Coal Combustion Residuals and Water Quality

Wes Austin*
Georgia State University
gaustin4@gsu.edu

March 19, 2019

Draft, please do not cite.

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. I geographically link the universe of municipal water quality tests in North Carolina to information on coal ash discharges from the Toxic Releases Inventory to demonstrate the average relationship between surface water releases and municipal water quality. Then, incorporating information on heavy rains and flooding from the National Oceanic and Atmospheric Administration, I show how these relatively common weather events exacerbate the risk of ash pond impounds impacting municipal water quality. Finally, I estimate the cost of coal ash water pollution in terms of municipal water system fines for water quality violations, finding that the burden of coal ash pollution on municipal water systems in North Carolina is approximately $950,000, or one fifth of all fines assessed from 2005-2017.

Keywords: Pollution; Fetal Health; Health; Coal ash; Water Quality
JEL:

*I would like to thank Eric Chai, Sean McGuire, Andrew Pitner, Julia Cavalier, Debra Watts, Eric Smith, and Nat Wilson with the North Carolina Department of Environmental Quality for their inestimable help in assembling and making sense of the state's extensive water quality information. I would also like to thank Dajun Dai, Garth Heutel, Dan Kreisman, Tom Mroz, Tim Sass and many other students and faculty members at Georgia State University for their comments, advice, and encouragement.

1 Introduction

Coal combustion residuals (CCRs) are the waste material from burning coal for electricity generation. Also known as coal ash, roughly 110 million tons of CCRs are produced each year in the United States. Most of this ash is stored in containment ponds or landfills, while 2.7 million tons of CCRs are released into surface waters (MacBride, 2013). Although surface-water discharges represent a small fraction of all coal ash disposal, they nevertheless account for one third of all industrial water pollution by toxicity and one half by mass (Bernhardt et al., 2016) (Boyce and Ash, 2016). No previous study has investigated whether coal ash discharges affect municipal water quality or human health.

Coal ash containment ponds and landfills pose a threat to drinking water because of the sheer quantity of ash produced, the relative toxicity of the pollutant, and the age of many confinement ash ponds. At least one third of this coal ash water pollution is composed of metals including arsenic, selenium, cadmium, chromium, and mercury (EPA, 2015). 70 percent of coal plants have virtually no limit on the quantities of heavy metals they may release into water sources (Duggan, 2013). In North Carolina, moreoever, the average construction year of a coal ash pond is 1969, when fewer regulations on lining practices were in place.

The contaminants found in CCRs find their way to water sources in three primary ways. First, ash ponds are occasionally or continually drained and the liquid is placed into nearby bodies of water. This type of release requires a National Pollutant Discharge Elimination System (NPDES) permit, and so the water released is tested frequently and is generally the least contaminated due to benthic settling of harmful substances. A second form of exposure is seepage through the side of containment facilities. Because ash ponds are uniformly constructed next to large bodies of water, this form of seepage is non-trivial. One study comparing water discharged with seepage water found 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, the seepage water killing all within the first 24, while control fish populations experienced no mortality (Coutant et al., 1978). CCR leachate can also make its way to deep groundwater sources if the pond is poorly lined, affecting public and private wells. Of the 14 North Carolina ash ponds used in this study, two thirds were found to have been leaching pollution into groundwater. Combined, these types of pollution are remarkably common; the EPA has identified 132 cases of surface-water contamination and 123 cases of ground-water contamination by coal power plants (Duggan, 2013).

Municipal water providers sourcing from surface waters run the risk of distributing improperly filtered and polluted water. More commonly, disinfectants used to treat the water interact with CCR compounds to create carcinogenic compounds known as disinfectant by-products (DBPs) (EPA, 2001). Violations for DBPs such as total trihalomethanes (TTHMs) and haloacetic acid are common in CCR-contaminated waters

(Watch, 2017). Less commonly, ash-pond leachate can reach groundwater sources and affect publicly- and privately-owned drinking wells.

In 2013, researchers at Duke University began testing water quality at sites exposed to coal ash effluent. Their findings of high arsenic, selenium, and boron concentrations across various types of surface-water led the North Carolina Department of Environment and Natural Resources to investigate quality of exposed water wells across the state (Harkness et al., 2016; Ruhl et al., 2012). The Department tested 313 drinking wells, and found that 93 percent failed to meet safe limits on certain pollutants including hexavalent chromium and vanadium (SELC, 2015). Separately, the EPA identified each unlined ash pond as damaging to human health, with two specific ponds representing particularly high hazard. In April of 2015, residents living near the fourteen unlined ash ponds in North Carolina received notification that their well water should not be used for drinking or cooking due to possible carcinogen exposure (see Appendix). North Carolina's ash ponds have subsequently garnered national attention in the discussion on coal and clean water.

2 Literature Review

Coal combustion residuals are a widespread and loosely-regulated water pollutant with several potential human exposure mechanisms deserving of further inquiry. This literature review will establish that the effects of such pollution exposure can be damaging to human health. Next, the review will cover the fetal origins hypothesis and other types of pollution exposure, arguing that the effects of pollution exposure can be quite large, persistent over the life cycle, and relevant to cognitive as well as physical health. Water pollution, in contrast to air pollution, is relatively difficult to study, so the literature review will describe previous sibling comparison research models that exploit either residential changes of a family or neighborhood changes with respect to pollution cleaning. Finally, the review will describe papers estimating how pollution capitalizes into housing values as a way to motivate the hedonic model employed in this paper.

