 separate regressions. The regressions are estimated using the individual-level data of the two samples. The dependent variables are third-grade reading scores, math scores and high school graduation rate. Panels A and B use the IV sample, and panel C uses the DID sample. Panels A and B report estimates from reduced-form models that include additional interaction terms between my preferred instrument and a group-specific dummy variable indicated in the column heading. I also the group-specific dummy variable and the instrument variables separately in the regression models. Panel C reports estimates from the DID model with the additional interaction term of the violation exposure in one's birth year and the group dummy, a group-specific dummy and violation status in one's birth year. I also include birth-year fixed effects, birth-county fixed effects, individual characteristics, neighborhood controls and weather as described before. Standard errors in parentheses and clustered at county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Agency for Toxic Substances and Disease Registry (2017), 'Lead toxicity'.
URL: *http://www.atsdr.cdc.gov/csem/csem.html.*

Aizer, A. & Currie, J. (2019), 'Lead and juvenile delinquency: new evidence from linked birth, school, and juvenile detention records', *Review of Economics and Statistics* **101**(4), 575–587.

Aizer, A., Currie, J., Simon, P. & Vivier, P. (2018), 'Do low levels of blood lead reduce children's future test scores?', *American Economic Journal: Applied Economics* **10**(1), 307–41.

American Water Works Association (1996), *Internal corrosion of water distribution systems*, American Water Works Association.

Baker, J., Bennear, L. & Olmstead, S. (2019), 'Does information disclosure reduce drinking water violations in the united states?'.

Baker, M. (1897), *The Manual of American Water-Works*, The Engineering News Publishing Co.

Banzhaf, H. S., Ma, L. & Timmins, C. (2019), 'Environmental justice: Establishing causal relationships', *Annual Review of Resource Economics* **11**, 377–398.

Baum, C. F., Schaffer, M. E. & Stillman, S. (2007), 'Enhanced routines for instrumental variables/generalized method of moments estimation and testing', *The Stata Journal* **7**(4), 465–506.

Belitz, K., Jurgens, B. C. & Johnson, T. D. (2016), Potential corrosivity of untreated groundwater in the united states, Technical report, US Geological Survey.

Bellinger, D. C., Stiles, K. M. & Needleman, H. L. (1992), 'Low-level lead exposure, intelligence and academic achievement: A long-term', *Pediatrics* **90**(6), 855.

Billings, S. B. & Schnepel, K. T. (2018), 'Life after lead: Effects of early interventions for children exposed to lead', *American Economic Journal: Applied Economics* **10**(3), 315–44.

Campbell, S. & Wessel, D. (2021), 'What would it cost to replace all the nation's lead water pipes?'.

URL: *https://www.brookings.edu/blog/up-front/2021/05/13/what-would-it-cost-to-replace-all-the-nations-lead-water-pipes/*

Carnevale, A. P., Cheah, B. & Rose, S. J. (2011), 'The college pay off'.

CDC (2004).
URL: *https://www.cdc.gov/nceh/lead/acclpp/meetingminutes/lessthan10mtgmar04.pdf*

Chetty, R., Hendren, N. & Katz, L. F. (2016), 'The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment', *American Economic Review* **106**(4), 855–902.

Chetty, R., Hendren, N., Lin, F., Majerovitz, J. & Scuderi, B. (2016), 'Childhood environment and gender gaps in adulthood', *American Economic Review* **106**(5), 282–88.

Christensen, P., Keiser, D. & Lade, G. (2021), 'Economic effects of environmental crises: Evidence from flint, michigan', *Michigan (January 01, 2021)* .

Clay, K., Troesken, W. & Haines, M. (2014), 'Lead and mortality', *Review of Economics and Statistics* **96**(3), 458–470.

Columbia Water Center (2016).
URL: *http://water.columbia.edu/files/2016/03/Developing-a-Water-Road-Map-Whitepaper.pdf*

Committee on Environmental Health and others (2005), 'Lead exposure in children: prevention, detection, and management', *Pediatrics* **116**(4), 1036–1046.

Cunningham, S. (2021), *Causal Inference*, Yale University Press.

Currie, J., Graff Zivin, J., Meckel, K., Neidell, M. & Schlenker, W. (2013), 'Something in the water: Contaminated drinking water and infant health', *Canadian Journal of Economics/Revue canadienne d'économique* **46**(3), 791–810.

Dave, D. M. & Yang, M. (2020), Lead in drinking water and birth outcomes: A tale of two water treatment plants, Technical report, National Bureau of Economic Research.

DeSantis, M. K., Triantafyllidou, S., Schock, M. R. & Lytle, D. A. (2018), 'Mineralogical evidence of galvanic corrosion in drinking water lead pipe joints', *Environmental science & technology* **52**(6), 3365–3374.

Deschenes, O. & Meng, K. C. (2018), Quasi-experimental methods in environmental economics: Opportunities and challenges, *in* 'Handbook of Environmental Economics', Vol. 4, Elsevier, pp. 285–332.

Edwards, M. & Triantafyllidou, S. (2007), 'Chloride-to-sulfate mass ratio and lead leaching to water', *Journal-American Water Works Association* **99**(7), 96–109.

Edwards, M., Triantafyllidou, S. & Best, D. (2009), 'Elevated blood lead in young children due to lead-contaminated drinking water: Washington, dc, 2001- 2004', *Environmental science & technology* **43**(5), 1618–1623.

