Social Impacts of Nonrenewable Resource Extraction

by

David Garrett

A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

Department of Resource Economics and Environmental Sociology
University of Alberta

Abstract

This thesis is composed of three studies.

First study (*Gold Mining and Disparities in Indigenous Infant Health in the Brazilian Amazon*): Regulations in mining industries can mitigate environmental pollution and health risks. The health of indigenous communities may be disproportionately harmed by mining because they are often remote and disadvantaged economically, socially, and politically. Using data on over 200,000 births across municipalities in the Brazilian Amazon, along with satellite mapping of gold mines, I compare health outcomes for indigenous and non-indigenous infants in municipalities with and without sites of illegal and legal mining. I find evidence of negative effects of illegal mines on birthweights, specifically for indigenous infants. My results also indicate heterogenous impacts of illegal mining on indigenous birthweights, with indigenous infants born to single mothers or on indigenous lands weighing significantly less. I do not find similar effects with respect to legal gold mining, suggesting that regulating the mining industry works for reducing health risks.

Second study (*Oil Well Pollution and Student Performance: Evidence from Alberta, Canada*): Studies have established links between increases in ambient pollution and decreases in measures of children's academic performance. But the effect of pollution attributed to the hundreds of thousands of oil wells across North America is less understood. I compare grade 9 math and science test score outcomes from 2015-2019 at over 500 schools across Alberta to the number of active and inactive oil wells within 4 km of the schools. My empirical strategy is rooted in spatial analysis, where fixed distances between pollution sources and areas of impact allow me to

measure the association of potential well pollution with education outcomes. I find evidence of a negative association between the number of oil wells and mean test scores, particularly for math. With a mean of approximately 14 wells within a 4 km radius of each school, math test scores may decrease as much as of 9.0 percentage points, while science test scores may decrease by an average of 3.5 percentage points. When considering subgroups of wells by activity status (i.e., active, suspended, abandoned, and reclaimed) in another model, math and science test scores still decrease by an average of 8.2 and 2.2 percentage points, respectively. I do not observe a significant effect of reclaimed wells on test scores in either subject. My results suggest that reducing the number of suspended and abandoned wells through the reclamation process would benefit student outcomes.

Third study (*Legacy Effect of Rural Coal Mining on Youth Population Health*): With prior environmental studies predominantly focused on air pollution, I seek to investigate associations of legacy coal mining operations and human health via water pollution. I compare average health care demand levels from 2002-2014 for cohorts of youths aged 13 and under across Alberta, based on their relative positions to nearby coal mines, the majority of which ceased operations prior to 2002. Using an intricate spatial analysis strategy, over 50,000 youths are identified as living either upstream or downstream from almost 750 waterway-adjacent coal mines with various operating periods since 1886. I find evidence of negative associations between coal mines and human health, via increases in yearly doctor visits and inpatient days for youths living downstream from one or more coal mines. I also observe heterogenous associations based on characteristics of the mines. In particular, doctor visits for downstream youths are higher when nearby mines i) operated closer to the observation year or ii) had longer durations of operations.

Preface

This thesis is an original work by David Garrett. No part of this thesis has been previously published. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Effects of Coal Mining in Alberta on Population Health", ID: Pro00094293, Dec. 11, 2019.

Acknowledgements

Words cannot express how truly grateful I am to my two supervisors, Dr. Bruno Wichmann and Dr. Marty Luckert, for everything they contributed. From start to finish, their advice, guidance, and wisdom were invaluable to my progress, and shaped me into the resource economist I am today. I will fondly remember these years and the time we spent working together.

I also want to extend my sincerest thanks to the other members of my defence committee, Dr. Vic Adamowicz, Dr. Brent Swallow, and Dr. Chad Lawley, for their time and suggestions, and to Dr. Henry An for chairing the examination.

My pursuit of a PhD was made immensely easier by the support and encouragement of my parents. I hope I made them proud. Lastly, I want to thank my personal assistant Mikasa, the fluffiest of black cats who brought so much joy to countless late nights of research and writing.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

Blending the fields of environmental and health economics, the three studies presented here have an overarching theme of estimating social impacts linked to pollution from local nonrenewable resource extraction. Each study makes extensive use of spatial analysis tools to identify areas of concern and estimate empirical models. Underlying each model is a dataset compiled from various government sources. The collective objective of this research is to identify potential source-specific pollution effects on measures of human well-being and productivity with respect to proximity. The studies all focus on youth, who may be particularly sensitive to such impacts.

The first study presents an investigation of how illegal gold mining activity in the Brazilian Amazon affects birth outcomes. I investigate whether the impacts of pollution vary with mine regulation (i.e., illegal versus legal), and also whether they are disproportionately distributed across demographics. I test these hypotheses by estimating impacts of the number of illegal and legal mines in a region on infant health outcomes (i.e., birth weight, premature birth incidence, and low Apgar score incidence). A discrepancy in impacts may imply that industry regulations are working, and that further regulating the illegal mining sector could therefore be warranted to foster health improvements throughout the region(s). I am also able to explore heterogeneity of impacts (i.e., health gaps) in a multitude of ways; by racial group (i.e., indigenous/non-indigenous), demographic characteristics (i.e., marital status, delivery age, education level), and regional policy characteristics (i.e., living in a municipality with indigenous reserves). My results provide direction for the allocation of limited municipal and federal government resources, such as introducing new mining regulations or revising those currently in place, to target segments of the population that suffer the most from health impacts.

The objective of the second study is to determine whether the number and activity status of oil wells surrounding schools in Alberta, Canada impact adolescent academic performance. My hypothesis is that student test scores may suffer due to oil well-borne pollution, and these impacts may vary based on characteristics of nearby oil wells. For instance, while some amount of pollution is expected from actively producing wells, there is significant potential for old, abandoned wells to leak and also pollute. To investigate this hypothesis, I compare standardized provincial achievement test scores in math and science from schools across Alberta to the number of oil wells located close (i.e., based on a threshold radius) to each school. While reclamation costs (i.e., the price of cleaning up old wells) can readily be estimated, there may be additional and hidden social costs, such as academic performance impacts, related to decades of potential pollution from oil wells in surrounding communities. Finding evidence of an effect may provide urgency to well clean-up initiatives or implore regulatory reform on the allowable distance between future locations of oil wells and schools.

In the third study, also based in Alberta, I analyze how health care demand varies between children living upstream and downstream from historical coal mining sites. My hypothesis is that, if mining negatively impacts water quality, children living downstream from mining activity (compared to similar individuals located upstream) are exposed to, on average, relatively higher levels of water contaminants (e.g., various heavy metals) due to acid mine drainage (AMD), and, in turn, will have relatively higher demand for health care. I restrict my analysis to rural areas, as I suspect the mechanism of transmission to largely stem from relatively less-treated drinking water sources. These sources include private water wells, which may or may not be treated by the owner, or public drinking water that may undergo less-robust treatment due to available funding or resources. To assess whether historical coal mining activity indeed has legacy health effects, I compare three measures of yearly average health care demand (i.e., doctor visits, emergency department visits, and inpatient days) between similar groups of individuals, with groups varying based on their relative positioning to a coal mine along a waterway. If health care demand significantly varies based on downstream/upstream assignment, then an evaluation of conditions at past coal mining sites may be warranted, which in turn may provide insight for the planning of future coal mining sites.

Taken together, these three papers show significant and substantial effects of non-renewable resource extraction that warrant the attention of policy makers; considerations that could be important to future development and restorative decisions and regulatory efforts.

Chapter 2 Gold Mining and Disparities in Indigenous Infant Health in the Brazilian Amazon

2.1) Introduction

The impacts of pollution are often disproportionately distributed across demographics. Disparities, or gaps, in outcomes such as health, earnings potential, or education have been observed across various group definitions including age (1), ethnicity (2-5), urban-rural residences (6), and resource access (7). There is an ever-growing body of literature on the impact of pollution on indigenous populations worldwide, which are often disadvantaged, relative to their peers, economically, socially, and politically[1]. Mounting evidence shows health disparities arising from environmental pollution among indigenous communities (8-10).

One such potential source of disparity-inducing pollution is gold mining. There are global environmental concerns for artisanal and small-scale gold mining (ASGM), which often operate informally or illegally (11). Individuals and communities in developing economies are incentivized to participate in such mining activity, legal or not, as unskilled workers stand to benefit economically (12). Increasing gold prices, from $400/ounce in 2002 to over $1,800/ounce in 2022, have driven rapid expansion of illegal gold mining activity (13). In one area of the Peruvian Amazon, illegal gold mining increased by over 200% between 1999 and 2012 (14). In Brazil, satellite imagery of an indigenous reservation in the Amazon showed a 20-fold increase in illegal mining activity over a five-year period, with estimates of over 20,000 illegal miners in the area (15).

In 2010, there were approximately 896,900 indigenous people throughout Brazil, belonging to 305 ethnic groups (16). Of these individuals, about one third lived in urban areas and two thirds in rural zones. Over 13% of land in Brazil is reserved for indigenous populations, with most of these reserves found in the Brazilian Amazon. The 1988 Constitution recognized indigenous peoples as primary landowners and states that they must be guaranteed participation in the benefits of authorized mining activities (16).

[1] See Appendix A.1.1 for more detail.

But the benefits of participating in gold mining may come at the expense of health problems associated with pollution. Regulating mineral exploration and extraction is important to the well-being of local populations, as gold mining can have short and long-term environmental and health consequences. Legacy effects of mercury use in gold separation in Brazil have been identified and monitored for decades (17-19). Mercury[2] enters the environment both as river deposits, a concern for drinking water sources, and as atmospheric vapour, which can be dangerous to inhale (20-21). This type of pollution can be especially important for indigenous communities, given their strong connection with the land and the fact that many communities are in remote regions with diminished government presence and public infrastructure (22).

Beyond direct health[3] effects, the negative impacts of gold mining may also extend to neighbouring economic activities. For example, several studies in Ghana have linked pollution from illegal gold mining to externalities ranging from community health care expenditure increases to total factor productivity reductions for nearby farmers (23-25). Illegal gold mining has also been linked to increased incidence of malaria in Colombia (26).

In investigating health impacts caused by gold mining, I consider infant health outcomes as measures. The sensitivity of infants to environmental factors makes them responsive candidates for studying pollution impacts on human health. Additionally, isolating the health effect of mining on this cohort is less challenging than similar analyses of adolescents and adults, whose health is more likely to be confounded by exposure to other events in previous years of life. I investigate three measures of infant health at birth: birthweight, gestational age (i.e., premature birth or not), and Apgar (i.e., a simple test at 1 and 5 minutes after birth of Appearance, Pulse, Grimace, Activity, and Respiration) scores.

Implementing preventative and corrective measures to reduce or eliminate health risks has both moral and economic motivations. Poor health outcomes in early life stages have been well-established as strong predictors of future health consequences (27). Investments in early childhood development have been shown to translate into lower crime rates, higher earnings

[2] See Appendix A.1.2 for more detail.
[3] See Appendix A.1.3 for more detail.

potential, greater educational attainment, and substantial gains in adult health outcomes (28). The ramifications of poor infant health may be felt long-term. Low birthweight, for instance, has been linked to reductions in adult outcomes such as height, IQ, and labour market earnings (29).

My research adds knowledge by addressing several questions. First, while previous research has established that people working and living near mines are faced with greater health risks (30-32), are there also municipality-wide observable impacts of illegal mining on human health? If health risks are municipal-wide, the costs of mining may be greater than previously thought. Second, are there similar impacts observed for legal and illegal mines? A difference may imply that industry regulations are working, and that further regulation of the illegal mining sector could be warranted to foster health improvements throughout the region(s). And third, are there apparent differences in impacts by not only race, but also by demographic[4] characteristics? My results could provide direction for the allocation of limited municipal and federal government resources to target segments of the population that suffer the most from health impacts.

To investigate these questions, I estimate impacts of the number of mines in a region on infant health outcomes (i.e., birth weight, premature birth incidence, and low Apgar score incidence). The breadth of my dataset allows me to not only examine impacts by regulation level (i.e., illegal versus legal mining activity), but also to explore heterogeneity (i.e., health gaps) in a multitude of ways; by racial group (i.e., indigenous/non-indigenous), demographic characteristics (i.e., marital status, delivery age, education level), and regional policy characteristics (i.e., living in a municipality with indigenous reserves).

This is among the first empirical studies in the field of resource economics to make use of a large and contemporary Amazonian mining dataset that illuminates the extent of illegal mining activity in Brazil, over time. [5] I combine new information on mining with a detailed health

[4] See Appendix A.1.4 for more detail.

[5] I also acknowledge the larger body of related previous studies in the science literature. Mining-related pollution and its subsequent impacts on human health are typically measured by mercury exposure. Methods of evaluating human health risk of mercury exposure have included analyzing environmental samples of air, soil, plants, and fish (33-34), human samples of hair, blood, urine (35-36), or neurological assessments (37). Child and infant-centric studies have also typically relied on analyzing mercury levels in human hair, blood, and urine (38-40). However, these science papers are usually constrained to the same limitations as the previous economic analyses, in both size (a study population below one thousand persons), and scope (a singular gold mining area, community, or village) (41-42)).

dataset, containing hundreds of thousands of birth observations across Brazilian municipalities overlapping the Amazon rainforest and spanning over a decade in time. The systematic approach to collecting this data eliminates, or at least greatly reduces, concerns of biases typical of studies utilizing self-reported or small-scale survey data.

As data on illegal mining has been notoriously difficult to acquire, previous economic studies in the same vein as ours are few and far between, typically restricted to either a legal mining dataset or confined to a local study area concerning one or two illegal mines and the small population living nearby. For instance, one study considered legal gold mining effects on low Apgar score incidence in the neighbouring country of Colombia (43). Comparing births outcomes in communities either situated upstream from a mine, situated downstream, or with no nearby mine, they find a positive (economic) impact living upstream from a mine, reducing the probability of a low Apgar score by 0.51 percentage points, while downstream births had a 0.45 percentage point increase in probability. In another study, researchers analyzed mining activity effects on adult and child health (and wealth) outcomes across 44 countries by making use of demographic and health surveys spatially overlayed with coordinate data for mines. They find evidence of a health-wealth trade-off, with asset gains offset by increased incidence of health conditions linked to heavy metal toxicity, such as anemia in women and stunting in children (44). There are also several studies which have considered proximity to mining and associated health impacts among a limited sample of mining town residents, as measured by blood lead levels, urinalyses, and survey data of chronic conditions (45-47). To my knowledge, empirical estimation of (gold) mining impacts on human health outcomes via proximity and/or density of mines to general populations (as opposed to a cohort of miners or mining village(s)) is a relatively unexplored space, making my work vital in expanding the knowledge base.

2.2) Methods

2.2.1) Data and Variables

I employ a health dataset of live births present in each municipality covering the entirety of the Amazon basin within Brazil. The dataset, found within the Brazil Live Birth Information System

(48)[6], contains live birth records for Amazonian municipalities between 2008-2017. Besides race[7], the dataset includes various other characteristics of infants (e.g., birthweight, Apgar score, congenital conditions) and of mothers (e.g., age, education, weeks pregnant, and marital status at birth). Data on illegal and legal mines were obtained from the Amazonian Network of Georeferenced Socio-Environmental Information, also known as RAISG (49). The dataset contains coordinates, mineral type(s) mined, and the most recent year in which a mine was observed (range of 2001-2020, mode of 2017).

My focus is on operating gold mines (where gold is the primary or secondary resource),[8] and my models measure the potential for mining pollution with a count variable of mines appearing in each municipality for a given observation year. I include legal mines listed as both operating and actively extracting; and exclude mines in pre-exploitative stages such as licensing and early exploration. The geographic data available from the Amazonian Network of Georeferenced Socio-Environmental Information, a consortium of eight civil society organizations from six Amazonian countries (Bolivia, Brazil, Colombia, Ecuador, Peru, and Venezuela), is compiled from various sources, including governments, RAISG member organizations, and other civil society organizations (50).

