ESSAYS IN ENVIRONMENTAL ECONOMICS

by

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A DISSERTATION

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Title: Essays in Environmental Economics

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DISSERTATION ABSTRACT

Rose Mueller

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This research examines both health effects and market responses from local changes in environmental quality. Both can be of significant interest to policy makers. I examine the health effects of population exposure to pollution from a primary resource-extraction industry and the housing-market effects when an area is officially designated as being at risk from water pollution exposure.

In Chapter II, I examine how adult mortality rates are affected by coal-mining activity in Appalachia. I find increased surface coal-mining activity leads to increased mortality attributable to internal causes, specifically among the population over age 65. Increased surface coal mining is most significantly associated with increases in mortality from cardiovascular disease, suggesting air pollution as a plausible mechanism.

Chapter III documents the association between infant health and coal-mining activity in Appalachia. Descriptive evidence implies infant health outcomes are

worse in certain Appalachian coal counties compared to other parts of the U.S., but after controlling for other sources of observed and unobserved heterogeneity, I find no evidence that changes in surface coal-mining activity directly affect birth outcomes in these counties.

In Chapter IV, I evaluate the effect of a policy intervention in Oregon which provided information to residents regarding potential exposure to groundwater pollution from agricultural runoff. I find that this policy led to an increase in home prices for properties that were more likely to be reliant on public water supplies, suggesting that consumer demand shifted away from well-water-dependent properties that were at risk of contamination. The heterogeneity of the policy effect is consistent with a heightened awareness of groundwater quality among residents and housing market participants after the information was announced.

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CHAPTER I

INTRODUCTION

This research aims to improve our understanding of the public health effects and housing market responses from local changes in certain types of pollution exposure. Chapters II and III evaluate some public health effects associated with residence near surface coal-mining activity. Knowledge of these health effects is important for determining the negative externality costs associated with the lifecycle of coal.

Previous research in the health and epidemiology literatures has highlighted that coal-producing counties in Appalachia have morbidity and mortality rates higher than those in the rest of the United States. Chapters II and III improve upon the largely descriptive analyses available in the existing literatures by making an effort to causally identify the effects of within-county changes in coal-mining activity on public health.

In Chapter II, I investigate the adverse impact that coal mining appears to have had on adult mortality. Using a 31-year panel dataset for coal-mining activity and county-level mortality rates, I find that within-county changes in surface coal-mining activity increase internal mortality rates for the population over age 65. Ambient air pollution from surface mining may be a mechanism contributing to increased mortality in Appalachia. Heterogeneity by gender indicates that individual risks may vary by each individual's cumulative exposure to coal mining throughout their lifetime.

In Chapter III, I investigate the potential adverse impact that coal mining appears to have had on infant health. Unlike adults, newborn infants do not experience much variation in cumulative pollution exposure during their nine-month gestational "lifetime." Thus, we are able to examine prenatal exposure to variation in environmental quality throughout the nine months prior to birth, assuming the mother's county of residence was relatively constant throughout her pregnancy. The link between an individuals health at birth and his/her future health and wellbeing is well-established in the literature.

Using data from individual birth certificates from 1989 to 2006, I find no evidence that increased surface coal mining leads to worse infant health outcomes. These results, combined with results from Chapter II, indicate that lifetime cumulative exposure may be more important to health impacts than short-term effects of contemporaneous exposure to coal-mining activity.

Chapter IV, in contrast, identifies a housing market response from a policy intervention in Oregon which provided information to residents regarding exposure to groundwater pollution from agricultural runoff. I find that this policy led to an increase in home prices for properties that were likely to be reliant on public water supplies, probably because consumer demand shifted away from well-water-dependent properties that were at risk of contamination. This heterogeneity in the effect of the information treatment reflects heightened awareness of environmental quality among residents and housing market participants after the information-policy-provision was implemented.

Chapter V summarizes the findings and briefly discusses the policy implications from the findings in each chapter.

CHAPTER II

THE IMPACT OF SURFACE COAL MINING ON MORTALITY: EVIDENCE FROM APPALACHIA

Introduction

Previous research has highlighted that coal-producing counties in Appalachia have morbidity and mortality rates higher than counties in the rest of the United States. Researchers have noted that mortality is particularly elevated in counties that participate in mountaintop removal (MTR) coal mining, a particularly destructive type of surface mining. Concern about these observed correlations has been sufficiently great that in August 2016, the government commissioned the National Academy of Sciences, Engineering, and Medicine (NAS) to undertake a review of the evidence linking surface coal mining to negative health outcomes.[1] The NAS committee includes specialists across many scientific fields, but no member of the committee appears to have been trained in the use of econometric methods for panel data.[2]

[1]See NAS project "Potential Human Health Effects of Surface Coal Mining Operations in Central Appalachia" `http://www8.nationalacademies.org/cp/projectview.aspx?key=49846` for more information regarding the committee's mandate and composition.

[2]We contacted Paul Locke, the committee chair, about this research project and explained our concerns about the statistical methods used in much of the existing research. In a personal communication dated August 8, 2017, he pointed out that "Our statement of task does not mention econometrics, nor does it involve an evaluation of any economic data or indicators, including cost-benefit analyses." However, he was very interested in our research and concludes with "I greatly appreciate your willingness to reach out to our committee and inform us about what sounds like very interesting and thoughtful research. I hope that we can receive something from you very soon."

Much of the previous research designed to evaluate the potential link between coal mining and negative health outcomes has been primarily descriptive. Even when controlling for observable factors—such as income, poverty, education, access to healthcare and smoking rates—cross-sectional analyses of the effects of coal mining on mortality may suffer from omitted-variable bias because they fail to account for unobserved heterogeneity across counties and/or over time. These earlier studies are generally careful to interpret their statistical findings merely as associations, rather than as evidence of causality, but there is clearly a need for more-rigorous longitudinal analyses.

The current study uses a spatial measure of county-level exposure to surface coal mining, rather than relying on coal mining within a county's geographic boundaries, as in much of the previous literature. This measure allows us to account for the potential for mining activity near the boundary of one county to affect the health of residents in a neighboring county.

Along with remedying some of the statistical shortcomings of the previous literature, the current study addresses the following main research questions:

1. Are mortality rates higher in MTR coal-mining counties, compared to other Appalachian counties, and how has this evolved over time?

2. Do within-county changes in surface coal-mining activity affect county-level mortality rates?

To address our first research question, we compare mortality trends between counties that participate in MTR mining and other Appalachian counties. We also compare trends in coal production between these groups of counties. We find that internal mortality rates have increased over time in MTR counties relative to other Appalachian counties.[3] This trend appears to somewhat correlate with increased coal production from surface-mining methods in MTR counties relative to other Appalachian counties.

For our second research question, we find that within-county increases in surface coal production leads to increases in internal mortality rates for adults aged 65 and over. Specifically in the sample of MTR counties, we also find that new surface mine openings increase mortality rates for adults aged 65 and over, primarily driven by increased mortality from cardiovascular diseases. These estimated effects are statistically significant; however, the largest estimated effect of new surface mining amounts to an increase in the elderly internal mortality rate of only about one-tenth of the standard deviation in elderly mortality rates across the sample of counties that have ever participated in mountaintop removal (MTR) coal mining. Scaling this estimate to the 1,071 county-years in the sample where a county opened a new surface mine during the time period, and reckoning for the average elderly population in the affected counties across the entire time period,

[3] Internal mortality includes illness-based mortality and excludes mortality from external causes such as physical accidents, suicides, and drug overdoses.

this estimate corresponds to roughly 3,500 total excess deaths over our 31-year panel.

Notably, descriptive evidence in this study supports prior literature that indicates mortality rates are higher in MTR counties compared to the rest of the U.S. and compared to other counties in Appalachia. Anecdotally, mountaintop removal coal mines are detrimental to the surrounding landscape and ecosystems, depress property values, and contribute to socioeconomic inequality. Thus, the existence of mountaintop removal coal mines remains a concern from the perspective of environmental justice. However, it is inappropriate to attribute the observed adverse health outcomes in this region to the existence of coal mining based on conclusions simply from cross-sectional analyses.

To be clear, the main concern that can be raised about many prior studies is that the conclusions they draw may be biased due to the omission of both observable and unobservable heterogeneity that may be correlated with coal-mining activity. County-level fixed effects, year fixed effects, and controls for time-varying spatial patterns in personal income and employment are included in all our specifications. These variables capture, to a fuller extent, the various types of heterogeneity (across Appalachian counties and over time) that may be correlated with mining activity, and may also affect public health.

In Section 2.2, we review the existing literature on public health from population exposure to coal mining, as well as the literature on public health effects attributable to pollution exposure more broadly. In Section 2.3, we discuss some background on the coal mining industry. In Section 2.4, we review the data used in the analysis, and present descriptive trends over time. In Section 2.5, we describe the empirical methodology used to identify whether within-county changes in coal mining impacts public health. In Section 2.6, we present results from the empirical model and offer some discussion of results, followed by concluding remarks in Section 2.8.

Literature

The first research question in this study has been addressed by many previous studies within the epidemiology literature. Many of these prior studies use cross-sectional data on county-level measures of mortality, and compare mortality in coal-producing counties to mortality in non-coal-producing counties. These studies have concluded that coal mining is associated with higher mortality rates from all causes (Hendryx and Ahern (2009)), all types of cancer (Hendryx (2009)), lung cancer (Hendryx et al. (2008)), and mortality from cardiovascular, respiratory, and kidney diseases (Hendryx (2009); Esch and Hendryx (2013)). These studies often rely on a small sample of counties, involve aggregating multiple years of data on mortality and coal production, and generally do not include any time variation in their econometric specifications. Hendryx and Ahern (2009) explicitly acknowledge that their results "suggest, but do not prove, that a coal-mining-dependent economy is the source of these continuing socioeconomic and health disparities."

Hendryx and Holland (2016) use time-varying annual age-adjusted all-cause mortality rates for 1968–2014, for counties in four states with mountaintop removal mining: Kentucky, Tennessee, Virginia, and West Virginia. The specification focuses on the differences in mortality rates (a) between categories of counties, and (b) between the interval of 1968-1989 (the pre-Clean-Air-Act period) and the interval of 1990-2014 (the post-Clean-Air-Act period). Their data do not feature within-county variation in the amount of MTR mining over time; instead, they treat the post-CAA period as implicitly capturing an increase in MTR mining in Central Appalachia.[4] In their paper, Hendryx and Holland (2016) calculate that there have been about "1180 to 1217 additional deaths experienced *every year* in the MTR region in the post-CAA period" [emphasis added].[5]

The main limitation of cross-sectional analyses is that they do not permit the researcher to control for omitted variable bias resulting from unobserved heterogeneity. Simply comparing (a) counties with coal mining to (b) counties without coal mining, fails to reflect other differences between these counties that may also be correlated with health outcomes. If we compare county-level mortality rates in counties with a long history of coal mining to mortality rates in counties with no coal mining, we cannot conclude that the presence of mining activity is the

[4] These authors cite a coal industry official that argued the acid rain provisions of the CAA fostered the increasing prevalence of mountaintop mining in the 1990s.

[5] With respect to the analysis by Hendryx and Holland (2016), we note that random-effects models are appropriate only when there is no correlation between these unobserved random effects and the key observed regressor(s) included in the model (in this case, the county's coal-mining status and the pre- and post-CAA time periods).

only factor that accounts for a difference in mortality rates between those counties. For example, a coal-mining rural county in Appalachian West Virginia is likely to be different in many ways, besides just its coal-mining activity, compared to a non-coal-mining suburban county in Appalachian Pennsylvania. Among other factors, these two counties may vary in their levels of income, their employment opportunities, and their healthcare accessibility.

There is a large related literature on the long-term negative effects of commercial exploitation of natural resources in a region on patterns of regional economic development. Many studies describe a "resource curse" wherein an area becomes focused on exploitation of the resource and fails to develop more broadly. The process of extracting natural resources can make coal-mining communities less attractive as places to live, causing outward migration. Appalachia has gone through several boom and bust cycles of coal mining. Furthermore, the Appalachian region has long been associated with higher levels of poverty, lack of quality healthcare and education, and overall poor socioeconomic conditions.[6]

The analysis in the present paper uses fixed-effects specifications to address explicitly the problem of unobserved heterogeneity, across counties and over time, that may be correlated with the presence of coal-mining activity of different types in different counties. This unobserved heterogeneity may not be completely

[6]In 1965, the Appalachian Regional Commission (ARC) was established to help alleviate poverty throughout the region. In the current study, we define ARC Counties as the 413 counties within the ARC. These counties encompass all of West Virginia plus portions of twelve other states.

captured by the types of explicit non-time-varying covariates employed by Hendryx and his coauthors. Our approach essentially uses counties as their own controls, comparing mortality rates in the same county, over time, as coal-mining activity changes. Our use of county-level and year fixed effects sweeps out all non-time-varying heterogeneity across counties, and all time-related effects that are shared across all counties. Additionally, our study includes annual data on county-level coal activity, and other annual controls, rather than relying simply on cross-sectional variation across counties.

A recent study by Fitzpatrick (2018) also addresses the failure of the previous literature to control for unobserved heterogeneity. This study finds that a one-standard-deviation increase in county exposure to surface coal mining in West Virginia is associated with increases in asthma hospitalizations. The results are robust to the inclusion of county fixed effects, controls for seasonality, and controls for healthcare accessibility. Fitzpatrick also uses a spatial measure of a county's exposure to coal mining, identifying surface mines within a 34-kilometer buffer of each county's population centroid.

Results from the current study further improve upon the prior literature, by examining whether within-county changes in coal-mining activity affect mortality across the broader Appalachian region. This research attempts to clarify the direction of causality in the relationship between coal mining and public health. Specifications that ignore the potential for bias due to omitted observed and unobserved heterogeneity may imply causation where there is only a correlation. Likewise, they may overstate the systematic effect of surface coal-mining activity on human health. Additionally, by upgrading from a simple within-county measure of coal-mining activity to a spatial measure of the *exposure* of each county's population to surface coal mining, the present study also captures the potential for cross-boundary spillover effects due to coal-mining activity in neighboring counties.

Background

Background on Coal Mining

Appalachia has a long history of coal mining as a predominant industry. However, increased mechanization in the mining industry has conferred relative cost advantages for other regions and has led to reduced coal production in Appalachia. Much U.S. coal production now occurs in the western U.S., with Wyoming now being the state with the greatest total annual coal production.

The current study focuses on Appalachia because there are many more coal mines in close proximity to population centers in this region. For example, Kanawha County, the most populated county in West Virginia, is also one of the top coal-producing counties in the state. This population/production relationship stands in stark contrast to coal production in the west, where production typically takes place in sparsely populated areas, such as the Powder River Basin in northern Wyoming.

Changes in coal-mining technologies have also been important. Surface mining, rather than underground mining, became increasingly prevalent in the 1970s. As underground coal reserves were depleted, mining techniques shifted towards surface mining to exploit reserves that were inaccessible by earlier underground mining techniques. Surface coal mining—which includes strip mining, open-pit mining, and MTR mining—involves first clearing away the overburden of soil and rock that typically covers the coal deposit. This contrasts with underground coal-mining methods where coal is removed through shafts and tunnels and the earth's surface above the mine is left mostly undisturbed. Surface mining is considered safer for coal miners, but is more destructive to the landscape and releases more environmental pollutants into surrounding air and watersheds. Surface mining is also more capital-intensive, and less labor-intensive, compared to underground mining. This systemic change in mining methods has substantially reduced the demand for labor in the coal-mining sector.

Among the different types of surface mining, MTR mining is the most destructive, as it involves first clear-cutting any forest cover on the land and then using explosives and heavy equipment to remove the tops of mountains to access underlying coal seams. MTR mining first emerged in the 1960s and became a major method of coal mining in West Virginia and Kentucky during the mid-1990s. MTR mining also occurs, although to a lesser degree, in parts of Virginia and Tennessee.

Mechanisms for Health Effects due to Coal Mining

The environmental impact of surface mining, and of MTR mining in particular, has made the practice highly controversial. Some non-economic studies suggest that air and water pollution from MTR and other surface-mining operations could be potential mechanisms for the heightened mortality rates from internal causes observed in parts of Appalachia. Of the air pollutants produced by coal-mining activities, particulate matter is probably the most significant health threat. Most research concerning general health threats from air pollution focuses on fine particulates, PM2.5 (measuring less than 2.5 micrometers in diameter) and PM10 (less than ten micrometers in diameter).

In the disciplines of health and epidemiology, there has been a considerable amount of research regarding how exposure to particulate matter affects morbidity and premature adult mortality (Dockery (1993); Pope et al. (2002); Pope et al. (2009)). It is commonly accepted that exposure to particulate matter increases risks for both cardiovascular and respiratory diseases (Brook et al. (2010); Dockery (2001); Pope and Dockery (2006)). Air pollution has been found to be particularly harmful to the elderly population (Pope (2000); Gourveia and Fletcher (2000); Cakmak et al. (2007); Ma et al. (2017)). In the economics literature, several quasi-experimental studies have found causal effects from exposure to particulate matter on increased mortality rates among the elderly (Chay et al. (2003); Anderson (2015); Deryugina et al. (2015)).

Specific to pollution from surface coal mining, some cross-sectional analyses have involved sampling of air quality near surface-mining sites and comparisons of PM levels in those areas to PM levels in control areas with either (a) underground mining only or (b) no mining operations at all. Aneja et al. (2012) consider air quality samples at two specific sites near a road in Virginia that experiences heavy coal-truck traffic. Kurth et al. (2014) consider air quality samples from five surface-mining sites in West Virginia. Both studies find elevated PM concentrations near mining sites but both sets of authors note that larger sample sizes would be needed to draw appropriate conclusions about causality.

As to measured air pollution data, a fine degree of temporal resolution is available from ground-monitoring stations administered by the EPA in collaboration with state and local governments. However, the geographic distribution of ground monitors is far from uniform. Additionally, a recent working paper suggests there may be considerable non-random selection regarding the geographic placement of ground-level pollution monitors, beyond just the differences warranted by the varying sizes of the exposed populations (Grainger et al. (2016)).

Unfortunately, the rural setting of Appalachia's coal country means there are very few EPA ground monitors collecting data on ambient air pollution. Using four air quality monitors in the state of West Virginia, Fitzpatrick (2018) finds that a one-standard-deviation increase in surface coal tonnage within 20 kilometers of an air quality monitor is associated with more hourly spikes in observations of PM10. But his study finds no discernible association between surface coal mining and PM2.5.

