

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. No previous study has investigated how this form of water pollution may impact municipal water quality or human health. I assess the relationship between coal ash surface water discharges and three relevant outcomes: surface water quality measurements from the Water Quality Portal, municipal system water quality, and an individual birth data-set with mother identifiers and addresses linked to municipal water service zones. Identification relies on geographic variation in downstream status of monitoring sites and municipal water intake locations within small watershed regions. I also incorporate variation arising from plant closures and the relative quantity of coal ash released. I find that coal ash release sites are associated with higher conductivity and pH in both downstream surface waters and municipal water supplies sourced from these waters. Releases of coal ash increase disinfectant byproducts in municipal water systems, and water systems affected by coal ash tend to have more water quality violations for these compounds. I quantify the costs of coal ash water pollution with respect to fetal health and home sales. A newborn potentially exposed to coal ash water pollution is 1 to 1.2 percentage points more likely to be low birthweight compared to an unexposed sibling, although differences are not statistically significant. 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 \$35,000.

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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 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 or 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 at least 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 in the sample used in this paper, the average plant has seven containment landfills totaling 176 acres at an average depth of 50 feet.⁶ At least 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 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 and human health. First, I replicate and generalize previous findings that CCRs affect surface water quality

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

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

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

⁴EPA (2015); Ibrahim (2015); Izquierdo and Querol (2012); Munawar (2018); Shy (1979).

⁵Yao et al. (2015).

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

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

⁸EPA (2015).

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

¹⁰Among 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.

using a larger geographic region and longer time horizon. Next, I estimate the impact of this surface water pollution on municipal water quality. Finally, I assess whether this point-source pollutant may affect human health. To answer these questions, I obtain four 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 four states, municipal water quality violations over six states, and birth records for 1.5 million children born in North Carolina. The sample covers 2005 to 2017. Identification of municipal water quality changes relies on two forms of variation. The first form of variation is “downstream” status of monitoring sites or municipal water intake regions within small watershed regions. The second is temporal variation in the quantity of coal ash released, which occurs naturally from year to year 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 housing willingness-to-pay to avoid coal water pollution by exploiting a legislative change leading to the discovery of unsafe drinking water at 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. 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 similar situations in Flint and Newark.

I find that contemporaneous coal ash releases increase the concentration of heavy metals in downstream surface waters; these include arsenic and lead, among others. Being downstream from a release site is also associated with altered properties of the water such as conductivity and pH. Municipal water systems sourcing from waters potentially affected are also more likely to have baseline differences in water properties. These water systems experience more water quality violations, with the increase driven in part by disinfectant byproducts, inorganic compounds, and lead and copper rule violations, although I find mixed evidence on whether this is driven by contemporaneous pollution releases. Children born in residences served by municipal water systems downstream from active coal ash sites, in comparison to unexposed siblings, are 1 - 1.2 percentage points more likely to be low birthweight, and slightly more likely to be preterm. These newborns are 0.5 to 0.8 ounces lighter than comparable siblings. Newborns of mothers with less education are more affected by coal ash pollution than average exposed children. Fetal health results are insignificant with full controls and standard error clustering. 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. Although health impact estimations provide relatively weak statistical

¹¹Currie et al. (2013).

evidence, the home sale analysis 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.¹² These health consequences are large both in magnitude and relative to the cost of the coal.¹³ 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.¹⁴ 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.¹⁵

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.¹⁶ Third, pressure from the weight of additional CCRs and water cause a leachate of dissolved compounds to flow into groundwater if a containment pond is unlined or poorly lined, affecting public and private wells and eventually also surface waters.¹⁷ 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.¹⁸ In general, these studies cover relatively small geographic regions and provide a snapshot temporal view of local water quality.¹⁹

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 increases

¹²Barreca et al. (2014); Clay et al. (2015, 2016); Kravchenko and Lyerly (2018); Liu et al. (2002); Pershagen et al. (1986).

¹³Jha and Muller (2017) found that the external costs from coal stockpile dust were four times the per-ton cost of the coal itself.

¹⁴Yu et al. (2007).

¹⁵Kravchenko and Lyerly (2018).

¹⁶Coutant 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.

¹⁷Of 14 North Carolina ash ponds, two thirds leach pollution into groundwater.

¹⁸Baba and Kaya (2004); EPA (2015); Kopsick and Angino (1981); L. Carlson and C. Adriano (2009).

¹⁹An exception is EPA (2015), 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.

the quantity of total dissolved solids in the water, which are associated with increased formation of trihalomethanes, a group of disinfectant by-products, during water treatment.²⁰ Bromide, a relatively harmless constituent of coal ash, interacts with chlorine to form another group of disinfectant by-products, haloacetic acids.²¹ 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.²² However, fluctuations in surface water quality leading to corrosivity changes may also pose a public health concern.²³ For example, chloride in coal ash, increasingly present in US surface waters, affects corrosivity and hence lead levels in drinking water.²⁴ 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.²⁵

Animal-based studies demonstrate that coal ash water pollution harms the reproductive health of a wide range of organisms.²⁶ 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.²⁷ Further, disinfectant byproducts may affect fetal health even if the same compounds in similar doses are low-risk to adults.²⁸ Prior work causally 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.²⁹ 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.³⁰ 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

²⁰[Handke \(2009\)](#).

²¹[Cowman and Singer \(1996\)](#); [Heller-Grossman et al. \(1993\)](#); [Liang and C Singer \(2003\)](#).

²²One third of drinking water wells in the United States have potentially corrosive water ([Belitz et al., 2016](#)).

²³[Neffand et al. \(1987\)](#); [Singley et al. \(1984\)](#).

²⁴[Stets et al. \(2012\)](#); [Zhu et al. \(2008\)](#).

²⁵[Davison et al. \(2005\)](#).

²⁶[Gillespie and Baumann \(1986\)](#); [Heinz and Hoffman \(1998\)](#); [Hopkins et al. \(2002\)](#).

²⁷[Clay et al. \(2010, 2018, 2019\)](#); [Gazze \(2015\)](#); [Miranda et al. \(2007\)](#).

²⁸Studies suggest that DBPs increase risk of bladder cancer when ingested at levels currently observed in industrialized countries ([Cantor et al., 2010](#); [Villanueva et al., 2004](#)).

²⁹[Currie et al. \(2013\)](#).

³⁰[Almond and Currie \(2011\)](#); [Osmond and Barker \(1991\)](#).

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.³¹ 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.³² 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 \(2018\)](#). The study also questions the exclusion assumption in a recent instrumental-variables estimation of local health impacts of coal stockpile dust.³³

3 Data

The study makes use of a wide array of information on coal ash disposal practices, surface water quality, municipal water quality, water distribution systems, natality statistics, air pollution measurements, and home sale information.

3.1 The Quantity and Location of Coal Ash Disposal

The Toxic Releases Inventory (TRI) provides facility-location-year information on the quantity of regulated substances released. More than 650 substances are regulated, including many of the compounds present in coal ash. All facilities releasing at least one of these compounds and employing at minimum ten employees must report their pollution release information annually.³⁴ 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 to

³¹[Currie and Walker \(2011\)](#); [Currie et al. \(2017\)](#); [Persico et al. \(2016\)](#).

