Throwing the Baby out With the Ashwater? Coal Combustion Residuals, Water Quality, and Fetal Health

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Abstract

Coal ash accounts for one third of industrial water pollution in the United States. I assess the relationship between coal ash surface water discharges and three relevant outcomes: surface water quality, municipal system water quality, and fetal health indicators from a birth certificate database in North Carolina. Identification relies on geographic variation in downstream status of monitoring sites and municipal water intake locations, plant closures or conversions, and the relative quantity of coal ash released over time. I find that coal ash releases are associated with higher conductivity and pH in both downstream surface waters and municipal water supplies sourced from these waters. Water systems affected by coal ash tend to have more Safe Drinking Water Act violations for disinfectant byproducts, inorganic chemicals, and health-based violations. I quantify the costs of coal ash water pollution with respect to fetal health and home sales. Exploiting variation arising from mothers' moves, I find that a newborn potentially exposed to coal ash water pollution is 1.7 percentage points more likely to be low birthweight compared to an unexposed sibling. I conclude by estimating how a legislative act mandating drinking well testing affected home sale prices in regions around coal ash plants. After the act, sale prices of homes within 1 mile of coal ash ponds declined by 12-14%, or over $37,000.

Keywords: Pollution; Coal ash; Water Quality; Fetal Health
JEL: *Q25, Q49, Q51, Q53, I14, I18, R21*

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†Stable link to most recent draft.

1 Introduction

Coal combustion residuals (CCRs) are the waste material from burning coal. Also known as coal ash, 110 million tons of CCRs are produced each year in the United States, of which 2.7 million tons are released into surface waters.[1] The remainder is primarily stored in wet landfills, while roughly one quarter is recycled.[2] Although surface-water discharges of coal ash effluent represent a small fraction of all coal ash produced, they account for one third of all industrial water pollution by toxicity and one half by mass.[3] No previous study has estimated how coal ash surface water discharges affect municipal water quality and human health.

Coal ash threatens water supplies because of the relative toxicity of constituent compounds, the quantity produced, and the quality of many confinement landfills. Heavy metals including arsenic, selenium, cadmium, chromium, lead, and mercury compose at least one third of coal ash.[4] Coal ash contains over four times as many heavy metals by mass as parent coal due to combustion of organic compounds.[5] Of the 63 steam-generating coal power plants incorporated in this paper, the average plant has seven containment landfills totaling 176 acres at an average depth of 50 feet.[6] Over 130 of these ponds were built before 1980, and at least 141 have no impermeable lining to protect groundwater.[7] Confinement and disposal practices increase the risk of surface-water and groundwater contamination. In a recent report, the EPA documented 149 damage litigation cases of coal ash impoundments affecting groundwater and 152 of coal ash affecting surface water.[8] Although municipal water providers filter most of the harmful compounds in coal ash, disinfectants used to treat the water interact with remaining CCRs to create harmful compounds known as disinfectant by-products (DBPs). The formation of DBPs decreases the effectiveness of disinfectants.[9] Moreover, changes to the properties of water such as pH, temperature, and conductivity can affect corrosivity of pipes, leading to increased lead and copper levels in drinking water. While water quality in the developing world is known to affect human health, few studies have investigated how municipal water quality in a developed country may affect health.[10]

The purpose of this paper is to determine how CCR water pollution affects municipal water quality, human health, and home values. First, I replicate and generalize previous findings that CCRs affect surface

[1] Gollakota et al. (2019); MacBride (2013). Globally, 750 million tons were produced in 2015, up from 500 million tons in 2005.

[2] See Gollakota et al. (2019); Yao et al. (2015) for reviews of alternative uses of coal combustion residuals.

[3] Bernhardt et al. (2016); Boyce and Ash (2016).

[4] EPA (2015a); Ibrahim (2015); Izquierdo and Querol (2012); Munawer (2018); Shy (1979).

[5] Yao et al. (2015).

[6] Ash (2019) For comparison, Disney Land is 85 acres.

[7] Many inactive ponds lack information on construction date or lining status. See Table 1 for more summary statistics on coal ash containment facilities.

[8] EPA (2015a).

[9] Davison et al. (2005); EPA (2001); Wang et al. (2012).

[10] Among many others, Brainerd and Menon (2014); Currie et al. (2017); Cutler and Miller (2005); He and Perloff (2016); Jalan and Ravallion (2003); Troesken (2008) explore the relationship between water quality and human health in developing countries. Currie et al. (2013) and Marcus (2019) use samples in New Jersey and North Carolina.

water quality using a larger geographic region and longer time horizon. Next, I estimate the impact of this surface water pollution on measures of municipal water quality and the likelihood of a Safe Drinking Water Act Violation. Then, I assess whether this point-source pollutant may affect human health. Finally, I quantify residential willingness-to-pay to avoid coal ash water pollution. To answer these questions, I obtain six types of information: annual coal ash surface water releases across 63 power plants, surface water monitoring tests over six states, municipal water quality monitoring tests over five states, municipal water quality violations over six states, birth certificates for 1.5 million children born in North Carolina, and home sale records for twelve counties in North Carolina. At a minimum, the sample covers 2005 to 2017. Identification of water quality changes associated with coal ash pollution relies on three forms of variation. The first form of variation is "downstream" status of monitoring sites or municipal water intakes within watershed regions. The second is temporal variation in the operating status of upstream coal ash facilities, which arises from plant closures and changes to confinement practices. The third is the relative quantity of coal ash released upstream from a water quality monitor or intake site, which occurs naturally over time and also due to plant closures and conversions. To test for health effects from water quality changes, I follow the literature in comparing fetal health indicators of siblings exposed to differential water quality.[11] I conclude by estimating household willingness-to-pay to avoid coal water pollution using repeat sales of homes near ash facilities in North Carolina. In this estimation procedure, I exploit a legislative change leading to the discovery of unsafe drinking water in many home wells surrounding coal ash plants. This study is the first to directly assess the impact of coal ash water pollution on drinking water supplies over a large geographic region and time horizon. I also add to a limited literature on the effect of water quality fetal health outcomes in a developed-country context. Estimation of the willingness-to-pay to avoid contaminated drinking wells has broad relevance to both the housing value effects of environmental crises and risk perception among households near potential disaster sites.[12]

I find that contemporaneous coal ash releases increase the concentration of heavy metals in downstream surface waters; these include arsenic, lead, and selenium. Surface water quality monitors downstream from coal ash release sites also have altered properties. They tend to have higher conductivity, lower dissolved oxygen, higher pH, and higher temperature. Municipal water systems sourcing from waters potentially affected are also more likely to have higher conductivity, an indicator of elevated suspended and dissolved compounds. These water systems experience more water quality violations for disinfectant byproducts, inorganic compounds, arsenic, and maximum contaminant level violations. I find evidence that maximum contaminant level, reporting, inorganic compound, arsenic, and health-based violations are driven by contemporaneous

[11] Currie et al. (2013).

[12] Christensen et al. (2019); Coulomb and Zylberberg (2016).

releases of coal ash pollution. Children born in residences served by municipal water systems downstream from active coal ash sites, in comparison to unexposed siblings, are 1.7 percentage points more likely to be low birthweight. On average, these newborns weight 1.2 ounces less than unexposed siblings, and they're 1.2 percentage points more likely to be preterm. Newborns of mothers with less education are more affected by coal ash pollution than average exposed children. I also find that these effects are driven both by adverse outcomes of mothers moving into coal-ash municipal water service zones and by improvements for mothers moving out of coal-ash municipal water service zones. Finally, residences within 1 mile of a coal ash pond, after discovery of well water considered unsafe to drink by the EPA, sold for \$37,000 - \$45,000 less than previously. Results provide strong evidence that coal ash water pollution negatively affects surface water quality and complicates the municipal water treatment process. These changes to municipal water quality likely affect human health, and the analysis of repeated home sales reveals that households care greatly about potential exposure to this form of pollution.

2 Motivation, Prior Work, and Contribution

An extensive literature documents the negative health consequences of exposure to coal through kitchen handling, home heating, mine drainage, mining dust, shipping and stockpile dust, and smokestack emissions.[13] These health consequences are large both in magnitude and relative to the cost of the coal.[14] Only one study investigates the health effects of coal-ash water contamination. The study found that coal-polluted well water is associated with skin cancers, toxicities to internal organs, neuropathy, nephrotoxicity, cirrhosis, ascites, and liver cancer.[15] However, the study relates to household disposal of cooking coal ash near shallow drinking wells rather than industrial coal ash containment practices, and it is also set in a developing country. In a recent literature review on the health effects of coal combustion residuals from steam power plants, the author found no study quantifying the extent of drinking water quality concerns and recommended future studies on the range of individual exposures to coal ash contaminants from water.[16]

CCRs primarily affect surface and ground waters in three ways. First, ash ponds are occasionally or continually drained into nearby bodies of water. CCRs also seep through the sides of containment facilities. Because coal plants and ash ponds are constructed next to large bodies of water, seepage is non-trivial.[17] Third, pressure from the weight of additional CCRs and water cause a leachate of dissolved compounds

[13] Barreca et al. (2014); Clay et al. (2015, 2016); Kravchenko and Lyerly (2018); Liu et al. (2002); Pershagen et al. (1986).

[14] Jha and Muller (2017) found that the external costs from coal stockpile dust were four times the per-ton cost of the coal itself.

[15] Yu et al. (2007).

[16] Kravchenko and Lyerly (2018).

[17] Coutant et al. (1978) compare intentional water discharges with seepage water, finding that the latter contained 44 times the amount of dissolved iron and had a pH of 2.9; both sources of water killed all experimental fish subjects within 72 hours, with the seepage water killing all fish within the first 24. Unexposed control fish populations experienced no mortality.

to flow into groundwater if a containment pond is unlined or poorly lined, affecting public and private wells and eventually also surface waters.[18] A broad literature demonstrates the chemical profile of coal ash water pollution, the conditions under which coal ash is mobilized, and the characteristics of affected surface waters.[19] In general, these studies cover relatively small geographic regions and provide a snapshot temporal view of local water quality.[20]

CCR source-water contamination may affect drinking water quality through the formation of disinfectant by-products, corrosion of pipes, and residual contaminants after water treatment. Coal ash effluent increases the quantity of total dissolved solids in drinking water supplies, which is associated with increased formation of trihalomethanes, a group of disinfectant by-products, during water treatment.[21] Bromide, a relatively harmless constituent of coal ash, interacts with chlorine to form another group of disinfectant by-products, haloacetic acids.[22] Corrosivity is the rate of pipe oxidation; high corrosivity indicates the potential for leaching of pipe materials such as lead and copper into drinking water. PH, conductivity, total dissolved solids, alkalinity, temperature, dissolved oxygen, and total hardness influence the corrosivity of water. Corrosivity is a major health concern for untreated groundwater sources.[23] However, fluctuations in surface water quality leading to corrosivity changes may also pose a public health concern.[24] For example, chloride in coal ash, increasingly present in US surface waters, affects corrosivity and hence lead levels in drinking water.[25] Properties of water related to coal ash, such as pH, also affect corrosivity and may impact human health. Clay et al. (2010) take advantage of variation in pipe materials and water pH across regions of the US from 1900-1920, finding that a slight normalizing of pH in locations with lead pipes would decrease fetal mortality by 7-33%. Troesken (2008) finds a similarly strong relationship between pH, lead pipes, and fetal health. Finally, variations in pollution releases, weather events, and accidents may impact the efficacy of treatment systems designed for different source-water quality.[26]

Animal-based studies demonstrate that coal ash water pollution harms the reproductive health of many organisms.[27] The potential influence of coal ash water pollution on pipe corrosion may also signal a public health concern because lead impairs child and fetal development.[28] Further, disinfectant byproducts may affect fetal health even if the same compounds in similar doses are low-risk to adults.[29] Prior work causally

[18] Of 14 North Carolina large coal ash confinement facilities, two thirds leach pollution into groundwater.

[19] Baba and Kaya (2004); EPA (2015a); Kopsick and Angino (1981); L. Carlson and C. Adriano (2009).

[20] An exception is EPA (2015a), which creates a model to estimate the effect of coal ash effluent discharges on nearby surface waters, taking characteristics of the pond and nearby body of water into consideration. The study examines five sites across the country, and uses the analysis to make effluent limitation policy suggestions.

[21] Handke (2009).

[22] Cowman and Singer (1996); Heller-Grossman et al. (1993); Liang and C Singer (2003).

[23] One third of drinking water wells in the United States have potentially corrosive water (Belitz et al., 2016).

[24] Neffand et al. (1987); Singley et al. (1984).

[25] Stets et al. (2012); Zhu et al. (2008).

[26] Davison et al. (2005).

[27] Gillespie and Baumann (1986); Heinz and Hoffman (1998); Hopkins et al. (2002).

[28] Clay et al. (2010, 2018, 2019); Gazze (2015); Miranda et al. (2007).

[29] Studies suggest that DBPs increase risk of bladder cancer when ingested at levels currently observed in industrialized

associates differential water quality with an increased risk of low-birthweight newborns, providing a basis for investigating whether residual coal ash pollutants, materials from pipe corrosion, or disinfectant byproducts may impact fetal health.[30] I use fetal health indicators for this analysis because of the greater vulnerability of newborns to pollution. Low-birthweight newborns are also costly to society. They are more prone to chronic and degenerative conditions like diabetes and heart disease; they also have lower test scores, educational attainment, and income.[31] The short time window of gestation also increases the likelihood of noticing health impacts that would take longer to manifest in adults and likely coexist with many pollutant exposures.

This study contributes to several literatures. I generalize previous findings on the effects of coal disposal practices on surface water quality to a region of six states, thirteen years of monitoring tests, and a wide array of compounds. I also contribute to a limited literature on the role that point-source pollution plays on municipal water quality, providing a relatively novel outcome in the form of regular state monitoring tests. In so doing, I provide the first evidence on the contemporaneous relationship between coal ash water pollution and municipal water quality. Adding to other studies on the fetal health consequences of local pollution, I estimate the relationship between coal ash sites and indicators of fetal health, incorporating both air and water quality information.[32] This study adds to our understanding of the life-cycle costs of coal, as many papers disregard water quality costs except those related to mining.[33] Similarly, the study provides an additional context through which to view the benefits of surface-water pollution abatement, recently found to be less than one fourth the costs of cleanup grants in Keiser and Shapiro (2018). Indeed, the EPA's own analyses rarely find that water quality regulations pass a cost-benefit test, with a median benefit-cost ratio of 0.37 across all regulations over the past several decades according to a recent study.[34] Because these previous cost-benefit analyses do not include health benefits via the municipal drinking water mechanism, this study sheds light on how a potentially missing benefit may affect the results of decades of federal cost-benefit analysis on surface water quality regulations.

3 Data

This study incorporates information on coal ash disposal practices, surface water quality, municipal water quality, natality outcomes, air pollution, and home sales. In the following sections, I summarize average differences across potentially affected and likely unaffected surface waters, municipal water systems, newborns, and homes. For detailed description of how I geographically assign treatment indicators, see Appendix

countries (Cantor et al., 2010; Villanueva et al., 2004).

[30] Currie et al. (2013).

[31] Almond and Currie (2011); Osmond and Barker (1991).

[32] Currie and Walker (2011); Currie et al. (2017); Jha and Muller (2017); Persico et al. (2016).

[33] Amigues et al. (2011); Muller et al. (2011).

[34] Keiser et al. (2019).

subsection 7.1, Appendix subsection 7.2, and Appendix subsection 7.3.

3.1 The Quantity and Location of Coal Ash Disposal

The Toxic Releases Inventory (TRI) provides facility-by-year-by-pollutant information on the quantity of over 650 regulated substances released into the environment. Many of the compounds present in coal ash are regulated substances. All facilities releasing at least one of these compounds and employing at minimum ten employees must report their pollution release information annually, ensuring that industrial steam-generating coal power plants are included in the TRI.[35] The pollutant compounds are split up by type of release, allowing separation of the quantity that is released into surface waters from the quantity that is impounded. I combine TRI reports with information on the age, depth, and lining status of each plant's confinement ponds or landfills assembled by the non-profit Southeast Coal Ash. I limit my sample of coal plant release sites to those with non-negative water pollution from 2005 to 2017 across six southern states. These states are Alabama, Georgia, North Carolina, South Carolina, Tennessee, and Virginia. Power plants not combusting coal were excluded from the sample. The remaining sample includes 63 steam electricity generating coal power plants. These sites are mapped in Figure 1. Table 1 displays annual facility-level information on coal ash loadings from 2005-2017, including toxicity weights for many of the constituent compounds of coal ash.[36] Additionally, Figure 4 shows the annual average distribution of toxic releases of coal facilities. The same figure plots these average releases over time. The average coal power plant releases approximately 10 tons of coal ash compounds into surface waters each year, and this level has remained roughly constant over the sample excluding a disastrous 2008 spill at the Kingston Fossil Plant in Tennessee. However, this average masks significant heterogeneity in the quantity of surface water pollution across plants. Meanwhile, the quantity of coal ash impounded in confinement landfills has decreased over the past decade from around 400 tons per plant per year to a little over 250 tons. Figure 5 provides a breakdown of coal ash surface water loadings by type of chemical. Of the tons that are released into surface waters, the bulk of the pollution is composed of relatively harmless compounds such as barium, copper, manganese, and nickel. However, it is not uncommon for plants to release multiple tons of more harmful compounds such as arsenic, chromium, lead, and vanadium into nearby surface waters in any given year.

[35] Self-reporting allows the possibility of under-reporting and measurement error. To the extent that firms under-report true pollution releases, regression estimates would be biased to zero. To limit the influence of mis-measured or poorly-estimated release figures by pollutant, I employ models with a binary indicator for whether surface-water pollution releases occurred and others with a variable for the total coal ash surface-water releases across all compounds.

[36] The EPA's Risk-Screening Environmental Indicators (RSEI) toxicity weights allow comparison of the toxicity of different compounds compiled in the TRI. See https://www.epa.gov/rsei/rsei-toxicity-weights for more information.

3.2 Surface Water Quality Monitoring Information

I retrieve surface water quality information from the Water Quality Portal (WQP), the largest standardized water quality dataset currently in existence.[37] Developed by researchers from the U.S. Geological Survey, the Environmental Protection Agency, and the National Water Quality Monitoring Council, the WQP combines the USGS National Water Inventory System, USGS BioData, USDA Stewards, and EPA Storets databases. The WQP features 2.4 monitoring sites and roughly 300 million analyte results over many decades and thousands of compounds. Decisions underlying the location of monitors and timing of tests are not observable.[38] I limit the sample to monitoring sites located in lakes, rivers, and streams. I also limit the analysis to eight core water quality analytes known to be associated with coal ash water pollution; these include arsenic, chromium, conductivity, dissolved oxygen, lead, pH, selenium, and temperature.[39] See Appendix Table 1 for a full list of compounds retrieved. All sample results that do not detect the tested compound are replaced with zeros, and I initialize an undetected flag for these observations. Measurements are converted to a standardized unit where possible (for example, milligrams/liter). Observations without convertible units of measurement are dropped.[40] After cleaning, the sample consists of 5.5 million measurements across 124,000 monitoring sites. Summary statistics are presented in Table 2. I also compare how these water quality indicators change over time for monitors that are within 25 miles downstream of coal ash release sites in Figure 6 and Figure 7. For ease of visualization, I drop extreme outliers above the 99th percentile before generating mean analyte levels over time. The figures nevertheless generally confirm the summary statistics presented in Table 2; coal-ash affected waters have higher conductivity, pH, and temperature across the entire sample window. Dissolved oxygen levels are also often lower in affected regions than in unaffected regions. Affected regions tend to have lower average levels of common pollutants including lead, arsenic, selenium, and chromium, although the trends are noisy and include a spike in all compounds from 2008-2011 that may relate to differential testing priorities over time.