The current study relies on existing anecdotal and epidemiological evidence of higher population exposures to particulate matter near surface coal mines as a potential mechanism for observed health effects. Recently available remotely sensed data from satellites may assist in obtaining accurate measures of ambient air quality in the vicinity of surface coal mines for future analyses.[7]

Descriptive Analysis

Data

Coal Mining: Our data on coal mine locations and production come from the Mine Safety and Health Administration (MSHA). These data include quarterly coal production and employment for individual mines since 1983. The dataset identifies the subtype of coal mine (underground versus surface), the precise geographic location of the mine, as well as total quarterly coal production, total quarterly hours of employment, and the quarterly average number of employees for each mine. Unfortunately, these data do not include information on the specific type of surface mine, thus we do not observe, based on this data source alone, whether a surface mine is specifically a mountaintop removal coal mine or some other type

[7] See the Appendix for a discussion of the air quality analysis conducted for this study and the data limitations encountered.

of surface mine. To identify MTR mines, approximately, we rely on an auxiliary spatial dataset from Skytruth which uses remotely sensed landcover data to identify locations of MTR mines.[8]

Mortality Data: Our outcome measures are obtained from the National Center for Health Statistics.[9] Mortality rates per 100,000 population are calculated based on annual county population estimates from the Surveillance, Epidemiology, and End Results (SEER) Program. The current analysis focuses on county-level mortality attributable to internal causes, based on the Center for Disease Control's (CDC) International Classification of Disease (ICD-9 for years 1983-1998, and ICD-10 for years 1999-2013). Internal causes specifically exclude mortality from external causes such as various physical accidents, suicides and drug overdoses.[10]

Age-adjusted mortality rates (based on the 2000 U.S. standard population) are calculated for the total internal and external mortality rates. Internal mortality rates are also calculated by age group, since some age groups (particularly the elderly) have often been found to be more susceptible to negative health outcomes

[8] Skytruth is a nonprofit organization that generates datasets from satellite imagery to improve analyses of environmental issues. See `https://www.skytruth.org/`.

[9] National Center for Health Statistics, Mortality – All County (micro-data) files (1983–2013) as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program

[10] Appalachia has been recognized as a region plagued by the opioid epidemic and other "deaths of despair."

from pollution exposure. Mortality rates are also calculated for specific causes-of-death. [11]

Economic Data: County-level annual measures of personal income are obtained from the Bureau of Economic Analysis (BEA). County-level annual employment data are obtained from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS).

FIGURE 1.
Map of Study Area

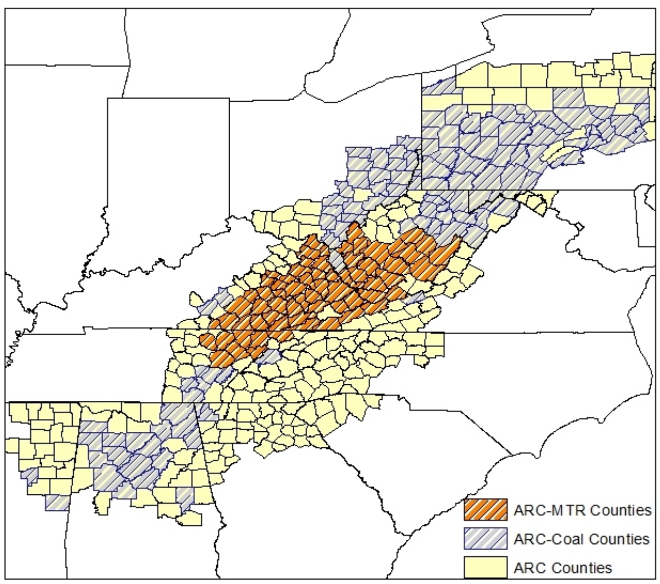


Figure 1 depicts Appalachian counties by coal status: ARC Counties (the 413 counties included in the Appalachian Regional Commission), ARC-Coal Counties (which include ARC Counties with any amount of coal production during our study

[11]The age-adjusted mortality rate is calculated as the total number deaths in a county per 100,000 county population, by age group, then weighted by the demographics of the 2000 U.S. standard population. This strategy controls for differences in mortality rates that would be expected, due to differences in the age distribution across jurisdictions.

period), and MTR Counties (which include ARC Counties with any MTR coal production during our study period).

Summary statistics for the key variables in this study are presented in Table 1. Data are reported for three nested samples:

1. All U.S. counties.

2. ARC = All Appalachian counties, namely the 413 counties designated by the Appalachian Regional Commission (ARC) in 1965.

3. MTR = Just those Appalachian counties where there is mountaintop removal (MTR) coal mining at *any time* during 1983–2013. The data limitation has ben noted that the MSHA data do not distinguish between surface coal mining and the narrower practice of MTR coal mining. However, any surface coal-mining in these counties is more likely to be MTR coal mining. This MTR sample focuses attention on smaller set of counties, and uses these counties without changes in surface coal-mining activity as "controls" for county-years in the sample "treated" with changes in surface coal-mining activity.

Based on simply cross-sectional comparisons, mortality rates from both internal and external causes of death appear to be higher in ARC counties compared to all U.S. counties. Mortality rates appear to be highest in MTR counties.

TABLE 1.
Summary Statistics: Coal-Mining Activity and Mortality (1983-2013)

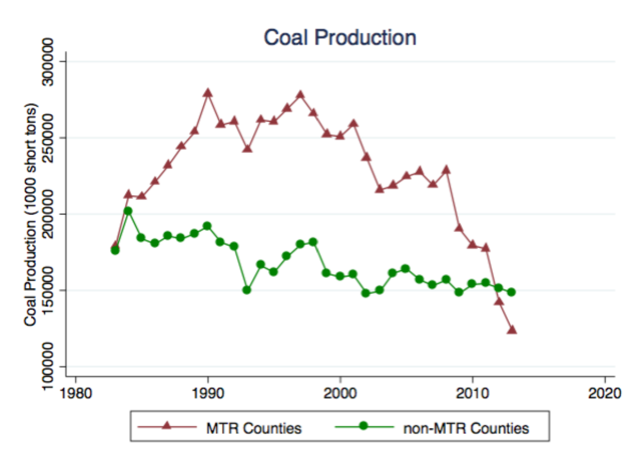
	U.S. Counties	ARC Counties	MTR Counties
County Demographics			
Population	87,560	56,154	31,448
Personal Income per Capita	22.74	20.00	17.66
Wage Employment per Capita	0.36	0.33	0.28
Total Coal Production (short tons)	333,882	957,402	3,455,998
Surface Coal Production (short tons)	211,715	329,903	1,338,734
Underground Coal Production (short tons)	119,904	613,335	2,062,148
I(New Surface Mine)	0.02	0.14	0.44
I(New Underground Mine)	0.03	0.19	0.64
I(MTR Mining County)	0.02	0.16	1.00
Mortality Rates (per 100,000 population)			
Infant Internal Causes (< 1 year)	688.77	720.58	692.50
Child Internal Causes (1-14 years)	11.45	11.40	11.94
Adult Internal Causes (15-64)	270.29	303.45	345.98
Elderly Internal Causes (>65 years)	4726.02	4834.41	5059.57
Age-Adjusted Internal Causes	795.93	848.44	914.43
Cardiovascular Disease	344.88	372.67	393.19
Respiratory Disease	69.35	76.67	94.01
Cancer	135.28	138.63	149.14
Kidney Disease	12.70	14.29	16.48
Age-Adjusted External Causes	63.28	67.24	82.28
Drug Poisonings	5.34	7.76	13.87
Observations	95,356	12,803	2,046
Counties	3,076	413	66
Years	31	31	31

Trends in Coal Production

Figure 2 depicts aggregate coal production in MTR Counties compared to non-MTR ARC-Coal counties, while Figure 3 depicts aggregate surface coal production between the two counties. Both groups of counties have experienced relatively similar trends in aggregate coal production. However, from 1983 to

2000, surface coal production significantly increased in MTR counties relative to underground coal production. Non-MTR counties in Appalachia have exhibited a steadier reliance on underground coal production. If surface coal production exposes the local population to increased pollution, as suggested anecdotally and by the epidemiology literature, we might expect health outcomes to have worsened in MTR counties relative to non-MTR counties within Appalachia during this time period.

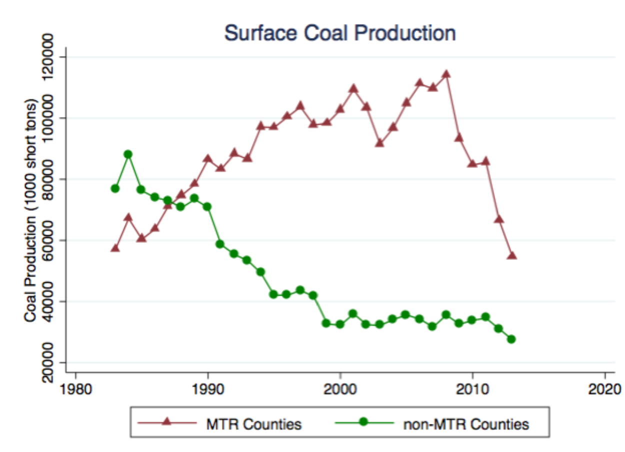
FIGURE 2.
ARC Trends in Coal Production



Trends in Mortality

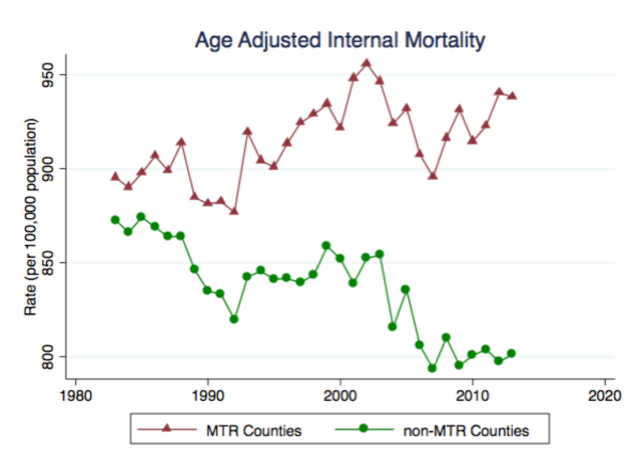
Figures 4-6 presents simple time trends of across-county averages of key variables for MTR counties compared to non-MTR Appalachian counties. Figures

FIGURE 3.
ARC Trends in Surface Coal Production



4 and 5 depict the age-adjusted internal mortality rate and age-adjusted external mortality rate for MTR counties and non-MTR ARC counties.[12]

FIGURE 4.
ARC Trends in Age-Adjusted Internal Mortality

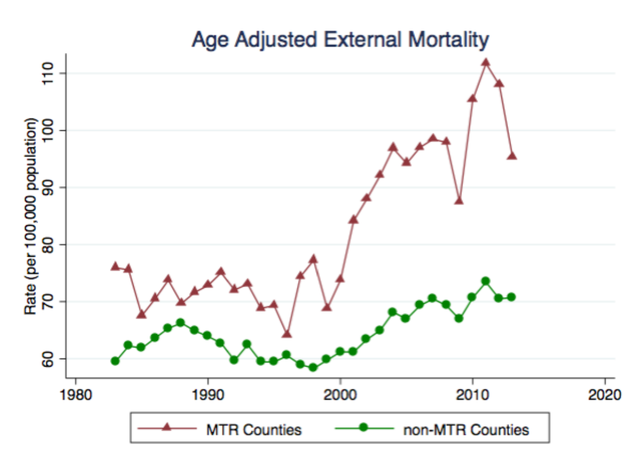


Mortality rates attributable to both internal and external causes appear to be higher in MTR counties compared to other Appalachian counties. Notably,

[12]The age-adjusted mortality rate is the total number of deaths in a county per 100,000 population, weighted by the age distribution of the overall U.S. population.

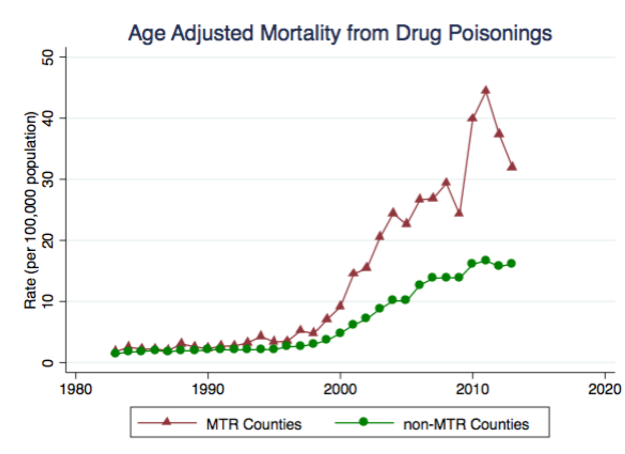
the difference in age-adjusted internal mortality rates (Figure 4) appears to be increasing over the entire sample period, accelerating in 1990, while the difference in the age-adjusted external mortality rate (Figure 5) appears to be fairly constant until 2000. However, MTR counties exhibit increasing external mortality rates relative to other Appalachian counties beginning in 2001. This trend may reflect increased deaths in the region related to the accelerating opioid epidemic.[13] Figure 6 depicts trends in the age-adjusted mortality rate attributable to drug poisonings. This includes poisonings from all types of drugs and other biological substances and includes use with intentional, accidental, and unknown intent. Mortality from drug poisonings (in Figure 6) depicts a near-identical trend compared to total external mortality (in Figure 5) suggesting that increased drug poisonings are driving the overall increase in external mortality since 2001.

FIGURE 5.
ARC Trends in Age-Adjusted External Mortality



[13]The CDC reports U.S. drug overdose deaths nearly tripled from 1999–2014, with West Virginia and Kentucky ranked among the top five states for opioid-related deaths (Rudd et al. (2016)).

FIGURE 6.
ARC Trends in Age-Adjusted Mortality from Drug Poisonings



Notably, compared to the trends in coal production, shown in figures 2 and 2, increasing internal mortality in MTR counties appears to correlate with increasing surface coal production until around 2008. Looking only at these trends in the aggregate raw data overtime, one might draw conclusions similar to those from the previous epidemiology studies discussed in our introduction. This preliminary descriptive analysis confirms results from previous epidemiology studies that find MTR counties experience higher mortality rates compared to non-MTR ARC counties that have never participated in MTR mining. This descriptive analysis also improves upon the analyses in earlier studies by showing how aggregate trends in mortality rates in MTR counties have changed over time relative to non-MTR counties. However, this descriptive analysis does not prove a causal relationship between MTR mining and increased mortality.

The current study next improves upon the analyses in earlier studies by analyzing how within-county changes in surface coal-mining activity affect mortality rates. If worsening internal mortality rates in MTR counties are due to pollution generated by coal mining, we would expect that changes in the actual level of surface coal-mining activity within a county would produce changes in mortality rates.

Methodology

To establish whether there is a causal relationship between coal-mining activity and mortality, we estimate several reduced-form regressions to explain different types of county-level mortality rates using specific measures of within-county variations over time in surface coal-mining activity. The empirical model is:

$$Mortality_{it} = \beta\, Treatment_{it} + \delta X_{it} + \alpha_t + \alpha_i + \gamma_i \times t + \epsilon_{it} \tag{2.1}$$

We consider different definitions of $Treatment_{it}$, noting that (unlike the case for simpler "event studies" or experimentally designed randomized controlled trials) these data involve multiple "treatments" that occur at different times in different counties. X_{it} includes time-varying controls for county-level income and employment, α_t is a year fixed effect, α_i is a county fixed effect, and γ_i is a county-specific linear time trend.

If we conceptualize the problem as a set of data with counties assigned to treatment and control groups, with observations before and after treatment, there are several different ways, given the available data, that "treatment" could be defined. Variation in surface mining activity that may affect mortality potentially includes at least two variables relating to surface coal-mining activity:

- $New\ Surface\ Mining_{it}$ = A discrete indicator that is switched on if any *new* surface coal mine is opened in that county and year (i.e. if any new mine has positive employment or positive production).[14]

- $Surface\ Coal\ Production_{it}$ = A continuous variable that is zero in all county-years with no surface coal mining, but positive and equal to annual production from surface coal mines in the county in all other years.

If most of the land disruption and resulting pollution occurs when a surface mine is first established, with lower pollution levels during the later ongoing production phase, we would expect new surface mining to produce the greatest adverse public health effects. The coefficient on the *New Surface Mining* indicator variable will capture the consequences of all activity during that first year when the county (or the new mine) first reports surface coal-mining activity. Pollution may also be generated from the ongoing production and transportation of coal after regular production commences, so we are also careful to consider the effect of the *Surface Coal Production* variable as well.

[14] There is unfortunately no usable information about the exact date *during a year* when a new coal mine "starts." Pollution generally begins during the preparation of the site, before any coal is actually produced. We know production in each year, but we do not know in which month the preparation of the site actually began. We count a mine as active if either (a) the mine reported positive employment in year t or (b) the mine reported positive coal production in year t.

We estimate the following model to determine how mortality rates are affected by the initiation of surface coal-mining activity (i.e. the addition of new surface coal mines) and/or changes in ongoing surface coal-mine production levels:

$$\begin{aligned} Mortality\ Rate_{it} &= \beta_1\ New\ Surface\ Mining_{it} \\ &\quad + \beta_2\ Surface\ Coal\ Production_{it} + \delta X_{it} + \alpha_t + \alpha_i + \gamma_i \times t + \epsilon_{it} \end{aligned} \tag{2.2}$$

We explore alternative definitions of the $Mortality\ Rate_{it}$ variable. County-level fixed effects control implicitly for any important non-time-varying determinants of mortality rates. County-specific linear time trends control for overall trends in county-level mortality independent of variation in coal-mining activity. Other variables are the same as defined above.

We first limit our measure of within-county surface coal-mining activity only to mines within a county's confined geographic boundaries. However, potential pollution from coal-mining activity is not confined by these auxiliary administrative boundaries. Many coal mines are located near county boundaries, creating the potential for transboundary spillover effects. To address this concern, we calculate an alternative measure of the exposure of each county's population to coal-mining activity by creating a buffer of 25 kilometers around the point location of each county's population centroid. We then re-define within-county exposure as any coal-mining activity within each county's population centroid buffer, regardless of the county wherein the mine is located. This measure allows the population of one county to be affected by nearby mining in other adjacent counties.[15]

Results

Coal Mining and Mortality

Table 2 reports the key parameter estimates from equation (2.2) for the relationship between county-level internal mortality rates and within-county changes in surface coal-mining activity for the sample of all ARC counties. Panel (a) defines exposure as coal-mining activity within a county's geographic boundary, while panel (b) defines exposure as coal-mining activity within 25 kilometers of a county's population centroid. Estimates are presented for the internal mortality rate by age group: infants (< 1 year), children (1-14 years), adults (15-64 years), and the elderly (> 65 years).