Inherently, there is less available information about illegal mines than legal mines. Ideally, I would also have data that would allow me to estimate the effect of the duration and intensity, or dosage, of illegal mining activity on infant health outcomes. It is unknown how long the mine existed before the observation date, or whether the mine is ongoing. Similarly, yearly mine-level production data is unavailable for illegal mines. However, in order to test my suspicion that illegal mines are more likely to impose health externalities, I need a shared observable characteristic to compare illegal mines to legal mines. As a result, I opt to use the count of mining sites, rather than the production level of said mines, as the measure of municipality-level exposure.

---

[6] For more information about the Brazilian health care systems, please refer to Appendix A.2.
[7] I note the distinction between race, defined as physical differences, and ethnicity, defined as shared cultural characteristics. The source of my health data, The Brazil Live Birth Information System (SINASC), categorizes births by five races or colours: white (branca), black (preta), yellow (amarela), mixed (parda), and indigenous (indígena).
[8] For more information, please refer to Appendix A.3.

To investigate my research questions, it would be ideal to have cross-sectional data over time. Unfortunately, I only have one observation year per illegal mine. In the absence of continuous mining data over time, I carry out a cross-sectional analysis that is based on selecting, for each municipality, one observation year of data for both mining and health variables. For municipalities with illegal mining, I select the most recent year between 2008-2017 for which mining activity is reported. For municipalities with no recorded illegal mining, the observation year corresponds to the most recent year of legal mining activity. For municipalities with neither legal nor illegal mining, the observation year is set to a base year of 2017 (i.e., the mode of illegal mine observation years).[9]

The uncertainty of operating timeframes for illegal mines presents an issue for my research. For each illegal mine, I know of their activity status at a single point in time (i.e., the last year observed). A municipality may have more than one illegal mine, each with differing last-observed years. As I am primarily concerned with short-term observable effects on infants, I elect to only include illegal mines from the most recent observation year, under the assumption that the effect of mines from past years (which may or may not be operating in the current year) are less important than contemporaneous effects. While this decision means my model does not account for accumulations of pollutants over time, it also removes potential guesswork. Therefore, I interpret my estimates as lower bound effects of mines on infant health outcomes.

My analysis uses health and mining data at the municipality level within the nine states of Brazil situated in the Amazon basin (Figure 2.1[10]). These states comprise the Legal Amazon (or Amazônia Legal), a political region established in 1953 for economic purposes (51). [11] This area incorporates about 60% (or 5.1 million sq. km) of Brazil's geographic territory, but less than 13% of its total population and below 8% of Brazil's GDP activity (52). Of the 5,570 municipalities of Brazil, the Amazon covers, at least partially, 755 municipalities. Within the Legal Amazon are regions designated as Indigenous Lands for protection of both peoples and ecosystems, requiring congressional authorization for mining – significantly deterring legal

[9] The mode of legal mine observation years is 2016.
[10] Appendix A.4 contains additional information about the data sources and frequency charts of mines, by type, per municipality.
[11] The Brazilian Legal Amazon, or Amazônia Legal in Portuguese, is a political and geographical region encompassing the nine states of Brazil which fall within the Amazon basin. The naming convention of Legal Amazon is unrelated to the designations of legal and illegal mining.

mining but largely failing to prevent illegal mining (53). As of the 2010 Brazilian Census, these 755 municipalities had an average of 31,374 residents (range 1,037 to 1,802,014 residents). I concentrate on rural areas by limiting my sample to municipalities that have under 200,000 residents (i.e., 742 municipalities).

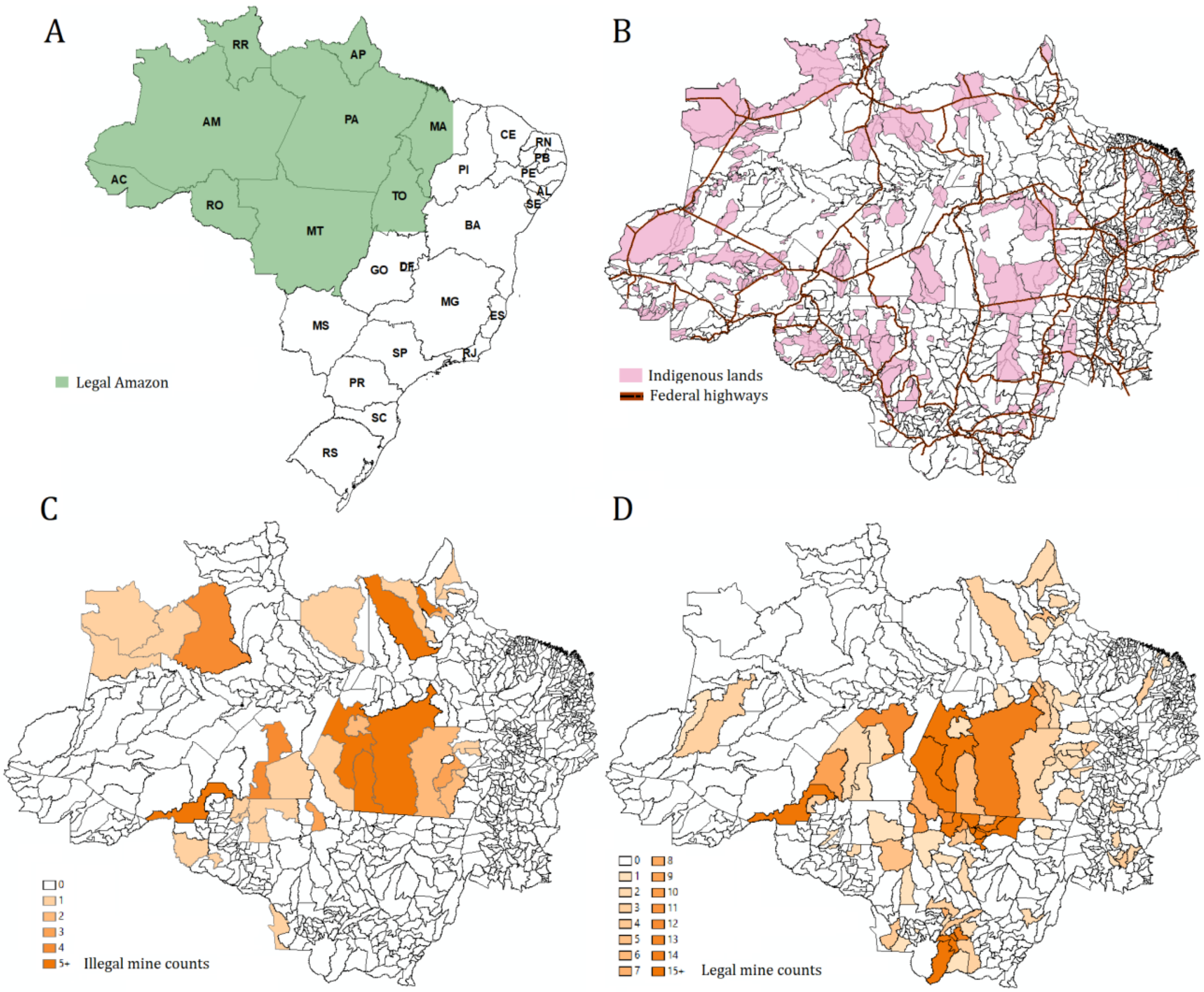

Figure 2.1 Distribution of illegal and legal gold mines in the Brazilian Legal Amazon.

(A) States of Brazil within the Brazilian Amazon boundaries. (B-D) States within the Amazon are further divided into municipalities. (B) Indigenous Lands may partially or fully cover one or more municipalities. Mining activity is prohibited in areas designated as Indigenous Lands but occurs illegally. Note that Indigenous Lands are not the source of my variation, as Indigenous births are defined by race and not by location of birth. The system of Federal Highways provides an observable measure of remoteness. (C-D) Heat map of illegal and legal mining counts per municipality. Note that this map does not reflect specific areas of mining (i.e., legal mining almost never overlaps with Indigenous lands). Density of mines are indicated on a scale of White (no mines) to Dark Orange (many mines). Counts of mines are based on the total number of mines observed in the most recent year of available data between 2008-2017. Legal gold mines are only counted if listed as actively extracting (versus exploring). Figure created using ArcMap (54).

2.2.2) Model

I estimate effects of gold mining, both legal and illegal, within a given municipality on health outcomes using the following fixed effects model:

$$H_{ij} = \alpha R_i + \beta I_j + \nu L_j + \delta(R_i \times I_j) + \rho(R_i \times L_j) + \sigma_m M_i + \sigma_d D_i + \sigma_J J_j + \lambda_s + \epsilon_{ij} \quad (1)$$

where *H* denotes one of three health outcomes measures (i.e., birthweights, premature births, and low Apgar scores) for infant *i* living in municipality *j*, in state s. The variable R is an indigenous race indicator; 1 for indigenous, 0 otherwise. *I* is a count of illegal gold mines in a municipality's observation year (as defined earlier), the majority of which occur in 2017. For municipalities with no illegal mines, *I* = 0. Similarly, L is a count of legal gold mines in a municipality's observation year, where *L*=0 for municipalities with no legal mines. The interaction between *R* and *I* captures the effect of illegal gold mining on indigenous infants. Similarly, the interaction between R and L captures the effect of legal gold mining on indigenous infants. These interactions allow me to compare birth outcomes between treated (i.e., illegal and/or legal mines present) and control (i.e., no mines) groups, and obtain the differential effects. The value δ (ρ) represents the magnitude of the mean effect, on a selected health outcome *H,* of being an indigenous infant *i* in municipality *j*, which has *I* (L) illegal (legal) mines. The sum of δ (ρ) and α, coefficient on race, is the total health effect incurred by indigenous infants due to illegal (legal) mines. [*M*] is a vector of mother-level control variables, including marital status, delivery age, and level of education. [*J*] is a vector of municipality-level control variables, including (all per one thousand people) GDP, health spending, education spending, Bolsa amount (a government cash transfer program to support low-income families), and number of ICU-equipped hospitals, and population density per square kilometre. [*D*] is a vector of year of birth dummy variables to control for year-specific shocks. λ is a state-level fixed effect, while ϵ is a random error representing idiosyncratic aspects of health.

2.2.3) Summary Statistics

Table 2.1 contains summary statistics for my sample. Approximately 5.2% of infants are identified as indigenous. Mean birthweight among non-indigenous infants is 3,231 g, consistent with other Brazilian birthweight data (55). Indigenous births are 69 g lighter on average. Approximately 12.6% of non-indigenous and 17.6% of indigenous births are categorized as premature, occurring before the 37th week of pregnancy. The mean 1-minute Apgar score is 8.22 out of 10 for non-indigenous and 8.13 for indigenous. Low Apgar score, defined as equaling 7 or below, is observed for 13.5% of non-indigenous and 14.5% of indigenous births. Regarding characteristics of mothers, there is little difference between indigenous and non-indigenous mothers with respect to delivery age and pregnancy duration. But about 59% of non-indigenous mothers are married, compared to 51% of indigenous. Non-indigenous mothers have higher mean education attainment, with 70.5% completing 8+ years of schooling versus 36.5% for indigenous mothers.

Table 2.1 Summary statistics of infant, mother, and municipality of the Brazilian Legal Amazon

	Indigenous			Non-indigenous		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Infants						
Birthweight (g)	15,476	3161.51	526.15	283,301	3230.72	546.03
Premature (< 37 weeks, %)	10,637	17.63	38.11	196,090	12.63	33.22
Low Apgar1 score (< 8, %)	10,291	14.52	35.23	270,789	13.53	34.20
Apgar1 score (1-10)	10,291	8.13	1.30	270,789	8.22	1.13
Indigenous (%)	15,865	1	0	283,606	0	0
Mothers						
Weeks pregnant	10,637	38.75	2.58	196,090	38.99	2.30
Delivery age	15,839	24.31	7.18	283,606	24.42	6.33
Married (%)	15,654	50.95	49.99	282,376	59.15	49.15
Education 1 (%)	14,888	16.58	37.19	277,870	0.98	9.87
Education 2 (%)	14,888	13.39	34.05	277,870	4.30	20.29
Education 3 (%)	14,888	32.07	46.68	277,870	24.22	42.84
Education 4 (%)	14,888	36.32	48.10	277,870	60.00	48.99
Education 5 (%)	14,888	0.16	12.70	277,870	10.48	30.64
Municipality						
GDP (R$/thousand people)	15,865	13.98	12.06	283,606	17.85	15.3
Health spending (R$/thousand people)	15,607	0.48	0.23	274,898	0.51	0.23
Education spending (R$/thousand people)	15,607	1.03	0.38	275,050	0.94	0.31
Bolsa spending (R$/thousand people)	15,865	0.44	0.19	283,606	0.32	0.19
ICU-equipped hospitals (#/thousand people)	15,865	0.004	0.018	283,606	0.04	0.11
Population density (thousand people/km^2)	15,865	0.039	0.03	283,606	0.03	0.03

Notes: Summary statistics are based on a total sample of 304,691 observations across 742 municipalities for their respective observation years. Education attainment of the mother is categorized into 5 groups: 1 for 0 years, 2 for 1-3 years, 3 for 4-7 years, 4 for 8-11 years, and 5 for 12+ years.

2.3) Results

Table 2.2 presents my main findings from three models, one for each health measure (i.e., birthweight, premature birth, low Apgar score). For birthweight, I find evidence of an indigenous health gap, irrespective of the impact of mines, as the *indigenous* coefficient is negative and significant (1% level). All else being constant, indigenous infants are 39.2 g lighter. The interaction between *illegal mine* and *indigenous* is similarly significant, indicating that each illegal mine causes a reduction of 22.6 g of birthweight in indigenous infants. All told, indigenous infants born in municipalities with one illegal mine are 61.8 g lighter than non-indigenous counterparts, [12] equivalent to a 1.91% reduction in weight.[13] Notably, the estimate for impacts of *illegal mine* by itself is insignificant, suggesting that illegal mines on their own do not impact birthweight; rather they interact with *indigenous* to have an effect on birthweight. For *legal mine* and birthweight, the coefficient estimate is positive, though small (0.05 g), and significant (1%), suggesting that every additional legal gold mine, relative to no legal gold mine present, causes a minor increase in birthweights. This result may be due to a small wealth effect from additional job opportunities, or better access to health care services as part of a modernization process in remote areas that are associated with legal mining companies. The interaction between *indigenous* and *legal mine* is insignificant suggesting that indigenous births are only negatively impacted by illegal mining.

---

[12] From the coefficients in Table 2.2, Indigenous birthweights are less than weights of non-indigenous by 39.2 + 22.6 (*I*) - 0.03 (*L*), where *I* and *L* are the counts of illegal and legal mines in a municipality, respectively.

[13] Compared to the mean non-indigenous birthweight from Table 2.1.

Table 2.2 Regressions Results: Effect of Mines on Infant Health Outcomes

Dep. Var.	Birthweight	Premature Birth	Low Apgar Score
Indigenous	-39.24***	0.036**	-0.000013
	(13.20)	(0.015)	(0.0098)
Illegal mine	1.91	0.0028	-0.0009
	(1.84)	(0.003)	(0.0029)
Legal mine	0.05***	-0.000001	0.00015***
	(0.02)	(0.00002)	(0.000024)
Indigenous*Illegal mine	-22.64***	-0.0018	0.0035
	(4.14)	(0.0031)	(0.0071)
Indigenous*Legal mine	0.03	0.00009	-0.00006
	(0.13)	(0.00009)	(0.00008)
Observations	270,534	189,909	254,132
R-squared	0.013	0.006	0.013

Notes: Birthweight is measured in grams. Premature birth is defined as occurring before 37 weeks. Low Apgar score indicates a value between 0-7 on a discrete scale between 0-10. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimates of control variables are not presented here and are available in Appendix Section A.5: Table A.1.