3.3 Municipal Water Quality Violations, Infrastructure, and Monitoring

The Safe Drinking Water Inventory System (SDWIS) provides violation histories, water system summaries, water system details, and geographic area.[41] These reports show when a water quality violation occurred, the nature of the violation, and the remediation action taken. Reports on water system summary, detail,

[37] Read et al. (2017). I use the DataRetrieval package in R to download and import the data (De Cicco et al., 2018).

[38] USGS hydrologists designed intentionally representative samples of US waters for common analytes such as pH and conductivity, but local governmental agencies and other researchers contributing to the WQP may have selected locations based on un-observable factors (Keiser and Shapiro, 2018). To limit the influence of selection, only monitors with at least three tests for a given compound are incorporated in regression models.

[39] EPA (2015a); Ibrahim (2015); Izquierdo and Querol (2012); Munawer (2018).

[40] I except pH from this decision rule and instead drop any pH observations outside the standard scale from 0-16.

[41] These reports were obtained through the SDWIS advanced search (https://ofmpub.epa.gov/apex/sfdw/f?p=108:1:::NO:1::).

and geographic area describe the population served, the number of facilities and service connections, and the geographic service region.[42] Summary statistics for SDWIS violations are presented in Table 2. Water systems affected by coal ash tend to be much larger and somewhat older than unaffected systems. They also have more health-based Safe Drinking Water Act violations. Much of this difference is evidently driven by violations for exceeding the maximum contaminant level of a given pollutant or breaking rules for arsenic, disinfectant byproducts, and inorganic chemicals. In Figure 8, I plot the violation rate over time for affected water systems across six types of infraction. Affected water systems tend to have more maximum contaminant level and health-based violations over the entire sample window. In Figure 9, I show that these infractions are primarily for breaking rules for inorganic chemicals and disinfectant byproducts. Water systems affected by coal ash tend to have lower violation rates for nitrates and coliform than unaffected systems. In Figure 10, I break down all SDWA violations by type of infraction and state. Clearly, most of the maximum contaminant level violations relate to elevated levels of disinfectant byproducts. Violations for inorganic chemicals and volatile organic chemicals are primarily monitoring-based, which means that these systems are not testing for all required compounds. Finally, in Figure 11, I show how these violations have trended over time by type of infraction and state. Monitoring violations appear to be the most common infraction type, and North Carolina tends to have the most SDWA violations since 2000.

I supplement SDWIS with state-provided water quality monitoring tests in Alabama, Georgia, North Carolina, South Carolina, and Virginia from 2005-2017.[43] These monitoring tests are used to determine violations of the Safe Drinking Water Act. Monitoring tests are samples of a water quality analyte taken at one facility.[44] According to the Safe Drinking Water Act, these monitoring tests must be performed by a third party at a frequency determined by the chemical and the population served by the water system.[45] 166 analytes are regularly tested across the sample states. These analytes may be grouped into 14 pollution classes. For all samples that do not detect the given compound, I replace the observed value with zero and initialize a non-detected flag. I also generate indicators for the type of facility where a test occurred, allowing me to control for likely differences that may exist across tests at wells or intakes from those at treatment and distribution centers. Summary statistics for state-level monitoring tests are presented in Table 2. Because coal-ash affected water systems are less likely to use groundwater, they tend to have lower average levels of arsenic, conductivity, and lead. However, they generally have higher levels of disinfectant byproducts and

[42] Geographic service regions may be a town, a zipcode, or a county centroid if missing more precise information.

[43] State agencies include the Alabama Department of Environmental Management, the Georgia Environmental Protection Division, the North Carolina Department of Environmental Quality, the South Carolina Department of Health and Environmental Control, the Tennessee Department of Environment and Conservation, and the Virginia Department of Environmental Quality. With the exception of Tennessee, each agency provided all available testing records over the sample window.

[44] For example, one observation may show that the level of lead in the water at a given facility on a given date was 0.005 mg/L.

[45] Currie et al. (2013).

pH. I show how these water quality indicators trend over time in Figure 12. Across the entire sample window, affected water systems have higher levels of disinfectant byproducts. Conductivity and arsenic, which are much higher in groundwater than in likely-affected surface waters, tend to be lower in affected municipal water systems.

I combine SDWIS data with state monitoring tests for two reasons. First, violation history provides a snapshot of municipal water quality. Samples conducted over time allow detection of more subtle differences in water quality that do not result in a violation. Second, the violation rate is an endogenous manipulable outcome.[46] It is likely that water systems sourcing from coal-ash-affected waters take precautionary treatment measures or perform compliance activities after any violation.

3.4 Birth Certificates and Fetal Health

The North Carolina State Center for Health Statistics provided birth certificate information for the period 2005-2017. These data report indicators of fetal health such as gestation length, birthweight, estimated gestation length, and presence of a congenital anomaly. They also include maternity characteristics such as age, education level, race, marital status, and smoking behavior.[47] The birth certificates track information on mother risk factors during pregnancy and delivery, such as hypertension, previous pregnancy termination, and number of prenatal visits. I obtained confidential records reporting mother's name and address at time of birth. Mother's full name, race, and birthday are used to link siblings. Mother's address of residence allows linking birth records to specific water service regions.[48] Birth records with missing addresses or mother's names are excluded from the sample. Similarly, addresses not corresponding to a service zone are dropped from all regressions. A key difficulty in working with the natality statistics relates to the different birth certificate forms used over the sample period. Three types of reporting forms are used over the sample period; one covers 2005-2009, another covers the transition year 2010, and then a third is used for 2011-2017. Although all forms record certain information in the same format, such as birthweight and gestation length, other variables change across birth reporting forms. For example, race and education status report different categories across the two main reporting forms. Where possible, these measurements are adjusted to create temporally-consistent variables. Notably, congenital anomaly indicators cannot be properly conformed across the different forms due to certain conditions not being listed in the post-2010 form. This discrepancy results

[46] Bennear et al. (2009).

[47] Paternal characteristics are limited to demographic information, and these records are often incomplete.

[48] Property parcels, obtained from the NCSU GIS Library, were merged by spatial location using geographic coordinates and service zone polygons obtained from NC OneMap Geospatial Portal. Mother residence addresses were then merged to property parcels, and hence water service zones, using address, zipcode, and county names by a fuzzy-string matching algorithm, the stata package matchit (Raffo, 2015). Poor-quality matches were manually cleaned. Remaining unmatched addresses were assigned to water systems based on city of residence if the city is known to use coal-ash affected water according to the Southern Environmental Law Center. See Appendix subsection 7.3 for a lengthier description of the address matching procedure.

in apparently dramatically different rates of congenital anomalies in the pre-2010 and post-2010 forms.[49]

In Table 3, I document systematic differences in fetal health across affected and unaffected mothers. Mothers ever served by municipal water systems affected by coal ash tend to have lower birthweight newborns and higher likelihood of preterm gestation. Affected mothers are more likely to be minority, unmarried, and have hypertension, although both affected and unaffected mothers tend to engage in similar rates of tobacco use and prenatal visits.[50] Interestingly, affected mothers are 5 percentage points more likely to move between pregnancies, perhaps reflecting perceived risk of coal ash pollution. Newborns of affected mothers are 0.8 ounces lighter, on average, and 0.5 percentage points more likely to be low birthweight (i.e., weigh less than 2500 grams). They also appear more likely to have congenital anomalies, although this discrepancy may relate to changes in recording practices for this outcome. Figure 13 displays four fetal health indicators over time between mothers ever potentially affected by coal ash and mothers likely not affected by coal ash.

3.5 Satellite-Based Monthly Air Quality

Air quality is an important determinant of fetal health.[51] I therefore incorporate satellite-based monthly fine particulate matter (i.e. particulate matter of size less than 2.5 micrometers in diameter) estimates as controls in the analysis. The Atmospheric Composition Analysis Group at Dalhousie University created these data by applying a machine-learning algorithm to repeated daily satellite images of aerosol optical depth, a measure of cloudiness, across small pixels on the earth's surface.[52] Using the extract raster to polygon feature in GIS software, I converted these pixel datapoints to county-level variables for the average, minimum, and maximum fine particulate matter for each month from 2000 to 2017. Infants are assigned air quality measurements based on the average and maximum county-level PM 2.5 reading over all months *in utero*. The advantage to satellite-based data is a wider coverage region than would be possible using air quality monitors, although prediction errors render these estimates less accurate for tiny regions or high pollution levels.[53] A recent study nevertheless demonstrates very similar fetal health outcomes using both satellite-based and monitor-based air quality measurements at the county level.[54]

[49] For all regressions, I exclude chromosomal anomalies and trisomy 21 because these conditions occur naturally in the human population and are not necessarily linked to pollution exposure.
[50] Lead exposure is associated with increased risk of hypertension (Gambelunghe et al., 2016).
[51] Chay and Greenstone (2003); Currie and Walker (2011); Currie et al. (2008); Jha and Muller (2017)
[52] van Donkelaar et al. (2019).
[53] Fowlie et al. (2019).
[54] Alexander and Schwandt (2019).

3.6 Home Sale Prices

I obtain home sale tax records for twelve counties with coal ash ponds North Carolina.[55] These records were obtained from multiple sources. County tax assessor websites occasionally list sales information on their website. In other cases, equivalents may be requested from the tax assessor directly. For six counties, I purchase home sale information from CoreLogic's Configurable Real Estate Data Report. I merge each home address to a North Carolina property parcel database to extract geographic coordinates for all homes. I then use ArcGIS to merge these homes to a series of buffer polygons created around coal ash ponds at distances of 1, 2.5, and 5 miles. Because of the fragmented home sale source data, variables commonly used in hedonic housing analyses are primarily missing. The exception is lot size. Summary statistics for home sales are presented in Table 3. Figure 14 plots average sale prices over time along with the distribution of sale prices in homes within 5 miles of a coal ash plant. Surprisingly, homes within five miles of a coal ash release site tend to be more expensive than more-distant homes over the entire sample period. On average, they sell for nearly $30,000 more than homes at greater distance from coal plants. This feature of the data likely represents lake-front properties having higher sale values, although these homes have slightly more bedrooms and bathrooms than other comparable homes.

4 Empirical Strategy

In the following sections, I describe the methods used to test the relationship between coal ash water pollution and surface water quality, municipal water quality, and fetal health. I also estimate how the revelation of unsafe well water affected home sale prices after a legislative act.

4.1 Surface Water Quality

I detect variations in surface water quality associated with coal ash water pollution with a surface water monitor fixed effects estimation procedure. Consider the following regression equation:

$$Y_{imwt} = \beta Ash_{it} + X_{it}\gamma' + \eta_i + \eta_{wm} + \eta_{wt} + \epsilon_{imwt} \quad (1)$$

In Equation 1, Y_{imwt} is the arsenic, chromium, conductivity, dissolved oxygen, lead, pH, or temperature detected at a given monitor i in month m, watershed w, and year t.[56] Equation 1 includes fixed effects

[55] Buncombe, Cleveland, Catawba, Chatham, Gaston, New Hanover, Person, Robeson, Rowan, Rockingham, Rutherford, and Stokes counties are included in the analysis.

[56] Watershed region refers to hydrologic unit (HU-6) geographies, which are watersheds roughly the size of an aggregation of several counties. See the USGS Watershed Boundary Dataset webpage for more information.

for monitor η_i, watershed-month η_{wm}, and watershed-year η_{wt}. X_{it} includes dummy indicators for sample medium type, a dummy indicator for abnormal weather event, dummy indicators for hydrologic condition type, and a dummy indicator if the analyte was not detected.[57] I two-way cluster all standard errors at the monitor and watershed level. I employ three versions of Ash_{it} to test related but distinct research questions. In the first, Ash_{it} is time-invariant binary indicator equal to one if a monitor is downstream from a release site.[58] In the second, Ash_{it} is a time-varying binary indicating whether the upstream coal sites are actively releasing water pollution in year t. In the third formulation, Ash_{it} is the annual quantity of coal ash released at a coal facility within 25 miles upstream of monitor i.[59] For the monitor-constant formulation of Ash_{it}, β measures how monitors that are ever downstream may differ from nearby monitors in the same year, controlling for watershed monthly variation arising from seasonal factors like temperature. In the time-varying binary variable for upstream coal water pollution releases, variation in Ash_{it} may arise from plants shutting down, converting from coal to natural gas, or changing disposal practices. The time-varying binary version of Ash_{it} asks whether downstream monitors show differences in levels of water quality analytes compared to themselves in years when pollution sites are inactive. In this formulation, β is the average within-monitor difference in analyte level in years when upstream pollution sites are actively releasing. The final formulation of Ash_{it}, the tons released upstream in a year, varies due to plant closures and conversions and also from natural fluctuations in plant coal usage in a year. With this version of Ash_{it}, β is the relationship between each ton of coal ash released and the measured water property or concentration downstream.

Intuitively, Equation 1 captures how coal ash sites affect the properties of water downstream. It does so by comparing a specific location to itself in years when more or less is released upstream, controlling for local characteristics that may vary by month and year. The first formulation of Ash_{it} is not causal, although large and statistically significant differences across monitors in otherwise comparable regions may relate to the legacy of many decades of coal-ash water pollution. Causal identification with the second and third formulations of Ash_{it} requires that no factors are correlated with the quantity of coal released and the property of water observed downstream, conditional on monitor, watershed-year, and watershed-month. Various concerns may arise with this estimation procedure. Previous studies demonstrate that standard statistical analyses are not ecologically relevant for physical and chemical properties of streams.[60] The same quantity of coal ash is likely to affect watersheds differently. Factors like total flow (and hence dilution), flow speed, temperature, agricultural activities, and tree coverage are all important determinants of how coal ash

[57] Sample media include surface water, sediment, and hyporheic zone. Abnormal weather events include backwater, dambreak, drought, flood, hurricane, regulated flow, snowmelt, spill, spring breakup, and storm. Hydrologic conditions indicate whether the water level is low, high, or stable.

[58] In this procedure, monitor fixed effects are dropped, leaving only watershed-year and watershed-month fixed effects.

[59] With multiple plants, the measure is calculated as: $Ash_{mt} = \Sigma_p 1[Downstream_m] * TonsReleased_{pt}$, where p represents a steam electricity generating coal power plant.

[60] Peterson et al. (2007).

impacts a water system.[61] Moreover, these determining factors are likely endogenous to the quantity of coal ash released because regions with greater potential to absorb pollution may receive more of it. The monitor, watershed-year, and watershed-month fixed effects should allay some of these concerns. The prevalence of coal ash water pollution relative to other point-source pollutant categories also diminishes the likelihood that some other pollutant source might affect water quality to a similar extent. In Appendix Table 3, I show that counties with coal ash pollution sites do not have statistically different quantities of water pollution or pollution impounded in landfills compared to other counties in the same state.

4.2 Municipal Water Quality

Local geography, source water, system design, and homeowner characteristics influence municipal water quality.[62] [63] State regulatory monitoring tests report quantities across multiple facilities with different functions and monitoring requirements. State-level water quality regulations also play a role in observed water quality.[64] To determine the relationship between coal ash water pollution and the outcomes of state regulatory monitoring tests, I address these factors with a municipal water system panel fixed effects specification. Consider the following regression:

$$y_{imst} = \beta Ash_{it} + X_{it}\gamma' + \eta_i + \eta_{st} + \eta_m + \epsilon_{imst} \tag{2}$$

y_{fmst} is the level of arsenic, conductivity, haloacetic acids, lead, pH, or trihalomethanes level observed in municipal water system i, state-year st, and month m. Ash_{it} is the the coal ash released into surface waters within 25 miles upstream of at least one of a municipal water system's intake locations in year t, where this value is replaced with zero if the Southern Environmental Law Center determined the water system not to be sourcing from coal-ash affected waters. η_i is a water system fixed effect, η_{st} is a state-year fixed effect, and η_m is a month fixed effect. I cluster all standard errors at the state and municipal water system level. X_{it} includes dummies for the facility type where the test occurred.[65] The facility type indicator controls for unobservable factors that differ across facilities within the same water system that may give rise to different pollutant levels. η_{st} controls for any changes to state policies or secular pollution trends that may affect the levels of different compounds in a water system. The coefficient β measures how an additional ton of

[61] EPA (2015a).

[62] Gray and Shimshack (2011); Pieper et al. (2016).

[63] Water systems may use more than one source of water with differing underlying characteristics. For example, a system might have a groundwater well, a surface water intake, and also purchase water from a nearby system. Municipal water systems use different treatment techniques.

[64] Gray and Shimshack (2011).

[65] Facility types include distribution centers, transmission lines, treatment plants, source waters, wells, and homeowner tap-level tests.

coal ash water pollution released upstream in a year correlates with the concentration of a compound in an affected water system, conditional on water system-facility characteristics and time controls.

Aside from a continuous measure of Ash_{it} representing the total tons released upstream, I test two alternative formulations of Ash_{it}. In the first, Ash_{it} is a simple binary indicating whether tons released is positive, testing how water quality changes when a plant shuts down, converts, or changes pollution release practices. I also test a time-invariant version of Ash_{it} that is equal to one if a municipal water system is considered to use water affected by coal ash pollution according to the Southern Environmental Law Center. In this formulation, I drop water-system fixed effects and add watershed fixed effects. This formulation asks whether likely affected water systems are notably different from other water systems within the same watershed, conditional on state-year and monthly variation. Intuitively, Equation 2 compares a municipal water system facility to itself in years with low or high releases, controlling for heterogeneity across state-year and month. The identifying assumption of Equation 2 is that, conditional on water system facility, state-year, and month fixed effects, no factor is correlated both with the quantity of coal ash released upstream and the level of a specific pollutant in the municipal water system. This assumption may be violated if polluting firms near power plants systematically pollute similar compounds into surface waters in a way that is correlated with the quantity of coal ash effluent and the levels of an analyte in a municipal water system.