The potential for CCR pollution to harm human health depends on the vector of exposure and a variety of plant- and pond-specific characteristics. Nevertheless, past studies have demonstrated that exposure to specific coal-related compounds can cause adverse health reactions. In one study on 3,000 Chinese individuals, arsenic poisoning from coal-polluted well-water was associated with skin cancers, toxicities to internal organs, neuropathy, nephrotoxicity, cirrhosis, ascites, and liver cancer (Liu et al., 2002; Yu et al., 2007). Aside from arsenic, chromium and nickel are known carcinogens that can appear in ash pond leachate (Shy, 1979). Another study demonstrated that exposure to coal water pollution increased infant mortality in India (Greenstone and Hanna, 2014). A complete accounting of the varied ways in which CCRs affect health is beyond the scope of this paper, but one potential consequence of coal pollution exposure is low-birth weight newborns leading to permanent early-childhood exposure effects. Low-birth weight babies have demonstrably worse health outcomes throughout their life cycle, a condition described by the Fetal Origins Hypothesis (Osmond and Barker, 1991). Low birth weight babies are more prone to chronic and degenerative conditions like diabetes and heart disease. Economists have expanded the list of consequences of in utero exposure to pollution include test scores, educational attainment, and income later in life (Almond and Currie, 2011). The harmful substances in CCRs have the potential to adversely affect fetal development even if the pollutants are harmless in small doses to most individuals.

Despite the many potential adverse effects of CCR water pollution, exposure is difficult to study in a rigorous way because individuals with greater exposure have different preferences, knowledge sets, and incomes than individuals with less exposure. These differences arise naturally because lower property prices near highly-polluted areas lead to differential sorting of low-income individuals into these regions (Banzhaf and Walsh, 2008; Graves et al., 1988). Therefore, the correlation of health outcomes to exposure partially reflects the effect of being poor, naïve, or apathetic to pollution. Generally, data limitations have made air pollution easier to study than water pollution. One paper that overcame air pollution endogeneity is Currie and Neidell (2005), which exploits variation in carbon monoxide exposure at the zip code, month, and year level to show that air quality improvements in California in the 1990s saved 1000 infant lives. This paper's use of zip code fixed effects to identify a causal relationship is robust to various issues that sometimes plague fixed effects, though this is not often the case with pollution exposure. A paper that moves beyond simple panel fixed effects is Currie et al (2009). This paper uses a difference-in-differences-in-differences identification strategy over school-year-attendance period cells, finding that even CO levels well below federal air quality standards significantly lower attendance at Texas schools. The DDD strategy deals with endogeneity by controlling for all stable characteristics of schools, years, and attendance periods as well as time-varying factors related to household sorting. In another paper, Currie and Walker (2011) are able to exploit actual exogenous variation in air pollution due to implementation of an EZ pass' effect on air pollution, showing that infant mortality decreased by 10-11 percent after traffic pollution was lowered.

The above papers are able to achieve exogenous variation because of daily EPA air monitoring data. Water pollution, on the other hand, is harder to measure nationally with great precision. Moreover, there is no straightforward way to link local water sources to actual exposure levels among the local population because the results of water treatment plant tests require a Freedom of Information Act request. One of the first causal papers to demonstrate a link between water pollution and infant health is a 2013 quasi-experimental paper (Currie et al., 2013). In this study, the researchers obtained records of drinking water tests at 488 water districts in the state of New Jersey and linked them to birth certificates for the years 1997 to 2007. Siblings were matched using mother's maiden name, race, birth date, father's name, and social security numbers, and birth addresses were linked to water districts using geographic software. Finally, the researchers separated chemical contaminants from bacterial contaminants to deal with heterogeneity of treatment and ran a linear probability model on low birth weight and premature birth. The most-preferred model has mother fixed effects, standard errors clustered by mother, and a full-term gestation instrument that corrects the mechanical correlation between actual gestation and exposure. Results show that exposure to chemicals raises the probability of low birth weight by 6-7 percent. Without the use of sibling fixed effects to control for unobserved mother heterogeneity, the results would have been far less compelling.

Exploiting variation at the sibling level is a straightforward econometric technique for grappling with endogeneity of treatment to parent characteristics or neighborhood sorting. One of the first studies to exploit sibling variation, Daniel Aaronson's 1998 study of neighborhood effects and student outcomes, discussed the imperfections of sibling matching. Aaronson noted that neighborhoods stratify along socioeconomic lines, leading to bias in the estimating equations. Valid instruments that determine neighborhood choice but not children's outcomes are also quite rare. As such, he argued that "latent family factors associated with neighborhood choice are sibling-invariant; households rarely move due to the differential ability of their children" (Aaronson, 1998). As such, family residential changes provided for Aaronson a source of background variation free from family-specific heterogeneity causing sorting along socioeconomic lines. In the paper, Aaronson acknowledged that unobserved within-family heterogeneity across siblings could lead to omitted variable bias, though he did not mention how moving itself could represent precisely this unobserved within-family heterogeneity if the move is correlated with wealth and child investment changes. Aaronson's study would prove influential to a later paper that tested this possibility directly.

An alternative to variation induced by residential change is to focus instead on variation caused directly by neighborhood changes. Currie, Greenstone, and Moretti (2011) studied the effects of Superfund site exposure to infant health. They made use of a difference-in-differences identification technique that compared siblings born before and after a site cleanup, finding that being born before a site cleanup was associated with a 20-25 percent increased risk of congenital deformities. Persico, Figlio, and Roth (2016) extend this research using an identical strategy to identify the effects of Superfund site exposure on education outcomes of Florida students between 1994 and 2002. Concentrating on outcomes like birth weight, test scores, behavioral probems, likelihood of grade repetition, and likelihood of cognitive disabilities, they find that exposed siblings are 7.4 percentage points more likely to repeat a grade, have 0.06 of a standard deviation lower test scores, and are 6.6 percentage points more likely to be suspended from school. These studies lend credence to the notion that coal-ash water contamination may impact education and health outcomes.