For incidence of premature birth, I find that indigenous births are approximately 3.6% more likely to be premature, significant at the 5% level. Coefficient estimates for all mine variables, including interactions between *indigenous* are insignificant. As for low Apgar score incidence, *indigenous* and interactions with both types of mining are insignificant. The count of legal mines exhibits a significant (1% level) but minor positive effect (0.02% increase). Overall, mines, whether illegal or legal, appear to have negligible impacts on the incidence of either premature birth or low Apgar score, regardless of race.

Beyond the differences between indigenous and non-indigenous infant health outcomes, I explore heterogeneity of mining effects among subgroups of my sample. For instance, while my initial regressions may show that indigenous birthweights are, overall, lower than non-indigenous birthweights, mothers may belong to discernible subgroups (e.g., mother's level of education) that disproportionately bring down the indigenous birthweight average. Identifying such subgroups could inform intervention strategies, government or otherwise, to improve resource allocations. As such, I consider heterogenous effects of mining within subgroup categories by splitting my sample.

I define four subgroup categories by characteristics of the birth mother and the municipality. First, adverse infant health outcomes may be associated with mothers at both ends of the delivery age spectrum (56). My age subgroups consist of those either 19 and younger or 35 and older. Second, infant health may be related to economic standing (57). I use educational attainment as a proxy for earnings potential, comparing births from mothers with 7 or less years of schooling against mothers with 8 or more years. Third, marital status of mothers may be related to infant health (58). Un-married mothers, with sole responsibilities for households, may be associated with decreased infant health. And finally, I investigate potential differences in impacts across municipalities with and without indigenous reserves. Municipalities with some percentage of their total area designated as indigenous reserves may be more remote, less industrialized, and/or have greater barriers to proper health care access. I divide the sample into births from municipalities with no indigenous reserves (i.e., 446 municipalities) versus those with some proportion of land designated as indigenous reserves (i.e., 272 municipalities).

Results from the subgroup models are illustrated in the coefficient plots of Figures 2.2-2.4. For each health outcome (i.e., birthweight, premature birth, low Apgar score), I present coefficient estimates of my five primary regression variables[14] (i.e., *indigenous, illegal mine*, *legal mine*, interaction between *indigenous* and *illegal mine*, and interaction between *indigenous* and *legal mine*) across four categories of sub-groups (i.e., marital status, delivery age, education level, and presence of indigenous reserves in a municipality). For each pair of subgroups within each category, the estimated coefficient markers (i.e., the dots in the figures) for the subgroups with hypothesized worse health outcomes (i.e., single, young, low educated, municipalities with reserves) are depicted in dark blue and appear above their counterpart's (i.e., married, old, higher educated, municipalities with no reserves), whose coefficient markers are depicted in light blue.

[14] Estimates from the full model (i.e., with control variable coefficients and constants) are provided in the Appendix (Section A.5: Tables A.2-A.4).

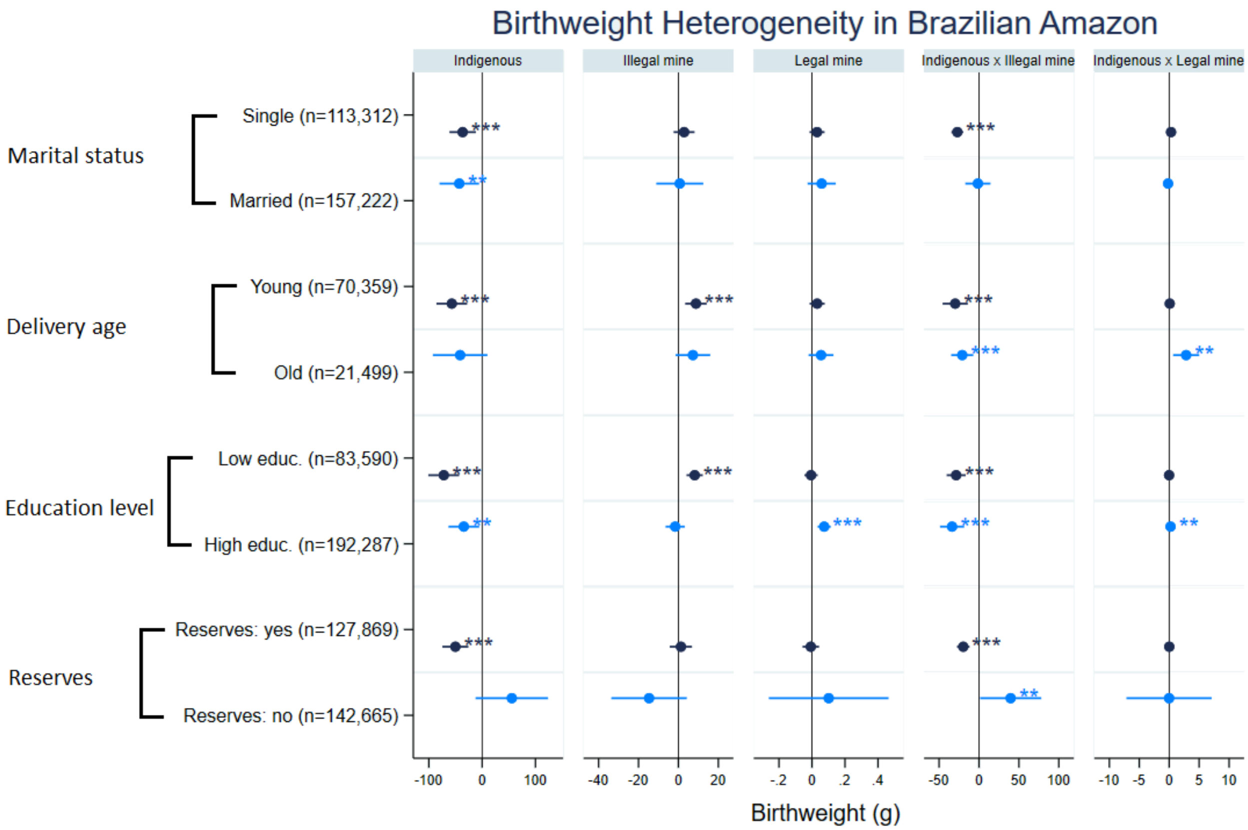

Figure 2.2 Heterogeneity among factors affecting impacts of illegal mining effects on birthweight.

Notes: Birthweight is measured in grams. Estimates of control variables are available in Appendix Section A.5: Table A.2. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

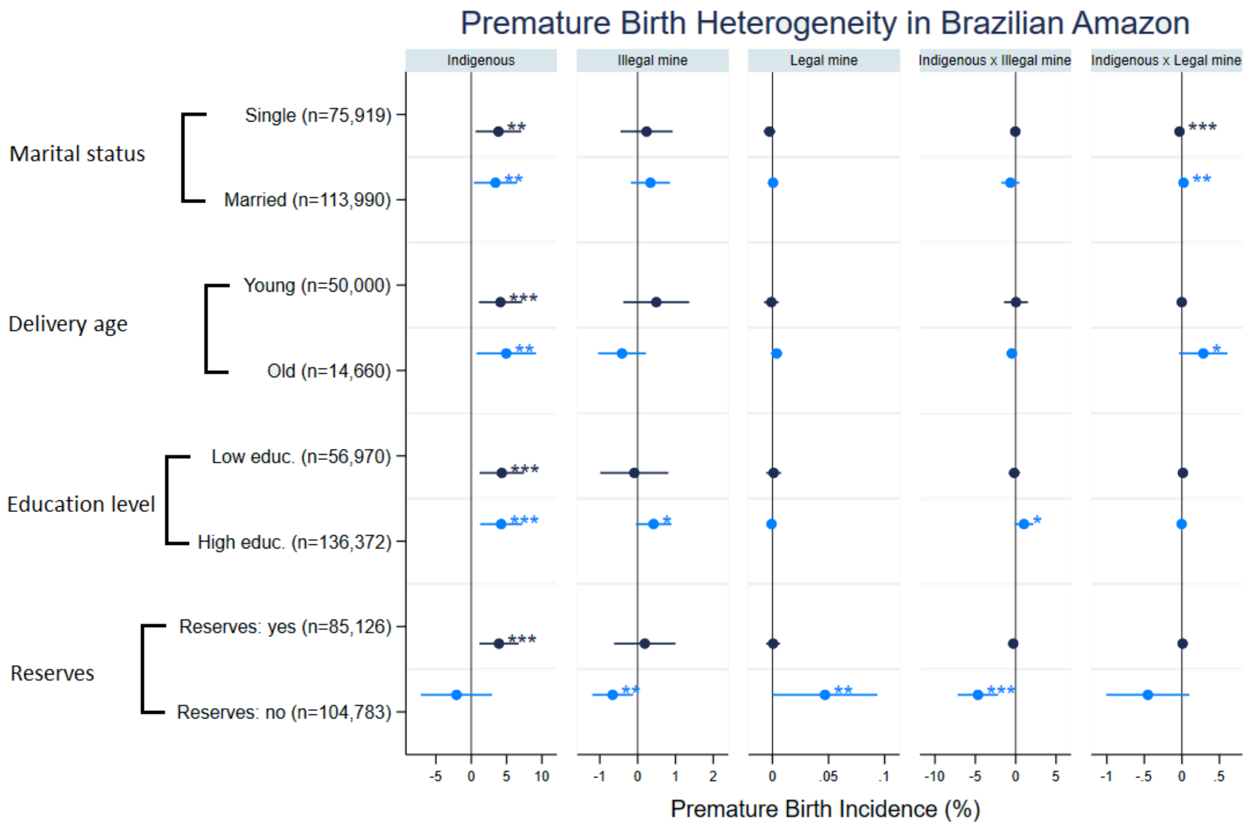

Figure 2.3 Heterogeneity among factors affecting impacts of illegal mining effects on premature birth incidence.

Notes: Premature birth is defined as occurring before 37 weeks. Estimates of control are available in Appendix Section A.5: Table A.3. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

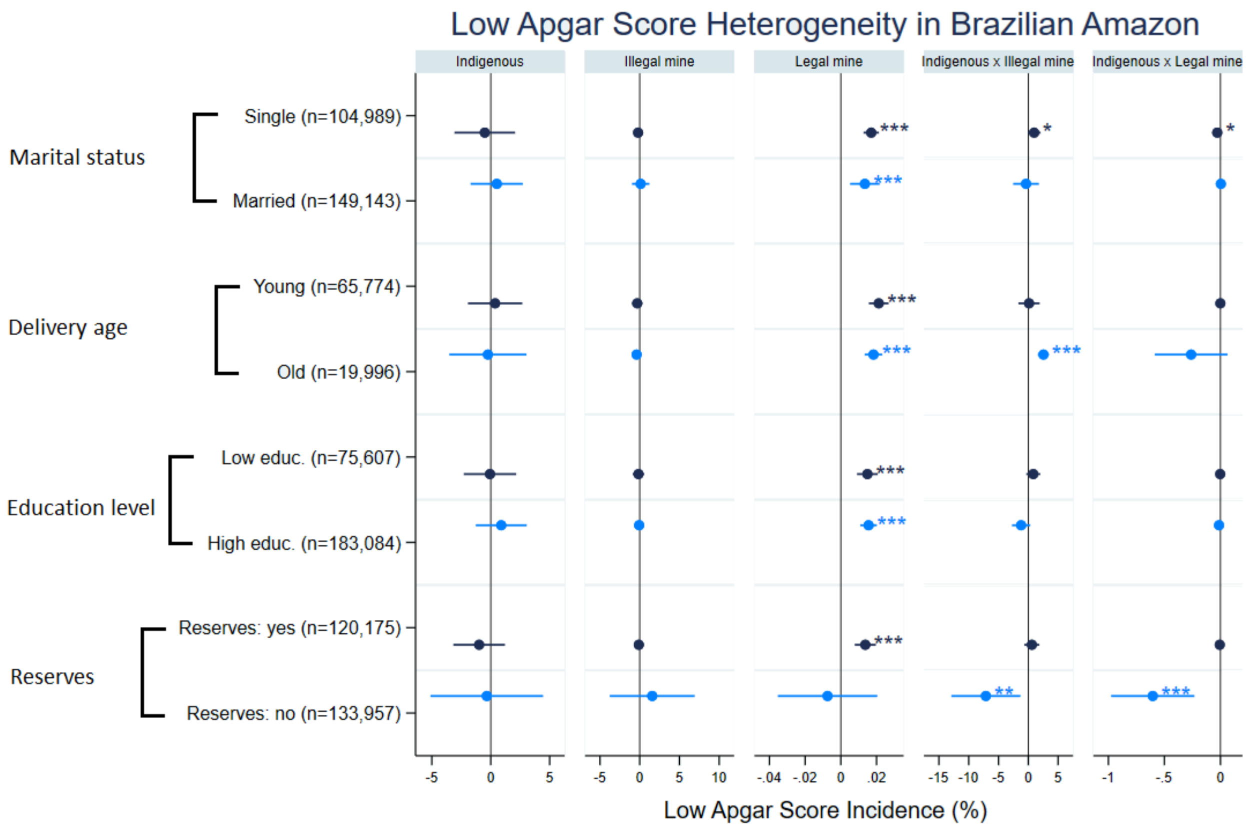

Figure 2.4 Heterogeneity among factors affecting impacts of illegal mining effects on low apgar score incidence.

Notes: Low Apgar score indicates a value between 0-7 on a discrete scale between 0-10. Estimates of control variables are available in Appendix Section A.5: Table A.4. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Within the marital status subgroup category, I observe that indigenous births to single or married mothers (significant at the 1% and 5% levels, respectively) are approximately 36-43 g lighter than non-indigenous births. However, there is an additional impact (-27.1 g) of illegal mines on indigenous birthweights observed in the interaction, which only affects single indigenous mothers. *Legal mines* do not significantly impact birthweights, regardless of race or marital status.

As for premature incidence, indigenous births to single or married mothers (both significant at the 5% level) are 3.4-3.8% more likely than non-indigenous births to be premature. Unlike the birthweight models, *illegal mines* do not exhibit a significant effect on either indigenous or non-indigenous premature incidence. However, there is a small but varying impact of *legal mines* on premature incidence. Births to single indigenous mothers are 0.03% less likely to be premature, while births to married indigenous mothers are 0.02% more likely to be premature. A plausible explanation is a local wealth effect of mining disproportionately benefitting single indigenous mothers.

In contrast to the previous two models, the coefficient estimates for *indigenous* are insignificant for both single and married mothers, but there are several significant mining effects within the subgroup category. First, *legal mines* (significant at the 1% level for both) increases low Apgar score incidence among single or married births by 0.01-0.02% per legal mine. Moreover, births to single indigenous mothers are impacted by both *legal* and *illegal mining*. Low Apgar score incidence among single indigenous births increases by 0.98% per illegal mine and decreases by 0.03% per legal mine. Children of single indigenous mothers would receive health benefits from more stringent regulation, either by converting illegal mines to legal or preventing illegal mines. Overall, my hypothesis of single mother indigenous birth outcomes being more sensitive to mining impacts is supported by my findings.

When comparing birthweights within the delivery age subgroup category, I observe a stark contrast in outcomes. Indigenous births among young mothers are approximately 57 g lighter than non-indigenous births, significant at the 1% level. The effect of *indigenous* on birthweight is not significant in the old mother subgroup. Interestingly, *illegal mine* increases birthweight among young mothers, indigenous or not, by 8.8 g per mine (significant at the 1% level). This observation likely arises from the same wealth effect enjoyed by single mothers discussed earlier. Lastly, the interaction between *illegal mines* and *indigenous* is significant at the 1% level for both young and old mother births, at 21-30 g lighter per illegal mine. Legal mining does not significantly affect young mother births but does exhibit a small and positive effect on old mother births, with these births being 2.8 g heavier per legal mine (significant at the 5% level). All told, indigenous births among young mothers are negatively impacted by illegal mining more so than their older counterparts, who also benefit from legal mining.