Our key explanatory variables are *New Surface Mining*, which indicates whether county i opened at least one new surface coal mine in year t, and *Surface Coal Production*, which includes the level of annual surface coal production. All specifications include county fixed effects, year fixed effects, county-specific linear time trends, and controls for county-level annual income and employment. Standard errors are clustered at the county level.

[15] This exposure measure is adapted from Fitzpatrick (2018). Alternative buffer distances were explored, but 25km seemed an appropriate measure to approximate the average county size in the Appalachian region.

TABLE 2.
Internal Mortality by Age Group

Annual Rate (per 100,000 population)

a.) ARC Counties - Coal Mining within County Boundaries

	(1) Infant (< 1 year) b/se	(2) Child (1-14 years) b/se	(3) Adult (15-64) b/se	(4) Elderly (>65 years) b/se
I(New Surface Mine)	17.324	0.654	-1.833	20.850
	(22.024)	(0.587)	(1.628)	(17.291)
Surface Coal Production	13.864	-0.334	-2.489	21.452*
	(10.593)	(0.337)	(1.689)	(12.749)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.085	0.050	0.322	0.313
Observations	12,803	12,803	12,803	12,803

b.) ARC Counties - Coal Mining within Buffers of County Population Centroids

	(1) Infant (< 1 year) b/se	(2) Child (1-14 years) b/se	(3) Adult (15-64) b/se	(4) Elderly (>65 years) b/se
I(New Surface Mine)	8.843	-0.011	-2.968*	8.354
	(23.483)	(0.568)	(1.639)	(16.853)
Surface Coal Production	19.391	-0.477	-3.661**	47.948**
	(14.409)	(0.439)	(1.822)	(18.888)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.085	0.050	0.322	0.314
Observations	12,803	12,803	12,803	12,803

In panel (a) of Table 2 we find no statistically significant effect of *New Surface Mining* on internal mortality for any age group. However, we do see a marginally significant effect of changes in *Surface Coal Production* on internal mortality among the elderly population. Our results indicate that a one-standard-deviation increase in surface coal production increases the elderly internal mortality rate by approximately 21 deaths per 100,000 population.

In panel (b) of Table 2, using coal mines within a 25-km buffer around the population centroid to define exposure, this effect increases in magnitude and becomes strongly statistical significant. Approximately 48 deaths per 100,000 population result from a one-standard-deviation increase in surface coal production. The magnitude of this effect is still relatively small, representing about one-twentieth of a standard deviation in our dependent variable. If air pollution is a plausible mechanism for adverse mortality effects from exposure to surface coal mining, this result is consistent with previous research that finds the elderly population to be more vulnerable to adverse effects from pollution exposure, compared to other age groups.

Notably, we see a small statistically signficant *negative* effect of increased surface coal-mining activity on mortality among adults aged 15-64. Since we include controls for income and employment, this cannot be explained simply by the benefits from more coal-mining jobs. However, these jobs may come with additional health benefits for workers and these result may warrant a closer examination.[16]

Given the strength of the result for elderly mortality, particularly using county population exposure based on 25-kilometer buffers, we next assess whether this effect is stronger within the subset of counties that have ever participated in MTR mining: MTR counties. We expect results for MTR counties to be more

[16]The statistically signficant negative effect on working-age adult mortality disappears with the exclusion of county-specific linear time trends.

clearcut, since the controls are better-matched to the treated county-years. Table 3, column (1) repeats estimates from column (4) of Table 2b, while column (2) contrasts those earlier results with new estimates specifically for MTR counties. Results suggest that, for MTR counties, both the opening of new surface mines and increased surface coal production lead to increases in the elderly internal mortality rate. The opening of a new surface coal mine increases elderly internal mortality in MTR counties by 53 deaths per 100,000 population, while a one-standard-deviation increase in surface coal production increases the elderly internal mortality rate by 50 deaths per 100,000 population. These results are consistent with anecdotal accounts of relatively worse pollution resulting from the preparation of MTR surface mining sites, relative to other types of surface coal mines outside of MTR counties in Appalachia.

TABLE 3.
Elderly Internal Mortality (over age 65)

Annual Rate per 100,000 population

	(1) ARC Counties b/se	(2) MTR Counties b/se
I(New Surface Mine)	8.354	56.003*
	(16.853)	(33.011)
Surface Coal Production	47.948**	49.739**
	(18.888)	(20.753)
Controls	Yes	Yes
Year Effects	Yes	Yes
County Effects	Yes	Yes
County-Specific Trends	Yes	Yes
R^2	0.314	0.270
Observations	12,803	2,046

Table 4 presents a sensitivity analysis of the results in Table 3: for ARC counties in panel (a), and for MTR counties in panel (b). Columns (1) through (5) report estimates with increasingly more-general specifications. Column (5) is our preferred specification reported in Table 3, which includes county-specific linear time trends. All estimates also report standard errors clustered at the county level. Table 4 again highlights the fundamental importance of the inclusion of county fixed effects, since the implications of our estimates change markedly from column (3) to (4).

The previous literature suggests that exposure to ambient air pollution can lead to premature mortality attributable specifically to cardiovascular disease. Table 5 presents results for the effect of surface coal mining on elderly mortality distinguished by cause of death. Results are documented for ARC counties in panel (a) and for MTR Counties in panel (b). Results for mortality attributable to all internal causes reproduced from column (1) of Table 3 is shown in column (1), with cardiovascular disease in column (2), respiratory disease in column (3), cancer in column (4), kidney disease in column (5), and mortality from external causes, as a falsification test, in column (6). For both panels of counties, increases in surface coal production leads to increased mortality rates attributable to all internal causes, cardiovascular disease, and cancer. The strength of the result for internal mortality attributable specifically to cardiovascular disease is consistent

TABLE 4.
Sensitivity Analysis

Elderly Internal Mortality
Annual Rate (per 100,000 population)

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
		Elderly Internal Mortality Rate (>65 years)			
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	158.877***	122.079***	167.480***	-3.986	8.354
	(43.890)	(45.422)	(45.327)	(18.321)	(16.853)
Surface Coal Production	90.804***	94.531***	83.009***	52.103***	47.948**
	(21.529)	(21.025)	(21.085)	(19.107)	(18.888)
Controls	No	Yes	Yes	Yes	Yes
Quarter Effects	No	No	Yes	Yes	Yes
County Effects	No	No	No	Yes	Yes
County-Specific Trends	No	No	No	No	Yes
R^2	0.031	0.068	0.129	0.173	0.314
Observations	12,803	12,803	12,803	12,803	12,803

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
		Elderly Internal Mortality Rate (>65 years)			
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	100.836	53.709	137.501	61.916*	56.003*
	(110.904)	(118.734)	(119.584)	(34.965)	(33.011)
Surface Coal Production	74.623***	81.366***	73.541***	35.522**	49.739**
	(24.738)	(23.363)	(23.832)	(15.752)	(20.753)
Controls	No	Yes	Yes	Yes	Yes
Quarter Effects	No	No	Yes	Yes	Yes
County Effects	No	No	No	Yes	Yes
County-Specific Trends	No	No	No	No	Yes
R^2	0.050	0.067	0.156	0.185	0.270
Observations	2,046	2,046	2,046	2,046	2,046

with a deterioration in air quality being a likely mechanism whereby surface coal-mining activity affects mortality rates.

TABLE 5.
Heterogeneity by Cause of Death

Elderly Internal Mortality
Annual Rate (per 100,000 population)

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)	(6)
	Elderly Mortality Rate (>65 years)					
	Total Internal	Cardiovascular	Respiratory	Cancer	Kidney	External
	b/se	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	8.354	5.444	2.750	-0.997	1.859	1.997
	(16.853)	(10.423)	(4.938)	(7.579)	(1.922)	(2.059)
Surface Coal Production	47.948**	24.619***	-4.546	13.985**	1.865	-3.433*
	(18.888)	(9.421)	(4.421)	(6.531)	(2.191)	(1.937)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.314	0.678	0.199	0.163	0.233	0.057
Observations	12,803	12,803	12,803	12,803	12,803	12,803

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)	(6)
	Elderly Mortality Rate (>65 years)					
	Total Internal	Cardiovascular	Respiratory	Cancer	Kidney	External
	b/se	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	56.003*	38.639*	12.476	8.855	0.627	7.862*
	(33.011)	(19.738)	(10.263)	(17.461)	(4.542)	(4.250)
Surface Coal Production	49.739**	19.865*	-0.016	14.720*	3.125	-3.969*
	(20.753)	(10.628)	(5.514)	(7.513)	(2.628)	(2.204)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.270	0.647	0.181	0.217	0.249	0.072
Observations	2,046	2,046	2,046	2,046	2,046	2,046

Robustness Checks

The Role of Occupational Exposure

Observed mortality effects may be driven by cumulative exposure to surface coal-mining activity. Occupational coal miners, in particular, often have a long history of cumulative exposure to coal-mining activity. Men are much more likely to work in the mining industry than are women, and men are also more likely to choose occupations which require them to work outdoors, also potentially increasing their exposure to potential pollution from surface coal mining. We split the sample by gender and estimate mortality effects related to surface coal-mining activity separately for men and women. Results by gender are reported in Table 6: for all ARC counties in panel (a), and for MTR counties in panel (b).

For both panels of counties, the effect of surface coal production on mortality is stronger, both by magnitude and statistical significance, for males than females. Thus, we might conclude that greater cumulative lifetime occupational exposures for men may increase the elderly male population's vulnerability to adverse health affects from later-life exposure to coal-mining activity. However, data limitations prevent any more-direct test of this hypothesis.

Addressing the Opioid Epidemic

The discussion of Figure 3.3 highlighted the co-occurrence in MTR counties of the recent opioid epidemic. The primary analysis in the current study focuses on mortality attributable to internal causes of death. Nevertheless, the potential for other secondary causes of death, perhaps related to opioid use, is not explicitly eliminated. To address this potentially confounding mortality trend, Table 7 reports estimates for specifications analogous to those reported in columns (1) and (2) of Table 5, but restricting the sample to the pre-2001 period, beyond which there is a marked change in the level of mortality rates within MTR counties compared to other ARC counties.

![h]

TABLE 6.
Heterogeneity by Gender to Address Occupational Exposure

Elderly Internal Mortality
Annual Rate (per 100,000 population)

a.) ARC Counties

	(1)	(2)	(3)	(4)
	Males		**Females**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	21.058	7.620	-3.491	3.532
	(23.479)	(15.770)	(19.189)	(13.461)
Surface Coal Production	74.847***	43.509***	31.786*	12.340
	(26.458)	(12.620)	(17.838)	(13.744)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.389	0.629	0.293	0.473
Observations	12,803	12,803	12,803	12,803

b.) MTR Counties

	(1)	(2)	(3)	(4)
	Males		**Females**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	62.137	42.708	49.345	35.660
	(46.123)	(30.863)	(35.022)	(23.857)
Surface Coal Production	87.504***	47.946***	23.445	-0.089
	(29.799)	(16.579)	(19.550)	(15.471)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.308	0.595	0.304	0.428
Observations	2,046	2,046	2,046	2,046

In Table 7(a) columns (3) and (4) we see our estimates for MTR counties, of the effects of new surface mining increase in both magnitude and significance, for both total internal mortality and mortality attributable to cardiovascular disease. However, our estimates of the effects of surface coal production for both panels of counties in Table 7(a) are not significantly different from zero.

In Table 7(b) we report estimates when omitting the county-specific trends. In this less-general specification, our results are consistent with those for the full sample of county-years reported in Table 4. The county-specific linear trends during the pre-2001 period appear to be too multicollinear with increasing trends in surface coal production to permit us to discernt their independent effects on mortality.

If, in contrast, we keep the full sample of onbservations from 1983 to 2013, include the county-specific trends, but control for the potentially confounding effect of the opioid epidemic by including drug poisonings as an explicit explanatory variable, the resulting estimates are qualitatively very similar to those in column (5) of Table 4(a) and (b). Retention of the full sample preserves the observed sharp downturn in surface coal production in MTR counties after 2008, breaking the earlier collinearity between this measure of surface coal production and a simple linear time trend. When surface coal production moved independently from a linear time trend, there is a greater opportunity to discern separate effects, and the statistically significant effects of coal production on elderly internal mortality in both ARC and MTR counties. Nevertheless, given the strength of the results for new surface mining and the consistency in Table 7(b), we are not concerned that our main results are somehow being driven by potential confounding factors related to the opioid epidemic.

TABLE 7.
Robustness Check to Address the Opioid Epidemic

Analysis Using Data from 1983-2000

Elderly Internal Mortality

Annual Rate (per 100,000 population)

a.) Preferred Specification (Including County-Specific Trends)

	(1)	(2)	(3)	(4)
	ARC Counties		**MTR Counties**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	19.796	7.298	83.924**	61.577**
	(22.428)	(14.796)	(36.869)	(28.169)
Surface Coal Production	6.247	9.031	-3.901	2.737
	(20.794)	(13.456)	(25.010)	(16.439)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.217	0.318	0.242	0.252
Observations	7,434	7,434	1,188	1,188

b.) Excluding County-Specific Trends

	(1)	(2)	(3)	(4)
	ARC Counties		**MTR Counties**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	15.871	20.837	73.902**	80.219***
	(20.815)	(14.347)	(35.028)	(26.632)
Surface Coal Production	43.825***	17.547**	24.390	15.395*
	(16.413)	(8.557)	(17.689)	(8.199)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	No	No	No	No
R^2	0.072	0.193	0.137	0.172
Observations	7,434	7,434	1,188	1,188

Lead and Lag Analysis

Mortality due to coal mining may stem from long-term chronic exposures or from acute effects. The models in equations (1) through (4) consider only contemporaneous effects. In Figure 4, we depict the key parameter estimates for a model with leads and lags of the surface-coal-mining variables. Estimated lagged effects of surface-coal-mining activity might indicate latent effects of multi-year exposure, while any statistically significant leading effects would constitute failure of a falsification test.

We re-estimate equation (3), expanded to incorporate three leads and three lags of each of our surface coal-mining indicators:

$$\begin{aligned} Mortality\ Rate_{it} = \alpha_i + \alpha_t + \sum_{j=-3}^{3} \beta_{1j} New\ Surface\ Mining_{i,t+j} \\ + \sum_{j=-3}^{3} \beta_{2j} Surface\ Coal\ Production_{i,t+j} + \gamma X_{it} + \epsilon_{it} \end{aligned} \tag{2.3}$$

The subscript j on each of the β coefficients represents a lead or lag, before or after year t, and all other variables are as defined previously.

Figure 7 depicts β_1 and β_2 coefficient estimates from equation (5) for the elderly internal mortality rate for the set of MTR counties, while Figure 8 depicts coefficient estimates for the elderly mortality rate attributable to cardiovascular disease. None of the leading or lagged terms of new surface mining have a statistically significant effect on either total internal mortality or mortality attributable to cardiovascular disease. However, one of the leading terms of surface coal production on total internal mortality is marginally significant.

FIGURE 7.
MTR Counties: Internal Mortality Event Study

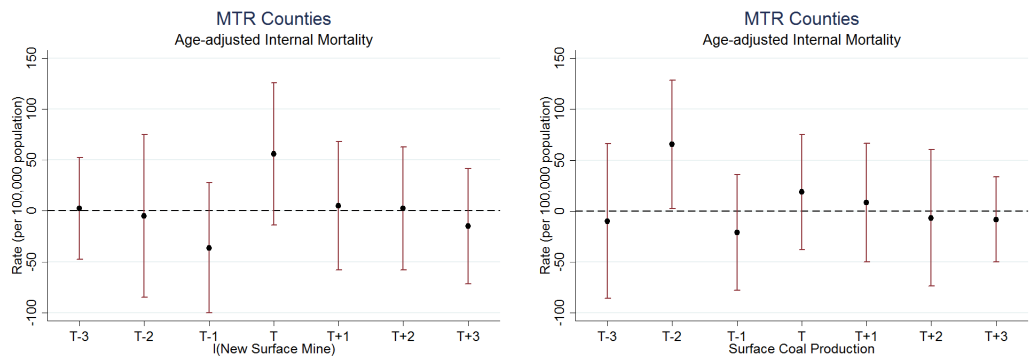
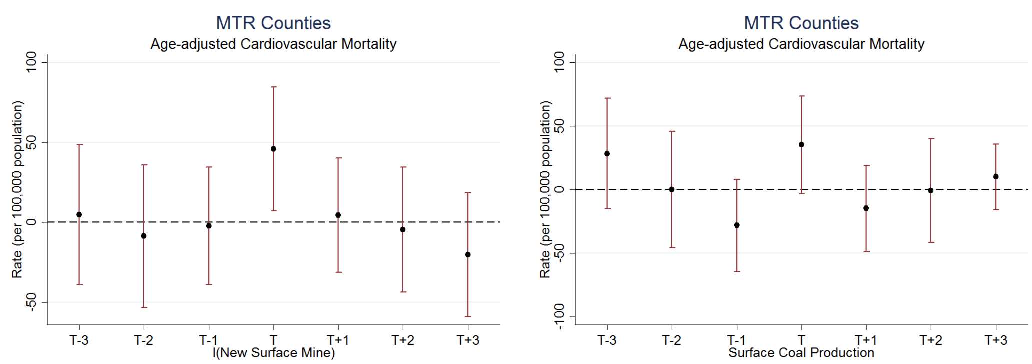


FIGURE 8.
MTR Counties: Cardiovascular Disease Mortality Event Study



Quarterly Analysis

We also construct quarterly mortality rates for each county, to further assess the strength of our contemporaneous result. Equation (2.2) is re-estimated using data at the quarterly level, but using year-by-quarter fixed effects, rather than simple year fixed effects. County-specific linear time trends are included and all other variables are as previously defined.

Table 8, panel (a) presents results for the effect of quarterly surface coal-mining activity on quarterly mortality rates. Results are presented for mortality attributable to all internal causes and to cardiovascular disease, for ARC counties in columns (1) and (2), and for MTR counties in columns (3) and (4). The effect of surface coal production on elderly mortality is largely consistent with our annual analysis across all four specifications. However, we find no discernible effect of contemporaneous new surface mining on either mortality measure.

Table 8, panel (b) again estimates the effect of surface coal mining on quarterly mortality rates, but now defines the surface coal-mining variables as aggregates of the prior four quarters of coal-mining activity. This specification slightly strengthens our results from panel (a). However, we find no statistically discernible effect of new surface mines on mortality in MTR counties. While, these results constitute a useful supplement to our annual analysis, we interpret these estimates cautiously and acknowledge the data limitations and potential for measurement error in this case.