Next, I test the relationship between coal ash water pollution and the likelihood of a Safe Drinking Water Act (SDWA) violation. The Safe Drinking Water Inventory System tracks all municipal water system violations of the SDWA. I construct a panel of each water system in the inventory system for each year in which the system operated over 2000 to 2017, assigning violation counts by infraction type to each water system-year. For completeness, I employ both probit and linear probability models. Consider the following estimation procedures:

$$Pr(Vio_{it} = 1) = \Phi(\beta Ash_{it} + X_{it}\gamma' + \eta_i + \eta_t) \tag{3}$$

$$Vio_{ist} = \beta Ash_{it} + X_{it}\gamma' + \eta_i + \eta_s t + \epsilon_{ist} \tag{4}$$

In Equation 3 and Equation 4, Vio_{it} equals 1 if water system i has a violation of the specific type in year t, and zero otherwise. I consider two types of violation outcome. In the first, I break up violations by type of infraction. In the second, I break up violations by the specific rule of the SDWA that was violated.[66]

[66] Violations of the SDWA are laid out in the Safe Drinking Water Act by "rule" and "infraction." Rules include Arsenic, Consumer Confidence Rule, Filter Backwash, Disinfectant Byproduct, Groundwater, Lead and Copper, Miscellaneous, Nitrates, Public Notice, Radiation, Synthetic Organic Compounds, Total Coliform, Treatment Technique, and Volatile Organic Compound. Infractions against each rule include maximum contaminant level violation, monitoring violation, reporting vio-

η_i is a water-system random effect in Equation 3 and a water-system fixed effect in Equation 4. η_t is a year dummy.[67] I cluster all standard errors at the municipal water system. X_{it} includes dummy indicators for five types of water system size, system type, owner type, school water system, surface-water sourcing water system, protected source-water, and water system age.[68] I test a time-varying binary and time-varying continuous formulation of Ash_{it}, as before. Equation 3 asks how being downstream from an active coal ash pollution site in a given year affects the probability of a water quality violation, or how each additional ton of upstream coal ash water pollution affects the probability of a water quality violation.

4.3 Fetal Health

Unobservable factors are likely endogenous to household sorting across municipal water systems and hence water quality. Water quality violations, moreover, may present with simultaneous aversive behavior on the part of households.[69] I therefore model the relationship between coal ash water pollution and fetal health with a mother panel fixed effects design. Consider the following regression:

$$Health_{imt} = \beta Ash_{it} + X'_{imt}\gamma + \eta_m + \eta_z + \eta_t + \nu_{imt} \quad (5)$$

$Health_{imt}$ is a fetal health indicator for newborn i to mother m in year t. Health indicators include ounces at birth, low-birthweight, preterm gestation, and presence of a congenital anomaly. η_i, η_t, and η_z are mother, year, and zipcode fixed effects. X_{imt} is a vector of time-varying birth and mother characteristics and county-level air quality measures.[70] Because the time-invariant version of Ash_{it} is identified by mothers' moves, X_{imt} also includes a dummy for whether the mother moved since the last observed pregnancy outcome.[71] I cluster all standard errors at the mother. Ash_{it} takes one of three forms. In the first, it is a time-invariant indicator applied to all water systems considered affected by coal ash according to the Southern Environmental Law

lation, and treatment technique violation. Infraction types tend to vary by type of rule. For example, a consumer confidence rule is often related to reporting failures. A volatile organic compound violation may be related to monitoring lapses or, less commonly, maximum contaminant level violations. For each violation, an associated compound is listed. For example, a monitoring violation and a maximum contaminant level violation for the disinfectant byproduct rule violations may both list total trihalomethanes as the related compound.

[67] I use the commands xtprobit , re and xtreg , fe in Stata.

[68] Federal types are community water system, non-community non-transient water system, and transient water system. Owner types are public and private, where public is the omitted category. School water systems are water systems that serve schools. Protected source-water indicates that a water systems source water is protected. I calculate age as the current year minus the date of first water system record in SDWIS. Note that many of these variables are dropped in Equation 4 because they are time-invariant.

[69] Banzhaf and Walsh (2008); Bennear and Olmstead (2008); Marcus (2019); Zivin et al. (2011).

[70] Air pollution controls are mean, maximum, and maximum PM 2.5 squared across in the county of residence across all months of gestation. Birth-specific controls include gender of the newborn and dummies for birth order. Mother-specific controls include age at time of birth, age squared, six dummy bins for number of clinic visits during gestation, and an indicator for tobacco use during gestation.

[71] For example, this variable equals one if the observed residence in period $t-1$ is different from the observed residence in t.

Center. In the second, Ash_{it} is a binary variable indicating whether coal ash was released within 25 miles upstream of a water system's intake in year t. In the third, it is a continuous variable representing the tons of coal ash released within 25 miles upstream. Intuitively, Equation 5 estimates the difference in health outcomes across siblings where one sibling receives more potential exposure to coal ash water pollution. Such variation may arise from mother moves, plant closures or plant conversions, and random variation in the quantity of water pollution in any year. In the time-invariant version of Ash_{it}, the identifying assumption is that mother's moves from or to coal-ash affected regions are not associated with unobservable improvements in mother's well-being that may also affect fetal health conditional on controls for zipcode and the dummy indicator for having moved since the last pregnancy. In the second and third formulations of Ash_{it}, identification requires that factors correlated with plant closure or the quantity of coal ash released do not independently affect fetal health outcomes, conditional on controls for mother, zipcode, and year. A potential violation of this assumption would be if plant closures are associated with economic changes to the community that may affect mother health. Alternatively, a violation of the identifying assumption might occur if mothers systematically avert exposure to pollution in years when plants are active or when more pollution is released.

The primary source of variation in Equation 5 is mother's moves. I therefore dis-aggregate the equation by mothers moving into and mothers moving out of coal ash-affected municipal water system service zones. Consider the following regression:

$$Health_{imt} = \beta_1[In - Move == 1]_{it} + \beta_2[Out - Move == 1]_{it} + X'_{imt}\gamma + \eta_m + \eta_z + \eta_t + \nu_{imt} \tag{6}$$

$Health_{imt}$, X_{imt}, η_i, η_t, and η_z are as before. Rather than Ash_{it}, I now include two indicator variable capturing whether a newborn has been differentially exposed to an affected water service zone in comparison to its siblings. $[In - Move == 1]_{it}$ equals one if the listed residence of newborn i to mother m is within a coal-ash affected water service zone while the listed residence for *previous* newborn j to mother m is *not* within an affected service zone. Conversely, $[Out - Move == 1]_{it}$ equals one if a newborn's listed residence is not within an affected municipal water service zone, while a previous newborn to the same mother was potentially exposed. In all cases where all children to the same mother are either exposed or not exposed, these indicators equal zero. In any case where multiple children are born after a transition to or away from an affected service zone, all subsequent children receive the same indicator.[72] Equation 6 includes an indicator for whether a moved since the last pregnancy to control for unobservable factors associated with a mother's

[72]For example, a mother has one child in an affected region, and subsequently the mother has three children in an unaffected service zone. All three subsequent children receive an indicator of one for $[Out - Move == 1]_{it}$.

move that may also affect fetal health. Standard errors are clustered at the mother. Intuitively, Equation 6 asks whether observable fetal health differences may arise from moving into or moving out of coal ash water service zones.

4.4 Willingness-to-Pay for Avoiding Coal Ash Contamination

During a weather event in February of 2014, an ash pond along the Dan River in North Carolina burst its banks, releasing 25 million tons of coal ash into the nearby river. By September, the state legislature had responded with the Coal Ash Management Act, Senate Bill 729, in an effort to better manage coal combustion wastes. As part of the legislation, homes within 500 feet of a coal ash pond received mandatory home well water quality tests, where applicable. Many of these homes were found to have water considered unsafe to drink by the EPA.[73] Duke Energy subsequently provided these homes with bottled water for drinking and cooking. I test how this event, which led to information disclosure about well water quality and provision of bottled water by Duke Energy, affected home prices near the ash ponds. Consider the following equation:

$$y_{it} = \delta treat_i * post_t + \lambda post_t + \eta_i + \eta_t + \epsilon_{it} \tag{7}$$

y_{it} is the sale price for home i in year t, where all prices are converted to 2014 dollars. Let $treat_i$ represent homes that are within a 1, 2.5, or 5 mile buffer region surrounding a coal ash pond. $post_t$ is a dummy equal to one if the sale occurred after 2014. $treat_i * post_t$ is the interaction of a dummy for the post period and an indicator for being within the circular buffer surrounding a coal ash pond. η_i is a fixed effect for either the home or the incorporated city of the home, and η_t is a year fixed effect.[74] I cluster standard errors at the county level in all analyses. The coefficient of interest in Equation 7 is δ, the average change in sale price of affected homes after 2014. The Dan River spill and the Coal Ash Management Act of 2014 made water quality concerns more salient at the same time as households adjusted to well-quality information patterns. Duke Energy also began providing bottled water to affected residents at the same time as these other events. δ should therefore be interpreted as a change resulting from a variety of factors rather than one causal mechanism. Comparing sale prices to previous sale prices of the same home controls for time-invariant factors that may be unique to regions near large power plants. Models using fixed effects at the city level require that homes nearer to coal plants would have similar sale price trends as other homes in the same city in the absence of the well water information disclosure, which is a stronger assumption.

[73] For more information, see this NC Department of Environmental Quality series of reports summarizing testing.

[74] I rule out using county fixed effects due to the substantial heterogeneity between homes near coal plants and other residences in the same county, both in average sale price and sale price trend. See Figure 14 for a trend comparison.

5 Results

5.1 Surface Water Quality

Table 4 shows the results of the surface water analysis for arsenic, chromium, conductivity, dissolved oxygen, lead, pH, selenium, and temperature. For each outcome, results are split into three columns depending on the Ash_{it} variable used in the estimation. The first column is a time-constant version of Ash_{it}, testing baseline differences in analyte between exposed and unexposed regions within the same watershed. Columns (2) and (3) display the monitor-specific fixed effects specification in Equation 1. These results regress a time-varying variable for coal ash releases on the relevant analyte, where column (2) is a simple binary if the monitor is exposed to positive releases in year t and column (3) is the annual tons released. The coefficient on arsenic in column (1) means that monitors ever exposed to coal ash pollution have 0.0863 mg/L greater concentration of arsenic than similar monitors in the same watershed-by-month and watershed-by-year cluster. For comparison, the standard maximum level in municipal water drinking supplies is 0.01 mg/L. In column (2), the coefficient of 0.0576 on arsenic suggests that downstream monitors have nearly six more mg/L of arsenic in years when upstream coal ash plants are actively releasing. Finally, the coefficient on arsenic in column (3) suggests that each ton released increases levels of arsenic in downstream monitors by roughly 0.002 mg/L. Scaling this by the typical quantity of coal ash effluent released into surface waters in any given year (i.e., 14 tons), this point estimate suggests that an average coal ash release site emits enough surface water pollution in a year to make nearby waters exceed drinking water standards at least two times over. Similarly, baseline levels of the pollutants chromium, lead, and selenium are all elevated in downstream water quality monitors within 25 miles, although these results are only statistically significant for selenium and arsenic. For selenium, the drinking water standard is 0.05 mg/L, suggesting that a typical coal ash release site increases nearby concentrations of selenium by less than half the safe drinking water standard, although selenium is known to bioaccumulate in fish populations. Point estimates in columns (2) and (3) are noisier and, for chromium and lead, actually negative. Since it is unlikely that increased pollution lowers levels of pollutants in nearby surface waters, these perverse results may stem from measurement error or unobservable factors such as shifts in testing priorities after coal plants stop polluting.

In the second panel of Table 4, column (1) demonstrates that surface waters downstream from coal ash sites have significantly deteriorated water quality indicators compared to nearby non-downstream bodies of water. Conductivity is nearly 1600 $\mu s/cm$ higher in these waters, which alone is nearly one third the average level observed in all non-downstream waters and slightly less than half of the average baseline difference observed between affected and unaffected water quality monitors.[75] Likewise, affected regions have lower

[75] A $\mu s/cm$ is a micro siemen per centimeter, a standard measurement of specific conductance.

baseline dissolved oxygen levels than comparable unaffected regions by roughly one tenth the mean level across all water quality monitors. Lower dissolved oxygen affects fish habitats and recreation value of water systems, although it also decreases the rate of pipe corrosion in municipal water systems that source from these waters. pH and temperature, meanwhile, are both significantly elevated in water systems affected by coal ash. pH tends to increase because of the many calcium and silica compounds present in coal ash; this effect is evidently only partially mediated by acid rain. Temperature, meanwhile, increases because power plants circulate nearby water in the electricity generation process. Strangely, the column (2) point estimate on conductivity suggests that closure of a coal plant is associated with an increase in conductivity of nearly 300 $\mu s/cm$. Indeed, the time-varying variables in column (2) and (3) often differ from the hypothesized relationships between pollution and water quality indices. These strange results, in combination with those for chromium and lead above, suggest that the time-varying pollution release variables may noisily capture true changes in surface water pollution.

Collectively, results in Table 4 suggest that surface waters downstream from coal ash sites differ substantially from other nearby unaffected surface waters, although I find mixed evidence on the extent to which these differences are driven by contemporaneous pollution releases. One potential explanation is that waters in these regions are naturally different from waters in other regions within the same watershed. One alternative explanation is that, over many decades of coal ash pollution, these waters have developed significantly higher conductivity and pH levels that are not greatly affected by the contemporaneous amount of pollution released. Yet another possibility is a measurement error issue; measurement error of coal ash pollution may relate to poor self-reported estimates on the part of coal ash effluent managers, but it may also relate to substantial undocumented leakage and seepage from coal ash pollution sites. I also display the results of a variety of inorganic compounds typically associated with coal ash in Appendix Table 2. In general, these results support the main findings in Table 4. In particular, I find evidence that coal ash water pollution increases levels of antimony, mercury, and thalliun.

5.2 Municipal Water Quality

Table 5 displays the results of estimation procedure Equation 2. In this specification, I estimate the relationship between coal ash water pollution releases and the results of regulatory monitoring tests in nearby municipal water systems. I split the analytes into three categories and show results associated with three types of treatment indicators. The analyte categories are disinfectant byproducts, inorganic compounds, and properties. I now include two new analytes not present in the surface water analysis presented in subsection 5.1.[76] These water quality analytes are trihalomethanes and haloacetic acid.[77] The three treatment indicators correspond to those employed in subsection 5.1. The first column, labeled downstream, shows baseline differences between water systems that are believed to be sourcing from coal ash affected waters by the Southern Environmental Law Center and those that are not. Columns (2) and (3) test how monitoring test results within the same water system change over time in response to variations in the quantity of coal ash released upstream. All models include state-by-year and month fixed effects to control for time-varying state regulations and monthly fluctuations in water quality. Column (1), instead of a municipal water system fixed effect, includes a fixed effect for the watershed HUC-8 region of a municipal water system's intake location, which is assigned using the procedure listed in Appendix subsection 7.2.

Municipal systems that are downstream from coal ash release sites, in comparison to other water systems within the same watershed and state-by-year combination that are not affected, tend to have lower conductivity, pH, and haloacetic acids.[78] Lead levels appear slightly larger but not statistically significantly so. No other coefficient in column (1) is statistically significant. These baseline differences, showing that coal-ash affected water systems actually have better water quality than nearby water systems, likely relate to the unique characteristics of these water systems. As is shown in Table 2, these water systems are substantially larger and therefore subject to increased regulatory oversight. In addition, a water plant affected by coal ash pollution is necessarily using some quantity of surface waters. Surface waters contain fewer metals such as arsenic than groundwater; these differences also lead to altered conductivity and pH profiles. These source-and size-based differences may explain some of the results in column (1).

The time-varying regressions of upstream coal ash pollution on water quality indicators provide mixed evidence of a link between coal ash water pollution and municipal water quality. All coefficients for disinfectant byproducts in columns (2) and (3) are negative and statistically indistinguishable from zero. The point estimate in column (2) for arsenic suggests that a plant closing upstream is associated with a 0.0084 mg/L improvement in arsenic levels. Compared to the water quality standard for arsenic of 0.01 mg/L, this improvement is quite dramatic. However, it is not statistically significant at the 10% level of confidence. For lead, I find that each ton of upstream coal ash water pollution increases downstream municipal lead

[76] I also drop chromium, selenium, dissolved oxygen, and temperature because these outcomes are either not tested frequently in municipal water systems (i.e., chromium and selenium) or not relevant to human health (i.e., dissolved oxygen and temperature).

[77] I analyze the relationship between coal ash releases and the two most common and most-frequently tested disinfectant byproducts, haloacetic acids and total trihalomethanes. Although at least 500 disinfectant byproducts have been identified, these two compose at least 94% of all disinfectant byproduct formation (58% TTHM and 36% HAA5). Since disinfectant byproducts form during the water treatment process, I do not show any analysis of these analytes in surface waters. See DHHS for more information.

[78] Lower pH tends to create more haloacetic acids, while higher pH tends to form more trihalomethanes. Consistent with the lower baseline pH in affected water systems, it then follows that trihalomethanes may be elevated and haloacetic acids lowered. The statistically lower haloacetic acid levels are therefore likely an artifice of baseline pH differences. See DHHS for more information.

levels by 0.0035 mg/L. This is roughly one fifth the maximum contaminant level for lead, 0.015 mg/L. Since the average quantity of coal ash released upstream in any given year for municipal water systems is 4 tons, this is a sizeable improvement in water quality. Next, I find that conductivity tends to be higher in these water systems in years when upstream coal plants are active. In years when no pollution was released, conductivity in downstream water systems was 45 $\mu s/cm$ lower. Each ton of coal ash released, meanwhile, is associated with a 3 $\mu s/cm$ increase in conductivity in downstream municipal water systems. Interestingly, neither of these effects would close the gap in conductivity between coal-ash affected and unaffected water systems with respect to conductivity.[79] This suggests that, although affected water systems have cleaner water on average, coal ash pollution may nevertheless lead to infra-marginal changes in water quality that affect pipe corrosion and tap lead levels without necessarily causing increased regulatory notice. In the last row of Table 5, estimates for the effect of coal ash pollution on pH are of opposite sign. This discrepancy may relate to the influence of acid rain on water pH profiles.

In the next municipal water quality analysis, I test how changes in coal ash water pollution affect the likelihood of water quality violations of the Safe Drinking Water Act. These results are displayed in Table 6 by type of infraction and type of rule.[80] I display all infraction types and rule types that are potentially related to coal ash water pollution.[81] In column (2), I find evidence that water systems experience fewer health-based violations, maximum contaminant level violations, reporting violations, arsenic violations, and inorganic compound violations after an upstream plant ceases polluting into surface waters. As shown in row (1), these differences exist despite affected water systems having statistically similar levels of violations after plant closure or when more pollution is released. I find evidence that each ton of coal ash released upstream increases the likelihood of violations for disinfectant byproducts and inorganic compounds. In the case of inorganic compounds, I find that a one ton increase in upstream pollution releases increases the likelihood of a violation by 0.0015 percentage points, which is a massive increase compared to the baseline mean violation rate for this rule of 0.0024. Conversely, an additional ton increases the likelihood of a disinfectant byproduct violation by only 0.001, which is a smaller fraction of the mean violation rate for that rule, 0.0134. In all specifications, volatile organic chemicals appear positively associated with variables for coal pollution releases, although in no specification are these relationships statistically significant. Puzzlingly, I find a negative and statistically significant relationship between the plant closure and lead and copper violations. Results are generally consistent across OLS and probit models.

[79] Unaffected systems average 299 $\mu s/cm$ and affected systems 183 $\mu s/cm$.

[80] Note that infraction types and rules are not mutually exclusive; infraction types are specific ways in which a water system might break a rule.

[81] The category "inorganic compounds" includes many potentially coal-associated compounds.