Environmental Defense Fund (2020).
URL: *https://www.edf.org/sites/default/files/u4296/LeadPipe_EnvironJustice_AU%20and%20EDF%20Report.pdf*

Fedinick, K. P. (2018), 'What's in your water? an updated analysis'.
URL: *https://www.nrdc.org/experts/kristi-pullen-fedinick/whats-your-water-updated-analysis*

Fedinick, K. P., Wu, M., Panditharatne, M. & Olson, E. D. (2017).
URL: *https://www.nrdc.org/sites/default/files/threats-on-tap-water-infrastructure-protections-report.pdf*

Ferrie, J. P., Rolf, K. & Troesken, W. (2012), 'Cognitive disparities, lead plumbing, and water chemistry: Prior exposure to water-borne lead and intelligence test scores among World War Two U.S. Army enlistees', *Economics and Human Biology* **10**(1), 98–111.

Gallicchio, L., Scherer, R. W. & Sexton, M. (2002), 'Influence of nutrient intake on blood lead levels of young children at risk for lead poisoning.', *Environmental Health Perspectives* **110**(12), A767–A772.

Gazze, L. & Heissel, J. (2021), 'Infrastructure upgrades and lead exposure: Do cities face trade-offs when replacing water mains?', *Journal of Environmental Economics and Management* **108**, 102472.

Grönqvist, H., Nilsson, J. P. & Robling, P.-O. (2020), 'Understanding how low levels of early lead exposure affect children's life trajectories', *Journal of Political Economy* **128**(9), 3376–3433.

Hanna-Attisha, M., LaChance, J., Sadler, R. C. & Schnepp, A. C. (2016), 'Elevated blood lead levels in children associated with the flint drinking water crisis: A spatial analysis of risk and public health response', *American Journal of Public Health* **106**(2), 283–290.

Heckman, J. J. & Karapakula, G. (2019), The perry preschoolers at late midlife: A study in design-specific inference, Technical report, National Bureau of Economic Research.

Hollingsworth, A. & Rudik, I. (2020), 'The social cost of leaded gasoline: Evidence from regulatory exemptions'.

Isen, A., Rossin-Slater, M. & Walker, W. R. (2017), 'Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970', *Journal of Political Economy* **125**(3), 848–902.

Jacob, B. A., Lefgren, L. & Sims, D. P. (2010), 'The persistence of teacher-induced learning', *Journal of Human resources* **45**(4), 915–943.

Jacobs, D. E., Clickner, R. P., Zhou, J. Y., Viet, S. M., Marker, D. A., Rogers, J. W., Zeldin, D. C., Broene, P. & Friedman, W. (2002), 'The prevalence of lead-based paint hazards in us housing.', *Environmental health perspectives* **110**(10), A599–A606.

Keiser, D. A. & Shapiro, J. S. (2019*a*), 'Consequences of the clean water act and the demand for water quality', *The Quarterly Journal of Economics* **134**(1), 349–396.

Keiser, D. A. & Shapiro, J. S. (2019*b*), 'Us water pollution regulation over the past half century: burning waters to crystal springs?', *Journal of Economic Perspectives* **33**(4), 51–75.

Kraft, M. A. (2020), 'Interpreting effect sizes of education interventions', *Educational Researcher* **49**(4), 241–253.

Krueger, A. B. (1999), 'Experimental estimates of education production functions', *The quarterly journal of economics* **114**(2), 497–532.

Kuwayama, Y., Olmstead, S. M., Wietelman, D. C. & Zheng, J. (2020), 'Trends in nutrient-related pollution as a source of potential water quality damages: A case study of texas, usa.', *The Science of the total environment* **724**, 137962.

Lanphear, B. P., Dietrich, K., Auinger, P. & Cox, C. (2000), 'Cognitive deficits associated with blood lead concentrations <10 microg/dL in US children and Adolescents', *Public health reports* **115**(6), 521–9.

Lanphear, B. P. & Roghmann, K. J. (1997), 'Pathways of lead exposure in urban children', *Environmental Research* **74**(1), 67–73.

Marcus, M. (2020), 'Testing the water: Drinking water quality, public notification, and child outcomes'.

Masten, S. J., Davies, S. H. & Mcelmurry, S. P. (2016), 'Flint water crisis: what happened and why?', *Journal-American Water Works Association* **108**(12), 22–34.

New Hampshire Department of Environmental Services (2010), 'Sodium and chloride in drinking water'.
URL: *https://www.cambridgema.gov/-/media/Files/waterdepartment/Distribution/ChloridesEnviroFactShe*

Olson, E. & Fedinick, K. P. (2016), *What's in Your Water? Flint and beyond analysis of EPA data reveals widespread lead crisis potentially affecting millions of Americans.*
URL: *https://www.nrdc.org/sites/default/files/whats-in-your-water-flint-beyond-report.pdf*

Osypuk, T. L., Galea, S., McArdle, N. & Acevedo-Garcia, D. (2009), 'Quantifying separate and unequal: racial-ethnic distributions of neighborhood poverty in metropolitan america', *Urban Affairs Review* **45**(1), 25–65.