Effect of Underground Mining

We may be concerned that population exposure to coal production, regardless of the method of production, may cause adverse health effects. Table 9 presents results from a specification similar to equation (2.2), but with treatment variables

TABLE 8.
Robustness Check using Quarterly Data

Elderly Internal Mortality
Quarterly Rate (per 100,000 population)

a.) Current Quarter Exposure

	(1)	(2)	(3)	(4)
	ARC Counties		**MTR Counties**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	0.241	-2.603	5.633	-3.671
	(4.387)	(2.728)	(7.236)	(4.225)
Surface Coal Production	8.719**	5.526***	8.607*	4.466*
	(4.295)	(2.116)	(4.679)	(2.524)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.231	0.403	0.206	0.369
Observations	51,625	51,625	8,250	8,250

b.) Current and Previous 3 Quarters Exposure

	(1)	(2)	(3)	(4)
	ARC Counties		**MTR Counties**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Surface Mine)	-0.012	-0.717	13.381	5.463
(current and last 3 quarters)	(4.136)	(2.516)	(9.053)	(5.276)
Surface Coal Production	12.172***	6.013**	12.677**	5.240*
(current and last 3 quarters)	(4.549)	(2.441)	(5.127)	(2.770)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.234	0.399	0.208	0.368
Observations	50,386	50,386	8,052	8,052

instead for new *underground* mining and *underground* coal production. Results are presented for mortality attributable to all internal causes, and to cardiovascular disease: for ARC counties in columns (1) and (2), and MTR counties in columns

(3) and (4). We find no discernible effect of underground mining activity on elderly mortality.

TABLE 9.
Falsification Test using Underground Mining

Elderly Internal Mortality
Annual Rate (per 100,000 population)

	(1)	(2)	(3)	(4)
	ARC Counties		**MTR Counties**	
	Total Internal	Cardiovascular	Total Internal	Cardiovascular
	b/se	b/se	b/se	b/se
I(New Underground Mine)	20.405	3.123	34.792	4.811
	(14.641)	(9.121)	(24.639)	(16.367)
Underground Coal Production	18.593	11.251	19.724	19.455
	(24.508)	(14.863)	(37.733)	(20.678)
Controls	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes
County-Specific Trends	Yes	Yes	Yes	Yes
R^2	0.313	0.677	0.266	0.646
Observations	12,803	12,803	2,046	2,046

Identifying Assumptions and Data Limitations

The critical assumption underlying the difference-in-differences methodology used in this setting is that changes in surface coal-mining activity are uncorrelated with other events occurring at the same time in the same counties that also affect county mortality rates. We assume there is no systemic violation of this assumption. The sheer number of mine-openings, for example (2,299 over the 12,803 county-years in the ARC sample), mitigates against this coincidence.

There might be some concern about identification if the opening of surface coal mines leads to significant amounts of in-migration and out-migration that systematically alters county-level mortality rates. For instance, suppose the opening of a surface coal mine causes less-healthy people to move out of the county and/or more-healthy people to move in. This would lead to an underestimate of any adverse effect of a new coal mine on health in that county relative to nearby untreated counties to which the less-healthy people may have escaped (or from which more-healthy people have arrived).

In contrast, an overestimate of the adverse effects of coal mining on health, due to migration, could occur if a new coal mine attracts less-healthy in-migrants and drives away the county's healthier residents. If a new coal mine drives down property values, property market dynamics could result in the departure of higher-income (healthier) individuals and their replacement by lower income (less-healthy) persons. Thus, we are careful to control for changes in average county income over time. We will rely on the assumption that county demographics, other than income, are not shifting contemporaneously and consistently with changes in surface mining activity in a way that would create a bias that would exaggerate the estimated effects of surface coal mining on health.[17]

It is important to control for county-level variations in income over time, since associated new jobs from mine openings may also increase incomes within a

[17] A simple analysis using Statistics of Income county-to-county migration data from the IRS reveals no obvious effect of surface mining activity on migration.

county. Higher income generally leads to decreased mortality, so failing to control for changes in income could attenuate our estimate of the effect of surface coal mining on health. Additionally, if higher income and thus presumably healthier people move out of the county, controlling for income should explicitly control for this potential source of bias. Notably, increased incomes from new jobs are most likely to help households for which the household head is younger than retirement age, whereas the most significant adverse health effects from coal mining are borne by the elderly.

Given the limitations of previous cross-sectional analyses linking exposure to coal mining and increased mortality, the current study gets closer to estimating a causal contemporaneous effect of surface coal mining on human health. However, data limitations prevent the current study from definitively identifying the specific causal physical mechanism that connects surface coal mining to increased mortality.

Ideally, we would like to differentiate the mortality effects specifically attributable to mountaintop removal coal mining from those due to other types of surface mines. Unfortunately, limitations in the available mining data prohibit any rigorous procedure for unambiguously identifying all MTR coal mines as distinct from other types of surface coal mines. Additionally, there exists no detailed information on the temporal variation in MTR status.

The current analysis is also limited by the geographic resolution of the publicly available mortality data, as well as our inability to observe individuals' residential and work locations throughout their lifetimes. While we know the precise location of each coal mine, the available mortality data provides only the county where individuals lived at their time of death. There is likely considerable variation in each individuals' lifetime exposure to pollution based on their residential and occupational history. An individual-level longitudinal analysis would be necessary to properly measure the longer-term and cumulative effects of exposure to surface coal mining.

Discussion

Our analysis confirms cross-sectional results in the previous literature that find MTR counties have higher mortality rates than are observed in the rest of Appalachia. This finding cannot be completely explained by systematic variation over time in income or employment or by unobserved county-level heterogeneity. This raises some concerns about environmental justice. However, there is no direct evidence that adverse health outcomes can be attributed unambiguously to exposure to pollution from coal-mining activity. County-level mortality data cannot be used for a rigorous assessment of the impact of long-term exposure to surface coal mining, since we are unable to control for each individual's lifetime exposure to coal mining or other environmental stressors.

The current study attempts to identify a more direct, contemporaneous link between coal mining and public health, using within-county variation over time in coal-mining activity. We find that the opening of new surface coal mines and increased surface coal production are associated with increased contemporaneous mortality rates for the population aged 65 years and older. The effect is most pronounced in Appalachian counties that initially or eventually participate in MTR surface coal mining. The effect also appears to be driven primarily by increases in mortality attributable to cardiovascular diseases. This suggests, indirectly, that increases in exposure to particulate matter may be at least one of the mechanisms contributing to these observed health effects.

There has been considerable recent interest in reviving the Appalachian coal-mining industry.[18] The current study contributes to our understanding of the likely public health impacts of surface coal mining, which may partially or completely offset any potential economic benefits from increased jobs. This information is important to any comprehensive benefit-cost assessment for proposed policy changes with respect to the coal industry. Our analysis also reveals an important insight about the potential distributional consequences of any policy to "bring back coal jobs". The working-aged population of the Appalachian coal region may benefit from the restoration of coal-mining jobs, but the over-65 population appears to bear most of the negative public-health externalities from coal mines, especially from new mines in MTR counties. This highlights some environmental equity considerations relevant to U.S. coal policy.

[18] In early October 2017, the Secretary of Energy proposed offering federal subsidies for the coal industry.

CHAPTER III

COAL MINING AND PUBLIC HEALTH IN APPALACHIA: EVIDENCE FROM THE ASSOCIATION BETWEEN COAL MINING AND BIRTH OUTCOMES

Introduction

Previous research in epidemiology and public health has highlighted health disparities in coal-producing counties in Appalachia compared to the rest of the United States. Researchers have found that coal mining activity is associated with an increased prevalence of cardiovascular disease, kidney disease, and respiratory disorders, compared to non-mining counties (Hendryx and Ahern (2008); Hendryx (2009); Brink (2014)). Other researchers have noted associations between surface coal mining and poor infant health outcomes. Ahern et al. (2011a) find an association between a mother's residence in a coal-mining community during her pregnancy and lower birth weight for her child, while Ahern et al. (2011b) link mothers' residence in coal-mining counties to a higher prevalence of birth defects. However, this former literature has been primarily descriptive, and reliant on cross-sectional data.

The current study uses Vital Statistics Data from individual birth certificates from 1989 to 2006. Results are presented for the following analyses:

1. Analyze trends over time in infant health outcomes in coal-mining counties compared to other Appalachian counties.

2. Estimate associations between coal mining and infant health, similar to previous epidemiological studies, and discuss some of the statistical shortcomings of these analyses.

3. Estimate whether within-county changes in coal mining activity affect county-level birth outcomes.

The current study contributes to our collective understanding of the association between coal mining and infant health. Even when controlling for observable factors—such as income, poverty, education, access to healthcare and smoking rates—cross-sectional analyses of the effects of coal mining on infant health may suffer from omitted-variable bias because they fail to account for unobserved heterogeneity across counties and/or over time. Previous cross-sectional studies are generally careful to interpret their statistical findings merely as associations, rather than as evidence of causality. However, it is inappropriate to attribute the observed adverse health outcomes in certain counties to the existence of coal mining based on conclusions simply from cross-sectional analyses.

Several recent papers have identified a causal relationship between surface coal mining and community health, identifying effects of surface coal mining on respiratory hospitalizations (Fitzpatrick (2018)) and mortality among the population over 65 (Mueller (2018)). However, there are currently no corresponding estimates of the effects of coal mining on infant health. Unlike adults, infants do not experience much variation in cumulative pollution exposure during their 9-

month gestational “lifetime”. Thus, we are able to examine prenatal exposure to variation in environmental quality throughout the 9 months prior to birth, while simply assuming the mother’s county of residence was relatively constant throughout her pregnancy.

Literature and Background

In-utero exposure to environmental pollution has been linked to adverse infant health outcomes in numerous settings. Prenatal exposure to to ambient air pollution has been studied extensively (Currie et al. (2014); Currie and Walker (2011); Leem et al. (2006); Glinianaia et al. (2004); Chay and Greenstone (2003)), with studies finding various effects of pollution exposure on birth weight, preterm birth, and infant and neonatal mortality. A meta-analysis evaluated 62 peer-reviewed studies examining the link between air pollution and infant health (Stieb et al. (2012)). This meta-analysis concluded that while there was considerable heterogeneity between studies, the majority of research consistently reported an increased likelihood of low birth weight with prenatal exposure to carbon monoxide (CO), nitrogen dioxide (NO_x) and particulate matter (PM_{10} and $PM_{2.5}$)

Exposure to other environmental hazards, where the physical pathway of exposure is less clear, has been studied in the context of proximity to toxic waste releases (Agarwal et al. (2010)), chemical spills (Guilfoos et al. (2017)), and fracking wells (Hill and Ma (2017); Currie et al. (2017)). These researchers find adverse effects of exposure on infant mortality, Apgar scores, and incidence of low birth weight, respectively.

Low birth weight and preterm birth are known to be associated with increased neonatal morbidity and mortality as well as poor motor and social development at birth (Hediger et al. (2002)). Health at birth, measured by these indicators, has also been associated with adverse effects into adulthood, including adult health, educational attainment, and labor market attachment (Currie and Rossin-Slater (2015)). Approximately two-thirds of low birth weight infants are born preterm, while about 40% of preterm infants are low birth weight, thus these indicators of infant health are commonly studied together.

Congenital birth anomalies comprise a heterogeneous group of 22 individually rare conditions affecting the heart, limbs, chromosomes, urinary system, neural tube, and facial features. Givern the rarity of each individual condition, birth defects are often studied as subgroups, or together, as an indicator of the presence of at least one of the 22 types of congenital birth anomalies. There is mixed evidence of a link between environmental pollution and congenital anomalies or birth defects. Dolk and Vrijheid (2003) review the epidemiological evidence of the potential link, and cite the challenges for researchers including the relative rarity of each individual anomaly and the increased availability of prenatal diagnosis which can result in the termination of pregnancy.

Descriptive Analysis

Data

Infant Health: For the current study, we obtain infant health and natality data from the National Vital Statistics System's Birth Data files from 1983 to 2013 obtained from the National Association for Public Health Statistics and Information Systems (NAPHSIS). These data include demographic information for each mother and health outcomes for the universe of birth records in the United States. The location of a birth is assumed to be the mother's county of residence. Births for this analysis are restricted to singleton births, as is standard in the infant health literature.

For this study, we focus on indicators for low birth weight (defined as less than 2,500 grams at birth), preterm birth (defined as birth at less than 37 weeks of gestation), and the presence of a birth defect (defined as the presence at birth of one of 22 types of congenital birth anomalies). In our primary specification, we aggregate individual birth outcomes to the county level, where each outcome is represented as the rate of occurrence per 1,000 births.

A consistent measure of birth weight is available throughout our sample period. However, the definition of gestational age (which is used to calculate whether an infant is preterm) was meaningfully changed in 2007.[1] The presence

[1] Starting in 2007, the obstetrician's estimate of gestational age at delivery replaced the former calculation of gestational age that relied on the date of the mother's last normal menstrual cycle.

of a birth defect, or congenital birth anomaly, is consistently reported only from 1989 to 2006. Thus, for most of our analyses, we use the sample of births from 1989 to 2006 to ensure consistency in the measurement of outcomes. This restriction also allows us to control for a mother's reported tobacco and alcohol use which is also consistently reported only from 1989 to 2006.

Economic Data: County-level annual measures of personal income are obtained from the Bureau of Economic Analysis (BEA). County-level annual employment data are obtained from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS). These data are reported at the annual level for each county from 1983 to 2013.

MSHA: Our data on coal mine locations and production come from the Mine Safety and Health Administration (MSHA). These data include quarterly coal production and employment for individual mines beginning in 1983. The dataset identifies the type and subtype of mine (including identifiers for underground versus surface operations), the precise geographic location of the mine, as well as quarterly coal production, quarterly hours of employment, and the quarterly average number of employees for each mine. Surface production is classified as strip, quarry, open pit, and auger mining.

While mountaintop removal coal mines are not specifically identified, we rely on a spatial database from Skytruth to identify counties that have ever participated in mountaintop removal (MTR) coal mining methods. Mountaintop mining sites were identified from remotely sensed images that classified whether surface coal mining site crossed a ridge or mountain peak, the size of the mining site and the volume of the removed ridgetop (Skytruth (2009)). We classify 66 counties in southern West Virginia, south-eastern Kentucky, north-eastern Tennessee, and north-western Virginia as “MTR Counties”.

For this study, we focus on aggregate county-level coal mining activity. Production and employment data are aggregated to the county level based on the geo-identified point location of each mine. Coal production is differentiated by surface and underground production methods. We also identify when new mines open, separately identifying new surface mines from new underground mines. We include a control variable for coal mining employment using quarterly hours worked divided by 520 hours, as an estimate of full-time-equivalent (FTE) employment due to coal mining in the county.

Trends in Coal Production

The current study focuses on Appalachian counties (defined as the 413 counties represented by the Appalachian Regional Commission and denoted “ARC counties”) and MTR counties (defined as the 66 Appalachian counties that have ever participated in mountaintop removal (MTR) coal mining methods). Figure 9 depicts ARC counties and MTR counties, within the eastern U.S. commonly referred as Appalachia. Also depicted are coal-producing counties within Appalachia, denoted ARC-Coal, which includes the set of MTR counties.

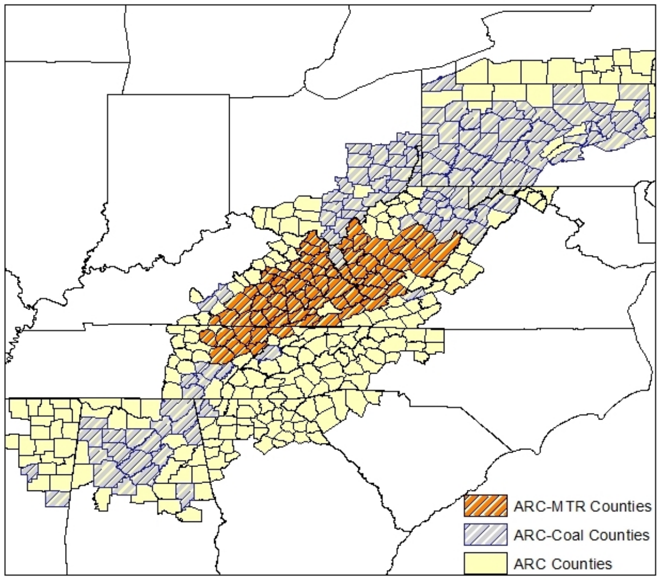


FIGURE 9.
Map of Study Area

Figure 10 depicts aggregate coal production in MTR Counties compared to non-MTR ARC-Coal counties, while Figure 11 depicts aggregate surface coal production between the two counties. Both groups of counties have experienced relatively similar trends in aggregate coal production. However, from 1983 to 2000, surface coal production significantly increased in MTR counties relative to underground coal production. Non-MTR counties in Appalachia have exhibited a steadier reliance on underground coal production. If surface coal production exposes the local population to increased pollution, as suggested anecdotally and by the epidemiology literature, we might expect infant health outcomes to have worsened in MTR counties relative to non-MTR counties within Appalachia during this time period.

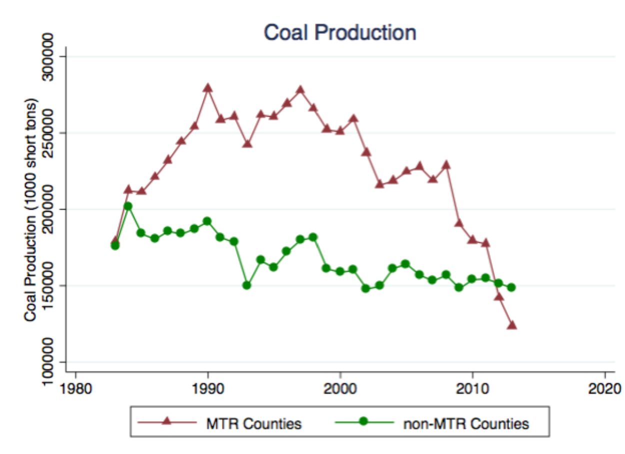


FIGURE 10.
ARC Trends in Coal Production

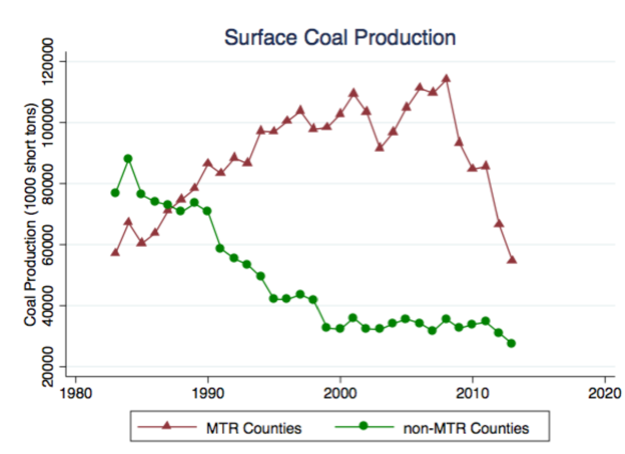


FIGURE 11.
ARC Trends in Surface Coal Production

Trends in Birth Outcomes

Next we present descriptive trends where birth outcome data are aggregated to the county level, and our three birth outcomes are measured as a rate per 1000 births within a county-year. We focus on the period from 1989 to 2006 because the reporting conventions for several of our key outcome and control variables have changed meaningfully over time. This time period allows us to use consistently measured data for all three birth outcomes of interest: low birthweight, preterm birth, and presence of a birth defect.