An important part of the proposed study is a comparison of the costs and benefits of cleaning ash ponds. The benefits will be represented in discounted lifetime value of the lost income associated linked to ash pond pollution through lowered test scores. The costs will be willingness-to-pay for cleaning as measured through changes in hedonic pricing of homes in regions close to ash ponds. There is a wide-ranging literature on capitalization of house prices through pollution changes (Davis, 2011; Gazze, 2015). In a notable paper, Chay and Greenstone (2005) use the natural experiment provided by the Clean Air Act's designation of 'attainment' and 'non-attainment' counties to assess capitalization of homes based on air quality, finding that the act increased housing values in nonattainment counties by $45 billion. A more recent paper estimated the effect of the Clean Water Act on water pollution concentrations and housing prices (Keiser and Shapiro, 2017). It found that water pollution has fallen since the act, though was decreasing at a faster rate prior to 1972. Moreover, the Act's grants to municipalities to clean their water did seem to have an effect, though the change in house prices associated with cleaner water was much smaller than the grants' overall costs. The paper's comparison of the costs and benefits of the Clean Water Act is an important contribution to the pollution literature because it grounds potential studies with the recognition that optimal pollution need not be zero.

This literature review has established that the effects of pollution exposure can be quite large, persistent over the life cycle, and relevant to cognitive as well as physical health. Water pollution, in contrast to air pollution, is relatively difficult to study for a variety of data reasons. Nevertheless, there is promise in advancing water pollution studies using sibling comparisons that exploit either residential changes of a family or neighborhood changes with respect to pollution cleaning. Finally, capitalization of pollution into housing values is a well-documented phenomenon with common hedonic methods to assess the costs and benefits of pollution cleaning.

3 Motivation

It is widely understood that coal is a dangerous and highly-polluting energy source. Mine worker safety remains a concern, acid mine drainage reduces the pH of water systems to that of battery acid, surface mining and mountain-top removal irreparably reduce the flow of environmental services, and coal-related air pollution is causally associated with chronic lung and cardiovascular health problems (Pershagen et al., 1986). Recent research also established that exposure to even just coal deliveries and stockpile dust contributes to local environmental costs of roughly four times the magnitude of the per-ton cost of coal itself (Jha and Muller, 2017). However, whereas labor, mine, transportation, and air-quality coal safety standards are currently highly regulated by standards set forth in legislation from the Clean Air Act to the Surface Mining Control and Reclamation Act, there remains a lack of regulation and public awareness of the negative effects of coal combustion wastes.

To the best of my knowledge, no other study has investigated the effects of CCR water pollution on any proxy for human health. The lack of epidemiological or cost-oriented studies on this externality of energy production is a primary reason for the public disregard for coal-waste water pollution relative to other harmful effects of coal consumption. Such a study would provide better information to consumers in addition to researchers interested in quantifying the life-cycle costs of coal or the relative merits of different energy sources (Amigues et al., 2011; Muller and Mendelsohn, 2006). More importantly, such information would be useful to policy-makers as they debate the relative merits of the Obama era "Effluent Limitations Guidelines" in the 2015 Clean Water Rule, which is under review by the Trump administration.

4 Data

The potential sample includes all students in North Carolina from 1996-2016. The study seeks to make use of a wide array of supplementary information on natality statistics, property values, municipal water information, and fine-grained air pollution measurements.

Student-level Information Duke University's North Carolina Education Research Data Center (NCERDC) includes over 100 variables on student achievement, teacher characteristics, and demographic information for all students of North Carolina from 1996 to 2016. More specifically, student development outcomes such as test scores, suspensions, attendance, grade repetition, and disability status will be used to discern student development disparities across coal regions. Crucially, the database provides the census block of a student's address from the 2000 and 2010 census. The census block information will be used to link students to exposed regions. For graduate students, the price for the basic data is free pending acceptance of the research study.

There are a number of additional pieces of information that offer greater credibility to the study design or open up related avenues of research. However, each additional request on the NCERDC raises the price tag of the data request. The first important supplementary data request is matching siblings. The database has linked siblings for other research projects, and doing so again for this project would cost approximately $10,000 (A. Qureshi, 2017). The ability to match siblings is a fundamental piece of the sibling comparison research model. A second supplementary task that the NCERDC could perform in exchange for a customization fee of $17,400-20,880 is linking 313 addresses of private residences with known levels of different well-water contaminants to actual students. Linking actual addresses to different students would allow for richer treatment models and comparisons of students with variation in the levels of different pollutants in their drinking water. Actual address information linkages could lend support to the research models outlined below or stand alone in their own identification strategy.

A final potential customization that the NCERDC may perform is linking detailed birth records housed at the North Carolina State Center for Health Statistics to students in the NCERDC. This process would require approval from the Center for Health Statistics, which may release vital records data for medical research. Because of the potential for birth defects, long-term health costs, and relative lack of understanding of coal-pollution health consequences, there is some hope that the Center for Health Statistics would consider the research project as related to medical research. Past studies have made use of both datasets to study the effects of blood lead levels, which is related to the proposed project Miranda et al. (2007). Including indicators for whether births occurred at coal-ash affected addresses allows observation of the crucial 0-5 window of child development and facilitates investigation of the fetal origins hypothesis through a comparison of siblings with different birth residences. The price tag for address at birth indicators is also $17,400-20,880, placing the potential total cost of all data at $44,800-51,760. Despite the high cost, the de-identification of students from their physical addresses means that the project's various data elements satisfy FERPA and HIPAA. For this reason, Kara Bonneau, the director of the NCERDC, stated that the project would probably pass inspection by an internal review board.

At this time North Carolina student-level data has not been acquired. Several sources of funding will be sought. The Andrew Young dissertation fellowship awards up to $25,000 for dissertation-related data acquisition. There is also a campus-wide GSU internal grant program that awards up to $2000 for support of dissertation research, with an additional $1,500 of possible award money if the graduate student is nominated by their dissertation chair for the William Settles Graduate Fellowship. Another potential source of funding is the Doris Duke Fellowships for the Promotion of Child Well-Being. Fellows are awarded annual stipends of $30,000 for up to two years to work on research that improves child development and prevents child maltreatment of all kinds. The proposed research clearly addresses child development disparities. Moreover, the award amount would independently afford all necessary data independently of any other potential grant.