Ouellet, V., St-Hilaire, A., Dugdale, S. J., Hannah, D. M., Krause, S. & Proulx-Ouellet, S. (2020), 'River temperature research and practice: Recent challenges and emerging opportunities for managing thermal habitat conditions in stream ecosystems', *Science of The Total Environment* **736**, 139679.

Panno, S. V., Hackley, K. C., Hwang, H., Greenberg, S. E., Krapac, I., Landsberger, S. & O'kelly, D. (2006), 'Characterization and identification of na-cl sources in ground water', *Groundwater* **44**(2), 176–187.

Pelley, J. (2018), 'Treatment for lead in drinking water is evolving. will the u.s. epa catch up?'. **URL:** *https://cen.acs.org/environment/water/Treatment-lead-drinking-water-evolving/96/i47*

Pieper, K. J., Martin, R., Tang, M., Walters, L., Parks, J., Roy, S., Devine, C. & Edwards, M. A. (2018), 'Evaluating water lead levels during the flint water crisis', *Environmental science & technology* **52**(15), 8124–8132.

Pieper, K. J., Tang, M. & Edwards, M. A. (2017), 'Flint water crisis caused by interrupted corrosion control: investigating "ground zero" home', *Environmental Science & Technology* **51**(4), 2007–2014.

Raymond, J. & Brown, M. (2017), Childhood blood lead level in children age, Technical Report 3. **URL:** *https://www.cdc.gov/mmwr/volumes/66/ss/pdfs/ss6603.pdf*

Reyes, J. W. (2015*a*), 'Lead exposure and behavior: Effects on antisocial and risky behavior among children and adolescents', *Economic Inquiry* **53**(3), 1580–1605.

Reyes, J. W. (2015*b*), 'Lead Policy and Academic Performance: Insights from Massachusetts', *Harvard Educational Review* **85**(1), 75–107.

Rockoff, J. E. (2004), 'The impact of individual teachers on student achievement: Evidence from panel data', *American economic review* **94**(2), 247–252.

Roy, S. & Edwards, M. A. (2019), 'Preventing another lead (pb) in drinking water crisis: Lessons from the washington dc and flint mi contamination events', *Current Opinion in Environmental Science & Health* **7**, 34–44.

Sampson, R. J. & Winter, A. S. (2016), 'The racial ecology of lead poisoning: Toxic inequality in chicago neighborhoods, 1995-2013', *Du Bois Review: Social Science Research on Race* **13**(2), 261–283.

Santucci, R. J. & Scully, J. R. (2020), 'The pervasive threat of lead (pb) in drinking water: Unmasking and pursuing scientific factors that govern lead release', *Proceedings of the National Academy of Sciences* **117**(38), 23211–23218.

Schlenker, W. & Roberts, M. J. (2009), 'Nonlinear temperature effects indicate severe damages to us crop yields under climate change', *Proceedings of the National Academy of sciences* **106**(37), 15594–15598.

Steele, M. & Aitkenhead-Peterson, J. (2011), 'Long-term sodium and chloride surface water exports from the dallas/fort worth region', *Science of the total environment* **409**(16), 3021–3032.

Stets, E. G., Lee, C. J., Lytle, D. A. & Schock, M. R. (2018), 'Increasing chloride in rivers of the conterminous us and linkages to potential corrosivity and lead action level exceedances in drinking water', *Science of the Total Environment* **613**, 1498–1509.

Stets, E. G., Sprague, L. A., Oelsner, G. P., Johnson, H. M., Murphy, J. C., Ryberg, K., Vecchia, A. V., Zuellig, R. E., Falcone, J. A. & Riskin, M. L. (2020), 'Landscape drivers of dynamic change in water quality of us rivers', *Environmental Science & Technology* **54**(7), 4336–4343.

Stock, J. H., Wright, J. H. & Yogo, M. (2002), 'A survey of weak instruments and weak identification in generalized method of moments', *Journal of Business & Economic Statistics* **20**(4), 518–529.

Stock, J. & Yogo, M. (2005), *Testing for Weak Instruments in Linear IV Regression*, Cambridge University Press, New York, pp. 80–108.

Texas Education Agency (2015).

Texas Natural Resources Information System (2014), 'Watershed boundaries 2014'.
URL: *https://data.tnris.org/*

Torrice, M. (2020), 'How lead ended up in flint's tap water'.
URL: *https://cen.acs.org/articles/94/i7/Lead-Ended-Flints-Tap-Water.html*

United States Bureau of Labor Statistics (2019), 'Median weekly earnings $606 for high school dropouts, $1,559 for advanced degree holders'.

URL: *https://www.bls.gov/opub/ted/2019/median-weekly-earnings-606-for-high-school-dropouts-1559-for-advanced-degree-holders.htm*

United States Census Bureau (2020), 'Tiger/line shapefiles'.

URL: *https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html*

United States EPA (2001), 'Appendix b lcrmr reporting guidance'.

United States EPA (2003), *Drinking water advisory: consumer acceptability advice and health effects analysis on sodium*, U.S. Environmental Protection Agency, Office of Water, Health and Ecological Criteria Division.

United States EPA (2012), 'Small drinking water systems variances'.

United States EPA (2016), 'Lead and copper rule revisions white paper'.

United States EPA (2017), Proposed Modeling Approaches for a Health- Based Benchmark for Lead in Drinking Water, Technical report.