Table 10 reports summary statistics by exposure to mountaintop removal coal mining. We compare health outcomes and demographics across Appalachian counties that participate in mountaintop removal coal mining (MTR Coal), counties that participate in other coal mining (Other Coal), and non-coal mining counties (No Coal). From simple cross-sectional comparisons, MTR coal counties appear to experience higher rates of low birthweight and preterm birth, and a higher prevalence of birth defects.

Cross-sectional comparisons from the summary statistics indicate birth outcomes are worse in MTR counties compared to other Appalachian counties. Next, we depict how infant health is changing over time in these counties and assess whether we see similar trends in coal production.

Figures 12 - 14 depict trends in birth outcomes in MTR coal counties compared to non-MTR counties within Appalachia. MTR counties experience a higher prevalence of all three birth outcomes, compared to other counties in Appalachia. For both the occurrence of low birthweight and preterm birth, the divergence in the trend appears to begin during the 1990's when surface coal production in MTR counties was increasing relative to underground coal production (shown in Figure 11) and relative to non-MTR counties.

TABLE 10.
Summary Statistics: Infant Health and Sociodemographics (1989-2006)

Quarterly Averages 1989-2006

	U.S. Average	Appalachia (ARC) Total	MTR Coal	Other Coal	No Coal
Number of Births	310.832	171.955	93.917	202.319	168.315
	(1171.673)	(291.533)	(85.678)	(358.223)	(251.622)
Low birthweight: <2500 grams (per 1000)	60.294	66.242	69.516	64.360	67.065
	(45.712)	(34.905)	(35.353)	(33.079)	(36.566)
Pre-term: <37 weeks (per 1000)	88.761	92.913	99.377	90.526	93.047
	(57.211)	(43.960)	(46.330)	(42.030)	(44.836)
One of 22 birth defects (per 1000)	16.526	16.311	22.017	15.757	14.712
	(28.115)	(21.367)	(26.543)	(19.545)	(20.681)
Average Number of Prenatal Visits	11.268	11.755	11.691	11.643	11.908
Alcohol use (fraction)	0.012	0.008	0.007	0.009	0.007
Tobacco use (fraction)	0.157	0.207	0.272	0.205	0.183
White mother (fraction)	0.865	0.923	0.984	0.939	0.880
Black mother (fraction)	0.103	0.069	0.013	0.054	0.107
Other Race (fraction)	0.031	0.009	0.003	0.007	0.013
Mother's Age <18 (fraction)	0.050	0.054	0.063	0.048	0.057
Mother's Age 18-22 (fraction)	0.273	0.304	0.352	0.289	0.301
Mothers Age 23-28 (fraction)	0.349	0.354	0.352	0.357	0.351
Mother's Age 29-34 (fraction)	0.237	0.213	0.175	0.225	0.214
Mother's Age >35 (fraction)	0.091	0.076	0.059	0.081	0.077
Educ < highschool (fraction)	0.210	0.239	0.287	0.211	0.251
Educ = highschool (fraction)	0.601	0.607	0.602	0.622	0.591
Educ = college (fraction)	0.179	0.147	0.106	0.161	0.147
Fraction married (fraction)	0.691	0.706	0.720	0.707	0.698
Observations	223,704	29,736	4,752	13,320	11,736
Number of Counties	3,107	413	66	185	163
Quarters	72	72	72	72	72

Notably, the prevalence of low birthweight and preterm birth in MTR counties appears to further diverge around 2003, possibly reflecting factors related to the opioid epidemic. Figure 15 depicts the mortality rate attributable to drug poisonings for adult females in MTR counties relative to non-MTR counties.

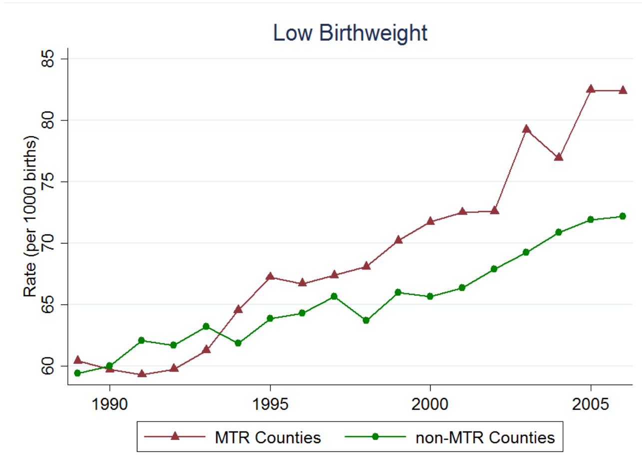


FIGURE 12.
ARC Trends in Low Birthweight

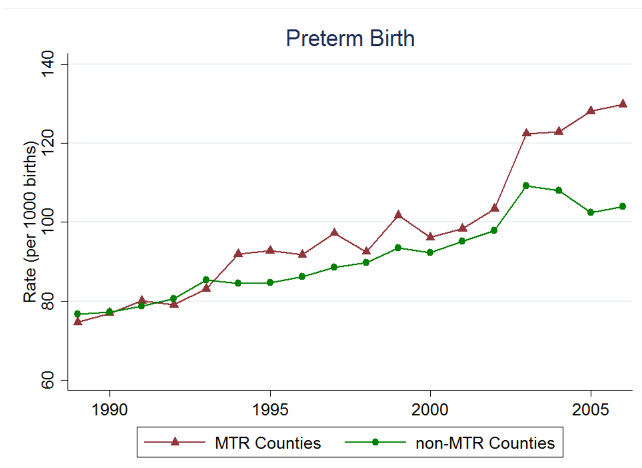


FIGURE 13.
ARC Trends in Preterm Birth

Mortality from drug poisonings serves as a reasonable proxy for opioid abuse, more generally.[2]

[2]The CDC reports U.S. drug overdose deaths nearly tripled from 1999–2014, with West Virginia and Kentucky ranked among the top five states for opioid-related deaths (Rudd et al. (2016)). Research has found infants born to opiate-dependent women frequently have low birth weights, as well as experience other adverse post-natal conditions (Finnegan (1985)).

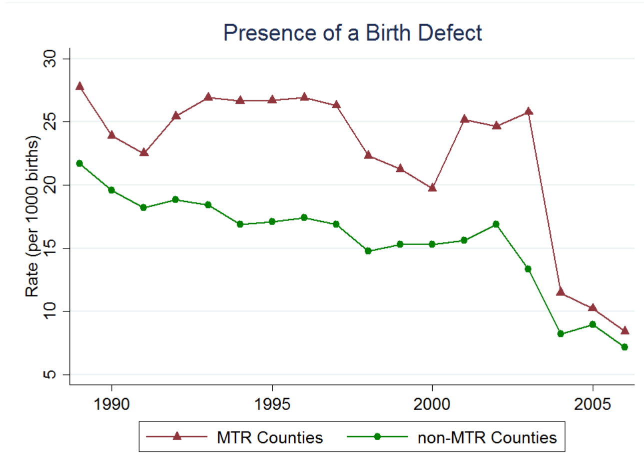


FIGURE 14.
ARC Trends in Birth Defects

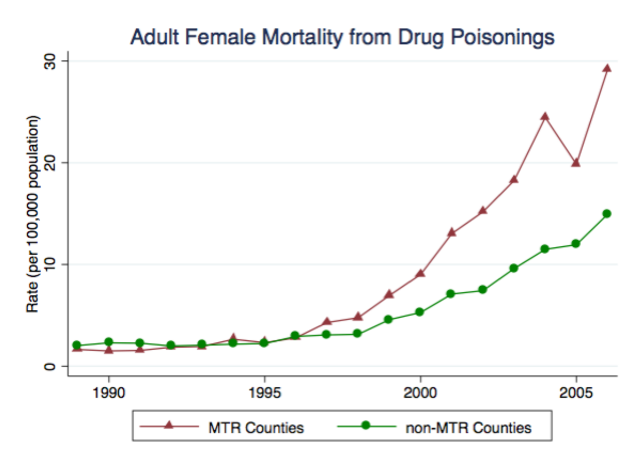


FIGURE 15.
ARC Trends in Drug Poisonings

Replication of Existing Literature

As mentioned above, several epidemiology studies present evidence that a mother's residence in coal mining counties is associated with adverse infant health outcomes. Ahern et al. (2011a) find that infants born in West Virginia counties classified as "high-coal-producing" have a 14-16% higher likelihood of low birthweight, compared to non-coal-producing counties in West Virginia. Ahern et al. (2011b) find that infants born in counties classified as mountaintop removal (MTR) counties have a 21-32% higher likelihood of the presence of a birth defect relative to other non-coal-producing counties in Kentucky, Tennessee, Virginia, and Tennessee.

The analysis in this section replicates these previous studies using comparable methods as the original authors. We distinguish counties based on specific coal-mining status, where each status is constant for a county over time and does not change with time-varying measures coal-mining activity within a county.

Tables 11 and 12 present results from our replication of these studies. Panel (a) in each table uses a sample as close as possible to the sample used by the original authors, and shows the sensitivity to the inclusion of explicit control variables as well as various types of fixed effects, to control for heterogeneity over time and across counties. Panel (b) shows results for a longer time horizon and a larger sample of counties than the original studies.

Table 11 presents results from a linear probability model for individual births, specified as:

$$Low\ Birth\ Weight_{it} = \beta_0 + \beta_1 High\ Coal_c + \beta_2 Mod\ Coal_c + \gamma X_{it} + \alpha_t + \alpha_c + \epsilon_{it} \tag{3.1}$$

TABLE 11.
Replication: Low Birthweight

Outcome: Low Birth Weight
Treatment: Categories of Coal production

a.) Births in WV Counties 2005-2007

	(1)	(2)	(3)	(4)
	Low Birthweight: <2500 grams			
	b/se	b/se	b/se	b/se
I(High-Coal-Producing)	0.016***	0.007*	0.007	0.000
	(0.004)	(0.004)	(0.004)	(.)
I(Moderate-Coal-Producing)	0.011**	0.005	0.005	0.000
	(0.005)	(0.004)	(0.004)	(.)
Controls	No	**Yes**	**Yes**	**Yes**
Month-Year Effects	No	No	**Yes**	**Yes**
County Effects	No	No	No	**Yes**
r2	0.000	0.038	0.039	0.038
N	38414	38414	38414	38414

b.) Births in ARC Countes 1989-2006

	(1)	(2)	(3)	(4)
	Low Birthweight: <2500 grams			
	b/se	b/se	b/se	b/se
I(High-Coal-Producing)	-0.001	-0.006	-0.005	0.000
	(0.003)	(0.004)	(0.004)	(.)
I(Moderate-Coal-Producing)	-0.000	-0.004	-0.003	0.000
	(0.002)	(0.003)	(0.003)	(.)
Controls	No	**Yes**	**Yes**	**Yes**
Month-Year Effects	No	No	**Yes**	**Yes**
County Effects	No	No	No	**Yes**
r2	0.000	0.026	0.027	0.028
N	4351524	4351524	4351524	4351524

where $High\ Coal_c$ and $Moderate\ Coal_c$ are time-invariant indicator variables for whether the county is high coal producing (above the 75th percentile among the estimating sample) or moderate coal producing (greater than 0 but below the 75th percentile), X_{it} is a vector of mothers' demographic controls including age, education, marital status, prenatal care, and reported alcohol and tobacco use, α_t is a month-year time fixed effect, and α_c is a county fixed effect.

Table 11a, column (1), where the sample is limited to West Virginia counties from 2005-2007, suggests that births in high-coal-producing counties and moderate-coal-producing counties experience a 1.6 percentage point and 1.1 percentage point higher likelihood of low birthweight relative to non-coal producers. After adding the X_{it} controls in column (2), the coefficient estimate on high-coal-producing counties decreases to 0.7 percentage points. Births in non-coal-producing counties in this sample, experience a 6.6% rate of low birthweight, thus the estimated coefficient represents an 11% higher probability of low birthweight for births in high-coal-producing counties compared to births in non-coal producing counties. This is comparable to the 14-16% higher likelihood of low birthweight found by Ahern et al. (2011a).

However, after adding the time fixed effects, α_t, in column (3), the estimated effect of coal mining on the incidence of low birth weight is indistinguishable from zero for both high-coal-producing counties and moderate-coal-producing counties. Column (4) shows, with the further inclusion of county fixed effects, we are unable to separately identify the effect of high versus moderate versus non-producing-coal status. This status is constant within each county over time, thus is absorbed by the county fixed effects. Table 2b shows the same specifications but for births in the larger sample of all Appalachian counties from 1989 to 2006. In the larger sample, we find no statistically-significant difference in the likelihood of low birthweight for births in high-coal-producing counties, moderate-coal-producing counties, and non-coal-producing counties.

TABLE 12.
Replication: Birth Defects

Outcome: Birth Defect
Treatment: MTR Status

a.) Births in KY, TN, VA, WV Counties: 1996-2003

	(1)	(2)	(3)	(4)
	One of 22 Birth Defects			
	b/se	b/se	b/se	b/se
I(MTR Coal)	0.007**	0.004	0.004	0.000
	(0.003)	(0.003)	(0.003)	(.)
I(Other Coal)	0.002	0.001	0.000	0.000
	(0.002)	(0.001)	(0.001)	(.)
Controls	No	**Yes**	**Yes**	**Yes**
Month-Year Effects	No	No	**Yes**	**Yes**
County Effects	No	No	No	**Yes**
r2	0.001	0.001	0.002	0.001
N	546124	546124	546124	546124

b.) Births in ARC Counties: 1989-2006

	(1)	(2)	(3)	(4)
	One of 22 Birth Defects			
	b/se	b/se	b/se	b/se
I(MTR Coal)	0.008***	0.006**	0.005**	0.000
	(0.003)	(0.003)	(0.003)	(.)
(I(Other Coal)	0.002	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(.)
Controls	No	**Yes**	**Yes**	**Yes**
Month-Year Effects	No	No	**Yes**	**Yes**
County Effects	No	No	No	**Yes**
r2	0.000	0.001	0.001	0.000
N	4353545	4353545	4353545	4353545

Table 12 reports results comparable to Ahern et al. (2011b), for the association between birth defects and residence in a MTR county for the following specification:

$$Birth\ Defect_{it} = \beta_0 + \beta_1 MTR_c + \beta_2 Other\ Coal_c + \gamma X_{it} + \alpha_t + \alpha_c + \epsilon_{it} \qquad (3.2)$$

where MTR_c and $Other\ Coal_c$ are time-invariant indicators for whether the county is an MTR county or non-MTR coal producing county, and other variables are as previously defined.

Table 12a, column (1), shows that births in MTR counties have a 0.7 percentage point higher likelihood of the presence of a birth defect. However, columns (2) and (3) of Table 12 demonstrate that with the inclusion of controls and time fixed effects, the estimated effects of time-invariant coal mining indicators again become indistinguishable from zero.

Analogous to Table 11b, Table 12b shows the same specification but for births in the broader set of all Appalachian counties from 1989 to 2006. In the simplest specification, presented in column (1), we see a statistically significant 0.8 percentage point increase in birth defects among births in MTR counties vs non-coal producing counties. In this case, however, by column (3) there remains a statistically significant effect even after the inclusion of individual and county-level controls and time fixed effects. About 1.4% of births in non-coal producing counties in this sample report the presence of a birth defect, so the estimated coefficient suggests a 36% higher probability of occurrence for birth defects in MTR counties compared to non-coal-producing counties. This is comparable to the 21-32% higher likelihood of the presence of a birth defect in MTR counties compared to non-coal producing counties found by Ahern et al. (2011b).

The current study next improves upon the descriptive analysis presented above and the analysis in earlier studies by analyzing how within-county changes in surface coal-mining activity affect infant health outcomes. We include county-level fixed effects, time fixed effects, and time-varying county-level controls for income and employment to capture different types of heterogeneity that may also be correlated with birth outcomes. If pollution generated from coal mining is responsible for higher rates of adverse birth outcomes in MTR counties, we would expect that changes in the actual level of coal-mining activity within a county would lead to changes in birth outcomes.

Methodology

We use mine-level data from the MSHA to examine whether within-county variation over time in the level of coal mining activity affects birth outcomes. We estimate reduced-form regressions to explain county-level birth outcomes as a function of coal-mining activity, controlling for county and quarter fixed effects and other time-varying county-level controls as described in the prior section.

We estimate:

$$\begin{aligned}\left(\frac{Birth\ Outcome}{1000\ Births}\right)_{ct} &= \beta_1 \textstyle\sum_{s=0}^{3} Surface\ Production_{c,t-s} \\ &+\beta_2 \textstyle\sum_{s=0}^{3} Underground\ Production_{c,t-s} \\ &+X_{ct}\gamma + \alpha_t + \alpha_c + \epsilon_{ct}\end{aligned} \tag{3.3}$$

where $Surface\ Production_{c,t}$ and $Underground\ Production_{c,t}$ are quantities of coal production from surface and underground mining methods in county c during quarter t. Thus, β_1 and β_2 represent the cumulative effects of the current and past three quarters of coal production on birth outcomes during each quarter. Other variables are as previously defined.

Anecdotal evidence suggest coal production from surface-mining methods is potentially more harmful to public health of the general population. Results from a recent working paper (Mueller 2018) also suggests the preparation of the mine site in the initial stages of the life of a surface coal mine may be the most destructive and polluting phase in the life-cycle of a surface coal mine. Thus, we estimate the following specification to test whether birth outcomes are affected by either the opening of new surface mines or surface coal production. We estimate:

$$\begin{aligned}\left(\frac{Birth\ Outcome}{1000\ Births}\right)_{ct} &= \beta_1 \left(\textstyle\sum_{s=0}^{3} I(New\ Surface_{c,t-s}) \geq 1\right) \\ &+\beta_2 \textstyle\sum_{s=0}^{3} Surface\ Production_{c,t-s} \\ &+X_{ct}\gamma + \alpha_t + \alpha_c + \epsilon_{ct}\end{aligned} \tag{3.4}$$

where $\left(\sum_{s=0}^{3} I(New\ Surface_{c,t-s}) \geq 1\right)$ is an indicator equal to 1 if at least one new surface mine opened in county c during quarter t or the 3 quarters prior to quarter t. $Surface\ Production_{c,t}$ is total surface coal production in county c during quarter t.