5.3 Fetal Health

In Table 7, I present the results of Equation 5 across four measures of fetal health: birthweight in ounces, an indicator for low birthweight, an indicator for preterm gestation, and an indicator for the presence of any congenital anomaly. I show these results in three panels, each corresponding to a different formulation of Ash_{it} as laid out in Equation 5.

In Panel A, all point estimates are identified off mothers moving into or out of geographies served by municipal water systems using coal-ash affected source waters. The coefficient in column (1) suggests that a newborn potentially exposed to coal ash pollution, in comparison to an unexposed sibling, is 1.2 ounces lighter. Such newborns, in comparison to their unaffected siblings, are 1.7 percentage points more likely to be low birthweight. They are also 1.3 percentage points more likely to be preterm. These newborns also appear slightly more likely to have a congenital anomaly, although this difference is not statistically significant. These differences in fetal health are large in magnitude relative to the baseline fetal health means across the state. They're also large relative to the effect of differential fine particulate matter exposure *in utero*. For example, the average difference in particulate matter exposure for mothers ever exposed to a coal-ash affected municipal water service zone is 0.5 $\mu g/m^3$. In combination with the point estimate in on air pollution exposure in row (2), this discrepancy suggests that, from air pollution exposure alone, these mothers would be expected to have newborns roughly 0.55 percentage points more likely to be preterm. The same estimate associated with potential water pollution exposure is over twice as large. Meanwhile, mothers with less education, who are expected to be less able to avert water pollution exposure using water filters and other pollution aversion strategies, are more affected across all fetal health indicators except congenital anomalies. All effects are also conditional on zipcode fixed effects and an indicator for moving since the previous pregnancy, which control for potential changes in life circumstance that may give arise to mother moves.

In Panels B, column (1), I show that cessation of upstream water pollution practices is associated with a decrease in infant weight of 0.41 ounces. This result is highly significant. Moreover, after cessation of upstream coal ash water pollution, newborns appear slightly less likely to be low birthweight and preterm. Panel C provides qualitatively similar estimates of different magnitude; an additional ton of coal ash released upstream is associated with an improvement in fetal birthweight of 0.014 ounces. These results are puzzling; it is certainly unlikely that more pollution would improve fetal health. Therefore, it seems likely that unobservable factors associated with coal plant operation and pollution also affect fetal health. For example, closure of a coal plant might change local economic conditions in a way that affects fetal health. Perhaps more likely, aversive behavior on the part of mothers might attenuate and even reverse the potentially negative impacts of coal ash water pollution. For example, in years with more pollution and active nearby pollution sites, mothers might be more likely to drink bottled water or purchase home filtration devices.

Because the results in Panel A are driven exclusively by mother moves, I also disaggregate these effects by moves into or out of coal-ash affected municipal water system service zones in Table 8. Mothers moving into affected service zones have newborns that are, in comparison to previous newborns, 1.8 ounces lighter. These affected newborns are also 2.8 percentage points more likely to be low birthweight, and they are 2.1 percentage points more likely to be preterm. Mothers moving out of coal-ash affected regions, meanwhile, see their newborns increase in birthweight by 0.58 ounces, although this difference is not statistically significant.[82] Similarly, out-movers see improvements in the likelihood of being low birthweight of one percentage point. Out-movers also appear to dramatically lower the likelihood of a congenital anomaly; this improvement should be prefaced with concerns about the congenital anomaly indicator discussed in subsection 3.4. For nearly all outcomes, point estimates suggest that moving into one of these service zones worsens fetal health, while moving out improves it. Since the association between tobacco use during pregnancy and low birthweight is roughly 4 percentage points, the increase in incidence of low birthweight in Table 8 of 2.8 percentage points is a dramatic change.[83]

5.4 Home Sale Prices

Table 9 shows how sale prices of homes near coal plants changed in North Carolina after 2014, the year of a large coal ash spill and the state's Coal Ash Management Act. The first three columns show the results of estimation procedures with city fixed effects; columns (4) to (6) show the results with home fixed effects. Homes within 1 to 5 miles of coal ash ponds experienced sale price decreases of 5% to 14% after 2014, depending on the distance cutoff and comparison group. Models with home fixed effects have smaller point estimates across all distance bandwidths, suggesting that within-city comparisons may confound differential trends of the comparison homes with the policy. All models, however, suggest large, negative, and significant sale price changes. Changes in sale price are between 12% and 14% depending on the type of fixed effect employed, a substantial decline in homeowner wealth. Homes closest experienced the largest changes in sale price, with the effect size decreasing monotonically with distance from the coal ash ponds. The price changes may relate to increased salience of coal pollution, the dis-amenity value of recently-discovered unsafe well water, or changing secular preferences for pollution.

[82] Among other potential explanations for the divergence in effects across in-movers and out-movers, it is possible that mothers moving out of coal-ash affected areas carry with them the legacy of previous exposure.

[83] Zheng et al. (2016)

5.5 Cost Analysis

I perform back-of-the-envelope calculations of the external cost of coal ash water pollution with respect to two outcomes: low birthweight newborns and changes in home sale prices. In Table 7, the coefficient of 0.017 implies that mothers served by municipal water systems affected by coal ash are 1.7 percentage points more likely to have a child of low birthweight. This implies roughly 700 additional newborns of low birthweight.[84] 7000 low birthweight newborns is approximately 0.5% of the total of low birthweight newborns in North Carolina from 2005-2017. These low birthweight newborns likely led to \$10.7m in additional hospitalization fees and \$2.8m in K-12 educational expenses for local communities.[85] These costs do not account for many additional expenses associated with low birthweight newborns, such as later-life health complications or increased social services excluding special education. As for real estate, Table 9 presents likely total changes in home sale value associated with the revelation of un-potable drinking wells in homes surrounding ash ponds. These estimations multiply the per-home change in sale price by the number of homes affected in each distance cutoff. Results suggest likely changes in home values between \$20 million and \$450 million, depending on the model and distance cutoff.

6 Policy Relevance

The Environmental Protection Agency recently promulgated two rules with respect to the management of coal ash waste. The first, known as the Effluent Limitation Guidelines, stipulates that certain types of coal ash waste are not to be released into surface waters and that ash pond effluent streams must not exceed limitations on the concentration of specific compounds.[86] The second rule modifies subtitle D of the Resource Conservation and Recovery Act, which allows the EPA to regulate pollutants from cradle to grave. Known as the Disposal of Coal Combustion Residuals from Electric Utilities Rule, it establishes requirements for surface impoundments receiving coal ash wastes; among other stipulations, the rule mandates structural integrity tests, groundwater monitoring, run-off controls, and record keeping requirements. The rule also creates new guidelines with respect to the closure of inactive coal ash impoundments. These rules reflect current understanding of best practices for the management of coal ash waste. The Effluent Limitation Guidelines, in particular, are estimated to decrease the quantity of coal ash that may affect surface waters

[84] 900,000 of 1.5m newborns in the sample are served by municipal water systems, and 1 in 22 are served by municipal water systems affected by coal ash. $0.017 * 900{,}000 * \frac{1}{22}$ is 695.45.

[85] These numbers generated assuming each low birthweight newborn costs an extra \$15,000 and that each low birthweight newborn is twice as likely to qualify for special education, with costs of roughly \$44,000 per student. I assume baseline likelihood of special education service provision is 10%. Cost estimates from Petrou (2003) and Russell et al. (2007). Note these estimates are based on associational evidence.

[86] Managed waste types include many relatively new forms of coal ash waste generated in larger quantities due to technical changes in the way that coal ash and coal-related air pollution are managed. For example, installation of scrubber technology creates flue gas desulfurization waste. See the Technical Development Document (EPA, 2015c) for more information.

by at least 95%.[87] However, the estimated benefit-cost ratios for the Effluent Limitation Guidelines are not always greater than one.[88] This study provides novel evidence that additional public health benefits from improved municipal drinking water quality are probable and likely economically meaningful.

Other policy levers may also ameliorate the potential influence of coal ash pollution on nearby surface waters, municipal water quality, and exposed populations. Remediating an older ash pond by treating the water, excavating the ash, and moving the ash to a new location is one such option; cleaning an ash pond has immediate effects on groundwater, improving arsenic levels by as much as 90 percent.[89] Such ash pond remediation, however, can be very expensive.[90] Increased recycling of coal ash into fertilizers and concrete, already commonplace, could also be expanded to reduce the environmental footprint of this waste.[91] For concerns related to the burden of payment for cleanup, local legislative acts have also been passed that prevent recuperation of costs from illegal coal ash discharges.[92]

7 Conclusion

I find evidence that coal ash surface water pollution affects nearby surface water quality. Discharges of coal ash are associated with increased conductivity and pH in downstream surface waters and municipal waters sourced from the same locations. These changes are driven in part by contemporaneous pollution releases, as heavy metal compounds found in coal ash are also found in higher concentrations in affected waters in years when more pollution is released. Differences in fetal health across siblings provide evidence that this pollution matters for human health, especially for mothers with less education who may be less able to avert pollution. Revelation of groundwater contamination decreased home sale prices in regions near coal plants in North Carolina across all models and specifications. Back-of-the-envelope calculations suggest substantial external costs of this form of pollution, which are likely understated.

[87] EPA (2015a).
[88] EPA (2015b).
[89] Fretwell (2016).
[90] In North Carolina alone, the cleanup is expected to cost in excess of $10 billion. https://www.utilitydive.com/news/duke-north-carolina-coal-ash-pond-excavation-order-to-cost-4-5b/551788/
[91] Yao et al. (2015).
[92] https://www.ncleg.net/Sessions/2013/Bills/Senate/PDF/S729v6.pdf

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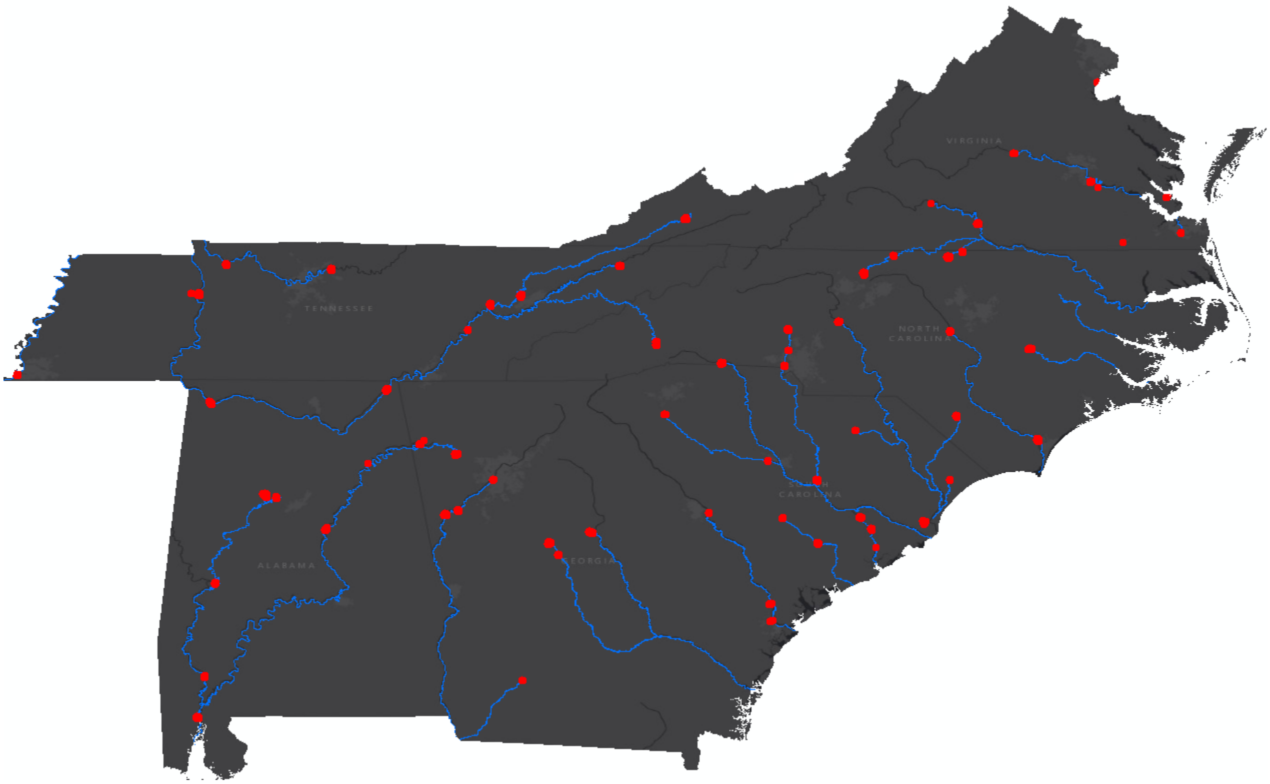
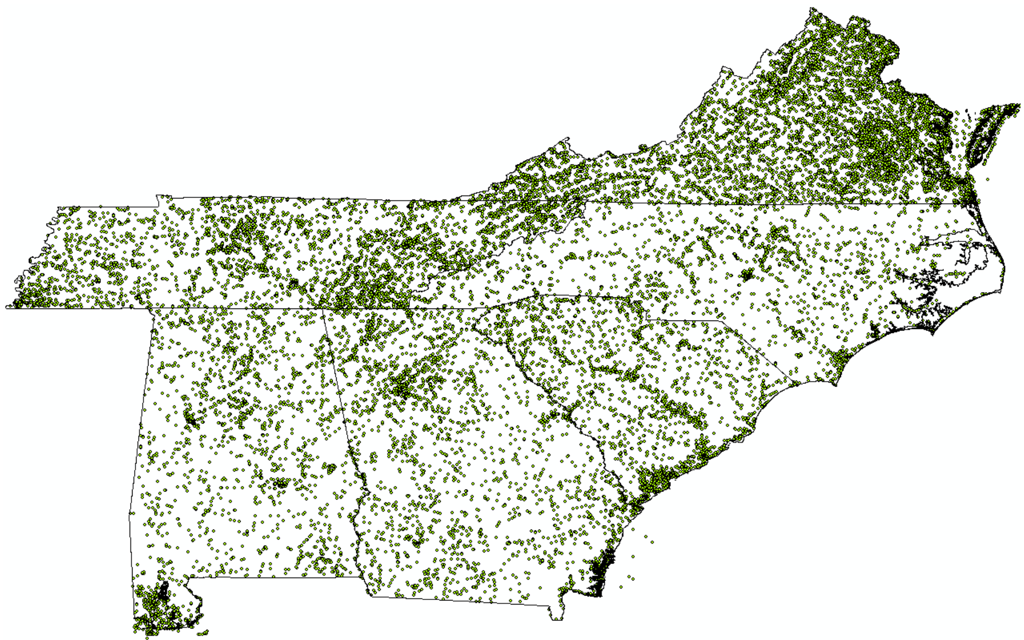
Figures

Figure 1: Coal Ash Release Sites and Downstream River and Stream Segments

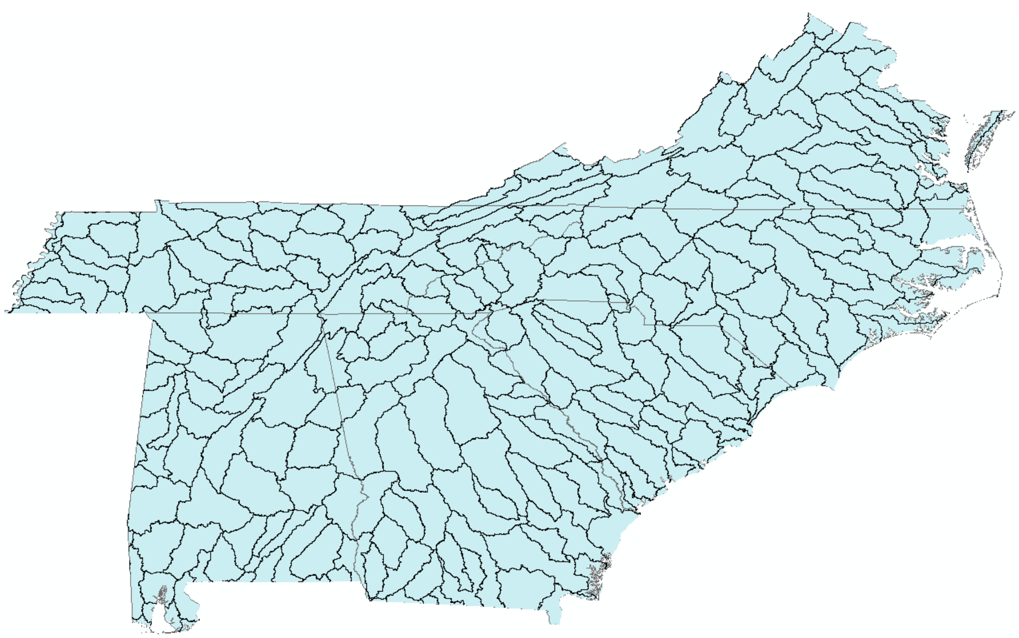


Notes: Red dots represent steam-generating coal power plants releasing a non-negative quantity of coal ash to surface waters from 2005-2017. Blue lines represent river and stream segments that are downstream from a coal ash release site.