URL: *https://www.epa.gov/sites/production/files/2017-01/documents/report_proposed_modeling_approaches*

United States EPA (2019*a*), 'Drinking water dashboard help'.

URL: https://echo.epa.gov/help/drinking-water-dashboard-help

United States EPA (2019*b*), 'Economic analysis for the proposed lead and copper rule revisions'.

URL: *https://www.regulations.gov/document/EPA-HQ-OW-2017-0300-0003*

United States EPA (2021*a*), 'How lead gets into drinking water'.

URL: https://www.epa.gov/ground-water-and-drinking-water/basic-information-about-lead-drinking-water#getinto

United States EPA (2021*b*), *national primary drinking water regulations: lead and copper rule revisions*, Vol. 86 FR 4198.

Willison, H. & Boyer, T. H. (2012), 'Secondary effects of anion exchange on chloride, sulfate, and lead release: Systems approach to corrosion control', *Water Research* **46**(7), 2385–2394.

Tables

Table 1: The association between lead concentration and lead violation

	(1)	(2)	(3)
	Lead violation	Lead violation	Lead violation
Lead concentration	17.930^{*}	30.180^{*}	32.750^{**}
	(9.258)	(17.080)	(14.160)
Year fixed effects	No	Yes	Yes
County fixed effects	No	No	Yes
Observations	6,900	2,497	1,949
R2	0.002	0.011	0.061

Notes: This table reports the coefficients of regressing lead concentration on an indicator of having lead violation in a given county c in year t. Column 1 reports the coefficient estimates without any fixed effects. Column 2 includes year fixed effects. Column 3 adds county fixed effects. The number of observation decreases across columns as observations dropped from regressions when adding fixed effects and the lead violation indicator do not change over time and across county. Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Summary statistics of the IV sample

	mean	median	sd	min	max
Reading score	1431.16	1427	174.51	100	4011
Math score	1464.78	1458	175.47	111	4378
Meet reading standard	0.40	0	0.49	0	1
Meet math standard	0.45	0	0.50	0	1
Lead action level exceedance	0.02	0	0.15	0	1
Lead concentration (ppb)	1.87	1.70	1.14	0.00	12.73
chloride concentration (mg/L)	190.69	73.91	473.37	7.97	23032.16
chloride-sulfate mass ratio (CSMR)	1.70	1.18	1.31	0.06	23.39
Presence of lead pipes	0.02	0	0.14	0	1
Female	0.50	0	0.50	0	1
Native American	0.01	0	0.08	0	1
Asian	0.04	0	0.19	0	1
Black	0.13	0	0.34	0	1
Hispanic	0.56	0	0.50	0	1
White	0.25	0	0.44	0	1
Free lunch	0.47	0	0.50	0	1
Reduced lunch	0.07	0	0.25	0	1
Other economic disadvantage	0.13	0	0.34	0	1
Age	8.09	8	0.28	8	9
Unemployment rate	6.54	6.70	2.00	1.90	15.30
Poverty rate	17.91	17.00	7.07	6.00	39.90
Median household income	48,757	47,159	12,354	23,096	83,968
Population	1,591,577	779,213	1,513,040	272	4,179,796
Maximum temperature	26.43	26.27	1.62	21.35	30.99
Precipitation	2.75	2.62	1.08	0.29	5.67

Notes: This table reports the summary statistics of the IV sample. The number of observations of this sample is 1,318,783. Education and individual characteristics data is from 2014 to 2019 Texas education data for individuals born between 2006 and 2011. Reading and math scores are the scaled standardized test scores in the third grade. Female, Native American, Asian, Black, Hispanic, White, Free Lunch, Reduced lunch, Other economic disadvantage are indicators of whether a student fits in each category. Lead concentration data are from the EPA's National Contaminants Occurrence Database. Lead action level exceedance shows if the county's water systems in a given year triggers federal regulatory actions, and is from the Safe Drinking Water Information System database. Lead concentration is the average concentration by county-year. Chloride concentration and chloride-sulfate mass ratio are average values estimated using data from the Water Quality Portal and the Texas Surface Water Quality Monitoring Information System. Presence of lead pipes is from Clay et al. (2014). Unemployment and population data is from Local Area Unemployment Statistics. Income and poverty estimates are from Small Area Income and Poverty Estimates. Maximum temperature and precipitation are from Schlenker & Roberts (2009).

Table 3: Summary statistics of the DID sample

	mean	median	sd	min	max
High school graduate	0.78	1	0.41	0	1
Enroll in public university	0.26	0	0.44	0	1
Lead violation status	0.20	0	0.40	0	1
Female	0.50	0	0.50	0	1
Native American	0.01	0	0.06	0	1
Asian	0.02	0	0.15	0	1
Black	0.15	0	0.35	0	1
Hispanic	0.48	0	0.50	0	1
White	0.35	0	0.50	0	1
Free lunch	0.39	0	0.50	0	1
Reduced lunch	0.08	0	0.27	0	1
Other economic disadvantage	0.07	0	0.25	0	1
Unemployment rate	7.33	6.30	4.23	0.90	39.30
Poverty rate	19.51	17.75	8.27	3.50	52.55
Population	1,011,788	1,109,330	424,312	331	3,471,291
Median household income	31,427	32,072	8,109	11,270	77,303
Maximum temperature	25.59	25.46	1.64	19.75	31.67
Precipitation	3.00	2.98	2.55	3.98	19.22