Results

Coal Mining Activity and Infant Health

Tables 13 through 15 present results from specification (3.3) examining the effect of within-county variation in coal production from surface and underground production methods on our three birth outcomes. Results are presented at the county level for the rate of low birthweight, preterm birth, and presence of a birth defect, respectively. In each table, the sample is restricted to ARC counties in panel (a) and MTR counties in panel (b). Column (1) of each table shows the specification without controls, column (2) adds individual and county level controls, column (3) adds quarter-by-year fixed effects, column (4) adds county fixed effects, and column (5) adds county-specific linear trends.

In Tables 13 and 14, we do not find a statistically significant effect of changes in surface or underground coal production on the rate of low birthweight or the rate of preterm birth, after inclusion of county fixed effects. Table 15b column (4) actually suggests that increased production of underground coal production *decreases* the rate of birth defects by 0.4 per 1000 births.

Tables 16 through 18 present results from specification (3.4), which estimates a separate effect of the opening of new surface mines versus the effect of surface coal production. We do not find a statistically significant effect of either new mine

TABLE 13.
Coal Production: Low Birthweight

Treatment: Normalized Coal Production
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	Low birthweight: <2500 grams (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	0.799***	0.872***	0.414	0.570	0.818
(current and last 3 quarters)	(0.304)	(0.311)	(0.304)	(0.579)	(0.619)
Underground Production	0.030	0.077*	0.028	0.040	0.064
(current and last 3 quarters)	(0.043)	(0.046)	(0.035)	(0.095)	(0.107)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.001	0.086	0.103	0.034	0.062
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	Low birthweight: <2500 grams (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	1.077***	0.239	0.121	0.421	0.935
(current and last 3 quarters)	(0.353)	(0.384)	(0.374)	(0.682)	(0.773)
Underground Production	-0.014	-0.124	-0.136	-0.210	0.077
(current and last 3 quarters)	(0.067)	(0.108)	(0.113)	(0.149)	(0.150)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.005	0.065	0.090	0.070	0.097
Observations	4,752	4,752	4,752	4,752	4,752

openings or surface production on any of our birth outcomes after inclusion of county fixed effects and county-specific linear trends.[3]

Identifying Assumptions and Data Limitations

The critical assumption underlying the difference-in-differences methodology in this setting is that changes in coal mining activity are uncorrelated with other

[3] A comparable analysis using linear probability models at the individual level was also completed. The results are qualitatively similar to the the county-level results.

TABLE 14.
Coal Production: Preterm Birth

Treatment: Normalized Coal Production
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	Pre-term: <37 weeks (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	0.795*	0.634	-0.442	-0.485	-0.116
(current and last 3 quarters)	(0.471)	(0.739)	(0.665)	(1.238)	(1.498)
Underground Production	-0.020	0.001	-0.137	-0.122	-0.014
(current and last 3 quarters)	(0.070)	(0.119)	(0.089)	(0.160)	(0.138)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.000	0.074	0.118	0.083	0.136
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	Pre-term: <37 weeks (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	0.607	-1.002	-1.022	-0.798	-0.193
(current and last 3 quarters)	(0.618)	(0.859)	(0.870)	(1.296)	(1.563)
Underground Production	-0.057	-0.238	-0.204	-0.088	0.252
(current and last 3 quarters)	(0.111)	(0.176)	(0.190)	(0.260)	(0.213)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.001	0.124	0.159	0.165	0.216
Observations	4,752	4,752	4,752	4,752	4,752

events occurring at the same time in the same counties, where these other changes also affect birth outcomes within the county. We assume there is no systemic violation of this assumption.

This analysis is limited by the geographic specificity of the available data. Ideally, we would want to know the precise locations of each mother's residence relative to each mine, to measure each individual's varying level of exposure to coal mining activity. Some researchers have obtained confidential birth data from individual states that includes the precise address of each mother's residence. When

TABLE 15.
Coal Production: Birth Defects

Treatment: Normalized Coal Production
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	One of 22 birth defects (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	0.506	-0.629	-0.622	0.586	0.446
(current and last 3 quarters)	(0.530)	(0.642)	(0.656)	(0.413)	(0.657)
Underground Production	0.070	-0.092	-0.097	-0.045	-0.149
(current and last 3 quarters)	(0.063)	(0.094)	(0.095)	(0.102)	(0.119)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.003	0.067	0.073	0.069	0.130
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	One of 22 birth defects (per 1000)				
	b/se	b/se	b/se	b/se	b/se
Surface Production	-0.745	-0.913	-1.005	0.241	0.128
(current and last 3 quarters)	(0.773)	(0.803)	(0.826)	(0.484)	(0.788)
Underground Production	0.112	-0.212	-0.258	-0.367*	-0.406**
(current and last 3 quarters)	(0.129)	(0.345)	(0.373)	(0.199)	(0.198)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.003	0.082	0.097	0.112	0.181
Observations	4,752	4,752	4,752	4,752	4,752

available, this type of confidential data allows a much more precise measure of exposure.[4]

Unfortunately, our primary states of interest for this study have not released these data to academic researchers. Thus, we must rely only on county identifiers of each mother's residential location. There may exist a relationship between in-utero exposure to surface coal mining activity and infant health for a portion of

[4]For example, such data have allowed researchers to vary intensity of exposure to pollution from traffic congestion (Currie and Walker (2011)), hazardous waste sites (Currie and Greenstone (2011)) and fracking wells (Currie et al. (2017)).

TABLE 16.
New Surface Mines: Low Birthweight

Treatment: New Surface Mines
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	Low birthweight: <2500 grams (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	-0.903	1.032	1.172	0.021	-0.211
(current and last 3 quarters)	(1.114)	(0.835)	(0.743)	(0.714)	(0.694)
Surface Production	1.076***	0.633**	0.292	0.514	0.745
(current and last 3 quarters)	(0.230)	(0.286)	(0.280)	(0.589)	(0.584)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.001	0.086	0.103	0.034	0.062
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	Low birthweight: <2500 grams (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	1.393	1.599	1.814	0.009	-0.617
(current and last 3 quarters)	(1.509)	(1.419)	(1.363)	(1.199)	(1.201)
Surface Production	0.901***	0.335	0.232	0.628	0.858
(current and last 3 quarters)	(0.268)	(0.388)	(0.385)	(0.737)	(0.705)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.005	0.065	0.090	0.069	0.097
Observations	4,752	4,752	4,752	4,752	4,752

expectant mothers who live *very* close to surface coal mines. If this were the case, censoring of geographic information could be attenuating our results towards zero, since in our identification we must assume that every expectant mother within a county is uniformly exposed to the potential adverse effects of coal mining.

TABLE 17.
New Surface Mines: Preterm Birth

Treatment: New Surface Mines
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	Pre-term: <37 weeks (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	-2.992*	0.126	0.470	-0.387	-0.190
(current and last 3 quarters)	(1.636)	(1.585)	(1.297)	(1.151)	(1.059)
Surface Production	1.095***	0.627	-0.112	-0.312	-0.102
(current and last 3 quarters)	(0.338)	(0.647)	(0.588)	(1.181)	(1.460)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.001	0.074	0.118	0.083	0.136
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	Pre-term: <37 weeks (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	0.150	2.556	2.908	1.043	0.674
(current and last 3 quarters)	(2.293)	(2.293)	(2.152)	(2.116)	(2.029)
Surface Production	0.317	-0.805	-0.860	-0.726	-0.437
(current and last 3 quarters)	(0.378)	(0.827)	(0.803)	(1.203)	(1.473)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.000	0.124	0.159	0.165	0.216
Observations	4,752	4,752	4,752	4,752	4,752

Discussion

This study reviews the evidence of the association between a mother's residence near coal mines and infant health, and presents new evidence that contradicts some of the conclusions from existing cross-sectional research. The results of the current study indicate that failing to account for unobservable differences across counties and over time may produce misleading conclusions about the relationship between coal mining and infant health. Only simplified

TABLE 18.
New Surface Mines: Birth Defects

Treatment: New Surface Mines
Sample: 1989-2006

a.) ARC Counties

	(1)	(2)	(3)	(4)	(5)
	One of 22 birth defects (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	3.309***	1.301	1.357	-0.036	0.113
(current and last 3 quarters)	(1.051)	(0.853)	(0.852)	(0.528)	(0.619)
Surface Production	0.424	-0.455	-0.435	0.649*	0.614
(current and last 3 quarters)	(0.450)	(0.612)	(0.621)	(0.379)	(0.545)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.004	0.067	0.073	0.069	0.129
Observations	29,734	29,734	29,734	29,734	29,734

b.) MTR Counties

	(1)	(2)	(3)	(4)	(5)
	One of 22 birth defects (per 1000)				
	b/se	b/se	b/se	b/se	b/se
I(New Surface Mine)	2.116	0.502	0.537	-0.721	-0.662
(current and last 3 quarters)	(1.883)	(1.803)	(1.803)	(1.095)	(1.323)
Surface Production	-0.359	-0.688	-0.706	0.614	0.522
(current and last 3 quarters)	(0.507)	(0.808)	(0.820)	(0.404)	(0.573)
Controls	No	**Yes**	**Yes**	**Yes**	**Yes**
Quarter Effects	No	No	**Yes**	**Yes**	**Yes**
County Effects	No	No	No	**Yes**	**Yes**
County-Specific Linear Trends	No	No	No	No	**Yes**
R^2	0.002	0.081	0.096	0.110	0.179
Observations	4,752	4,752	4,752	4,752	4,752

models relying on cross-sectional indicators for the presence of coal mining in a county regularly suggest statistically significant adverse effects of coal mining on birth outcomes. The presence of coal mining may be correlated with systematic differences in maternal behaviors, different demographics, and different historical settlement patterns within mountaintop removal coal mining counties compared to other counties in Appalachia.

However, given the coarse spatial resolution of our data, we cannot definitely conclude that there is no causal relationship between coal mining and infant health. Ideally, we would like to know the exact address of each mother and examine the effects for mothers and infants living in close proximity to mining sites, rather than simply to assume that infants within a county are uniformly exposed to coal mining activity. Fine geospatial data on each mother's residence would vastly improve identification. The ideal study would also incorporate precise measurements of local air and water quality, but current data limitations prevent such a study.

Descriptive evidence from this study still indicate poorer infant health outcomes in mountaintop-removal coal-mining counties compared to other counties in Appalachia. Even if we could definitively state that coal mining does not itself affect public health, we may still be concerned about negative outcomes for local residents of these communities that can be attributed to other causes. Anecdotally, mountaintop removal coal mines are detrimental to the surrounding landscape and ecosystems, depress property values, and contribute to socioeconomic inequality. Thus, the negative correlation between mountaintop removal coal mining and public health remains a concern from the perspective of environmental justice. However, it is inappropriate to attribute the observed adverse health outcomes in this region to the existence of coal mining based on conclusions simply from cross-sectional analyses.

CHAPTER IV

GROUNDWATER POLLUTION IN OREGON'S SOUTHERN WILLAMETTE VALLEY: A HEDONIC PROPERTY VALUE ANALYSIS OF A POLICY INTERVENTION

Introduction

In 1989, Oregon passed two laws enabling statewide monitoring of groundwater quality: the Groundwater Protection Act (GWPA) and the Domestic Well Testing Act (DWTA). The GWPA gives the state of Oregon the authority to designate groundwater management areas (GWMAs) where groundwater quality poses a threat to human health. The DWTA requires homeowners to test the quality of their well water at the time of a real estate transaction. Thus, the data on the quality of water in private wells should be readily available to participants in the housing market. However, compliance with this program is not uniformly enforced and results reported to the state suggest that compliance with the testing requirement may be low.[1]

[1] Since 1989, the Oregon Health Authority has recorded test results for about 20,000 private wells. This total implies a low level of compliance with the DWTA, given that the Oregon Water Resources Department estimates there are roughly 235,000 private wells throughout the state. Compliance with the DWTA is not routinely verified, so testing remains effectively voluntary. Anecdotally (based on conversations with area realtors and well-testing laboratories), testing at the time of real estate transactions is actually a common practice. The failure seems to occur because the required test results are rarely reported to the state for archiving. Additionally, there is no oversight for quality control for private-well testing.

In 2004, a groundwater management area (GWMA) was established in the southern Willamette Valley of Oregon in response to a study conducted by the Oregon Department of Environmental Quality (ODEQ) that indicated the presence of significantly elevated nitrate concentrations. If homebuyers were previously unaware of area nitrate contamination, the GWMA establishment may have served as an information shock, leading to a decrease in property values. However, if nitrate contamination was salient to residents prior to the ODEQ study, the GWMA designation may signal official plans to improve water quality in the GWMA area, leading to an appreciation of property values within the GWMA boundary.

The primary research questions addressed in this study include: (1) Do housing values in Oregon's Southern Willamette Valley reflect groundwater nitrate concentrations? (2) Did the establishment of the GWMA affect housing values inside versus outside the GWMA boundary? (3) Are there sub-areas or particular types of properties that were differentially affected by this policy intervention?

Results of a groundwater study conducted by ODEQ in 2000-2001 are used for spatial interpolation of approximate nitrate concentrations for each property. The boundary of the established GWMA (which covers about one-third of the original study area) is used in a difference-in-differences (DiD) analysis to estimate the effect of the establishment of the GWMA on housing values before and after designation. Fixed effects at the census block-group level are included to capture spatial heterogeneity in other amenities of properties in the region that may be correlated with nitrate concentrations.

I find that higher nitrate concentrations are associated with lower housing values, particularly for rural residential properties or those located outside of city limits. On average, an additional 1 mg/L of nitrate concentration reduces expected housing values by about 1.2%. However, this estimated effect increases to 2.8-3% for rural properties that are more likely to be reliant on a private well for their water. The designation of the GWMA is associated with a 3.2% increase in property values within the GWMA boundary, presumably due to expectations of future cleanup of nitrate concentrations. The incremental positive effect of the GWMA designation is strongest for properties located within city limits, likely due to the properties' higher reliance on public water utilities which are less likely to be affected by groundwater nitrate contamination relative to properties outside of city limits.

The current study seeks market evidence of how people respond to information about environmental quality. The establishment of the GWMA serves as both an information intervention and a policy intervention. Regional well testing by the Oregon Department of Environmental Quality (ODEQ) provided initial information to area residents regarding nearby groundwater quality and the GWMA designation potentially signaled a policy response. Results of this study could be informative for policy makers who are considering environmental assessments in advance of potential policy interventions to address local environmental quality concerns.

Related Literature

The current study is related to several strands of literature concerning the non-market valuation of environmental quality. These strands include hedonic property valuations of observed environmental quality, information disclosure regarding environmental quality, and proximity to potential contamination sources. The hedonic property value (HPV) model is a standard economic model used extensively in valuing environmental amenities (or disamenities). Hedonic analyses have also been used to value the benefits of environmental cleanup efforts. The analysis in this paper embeds a difference-in-differences analysis within an HPV framework.

Numerous hedonic property value studies have analyzed changes in air quality (Smith and Huang (1995); Chay and Greenstone (2005)), but fewer papers have analyzed housing market effects of changes in water quality. Several early studies find no effect of groundwater contamination on housing prices (Malone and Barrows (1990); Dotzour (1997)); however, more-recent papers have found statistically discernible effects.

Boyle et al. (2010) look at the effect of private drinking-water well contamination on housing prices in two rural towns in Maine. They find that the discovery of arsenic contamination, in 1993, led to a significant but temporary decrease in housing prices lasting just two years. Using neighborhood-based measures of arsenic levels, Boyle et al. find that housing prices declined by 0.5% to 1% for each 0.01 mg/l of arsenic above the standard set by the U.S. Environmental Protection Agency.

Using property-specific well-water tests in Lake County, Florida, Guignet et al. (2015) find that a positive contamination test result in the three years prior to a real estate transaction yields, on average, a 2-6% depreciation in housing values. Focusing specifically on nitrate contamination, Guignet et al. find that home values decrease by 7-15% at concentrations above the EPA's maximum contaminant level.

The current study also contributes to a fairly rich literature investigating housing market responses to information disclosure about environmental risks. Several studies have analyzed the housing market response to publication of the Toxic Release Inventory which disclosed locations of toxin-emitting firms. Oberholzer-Gee and Mitsunari (2006) and Mastromonaco (2014) both find that housing values declined as nearby firms were listed in the Toxic Release Inventory.

McLaughlin (2011) examines the effect on residential property values of several information disclosure events regarding possible groundwater contamination due to a plume of trichloroethylene (TCE) in Washington County, Minnesota. He finds that homeowners were initially well-informed about the true contamination risk, until a government disclosure law created an imperfect geographic boundary delineating the contamination area. McLaughlin finds residents relied on the geographic boundary as a proxy for the probability a house will have contaminated groundwater despite this boundary being an imperfect measure of risk. He ultimately finds that this policy resulted in a negative effect on real estate prices within the boundary, even for houses that were not actually at risk from groundwater contamination.

The current study is also related to the literature on the effects of groundwater contamination risk measured by proximity to potential contamination sources, such as hazardous waste sites (Boyle and Kiel (2001); McCluskey and Rausser (2003); Kiel and Williams (2007); Messer et al. (2006)), leaking underground storage tanks (LUSTs) (Guignet (2013)), and fracking wells (Muehlenbachs et al. (2015)). Gayer, Hamilton, and Viscusi (2000) find, in general, that people overestimate the health risks of proximity to potential contamination sites, and housing prices respond more to perceived environmental risks than to measured objective levels of risk.