There are few differences within the delivery age subgroup category with respect to premature incidence. Young or old, births among indigenous mothers are 4.1-5.0% more likely to be premature, significant at the 1% and 5% levels, respectively. Indigenous births to old mothers are 0.28% more likely per legal mine to be premature (significant at the 10% level). There are no significant impacts of illegal mining on premature incidence within the delivery age subgroup.

As was the case with the marital status subgroup category, *indigenous* is not significant within the delivery age subgroup category for the low Apgar score incidence models. *Legal mines* increase low Apgar score incidence for young and old births by 0.02% per legal mine, significant at the 1% level for both. Exclusive to the old mother subgroup, indigenous births are 2.54% more likely to be premature per illegal mine, significant at the 1% level. While I hypothesized that young indigenous mothers would be more harmed by illegal mining due to fewer economic opportunities, health complications among older mother births may be relatively more compounded by illegal mining pollution.

In the third subgroup category, education level, indigenous births are 72 g lighter for lower educated mothers and 34.5 g lighter for highly educated mothers (significant at the 1% and 5% levels, respectively). Compared to the marital status and delivery age subgroup categories, the difference in effect of *indigenous* on birthweight in the education level subgroups is much more pronounced, with the magnitude of the estimate in the low educated model being more than twice as large as that of the higher educated estimate. *Illegal mines* have a significant and positive effect on births from lower educated mothers, regardless of race, with births being 8.1 g heavier per illegal mine. Conversely, *legal mines* have a significant and positive effect on births from highly educated mothers, regardless of race, increasing birthweights by 0.07 g per legal mine. Illegal mines decrease indigenous birthweights, among lower and highly educated mothers, by 28.5-33.7 g, both significant at the 1% level. There is a small positive effect of legal mining on indigenous births to highly educated mothers increasing birthweight by 0.23 g per legal mine. Together, these results suggest that lower educated indigenous mothers are relatively more harmed by illegal mining than their higher educated counterparts, while the highly educated indigenous mothers also enjoy small benefits from legal mining.

With respect to premature birth incidence models, indigenous births are 4.2-4.3% more likely to be premature among either lower or highly educated mothers, both significant at the 1% level. Illegal and legal mining effects are insignificant in the lower educated subgroup. As for highly educated mothers, *illegal mines* increase premature birth incidence by 0.42% per illegal mine (significant at the 10% level), regardless of race. For indigenous mothers, *illegal mines* increase premature birth incidence by 1.03% per illegal mine (significant at the 10% level). While children of lower-educated mothers do not appear to particularly gain or lose from any type of mining activity in the premature incidence models, children of highly educated mothers are only made worse off by illegal mining activity. The health benefits typically associated with higher education appear to be mitigated by unregulated mining pollution.

There are no large and significant differences within the education level subgroups with respect to low Apgar score incidence models. *Legal mines* increase low Apgar score incidence among all-race births by 0.01-0.02% per legal mine among lower and highly educated mothers, both significant at the 1% level. *Indigenous* and other mining effect variables are insignificant across both models. My hypothesis of birth outcomes to lower educated indigenous mothers being disproportionately affected by mining is supported for birthweight, with weaker evidence of the opposite for premature birth incidence.

In the final subgroup category, I consider whether living in a municipality with some percentage of land designated as indigenous reserve(s) has significant impacts on birth outcomes.

In the birthweight models, indigenous births in municipalities with reserves are 50.2 g lighter than non-indigenous births, significant at the 1% level. *Indigenous* is not significant in municipalities with no reserves. Legal mining does not exhibit significant impacts within this subgroup category. *Illegal mines* reduce indigenous birthweights by -19.7 g per illegal mine in the reserves model (significant at the 1% level) and increases indigenous birthweights by 39.7 g per illegal mine in the no-reserves model (significant at the 5% level). All told, indigenous birthweights are -50.2 -19.7(*I*) g lighter than non-indigenous birthweights in municipalities with reserves. Indigenous births in municipalities with reserves are evidently at a much higher risk of low birthweight and, by extension, experiencing low birthweight-related health complications.

Indigenous births in municipalities with reserves are 3.9% more likely to be premature, significant at the 1% level. Mining effects on premature birth incidence are insignificant in municipalities with reserves. As for no-reserve municipalities, all-race births are 0.66% less likely to be premature per illegal mine and 0.05% more likely per legal mine, both significant at the 5% level. Indigenous births are 4.67% less likely per illegal mine to be premature than non-indigenous births in the no-reserve municipalities. Indigenous births are overall less likely to be premature in municipalities with no reserves, whether or not there is illegal mining activity.

In the low Apgar score incidence models, *Indigenous* is insigificant across the reserves subgroups. All-race births are 0.01% more likely per legal mine to have low Apgar score in municipalites with reserves, significant at the 1% level. Indigenous births are 7.1% less likely per illegal mine (significant at the 5% level), and -0.6% per legal mine (significant at the 1% level), to be have low Apgar score in the no-reserves subgroup. Indigenous births are overall less likely to have low Apgar score in the no-reserves municipalities. The results for each birth outcome measure suppport my hypothesis of indigenous births in municipalities with reserves being more adversely affected by illegal mining.

In addition to the subsamples above, I explore two other model specifications (refer to Appendix A.6 for further details). In the first specification, I consider the explicit effect of illegal and legal mines by using mine type-specific subsamples of the municipalities (i.e., including municipalities with only illegal mines or only legal mines, but not both). I also include a second specification to address possible concerns of endogeneity between illegal mines and unobservable determinants of health. In this specification, I employ several distance-based instramental variables to capture the “remoteness” of an illegal mine. In both cases, findings support the main results discussed above.

2.4) Conclusions

There are significant consequences of illegal mining activity for infant health outcomes in the Brazilian Amazon. With respect to three different infant health outcomes, I find negative effects of illegal mining on birthweights, specifically for indigenous infants. Moreover, the impacts of illegal mining are not uniform across indigenous infant subgroups. There is significant variation among indigenous health outcomes between subgroup categories divided by mother characteristics such as marital status, delivery age, and educational attainment, as well as by municipalities with and without indigenous reserves. In particular, illegal mining disproportionately impacts births to single (versus married) indigenous mothers, lowering birthweight and increasing both premature and low Apgar score incidence within the subgroup. Births to young or lower educated indigenous mothers, or those living in municipalities with reserves, are also more likely to be underweight due to illegal mining. Indigenous births in municipalities with no reserves are less likely to be premature or exhibit low Apgar score. I do not find similar effects with respect to legal gold mining, suggesting that regulating the mining industry seems to work in terms of reducing health risks.

Given these findings, investments in dismantling illegal mines may yield the highest infant health returns in birthweight outcomes. Societal efforts to protect human health can be framed positively (e.g., as lives saved) or negatively (e.g., as monetary costs). For instance, pollution abatement measures were estimated to save approximately 1,000 infant lives in California (59). Conversely, the cost of low birth weight has been estimated to be as much as \$114,437 (2016 USD) for low-birthweight status (<2500 g) infants born across the United States (60), or, in another study of U.S. births, as high as \$550,000 (2006 USD) for very low birthweights near 1500 g (61). Using these estimates, it would only take 10 more otherwise-low birthweight births instead being above 2,500 g to justify \$1 million USD in spending toward taking down an illegal mine. And since the interaction between *illegal mine* and *indigenous* is similar in magnitude to the standard deviation of birthweight (see Table 2.4), it does not seem improbable to achieve this outcome given the hundreds, or sometimes thousands, of births in each municipality's observation year. However, the delay in observing health returns (i.e., births occurring a year later) as well as the challenge[15] of directly attributing health improvements to the previous efforts taken and money spent may not readily motivate government intervention.

By examining the effects of mining pollution on infant health outcomes in the Brazilian Amazon, I have identified the presence of a minority health gap. Illegal gold mining is a growing problem in the Brazilian Amazon, as evident from recent satellite imagery, with disproportionately negative health effects on indigenous populations. Increasing efforts to curtail these illegal mines or, at minimum, forcing them to comply with legislation, would likely yield disproportionately larger benefits to vulnerable minority populations. Note that these results are based on data from hundreds of jurisdictions (i.e., municipalities) and multiple racial minority groups (i.e., numerous indigenous tribes defined as one race or colour) using unbiased (i.e., public health care system and satellite mapping) data sources.

Unfortunately, these results are almost certainly not unique to the study region, as concerns about illegal and small-scale mining stretch far beyond Brazil and South America. But fortunately, with increasing global efforts to mitigate future environmental impacts of non-renewable resource extraction, the potential benefits of these efforts will be to disproportionately help vulnerable indigenous populations.

[15] Moreover, cross-sectional estimates on returns to low birth weight-prevention may also be biased by omitted variables, such as genetics (62), and any proposed value should be scrutinized accordingly.

Chapter 3 Oil Well Pollution and Student Performance: Evidence from Alberta, Canada

3.1) Introduction

Non-renewable resource extraction is a significant contributor to global air pollution, which can have substantial ramifications for health outputs such as mortality rates (63). Governments have a number of regulatory tools (e.g., regulations and pollution taxes) that they can use to attempt to reduce emission levels. There is substantial evidence, particularly out of China (64-66), suggesting that such measures are effective at mitigating haze and CO_2 pollution. The human health benefits of reducing air pollution, a potent policy motivator, can also be estimated. For instance, one health benefit analysis found that stringent carbon and air pollution policies in China could reduce mortalities related to $PM_{2.5}$ and ozone (O_3) exposure by up to 23% in 2030 (67). Another study of air pollution in Sydney, Australia found that a 10% reduction in 2007 levels of $PM_{2.5}$ exposure over a 10-year period may have resulted in approximately 650 fewer premature deaths and 700 fewer respiratory and cardiovascular hospital visits (68). Even a 1% increase in yearly exposure to fine particulate matter ($PM_{2.5}$) can increase household healthcare expenditure by almost 3% (69).

The effects of air pollution on human health and productivity are not homogeneous, however, with some groups more vulnerable than others (e.g., youth) (70). Past research has established links between ambient or source-specific air pollution and reduced health (71) as well as poorer academic performance in school-aged children (72). However, evidence regarding the relationship between pollution originating from oil and gas wells and student performance is scarce. This absence is surprising given that, historically, there have been over 400,000 wells drilled in the province of Alberta, Canada alone (73) and another 2 million wells throughout the United States (74-75).

As resource extraction activities continue to expand, there are growing concerns about the number of people living near oil and gas wells, even in dense urban areas (76). In Los Angeles, about 75% of active oil and gas wells are within half of a kilometre of a home, school, childcare facility, park, or senior residential facility (77). Residents may be unaware of the locations of oil wells, as some have been hidden inside decorative buildings by the operator (78). At least five states (Texas, Ohio, California, Oklahoma, and Pennsylvania) have at least one million people living within 1.6 kilometres (1 mile) of a well (79), and nationwide, over 18 million Americans live within this same distance of a well (80).

Despite legislation, the potential impacts of oil and gas pollution can be exacerbated when well operators go bankrupt before permanently sealing their wells and/or restoring the surrounding area to its original state (reclamation), leaving the responsibility, and financial burden, to the public sector (81). In the case of Alberta, the Orphan Well Association (OWA) was established in the 1990s, and acts as an industry-funded agency (funded through a levy on energy companies) under the Alberta Energy Regulator's (AER) authority to close and reclaim orphan wells (82). While the OWA spends a considerable amount each year on abandonment and reclamation efforts, estimated to be $200 million in 2016, it would take approximately 177 years ($36 billion) to finish clean-up at the current pace (83). There are also concerns that costs are being underestimated, with the Alberta Liabilities Disclosure Project (ALDP) reporting that costs as of 2018 could be as high as $70 billion, while the AER had calculated the liability estimate at $58.7 billion (84). These large clean-up costs are not unique to Alberta, however. In 2022, the Department of the Interior stated that there are over 130,000 wells with no identifiable owner across the U.S., whose clean-up could cost up to $19 billion (85).

While reclamation costs can readily be estimated, there may be additional and hidden social costs, such as academic performance impacts, related to decades of potential pollution from oil wells in surrounding communities. Local industrial pollution has been shown to have adverse outcomes on measures of academic success. For instance, schools in areas of Michigan with the highest levels of air pollution were observed to have the lowest attendance rates as well as the highest proportion of students failing to meet local testing standards (86). In Florida, schools within 1-2 miles of a Toxic Release Inventory site were associated with a 0.024 standard deviation decrease in test scores and increased likelihood of school suspensions (87). Air pollution in rural India was also found to decrease reading and math outcomes (by 1.11-2.39 and 0.53-1.90 percentage points, respectively) for children aged 5-16, with greater impacts on girls and older children (88). The potential impacts of pollution on educational outcomes are not all necessarily contemporaneous. In Texas, a decrease of one standard deviation in prenatal exposure to total suspended particulate (TSP) during a student's birth year was associated with an increase in high school test scores from 2% - 6% (89).

Though studies have established that, in general, environmental pollution is detrimental to educational attainment, in this paper, I investigate more specifically associations between oil production and adolescent academic outcomes. These associations are important for several reasons. First, academic performance can be interpreted as a productivity measure, which has also been negatively linked to pollution (90). Second, educational attainment is closely related to human capital attainment, where poor academic performance can translate into potential losses in future earnings (91). Third, academic performance levels can act as a proxy for short-term health and well-being, as pollution has been linked to increased incidence of illness and school absences, which in turn can reduce educational attainment (92). And fourth, evidence suggests children may be especially vulnerable to pollution impacts as they, on average, have higher minute ventilation (i.e., volume of gas inhaled/exhaled per minute), higher levels of physical activity, an immature immune system, and spend more time outdoors (93).

Student performance may be impacted by methane, which comprises 95-99% of emissions emitted from wells (94). Methane emissions are of global concern as, after carbon dioxide (CO_2), methane is the most prolific anthropogenic greenhouse gas (20% of global greenhouse gas emissions) and is at least 25 times more effective at trapping atmospheric heat than CO_2 (95). A high atmospheric concentration of methane can influence humans, as it displaces oxygen and can influence inhalation, with symptoms including mood changes, slurred speech, vision problems, memory loss, nausea, vomiting, facial flushing, and headaches (96). Methane emissions also contribute to ground-level ozone formation, which has been linked to reduced human productivity (97). Moreover, methane emissions are often co-emitted with particulate matter and other hazardous air pollutants (98-99). Such pollutants have also been shown to impact various measures of human productivity (100-101) and performance (102). It is therefore possible that schools with more nearby oil wells will exhibit lower student performance, measured via standardized test scores, with further variation arising from well activity status (e.g., active or abandoned).

The potential for wells to impact performance can be substantial, given prior research showing that emissions from both active and inactive wells are often underestimated (103), and even low-level production wells can emit significant amounts of methane (104). Direct methane emission measurements of a sample of inactive wells in the United States found that 6.5% exhibited measurable methane emissions, with higher emissions observed from wells that had not yet been plugged (105). Further geophysical research suggests methane emissions from oil and gas wells are underestimated by 20% in the U.S., and as much as 150% in Canada (i.e., in British Columbia and New Brunswick) (106).