Air and Water Quality Several databases may be used to establish differential air and water quality in the regions surrounding coal plants over the study period. Information on air pollution will be obtained from the EPA Air Quality Index Report. The database reports annual county-level median air quality index values from 1996-2015. The air quality reports will be used to control for annual fluctuations in air quality that may affect infant and student health.

Three sources of information on water quality will be used to demonstrate water quality differentials between well- and surface-water sources and differentials across regions exposed or not exposed to coal ash ponds. The first source is the EPA Safe Drinking Water Information System published online by Clean Water for North Carolina. It is a searchable database of all private wells, publicly-owned water systems, and privately-owned water systems in the state. The database also includes a county-level list of all water systems, their sources, population served, and list of all violations with descriptions of violations.

Two supplemental sources of information to be summarized in the appendix are the EPA's toxic releases inventory (TRI) and the EPA's NPDES permits. The TRI includes information on land, water, and air emissions of all polluting facilities in the state of North Carolina from 2002 to 2016. The TRI information can be used to demonstrate that regions with coal ash ponds are not necessarily more toxic from other sources, ruling out one potential source of omitted variable bias. Next, NPDES permit test results from the ash pond sites from 2010 to 2014 are published online by the North Carolina Department of Environmental Quality. The results are bi- or tri-annual water tests for pH, lead, arsenic, hexavalent chromium, cadmium, mercury, and other regulated pollutants. These tests can be used to support notions of the toxicity of ash containment sites. The results can also be used to assess how variation in the composition of pollutants across sites may contribute to different health outcomes.

Housing Characteristics The study will use National Historical Geographic Information System (NHGIS) to find information on housing characteristics. These variables will be used in the willingness-to-pay for ash pond cleaning section of the proposed study. The NHGIS database houses ACS linked geographic data at the census block level, with house values and characteristics (eg. Kitchen fixtures, rooms, etc.) and demographic profiles of localities. A second source of information on houses is the North Carolina State University County Geographic Information Systems Database. The database includes parcel value information for every plot of land in North Carolina from 2013 to 2016. Separately from the value over time, the GIS database also includes information on the most recent sale value and date, which can be used to construct valuation measurements that are plausibly not prone to reporting bias.

5 Empirical Strategy

This section details two empirical strategies that will be employed in the case where only sibling match identifiers are provided by the NCERDC. Of course, if contemporaneous and birth address indicators are acquired, then the identification strategies can be improved accordingly. The first identification strategy relies on sibling variation in length of exposure, while the second takes advantage of natural geographic differences in the subterranean infiltration rate of pollutants into groundwater. The two strategies complement each others' weaknesses, strengthening the credibility of the research proposal.

5.1 CCRs and Municipal Water Quality

5.2 CCRs, Floods, and Municipal Water Quality

5.3 Quantifying Water Quality Fines from CCRs

5.4 CCRs and Fetal Health: County-Level 2SLS

5.5 CCRs and Fetal Health: Service Region Sibling Comparison

[Placeholder]

5.6 Willingness-to-Pay for Ash Pond Cleaning

[Placeholder]

5.7 Cost-Benefit Analysis

[Placeholder]

5.8 Sibling Variation in Exposure

This study deals with the issues of adverse selection of low-income families into coal-plant regions by exploiting sibling variation in potential exposure to ash pond pollution. Such variation arises when, for example, a family with multiple children moves out of an affected area or when a family moves into an affected area and has an additional child after doing so. The comparison of siblings will require fixed effects for the family to control for unobserved heterogeneity across families and residential locations. Outcomes of interest are test scores, class grades, attendance, grade repetition, and disability status.

A simple conceptual framework for modeling the outcomes of interest for each student i in family f and year t is the following reduced-form equation:

$$y_{ift} = \theta_f + X_{ift}\beta + \tau_{it}\delta + \epsilon_{ift} \tag{1}$$

In this equation, θ_f is a family fixed effect, X_{ift} is a vector of student, school, teacher, and locality characteristics including air pollution, and τ_{it} is a vector of dummies for specific ages of exposure. The coefficient of interest is the vector δ, which conveys the age-specific effect of ash-pond leachate exposure. The identifying assumption is that children whose parents move from ash pond-affected areas when they have less exposure have comparable potential outcomes to children whose parents move when they have more exposure, differing only with respect to exposure to the ash pond. In other words, there should not be within-family heterogeneity related to the timing of the residential change. This assumption would be violated if parents move and subsequently invest more in the child with less exposure. If parental wealth changes after the move, this would only violate the identification assumption if the parents increase child investment differentially across siblings in a way that is correlated with exposure differentials. Although this seems unlikely, it could be tested by isolating the subset of residential changes that are caused by exogenous natural disasters or employment shocks.

There are a few other problems with this research design. To start, there is uncertainty in housing location before starting school. Linking state birth records from the North Carolina Center for Health Statistics, such as in Persico et al. (2015), would correct this problem for students who stay in state for public education. However, this issue is not necessarily problematic for the study of contemporaneous effects. A second issue is sample size. There are only 14 coal ash ponds, with data on residents from 1996-2015. This limitation could result in high standard errors. A final issue is that the results need not be causal if the identification assumption above is flawed. Controlling for observable factors at the census block level in addition to the student level may deal with potential additional unobserved heterogeneity. However, the best solution is to observe a subset of residents with exogenous residential change decisions.