Figure 2: Surface Water Quality Monitoring Sites and Watershed (HUC-8) Regions



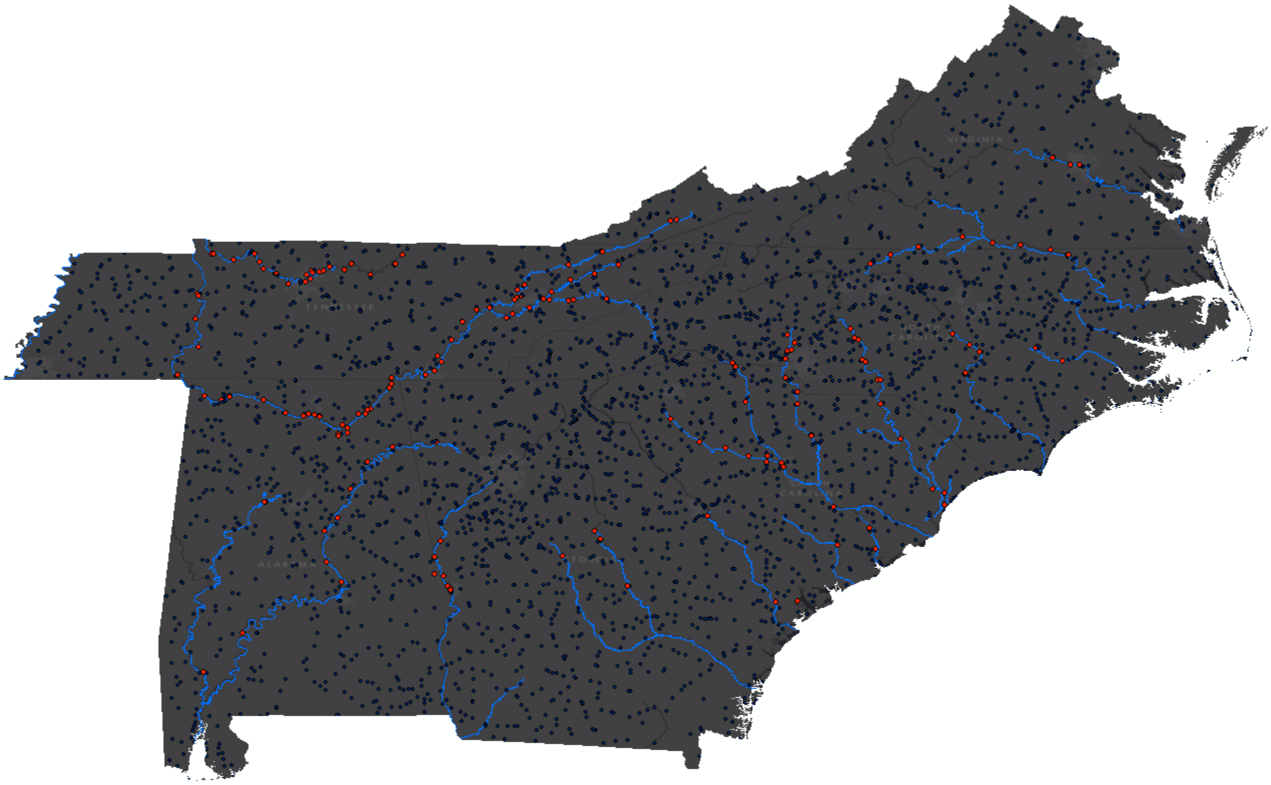
(a) Monitor Locations



(b) Watershed Regions

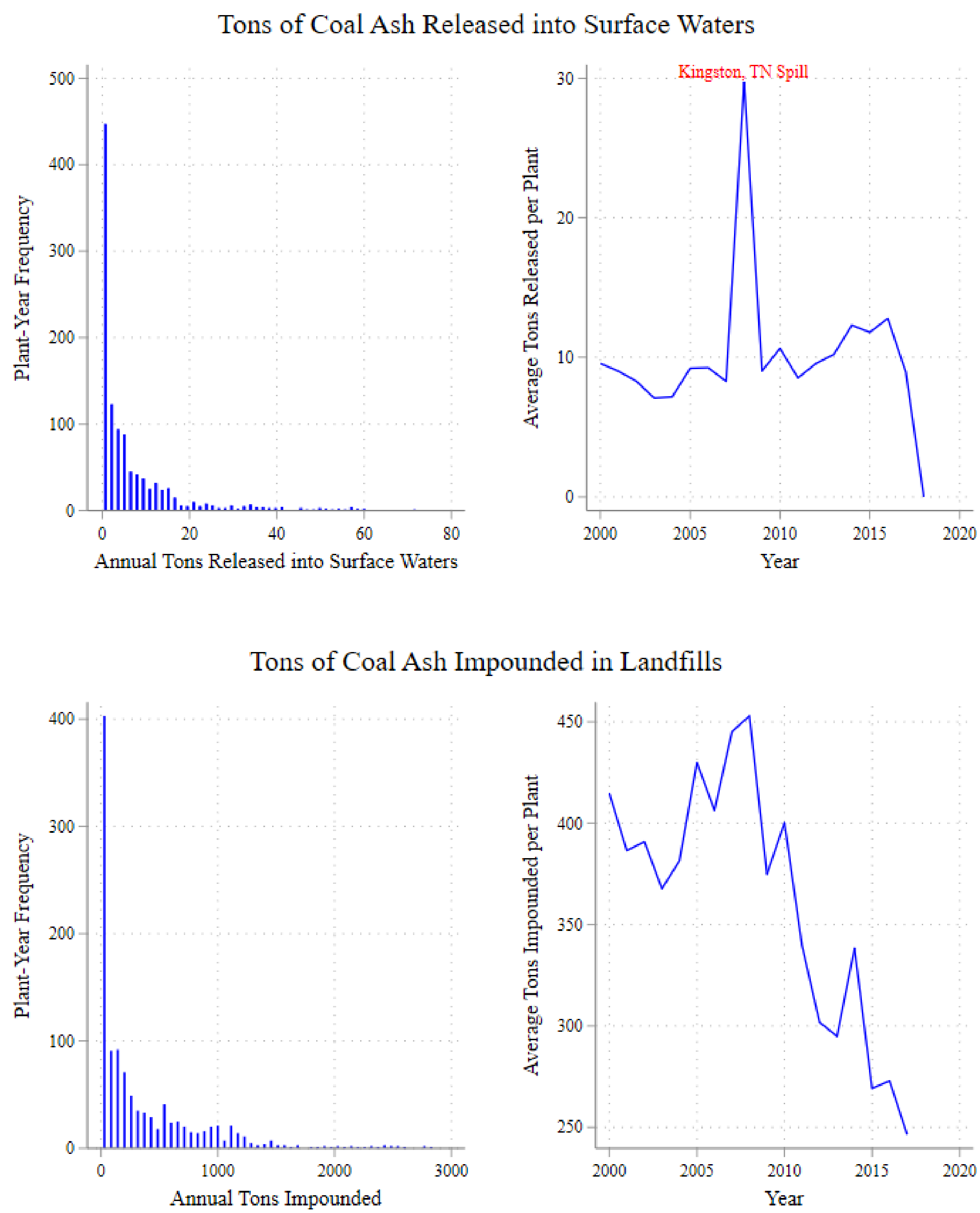
Notes: In Panel (a), green dots represent surface water quality monitor locations in the Water Quality Portal, while in Panel (b) each polygon represents a watershed of size Hydrologic Unit Code – 8.

Figure 3: Municipal Water System Intake Locations Affected by Coal Ash



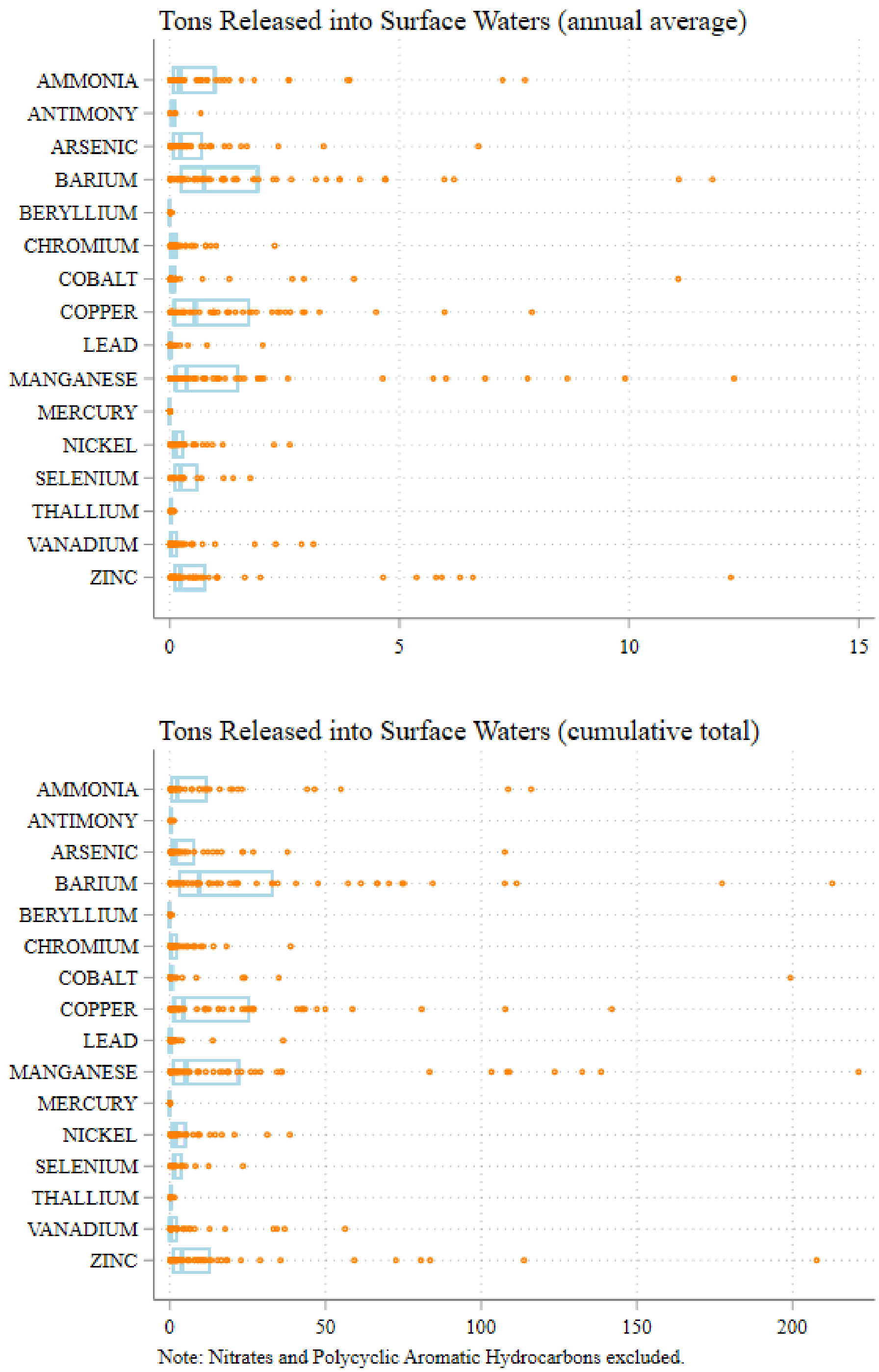
Notes: Darker blue dots represent municipal water system intake locations that are not affected by coal ash, whereas red dots are intake locations of likely affected municipal water systems. Blue lines represent river and stream segments that are downstream from a coal ash release site. Surface water intake locations provided courtesy of the Southern Environmental Law Center.

Figure 4: Toxic Releases by Coal Ash Plants (2000-2017)



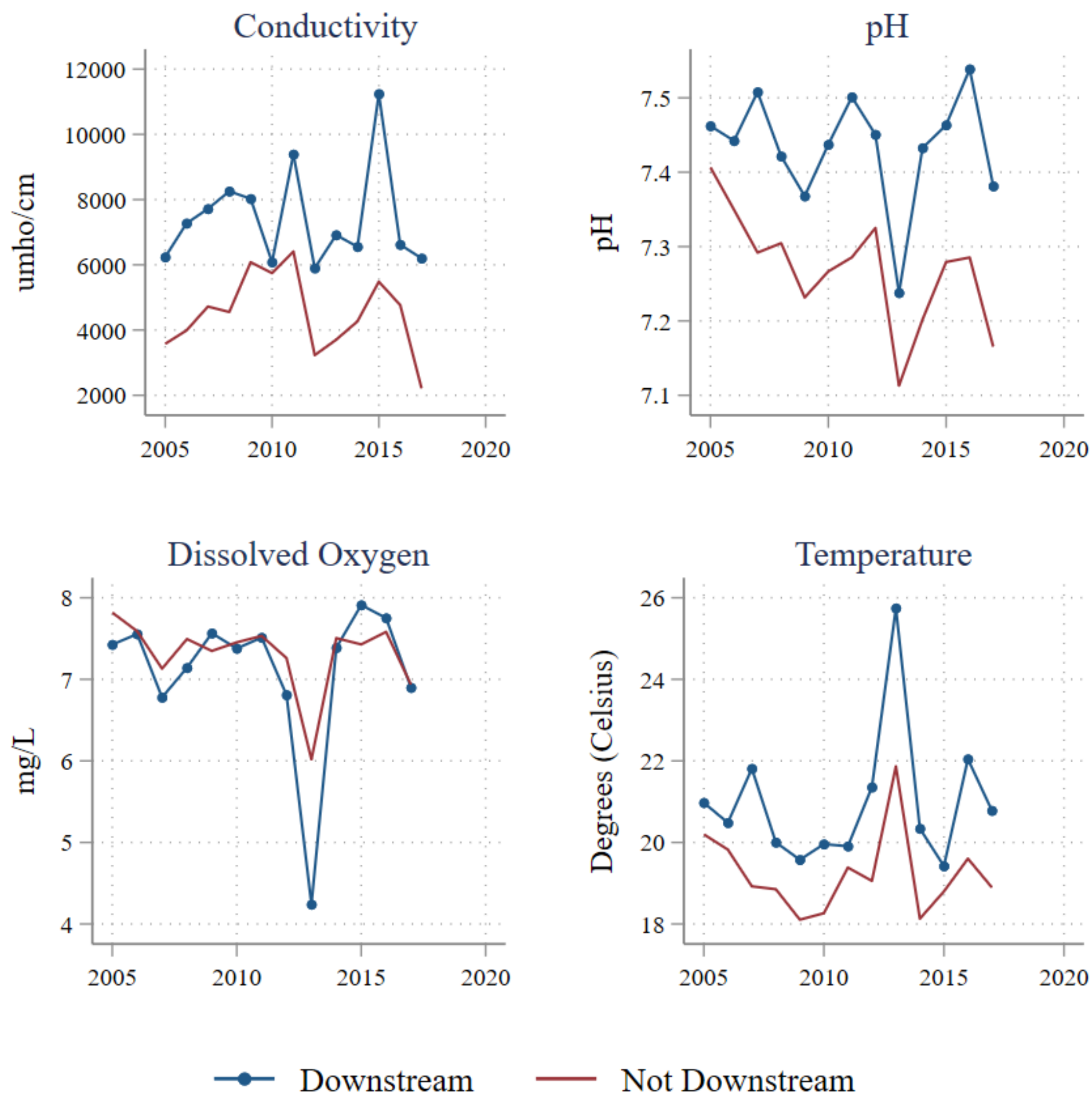
Notes: Bar charts on the left display variation in the quantity of coal ash released or impounded across all coal plants in the sample. Line charts plot the change in the quantity of coal ash effluent released into surface waters or impounded over time. Release values of zero are included.

Figure 5: Toxic Releases by Coal Ash Plants into Surface Waters by Compound (2000-2017)



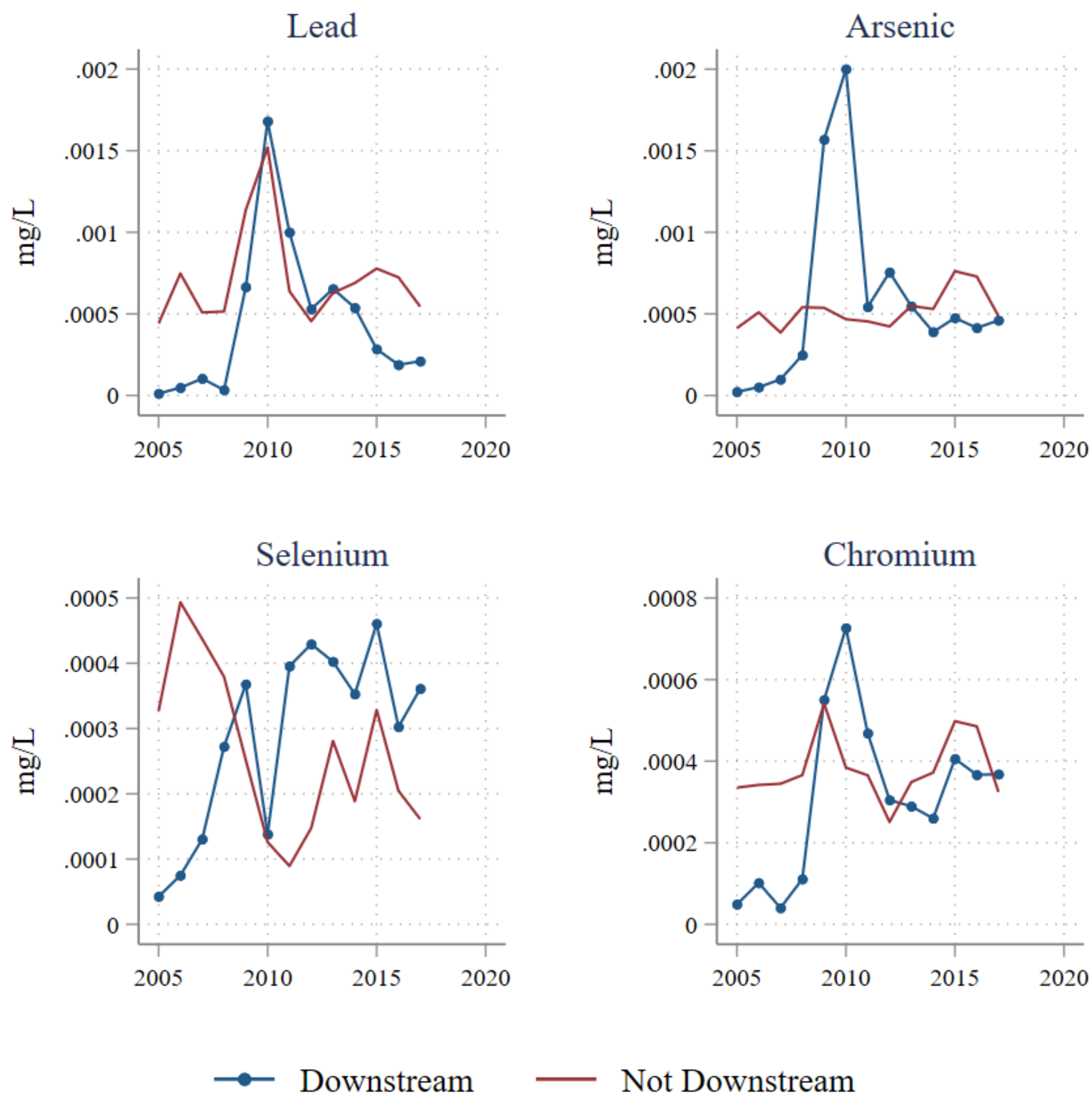
Notes: Light blue bars represent confidence intervals of the level released of each chemical across all plants, while each dot represents an individual plant observation. Release values of zero are included. Barium, nitrates, and polycyclic aromatic hydrocarbons excluded because relatively few plants release these compounds. Outliers of greater than 20 tons on average per year or greater than cumulative 300 tons are excluded.