I contribute to this literature by investigating associations between oil well-borne pollution and adolescent academic outcomes. I compare standardized provincial achievement test scores in math and science from up to 543 junior high schools across Alberta, during a 5-year period, 2015-2019, related to the number of oil wells located close to each school. Geocoded data allow me to measure the distance between wells and schools and, for each school year, compute the number of wells within a threshold radius of the school. In addition to time-varying school-level characteristics, I use school fixed effects to control for persistent local determinants of school-level academic performance, therefore reducing the potential for a number of possible confounding effects. I also use year fixed effects to control for common shocks across all schools, e.g., province educational policies such as variations of overall funding or variations in standardized tests.

The results show that nearby oil wells are negatively associated with grade 9 test scores. For each oil well within 4 km, mean math and science test scores decrease by 0.64 and 0.26 percentage points, respectively. When considering the stock of wells by life cycle stage, each active, suspended, and abandoned oil well is associated with a decrease of mean math test scores of 0.69, 0.64, and 0.76 percentage points, respectively. I observe a similar, albeit weaker, pattern when examining science scores. In both cases, I do not observe a significant effect of reclaimed wells on test scores, suggesting that the reclamation process of old and/or inactive wells is beneficial to student outcomes.

The remainder of the paper is organized as follows. Section 3.2 discusses the empirical strategy and models used in my investigation. Section 3.3 describes the datasets and discusses summary statistics of key variables. Main results are presented in Section 3.4, followed by a summary of robustness checks (found in the Appendix) in Section 3.5. Finally, Section 3.6 offers concluding remarks.

3.2) Models

I develop two empirical models that differ in how the stock of oil wells in proximity of a school is measured. The first model uses a cumulative count of existing oil wells as the principal variable of interest. The model hypothesis is that, since the number of wells is correlated with the emissions of pollutants (107), students attending schools in areas with a larger number of wells may be exposed to lower air quality. In turn these schools may, on average, produce lower academic performance. However, wells can be heterogeneous, and their impacts may depend on their activity status. I subsequently test for this heterogeneity by considering life cycle stages of wells. The second model splits the stock of oil wells W into subgroups based on activity status as they progress through their life cycle.

My analysis requires a rationale for defining which oil wells are sufficiently “nearby” a school (i.e., close enough to potentially cause harm). This threshold distance has important implications. Choosing too small a radius will reduce the sample size of wells and may underestimate the total impacts, while too large a radius may cause diluted levels of pollution, thereby increasing the likelihood of not finding significant associations, when, indeed, associations may exist. Previous literature provides some guidance with respect to the choice of a threshold distance. One study investigated distances within 10 km of communities downwind from oil and gas wells in preproduction and production stages (107). Results indicated significantly higher concentrations of ambient air pollutants up to 4 km downwind of such wells, with adjustments made for geographic, meteorological, seasonal, and time-trending factors.

Following these results, I estimate empirical models for radiuses between 1-5 km[16], and ultimately define "nearby" as wells within a 4 km radius of schools.

Note that I am unable to distinguish pollution effects by type (i.e., air or water) given the constraints of my dataset. If wells are indeed polluting, a student's cumulative exposure to pollution is a function of their time spent at school and at home, but I do not have information on student household locations. Without these coordinates, I cannot compare students living downwind[17] (air) or downstream (water) to their counterfactuals.

3.2.1) Model 1

Employing a fixed effects approach, the first empirical model is:

$$T_{ijt} = \theta W_{it} + \beta_X X_{ijt} + \beta_Z Z_{jt} + \mu_i + \lambda_t + \epsilon_{ijt} \quad (1)$$

where T denotes one of two test outcomes measures (i.e., math or science) for school i located in Forward Sortation Area (FSA)[18] j in year t. The variable W is the cumulative count of existing oil wells within 4 km from the school in each year. For schools with no nearby wells, $W = 0$. I elect to use a count over other options, such as a binary indicator for having a nearby well or not, to capture the large spatial and time variation in well counts. X is a vector of school-level control variables, including school population, average class size, and school authority funding per student. Z is a vector of FSA-level control variables. The term λ_t is a time fixed effect that captures unobservable common shocks across schools, while μ_i captures unobservable, school-specific determinants of test scores. ϵ is a random error representing idiosyncratic aspects of test scores.

---

[16] I observe increases in both significance and magnitude of coefficient estimates when moving from 5 km to 4 km. Results become progressively less consistent at radiuses below 4 km, with some subgroup variables having to be omitted due to lack of observations.

[17] I note the omission of wind direction from my models for two reasons. First, student exposure to well-borne pollution is not only a factor of time at school, but also time at home. While I could assign schools as upwind or downwind from wells, I would still not know what proportion of students, per school, lived upwind or downwind from the same wells. Second, my dependent variable, mean test scores, is a function of the students' accumulated educational attainment over a whole school year, while wind direction can vary substantially within the same year. This variation (e.g., monthly) would be lost if included in the model, as all other model variables are only available on a yearly basis. For these reasons, I rely on the variation between schools with few nearby wells and schools with many nearby wells to identify impacts of well pollution on mean test scores and allow wind direction to be captured by the school-level fixed effects.

[18] An FSA, represented by the first three characters of a six-digit postal code, designates a postal delivery area within Canada.

3.2.2) Model 2

Oil wells are expected to gradually reduce their greenhouse gas emissions, particularly methane, as they advance through the stages of their life cycle (108). The average life span of production for Alberta oil wells is 20-30 years, otherwise known as the *active* phase of a well's life cycle (109). If, for any reason, a well does not produce[19] for up to 12 months, it becomes known as *inactive*.[20] An inactive well can either resume production within the next 12 months or else must be *suspended*, which involves securing the well to prevent leaks. A suspended well can be reactivated later at the discretion of the owner. Following suspension is *abandonment*, also known as decommissioning, which permanently seals the well. The final step is reclamation, i.e., returning the land to the way it was before the well appeared (or sufficiently close, as deemed by the regulator). Unlike the 12-month period between active and inactive or between inactive and suspended, there are no set timelines in Alberta between suspension and abandonment or between abandonment and reclamation (111). These non-urgent requirements toward moving a well through its life cycle opens the door to potentially years, or even decades, of leaks, detected or not. After a well undergoes the reclamation process, the operator can apply for a certificate that deems it *reclaimed* (or reclamation certified). Some well sites can be granted a *reclamation exempt* status if the site overlaps with another activity, such as when sites share an access road, when a pit or mine goes through the site, or when site leases overlap (112). Finally, many wells are known as *orphan*, an umbrella term for inactive, suspended, or abandoned wells with no identifiable owner, often due to the operator going bankrupt before reclaiming the site.

Among the complexity of these stages, my data allows me to delineate 4 categories of wells: active, suspended, abandoned, and reclaimed. Due to dataset limitations, inactive wells are included in the total of suspended wells, and orphan wells are recorded as either suspended, abandoned, or reclaimed, depending on the stage they were left at by the previous owner, or the stage they reached under the control of the Orphan Well Association (OWA)[21]. I also include the small number of reclamation exempt wells in the total of abandoned wells.

[19] I only know the location of wells; I do not have production-level data.
[20] In some cases, only 6 months need to pass to deem a well inactive, depending on well type and public and/or environmental risk potential (110).
[21] As of October 2022, 710 of the 6,115 wells in my dataset were classified as orphan wells (113). However, as I do not know which wells were orphans during 2015-2019, I cannot use orphan wells as a category.

To account for life-cycle stages of wells, I estimate the following equation:

$$T_{ijt} = \alpha A_{it} + \beta S_{it} + \gamma B_{it} + \delta R_{it} + \beta_X X_{ijt} + \beta_z Z_{jt} + \mu_i + \lambda_t + \epsilon_{ijt} \quad (2)$$

where A, S, B, and R are the counts of active, suspended, abandoned, and reclaimed wells, respectively. Unlike W in model 1, A may increase or decrease between years depending on the number of new wells added and the number of previously active wells turning inactive. While it is also possible for some suspended wells to resume production and become active again, almost all remain inactive due to unprofitability[22] or no longer having an owner.

3.3) Data

My dataset has four components: test scores, school controls, well data, and demographic controls. Summary statistics for each variable in these components are contained in Table 3.1. The Ministry of Education in Alberta administers annual, standardized tests to all grade 9 students known as the Provincial Achievement Tests, which cover several disciplines including math and science (115). Results were traditionally made available in 5-year reports and exams were consistently administered up until the Covid-19 pandemic, which led to Provincial Achievement Tests being cancelled in 2020 and 2021 (116). My models use the most recent five years of results (2015-2019) available before testing conditions were significantly altered (117).

As of 2019, there were 605 schools with grade 9 classes in Alberta, which fall under various school authorities, including public, separate (i.e., Catholic), charter, and private. As school funding information is not publicly available for private schools, they are excluded from my models. In total, my analysis covers 541 schools for math test scores and 543 for science.[23]

Table 3.1 shows that the mean Provincial Achievement Test score over 5 years across the sample of Alberta schools is 57.0% for grade 9 math and 66.2% for grade 9 science. Figure 3.1 displays the 541 schools with available grade 9 math test scores, along with the set of nearby wells in 2019. With respect to math, there are 247 (45.7%) schools within 4 kilometres of one or

[22] One model showed that even if oil prices drastically rose 200%, only 12% of inactive Alberta oil wells would reactivate (114).
[23] The number of schools, and subsequently the mean number of nearby oil wells, differs slightly by subject due to i) test results not being publicly released for classes of fewer than six students (118) and ii) a few cases of missing class size data.

more oil wells, which comprise the treatment group; the remaining 294 (54.3%) schools comprise the control group.

Table 3.1 Summary statistics of Alberta schools administering Provincial Achievement Tests in Math and Science, 2015-2019, surrounding demographics, and wells. N=2,418* (2,423) for math (science)

	Mean	St. Dev.
Dependent Variable		
Mean test score – math (%)	56.99	10.04
Mean test score – science (%)	66.15	8.74
Independent Variables – math (science)		
Well categories (# of wells within 4 km)		
All	14.11 (13.59)	45.50 (44.76)
Active	5.57 (5.27)	20.60 (20.04)
Suspended	3.73 (3.64)	15.05 (14.96)
Abandoned	2.59 (2.53)	9.58 (9.46)
Reclaimed	2.21 (2.15)	8.70 (8.55)
School controls		
School population (#/100)	4.54	2.54
Average class size	23.19	6.05
Authority funding ($100 per student)	60.20	15.77
FSA controls		
Senior share of population	13.59	3.70
Population (#/1,000)	42.48	21.69
Household income, avg. after-tax ($/1,000)	96.32	24.23

*N=2,418 (2,423) comprises 5 years of observations across 541 (543) schools with available test scores for grade 9 math (science).

I control for attributes of schools with information on class and overall school population size (119), as well as annual levels of funding at the school authority level (120). School authorities, also referred to as school boards, districts or divisions, may include one or more schools. The average school in my sample has 454 students, with an average class size of 23.2, and funding at the school authority-level is approximately $6,020 per student per year.

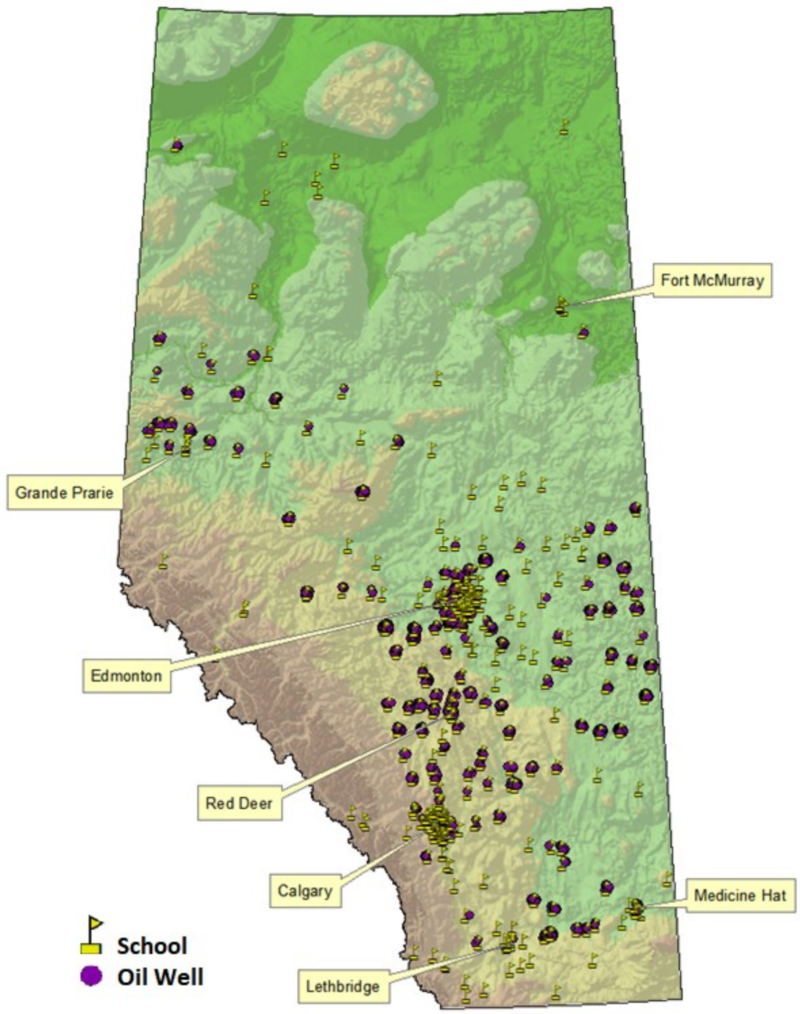

Figure 3.1 Oil wells within 4 kilometres of schools with grade 9 classes in Alberta, 2019.

For each year of test scores, I obtained annual well reports from the Alberta Energy Regulator (AER), which include information such as the well name and licence number, licence status and issue date, and date of drilling (121). In 2015, there were a total of 5,957 oil wells within 4 km of a school. By 2019 (Figure 3.1), the total increased by 2.7% to 6,115. Of the 5,957 oil wells present in 2015, 2,732 were active, 1,458 were suspended, 964 were abandoned, and 803 were reclaimed. By 2019, there were 2,227 active, 1,726 suspended, 1,235 abandoned, and 927 reclaimed. The stock of active oil wells decreased by 18.4% between 2015-2019, while the stock of suspended, abandoned, and reclaimed oil wells increased over the same period by 18.4%, 28.1%, and 15.4%, respectively. Schools in the sample have an average of 14.1 oil wells within 4 km (Table 2.1). By well life cycle stage, schools are, on average, within 4 km of 5.6 active wells, 3.7 suspended wells, 2.6 abandoned wells, and 2.2 reclaimed wells.

I also control for differences in demographic characteristics of schools at the FSA level using data found in the 2016 Canadian census (122-123). I control for variable-specific linear trends for the following demographic characteristics: the FSA population, the share of the FSA population made up of seniors (65 years or older), and the average, after-tax household income of the FSA. These metrics, often associated with economic growth (124), are included as various measures of a school area's prosperity. Referring to Table 2.1, the average proportion, or share, of seniors by FSA population is 13.6%, while the average FSA population is 42,480. The average after-tax income per household is $96,320.

3.4) Results & Discussion

Table 3.2 presents my main findings from two models, each estimated with two dependent variables (i.e., math and science mean test scores). Starting with model (1), I find evidence that *all* oil wells within 4 kms, without considering life cycle stage, are negatively associated with math score outcomes (column M1) at the 0.01 significance level. Each oil well is associated with a decrease of math test scores of 0.64 percentage points. With a mean value of 14.1 oil wells within 4 km of schools, this coefficient implies an average decrease of 9.0 percentage points in math test scores. With respect to science, I find a similar relationship between the presence of nearby oil wells and lower test scores, albeit smaller in magnitude and lower significance overall. Column S1 shows that an additional oil well within 4 km of a school is associated with a decrease of science test scores of 0.26 percentage points (significant at the 0.1 level). Together with the mean value of 13.6 wells, this suggests an average decrease of 3.5 percentage points in science test scores per school.