Notes: This table reports the summary statistics of the DID sample. The number of observations of this sample is 1,341,729. Education and individual characteristics data is from 2009 to 2019 Texas education data for individuals born between 1991 and 2001. High school graduate is an indicator if an individual student graduated from Texas public high schools. Enroll in public university is an indicator of an individual enrolled in public universities in Texas. Lead violation status data is from EPA's Safe Drinking Water Information System data set. It is an indicator of if the water system serving a student's county of birth has a new lead violation in the student's year of birth. Female, Native American, Asian, Black, Hispanic, White, Free Lunch, Reduced lunch, Other economic disadvantage are indicators of whether a student fits in each category. Unemployment and population data is from Local Area Unemployment Statistics. Income and poverty estimates are from Small Area Income and Poverty Estimates. Maximum temperature and precipitation are from Schlenker & Roberts (2009).

Table 4: OLS estimates of the impacts of lead concentration on third-grade standardized tests

	(1)	(2)	(3)	(4)	(5)
	A: third-grade reading				
log(lead)	-2.335***	-2.296***	-2.191***	-2.029***	-1.299**
	(0.624)	(0.609)	(0.696)	(0.684)	(0.506)
R2	0.021	0.086	0.086	0.086	0.086
	B: third-grade math				
log(lead)	-1.200	-1.235*	-0.882	-0.863	0.898
	(0.758)	(0.706)	(0.817)	(0.774)	(0.976)
R2	0.028	0.088	0.088	0.088	0.089
	C: Met reading standard				
log(lead)	-0.006***	-0.006***	-0.006***	-0.006***	-0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R2	0.018	0.093	0.093	0.093	0.093
	D: Met math standard				
log(lead)	-0.003	-0.003*	-0.002	-0.002	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R2	0.021	0.084	0.084	0.084	0.084
Observations	1,323,142	1,323,142	1,323,142	1,323,142	1,323,142
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the effects lead concentration on 3rd grade standardized test results using OLS regressions. Panels A and D report results on reading, and panels B and D report the results on math. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level controls. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 also includes weather control variables. Column 5 uses birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: First stage results of the instruments

	(1)	(2)	(3)	(4)	(5)
	A: Lead concentration				
Mean chloride * presence of lead pipes in 1900	0.0017***	0.0017***	0.0016***	0.0015***	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Observations	361,103	361,104	361,105	361,106	361,106
R2	0.74	0.74	0.87	0.94	0.95
F statistics	3748.53	3860.22	1761.13	529.17	30.86
SW Chi-sq test (p-value)	0.00	0.00	0.00	0.00	0.00
Hansens J statistic	0.00	0.00	0.00	0.00	0.00
	B: Lead action level exceedance				
Mean chloride	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,318,783	1,318,783	1,318,783	1,318,783	1,318,783
R2	0.35	0.35	0.41	0.42	0.41
F statistics	6.12	6.12	5.97	5.67	6.79
SW Chi-sq test (p-value)	0.01	0.01	0.01	0.02	0.01
Hansens J statistic	0.00	0.00	0.00	0.00	0.00
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the first-stage regressions of two instruments: the interaction of chloride and historical lead pipes, and surface water chloride concentration. Panel A regresses the interaction of surface water chloride and lead pipes on lead concentration, while panel B shows the relationship between surface chloride concentration and federal regulatory action level exceedance. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level controls. Column 3 includes neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 includes weather control variables. Column 5 also includes county-by-year trends. Standard errors in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: IV estimates of lead impact on third-grade test scores using interaction of chloride and lead pipes as instrument

	(1)	(2)	(3)	(4)	(5)
			A: Reading scores		
Lead	-0.910***	-2.192***	-2.304***	-1.453	-3.911**
	(0.061)	(0.039)	(0.121)	(0.886)	(1.956)
			B: Math scores		
Lead	-2.416***	-3.537***	-4.093***	-5.637***	-5.198**
	(0.095)	(0.040)	(0.063)	(0.520)	(2.345)
			C: Meet reading standard		
Lead	-0.001***	-0.005***	-0.006***	-0.008***	-0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)
			D: Meet math standard		
Lead	-0.007***	-0.010***	-0.011***	-0.017***	-0.007
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
Observations	361,106	361,106	361,106	361,106	361,106
First stage F statistics	3,748.53	3,860.22	1,761.13	529.17	30.86
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the effects of average lead concentration on third-grade reading and math test results using the interaction of surface water chloride and the historical presence of lead pipes as an instrument. Panels A and D report results on reading, and panels B and D report the results on math. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level controls. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 also includes weather control variables. Column 5 uses birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Long-run impact on high school graduation rate and public university enrollment