Background

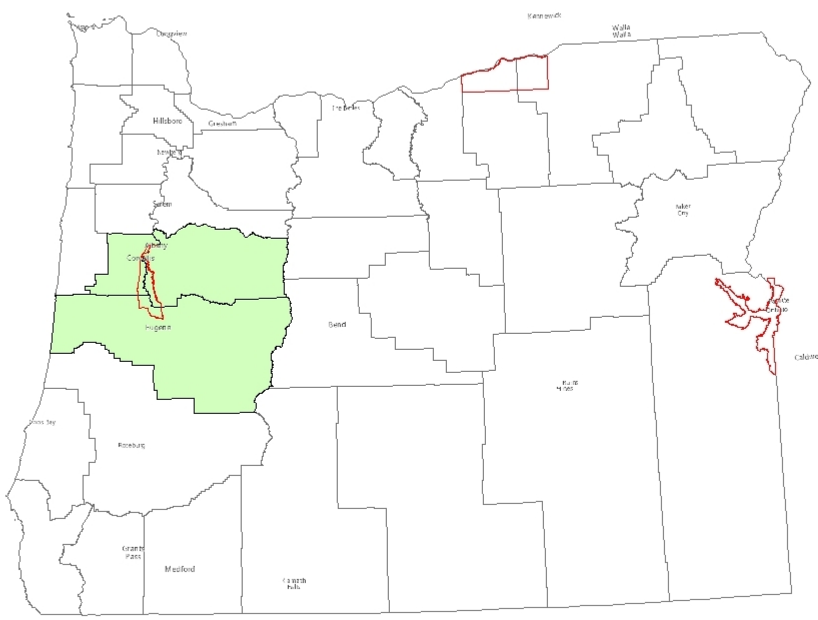
In rural Oregon, non-point-source pollution from agricultural practices is the predominant source of groundwater contamination, with nitrate being the most commonly cited contaminant. Nitrate is a form of dissolved nitrogen that occurs naturally at low levels in soil and water. However, elevated nitrate concentrations are generally an indication of anthropogenic sources, such as use of nitrogen fertilizers, septic systems, animal feedlot operations, and above-ground applications of wastewater (Eldridge (2003)). Nitrate is a remarkably stable stock pollutant and is resistant to degradation, often accumulating until it becomes a long-term water resource problem (Dubrovsky et al. (2010)). Contamination is complicated and expensive to remediate because common residential water filtration systems (such as charcoal filters, water softeners and use of chlorine) are not effective in reducing nitrate. Detection of nitrate is also difficult because nitrate is both tasteless and odorless. Nitrate exposure has been linked to methemoglobinemia or "blue baby syndrome" as well as a variety of cancers, respiratory problems, and reproductive issues. The EPA's maximum contaminant level for nitrate in drinking water in public water systems is 10 mg/L, while amounts above 3 mg/L suggest potential contamination.

Absent regulation, and given the cost of testing, many households neglect regular monitoring of their private wells for common contaminants. Some states and local governments have enacted legislation for quality control of water from private wells, but very few states have programs in place to monitor domestic well-water quality on an ongoing basis. Just three states—Oregon, New Jersey and Rhode Island—appear to require testing of private well at the time of a real estate transaction.

Oregon has established three GWMAs in response to elevated nitrate concentrations: the Northern Malheur County GWMA in 1989, the Lower Umatilla

Basin GWMA in 1990 and the Southern Willamette Valley GWMA in 2004. These GWMA locations are depicted in Figure 16 This study will focus on the most recent GWMA, established in the more heavily populated Southern Willamette Valley. This particular GWMA provides an opportunity to analyze the response of housing prices to nitrate contamination, before and after the geographic boundary of this GWMA was established.

FIGURE 16.
Groundwater Management Areas: State of Oregon, USA



The establishment of the Southern Willamette Valley GWMA followed a comprehensive groundwater study conducted by the Oregon Department of Environmental Quality (ODEQ). In 2000-2001, ODEQ selected an area within which to study the levels of nitrate contamination in groundwater in the Southern Willamette Valley. This area encompassed approximately 780 square miles, extending east to west from the Cascade Range to the Oregon Coast Range, and north to south from the Salem Hills to the city of Eugene's urban growth boundary. The area was identified by the ODEQ as a priority area for groundwater assessment and protection due to (a.) the suspected severity and extent of non-point source groundwater contamination, (b.) the vulnerability of shallow groundwater in the region, (c.) the rapidly expanding population, and (d.) the high reliance on groundwater for drinking water among residents in the area (Kite-Powell and Harding (2006)).

ODEQ selected 476 wells throughout the area to be sampled and tested for nitrate. One hundred wells in the study area had measured nitrate concentrations greater than 7 mg/L, while 34 wells had nitrate concentrations above the EPA's maximum contaminant limit of 10 mg/L. In 2002, those wells identified as having nitrate concentrations above 7 mg/L were retested, with 64 exhibiting increases in nitrate concentrations. Furthermore, at least one pesticide, most commonly atrazine, was found in 81 of these 100 wells (Kite-Powell (2004)). Nitrate is often correlated with the presence of bacteria and pesticides, which are also often linked to intensive agricultural land use.

In addition to contamination identified in private wells, 15 public water utilities in this area were found to have nitrate concentrations above 7 mg/L during this same time period (ODEQ 2004). Public water utilities must monitor water quality on a regular basis, report results and provide treatment when necessary.

However, despite regular monitoring, it takes time to implement treatment systems to remove nitrate and pesticides from public water systems. Households who relied upon these water systems may have been informed of the contamination but may have continued to be exposed to elevated nitrate concentrations in their drinking water until remediation was completed (if they did not undertake treatment on their own, or avoid consuming this water).

In May 2004, following the ODEQ investigation and a public comment period, the Southern Willamette Valley GWMA was established. In addition to nitrate, ODEQ also cited the need to identify other potential contaminants in groundwater in this area. ODEQ formed a GWMA Committee to develop an action plan for nitrate reduction strategies across land uses in the region. The primary goal of the action plan is to reduce nitrate levels, to less than 7 mg/L throughout the region, by disseminating information to residents across all types of land uses about actions to protect groundwater. The program emphasizes development of specific voluntary strategies that limit the leaching of nitrate into groundwater (ODEQ 2006). A sample of monitoring wells has since been tested regularly from 2005 through 2012 in the course of ongoing efforts by the ODEQ to monitor any trends in nitrate levels in the area.

Data

The current study focuses on Benton, Lane, and Linn counties in the Southern Willamette Valley of Oregon. The GWMA established in this area intersects portions of all three counties and overlaps parts of the populated metropolitan areas of Eugene, Corvallis, and Albany. The region is historically agricultural but has experienced rapid population growth over the past several decades.

Data on real estate transactions are available from county tax assessors since 2000 for Benton and Lane Counties and since 2001 for Linn County. Sales after 2007 are excluded to avoid potentially confounding factors that affected real estate prices during the Great Recession. Data are restricted to "arm's-length," non-distressed residential real estate transactions. Sales of vacant land and real estate selling for less than $10,000 are also excluded. Some additional outliers that may not accurately reflect standard market transactions are also excluded.[2] To incorporate spatial information associated with property locations, addresses are spatially located using the online geocoder available from the U.S. Census Bureau. Information on the specific source of drinking water for each household is not recorded by Oregon county tax assessors, so it is unfortunately not feasible to include water source as a specific property attribute for this hedonic property value analysis.[3]

There may be other ways to approximate whether a property at a specific physical location is served by a public water system or must rely on water from

[2]Further incidental exclusion restrictions are listed in more detail in the Appendix.

[3]The Oregon Water Resources Department logs information on well construction of new wells, but there are many older wells not in their database. Furthermore, most of the well data cannot be geolocated with sufficient accuracy to be matched unambiguously to specific real estate transactions, rendering the well-log data unsuitable for this analysis.

a private well. Individual water utilities have data on the addresses of their subscribers, but the State of Oregon has at least 495 different water utilities, and each is likely to have its own policy on sharing the addresses of its subscribers.[4] The type of water service for every property transaction would be a valuable explanatory variable, but I must rely on proxies for this variable.

The Southern Willamette Valley GWMA encompasses approximately 270 square miles. The GWMA extends from the northern edge of the Eugene-Springfield urban growth boundary about 50 miles north to a point just past Corvallis. The GWMA boundaries are defined primarily by roadways and natural geological features. Nitrate contamination in groundwater is a significant concern only in agricultural areas, so the coastal and forested regions of these counties are not likely to be a valid control group for this analysis. Lane County, in particular, is very large. Just a small portion of the county has been affected by the GWMA. Rather than using all real estate transactions from these counties, the data for this analysis are restricted to the GWMA area plus a two-mile buffer outside of this area, with properties in this buffer zone constituting a more appropriate control group for this analysis.[5] Table **??** depicts summary statistics for data used in my preferred sample of real estate transactions.

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[4]These 495 utilities are reported as regular members by the Oregon Association of Water Utilities $http://oawu.net/membership/regular-members/$ (accessed 09/01/2016).

[5]Several different subsets of the data can be considered, with no substantial qualitative changes in the results.

TABLE 19.
Summary Statistics: Real Estate Transactions within 2 miles of GWMA

	Mean	St. Dev.	Min	Max
SalePrice ($)	$196,988	$112,822	$11,000	$1,665,000
SaleYear	2004	2	2000	2007
SQFT	1421	771	0	7392
Age	34.67	27.25	0	157.00
Num Bedrooms	3.05	0.74	1.00	8.00
Num Bathrooms	1.76	0.66	0.50	8.00
Acres	0.89	8.36	0.02	375.97
Dist GWMA (km)	1506.58	1021.92	0	3219.93
GWMA	0.18	0.38	0	1
Dist City Limit (km)	212.67	947.29	0	11130.37
Predicted Nitrate (mg/L)	3.23	1.25	0.23	11.00

Test results from studies conducted by ODEQ are used as a static measure of nitrate concentrations in groundwater. From late 2000 to early 2001, as noted, 476 wells were sampled for nitrate in groundwater throughout the area covered in this study. Of the initial broader geographic area tested by ODEQ during 2000-2001, about one-third was included within the eventual GWMA boundary established in 2004. Figure 17 depicts the 476 well locations tested in the ODEQ study, and the red line is the boundary of the eventual GWMA. Figure 18 further depicts nitrate concentrations of the wells tested in ODEQ's 2000-2001 study.

FIGURE 17.
2000-2001 ODEQ Well Tests

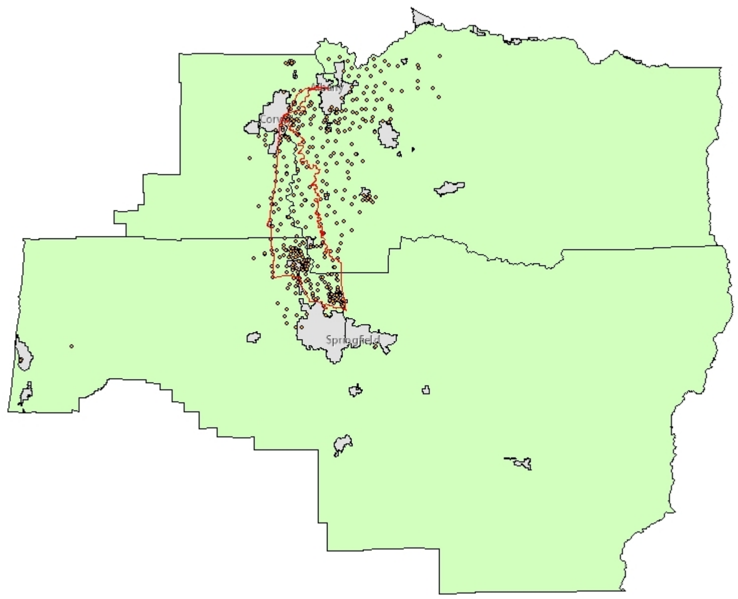
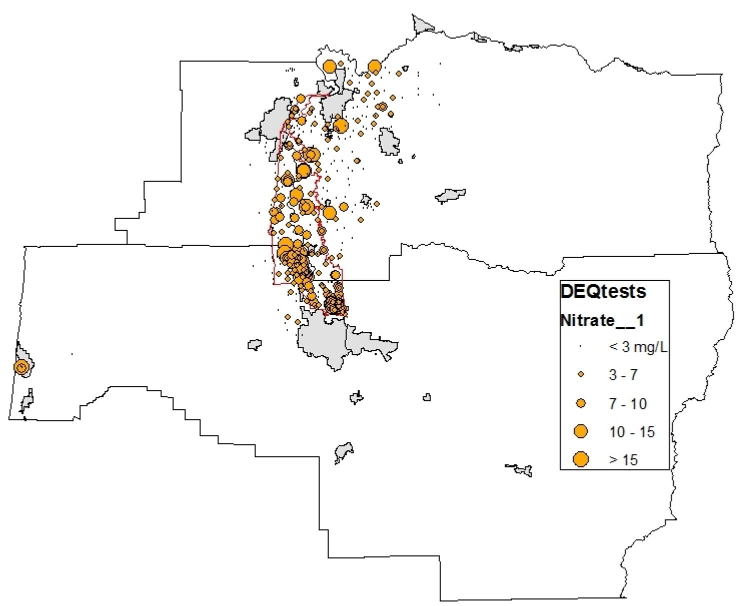


FIGURE 18.
2000-2001 Nitrate Concentrations



Kriging was used to interpolate likely water quality levels between the point locations of the the initial ODEQ well test results across the study area, under the assumption that nitrate levels vary reasonably smoothly across this area.[6] I treat the 2000-2001 interpolated nitrate levels as the baseline measure of nitrate concentration in the area, and these nitrate levels are matched to individual real estate transactions.

Nitrate concentrations are treated as approximately fixed over the medium term, since nitrate in groundwater is considered a stock pollutant that accumulates over a long period of time. Additional well tests were conducted by ODEQ in 2002 and in subsequent years, but wells were retested only in areas known to have high nitrate concentrations, so this information reflects a selected sample. This data limitation is unlikely to bias the results significantly since I am looking primarily at the treatment effect of a policy announcement conditional on original nitrate concentrations, rather than studying the evolution of nitrate concentrations over time.[7]

[6] Results are also robust to the use of inverse-distance weighting for interpolation. Other factors are important indicators of susceptibility of well water to nitrate contamination such as age and depth of wells, groundwater flow, and soil characteristics (Kite-Powell and Harding (2006)). It is not possible to control for all of these factors in this analysis.

[7] If and when comprehensive follow-up testing is undertaken across the entire area, there might be sufficient data to permit such an analysis.

Empirical Model

A hedonic property value model is used to estimate the implied value of the expected water quality clean-up among property owners in the Southern Willamette Valley who are affected by nitrate contamination. Originally developed by Rosen (1974), the hedonic valuation methodology posits that the price of a heterogeneous good can be decomposed into implicit prices associated with the different attributes of the good.

Assume the price of a house is a function of structural characteristics and neighborhood characteristics, including (a.) whether the property is inside or outside the GWMA boundary and (b.) groundwater nitrate concentrations. Formally, let the price function for a house i at time t be given by $P_{it} = f(X_{it}, Z_{it}, \hat{N}_i, GWMA_i)$, where X_{it} is a vector of property specific characteristics, Z_{it} is a vector of neighborhood characteristics, $\hat{N}_i$ is the interpolated nitrate concentration of the property's groundwater at the beginning of the study period, and $GWMA_i = 1$ indicates that the property is inside the state-designated groundwater management area.

A difference-in-differences approach is used to estimate the effect of the GWMA designation on housing prices in the study area. The following log-linear specification is estimated:

$$\begin{aligned} ln(Price)_i =& \alpha_0 + \alpha_1 GWMA_i + \alpha_2 Post_t + \alpha_3 (GWMA_i Post_t) \\ &+ \beta \widehat{N_i} + \gamma X_i + \tau_t + \mu_c + \epsilon_i \end{aligned} \tag{4.1}$$

where $\widehat{N}_i$ represents a property-specific interpolated nitrate value, X_i is a vector of property characteristics, τ represents year-of-sale fixed effects to capture overall market trends, and μ represents geographic fixed effects to control for unobserved neighborhood influences. $Post_t = 1$ indicates that the propert sale occurred after May 2004 when the GWMA was established.[8]

Equation (4.1) is also estimated using $GWMA_i$ status interacted separately with each year in the study period to determine whether there may be an effect that can be attributed to anticipation of the GWMA designation. Announcement-type effects seem likely, since there were several related events leading up to the establishment of the GWMA, including the ODEQ well testing study followed by a public comment period.

Additionally, a richer model is estimated to allow the effect of interpolated nitrate concentration on housing prices to differ before and after the establishment of the GWMA:

$$\begin{aligned} ln(Price)_i = &\alpha_0 + \alpha_1 GWMA_i + \alpha_2 Post_t + \alpha_3(GWMA_i Post_t) \\ &+ [\beta_0 + \beta_1 GWMA_i + \beta_2 Post_t + \beta_3(GWMA_i Post_t)]\, \widehat{N}_i \\ &+ \gamma X_i + \tau_t + \mu_c + \epsilon_i \end{aligned} \tag{4.2}$$

[8]Ideally, I would also include property-level fixed effects to control for time-invariant unobservable differences across properties. Unfortunately, there are few repeat sales within the study area from 2000-2007, making this analysis infeasible.

In this specification, α_3 represents the "level shift" from the simple difference-in-differences specification and β_3 is the "slope shift" which captures how the establishment of the GWMA may have altered the effect of interpolated nitrate concentrations on housing values.

If residents were unaware of potential contamination, establishment of the GWMA may have served as an information shock leading to lower housing values within the GWMA boundary. However, if residents were already aware of nitrate contamination, establishment of the GWMA may have a positive impact on housing values in areas with high nitrate concentrations. Housing values reflect the present value of a stream of future net benefits. Consequently, the GWMA designation may indicate a higher probability of future cleanup, increasing the expected future benefits from property ownership due to clean water.

Additionally, some types of systematic heterogeneity are explored, using (1) variation in properties' locations within or outside of defined city limits and (2) variation in specific residential property class. Property class is split between properties classified as either "Urban Residential" or "Rural and Farm Residential" which includes properties on larger lots and those that include farmland. This heterogeneity analysis allows us to estimate whether there is a differential response to nitrate contamination for different property types based on their expected water source. Table 20 gives a breakdown of the estimating sample by county and specific residential property class.

TABLE 20.
Number of Transactions by County and Property Class

	Benton	Lane	Linn	Total
Residential	2,896	5,276	2,846	11,018
Rural Residential	135	299	200	634
Farmland Residential	36	170	30	236
Total	3,067	5,745	3,076	11,888

Results

Selected coefficients for several specifications of equation (1) are reported in Table 21. Columns (1)-(3) report the simple difference-in-differences specification with various levels of geographic fixed effects included. From the specification in column (3), which includes census-block-group fixed effects, properties within the GWMA boundary exhibit an average 3.2% increase in price following the official establishment of the GWMA in May 2004. The pre-treatment mean sale price is $180,545, thus this treatment effect corresponds to a $5,937 price increase.

Columns (4)-(6) show that this result is robust to inclusion of the predicted nitrate level spatially interpolated from ODEQ's 2000-2001 study. Results for the most-general specification, shown in column (6) indicate that an additional 1 mg/L of nitrate concentration reduces expected housing values by 1.2%. The mean interpolated nitrate concentration in the study area is 3.2 mg/L with a standard deviation of 1.25.