Separating the stock of wells by life cycle stages in model (2), I find *Abandoned* wells to be the most detrimental to math test scores outcomes (column M2), followed by *Active* and then *Suspended* (all significant at the 1% level). Each *Abandoned* well is associated with a decrease of math test scores of 0.76 percentage points, while *Active* and *Suspended* wells are associated with decreases of 0.69 and 0.64 points, respectively. *Reclaimed* wells do not exhibit a statistically significant correlation with math test scores. Considering the mean values of *Active* (5.6), *Suspended* (3.7), and *Abandoned* (2.6) wells, the total effect is an average decrease of 8.2

percentage points per school. For science, results in column S2 indicate that average test score decreases by 0.32 percentage points per *Abandoned* well (0.05 significance level) and 0.26 per *Active* well (0.1 significance level). The coefficients of both *Suspended* and *Reclaimed* wells are insignificant. Altogether, this imputes an average decrease of 2.2 percentage points per school.

Table 3.2 Regressions Results

Model	(1)	(2)	(1)	(2)
Subject	Math		Science	
Column	(M1)	(M2)	(S1)	(S2)
Wells (counts)				
All	-0.64***		-0.26*	
	(0.17)		(0.15)	
Active		-0.69***		-0.26*
		(0.15)		(0.15)
Suspended		-0.64***		-0.19
		(0.16)		(0.16)
Abandoned		-0.76***		-0.32**
		(0.15)		(0.15)
Reclaimed		-0.40		-0.17
		(0.30)		(0.29)
School				
School population	0.62**	0.62**	0.29	0.29
	(0.24)	(0.24)	(0.21)	(0.21)
Average class size	-0.01	-0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Authority funding	-0.05*	-0.05*	-0.05**	-0.05**
	(0.03)	(0.03)	(0.02)	(0.02)
Constant	68.49***	68.42***	72.69***	72.29***
	(3.71)	(3.48)	(3.10)	(3.09)
Observations	2,418	2,418	2,423	2,423
R-squared	0.82	0.82	0.80	0.81

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As for the school controls, I find several significant variables, though none have large effects on performance. School population size has a positive and significant coefficient in the math model, but it is statistically insignificant in the science model. For every 100-student increase in school population size, math test scores increase by 0.62 percentage points. The coefficient of average class size is insignificant in both math and science models. Lastly, school authority funding per student appears to have a small but negative correlation with test scores, decreasing both math (at the 0.1 level) and science test scores (at the 0.05 level) by 0.05 percentage points per one hundred dollars per student spent. This somewhat unintuitive relationship between increased school spending and decreasing test scores has also been reported elsewhere (125-126) and, moreover, studies (127-129) have shown that school funding has limited correlation to student outcomes. My data on school funding is also restricted to the school authority level, which can cover one or more schools, making it an imprecise measure of true spending per school.

Next, I consider how the relationship between wells and test scores may vary between urban and rural schools. Prior research has shown that, on average, rural residents spend more time outdoors (for leisure or work) and have a higher proportion working in industrial sectors, which both may contribute to increased ambient air pollution exposure, and they often utilize private wells for drinking water over more-regulated public water systems (130). Specific to wells, one study found increased incidence of adverse birth outcomes to Californian mothers living near oil and gas development in rural areas relative to urban counterparts (131). For these reasons, I hypothesize that rural students may be more vulnerable to potential well pollution.

To investigate this hypothesis, I gradually remove municipalities from my original sample, based on i) urban classification from the 2016 Canadian Census (132) and ii) natural break points in population size. Starting with the full sample, I first remove the two largest urban cities (Calgary and Edmonton) which have populations over 900,000. Second, I remove the largest five cities, with populations over 90,000. Third, I remove the largest 10 cities, with populations over 60,000. Finally, I remove all 14 cities classified by Statistics Canada as urban in 2016, which coincide with all Albertan cities with populations over 25,000.

When comparing results between rural and urban areas, it is important to consider changes in the spatial distribution of wells. For instance, the mean number of nearby oil wells to schools significantly increases as the sample becomes progressively more rural. Table 3.3 provides the respective number of observations for each of these samples, as well as the mean number of wells. For math (science)[24], the mean number of wells rises from 14.1 (13.6) in the full sample to 25.4 (24.7) wells in the rural-only sample.

[24] Note again that the number of schools, and subsequently the mean number of nearby oil wells, differs slightly by subject due to i) test results not being publicly released for classes of fewer than six students (118) and ii) a few cases of missing class size data.

Table 3.3 Mean wells and total observations from a progressively rural sample of Alberta schools administering Provincial Achievement Tests in Math and Science, 2015-2019

	Math			Science		
	N	Mean	St. Dev.	N	Mean	St. Dev.
All Wells (# of wells within 4 km)						
Full sample	2,418	14.11	45.50	2,423	13.59	44.76
Exclude 2 cities with largest pop.	1,481	20.27	53.73	1,481	19.47	52.87
Exclude 5 cities with largest pop.	1,258	22.25	56.65	1,251	21.42	55.87
Exclude 10 cities with largest pop.	1,110	24.64	59.85	1,104	23.68	59.04
Rural only	1,044	25.44	61.20	1,048	24.74	60.39

Figure 3.2 presents the total effect of *All* wells, i.e., estimates of θ in equation (1), on math and science test scores given a progressively rural sample.[25] Figure 3.2 is constructed by considering the marginal effects (indicated by the coefficients in the Appendix) combined with the mean values of nearby wells. With respect to math, the effect of *All* wells is significant at the 1% level across all samples, with the marginal effect falling from -0.64 percentage points per well with the original full sample to -0.56 per well with the rural-only sample. When I factor in the respective means of 14.1 and 25.4 nearby wells, however, I observe the total effect significantly increases from -9.0 mean percentage points across the full sample to -14.2 mean percentage points for the rural-only sample. As for science, I find a similar pattern of effects, albeit weaker. The coefficient for *All* wells is only significant (and only at the 10% level) when using either the full sample, the largest two cities excluded sample, or the largest 10 cities excluded sample. When comparing the two extremes with significant impacts, the marginal effect of *All* wells decreases from -0.26 with the full sample to -0.25 with the largest 10 cities excluded sample, while the total effect on test scores increases from -3.5 mean percentage points to -6.2 percentage points, respectively. Altogether, while the marginal effect of each oil well is higher in more-urban samples (i.e., as indicated by the coefficients in the Appendix), the sheer number of oil wells in more-rural areas equates to relatively greater harm to both math and science test scores at these schools.

[25] The full regression results from models (1) and (2) can be viewed in the Appendix (Section B.1: Tables B.1-B.5).

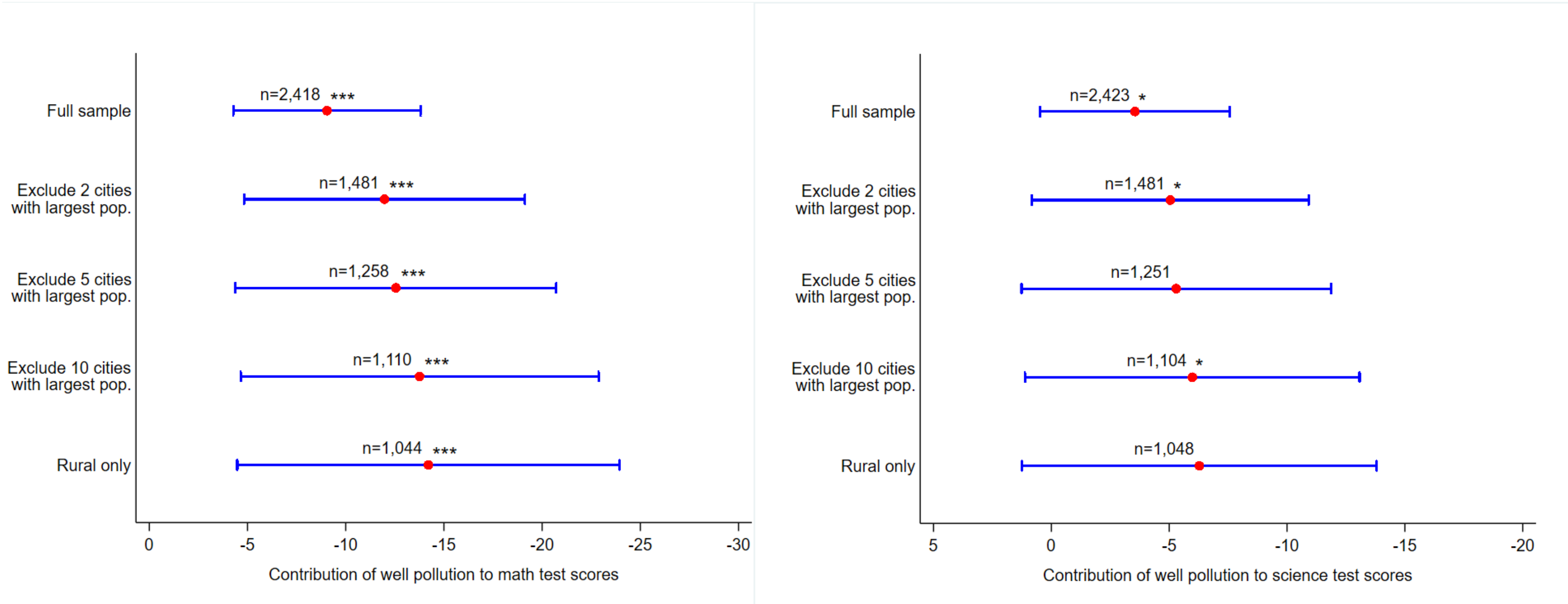

Figure 3.2 Coefficient on wells with a progressively more rural sample.[26]

[26] Naturally, the width of the confidence intervals increase as the sample size decreases. However, for both subjects, as the sample becomes progressively more rural, the lefthand endpoint (toward a smaller negative effect) remains relatively constant (within 1 percentage point) while the righthand endpoint (toward a larger negative effect) continuously extends outward by multiple percentage points. These trends in the confidence intervals support my conclusions.

3.5) Robustness Checks

In addition to the prior results, I perform several robustness checks.[27] First, my analysis has so far assumed that the relationship between oil wells and test scores is not endogenous. If one suspects the number of oil wells near a school is correlated with unobservable determinants of test scores, then estimates from ordinary least squares (OLS) may be biased and inconsistent. However, consistent estimates can still be obtained via instrumental variable (IV) estimation. To do so, I need to carefully select an instrument that only affects the dependent variable (i.e., test scores) indirectly through its effect on the potentially endogenous explanatory variable (i.e., the stock of oil wells). A potential IV may be found in the tenure system in Alberta that allocates rights to oil exploration and extraction. There are two types of agreements: Petroleum and Natural Gas (PNG) and Oil Sands (OS). These Agreements, or leases, typically last for 5-year terms and vary in parcel size, from a minimum of a quarter-section of land (160 acres), the minimum amount of land that must be associated with each well, to as large as 36 sections (23,040 acres) (133). Agreements can continue indefinitely beyond the end of the initial 5-year term (134). Since Agreements are required for drilling but do not, on their own, influence test scores, I use a characteristic of these Agreements as an instrument. My instrumental variable is the mean age of contemporary Agreements within 4 km of schools (see Appendix Section B.2 for further description). I still find a negative and significant (5% level) effect of nearby oil wells on math test scores using the IV estimator (see Appendix Section B.2: Table B.6). However, test score predictions using my IV coefficient have significantly higher variance than that of my original OLS coefficient, which leads me to believe my OLS coefficient to be closer to the true effect. This inference is corroborated by a prior study that found IV estimation to only outperform OLS with a sufficiently large sample size (135).

Second, one could also reasonably expect the age of wells to be a significant factor in evaluating the relationship between well pollution on test score outcomes, or perhaps even more relevant to test score outcomes than the sheer number of wells. I test for the potential of well age effects with two control variables: mean age of wells and oldest well age. Since schools in the control group have no nearby wells, and therefore no well ages, I assign them age values of 0

[27] Refer to Appendices 3.A-3.F for further details.

years. In both cases, I once again find no significant coefficient of the control variable nor significant changes to coefficients present in my original results (see Appendix Section B.3: Tables B.7 & B.8).

Third, I consider that the percentage of students writing may be influenced by well pollution and, in turn, influence test scores. My hypothesis is that students feeling unwell, perhaps due to well pollution, may be absent during the day of the provincial achievement test. Whether or not these students also felt unwell on other days leading up to the test, I can reasonably suspect that sick students are more likely to do poorly than healthy students. Moreover, mean test scores only include scores from students who wrote the test. Therefore, by staying home, these students may artificially increase the mean test score. If that is the case, my main models may be plagued by selectivity and estimates would capture confounding impacts. To account for this possibility, I add a variable controlling for the percent of students writing the tests out of those enrolled in the subject. Once again, I find no significant changes when adding this control variable (see Appendix Section B.4: Table B.9).

Fourth, it could be argued that the set of schools with one or more nearby wells is inherently different than the set of schools with no nearby wells. This theoretical divide may have multiple explanations. For example, schools with more nearby wells may be in more industrial or rural areas, with inherently different socioeconomic characteristics, which I may have failed to include in my other controls. The timing of new school and well openings may also be relevant. If wells are considered an indicator of area development and subsequent prosperity, then school construction may follow wells. In contrast, a school being built first might deter future well construction due to environmental concerns or zoning regulations. Therefore, I consider a truncated model which excludes the set of schools with zero nearby wells. As this approach decreases the sample size by over 50%, I would expect some changes in the coefficients. However, the negative and significant relationship between oil wells and test scores, particularly math, is still maintained in the case of zero truncation (see Appendix Section B.5: Table B.10).

Lastly, I consider whether the average distance of nearby wells has an impact on test scores. I may expect test scores from schools with an average well distance closer to 0 km to be more strongly (negatively) associated with well pollution than those with average distances closer to the 4 km maximum distance, ceteris paribus. Naturally, only schools in the treatment group (i.e., with at least 1 nearby well) can have an average well distance, so I continue to use the sample truncated at zero from the previous robustness check. I once again find no significant coefficient for the control variable nor significant changes to the previously obtained coefficients from zero truncation (see Appendix Section B.6: Table B.11).

3.6) Conclusions

A long history of oil well drilling in Alberta has had significant consequences on recent student test score outcomes. With respect to provincial achievement exam results from 2015-2019 across hundreds of schools, I find evidence of a significant relationship between the presence of nearby (i.e., within 4 km) oil wells and lower test scores. With a mean of approximately 14 wells per school, I found that the stock of nearby wells (i.e., *All* wells) is associated with a decrease of mean math and science test scores of 9 and 3.5 percentage points, respectively.

Moreover, I find significant variation in coefficients by well life cycle stage. *Abandoned* wells are, on average, the most harmful individually, followed by *Active* and *Suspended*. However, when considering the mean number of each type of nearby well, *Active* wells overall have the greatest associations with mean test scores. *Active* wells are associated with a decrease of mean math and science test scores of 3.84 and 1.37 percentage points, respectively, compared to 1.97 and 0.81 percentage points for *Abandoned*. *Suspended* wells also have a negative and significant coefficient in the math model, associated with a decrease of mean test scores of 2.39 percentage points. *Reclaimed* wells, however, do not have a significant coefficient on either subject outcome. Additionally, when I alter the sample size by excluding schools in cities with larger populations, I find that while the marginal association per well (i.e., the coefficient) decreases in more-rural samples, the corresponding total association increases, given a relatively higher mean number of nearby wells in more-rural samples.