5.9 Subterranean Pollution Variation in Exposure

The potential issues with the sibling effects model, including uncertainty on the identifying assumptions, parental investment differentials, or the location of students before starting school, necessitate either onerous robustness checks or an additional research model to verify the findings. An alternative research model relies on differential exposure to CCR pollution in the form of ash pond leachate. Differential exposure to leachate arises from natural variation in the flow patterns of pollution plumes in groundwater. Such pollution plumes more easily travel through preferential flow pathways created by subterranean springs, and they generally do not cross flowing bodies of water. Students living at the same distance from an ash pond who differ only with respect to well water sources provide a natural comparison to each other, irrespective of their family characteristics. The reduced form estimate of effects on test scores, disability status, absences, and grade repetition in this model is:

$$y_{iabt} = (\tau_{it} * WV_b)\delta + X_{it}\beta + \eta_a + \eta_t + \epsilon_{iabt} \quad (2)$$

where WV_b represents the well susceptibility to pollution in census block b of student i in year t. For an explanation of how well susceptibility can be calculated, see Appendix section A.A.1. As before τ_{it} represents a vector of student ages to allow for differential exposure effects. X_{ift} is a vector of student, school, teacher, and locality characteristics including inverse distance from the census block population-weighted centroid to the coal ash pond. The inverse distance term controls for air pollution differentials. η_a is a fixed effect for each ash pond in the sample, η_t is a year fixed effect to allow for variation over time in student outcomes. The equation is estimating how students living in census blocks less affected by potential wellwater pollution differ from students of equal distance to the coal plant (i.e. of equal air pollution exposure) who differ only with respect to well-water contamination.

5.10 Willingness-to-Pay for Ash Pond Cleaning

Determining the willingness to pay for cleaning of an ash pond is straightforward. Evidence suggests that cleaning an ash pond has immediate effects on groundwater, improving arsenic levels by as much as 90 percent (Fretwell). Due to a series of state bills such as Coal Ash Management Act (SB 729), there exists variation across ash ponds in both mandated clean-up and actual ash pond cleaning. The former can be used to estimate the effect of anticipated cleaning, while the latter can be used to estimate the effect of actual cleaning on housing values. The estimating equation will be of the form:

$$y_{it} = \lambda * post_t + \delta(\tau * post)_{it} + X_{it}\beta + \eta_t + \eta_i + \epsilon_{it} \tag{3}$$

The outcome of interest is the sale value of a specific home located in a census block within two miles of a cleaned ash pond. Because ash pond cleaning does not relate to closure of coal plants, the change in sale prices should reflect only ash pond cleaning. βX_{it} is a set of locality characteristics including demographics, rooms per home, housing age, housing characteristics, proportion renting, etc. η_t is a set of year effects to control for fluctuations in the housing market. τ_i is a dummy equal to one if the house is within a census block that has a current or former ash pond within 2 miles. The post variable indicates that the ash pond has been cleaned. The effect of interest is δ which reflects the plausibly causal effect of cleaning an ash pond on local home sale values.

6 Results

6.1 Robustness

6.2 Benefit-Cost Analysis

7 Conclusion

The data acquisition process for this study is in progress, so there are no preliminary results to share at this time. Applications for the AYS Dissertation Fellowship and the Doris Duke Dissertation Fellowship are due at the beginning of December, but both require successful completion of the proposal defense to apply. Because data acquisition depends on securing funding, results will not be available until after the December application due dates.

References

J. A. Qureshi. Siblings, teachers, and spillovers on academic achievement. *Journal of Human Resources*, pages 0815–7347R1, 04 2017.

D. Aaronson. Using sibling data to estimate the impact of neighborhoods on children's educational outcomes. *The Journal of Human Resources*, 33(4):915–946, 1998. ISSN 0022166X. URL http://www.jstor.org/stable/146403.

D. Almond and J. Currie. Killing me softly: The fetal origins hypothesis. *The Journal of Economic Perspectives*, 25(3):153–172, 2011. ISSN 08953309. URL http://www.jstor.org/stable/23049427.

J.-P. Amigues, M. Moreaux, and K. Schubert. Optimal use of a polluting non-renewable resource generating both manageable and catastrophic damages. *Annals of Economics and Statistics*, (103/104):107–141, 2011. ISSN 21154430, 19683863. URL http://www.jstor.org/stable/41615496.

H. S. Banzhaf and R. P. Walsh. Do people vote with their feet? an empirical test of tiebout. *American Economic Review*, 98(3):843–63, June 2008. doi: 10.1257/aer.98.3.843. URL http://www.aeaweb.org/articles?id=10.1257/aer.98.3.843.

C. Bernhardt, A. Russ, and E. Schaeffer. Toxic wastewater from coal plants. Technical report, Environmental Integrity Project, 8 2016. URL https://www.eenews.net/assets/2016/08/11/document_gw_05.pdf.

J. Boyce and M. Ash. Toxic 100 water polluters index: 2016 report, based on 2014 data. Technical Report 2, Political Economy Research Institute, Office of Water, Washington DC, 20460, 9 2016. URL http://www.peri.umass.edu/publication/item/765-toxic-100-names-top-climate-polluters.

C. C. Coutant, C. S. Wasserman, M. S. Chung, D. B. Rubin, and M. Manning. Chemistry and biological hazard of a coal ash seepage stream. *Journal (Water Pollution Control Federation)*, 50(4):747–753, 1978. ISSN 00431303. URL http://www.jstor.org/stable/25039619.

J. Currie, J. G. Zivin, K. Meckel, M. Neidell, and W. Schlenker. Something in the water: contaminated drinking water and infant health. *The Canadian Journal of Economics / Revue canadienne d'Economique*, 46(3):791–810, 2013. ISSN 00084085, 15405982. URL http://www.jstor.org/stable/42705901.

L. W. Davis. The effect of power plants on local housing values and rents. *The Review of Economics and Statistics*, 93(4):1391–1402, 2011. ISSN 00346535, 15309142. URL http://www.jstor.org/stable/41349119.

J. Duggan. Closing the floodgates: How the coal industry is poisoning our water and how we can stop it. Technical report, Environmental Integrity Project, The Sierra Club, Clean Water Action, Earth Justice, Water Keeper Alliance, The address of the publisher, 2013.

EPA. Stage 1 disinfectants and disinfection byproducts rule. Technical report, EPA, 2001.