³²[Amigues et al. \(2011\)](#); [Muller et al. \(2011\)](#).

³³[Jha and Muller \(2017\)](#).

³⁴Self-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.

releases taking place between 2005-2017 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. [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.³⁵

3.2 Surface Water Quality Monitoring and Daily Discharge

Surface water quality information comes from the Water Quality Portal (WQP), the largest standardized water quality dataset currently in existence.³⁶ 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 million 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.³⁷ I limit the sample to monitoring sites located in lakes, rivers, and streams. I also limit the analysis to water quality analytes potentially related to coal ash water pollution in addition to a few placebo variables.³⁸ See [Appendix Table 1](#) for additional compounds not included in this analysis. All sample results that do not detect the tested compound are replaced with zeros. Measurements are converted to a standardized unit where possible (for example, milligrams/liter). Observations without convertible units of measurement are dropped. I except pH from this decision rule and instead drop any pH observations outside the standard scale from 0-16. After cleaning, the sample consists of 12 million measurements across 28,000 monitoring sites and 35 analytes. I limit this sample further to four primary analytes, leaving 4.5 million observations over 24,000 monitoring sites. Summary statistics are presented in [Table 2](#).

3.3 Municipal Water Quality Violations, Infrastructure, and Monitoring

The Safe Drinking Water Inventory System (SDWIS) and state environmental protection divisions provide information on municipal water quality.³⁹ This study uses reports on violations, water system summaries,

³⁵The 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.

³⁶[Read et al. \(2017\)](#).

³⁷USGS 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.

³⁸[EPA \(2015\)](#); [Ibrahim \(2015\)](#); [Izquierdo and Querol \(2012\)](#); [Munawer \(2018\)](#).

³⁹State 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.

water system details, and geographic area obtained through the SDWIS advanced search.⁴⁰ 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, and geographic area describe the population served, the number of facilities and service connections, and the geographic service region.⁴¹ I supplement SDWIS with state-provided water quality monitoring tests in Alabama, Georgia, North Carolina, and South Carolina from 2005-2017. Monitoring tests are samples of a water quality analyte taken at one facility.⁴² 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.⁴³ 166 analytes are regularly tested across the sample states. These analytes may be grouped into 14 pollution classes. I limit the sample of monitoring tests to only those that occur at treatment plants and distribution centers (excluding, for example, tests of wells). For all samples that do not detect the given compound, I replace the observed value with zero. I supplement SDWIS data with state monitoring tests for two reasons. First, violation history provides a snapshot glimpse 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.⁴⁴ It is likely that water systems sourcing from coal-ash-affected waters take precautionary treatment measures or perform compliance activities after any violation. Summary statistics for SDWIS violations and state-level monitoring tests are presented in Table 2. Water systems affected by coal ash tend to have fewer total SDWIS violations than comparable non-affected water systems, although they have nearly twice as many health-based violations as other water systems. Ash-affected water systems have higher levels of violations for many toxic inorganic compounds such as arsenic, mercury, and thallium.

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, and presence of a congenital anomaly. They also include maternity characteristics including age, education level, race, marital status, and smoking behavior, among others.⁴⁵ 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.

⁴⁰<https://ofmpub.epa.gov/apex/sfdw/f?p=108:1::NO:1::>

⁴¹Geographic service regions may be a town, a zipcode, or a county centroid if missing more precise information.

⁴²For 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/kg.

⁴³Currie et al. (2013).

⁴⁴Bennear et al. (2009).

⁴⁵Paternal characteristics are limited to demographic information, and these records are often incomplete.

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.⁴⁶ Birth records with missing addresses or mother’s names are excluded from the sample. Similarly, addresses not corresponding to a service zone are dropped. The natality statistics correspond to three separate types of reporting forms, one for 2005-2009, a transition form for 2010, and then another for 2011-2017. Although all forms record certain information in the same format, such as birthweight, other variables change across birth reporting forms. For example, race and education status report different categories across the two reporting forms. Summary statistics are presented in [Table 3](#).

3.5 Satellite-Based Monthly Air Quality

Air quality is an important determinant of fetal health.⁴⁷ 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.⁴⁸ 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.⁴⁹ A recent study nevertheless demonstrates very similar fetal health outcomes using both satellite-based and monitor-based air quality measurements at the county level.⁵⁰

3.6 Home Sale Prices

I obtain home sale tax records for twelve counties with coal ash ponds North Carolina.⁵¹ 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

⁴⁶Property 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.

⁴⁷[Chay and Greenstone \(2003\)](#); [Currie and Walker \(2011\)](#); [Currie et al. \(2008\)](#); [Jha and Muller \(2017\)](#)

⁴⁸[van Donkelaar et al. \(2019\)](#).

⁴⁹[Fowlie et al. \(2019\)](#).

⁵⁰[Alexander and Schwandt \(2019\)](#).

⁵¹Buncombe, Cleveland, Catawba, Chatham, Gaston, New Hanover, Person, Robeson, Rowan, Rockingham, Rutherford, and Stokes counties are included in the analysis.

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](#).

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:

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

In [Equation 1](#), Y_{imwt} is the arsenic, conductivity, lead, or pH detected at a given monitor i in month m , watershed w , and year t .⁵² [Equation 1](#) includes fixed effects for monitor η_i , watershed-month η_{wm} , and watershed-year η_{wt} . 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 a binary equal to one if a monitor is ever downstream from an active release site.⁵³ In the second, Ash_{it} is a binary for 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 .⁵⁴ 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

⁵²Watershed 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.

⁵³In this procedure, monitor fixed effects are dropped, leaving only watershed-year and watershed-month fixed effects.

⁵⁴With multiple plants, the measure is calculated as: $Ash_{mt} = \sum_p 1[Downstream_m] * TonsReleased_{pt}$, where p represents a steam electricity generating coal power plant.

in levels of water quality analytes compared to themselves in previous years. 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.⁵⁵ 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 impacts a water system.⁵⁶ 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.

4.2 Municipal Water Quality

Local geography, source water, system design, and homeowner characteristics influence municipal water quality.^{57 58} 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.⁵⁹ To determine the relationship between coal ash water pollution and the outcomes of state regulatory monitoring tests, I address these factors with a water system-facility panel fixed effects specification.

⁵⁵Peterson et al. (2007).

⁵⁶EPA (2015).

⁵⁷Gray and Shimshack (2011); Pieper et al. (2016).

⁵⁸Water 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.

⁵⁹Gray and Shimshack (2011).