Figure 6: Water Quality Criteria in Coal Ash-Affected Surface Waters (2005-2018)



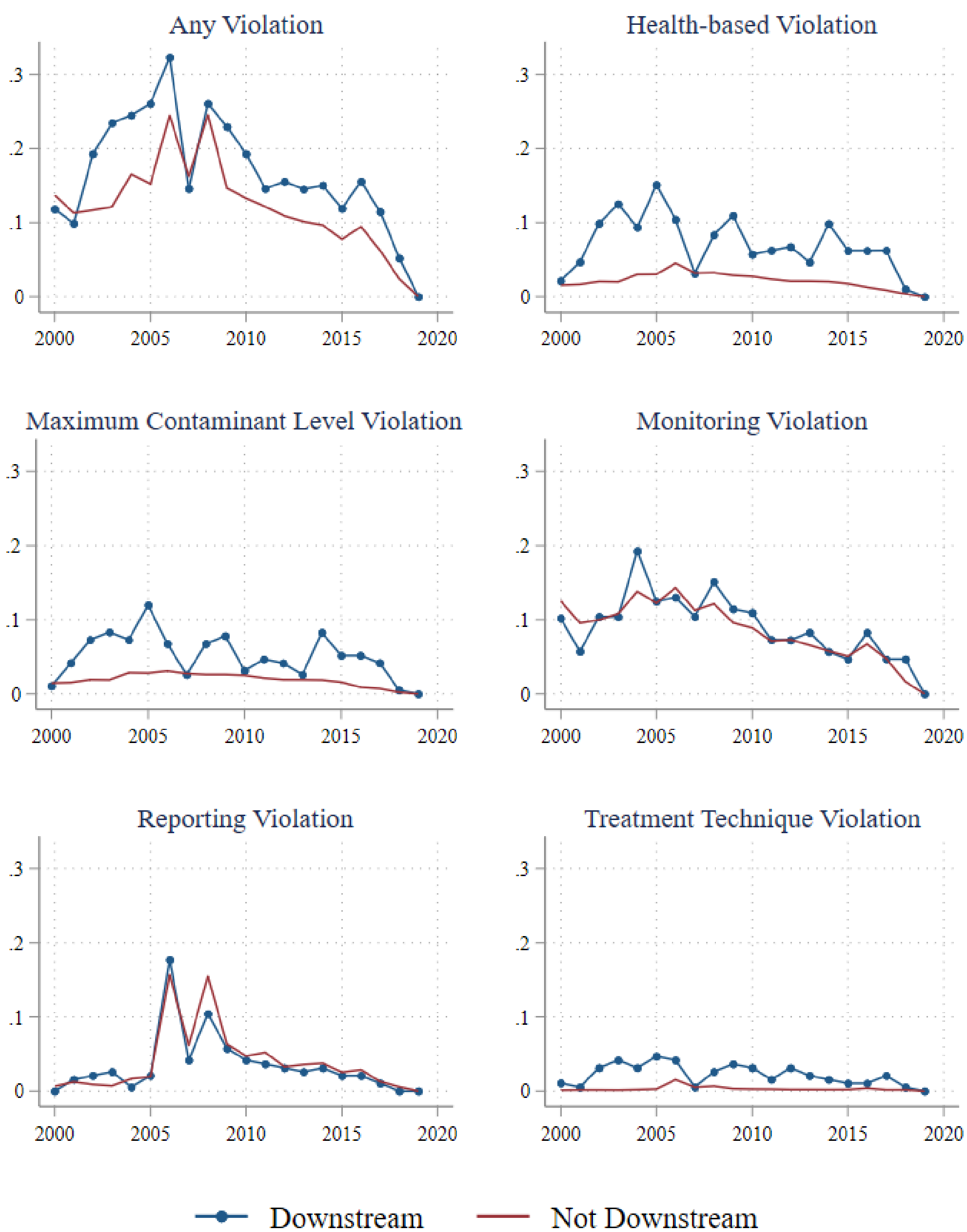
Notes: Average levels across all surface water monitor tests, excluding tests of sediment and hyporheic zone. Outlier observations above the 99th percentile are excluded. The downstream category includes surface water quality monitors within 25 miles downstream of a coal ash site. Not downstream includes all other surface water monitors in the sample states from 2005-2017.

Figure 7: Concentration of Water Pollutants in Coal Ash-Affected Surface Waters (2005-2018)



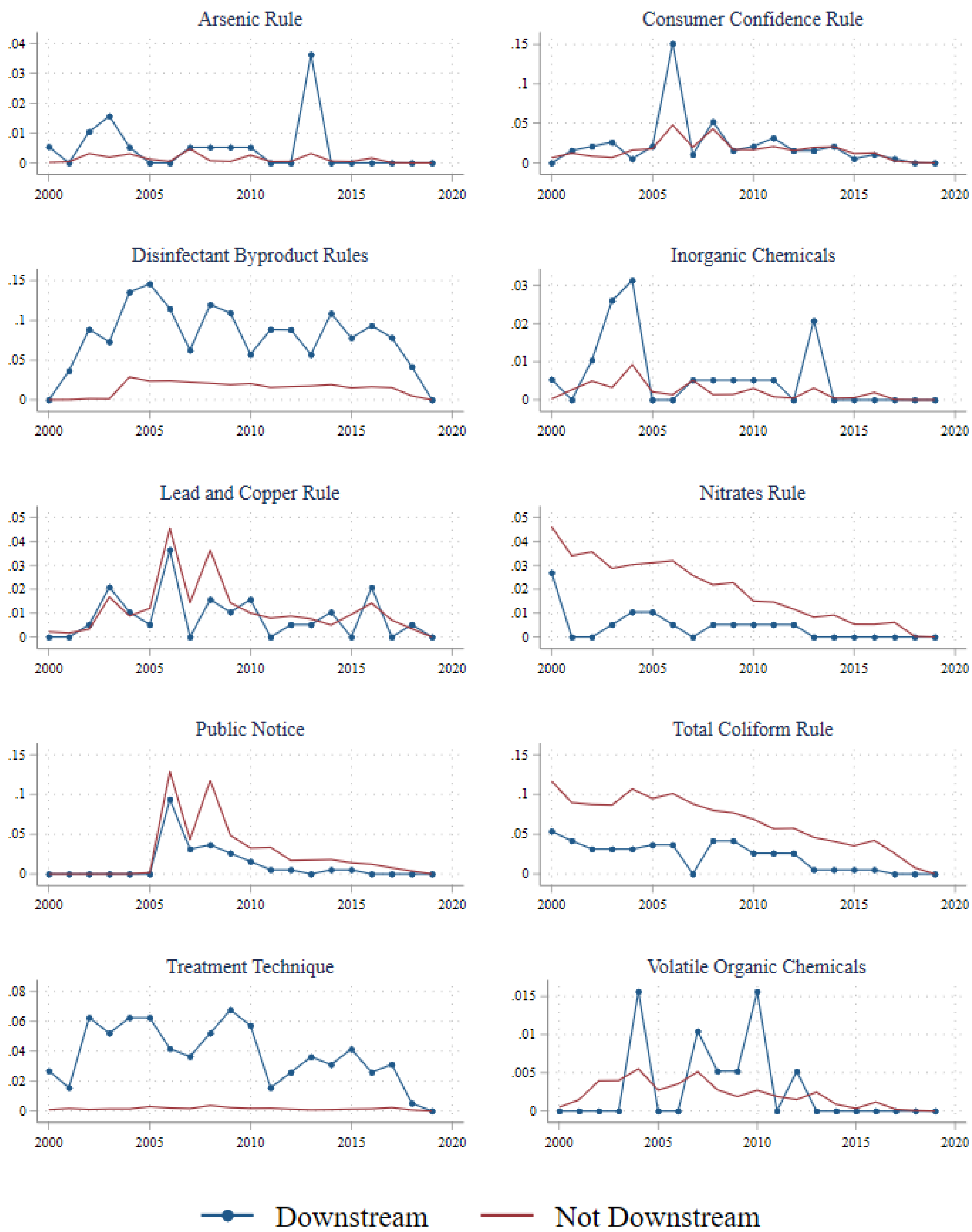
Notes: Average levels across all surface water monitor tests in a year, excluding tests of sediment and hyporheic zone. Outlier observations above the 99th percentile are excluded. The downstream category includes surface water quality monitors within 25 miles downstream of a coal ash site. Not downstream includes all other surface water monitors in the sample states from 2005-2017.

Figure 8: Safe Drinking Water Act Violations by Type of Infraction (2000-2018)



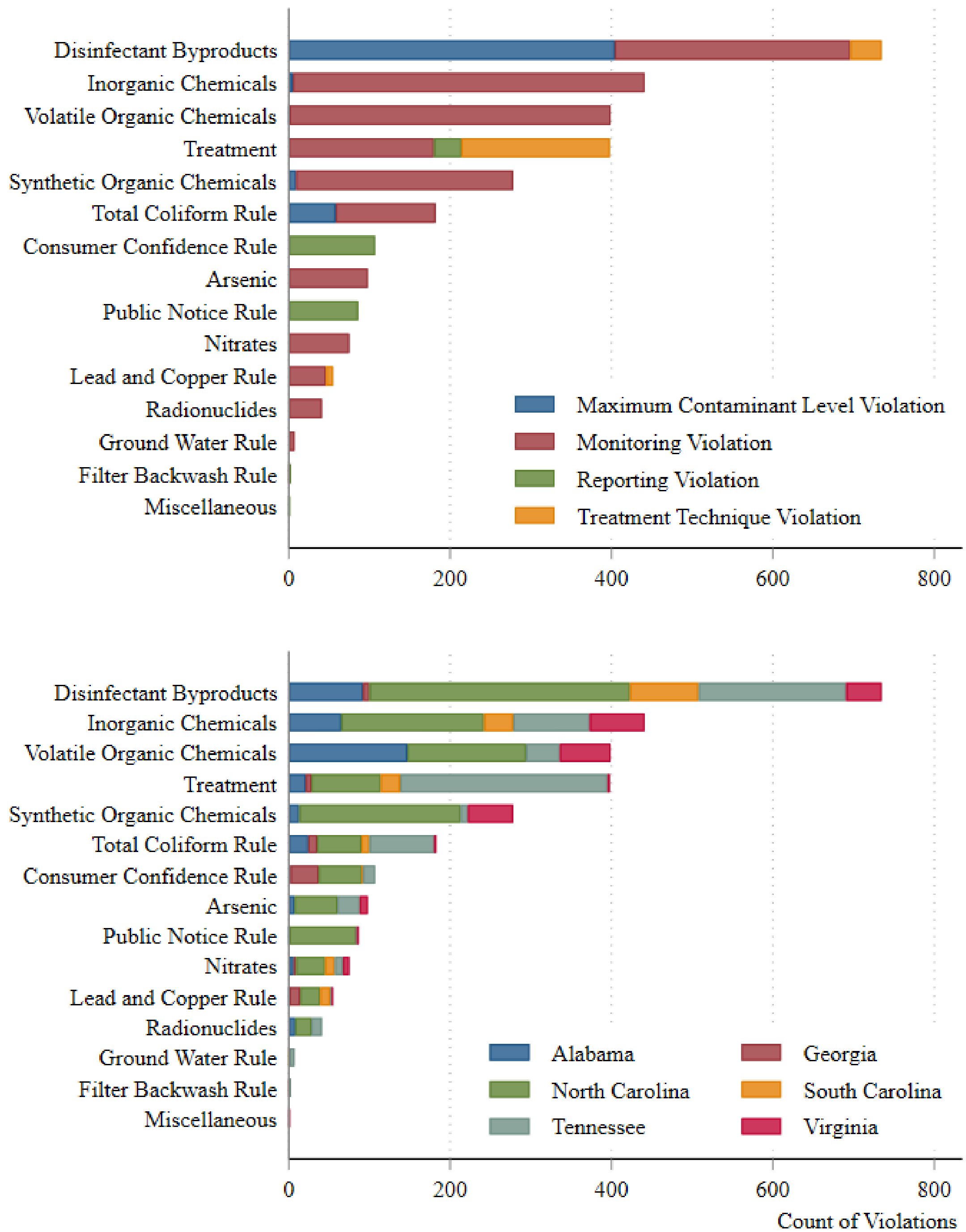
Notes: Average violation rate plotted. Downstream water systems are water systems sourcing from coal-ash affected waters according to the Southern Environmental Law Center. Not downstream water systems are all other active water systems.

Figure 9: Safe Drinking Water Act Violations by Rule (2000-2018)



Notes: Annual violation rate across all water systems plotted. Filter backwash, radiation, groundwater, and synthetic organic chemical rules not included. Y axes is not constant across rule names. Downstream water systems are water systems sourcing from coal-ash affected waters according to the Southern Environmental Law Center. Not downstream water systems are all other active water systems.

Figure 10: Safe Drinking Water Act Violations in Municipal Water Systems Downstream from Coal Ash Sites (1980-2018)

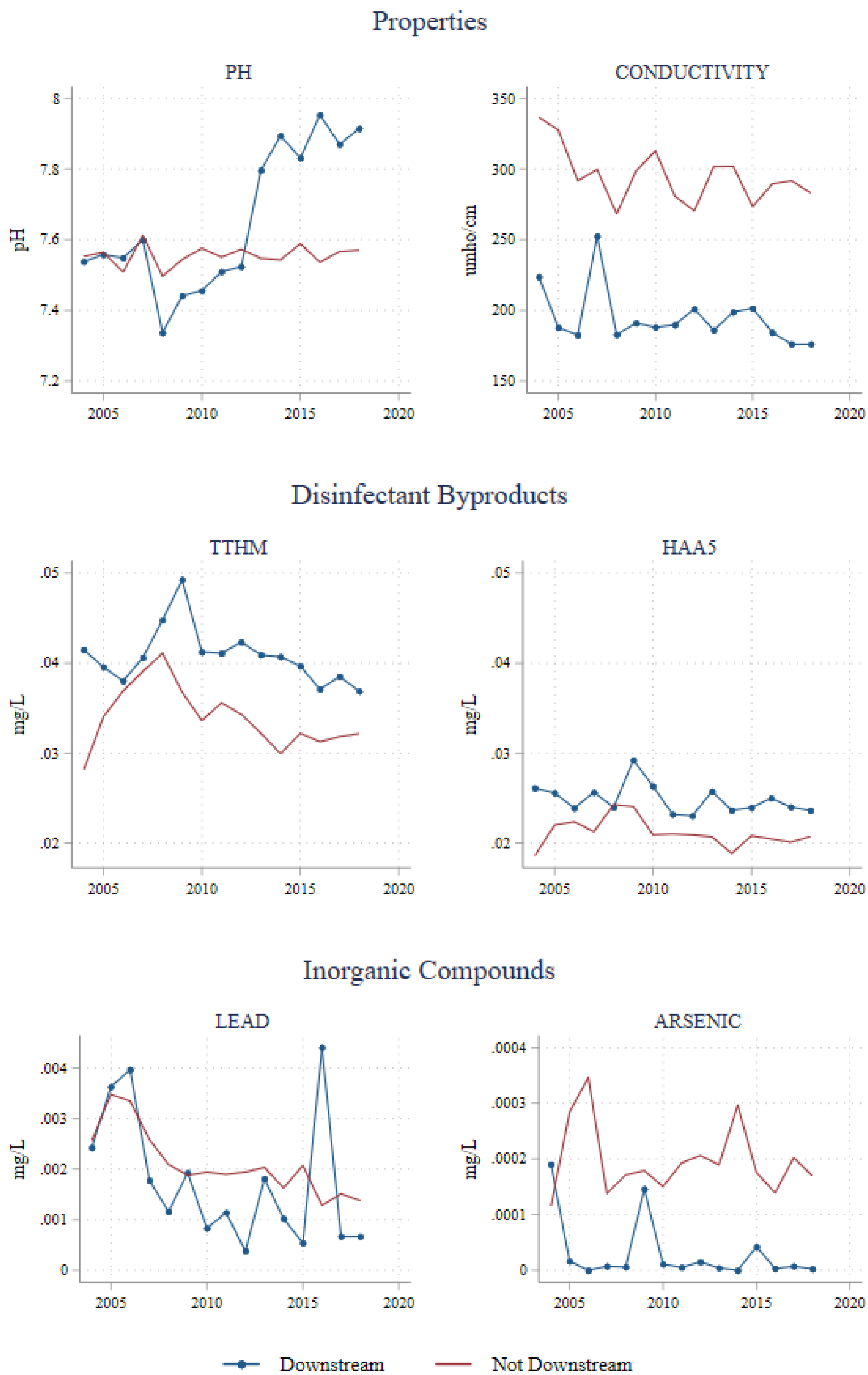


Notes: Each row represents the count of Safe Drinking Water Act violations for any given rule, where the rules are listed down the y-axis. Only municipal water systems designated to be influenced by coal ash according to the Southern Environmental Law Center are included. The top panel provides a breakdown by type of infraction, while the bottom panel shows the state-level burden of these violations.

Figure 11: Safe Drinking Water Act Violations in Municipal Water Systems Downstream from Coal Ash Sites (1980-2018)

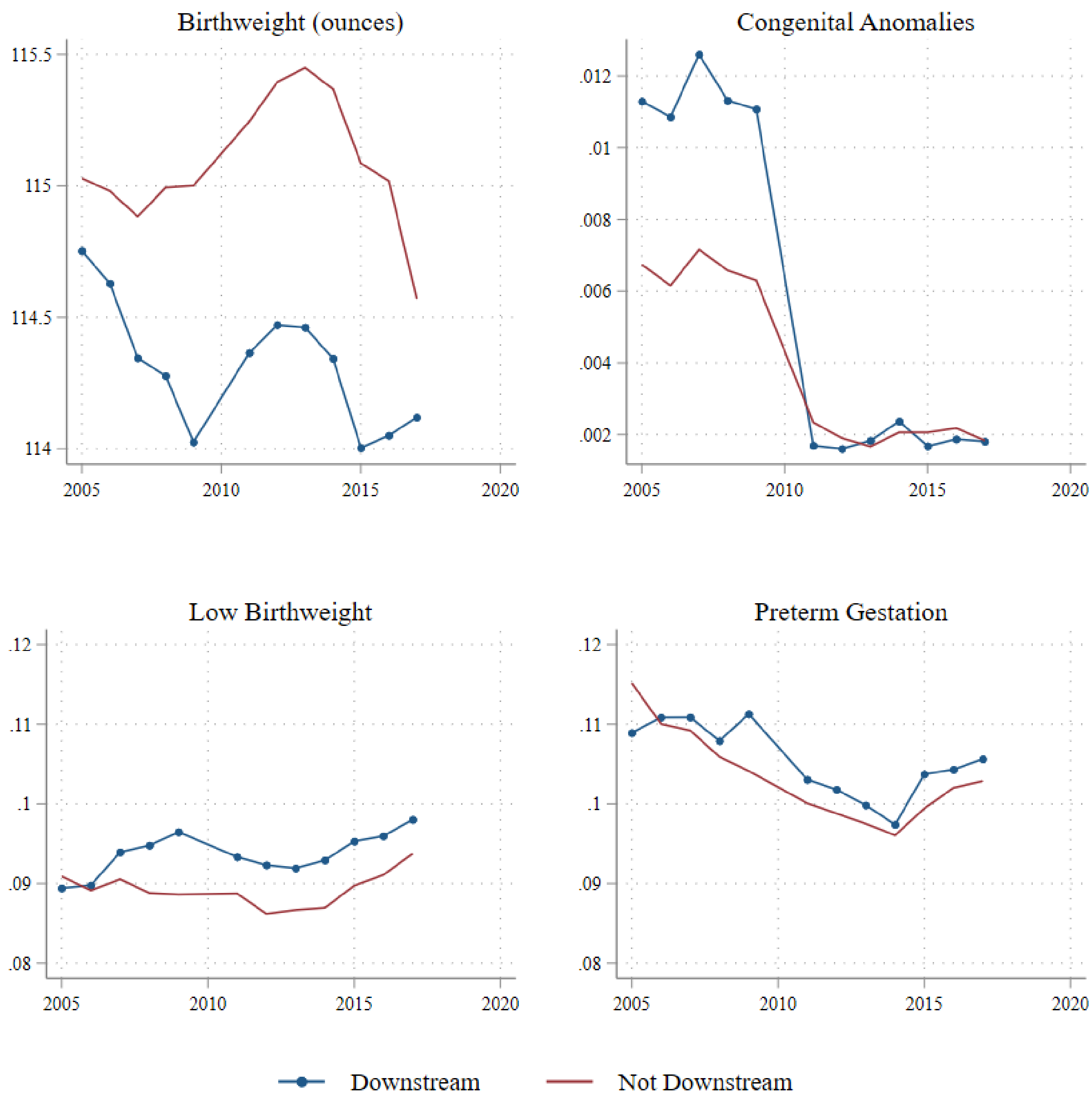
Notes: Each dot represents the count of violations in the given category in a year. Only water systems sourcing from coal-ash affected waters according to the Southern Environmental Law Center are included. The top panel provides a breakdown by type of infraction, while the bottom panel shows the state-level burden of these violations.