EPA. Environmental assessment for the effluent limitations guidelines and standards for the steam electric power generating point source category. Technical report, EPA, Office of Water, Washington DC, 20460, 9 2015. URL https://www.epa.gov/sites/production/files/2015-10/documents/steam-electric-envir_10-20-15.pdf.

S. Fretwell. Coal ash cleanup results in cleaner groundwater, greens say.

L. Gazze. The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates. Nber working papers, National Bureau of Economic Research, Inc, Dec. 2015. URL file:///C:/Users/AYSPS/Downloads/ThePriceOfASafeHomeLeadAbatement_preview%20(2).pdf.

P. Graves, J. C. Murdoch, M. A. Thayer, and D. Waldman. The robustness of hedonic price estimation: Urban air quality. *Land Economics*, 64(3):220–233, 1988. ISSN 00237639. URL http://www.jstor.org/stable/3146246.

M. Greenstone and R. Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *The American Economic Review*, 104(10):3038–3072, 2014. ISSN 00028282. URL http://www.jstor.org/stable/43495313.

J. S. Harkness, B. Sulkin, and A. Vengosh. Evidence for coal ash ponds leaking in the southeastern united states. 50(12):6583–6592, 2016. ISSN 10.1021/acs.est.6b01727. URL http://pubs.acs.org/doi/abs/10.1021/acs.est.6b01727.

A. Jha and N. Z. Muller. Handle with care: The local air pollution costs of coal storage. w23417:1–64, 2017. URL https://www.eenews.net/assets/2017/07/05/document_pm_01.pdf.

D. A. Keiser and J. S. Shapiro. Consequences of the Clean Water Act and the Demand for Water Quality. Working Papers 17-07, Center for Economic Studies, U.S. Census Bureau, Jan. 2017. URL https://ideas.repec.org/p/cen/wpaper/17-07.html.

J. Liu, B. Zheng, H. V. Aposhian, Y. Zhou, M.-L. Chen, A. Zhang, and M. P. Waalkes. Chronic arsenic poisoning from burning high-arsenic-containing coal in guizhou, china. *Environmental Health Perspectives*, 110(2):119–122, 2002. ISSN 00916765. URL http://www.jstor.org/stable/3455366.

S. MacBride. The archeology of coal ash: An industrial-urban solid waste at the dawn of the hydrocarbon economy. *IA. The Journal of the Society for Industrial Archeology*, 39(1/2):23–39, 2013. ISSN 01601040. URL http://www.jstor.org/stable/43958425.

M. L. Miranda, D. Kim, M. A. O. Galeano, C. J. Paul, A. P. Hull, and S. P. Morgan. The relationship between early childhood blood lead levels and performance on end-of-grade tests. *Environ Health Perspect*, page 1242–1247, August 2007.

N. Z. Muller and R. Mendelsohn. The air pollution emission experiments and policy analysis model. Technical report, School of Forestry and Environmental Studies at Yale University, 230 Prospect Street New Haven, CT, 2006. An optional note.

C. Osmond and D. J. P. Barker. Ischaemic heart disease in england and wales around the year 2000. *Journal of Epidemiology and Community Health (1979-)*, 45(1):71–72, 1991. ISSN 0143005X, 14702738. URL http://www.jstor.org/stable/25567133.

G. Pershagen, N. Hammar, and E. Vartiainen. Respiratory symptoms and annoyance in the vicinity of coal-fired plants. *Environmental Health Perspectives*, 70:239–245, 1986. ISSN 00916765. URL http://www.jstor.org/stable/3430360.

L. Ruhl, A. Vengosh, G. S. Dwyer, H. Hsu-Kim, G. Schwartz, A. Romanski, , and S. D. Smith. The impact of coal combustion residue effluent on water resources: A north carolina example. 46(21):12226–12233, 2012. ISSN 10.1021/es303263x. URL http://www.jstor.org/stable/3650981.

SELC. North carolina drinking water contamination near duke energy coal ash sites. Technical report, Southern Environmental Law Center, 10th St NW, Atlanta, GA 30309, 2015. URL https://selcgis.maps.arcgis.com/apps/MapSeries/index.html?appid=95ddc8ae572b4e539fd8d4be07733e6c.

C. M. Shy. Toxic substances from coal energy: An overview. *Environmental Health Perspectives*, 32:291–295, 1979. ISSN 00916765. URL http://www.jstor.org/stable/3429030.

D. W. Watch. Drinking water watch, 2017. URL https://www.pwss.enr.state.nc.us/NCDWW2/.

G. Yu, D. Sun, and Y. Zheng. Health effects of exposure to natural arsenic in groundwater and coal in china: An overview of occurrence. *Environmental Health Perspectives*, 115(4):636–642, 2007. ISSN 00916765. URL http://www.jstor.org/stable/4150368.

Tables

Table 1: Analyte Testing, Violation Rates, and Water System Characteristics 2005-2017