Consider the following regression:

$$y_{fms} = \beta Ash_{ft} + \eta_f + \eta_{st} + \eta_m + \epsilon_{fms} \quad (2)$$

y_{fms} is the concentration of haloacetic acids, trihalomethanes, arsenic, or lead, or the conductivity or pH level observed in municipal water system facility f , state-year st , and month m . Ash_{ft} is 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 applied to all water-system facilities f within the municipal water provider.⁶⁰ η_f is a water system facility 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. I adopt water system-facility fixed effects, rather than water system fixed effects, to control for unobservable factors that differ across facilities within the same water system. 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 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_{ft} representing the total tons released upstream, I test two alternative formulations of Ash_{ft} . In the first, Ash_{ft} 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. A time-varying binary version of Ash_{ft} allows different water systems to be affected differently by varying quantities of coal ash pollution; since the permissible quantity of coal ash released is likely endogenous to local watershed characteristics and water system treatment plans, this is a desirable characteristic. I also test a version of Ash_{ft} that is equal to one if a municipal water system is ever downstream. In this formulation, I drop water-system facility 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

⁶⁰For example, a municipal water system might have two treatment plants, four distribution centers, and three water intake locations. Each of these is a unique facility. If any water system intake is downstream, all facilities in that water system receive the same variable Ash_{ft} .

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 releases and the probability of Safe Drinking Water Act (SDWA) water quality violations. 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 1987 to 2017, assigning violation counts by infraction type to each water system-year. Consider the following probit estimation procedure:

$$Pr(Vio_{it} = 1) = \Phi(\beta Ash_{it} + \eta_i + \eta_t) \quad (3)$$

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 type of offending compound.⁶¹ Ash_{it} is a time-varying variable for the quantity of ash released within 25 miles upstream, where I test a continuous variable and a simple binary if positive. η_i is a water-system random effect and η_t is a year random effect.⁶² I cluster all standard errors at the municipal water system. Due to the incidental parameters problem and the likelihood that water system characteristics may be correlated with the water system random effect, I do not include additional explanatory variables. In words, Equation 3 asks how being downstream from coal ash pollution in a given year 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.⁶³ I therefore model the relationship between coal ash water pollution and fetal health with a mother panel fixed effects design and a treatment variable related to the quantity of coal ash released rather than a violation rate. Consider the following regression:

⁶¹Infraction types are laid out in the Safe Drinking Water Act by “rule.” These 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. Offenses against these rules 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 violation for Disinfectant Byproduct rule violations may each list total trihalomethanes as the related compound.

⁶²The command `xtprobit`, `re` in Stata.

⁶³Banzhaf and Walsh (2008); Benneer and Olmstead (2008); Marcus (2019); Zivin et al. (2011).

$$Health_{imt} = \beta Ash_{it} + X'_{imt}\gamma + \eta_m + \eta_t + \nu_{imt} \quad (4)$$

$Health_{imt}$ is the 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. Ash_{it} is a binary for whether coal ash was released within 25 miles upstream of a water system's intake in year t . X_{imt} is a vector of time-varying birth and mother characteristics and county-level air quality measures including mean, maximum, and maximum PM 2.5 squared across all months of gestation.⁶⁴ η_i and η_t are mother and year fixed effects. I cluster all standard errors at the mother. Intuitively, Equation 4 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. Identification requires that factors correlated with the quantity of coal ash released do not independently affect fetal health outcomes, conditional on controls for mother and year. A potential violation of this assumption would be if unobservable factors correlate with plant conversions and closures and fetal health outcomes, or if mother moves away from potentially-affected coal ash locations are systematically correlated with improvements in fetal health outcomes due to neighborhood changes.

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.⁶⁵ 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:

$$y_{it} = \delta treat_i * post_t + \lambda post_t + \eta_i + \eta_t + \epsilon_{it} \quad (5)$$

⁶⁴Additional 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.

⁶⁵For more information, see [this NC Department of Environmental Quality](#) series of reports summarizing testing.

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.⁶⁶ I cluster standard errors at the county level in all analyses. The coefficient of interest in Equation 5 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-varying 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.

5 Results

5.1 Surface Water Quality

Table 4 shows the results of the surface water analysis for arsenic, conductivity, lead, and pH. 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 conductivity in column (1) means that monitors ever exposed to coal ash pollution have 3515 $\mu s/cm$ more conductivity than comparable monitors in the same year, a difference that is nearly as large as the average value observed across all monitors.⁶⁷ The column (2) result on conductivity means that a surface-water monitor, compared to itself and other monitors in the same watershed-year and watershed-month, has 4132 more observed $\mu s/cm$ of conductivity in years when upstream pollution sites are active than in years when the same sites are inactive. In column

⁶⁶I 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 4 for a trend comparison.

⁶⁷A $\mu s/cm$ is a micro siemens per centimeter, a standard measurement of specific conductance.

(3), the coefficient on conductivity means that each additional ton of coal ash released is associated with an increase in conductivity of $3.08 \mu s/cm$. Similarly, the coefficient of 0.006 in column (3) with respect to lead means that each additional ton of coal ash released increases concentrations of lead within 25 miles downstream by approximately $0.006 mg/L$. When scaled by the average upstream releases in a given year for affected monitors (i.e. 14 tons), the lead coefficient in column (3) suggests that coal ash releases increase downstream lead concentrations by roughly 5% on average.

Results in column (3) suggest that the per-year releases are associated with downstream concentrations of arsenic and lead, despite the fact that column (1) does not show that these downstream monitors are likely to have higher levels of these compounds otherwise. On the other hand, pH and conductivity results suggest that affected regions may have very different baseline properties that do not vary greatly with releases on a year-to-year basis. One potential explanation is that waters in these regions are naturally different from waters in other regions within the same watershed. An 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. Taken together, the results in [Table 4](#) provide evidence that regions downstream are different from other regions within the same watershed. Contemporaneous releases may affect the levels of arsenic and lead, but not greatly alter properties such as conductivity and pH. I also display the results of a variety of inorganic compounds typically associated with coal ash in [Appendix Table 2](#). These results support the main findings in [Table 4](#); in particular, they demonstrate that ever-affected regions are not necessarily more likely to have statistically higher levels of inorganic compounds antimony, cadmium, chromium, copper, mercury, selenium, thallium or zinc. However, the annual quantity released appears to greatly increase observed concentrations of antimony, chromium, copper, selenium, and thallium. Similar to pH and conductivity results, affected regions have higher baseline turbidity that is not greatly affected by contemporaneous releases.

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, which are the same analytes in [subsection 5.1](#) with the exception of two new disinfectant byproducts.⁶⁸ The three treatment indicators correspond to those employed in [subsection 5.1](#). The first

⁶⁸I 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,

column, labeled downstream, shows baseline differences between water systems that are ever downstream and other water systems that are in the same watershed but not downstream. Columns (2) and (3) test how monitoring test results within the same water-system facility change over time in response to variations in the quantity of coal ash released upstream. All models include state-year and month fixed effects to control for time-varying state regulations and monthly fluctuations in water quality.

Municipal systems that are downstream from coal ash release sites, in comparison to other water systems within the same watershed and state that are not affected, tend to have higher conductivity, pH, and total trihalomethane levels. Levels of haloacetic acids, meanwhile, are lower. Only differences in trihalomethanes and haloacetic acids are statistically significantly different from other water systems in the same state and watershed.⁶⁹ The baseline differences in conductivity and pH resemble those observed in affected surface waters, reported in Table 4. Baseline levels of arsenic and lead in potentially affected water systems are not statistically different from nearby municipal water systems. When incorporating temporal variation in the quantity of ash released, in columns (2) and (3), results suggest that releases are associated with statistically significant increases in trihalomethanes, haloacetic acids, and conductivity. Results are not significant and small for arsenic and lead, suggesting that water treatment substantially reduces the levels of these compounds, especially for arsenic. Observed relationships nevertheless provide suggestive evidence; lead and arsenic each achieve near significance in one specification. Given the tightness of the identifying variation in Equation 2, which only permits within-facility differences in outcomes, and the two-way clustering at municipal water system and state, it is not surprising that the standard errors are relatively large across all estimation procedures.