The economic significance of these results can be approximated using estimates from related research. For example, one study associated a gain of one standard deviation in math scores among 16-year-olds in the United Kingdom with up to 14% more earnings by age 33 and 18% by age 50, albeit with greater benefits accrued by men than women (136). Looking at the results from model (2) for math, reclaiming 5 *abandoned* wells is required to increase the average math test score (68.4) by one standard deviation (3.48). At an estimated cost of roughly $78,000 to plug and reclaim an Alberta well (137), it would only take a combined increase in future earnings of $390,000 among affected students to break-even against the clean-up cost.

In summation, this study, rooted in spatial analysis, establishes a causal link between nearby oil wells (and their associated emissions) and reductions in human capital attainment, as measured in student test score outcomes. While my sample is limited to Alberta, it is hard to imagine these findings are exclusive to the province. *Active* wells has the potential to have the largest detrimental effect on student test outcomes. Along these lines, the AER was directed by the Government of Alberta in 2015 to develop requirements to reduce upstream oil and gas operation-borne methane emissions, which accounted for 70% of Alberta's methane emissions in 2014, by 45% of 2014 emission levels by 2025 (138). My findings also suggest that further benefits to future student test score outcomes may be accrued by introducing legislation that accelerates the reclamation process of *Abandoned* and *Suspended* wells. I have also identified a disparity in the negative associations between oil well pollution and education outcomes, with students in more rural areas disproportionately affected. Prioritizing reclamation of these rural oil wells may be warranted. More stringent regulations on how close a new oil well can be drilled to existing communities and their schools, or vice versa, can also help mitigate future harm to student outcomes.

Chapter 4 Legacy Effect of Rural Coal Mining on Youth Population Health

4.1) Introduction

Choices related to energy development strategies are arguably among the most important decisions modern societies face. While hydrocarbons have been the main source of worldwide energy production for over a century, there have been increasing concerns in modern times regarding the emissions of pollutants associated with the consumption of fossil fuels. Coal-generated pollution has been well-researched as a major contributor to climate change (139-142), and ongoing conversations of phasing out coal are taking place globally (143-147). However, there are additional reasons to expedite the reduction in coal reliance, including known negative impacts on human health (148-149). Residential proximity to coal mining has been associated with higher rates of chronic ailments including hypertension, lung disease, and kidney disease (150), as well as various forms of cancer (151). In an investigation of effects of air pollution, researchers found that a 10% increase in coal stockpiles held by U.S. power plants results in a 0.09% increase in average $PM_{2.5}$ concentration levels within a 25-mile radius of power plants (152). Moreover, a 10% increase in $PM_{2.5}$ causes a 1.1% increase in average adult mortality rates and a 3.2% increase in infant mortality rates. Another study found that county exposure to West Virginia surface coal mining-borne air pollution caused 9.85 more asthma hospitalizations per 100,000 residents per standard deviation increase in exposure, with associated health care costs of over $11 million across a 6-year period (153). In a more global analysis, ambient air pollution was estimated to be responsible for around 3.2 million deaths across 41 OECD countries in 2015, with the economic cost of these mortalities calculated at around $5.1 trillion USD (154). Other methods of estimating the hidden costs of air pollution include hedonic analyses (155) and productivity measures (156). Beyond air, there is also significant concern about soil (157) and water (158) contamination in the surrounding areas of coal mines, both active and abandoned.

Despite knowledge of the potential for negative environmental and human health impacts, energy from fossil fuels continues to be developed due to its relatively low cost compared to cleaner, renewable alternatives. As recent as 2017, coal supplied as much as 27% of the world's energy supply, and global coal production reached 7.9 billion tonnes in 2019 (159). While the Covid-19 pandemic led to a temporary decrease in global production levels, they have since recovered and even surpassed pre-pandemic output at over 8 billion tonnes (160).

Canada was the world's fourth largest coal exporter in 2019, producing 57 million tonnes and exporting 37 million tonnes, with 83% of the coal produced in just two of its provinces: Alberta and British Columbia (159). Of these 57 million tonnes, about 53% was less polluting metallurgical coal, used for steel manufacturing, and the remaining 47% was more polluting thermal coal, used to generate electricity. In 2018, Canada introduced legislation to phase out the domestic use of thermal coal by 2030, but might continue exporting it elsewhere, thereby contributing to global pollution problems (161-162). While the future of coal exploration is uncertain, the history of coal production is known, which allows investigations into the potential legacy effects of coal mining on human health.

In the case of Alberta, Canada, over 2,000 commercial mines have operated since 1874, producing a combined total of over 1 billion tonnes of coal (163). These mines fall under the jurisdiction of the Alberta Energy Regulator (AER), a subsidiary of the Government of Alberta that imposes reclamation requirements for all end-of-life coal mines, requiring operators to remove infrastructure and return the land to an equivalent state pre-development (164). Despite these regulations, there are growing concerns about water contamination from coal mining (165). Moreover, a previously paused expansion of coal mining activity in the Rocky Mountains of Alberta (166) may be revisited under new leadership (167). By assessing potential human health costs of coal mine pollution, my analysis may help inform future policy decisions in the region.

The local impact and extent of air pollution from coal mines can be difficult to measure, due to variability in wind dispersion. In contrast, coal-related water contamination from the mining process is confined to surrounding rivers and watersheds, allowing for a more precise analysis of the effect of coal mining on human health in nearby communities. For instance, diseases in China have been linked to drinking water pollution with associated human health costs of $2 billion annually (168). But such studies are rare. A review of published evidence linking surface coal mining to public health effects indicates that there is an 'urgent' need for studies that directly link environmental exposure, dose, and biological impacts (in humans) (169).

Coal mines situated near bodies of water create the potential for acid mine drainage (AMD); highly acidic and heavy metal-rich water formed through a chemical reaction involving sulphur-bearing materials exposed by mining activity (170). Entire watersheds (i.e., both surface and groundwater) can be impacted by AMD, which in turn can pollute riverbeds and soils (171). Cultivated soils around abandoned mine sites may result in elevated human ingestion of harmful heavy metals (172). Moreover, AMD is not a problem unique to active mines. One study investigated the extent of AMD around the city of Potosí, Bolivia, which has been a central location of various mineral mining operations since 1545 (173). Not only did they find evidence of AMD being produced from active and abandoned mines alike, but they also stressed the ongoing environmental threat of AMD if sulphur-bearing material (pyrite) is left exposed, as AMD can be continually released into surrounding areas for decades. The hidden costs of a large inventory of old mines, as is the case of Alberta, may be substantial.

The contributions of this study stem from my focus on spatially explicit water pollution as a mechanism of exposure from a large number of coal mines. Specifically, my study covers 749 coal mines (the majority no longer active) within 5 km of a *waterway* (i.e., any perennial body of water, such as rivers or lakes, or likely areas of drainage, such as seasonal streams), and 56,633 individuals living near these mines (within 10 km[28]). A comprehensive health dataset provides me with individual level information on their approximate location of residence relative to a mine site (exposure); how many years they lived in that location (dose); and their yearly level of health care demand (a proxy for human impacts). To assess whether historical coal mining activity has legacy health effects, I compare three measures of yearly average health care demand (i.e., doctor visits, emergency department visits, and inpatient days) that occur from 2002 (the first year of digitized inpatient care records across the province) to 2014 (the last

[28] This 10 km distance refers to the distance between *projected points* of coal mines and *clusters* of postal codes onto waterways, which is explained in detail in the *Data* section.

updated year of a historical record of mines) between similar groups of individuals (i.e, Alberta-born youths up to age 13). By design, individuals are identified as living either upstream or downstream from a rural coal mine. My hypothesis is that, if mining is negatively associated with water quality, residents living downstream from mining activity (compared to similar individuals located upstream) are exposed to, on average, relatively higher levels of water contaminants (e.g., various heavy metals) due to AMD, and, in turn, will have relatively higher demand for health care.

I employ mine-level fixed effects to control for persistent local determinants from unobserved coal mine attributes, as well as year fixed effects to control for common health care demand (e.g., province-wide fluctuations in the number of doctors or funding for hospitals). Notably, my investigation is based in Canada, a country with free public healthcare. This publicly funded system, known as Medicare, covers doctor visits and hospital stays for Canadian citizens and permanent residents (174). Access to free healthcare significantly reduces the potential for selection bias (e.g. based on income) of individuals seaking treatment. To limit other confounding effects on health care demand, I restrict my analysis to individuals born in Alberta that never moved out of the observable sample area (but are allowed to move between observabled areas). Using this approach, my sample only reflects individuals, hereafter referred to as youths, living near mines for continuous periods since birth, and omits youths with unknown periods of potential pollution exposure, i.e., those born before the observation window or those who moved out of the observable sample area and then moved back.[29] In other words, I only include youths that were born in Alberta during or after 2002 (up to 2014[30]) for whom I have data (e.g. place of resident) for every year thereafter (including years of no health demand). My focus on youths also allows me to compare my results with several other mine pollution-related investigations that have focused on adolescent health impacts (175-179).

[29] There are 646,603 individuals observed in my study area. Of these individuals, 87,438 (13.5%) satisfy my definition of youths (i.e., 13 and under). Of these youths, 56,633 (64.8%) satisfy my conditions of being born in the sample and being continuously observed (i.e., no missing years or years of partial/erroneous information).

[30] Or until the year of death.

I find evidence of higher health care demand of youths living downstream from historical coal mining sites compared to their upstream counterparts. For downstream youths, the average number of yearly doctor visits and inpatient days were 3.75% and 18.4% higher, respectively. While there is no statistically significant difference observed for yearly emergency department visits in my main model, I do observe differences when using (exact) nearest neighbour matching (see Section 4.5.2: Matching Evidence) and subsets of mines based on most recent decade of operation (see Section 4.5.3: Health Care Demand Heterogeneity by Temporal Mine Characterstics).

The remainder of the paper is organized as follows. Section 4.2 discusses the data sources and strategy for identifying relationships between coal mines and youths. Section 4.3 presents summary statistics. Section 4.4 describes the empirical models. Main results are presented in Section 4.5, including additional checks using nearest neighbour matching and coal mine heterogeneity. Finally, Section 4.6 offers concluding remarks.

4.2) Data and Variable Construction

I utilize four datasets in my analysis. The first dataset, constructed in ArcMap (180), contains geospatial information (i.e., elevation) for Alberta, which I use to delineate the drainage network (i.e., water flow direction) throughout the province. Elevation is a key component of my research, as flows of water may disperse pollutants from mines. Knowing the direction of water flows, and the locations of households and mines, allows me to assign residents into treatment and control groups, based on whether they live downstream or upstream from mines, respectively. Figure 4.1 shows the provincial drainage network, with water predominantly flowing from southwest (from the Rocky Mountains) to northeast. Thinner, lighter-coloured waterways, belonging to higher elevation regions (3,354 metres at the highest point), drain into gradually thicker, darker-coloured waterways (167 metres at the lowest point).

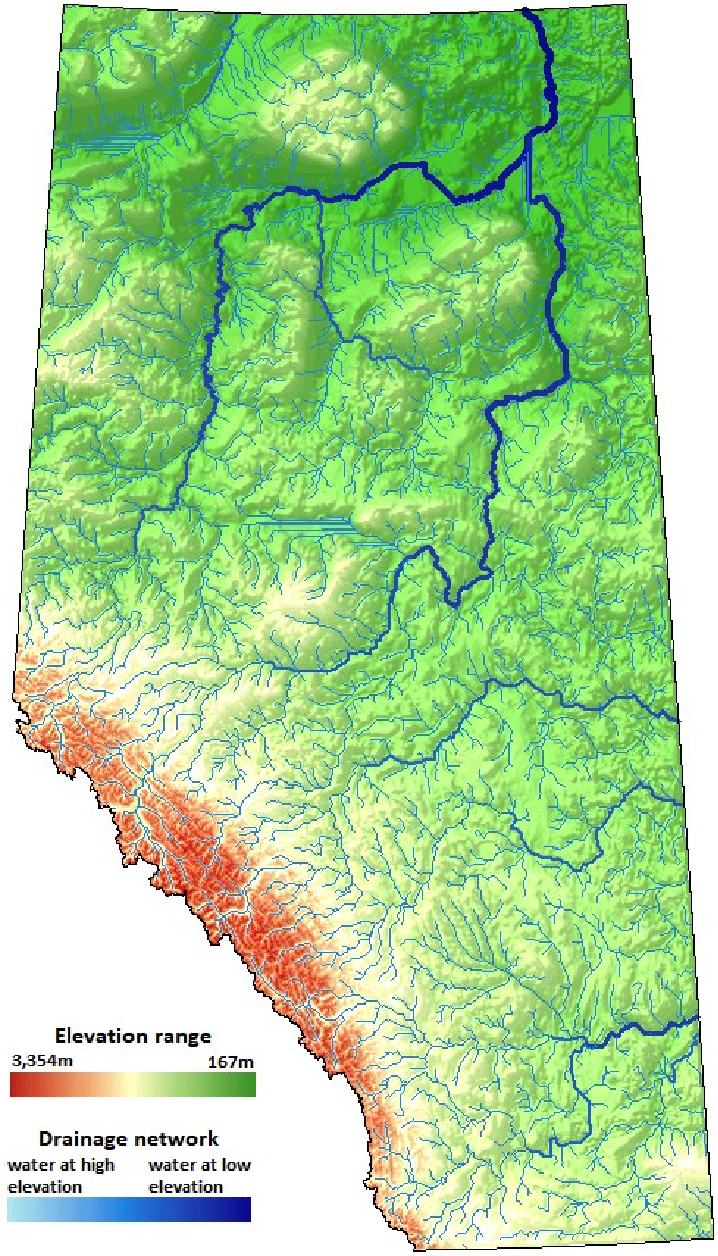

Figure 4.1 Alberta drainage network.

The second dataset organizes mining data from Alberta Energy Regulator's Coal Mine Atlas (162) and contains historical mine-level information, including years of operation, for all (n=2,439) Alberta coal mines that were established since 1874, up to 2014.[31] The location of each mine is mapped at the centroid of the closest square mile section, as per the Alberta

[31] The Coal Mine Atlas was last updated May 15, 2015.

Township Survey System (181). In total, these mines have occupied 1,112 sections across Alberta, as multiple mines have coexisted, sometimes in different periods, within the same section. As I am concerned with potential legacy effects of coal mining given previous research (discussed prior in Section 4.1), I do not exclude any mines from the sample based on the age of the mines. I do, however, investigate how results change when considering subsets of these mines based on the most recent decade of operation and length of mining operations (see Section 4.5.3: Health Care Demand Heterogeneity by Temporal Mine Characterstics).

To select the subset of Alberta coal mines relevant to my study, I first use proximity analysis to identify mines within 5 kilometres of a waterway; mines beyond this distance were dropped. My choice of 5 km is informed by previous research considering the spatial extent of measurable human health impacts arising from mine pollution (albeit with no distinction between air or water), with such impacts including increases of 3-10 percentage points of anemia in adult women and a 5-percentage point increase of stunting among newborns exposed in utero (182). Additionally, as urban areas tend to have more sophisticated water treatment methods than rural regions, which mitigate effects of water pollution on health, I eliminate all mines within the city limits of metropolitan areas with population sizes greater than 40,000 in the year 2011 (i.e., the latest Canadian census year within my observation window).[32] After accounting for the above exclusions, as well as excluding mines with no nearby postal codes (explained below), Figure 4.2 depicts the location of the 749 mines included in my sample, which were established between 1874 and 2014 across central and southern Alberta where most coal deposits are located (183).

[32] The population size of 40,000 is a natural breakpoint (circa 2011) in the size of metropolitan areas in Alberta, which I use to exclude the largest cities in Alberta. From largest to smallest, these are: Calgary, Edmonton, Red Deer, Lethbridge, St. Albert, Medicine Hat, Grande Prairie, and Airdrie.