	(1)	(2)	(3)	(4)	(5)
	A: High school graduation rate				
Lead violation	-0.860***	-0.860***	-0.570***	-0.570***	-0.530***
	(0.320)	(0.290)	(0.260)	(0.260)	(0.300)
Observations	1,341,729	1,341,729	1,341,729	1,341,729	1,341,729
R2	0.024	0.052	0.052	0.052	0.053
	B: Public university enrollment				
Lead violation	-0.240	-0.190	0.240	0.270	0.350*
	(-0.280)	(-0.270)	(-0.220)	(-0.230)	(-0.190)
Observations	1,341,757	1,341,757	1,341,757	1,341,757	1,341,757
R2	0.023	0.088	0.088	0.088	0.088
	C: High school graduation rate with all violation years				
Lead violation	-0.760***	-0.670***	-0.250	-0.260	-0.400
	(0.260)	(0.250)	(0.190)	(0.190)	(0.270)
Observations	1,341,757	1,341,757	1,341,757	1,341,757	1,341,757
R2	0.024	0.052	0.052	0.052	0.053
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: Panel A reports the effects of lead violation exposure in one's birth year on high school graduation rate, and Panel B reports the effects of violation exposure in one's birth year on Texas public university enrollment rate. Panel C reports the effects of violation exposure in one's birth year on high school graduation rate using all violation years. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level controls. Column 3 includes neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 includes weather control variables. Column 5 includes birth-county-by-birth-year trends. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: IV estimates of lead impact on third-grade test scores using chloride level as instrument

	(1)	(2)	(3)	(4)	(5)
			A: Reading scores		
Lead action level exceedance	-17.990***	-19.830***	-18.990***	-18.300***	-14.880**
	(3.257)	(5.126)	(5.583)	(5.170)	(6.856)
			B: Math scores		
Lead action level exceedance	-4.116	-5.480	-4.044	-1.525	5.065
	(3.725)	(5.035)	(5.391)	(6.804)	(6.513)
			C: Meet reading standard		
Lead action level exceedance	-0.647***	-0.070***	-0.068***	-0.068***	-0.065*
	(0.009)	(0.013)	(0.014)	(0.013)	(0.036)
			D: Meet math standard		
Lead action level exceedance	-0.008	-0.012	-0.006	0.005	0.058
	(0.014)	(0.015)	(0.017)	(0.018)	(0.046)
Observations	1,318,783	1,318,783	1,318,783	1,318,783	1,318,783
First stage F statistics	6.12	6.12	5.97	5.67	6.79
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the effects of lead exposure in one's birth year on third-grade standardized test scores using chloride as an instrument. Panel A reports the effects of lead concentrations exceeding the federal regulatory level on third-grade reading scores, and panel B presents the impact on scaled math scores. Panels C and D also present effects of exceeding lead regulatory levels on meeting reading and math standards. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level controls. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 includes weather control variables. Column 5 also includes birth-county-by-birth-year trends. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Robustness checks with housing age

	Lead	Reading		Math	
	(1)	(2) Scores	(3) Meeting standards	(4) Scores	(5) Meeting standards
Chloride * lead pipe	0.002***				
	(0.000)				
Lead		-2.647*	-0.009***	-8.844***	-0.027***
		(1.365)	(0.001)	(0.939)	(0.002)
Observations	361,106	361,106	361,106	361,106	361,106
First stage F statistics	134.64	134.64	134.64	134.64	134.64
SW Chi-sq (p-value)	0.00				
Hansens J statistics	0.00				

Notes: This table reports regression coefficients using the interaction of surface water chloride and the historical presence of lead pipes as an instrument controlling for the median housing price by county. Columns 2 and 3 report the effects of lead concentrations on third-grade reading and math scores. Columns 4 and 5 present effects on meeting reading and math standards. I also include birth-year fixed effects, birth-county fixed effects, individual characteristics, neighborhood characteristics, and weather as described before. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Robustness checks controlling for water system size

	(1)	(2)	(3)	(4)
	Population served		Number of small and very small systems	
Lead violations	-0.006**	-0.005*	-0.006**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	1,340,066	1,340,066	1,340,066	1,340,066
R2	0.052	0.053	0.052	0.053
Birth-year fixed effects	Yes	Yes	Yes	Yes
Birth-county fixed effects	Yes	Yes	Yes	Yes
County-by-year trends	No	Yes	No	Yes
Individual controls	Yes	Yes	Yes	Yes
Neighborhood controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes

Notes: This table reports regression coefficients using DID model controlling for population size served by each public utility as robustness checks. Column 1 reports first stage results. Columns 2 and 3 control for the population served by public water systems, and columns 3 and 4 control for the number of small and very small systems. Columns 1 and 3 are results with birth-year fixed effects, birth-county fixed effects, individual characteristics, neighborhood controls, and weather in specification (1). Columns 2 and 4 add birth-county-by-birth-year trends. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: First stage of IV using the choloride-sulfate mass ratio and lead pipes as instruments

	(1)	(2)	(3)	(4)	(5)
A	Lead concentration				
chloride-sulfate ratio * presence of lead pipes in 1900	0.564***	0.565***	0.765**	0.657***	0.586***
	(0.006)	(0.006)	(0.140)	(0.110)	(0.030)
Observations	361,106	361,106	361,106	361,106	361,106
R2	0.574	0.575	0.775	0.872	0.895
F statistics	10,289.35	10,119.34	31.24	38.06	121.97
SW Chi-sq test (p-value)	0.00	0.00	0.00	0.00	0.00
Hansens J statistic	0.00	0.00	0.00	0.00	0.00
B	Lead action level exceedance				
chloride-sulfate mass ratio	0.062	0.062	0.061*	0.058	0.062*
	(0.040)	(0.040)	(0.037)	(0.035)	(0.037)
Observations	1,318,783	1,318,783	1,318,783	1,318,783	1,318,783
R2	0.281	0.281	0.354	0.369	0.361
F statistics	2.34	2.34	2.77	2.79	3.08
SW Chi-sq test (p-value)	0.13	0.13	0.10	0.09	0.08
Hansens J statistic	0.00	0.00	0.00	0.00	0.00
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports first stage results using the interaction of chloride-sulfate mass ratio and lead pipes and the ratio alone as instruments. Panel A shows first stage results between my instrument and lead concentration, while panel B shows the relationship between the ratio and indicator of exceeding lead regulatory level. Column 1 reports the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level characteristics. Column 3 add neighborhood characteristics including poverty rate, unemployment rate, and median household income. Column 4 adds weather control variables. Column 5 includes birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: IV estimates results using chloride-sulfate mass ratio and lead pipes as instrument