In the next municipal water quality analysis, I test how changes in coal ash water pollution affect the likelihood of water quality violations according to the Safe Drinking Water Act. These results are displayed in Table 6 by type of infraction and compound.⁷⁰ I display only violations associated with compounds explored in Table 5 and subsection 5.1.⁷¹ Both binary and continuous formulations of the time-varying Ash_{it} variable suggest that affected water systems have more lead and copper, inorganic compound, and disinfectant byproduct violations. The coefficient in column (2) with respect to disinfectant byproduct

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.

⁶⁹Concentrations of trihalomethanes and haloacetic acids are often inversely proportional because lower pH tends to create more haloacetic acids, while higher pH tends to form more trihalomethanes. Consistent with the elevated pH in affected water systems, it then follows that trihalomethanes may be elevated and haloacetic acids lowered. See DHHS for more information.

⁷⁰Note that there are no violations for lead or copper compounds, but only violations of the lead and copper rule. I therefore present results on the entire category of lead and copper violations.

⁷¹The category “inorganic compounds” includes many potentially coal-associated compounds. Associations between coal ash releases and detected levels of these compounds in nearby surface waters are displayed in Appendix Table 2. I also regress coal ash releases on many of these additional violation categories directly in Appendix Table 3.

violations of 0.0012 suggests that nearly all of the difference between coal-affected and unaffected water system violations, shown in [Table 2](#), may be explained by coal ash water pollution. Row (2) and (3) suggest that coal ash water pollution is associated with increased violation rates nearly as large as the mean annual violation rates for both type of rule category. Results by type of compound are generally less consistent. Arsenic is positive and significant in the binary Ash_{it} formulation but not quite significant in the continuous formulation of Ash_{it} . Results over the same formulations of Ash_{it} are actually distinctly opposite for trihalomethanes and haloacetic acids, which is not consistent with the overall result for these pollutant categories displayed in the first row.

5.3 Fetal Health

In [Table 7](#), I present the results of [Equation 4](#) across four indicators 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. The interpretation of the coefficient in column (1) on the binary indicator for coal ash suggests that a newborn potentially affected by coal ash is approximately 0.5 ounces, or fourteen grams, lighter than a sibling with no exposure. In column (2), the interpretation of the same coefficient is that a newborn potentially affected by coal ash is 1 percentage point more likely to be low birthweight in comparison to their unaffected sibling; columns (3) and (4) have the same interpretation; an exposed sibling is 1.08 percentage points more likely to be preterm and 0.05 percentage points more likely to have a congenital anomaly. For no outcome are results statistically distinguishable from zero, although consistent direction and reasonable magnitudes provide weakly suggestive evidence of potential differences across siblings. Results for mothers with less than a college degree, who may be expected to be more affected by pollution for a variety of reasons, show effects of larger magnitude than those for the entire sample for all outcomes excepting congenital anomalies, which are noisier. The point estimates in column (2) and (6), roughly between 0.01 and 0.012, is small in magnitude but large relative to the baseline averages for these conditions depicted at the bottom of the table. An effect on low birthweight of 0.01 is roughly a quarter the association between smoking during pregnancy and incidence of low birthweight.⁷²

5.4 Home Sale Prices

[Table 8](#) shows how affected home sale prices 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

⁷²[Zheng et al. \(2016\)](#)

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.

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 0.009 implies that mothers served by municipal water systems affected by coal ash are one percentage point more likely to have a child of low birthweight compared to themselves in years when they are not served by such water systems or these systems are no longer affected by coal ash. This implies 405 additional newborns of low birthweight.⁷³ This is likely to lead to \$6.1m in additional hospitalization fees and \$1.6m in K-12 educational expenses for local communities.⁷⁴ 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 8](#) 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

There are many potential policy levers that may substantially ameliorate the potential influence of coal ash pollution on nearby surface waters, municipal water quality, and fetal health. A recent EPA report estimated that switching to a new set of guidelines on the management of coal ash effluent would decrease the quantity

⁷³900,000 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. $0.009 \times 900,000 \times \frac{1}{22}$ is 405.

⁷⁴These 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.

of coal ash affecting surface waters by at least 95% across a range of compounds.⁷⁵ Among other policies, the guidelines suggest lining ash pond containment facilities. Remediating an older ash pond by treating the water and moving the ash to a new location is an alternative policy lever; cleaning an ash pond has immediate effects on groundwater, improving arsenic levels by as much as 90 percent.⁷⁶ Increased recycling of coal ash into fertilizers and concrete, already commonplace, could also be expanded to reduce the environmental footprint of this waste.⁷⁷ Local legislative acts have also been passed that prevent recuperation of costs from illegal coal ash discharges.⁷⁸

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 weak but suggestive 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.

⁷⁵EPA (2015).

⁷⁶Fretwell.

⁷⁷Yao et al. (2015).

⁷⁸<https://www.ncleg.net/Sessions/2013/Bills/Senate/PDF/S729v6.pdf>

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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	7.6	(4.24)	0%
Average Acres per Pond	72.2	(101.4)	69%
Height (<i>ft</i>)	50.5	(50.0)	71%
Lining	0.37	(0.48)	37%
Leachate	0.22	(0.41)	36%
Average Annual Coal Ash Production (tons)			
Coal Ash	6,506.8	(7766.6)	
Heavy Metals	2,924.0	(3113.7)	
Carcinogenic Compounds	268.7	(305.1)	
Quantity Impounded	6,326.8	(7,646.9)	
Surface Water Releases	180.0	(393.6)	
All-Time Surface-Water Releases by Compound (tons)			RSEI Toxicity
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 pollution site-year level, reflecting averages across all plants in all years 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)				
Annual Samples*	3,218.0	(9,398.76)	13,193.1	(11,989.7)
Arsenic (mg/l)	0.662	(2.66)	0.670	(6.54)
Conductivity (us/cm)	10,374.8	(14,654.0)	5,347.7	(11,720.5)
Lead (mg/l)	0.969	(5.10)	3.158	(65.98)
PH	7.34	(0.868)	7.29	(9.24)
Monitor Observations	510,053		4,010,632	
Monitors	421		23,770	
Municipal Water Systems				
Service Population (thousands)	22.638	(81.829)	3.519	(20.064)
Service Connections (thousands)	7.937	(25.640)	1.334	(7.641)
Age in 2018	31.65	(9.91)	30.65	(9.89)
No. Facilities	6.377	(7.94)	7.622	(11.29)
State Regulatory Monitoring Tests (2005-2017)				
Annual Samples	701.45	(801.4)	642.0	(724.4)
Arsenic (mg/l)	0.00002	(0.0004)	0.00001	(0.0001)
Conductivity (us/cm)	192.22	(336.37)	209.245	(1489.7)
Lead (mg/l)	0.0021	(0.0680)	0.0028	(0.1927)
Haloacetic Acids (mg/l)	0.0234	(0.0168)	0.0262	(0.0579)
PH	7.796	(.6041)	7.725	(0.6806)
Trihalomethanes (mg/l)	0.0422	(0.0268)	0.0411	(0.0285)
Safe Drinking Water Inventory System Violations (2000-2018)				
Total Violations	19.1982	(44.2353)	23.1977	(56.8136)
Health-Based Violations	4.4035	(12.4411)	2.3673	(7.8885)
Annual Violation Rate	0.1220	(0.3274)	0.1127	(0.3163)
Consumer Confidence	0.0142	(0.1268)	0.0331	(0.1839)
Disinfectant By-Product	0.2297	(1.1771)	0.1060	(0.8255)
Inorganic Compounds	0.0112	(0.3507)	0.0077	(0.2356)
Lead & Copper	0.0508	(0.4390)	0.0479	(0.3482)
Public Notice	0.0030	(0.0713)	0.0281	(0.5754)
Arsenic	0.0020	(0.0451)	0.0015	(0.0634)
Trihalomethanes	0.1037	(0.6579)	0.0428	(0.4219)
Haloacetic Acids	0.0976	(0.7036)	0.0373	(0.3490)
Water System Samples	543,814		2,111,875	
Water System Years	24,123		129,985	
Water Systems	984		5,473	