Figure 12: Municipal Water Quality Criteria Water Quality Criteria (2005-2018)



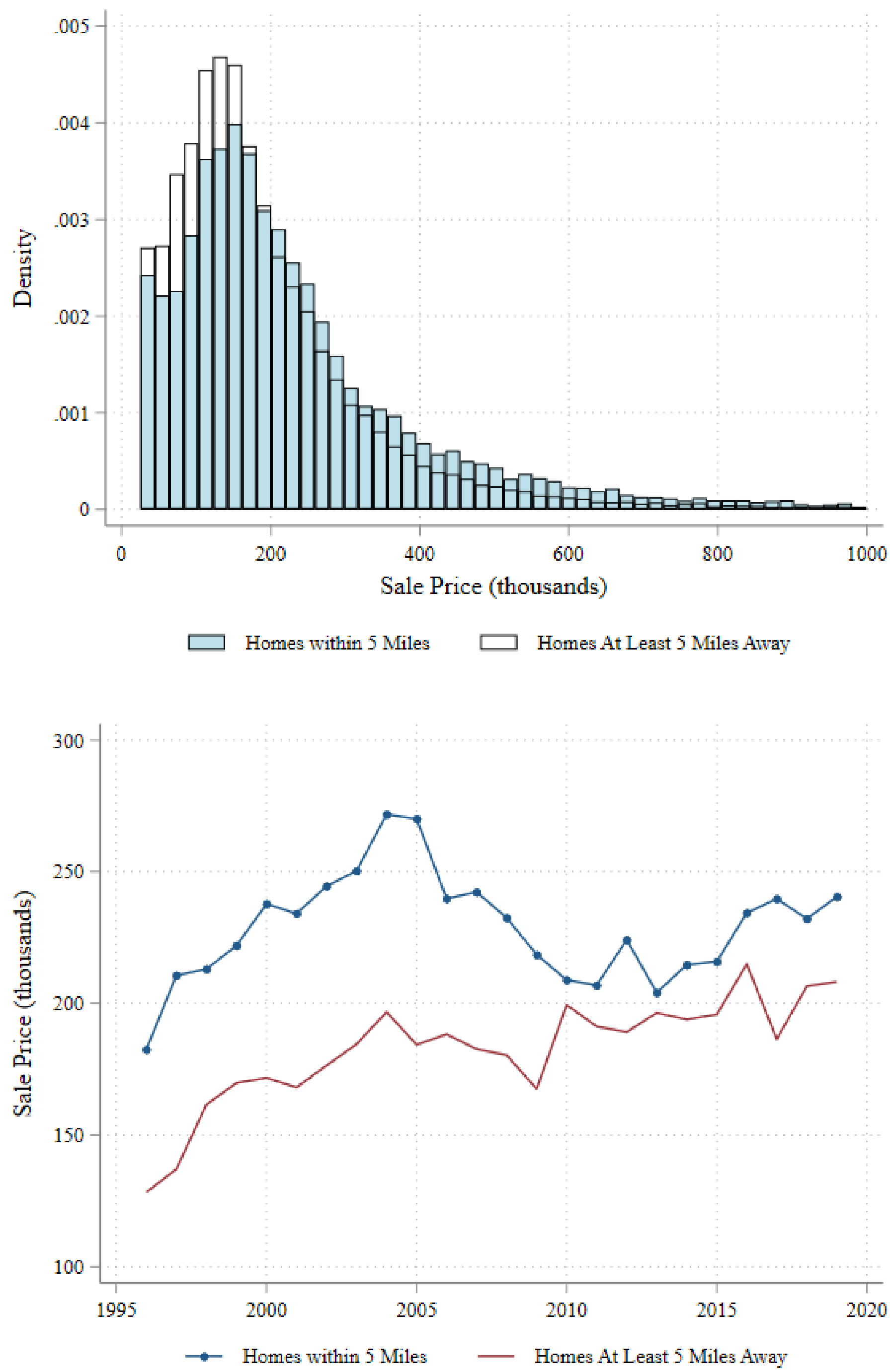
Notes: Average value calculated across all water system tests in Alabama, Georgia, North Carolina, South Carolina, and Virginia. Downstream water systems are water systems sourcing from coal-ash affected waters according to the Southern Environmental Law Center. Not downstream water systems are all other active water systems. Municipal water systems sourcing from surface and groundwater are included, as are water systems of public, private, and transient designations.

Figure 13: Fetal Health Indicators (2005-2017)



Notes: Downstream represents births to mothers ever known to live in service zones of municipal water systems using coal-ash affected source waters according to the Souther Environmental Law Center. Not downstream represents all other births. Low birthweight is the rate of all newborns born weighing less than 2500 grams. Preterm gestation represents newborns born with estimated gestation length of less than 37 weeks. Congenital anomalies include all fetal abnormalities except chromosomal disorders. The sharp discontinuity in congenital anomalies in 2010 is due to a change in recording practices in that year. In the pre-2010 forms, practitioners recorded a wider variety of conditions on the regular birth form. After the change to the new form, a smaller subset of conditions are reported.

Figure 14: Home Sale Prices in Counties with Coal Ash Ponds (1996-2019)



Notes: Homes with sale prices over $1m are excluded from both panels. Certain counties do not have sale information before 2009, leading to the sharp change in that year. Counties with no homes within five miles of a coal ash pond are not included.

Tables

Table 1: The Quantity of Coal Ash Released by Facility and Type of Compound (2005-2017)

	Mean	SD	
Facility Containment Information			% Missing
Total Ponds	6.73	(3.52)	0%
Average Acres per Pond	85.52	(112.29)	69%
Height *(ft)*	50.58	(42.67)	71%
Lining	0.31	(0.46)	37%
Leachate	0.22	(0.41)	36%
Average Total Coal Ash Production by Plant (tons)			
Coal Ash	6,002.58	(7656.94)	
Heavy Metals	2,717.59	(3066.78)	
Carcinogenic Compounds	248.04	(297.9)	
Quantity Impounded	6,002.58	(7,646.9)	
Surface Water Releases	173.5	(393.6)	
All–Time Surface–Water Releases by Compound (tons)			RSEI Toxixity
Ammonia	11.9	(25.8)	NA
Antimony	1.8	(8.4)	1300
Arsenic	166.4	(249.9)	3000
Barium	3524.9	(5486.1)	2.5
Beryllium	14.8	(30.6)	250
Chromium	290.2	(317.9)	170
Cobalt	99.6	(143.9)	NA
Copper	359.3	(388.0)	750
Lead	155.8	(161.1)	8800
Manganese	509.6	(534.7)	3.6
Mercury	0.002	(0.003)	5000
Nickel	253.0	(280.1)	10
Nitrate	45.7	(264.9)	0.31
Selenium	16.5	(35.5)	100
Thallium	19.3	(66.8)	7100
Vanadium	632.7	(652.6)	71
Zinc	404.2	(449.8)	1.7
Plant-Year Observations with Positive Releases	526		
Steam–Generating Coal Electricity Plants	63		

Mean coefficients reported; standard deviations in parentheses. Observations in the second panel are at the plant level, reflecting averages totals across all plants in all years from 2005-2017. The third panel displays average sum of all surface water releases by compound across pollution release sites.

Table 2: Analyte Testing, Violation Rates, and Water System Characteristics 2005-2017

	Within 25 Miles Downstream		Not Within 25 Miles Downstream	
Surface Water Monitors (2005-2017)				
Arsenic (mg/l)	0.3958	(1.8176)	0.7785	(6.877)
Chromium (mg/l)	1.9103	(8.9721)	2.7691	(15.1431)
Conductivity (us/cm)	8994.3	(14089.9)	5030.7	(11422.4)
Dissolved Oxygen (mg/l)	5.073	(2.688)	7.393	(24.506)
Lead (mg/l)	1.0357	(4.8987)	3.6671	(50.27)
PH	7.32	(0.605)	7.27	(0.753)
Selenium (mg/l)	0.1218	(0.7242)	0.1115	(0.5329)
Temperature (c)	24.310	(7.598)	19.639	(12.640)
Monitor Observations	748,988		4,848,838	
Monitors	2,064		122,163	
Municipal Water Systems				
Service Population (thousands)	50.732	(97.585)	2.308	(19.691)
Service Connections (thousands)	20.412	(40.155)	0.517	(5.46)
Age in 2018	35.62	(6.34)	27.334	(11.72)
State Regulatory Monitoring Tests (2005-2017)				
Arsenic (mg/l)	0.00002	(0.0005)	0.0020	(0.4723)
Conductivity (us/cm)	183.44	(264.4)	299.10	(1012.6)
Lead (mg/l)	0.0017	(0.0309)	0.0058	(2.423)
Haloacetic Acids (mg/l)	0.0246	(0.0150)	0.0228	(0.4034)
PH	7.796	(.6041)	7.725	(0.6806)
Trihalomethanes (mg/l)	0.0417	(0.0219)	0.0359	(0.4431)
Safe Drinking Water Inventory System Violations (2000-2018)				
Total Violations	10.396	(14.781)	7.996	(28.322)
Health-Based Violations	2.734	(4.145)	0.7357	(2.9364)
Annual Violation Rate	0.1670	(0.3730)	0.1285	(0.3347)
Health-based Violation Rate	0.0698	(0.2549)	0.0225	(0.1482)
Maximum Contaminant Level	0.0511	(0.2201)	0.0197	(0.1390)
Monitoring Violation	0.0901	(0.2864)	0.0935	(0.2912)
Reporting Violation Rate	0.0344	(0.1822)	0.0371	(0.1890)
Treatement Technique	0.0219	(0.1463)	0.0029	(0.0542)
Arsenic	0.0047	(0.0683)	0.0014	(0.0374)
Consumer Confidence Rule	0.0279	(0.2092)	0.0218	(0.2185)
Disinfectant Byproducts	0.1771	(0.7811)	0.0308	(0.3496)
Inorganic Compounds	0.0477	(0.7468)	0.0165	(0.4333)
Lead and Copper	0.0109	(0.1287)	0.0163	(0.1911)
Public Notice	0.0224	(0.2824)	0.0603	(0.6036)
Volatile Organic Chemicals	0.0711	(1.3958)	0.0688	(1.6584)
Water System Samples	162,790		1,185,225	
Water System Years	42,722		491,892	
Water Systems	193		3,839	

Mean coefficients reported; standard deviations in parentheses. Observations are at the water system and water-system-year level. Surface monitor sample restricted to samples in streams, lakes, or rivers. Observations include only monitors reporting results for arsenic, conductivity, lead, or pH. Municipal water system sample restricted to community water systems not sourcing from ground water. Sample time window is 2005-2017 for surface water and municipal monitoring information and 2000-2018 for Safe-Drinking Water Inventory System (SDWIS) violation reports. *The total number of samples taken in a given year, on average, of the listed analytes.

Table 3: Mother, Birth, and Home Sale Information in Potentially Affected and Unaffected Regions

	Ever Served by Affected Municipal Water System		Never Served by Affected Municipal Water System	
Mother Characteristics (2005-2017)				
Age	27.58	(5.99)	27.54	(6.01)
Asian	0.042	(0.201)	0.031	(0.173)
Black	0.303	(0.459)	0.212	(0.409)
Hispanic	0.161	(0.367)	0.155	(0.362)
White	0.552	(0.497)	0.656	(0.478)
Married	0.567	(0.495)	0.604	(0.489)
HS diploma or Less	0.424	(0.494)	0.443	(0.496)
Prenatal Visits	11.86	(4.27)	12.20	(4.23)
Tobacco	0.089	(0.286)	0.104	(0.305)
Hypertension*	0.049	(0.217)	0.044	(0.204)
Diabetes*	0.039	(0.194)	0.036	(0.187)
Birth Characteristics (2005-2017)				
Ounces	114.32	(21.82)	115.08	(21.84)
Low Birthweight (2500 grams)	0.094	(0.291)	0.089	(0.285)
Preterm Gestation (37 weeks)	0.106	(0.307)	0.103	(0.304)
Congenital Anomalies	0.005	(0.069)	0.003	(0.053)
Female	0.489	(0.499)	0.488	(0.499)
Movers	0.150	(0.357)	0.098	(0.298)
PM 2.5 Mean	10.49	(2.29)	9.97	(2.28)
PM 2.5 Max	16.32	(4.84)	15.97	(5.03)
Birth Observations	356,868		1,101,204	
Unique Mothers	241,188		779,974	
	Homes Within 5 Miles of Ash Pond		Homes Not Within 5 Miles of Ash Pond	
Properties and Sales (1996-2018)				
Average Sale Value (thousands)	228.1	(201.2)	192.7	(163.1)
Avg. No. Sales	1.537	(0.938)	1.590	(0.985)
Lotsize (thousands sq ft.)	50.6	(351.5)	110.6	(1,080.0)
Bedrooms	2.797	(1.289)	2.678	(1.615)
Baths	1.811	(0.999)	1.753	(1.231)
Home Sales	37,224		248,743	
Unique Homes	24,699		157,000	

Mean coefficients reported; standard deviations in parentheses. Sample of mothers includes only residents of addresses within any municipal water service zone. Sample of home sales limited to 14 counties with a coal ash containment facility. *Refers to either gestational diabetes and gestational hypertension or pre-existing diabetes and pre-existing hypertension.

Table 4: Water Quality Indicators of Surface Waters Downstream from Coal Ash Sites (2005-2017)

	Downstream (1)	Releases (binary) (2)	Releases (continuous) (3)
Inorganic Compounds			
Arsenic	0.0863**	0.0576	0.0021
Dep. Var. Mean = 0.4596	(0.0373)	(0.0366)	(0.0022)
Observations	[36,715]	[36,715]	[36,715]
Chromium	0.1538	-0.0313	-0.0018*
Dep. Var. Mean = 1.627	(0.3353)	(0.0757)	(0.0007)
Observations	[57,089]	[57,089]	[57,089]
Lead	0.1730	0.4992	-0.0124***
Dep. Var. Mean = 1.516	(0.1662)	(0.3538)	(0.0020)
Observations	[61,731]	[61,731]	[61,731]
Selenium	0.0190***	0.0179***	0.0008*
Dep. Var. Mean = 0.0536	(0.0066)	(0.0020)	(0.0005)
Observations	[28,928]	[28,928]	[28,928]
Properties			
Conductivity	1567.42	-333.19**	1.050
Dep. Var. Mean = 5279.45	(1932.85)	(147.58)	(3.077)
Observations	[1,119,939]	[1,119,939]	[1,119,939]
Dissolved Oxygen	-0.6367**	0.0237	-0.0006
Dep. Var. Mean = 6.982	(0.2491)	(0.0362)	(0.0011)
Observations	[1,097,515]	[1,097,515]	[1,097,515]
pH	0.1948***	0.0464**	0.0007
Dep. Var. Mean = 7.28	(0.1384)	(0.0174)	(0.0011)
Observations	[1,227,668]	[1,227,668]	[1,227,668]
Temperature	1.0293***	-0.0435	-0.0009*
Dep. Var. Mean = 20.275	(0.0407)	(0.0407)	(0.0006)
Observations	[1,240,357]	[1,240,357]	[1,240,357]
Monitor		✓	✓
Watershed-by-Year	✓	✓	✓
Watershed-by-Year	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the monitor and watershed in parentheses. The first column regresses an indicator for whether a monitor is within 25 miles downstream of a coal ash release site on a compound concentration or property depicted in the row title. Column (2) regresses an indicator for whether coal ash is released upstream of a monitor in year t on the compound's concentration. Column (3) regresses a continuous measure of the sum of coal ash released upstream in any given year on the water quality indicator. Controls include a dummy for abnormal weather events, dummy indicators for the hydrologic conditions of the river system, and dummy indicators for the sample medium (e.g., sediment or surface water). Analytic sample weights included. All regressions performed assuming coal ash influence cutoff distance of 25 miles (40 kilometers). Note mean analyte levels may differ from figures because analytes of different media are included with corresponding controls.

Table 5: Water Quality Indicators of Municipal Waters Downstream from Coal Ash Sites (2005-2017)

	Downstream	Releases Binary	Annual Tons Released
	(1)	(2)	(3)
Disinfectant Byproducts			
Haloacetic Acids (HAA5)	-0.0026*	-0.0032	-0.0001
Dep. Var. Mean= 0.0220	(0.0010)	(0.0047)	(0.0001)
Observations	[249,467]	[249,467]	[249,467]
Trihalomethanes (TTHM)	0.0007	-0.0099	-0.0003
Dep. Var. Mean= 0.0362	(0.0030)	(0.0088)	(0.0002)
Observations	[249,132]	[249,132]	[249,132]
Inorganic Compounds			
Arsenic	-0.0058	0.0084	0.0007
Dep. Var. Mean= 0.0027	(0.0075)	(0.0123)	(0.0009)
Observations	[46,729]	[46,729]	[46,729]
Lead	0.0081	-0.0033	0.0035***
Dep. Var. Mean= 0.0070	(0.0089)	(0.0014)	(0.0003)
Observations	[364,643]	[364,643]	[364,643]
Properties			
Conductivity	-120.43	45.99**	3.37***
Dep. Var. Mean = 291.00	(75.03)	(19.10)	(1.08)
Observations	[29,697]	[29,697]	([29,697]
pH	-0.3765**	-0.0172***	0.0070**
Dep. Var. Mean= 7.76	(0.0427)	(0.0001)	(0.0008)
Observations	[71,059]	[71,059]	[71,059]
Water System		✓	✓
State-by-Year	✓	✓	✓
Month	✓	✓	✓
Watershed	✓		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the municipal water system and state in parentheses. The first column regresses an indicator for whether a municipal water system sources from coal-ash affected waters according to the Southern Environmental Law Center. Column (2) regresses an indicator for whether coal ash is released upstream of a municipal water system's intake in year t on the compound's concentration. Column (3) regresses a continuous measure of the sum of coal ash released upstream in any given year on the water quality indicator. Transient non-community water systems are excluded, as are any water systems with fewer than three tests of the given water quality analyte over the sample period. Analytic sampling weights included. All regressions control for the facility type where the test occurred.