Figure 19 depicts the treatment effect of GWMA designation interacted with each year of the study period (along with 95% confidence intervals). There is no statistically discernible effect of GWMA designation in the pre-treatment

TABLE 21.
Results: GWMA plus a two-mile buffer zone

	Dependent variable:					
	Log(Sale Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
GWMA	-0.0866***	-0.0164	-0.103***	-0.0887***	-0.00723	-0.0870**
	(0.010)	(0.023)	(0.039)	(0.011)	(0.024)	(0.041)
Post	0.0574***	0.0530***	0.0530***	0.0574***	0.0530***	0.0529***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
GWMA_Post	0.0383***	0.0320***	0.0320***	0.0380***	0.0323***	0.0329***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Predicted_Nitrate				0.00141	-0.00770	-0.0123*
				(0.003)	(0.005)	(0.007)
Property-Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-of-Sale Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Effects	Yes	No	No	Yes	No	No
Census-Tract Effects	No	Yes	No	No	Yes	No
Census-Block-Group Effects	No	No	Yes	No	No	Yes
R^2	0.679	0.715	0.731	0.679	0.715	0.731
Observations	11,059	11,059	11,059	11,059	11,059	11,059

*p<0.1; **p<0.05; ***p<0.01

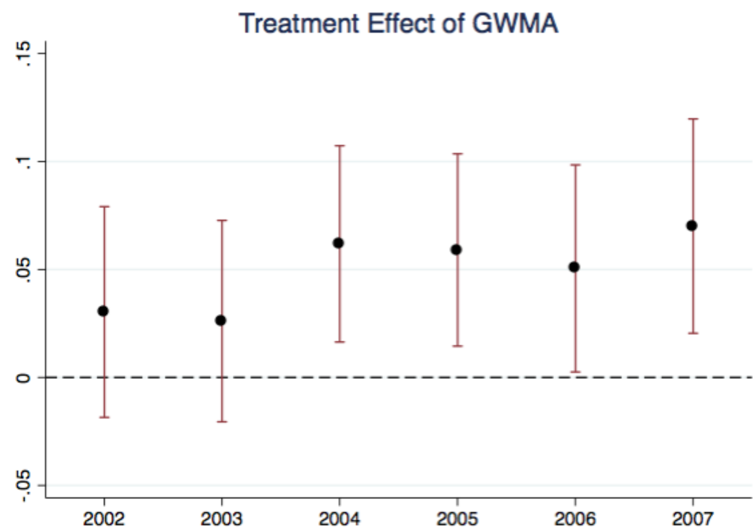
Note: Selected coefficients. All specifications include year-of-sale fixed effects and control for housing characteristics. Heteroskedastic robust standard errors are reported.

years, 2002 and 2003. However, beginning in 2004 there is a sustained positive treatment effect of GWMA designation on real-estate transactions within the GWMA boundary.

Heterogeneity Analysis

On average, I find a positive effect of GWMA designation on affected property sales. However, one might expect to see differences based on a property's likely water source. For example, one might expect a different treatment effect between (a.) properties served by public water utilities (and thus less likely to be exposed to the nitrates in groundwater due to the services of water treatment facilities) and (b.) properties that rely on water from private wells (and thus are

FIGURE 19.
Treatment Effect of GWMA by Year



exposed to whatever levels of nitrates exist in their supply of drinking water). The information shock provided by the discovery of high nitrate levels in groundwater can be expected to decrease the demand for properties with risk of exposure to contaminated groundwater. As demand for these properties decreases, buyers will shift demand toward substitute properties. Properties on city water in roughly the same area will be the best available substitute in terms of properties without a nitrate problem, so demand for city-water-dependent properties will likely increase. In general, if the sample can be split into groups which are (a.) more likely to rely on well water, versus (b.) more likely to be connected to city water, one would expect that the GWMA treatment effect and the predicted nitrate variable will tend to bear coefficients with opposite signs.

Within the available data, there are several candidate proxies for splits of the sample according to a "well water versus city water" distinction. I explore these proxies by splitting the sample into subsamples along each of these dimensions, one at a time. One might expect different responses to predicted nitrate levels based on the initial testing program, as well as different reactions to the designation of some properties as being inside the GWMA and others remaining outside of this area. These splits, with their corresponding table numbers are:

1. Table 22 Properties within the city limits as designated by land use regulations for each municipality (as an indicator for city water) versus properties outside city limits (as an indicator for well water).

2. Table 23: Properties classed as "urban residential" (as an indicator for city water) versus properties classed as "rural residential" or "farm residential" (as an indicator for well water);

Table 22 reports estimates for urban versus rural properties, designated according to their locations relative to the city-limit boundaries. Rural properties represent lots located outside of city-limit boundaries. These properties are much more likely to be reliant on private well water, whereas urban properties are more likely to be connected to public water utilities. A positive and statistically significant coefficient on predicted nitrate concentration is found for properties within city limits, while a negative and statistically significant coefficient is found for properties located outside of city limits. Additionally, a positive treatment effect

TABLE 22.
Results by City Limits

	Dependent variable:		
	Log(Sale Price)		
	Within City	Outside City	All
	(1)	(2)	(3)
GWMA	-0.159	-0.0494	-0.0870**
	(0.097)	(0.049)	(0.041)
Post	0.0551***	0.0411***	0.0529***
	(0.007)	(0.013)	(0.007)
GWMA_Post	0.0432***	0.0173	0.0329***
	(0.012)	(0.032)	(0.012)
Predicted_Nitrate	0.0338***	-0.0283***	-0.0123*
	(0.011)	(0.008)	(0.007)
Controls	Yes	Yes	Yes
Year-of-Sale Effects	Yes	Yes	Yes
Census Block Group Effects	Yes	Yes	Yes
R^2	0.753	0.715	0.731
Observations	8,527	2,532	11,059

*p<0.1; **p<0.05; ***p<0.01

Note: Selected coefficients. All specifications include year-of-sale and census-block-group fixed effects and control for housing characteristics. Heteroskedastic robust standard errors are reported.

for urban properties, versus no effect for rural properties, indicates a differential policy response. This aligns with the prediction that demand shifted away from rural properties (on well water) and toward urban properties (on city water) as a result of information provided by designation of the GWMA.

Table 23 estimates separate effects of the GWMA designation for a sample of partitions based on property class. Column 1, denoted "Urban Residential", represents traditional residential properties (more likely on city water), while Column 2, denoted "Rural-and-Farm Residential", represents rural-residential and farm-residential properties (more likely dependent on well water). The coefficient on predicted nitrate levels is positive for urban residential properties, reflecting the higher reliance on municipal water systems and lower concern regarding nitrate contamination. A negative and statistically significant coefficient on predicted nitrate concentration is found for rural and farm residential properties. In this case, a positive treatment effect is found for both urban residential and rural-and-farm residential properties. Rural-and-farm residential properties also see a large negative coefficient on the indicator for time-invariant GWMA status. This is driven largely by the small portion of residential properties in the sample that include farmland, likely reflecting the role of farming as a source of nitrate contamination. In this case, the policy intervention resulted in a positive price effect for residential farmland properties since the policy did not include any direct financial burden on owners of farmland. Thus, the GWMA policy announcement led to a slight rebound in prices for these properties.

Clearly, the GWMA designation is correlated with measured nitrate levels. Properties eventually within the GWMA will have higher levels of nitrate contamination than properties outside the eventual GWMA. In each of these tables for properties that are more likely, versus less likely, to be on well water, there is a clear tendency for there to be opposite signs on this indicator. Across Tables 22 and 23, for whichever partition of the data that is more likely to rely on well water, higher predicted nitrate levels in groundwater are associated with lower property prices because these properties come with exposure to nitrate contamination. Conversely, for the particular subset of the data that is more likely

TABLE 23.
Results by Property Class

	Dependent variable:		
	Log(Sale Price)		
	Urban Residential	Rural and Farm Residential	All
	(1)	(2)	(3)
GWMA	-0.120	-0.195***	-0.0870**
	(0.079)	(0.060)	(0.041)
Post	0.0553***	-0.0160	0.0529***
	(0.006)	(0.046)	(0.007)
GWMA_Post	0.0333***	0.0897*	0.0329***
	(0.011)	(0.052)	(0.012)
Predicted_Nitrate	0.0341***	-0.0298***	-0.0123*
	(0.009)	(0.010)	(0.007)
Controls	Yes	Yes	Yes
Year-of-Sale Effects	Yes	Yes	Yes
Census Block Group Effects	Yes	Yes	Yes
R^2	0.747	0.646	0.731
Observations	10,259	800	11,059

*p<0.1; **p<0.05; ***p<0.01

Note: Selected coefficients. All specifications include year-of-sale and census-block-group fixed effects and control for housing characteristics. Heteroskedastic robust standard errors are reported.

to be on city water, higher predicted nitrate levels in groundwater are associated with higher property prices because occupants of these properties can avoid the nitrate problem, making these properties relatively more attractive.

Table 24 reports results for a richer difference-in-differences specification that allows for the effect of nitrate concentration (i.e. the key slope coefficient) to vary with treatment (i.e. the model presented in equation (2)). Results from this specification are shown for all properties within two miles of the GWMA boundary in column (2) and broken down between urban and rural properties, as in Table 22, in columns (4) and (6). Properties within city limits exhibit an 8% increase in prices following GWMA establishment, and there is no effect of interpolated nitrate concentrations on prices either before or after GWMA establishment. Properties outside of city limits see a 17% increase in prices following GWMA establishment, but in these areas there is an increase in magnitude of the effect of predicted nitrate concentrations on home prices. These estimates suggest that the GWMA establishment may have heightened awareness regarding nitrate contamination within the GWMA. Urban properties, and rural properties with low nitrate concentrations located inside of the GWMA, experienced the largest positive price effects following the GWMA establishment.

TABLE 24.
Results: Allowing for Slope Change on Predicted Nitrate

	Dependent variable:					
	Log(Sale Price)					
	All		Within City		Outside City	
	(1)	(2)	(3)	(4)	(5)	(6)
GWMA	-0.0870**	-0.194***	-0.159	-0.199*	-0.0494	-0.152
	(0.041)	(0.069)	(0.097)	(0.109)	(0.049)	(0.101)
Post	0.0529***	-0.00378	0.0551***	0.0209	0.0411***	-0.0277
	(0.007)	(0.023)	(0.007)	(0.024)	(0.013)	(0.052)
GWMA_Post	0.0329***	0.118***	0.0432***	0.0797**	0.0173	0.175*
	(0.012)	(0.035)	(0.012)	(0.035)	(0.032)	(0.100)
Predicted_Nitrate	-0.0123*	-0.0363***	0.0338***	0.0229	-0.0283***	-0.0444***
	(0.007)	(0.012)	(0.011)	(0.017)	(0.008)	(0.016)
Predicted_Nitrate ∗ GWMA		0.0328**		0.0176		0.0261
		(0.015)		(0.022)		(0.020)
Predicted_Nitrate ∗ Post		0.0191***		0.0118		0.0214
		(0.007)		(0.008)		(0.014)
Predicted_Nitrate ∗ GWMA ∗Post		-0.0256***		-0.0125		-0.0380*
		(0.009)		(0.009)		(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-of-Sale Effects	Yes	Yes	Yes	Yes	Yes	Yes
Census-Block-Group Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.731	0.731	0.753	0.753	0.715	0.716
Observations	11,059	11,059	8,527	8,527	2,532	2,532

*p<0.1; **p<0.05; ***p<0.01

Note: Selected coefficients. All specifications include year of sale and Census block group fixed effects and control for housing characteristics. Heteroskedastic robust standard errors are reported.

Discussion

The analyses described in this paper point to the importance of differentiating between properties reliant on well water and properties connected to municipal water service. Specifications that pool all types of properties to estimate price effects of nitrate concentrations and the GWMA designation fail to capture these differentiated effects. These differences are revealed when the sample is split according to the likely water source for the property. The evidence from split samples certainly supports the contention that the two types of properties (those on well water and those on city water) are substitutes and that the demand curves for each type of property shift in response to information about nitrate contamination and information about the geographic scope of future remediation efforts. Instead of using a simple difference-in-differences analysis for "pre-GWMA" and "post-GWMA" periods, for the "within-GWMA" and "outside-GWMA" properties, it is clear that a triple-difference specification is preferred, with the third difference being across "likely well water dependence" and "likely city water connection." Future analyses would benefit from high-resolution geographic information about public water-utility service areas.

Results of this study indicate that the GWMA designation resulted in a heightened awareness of groundwater nitrate contamination among residents and housing market participants in Oregon's Southern Willamette Valley. The differential effects based on likely water source and predicted nitrate levels suggests that home buyers may be reasonably well-informed about actual risks, rather than perceived risks. The results from this study could be informative for other policy makers who are considering potential policy interventions to address local environmental quality concerns that may have heterogeneous effects across different contexts.

CHAPTER V

CONCLUSION

This dissertation consists of a set of three empirical analyses concerning resource extraction. Specifically this research explores some public health externalities associated with coal extraction, as well as pollution externalities from agriculture that affect the quality of local groundwater resources and subsequently affect market values of properties that depend upon groundwater extraction for their water supply.

In Chapter II, compared to the existing literature, we identify a more direct contemporaneous link between coal mining and public health, using within-county variation over time in coal-mining activity. We consider both the opening of new surface coal mines, and increased surface coal production, in the subset of Appalachian counties that participate in mountaintop-removal coal mining. Both new mines and greater coal production are associated with increased contemporaneous mortality rates for the sub-population aged 65 years and older. The effect appears to be driven primarily by increases in mortality attributable to cardiovascular diseases. This suggests, indirectly, that increases in exposure to particulate matter may be at least one of the mechanisms contributing to observed adverse health effects in mountaintop-removal coal-mining in Appalachia.

Chapter III reviews the evidence concerning the association between a mother's residence near coal mines and infant health, and presents new evidence that contradicts some of the conclusions draw in previous, mainly cross-sectional, research. The only models that regularly suggest statistically significant adverse effects of coal mining on birth outcomes are simplified models that rely on cross-sectional indicators for the presence of coal mining in a county. The presence of coal mining may be correlated with systematic differences in maternal behaviors, different demographics, and different historical settlement patterns within mountaintop removal coal mining counties compared to other counties in Appalachia.

Together, the results from chapters II and III suggest that cumulative long-term exposure to coal-mining activity contributes to individual vulnerability from contemporaneous exposure. The largest estimated health effects are exhibited among males over age 65. We find no discernible effects of coal-mining-activity on infant health, but infants' health outcomes are much less likely to be impacted by cumulative exposure to coal-mining activity. Additional research is needed to more-rigorously assess the effects of long-term exposure, and also to indentify the underlying physcial mechanisms for these observed health effects (i.e. whether there is a more-direct link between coal mining and air pollution, or between coal mining and water pollution).

The research presented in Chapter IV considers the water quality externalities associated with agriculture, rather than coal mining. The designation of a groundwater management area (GWMA) is found to result in heightened awareness of groundwater nitrate contamination among residents and housing market participants in Oregon's Southern Willamette Valley. Results reflect different estimated effects on property values depending on the property's likely source of water and predicted nitrate levels in each location. This suggests that homebuyers are reasonably well-informed about actual risks and respond to these actual risks, rather than merely to perceived risks.

APPENDIX

PM2.5 RESULTS

We hypothesized that air pollution may be one mechanism by which surface coal-mining activity leads to increases in the elderly mortality rate. We attempt to test the validity of air pollution as a potential mechanism, although data limitations prevent a truly comprehensive analysis.

We rely on concentrations of PM2.5 derived from remotely sensed satellite observations. The dataset, described by van Donkelaar et al. (2016), uses multiple satellite sources to infer ground-level concentrations of PM2.5 from observations of aerosol optical depth. The PM2.5 data are available on a 0.01 x 0.01 degree grid, which is approximately 1 km x 1 km at the equator. This dataset provides substantially more-uniform spatial coverage than the unevenly (and potentially endogenously) distributed ground-level EPA monitors. Inverse-distance weighting is used to interpolate the grid of remotely-sensed pollution concentrations to the centroid of each census tract following Voorheis (2017). These data are then aggregated to the county level. *Annual* averages of remotely sensed PM2.5 levels are available since 1998, corresponding to the second half of the study period used for our other analyses. Figure Al depicts average PM2.5 concentrations in ARC counties compared to the overall U.S. average. Notably, PM2.5 concentrations throughout the country have experienced a significant downward trend since 1998.

Table A1 reports estimates for equation (2.2), but now with remotely sensed PM2.5 concentrations as our dependent variable. We estimate the effect of variation in surface mining activity on particulates using exposure defined as the county boundaries in panel (a) and using 25-kilometer buffers around each county population centroid in panel (b). In the sample of ARC counties, depicted in panel (a) column (1), we find increased surface coal production leads to a statistically signficant increase in average PM2.5 concentrations. This estimate increases in magnitude in panel (b), which uses coal-mining activity within 25 kilometers of county population centroids, rather than rely on coal mining within county boundaries. We find no discernible effect of $Surface\ Production$ on PM2.5 concentrations in the sample of MTR counties, and no discernible effect of $New\ Surface\ Mining$ on county-level annual PM2.5 concentrations for either sample of counties.

Interpretation of these results are limited given the annual aggregation of data. It may be the case that short-term spikes in particulate air pollution, perhaps over the course of only a few days or weeks of initial mining-site preparation, account for a significant share of observed mortality over the course of a year when a new mine is opened. These short-term spikes in PM2.5 could easily be obscured in the annual PM2.5 data. Just as short-term extremes of temperature, not average temperature, account for most heat-related mortality, perhaps only short-term extremes of PM2.5 exposure, not average exposure, account for most coal-mining-related mortality.

TABLE 25.
PM2.5 Concentrations

Annual County Average (mg/m^3)

a.) Coal Mining within County Boundaries

	(1)	(2)
	PM2.5 Concentrations (mg/m^3	
	b/se	b/se
I(New Surface Mine)	-0.007	-0.017
	(0.039)	(0.044)
Surface Coal Production	0.064***	-0.007
	(0.024)	(0.019)
Controls	Yes	Yes
Year Effects	Yes	Yes
County Effects	Yes	Yes
County-Specific Trends	Yes	Yes
R^2	0.951	0.980
Observations	6,608	1,056

b.) Coal Mining within Buffers of County Population Centroids

	(1)	(2)
	PM2.5 Concentrations (mg/m^3	
	b/se	b/se
I(New Surface Mine)	-0.022	-0.044
	(0.038)	(0.045)
Surface Coal Production	0.089***	-0.017
	(0.025)	(0.023)
Controls	Yes	Yes
Year Effects	Yes	Yes
County Effects	Yes	Yes
County-Specific Trends	Yes	Yes
R^2	0.951	0.980
Observations	6,608	1,056

Note: Selected coefficients. Standard errors are clustered by county. Surface coal production is normalized (scaled by the standard deviation in the ARC sample).

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