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

	Residents EverServed by Municipal Water System Within 25 Miles		Residents Served by Municipal Water System Not Within 25 Miles	
Mother Characteristics (2005-2017)				
Black	0.19	(0.39)	0.17	(0.36)
Hispanic	0.12	(0.31)	0.13	(0.33)
White	0.696	(0.46)	0.607	(0.48)
Age	28.1	(5.99)	28.5	(5.96)
Married	0.66	(0.47)	0.66	(0.47)
HS diploma or Less	0.348	(0.476)	0.298	(0.457)
Post-Secondary Degree	0.408	(0.491)	0.419	(0.493)
Prenatal Visits	12.42	(3.8)	11.56	(4.22)
Alcohol	0.003	(0.07)	0.005	(0.06)
Tobacco	0.02	(0.13)	0.04	(0.19)
Hypertension*	0.04	(0.18)	0.05	(0.21)
Diabetes*	0.04	(0.18)	0.03	(0.16)
Birth Characteristics (2005-2017)				
Ounces	116.43	(20.93)	116.1	(21.1)
Low Birthweight (2500 grams)	0.074	(0.262)	0.77	(0.27)
Preterm Gestation (37 weeks)	0.091	(0.28)	0.092	(0.289)
Congenital Anomalies	0.029	(0.16)	0.017	(0.13)
PM 2.5 Mean	10.56	(2.29)	9.44	(2.05)
PM 2.5 Max	16.88	(4.9)	14.8	(4.69)
Birth Observations	142,140		263,198	
Unique Mothers	72,287		225,642	
	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: The Properties and Chemical Composition of Surface Waters Downstream from Coal Ash Sites (2005-2017)

	Downstream (1)	Releases Binary (2)	Annual Tons Released (3)
Inorganic Compounds			
Arsenic	-0.000	0.000	0.001***
Dep. Var. Mean = 0.011	(0.000)	(0.000)	(0.000)
Lead	-0.006	0.0173	0.006**
Dep. Var. Mean = 1.516	(0.015)	(0.029)	(0.002)
Properties			
Conductivity	3515.6**	4132.0**	3.08
Dep. Var. Mean = 4126.2	(1634.6)	(1579.6)	(2.32)
pH	0.262	0.0327	-0.0001
Dep. Var. Mean = 7.25	(0.1384)	(0.029)	(0.0011)
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. Observations for each model, in vertical order, are 31,410, 41,495, 1.36 million, and 1.87 million. The first column for each compound or property, labeled downstream, 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. The second column regresses a binary indicator for whether a coal ash pond within 25 miles upstream is active and releasing surface-water pollution in the year of the monitor test on the same outcomes. Annual tons released, column (3), regresses the tons released upstream of a monitor in a given year on the values detected in monitors downstream. All regressions performed assuming coal ash influence cutoff distance of 25 miles (40 kilometers) upstream.

Table 5: The Properties and Chemical Composition of Municipal Waters Downstream from Coal Ash Sites (2005-2017)

	Downstream (1)	Releases Binary (2)	Annual Tons Released (3)
Disinfectant Byproducts			
Haloacetic Acids (HAA5) Dep. Var. Mean= 0.0257	-0.0026*** (0.0009)	0.00174 (0.0007)	0.00004*** (1.44e-06)
Trihalomethanes (TTHM) Dep. Var. Mean= 0.0415	0.0029** (0.0012)	0.0022** (0.00049)	-0.00005 (0.00004)
Inorganic Compounds			
Arsenic Dep. Var. Mean= 0.00001	8.32e-06 (0.0000)	1.40e-07 (4.36e-06)	1.39e-07 (1.40e-07)
Lead Dep. Var. Mean= 0.0027	-0.0004 (0.00116)	0.00165 (0.0022)	-0.00003 (.00003)
Properties			
Conductivity Dep. Var. Mean= 192.82	4.355 (18.837)	25.773** (3.70)	0.5312 (0.5312)
pH Dep. Var. Mean= 7.76	0.20304 (0.1384)	0.0031 (0.0181)	0.0020 (0.0025)
Water-System Facility		✓	✓
State-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 in indicator for whether a municipal water system intake is ever within 25 miles downstream of a coal ash release site on a compound's concentration in any facility within the same water system. Columns (1) and (2) regress an indicator for whether coal ash is released within 25 miles upstream of a municipal water system's intake in year t on the compound's concentration. Tons released is the total coal ash released into surface waters within 25 miles upstream. Sample excludes all water well tests and systems sourced exclusively from ground water. All regressions performed assuming coal ash influence cutoff distance of 25 miles (40 kilometers) upstream.

Table 6: Upstream Coal Pollution and the Probability of a Water Quality Violation (2000-2017)

	Time-Varying Binary Coal Ash Releases		Time-Varying Continuous Coal Ash Releases	
	(1)	(2)	(3)	(4)
	β	dy/dx	β	dy/dx
Violations by Rule Infraction				
Disinfectant By-Product	0.0607***	0.0012***	0.0007***	0.0000***
Dep. Var. Mean = 0.013	(0.019)	(0.000)	(0.0002)	(0.0000)
Inorganic Compounds	0.4287***	0.0045***	0.0015**	0.0000**
Dep. Var. Mean = 0.004	(0.023)	(0.000)	(0.0003)	(6.04e-06)
Lead and Copper	0.2517***	0.0061***	0.0010**	0.0000**
Dep. Var. Mean = 0.012	(0.016)	(0.000)	(0.0004)	(0.0000)
Violations by Compound				
Arsenic	0.3664***	0.0035***	0.0004	4.62e-06
Dep. Var. Mean = 0.005	(0.020)	(0.000)	(0.0004)	(4.85e-06)
Trihalomethanes (TTHM)	-0.1574***	-0.0046***	0.0007**	0.00001**
Dep. Var. Mean = 0.006	(0.0438)	(0.0013)	(0.0013)	(4.30e-06)
Haloacetic Acids (HAA5)	-0.1460***	-0.0042***	0.0005*	7.12e-06*
Dep. Var. Mean = 0.0056	(0.0436)	(0.0012)	(0.0003)	(3.96e-06)
Observations	457,615		457,615	
Water Systems	50,225		50,225	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 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.