	(1)	(2)	(3)	(4)	(5)
	A: Reading scores				
Mean lead	-2.396***	-4.081***	-4.070***	-3.902***	-7.387***
	(0.144)	(0.220)	(0.932)	(1.124)	(2.307)
	B: Math scores				
Mean lead	-2.943***	-4.402***	-5.049***	-7.623***	-8.184***
	(0.292)	(0.222)	(0.623)	(0.743)	(2.241)
	C: Meet reading standard				
Mean lead	-0.004*	-0.009*	-0.011**	-0.013**	0
	(0.001)	(0.000)	(0.002)	(0.003)	(.)
	D: Meet math standard				
Mean lead	-0.007***	-0.011***	-0.013***	-0.023***	0
	(0.001)	(0.001)	(0.002)	(0.003)	(.)
Observations	361,106	361,106	361,106	361,106	361,106
First stage F statistics	10289.35	10119.34	31.24	38.06	121.97
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the effects of average lead concentration on third-grade reading and math test results using the interaction of the chloride-sulfate mass ratio and the historical presence of lead pipes as an instrument. Panels A and B report results on standardized test scores, and panels C and D present effects on meeting standards. Panels A and C report results on reading, while panels B and D report the results on math. Column 1 show the coefficient estimates using birth-county and birth-year fixed effects. Column 2 includes individual-level characteristics. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 also includes weather variables. Column 5 has birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

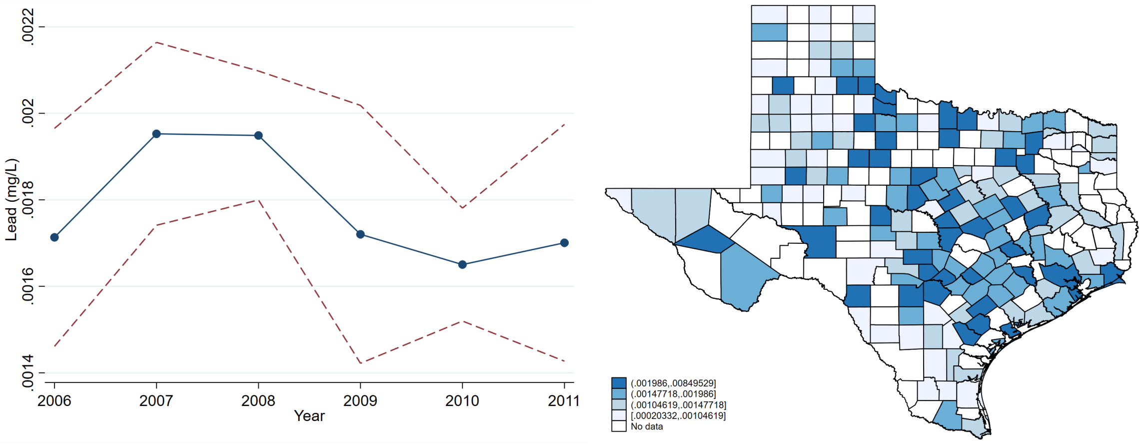
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: IV estimates results using chloride-sulfate mass ratio as instrument

	(1)	(2)	(3)	(4)	(5)
	A: Reading scores				
Lead action level exceedance	-14.520*	-18.250*	-22.690*	-25.550**	-16.500
	(8.529)	(9.583)	(10.250)	(11.080)	(14.030)
	B: Math scores				
Lead action level exceedance	-5.431	-9.267	-10.530	-5.265	20.340
	(10.870)	(12.120)	(13.080)	(12.760)	(18.330)
	C: Meet reading standard				
Lead action level exceedance	-0.056**	-0.068**	-0.070**	-0.083***	-0.065*
	(0.027)	(0.030)	(0.031)	(0.031)	(0.036)
	D: Meet math standard				
Lead action level exceedance	-0.028	-0.040	-0.046	-0.021	0.058
	(0.027)	(0.032)	(0.035)	(0.031)	(0.046)
Observations	1,318,783	1,318,783	1,318,783	1,318,783	1,318,783
First stage F statistics	2.34	2.34	2.77	2.79	3.08
Birth-county fixed effects	Yes	Yes	Yes	Yes	Yes
Birth-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-by-year trends	No	No	No	No	Yes
Individual controls	No	Yes	Yes	Yes	Yes
Neighborhood controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes

Notes: This table reports the effects of average lead concentration using the chloride-sulfate mass ratio as an instrument. Panels A and B report results on standardized test scores, and panels C and D report results on meeting the standards. Column 1 shows the coefficient estimates using only birth-county and birth-year fixed effects. Column 2 includes individual-level characteristics as controls. Column 3 adds neighborhood controls including poverty rate, unemployment rate, and median household income. Column 4 also includes weather control variables. Column 5 has birth-county-by-birth-year trends as a robustness check. Standard errors are in parentheses and clustered at the county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

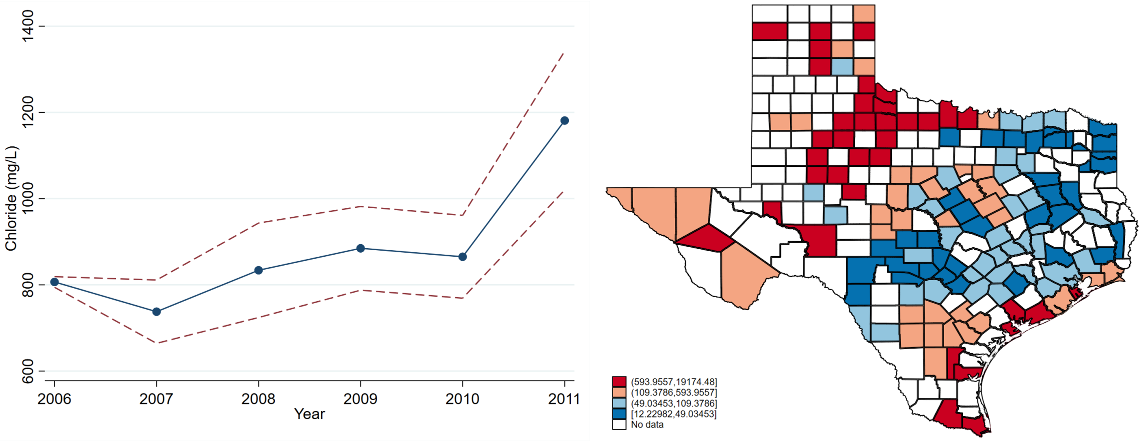


(a) By year

(b) By county

Figure 1: Lead concentration by year and county 2006-2011

Notes: Panel (a) shows year fixed effects plus a constant from regressions that control for county fixed effects following Keiser & Shapiro (2019*a*). Blue connected dots show yearly values and red dashed lines show the 95% confidence interval for year fixed effect estimates, with 2006 as the reference year. Standard errors are clustered by county. Panel (b) shows the county average lead concentration over the full period, 2006-2011.

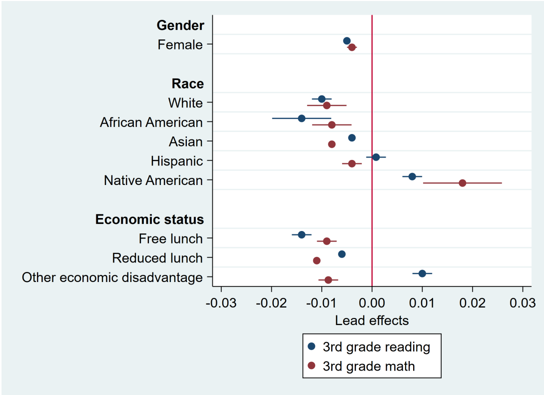


(a) By year

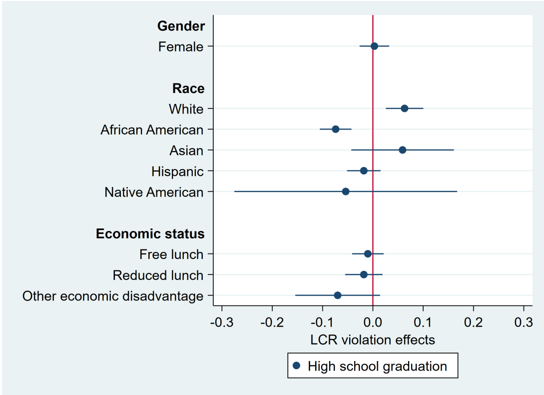
(b) By county

Figure 2: Chloride concentration by year and county 2006-2011

Notes: Panel (a) shows year fixed effects plus a constant from regressions that control for county fixed effects following Keiser & Shapiro (2019*a*). Blue connected dots show yearly values and red dashed lines show the 95% confidence interval for year fixed effect estimates, with 2006 as the reference year. Standard errors are clustered by county. Panel (b) shows the county average chloride concentration over the full period, 2006-2011.



(a) IV



(b) DID

Figure 3: Heterogeneity impact of drinking water lead exposure

Notes: This figure reports regression coefficients on the interaction term of treatment variable and an indicator of race, gender and economic background groups from 30 separate regressions. The regressions are estimated using the individual-level data of the two samples. The dependent variables are third-grade reading scores, math scores and high school graduation rate. Figure 3a uses the IV sample and 3b uses the DID sample. Figure 3a reports estimates from reduced-form models that include additional interaction terms between the preferred instrument and a group-specific dummy variable. I also the group-specific dummy variable and the instrument variables separately in the regression models. Figure 3b reports estimates from the DID model with the additional interaction term of the lead violation exposure in one's birth year and the group dummy, a group-specific dummy and violation status in one's birth year. I also include birth-year fixed effects, birth-county fixed effects, individual characteristics, neighborhood controls and weather.