	(1) Ash WS		(2) Non-Ash WS	
Annual Testing Frequency				
All Tests	432.6	(520.3)	389.5	(725.0)
Disinfectant By-Products	55.18	(51.98)	40.13	(41.31)
Inorganic Compounds	70.35	(91.19)	56.76	(99.43)
Lead & Copper	77.63	(76.57)	89.11	(193.0)
Radiation	32.05	(28.58)	86.42	(197.7)
Synthetic Organic Compounds	187.9	(193.1)	288.0	(504.1)
Volatile Organic Compounds	130.2	(126.2)	111.3	(169.7)
Water Quality Policy	374.5	(280.0)	107.3	(134.8)
Percent over MCL				
All Violations	0.0181	(0.133)	0.0161	(0.126)
DBP Violations	0.0682	(0.252)	0.0585	(0.235)
Inorganic Compounds	0.0116	(0.107)	0.0201	(0.140)
Volatile Organic Compounds	0.000335	(0.0183)	0.000249	(0.0158)
Lead & Copper	0.0114	(0.106)	0.0167	(0.128)
Radiation	0.0586	(0.235)	0.0929	(0.290)
Synthetic Organic Compounds	0.000158	(0.0126)	0.000153	(0.0124)
Water Quality Rule	0.966	(0.181)	0.1705	(0.376)
Water Systems				
Population Served	486452.3	(849691.8)	204402.7	(603888.2)
Percent Well	0.655	(0.470)	0.876	(0.324)
Recharge Rate	3220791.8	(6049197.0)	3974073.4	(8735128.5)
Average Production Capacity	68199353.9	(133533840.7)	14977741.6	(53099549.6)
Connections to System	161552.9	(284263.9)	79108.3	(236419.0)
Population	140838.2	(318485.5)	17123.3	(57431.6)
Water Systems Pipes				
Average Age	48.18	(19.16)	51.40	(16.73)
Pct. Asbestos	0.177	(0.250)	0.132	(0.203)
Pct. Metal	0.230	(0.296)	0.314	(0.346)
Pct. PVC	0.593	(0.430)	0.525	(0.367)
Pct. Missing	0	(0)	0.0296	(0.144)
Pct. Corrosive	0.0992	(0.200)	0.207	(0.280)
Analyte Tests	138,004		1,635,890	
Water Systems	138,004		1,635,890	
Observations	138,004		1,635,890	

Mean coefficients reported; standard deviations in parentheses. Observations are at the water system level. Asbestos, Chlorite, Nitrate, Nitrite, and heterotrophic bacteria tests not shown because of sample size. MCL is the maximum contaminant level as determined by the current Safe Drinking Water Standards.

Table 2: Coal Ash Pollutants by Facility 2005-2017

	(1)	
Average Annual Releases		
Surface-Water Releases (tons)	3.622	(8.326)
Impounds (tons)	135.6	(234.8)
Heavy Metals (tons)	2.721	(7.549)
Carcinogens (tons)	0.992	(5.534)
Types of Heavy Metals	5.382	(4.343)
Types of Carcinogens	1.313	(1.122)
Types of All Releases	11.07	(7.258)
Specific Compounds Released (lbs.)		
Ammonia	401.4	(1467.9)
Arsenic	119.1	(330.4)
Barium	1401.8	(2493.6)
Beryllium	1.592	(13.20)
Chromium	258.5	(1891.9)
Cobalt	1983.5	(11068.4)
Copper	397.1	(1233.6)
Lead	38.25	(152.5)
Manganese	2201.4	(7233.5)
Mercury	1.806	(8.287)
Nickel	86.04	(226.3)
Selenium	40.99	(134.1)
Thallium	0.145	(1.657)
Vanadium	76.98	(138.0)
Zinc	236.0	(514.7)
Observations	262	
Locations	27	

Mean coefficients reported; standard deviations in parentheses. Observations are at the disposal-location-year level.

Table 3: Coal Ash Releases and Storage and All Violations within 5 Miles (2005-2017)

	(1) Tons Released	(2) Carcinogens	(3) Tons Impounded
All Violations	0.00025*	0.00014*	-0.00001
	(0.00)	(0.00)	(0.00)
R2	0.354	0.365	0.354
N	21,007	18,044	21,007
n	1,667	1,660	1,667
Synthetic Organic Compounds	-0.00011	-0.00009	-0.00000
	(0.00)	(0.00)	(0.00)
R2	0.106	0.112	0.106
N	9,905	8,473	9,905
n	1,667	1,636	1,667

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variables are the annual violation rates for all analytes regulated under the Safe Drinking Water Act and the annual violation rate for synthetic organic compounds, both collapsed to the water-system year level. With an annual violation rate of 0.0181, the point estimate in column (1) suggests that each ton of coal ash released increases the violation rate by %1.4. Since 3.6 tons are released on average, this suggests that coal ash surface water discharges increase the annual violation rate by 5%. Synthetic organic compounds serve as a placebo test because coal ash pollution does not affect these pollutants. The independent variables are the annual tons released into surface waters, the annual tons carcinogenic compounds released into surface waters, and the tons of coal ash impounded in ash ponds.

Table 4: Coal Ash Releases and Storage within 5 Miles and Violations by Type (2005-2017)

	(1) Tons Released	(2) Carcinogens	(3) Tons Impounded
Disinfectant Byproducts	0.00255*	-0.0001	0.00023**
	(0.00)	(0.00)	(0.00)
R2	0.407	0.420	0.410
N	11,043	9,492	11,043
n	1,667	1,640	1,667
Volatile Organic Compounds	0.00000	0.00000	0.00000
	(0.00)	(0.00)	(0.00)
R2	0.219	0.226	0.219
N	12,150	10,445	12,150
n	1,667	1,640	1,667
Synthetic Organic Compounds	-0.00011	-0.00009	-0.00000
	(0.00)	(0.00)	(0.00)
R2	0.107	0.113	0.106
N	9,905	8,473	9,905
n	1,667	1,636	1,667
Inorganic Compounds	0.00001	-0.00001	-0.00000
	(0.00)	(0.00)	(0.00)
R2	0.367	0.404	0.367
N	12,394	10,389	12,394
n	1,667	1,632	1,667
Lead and Copper	0.00013	-0.00003	0.00000
	(0.00)	(0.00)	(0.00)
R2	0.254	0.270	0.254
N	9,226	7,997	9,226
n	1,664	1,636	1,664
Water Quality Policy	0.00017	-0.00008	-0.00009
	(0.00)	(0.00)	(0.00)
R2	0.457	0.472	0.457
N	8,867	7,580	8,867
n	1,667	1,621	1,667

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variables are the annual violation rates for analytes regulated under the Safe Drinking Water Act broken up by analyte class and collapsed to the water-system year level. With an annual violation rate of 0.068, the point estimate in column (1) of 0.0026 for disinfectant byproducts suggests that each ton of coal ash released increases the DBP violation rate by %4. Since 3.6 tons are released on average, this suggests that coal ash surface water discharges increase the annual DBP violation rate by 15%. Volatile organic compounds are a wide variety of carcinogenic compounds typically related to industrial and petroleum-related activites. Synthetic organic compounds are a class of pollutant including pesticides and herbicides such as dieldrin or glyphosate. Inorganic compounds are metals such as arsenic and mercury. Lead and copper are violations typically related to leaching of these materials from water system pipes. Water quality policy violations exclusively come from having PH lower than 6.5 or greater than 8.5.