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
Releases Binary	-0.4826 (0.924)	0.0099 (0.013)	0.0108 (0.018)	0.005 (0.004)	-0.8317 (0.017)	0.012 (1.587)	0.0175 (0.033)	-0.0003 (0.0325)
PM2.5	-0.8041***	0.0103***	0.0175***	0.0032	-0.5418**	0.006	0.0174**	0.0011
Mean= 10.1	(0.224)	(0.004)	(0.004)	(0.0027)	(0.223)	(0.003)	(0.008)	(0.004)
Max $PM_{2.5}^2$	-0.014*	0.0002***	0.0003***	0.0000	-0.016***	0.0003	0.0004**	0.0000
Mean= 259.21	(0.005)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Birth Observations	142,140	142,140	142,140	142,140	48,554	48,554	48,554	48,554
Dep. Var. Mean	116.2	0.0743	0.091	0.0234	113.37	0.0907	0.102	0.0313

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

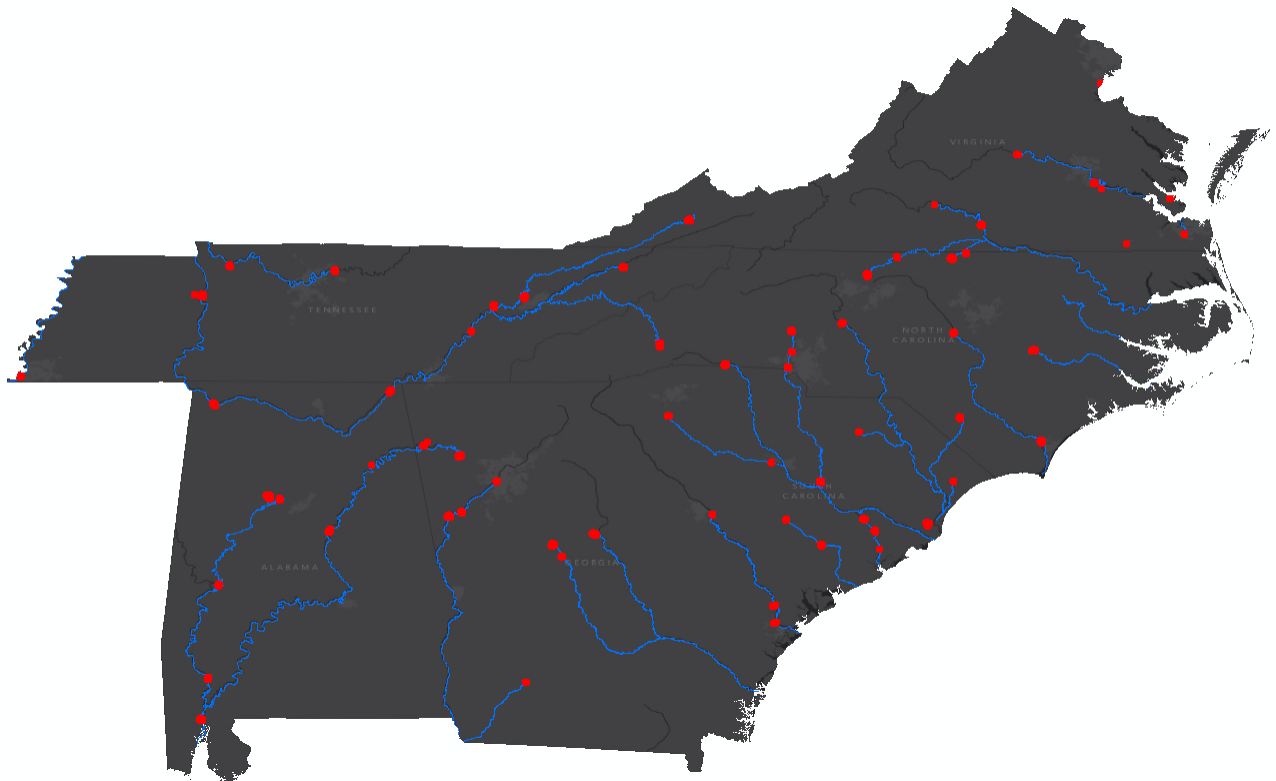
Table 8: How Mandatory House Well Testing Affected House Sale Values After the Coal Ash Management Act of 2014

Distance Cutoff	(1) 1 Mile	(2) 2.5 Miles	(3) 5 Miles	(4) 1 Miles	(5) 2.5 Miles	(6) 5 Miles
Near*Post	-45,295.4*** (17,403.2)	-36,406.9*** (5,151.2)	-24,691.8*** (2,371.5)	-37,333.5*** (12,591.3)	-16,090.1*** (2,784.1)	-12,673.9*** (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.