Table 6: Upstream Coal Pollution and the Probability of a Water Quality Violation (2000-2018)

	Time-Varying Binary Coal Ash Releases		Time-Varying Continuous Coal Ash Releases	
	(1)	(2)	(3)	(4)
	β	dy/dx	β	dy/dx
Violations by Infraction Type				
Any Violation	-0.0370	-0.0045	-0.0002	-0.0005
Dep. Var. Mean = 0.1278	(0.0279)	(0.0183)	(0.0002)	(0.0004)
Health-based Violation	-0.0035	0.0121**	-0.0001	-0.0000
Dep. Var. Mean = 0.0228	(0.0148)	(0.0062)	(0.0001)	(0.0001)
Maximum Contaminant Level	-0.0004	0.0103*	-0.0000	-0.0000
Dep. Var. Mean = 0.0199	(0.0138)	(0.006)	(0.0000)	(0.0001)
Monitoring Violation	-0.0581*	-0.0165	-0.0001	-0.0001
Dep. Var. Mean = 0.0935	(0.0252)	(0.0164)	(0.0002)	(0.0002)
Reporting Violation	0.0320*	0.0250**	-0.0000	-0.0001
Dep. Var. Mean = 0.0370	(0.0173)	(0.0106)	(.0001)	(.0001)
Violations by Rule Type				
Arsenic	0.0078**	0.0034***	2.77e-06	8.80e-06
Dep. Var. Mean = 0.0014	(0.0040)	(0.000)	(0.0002)	(6.91e-06)
Disinfectant Byproducts	-0.0071	0.0033	0.0010**	-0.0001
Dep. Var. Mean = 0.0134	(0.012)	(0.0038)	(0.0001)	(0.0000)
Inorganic Compounds	0.0088**	0.0039***	0.0015**	-4.66e-06
Dep. Var. Mean = 0.0024	(0.0045)	(0.000)	(0.0000)	(9.52e-06)
Lead and Copper	-0.0077	-0.0109**	-9.85e-06	-0.0003
Dep. Var. Mean = .0112	(0.0103)	(0.0000)	(0.0004)	(0.0003)
Volatile Organic Compounds	0.0015	0.0012	2.33e-06	8.71e-06
Dep. Var. Mean = 0.0024	(0.0048)	(0.0021)	(0.0000)	(0.0000)
Observations	247,794	247,794	247,794	247,794
Water Systems	15,493	15,493	15,493	15,493

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the water system in parentheses. Standard error of the marginal effect dy/dx calculated using the delta method. Dependent variable means are the average of all active water system-year combinations, where a water system-year is equal to one if the water system experienced a violation of the specified type and zero otherwise. Time-varying binary coal ash releases is equal to one if a municipal water system was potentially affected by any coal ash releases in a given year and zero otherwise. Time-varying continuous coal ash releases is equal to the tons of coal ash released within 25 miles upstream and zero otherwise. In the probit model, controls include system size dummies, federal water system type (e.g., community water system), owner type, school water system, surface water-sourced system, protected source water system, and age of the municipal water system.

Table 7: CCRs, Water Quality, and Fetal Health 2005-2017

	Full Sample				Mothers with a High School Degree or Less			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Birthweight (ozs)	Low Birthweight	Preterm Gestation	Congenital Anomalies	Birthweight (ozs)	Low Birthweight	Preterm Gestation	Congenital Anomalies
Panel A.								
Downstream	-1.2411***	0.0171***	0.0126*	0.0032	-2.2118***	0.0286***	0.0255**	0.0021
	(0.4127)	(0.0065)	(0.0020)	(0.0017)	(0.6251)	(0.0107)	(0.0109)	(0.0034)
PM2.5	-0.949***	0.0111***	0.0195***	0.0001	-1.001**	0.0126***	0.0230***	0.0002
	(0.0514)	(0.0007)	(0.0012)	(0.0002)	(0.0794)	(0.0012)	(0.0012)	(0.0003)
Panel B.								
Releases (binary)	0.4147***	-0.0029	-0.0043**	-0.0007	0.8128***	-0.0068**	-0.0087**	-0.0014*
	(0.1241)	(0.0021)	(0.0020)	(0.0004)	(0.2023)	(0.0033)	(0.0034)	(0.0006)
PM2.5	-0.954***	0.0111***	0.0195***	0.0001	-1.018***	0.0126***	0.023***	0.0002
	(0.0514)	(0.0007)	(0.0008)	(0.0002)	(0.0794)	(0.0012)	(0.0013)	(0.0003)
Panel C.								
Releases (continuous)	0.0143	-0.0002	-0.0088**	-0.0001	0.0161	-0.0004	-0.0002	-0.0001*
	(0.0127)	(0.0002)	(0.003)	(0.0002)	(0.0184)	(0.0005)	(0.0003)	(0.0001)
PM2.5	-0.952	0.0111***	0.0231***		-1.012***	0.0195***	0.0231***	0.0002
	(0.0514)	(0.0007)	(0.0013)	(0.0008)	(0.0794)	(0.0012)	(0.0018)	0.0003
Mother Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Zipcode Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	114.89	0.0903	0.1040	0.0044	114.89	0.0903	0.1040	0.0044
Observations	747,468	747,468	747,468	747,468	303,110	303,110	303,110	303,110

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the mother in parentheses. Mother fixed effects included. Low birthweight refers to births of less than 2500 grams. Preterm gestation represents a birth with gestation of less than 37 weeks. Mean PM 2.5 represents the average PM2.5 concentration in the mother's county of residence over the entire gestational period, while max PM2.5 squared is the the squared maximum monthly maximum PM2.5 level over the length of gestation. Additional controls include gender of the newborn, mother diabetes or hypertension, six dummy bins for number of clinic visits during gestation, mother's educational status, mother's age, mother's age squared, and indicators for smoking or drinking during gestation.

Table 8: CCRs and Fetal Health by In- and Out-Movers 2005-2017

	(1) Birthweight (ozs)	(2) Low Birthweight	(3) Preterm Gestation	(4) Congenital Anomalies
In Movers (=1)	-1.8378***	0.0280***	0.0211**	-0.0001
	(0.4419)	(0.0069)	(0.0073)	(0.0022)
Out Movers (=1)	0.5801	-0.0100	-0.0023	-0.0055**
	(0.4342)	(0.0068)	(0.0072)	(0.0021)
PM2.5	-0.9502***	0.0111***	0.0196***	0.0001
	(0.051)	(0.0007)	(0.0008)	(0.0002)
Mother Fixed Effects	✓	✓	✓	✓
Zipcode Fixed Effects	✓	✓	✓	✓
Dep. Var. Mean	114.89	0.0903	0.1040	0.0044
Observations	747,468	747,468	747,468	747,468

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the mother in parentheses. Mother fixed effects included. Low birthweight refers to births of less than 2500 grams. Preterm gestation represents a birth with gestation of less than 37 weeks. Mean PM 2.5 represents the average PM2.5 concentration in the mother's county of residence over the entire gestational period, while max PM2.5 squared is the the squared maximum monthly maximum PM2.5 level over the length of gestation. Additional controls include gender of the newborn, mother diabetes or hypertension, six dummy bins for number of clinic visits during gestation, mother's educational status, mother's age, mother's age squared, and indicators for smoking or drinking during gestation.

Table 9: How Mandatory House Well Testing Affected House Sale Values After the Coal Ash Management Act of 2014

	(1)	(2)	(3)	(4)	(5)	(6)
Distance Cutoff	1 Mile	2.5 Miles	5 Miles	1 Miles	2.5 Miles	5 Miles
Near*Post	-45,295.4***	-36,406.9***	-24,691.8***	-37,333.5***	-16,090.1***	-12,673.9***
	(17,403.2)	(5,151.2)	(2,371.5)	(12,591.3)	(2,784.1)	(2,229.5)
Mean Sale Price	320,307.6	259,978.8	248,597.3	320,307.6	259,978.8	248,597.3
% Change	-14.1	-13.9	-9.7	-11.6	-6.1	-4.8
Δ Total House Value	-24.4M	-180.2M	-448.2M	-19.9M	-79.6M	-228.7M
City and Year FEs	✓	✓	✓			
House and Year FEs				✓	✓	✓
Home Sales in Sample	226,973	226,973	226,973	163,077	163,077	163,077
Unique Homes	181,669	181,669	181,669	63,963	63,963	63,963
Affected Home Sales	294	2,990	13,540	308	2,238	8,377

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the county in parentheses. The dependent variable is house sale price. The independent variable is the interaction of being within the specified distance of a coal ash pond and an indicator for sales occurring after 2014. Total change in home value is the product of the change in home values and the number of sales after 2014, where the number of sales is 538, 4950, and 18,154, ordered by distance cutoff. Regressions (1) to (3) may have more or fewer observations than (4) to (6) because many homes are not incorporated into cities. The counts of affected homes, unique homes, and sales reflect the number of sales in the regression sample rather than the total number of sales. Sample excludes home sales with valuation in excess of $1.5 million. The Coal Ash Management Act mandated testing drinking wells of homes within 2,500 feet of ash ponds, leading to information disclosure that over 97% of homes had been using well-water considered unsafe to drink by the EPA.

Appendix

7.1 Assigning Downstream Status to Monitors and Water Systems

The National Hydrography Dataset Plus (NHD) is a GIS database of every water network in the United States. It features "edges," or river system segments and polygons identified by their COMID identifier, and "nodes," or midpoints of river system segments or polygons. I use the STARS package, an ArcGIS add-on, to assign coal ash release sites to river system edges in the NHD using the snap tool.[93] I then trace out downstream segments using the downstream tool, which creates polygons for the downstream regions from each coal ash release site. I then calculate distance downstream from each coal ash plant for each river edge, allowing sites with multiple upstream coal ash plants to have at least two unique observations. All monitoring locations in the Water Quality Portal are then joined by nearest spatial location to edges in the NHD. This allows merging river edge information on coal ash releases to water monitoring sites located on those edges. I can then calculate the total quantity of upstream coal ash released across different distance cutoffs, or weight the quantity released by the distance to each plant.

7.2 Assigning Municipal Water System Location

Performing an analysis of the relationship between water pollution and municipal water quality requires relatively accurate placement of wells and intakes. Due to security reasons, the location of these wells or intakes is typically not published online or accessible.[94] Moreover, municipal water systems often have wells or surface water intakes that are many miles away from their service zone, and larger systems typically have many intake locations. To assign municipal water systems to water source locations, I rely on three datasets and multiple linking procedures. First, I secure North Carolina's public water ground- and surface-water supply shapefile.[95] To this, I then add the Southern Environmental Law Center's public water system intake geodatabase, which shows surface-water intake locations for Alabama, Georgia, Tennessee, and Virginia. In some cases, these locations are approximated. Both well and surface water intake locations are included in the SELC database for North and South Carolina. Intake locations accessible online and the SELC geodatabase do not include many intake locations over the remaining states and even some within North and South Carolina. I supplement these data by approximating the remaining intake locations using the Safe Drinking Water Inventory System (SDWIS). SDWIS provides water system addresses, but these addresses

[93] Peterson and Hoef (2014)

[94] A notable exception is North Carolina, which makes available all municipal water system intake locations as a geographic shapefile through its NC Onemap service. However, conversations with state water system planners suggests that even these locations are published with some imprecision for security reasons.

[95] See here to download or see more information.

are inaccurate. They represent the location of the water system managing office or long-distance owner. For example, some water system addresses were in California and New York State, while others were located in larger cities within the same state but hundreds of miles away. I therefore approximate intake location based on service zone city or zipcode, county, and state. I then spatially join these locations to the nearest "downstream" polygons of river segments, excluding any link with a distance greater than 75 kilometers. The assumption is that any link greater that 75 kilometers away is very likely not using, purchasing, or otherwise influenced by the downstream water segment. I only use these approximated locations in instances where the intake or well location is not already known.

7.3 Assigning Air and Water Quality to Birth Residences

The North Carolina State Center for Health Statistics provided residential address information for all births in the state. These addresses included county information, which is used to assign air quality information at the county-month level to each birth. Since a birth is potentially affected by air quality across its entire gestational period, I assign mean and maximum PM 2.5 to each birthday-county-gestation length combination. The mean fine particulate matter control is the mean level observed in the county over the entire gestational period, while the maximum value is the maximum county-month value over the entire gestational period. Averaging over the entire gestational period allows children with the same birthday and county of residence to potentially have different air quality controls if their gestational length differs. For example, a birth with gestation length of nine months receives a particulate matter control of the average of each of the nine months prior to birth, while a birth in the same county in the same month with gestational length of eight months will have a mean particulate matter control constructed over a different time period. Likewise, the maximum particulate matter control, the highest monthly average PM 2.5 observed during the entire gestational period, could differ across births within the same county and month if gestational length differs.

Assigning gestational periods to water quality information first requires linking residences to municipal water service zones. I therefore geo-code a statewide property parcel database to geographic shapefiles of all municipal water service zones. After linking these addresses to service zones, I string match the addresses listed in the birth certificates database to the addresses in the state parcel database using the Stata program matchit.[96] Next, I list out all North Carolina cities associated with coal-ash sourcing water systems according to the Southern Environmental Law Center, and I merge any unmatched births to these city-water system combinations where applicable. After these steps, roughly 700,000 of 1.6 million birth residences are matched. Finally, I create a variable for the mode municipal water system by zipcode, and I replace any missing water

[96] Raffo (2015).

system links with the mode water system for that zipcode. Because this imputation procedure is likely imperfect, I flag these imputed water system links and control for the imputation in all birth regressions. After all merges are complete, 1.1 million birth residences are linked to municipal water systems. Since roughly two thirds of individuals in North Carolina use municipal water and the remainder use home wells, the linkage procedure assigned roughly the correct proportion of addresses to municipal water systems.

Table 1: Surface Water Monitoring Tests in the Water Quality Portal (2005-2017)

Constituent *(units)*	N	%BDL	Min	Median	Max	Monitors	Watersheds
Aluminum (mg/kg)	110,768	20.21	0	0.102	120,000	5402	230
Antimony (mg/kg)	40,714	58.09	0	0.001	55	3998	199
Arsenic (mg/kg)	107,107	53.61	0	0.001	430	5959	232
Beryllium (mg/kg)	50,839	69.54	0	0.0003	55	2785	160
Bromide (mg/kg)	10,064	20.21	0	0.038	60.3	448	70
Cadmium (mg/kg)	151,379	71.72	0	0.0005	1100	7821	236
Calcium (mg/kg)	104,525	4.35	0	7.8	52000	6026	234
Chemical oxygen demand (mg/kg)	15,366	15.78	0	7.8	1700	740	102
Chromium (mg/kg)	147,469	65.43	0	0.001	970	7615	236
Conductivity (uS/cm)	2,237,496	0.22	-2.47	167	511170	20629	239
Copper (mg/kg)	175,735	61.93	0	0.002	3100	8065	236
Fixed suspended solids (mg/kg)	104,996	4.40	0	8	26067	2435	62
Iron (mg/kg)	192,100	13.50	0	0.339	314000	8185	236
Lead (mg/kg)	156,963	61.56	0	0.001	11000	8015	236
Magnesium (mg/kg)	106,114	4.86	0	2.42	21300	6101	236
Manganese (mg/kg)	191,461	17.03	0	0.048	26000	7904	236
Mercury (mg/kg)	123,183	61.66	0	0.0002	274	7044	234
Nickel (mg/kg)	139,411	61.14	0	0.0258	490	7336	236
Nitrogen (mg/kg)	220,222	11.21	0	0.56	4587	6698	111
pH	2,762,327	0.09	0	7.24	16	21559	240
Phosphorus (mg/kg)	706,766	10.79	0	0.05	8700	17276	238
Selenium (mg/kg)	93,791	64.52	0	0.0007	25	5423	231
Silicon (mg/kg)	93,791	5.38	0	2.490	53.71	223	36
Thallium (mg/kg)	39,476	69.14	0	0.0001	100	3483	177
Titanium (mg/kg)	39,476	74.10	0	0.007	14000	1018	83
Total Coliform (MPN/100 ml)	30,102	7.05	0	2200	2.00e+07	302	46
Total dissolved solids (mg/kg)	173,964	2.24	0	81	1010000	3791	173
Total solids (mg/kg)	78,048	1.16	0	104	151000	2953	133
Total suspended solids (mg/kg)	504,347	15.51	0	9.21	38400	14002	239
Total volatile solids (mg/kg)	56,643	1.77	0	8	18500	2106	67
Trihalomethanes (mg/kg)	5,514	79.09	0.0001	0.0003	4.5	202	32
Turbidity (ntu)	674,007	2.62	-1.6	6.7	7417434	13140	239
Vanadium (mg/kg)	20,468	32.83	0	0.0014	570	1348	129
Volatile suspended solids (mg/kg)	39,862	10.89	0	3.6	1150	408	43
Zinc (mg/kg)	182,069	46.63	0	0.01	4500	8063	236

%BDL is the percent of samples that are below the detection limit.

Table 2: Additional Chemical Compounds in Surface Waters Downstream from Coal Ash Sites (2005-2017)

	Ever Affected	Releases (binary)		Releases (continuous)	
	(1)	(2)	(3)	(4)	(5)
Antimony	0.0096	0.00149	0.00003	0.00014***	0.00071***
	(0.00169)	(0.0026)	(0.00002)	(0.00004)	(0.00010)
Cadmium	-0.01937	-0.02575	-0.05171*	0.00009	-0.00055
	(0.04562)	(0.05915)	(0.02911)	(0.00039)	(0.00067)
Copper	-0.00021	-0.00012	-0.00055*	0.00052***	0.00165*
	(0.00397)	(0.00481)	(0.00029)	(0.00011)	(0.00091)
Mercury	-0.01709	-0.02371	0.00257*	-0.00071	-0.00092
	(0.01952)	(0.02629)	(0.00139)	(0.00058)	(0.00121)
Thallium	-0.00008	-0.00012	6.80e-06**	5.74e-06	0.000039***
	(0.00019)	(0.00028)	(2.47e-06)	(5.30e-06)	(8.38e-06)
Turbidity	3.3230	.59735	-17.409	0.04202	-0.1099
	(2.6664)	(1.7026)	(18.477)	(0.03597)	(0.2396)
Zinc	0.01830	0.02136	-0.00253	0.00065***	-0.00103
	(0.02008)	(0.02286)	(0.00268)	(0.00014)	(0.00596)
Monitor			✓		✓
Watershed-Year	✓	✓	✓	✓	✓
Watershed-Month	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors two-way clustered at the monitor and watershed in parentheses. The first column regresses in indicator for whether a monitor is ever within 25 miles downstream of a coal ash release site on a compound's concentration. Columns (2) and (3) regress an indicator for whether coal ash is released within 25 miles upstream in year t on the compound's concentration. Tons released is the total coal ash released into surface waters within 25 miles upstream. All regressions performed assuming coal ash influence cutoff distance of 25 miles (40 kilometers) upstream.

Table 3: Do Counties with Coal Ash Releases Have More Surface Water Pollution from Other Sources? (2005-2017)

	(1) Tons of Surface Water Pollution	(2) Tons of Impounded Pollution
Coal Plant County (=1)	18.45	177.19
	(33.57)	(140.82)
State Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Dep. Var. Mean	74.18	101.23
Observations	6,406	6,406

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state in parentheses. The first column regresses an indicator for whether a county has a coal ash pollution site on the quantity of non-coal ash surface water pollution. The second column regresses an indicator for whether a county has a coal ash site on the quantity of pollution impounded in any landfill.