Table 5: Lead and Copper Violations, Continuous Levels, and Detectable Levels (2005-2017)

	(1) Violations	(2) MG/L	(3) Detectable
Lead Released (tons)	0.0313	0.0034**	0.2055**
	(0.03)	(0.00)	(0.10)
R2	0.041	0.009	0.187
N	12,838	12,838	12,838
n			
Copper Released (tons)	0.0059***	0.0028	-0.0136**
	(0.00)	(0.00)	(0.01)
R2	0.138	0.250	0.351
N	12,837	12,837	12,841
n			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variables are the violations, continuous detectable quantities, and binary indicator for whether a compound is detecablte. Inorganic compounds arsenic, ammonia, barium, beryllium, manganese, mercury, nickel, selenium, and thallium were not included due to sample size concerns, lack of violations, or some other issue preventing consistent estimation.

Table 6: Relevant Analytes with Few Violations (2005-2017)

	(1) Conductivity	(2) Alkalinity	(3) Total Carbon	(4) PH
Tons Released	1.3696***	0.1790	0.0117***	-0.0050**
	(0.21)	(0.16)	(0.00)	(0.00)
R2	0.624	0.824	0.194	0.002
N	14,856	47,129	43,941	46,813
n	283	391	128	1,666

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variables are the continuous average detected level of conductivity, alkalinity, total carbon including dissolved carbon, and PH. The independent variable is the tons of coal ash released within 5 miles of the municipal water system intake region.

Table 7: Flood Days and Violations 2005-2017

	(1) DBP	(2) DBP	(3) WQP	(4) WQP	(5) Conduc	(6) Conduc	(7) Carbon	(8) Carbon	(9) PH	(10) PH
Flood Days	0.00026***	0.00025**	-0.00103**	-0.00100**	0.02746	0.03040	0.00625*	0.00622*	0.01306	0.01260
	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.2994)	(0.2977)	(0.0032)	(0.0032)	(0.0124)	(0.0121)
Releases	0.00003*		0.00008		0.10336		0.00150***		-0.00126	
	(0.0000)		(0.0001)		(0.0929)		(0.0004)		(0.0011)	
Impounds		0.00000***		0.00000		0.00565*		0.00003**		0.00002
		(0.0000)		(0.0000)		(0.0030)		(0.0000)		(0.0000)
R2	0.409	0.410	0.461	0.461	0.623	0.623	0.192	0.192	0.002	0.002
N	10,853	10,853	8,717	8,717	14,772	14,772	43,692	43,692	46,529	46,529

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variables are the violation rates for disinfectant byproducts (DBP) followed by those for water quality policy (WQP) violations. Conduc represents the ontinuous average detected level of conductivity, while carbon is the carbon content of water including dissolved carbon. PH is a continuous variable for PH. The independent variables are the number of flood days and either the tons released within 5 miles of a municipal water system intake interacted with the number of flood days or the tons impounded interacted with the flood days.

Table 8: Coal Ash Releases and Fines 2005-2017

	(1) Fines	(2) Fines	(3) Fines	(4) Fines
Releases (tons)	4224.11	12691.31		
	(11109.50)	(10057.88)		
Impounds (tons)	592.70*		646.06**	
	(330.36)		(299.06)	
Binary Exposure				426.80**
				(172.22)
R2	0.663	0.663	0.663	0.030
N	20,693	20,693	20,693	20,693

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included for all models except (4), which is a binary exposure dummy that would be dropped with fixed effects. The dependent variables are the total annual fines assessed across different water systems. The independent variables are the tons of coal ash released within 25 miles of the municipal water system intake region, the total impounds within 25 miles of a municipal water system, and a dummy variable equal to one if a water system has an ash pond nearby. The coefficients in model (1) suggest that, for each ton of coal ash released, annual fines increase by \$4224. Meanwhile, for each ton of coal ash impounded, fines increase by \$592. Multiplying the these estimates by 3.6 and 107 for the average annual tons, respectively, and then multiplying over 12 years yields a total fine amount of \$182,481+ \$760,128 = \$942,609.

Appendix

Table A1: Disinfectant Byproducts across Different Buffer Regions (2005-2017)

	(1) 2.5 Miles	(2) 5 Miles	(3) 10 Miles	(4) 15 Miles	(5) 25 Miles
Fixed Effects					
Tons Released	0.00105	0.00255*	0.00014	0.00005	-0.00001
	(0.00064)	(0.00096)	(0.00025)	(0.00018)	(0.00013)
R2	0.406	0.406	0.406	0.406	0.406
N	11,043	11,043	11,043	11,043	11,043
n	1,667	1,667	1,667	1,667	1,667
Probit Model					
Dummy Present	0.13370***	0.10792***	0.12351***	0.10603***	0.10304***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Pseudo R2	0.0366	0.0367	0.0376	0.0374	0.0373
N	103,908	103,908	103,908	103,908	103,908
n	1,667	1,667	1,667	1,667	1,667

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at the municipal water system in parentheses. Year and municipal water system fixed effects included. The dependent variable is the annual violation rates for disinfectant byproducts collapsed to the water-system year level. With an annual violation rate of 0.068, the point estimate in column (1) of 0.0026 for disinfectant byproducts suggests that each ton of coal ash released increases the DBP violation rate by %4. Since 3.6 tons are released on average, this suggests that coal ash surface water discharges increase the annual DBP violation rate by 15%.