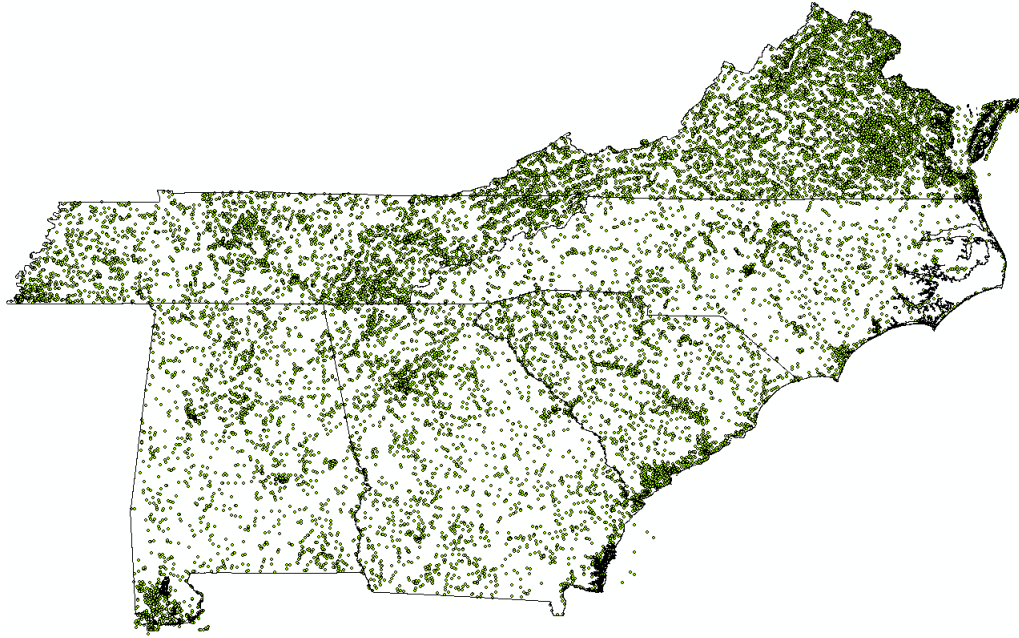
Figures

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

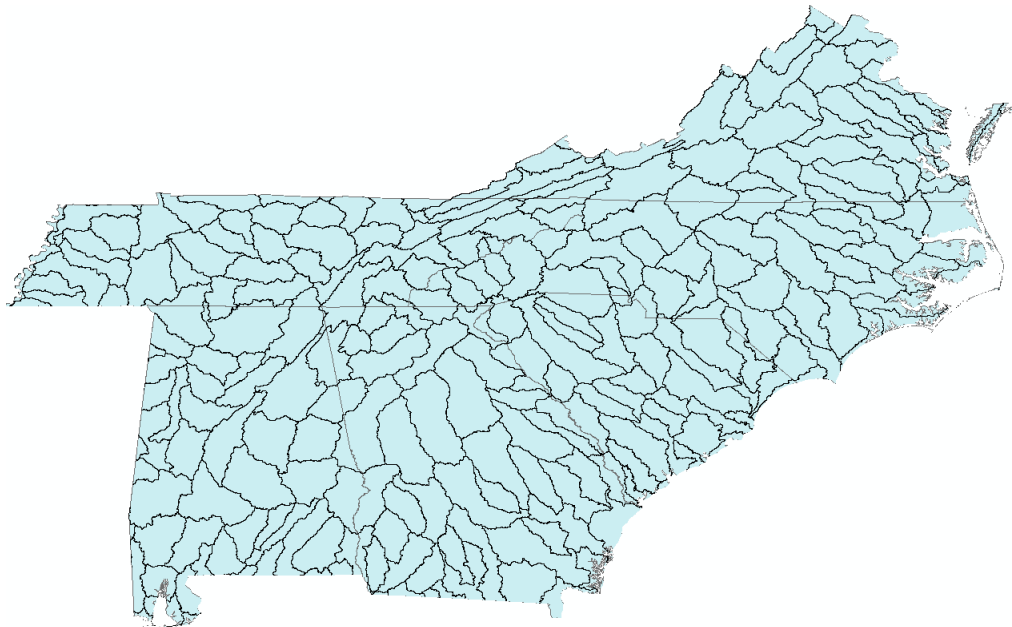


Notes: Red dots reflect coal ash release sites, or steam generating power plants that release a non-negative quantity of coal ash to surface waters from 2005-2017. Blue lines represent river and stream segments that are downstream from a coal ash release site.

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



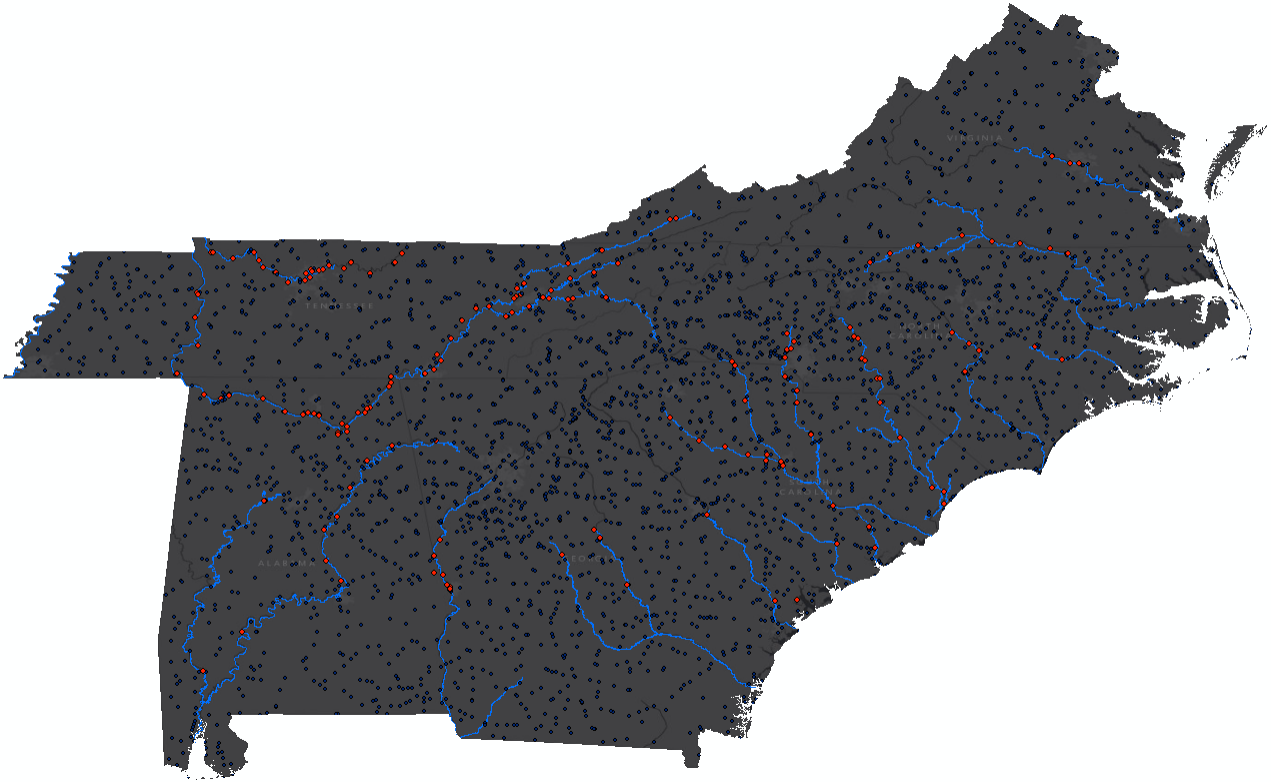
(a) Monitor Locations



(b) Watershed Regions

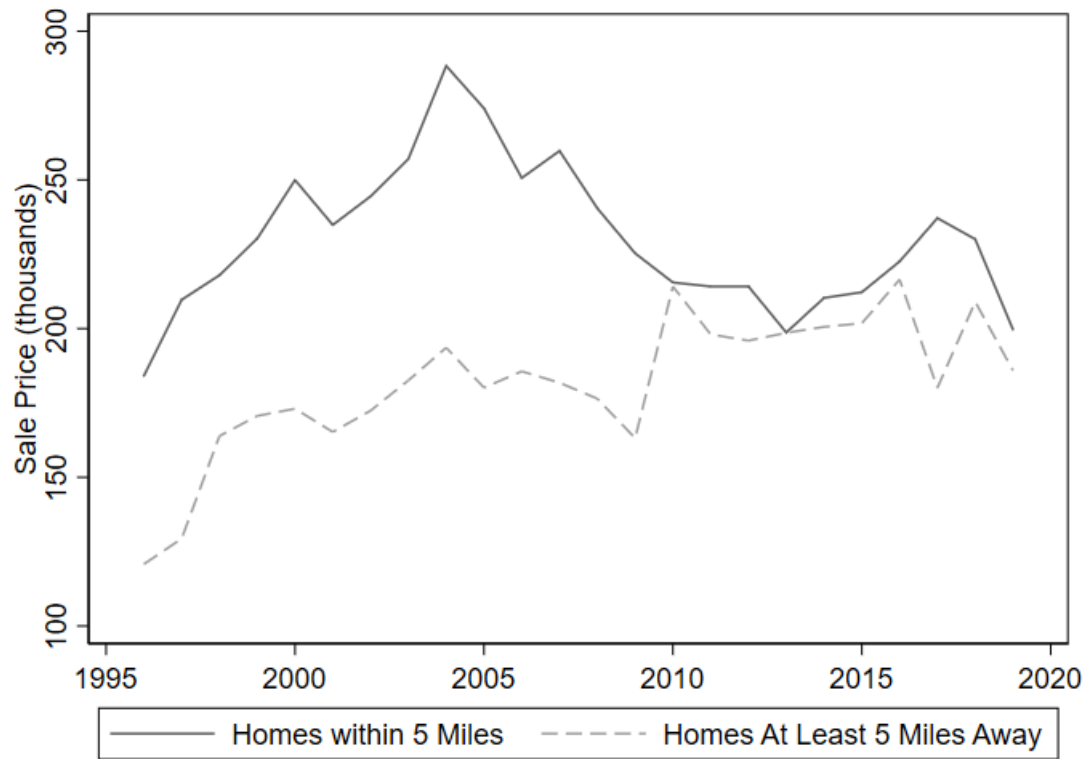
Notes: In Panel (a), green dots represent monitor locations, while in Panel (b) each polygon represents a watershed of size Hydrologic Unit Code – 8.

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. Many surface water intake locations, and their status as affected water systems, was provided by courtesy of the Southern Environmental Law Center.

Figure 4: Home Sale Prices in Counties with Coal Ash Ponds (1996-2019)



Notes: Homes with sale prices over \$1.5m are excluded from the averages. 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.

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.⁷⁹ 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.

To assign municipal water systems downstream status, I rely on three datasets: the Southern Environmental Law Center’s database of water system intake locations, the Safe Drinking Water Inventory System city of service zone I expand traced downstream river networks to 2.5 mile buffers on either side. I then spatially intersect downstream status to municipal water system locations. Municipal water system intake locations are only observable for a subset of North Carolina water systems. I therefore assign geographic location to water systems based on the town, county, and state of the geographic service zone reported in the SDWIS Geographic Area reports. In cases where town is not observed, I use county centroid.

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.⁸⁰ 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

⁷⁹Peterson and Hoef (2014)

⁸⁰A 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.

supply shapefile.⁸¹ To this, I then add the Southern Environmental Law Center’s public water system intake geodatabase, which shows approximate surface-water intake locations for Alabama, Georgia, Tennessee, and Virginia. Both well and surface water intake locations are included in the SELC database for North and South Carolina. The SELC database does not always display the same information as the NC Onemap shapefile, so I use the Onemap shapefile locations first and then incorporate SELC information when not available. Unfortunately, these locations still do not include many intake locations over the remaining states and even some within North and South Carolina. I supplement these datasets by approximating intake locations using the Safe Drinking Water Inventory System (SDWIS). SDWIS provides water system addresses, but these addresses are inaccurate. They likely 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, 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 than 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 Births

A birth is potentially affected by air quality across its entire gestational period. I therefore 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 gestational period, while the maximum value is the maximum county-month value over the 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.

⁸¹See [here](#) to download or see more information.

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

Constituent (<i>units</i>)	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)	47,779	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 (1)	Releases Binary (2)	Binary (3)	Tons Released (4)	(5)
Antimony	0.0096 (0.00169)	0.00149 (0.0026)	0.00003 (0.00002)	0.00014*** (0.00004)	0.00071*** (0.00010)
Cadmium	-0.01937 (0.04562)	-0.02575 (0.05915)	-0.05171* (0.02911)	0.00009 (0.00039)	-0.00055 (0.00067)
Chromium	-0.00325 (0.00282)	-0.00424 (0.00363)	0.00013 (0.00011)	0.00017** (0.00007)	0.00053 (0.00046)
Copper	-0.00021 (0.00397)	-0.00012 (0.00481)	-0.00055* (0.00029)	0.00052*** (0.00011)	0.00165* (0.00091)
Mercury	-0.01709 (0.01952)	-0.02371 (0.02629)	0.00257* (0.00139)	-0.00071 (0.00058)	-0.00092 (0.00121)
Selenium	0.00720 (0.02800)	0.01146 (0.04393)	-0.00271 (0.00289)	-0.00001 (0.00050)	0.00111*** (0.00017)
Thallium	-0.00008 (0.00019)	-0.00012 (0.00028)	6.80e-06** (2.47e-06)	5.74e-06 (5.30e-06)	0.000039*** (8.38e-06)
Turbidity	3.3230 (2.6664)	.59735 (1.7026)	-17.409 (18.477)	0.04202 (0.03597)	-0.1099 (0.2396)
Zinc	0.01830 (0.02008)	0.02136 (0.02286)	-0.00253 (0.00268)	0.00065*** (0.00014)	-0.00103 (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: Upstream Coal Pollution and the Probability of a Water Quality Violation (2000-2017)

	Time-Varying Binary Coal Ash Releases		Time-Varying Continuous Coal Ash Releases	
	(1)	(2)	(3)	(4)
	β	dy/dx	β	dy/dx
Violations by Rule Infraction				
Consumer Confidence Rule Dep. Var. Mean = 0.017	0.3214*** (0.019)	0.0076*** (0.000)	0.0033*** (0.0002)	0.0000*** (2.61e-06)
Groundwater Rule Dep. Var. Mean = 0.013	-0.0125 (0.0277)	-0.0001 (0.000)	-0.0001 (0.0016)	-6.56e-07 (8.48e-06)
Public Notice Dep. Var. Mean = 0.024	0.5233*** (0.015)	0.0201*** (0.001)	0.0023*** (0.0003)	0.0001*** (0.0000)
Radiation Dep. Var. Mean = 0.004	0.4412*** (0.057)	0.0039*** (0.0002)	0.0013** (0.000)	0.0000** (0.000)
Violations by Compound				
Antimony Dep. Var. Mean = 0.002	0.3886*** (0.0275)	0.0021*** (0.000)	0.0023*** (0.0003)	6.44e-06*** (9.02e-07)
Cadmium Dep. Var. Mean = 0.003	0.3934*** (0.020)	0.0034*** (0.000)	0.0014*** (0.0003)	0.00002*** (4.77e-06)
Chromium Dep. Var. Mean = 0.003	0.3913*** (0.020)	0.0034*** (0.000)	0.0015*** (0.0003)	0.00004*** (9.46e-06)
Mercury Dep. Var. Mean = 0.003	0.3892*** (0.021)	0.0034*** (0.000)	0.0014*** (0.0003)	0.00004*** (9.42e-06)
Selenium Dep. Var. Mean = 0.003	0.3909*** (0.021)	0.0034*** (0.000)	0.0015** (0.0003)	0.0000*** (0.000)
Thallium Dep. Var. Mean = 0.0020	0.428*** (0.0706)	0.0038*** (0.0006)	0.0013*** (0.0004)	0.0000*** (3.74e-06)
Observations	457,615		457,615	
Water Systems	50,225		50,225	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 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.