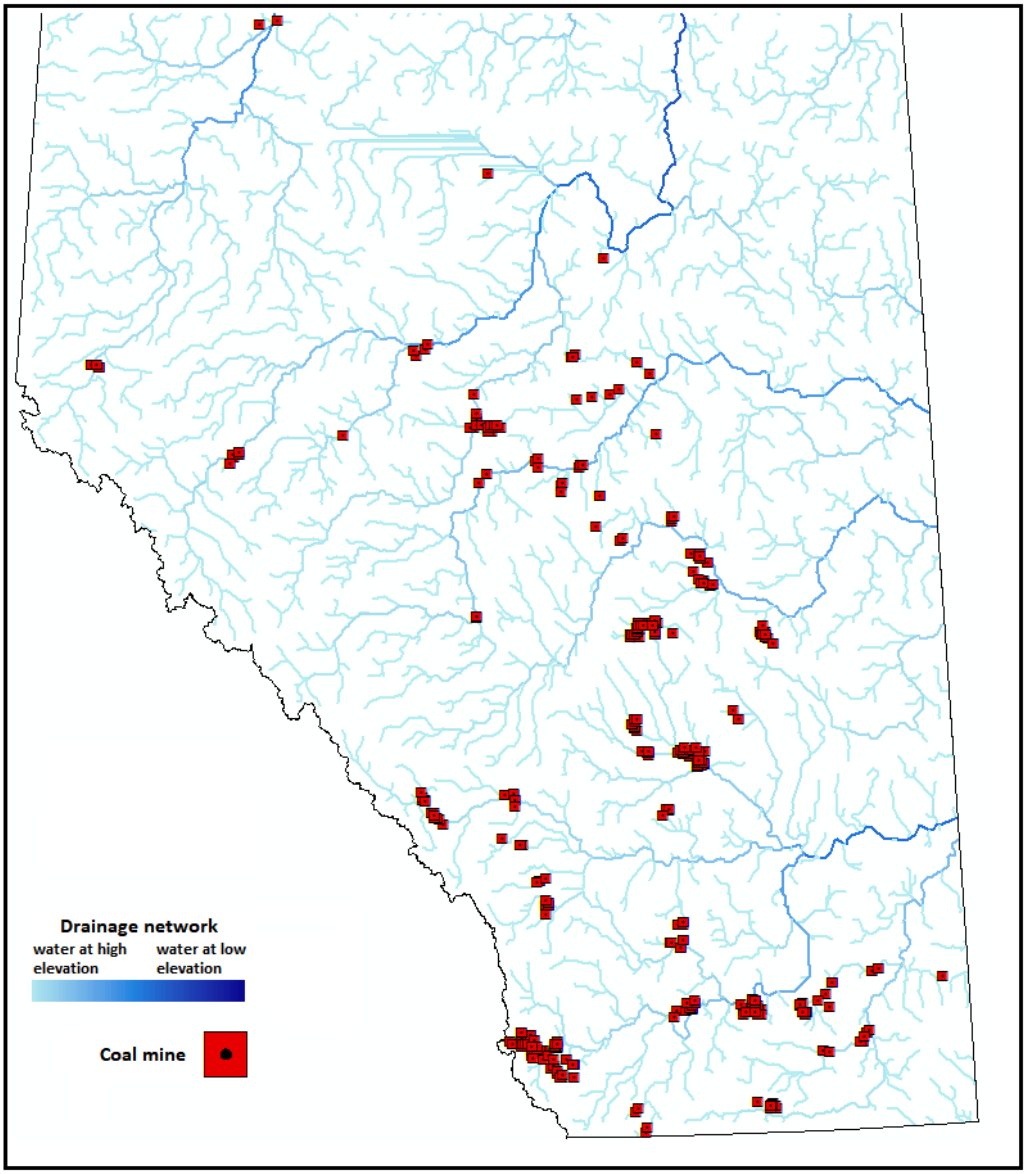

Figure 4.2 Location of coal mines in the sample.

The third dataset is derived using the Postal Code^{OM} Conversion File Plus (PCCF+), corresponding to the 2011 census, to find postal codes near coal mines (184). The PCCF+ is provided through Statistics Canada to its share partners (including The University of Alberta), and links six-character postal codes, used in countrywide mail sorting, to standard geographic areas. The PCCF+ data, layered onto my elevation map, is characterized by population centroid-weighted "pins" (yellow marks in Figure 4.3).[33] Canadian postal codes have six characters. The first three characters identify the province, setting (i.e., urban or rural), and region type (i.e., city, town, or other geographic area), while the last three characters identify a city block, building, or large-volume mail receiver in urban areas, or a specific community in rural areas (185). This data allows me to identify locations with reasonable precision. In 2009, the average number of households served by a postal code in Canada was approximately 19 (186).

The fourth dataset, provided by the Alberta SPOR (Strategy for Patient Oriented Research) Support Unit (187), organizes health information from Alberta youths. SPOR has maintained digital health records since 2002 up to the present, but limitations of the mining dataset (see above) restrict my analysis to the period of 2002-2014. There were three key considerations associated with receiving data from SPOR. First, to maintain patient anonymity, data for individual healthcare demand was aggregated from daily to yearly records by SPOR. Given the time scale involved in legacy mining and the infrequency of medical events among youth, this temporal resolution is sufficient. Second, for further privacy concerns, data could not be received at the postal-code level, but rather by *clusters* of postal codes. These clusters were pre-selected, based on relative positioning of postal codes to mines and waterways, and ultimately correspond to treatment (downstream) and control (upstream) groups (an in-depth explanation of cluster formation is presented below). Finally, for practical reasons, my data request could not contain health records associated with every postal code across Alberta. Only health records associated with postal codes deemed relevant by the study design were included. The remainder of this section describes the process of identifying relevant postal codes and subsequently clustering them in a way that maintains sufficient spatial resolution.

To identify relevant postal codes, a cut-off distance between postal codes (i.e., the population-weighted centroids, or pins, described earlier) and coal mines needs to be specified. I compare various distances to find the minimum range that produces enough variation between downstream (i.e., treatment) and upstream (i.e., control) postal codes to present a reasonable

[33] As detailed within the Statistics Canada PCCF+ Reference Guide (2015), these pins represent the usual place of residence in densely populated (urban) areas, while postal codes in scarcely populated (rural) areas are assigned (via an accompanying weighted conversion file) geographic codes randomly in proportion to the distribution of population with that postal code.

counterfactual to capture potential health impacts among downstream individuals. This decision is guided not only by the conditions given to me by SPOR to limit the number of postal codes, but also prior research on the likely extent of mine pollution impacts (188). Ultimately, I find that a distance of 10 km between postal codes and mines satisfies the needs of my research. As of August 2011, there were 85,075 unique postal codes throughout Alberta. From this list, I identified 6,540 postal codes throughout central and southern Alberta as being sufficiently proximate (i.e., within 10 km) to mines to represent potential affected areas hence suitable for an empirical test of whether health outcomes are related to historical coal mining activity.

I now need to group these postal codes such that identities are cloaked, while maintaining their relative positioning for upstream/downstream identification. A series of Figures presented throughout the remainder of this section, which all feature a zoomed-in area from Figure 4.2, serve to illustrate the process taken to form clusters of postal codes, and later define their spatial relationships with coal mines. I begin with the geographic coordinates of coal mines (Mine IDs #733-741) and postal codes in relation to nearby waterways (Figure 4.3). Waterways are depicted in line segments (blue lines in Figure 4.3).[34] Starting from the first segment of a given waterway (i.e., the highest point of drainage), a new segment is created when the waterway changes direction or when it intersects with one or more other waterways. The proximities of coal mines to waterways are indicated by the shortest linear distance (black lines in Figure 4.3). Further to the discussion above, every included mine is within 5 km of a waterway. Mining sites with two ID numbers indicate that two coal mines occupied the same square-mile section at different points in time.

[34] An ArcMap stream network is comprised of raster (grid of cells) linear features, delineated from a digital elevation model (189).

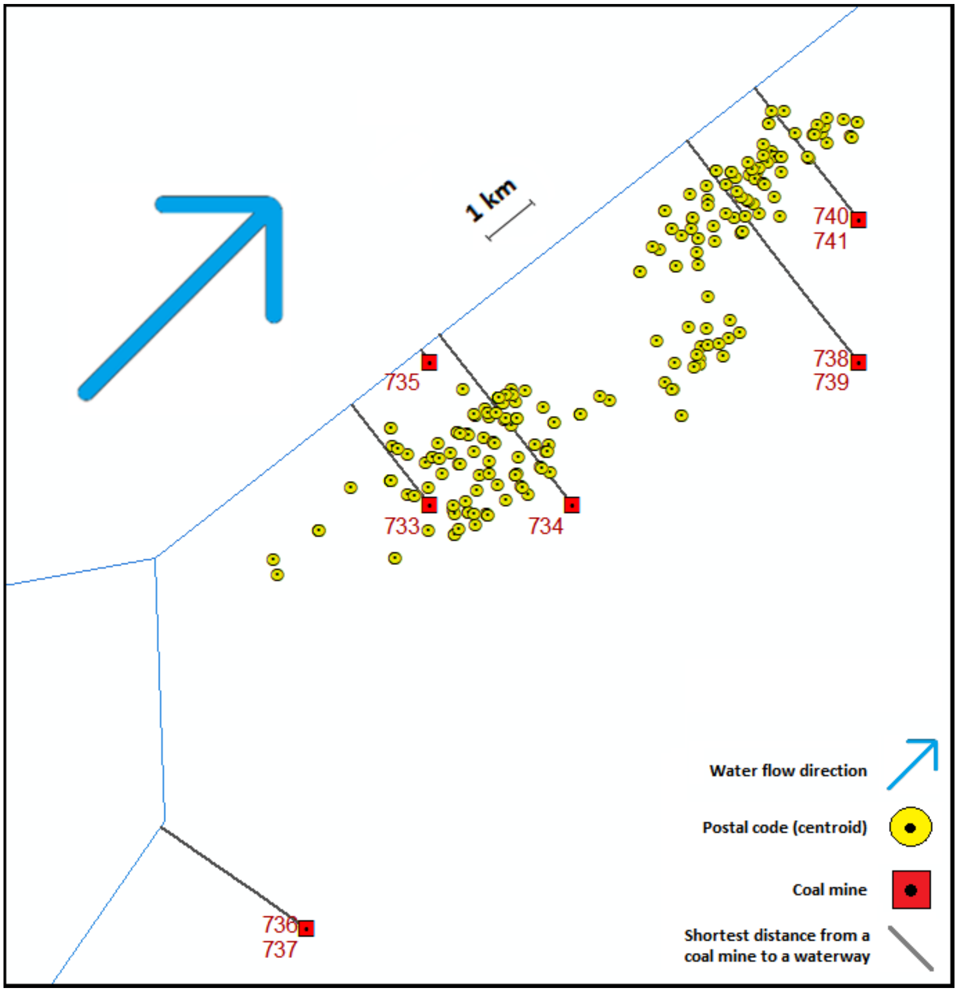

Figure 4.3 Finding the shortest linear distance of coal mines to waterways.

Next, Figure 4.4 shows how postal codes are located amongst mines according to *regions*. Regions are formed as being bounded by a waterway segment and the lines indicating distances from mines to waterways (regions #R1-R9). The extent to which these regions are depicted[35] extending away from waterways is dictated by the need to encompass existing postal codes within 10 km. Postal codes within the same region are assigned a common number, and postal codes within the same region form a *cluster.*[36] For each cluster, I aggregate postal codes into *cluster centroids,* which are established based on the weighted locations of postal codes.

[35] In Figure 4.4, these depictions of regions as polygons are for illustration purposes only and are simplified for readability. Also, while it does not appear in these figures, postal codes that fall on the opposite side of a waterway, but still within 10 km of a mine, are assigned to their own side-specific regions to increase model resolution.
[36] Note that I differentiate regions from clusters. Clusters are effectively regions with postal codes. There are many empty regions (e.g., #R7-9) across the map where no postal codes fall (i.e., people do not live everywhere).

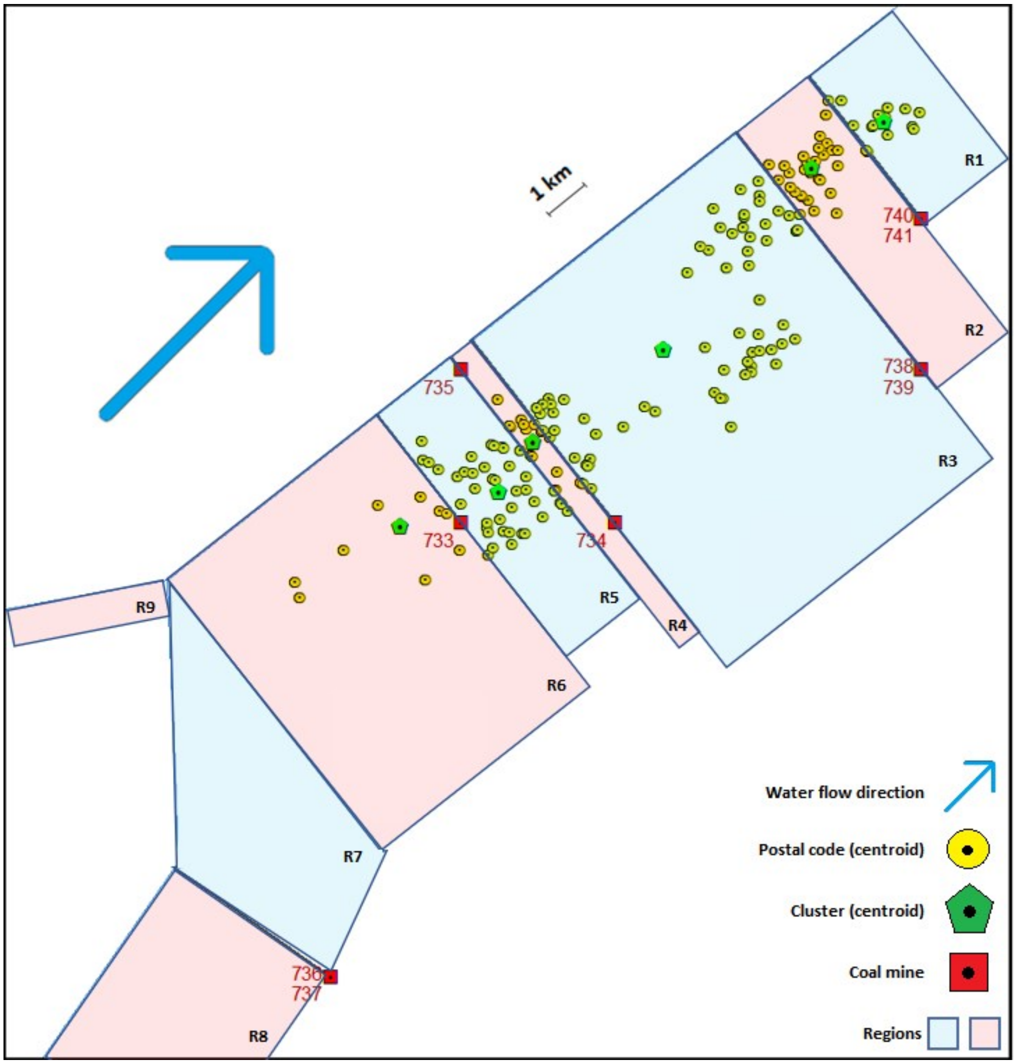

Figure 4.4 Cluster assignment of postal codes in the regions formed by i) waterway segments and ii) intersections of waterway segments with mine distance segments.

I now begin to define the relationship between a cluster and a mine as they appear in my models. While the initial criteria of up to 10 km between coal mines and postal codes was sufficient in identifying the study area, I employ a modified decision rule to better capture the role of waterways as potential conduits for pollution in my analysis. My next step is to project mines and *cluster centroids* to the closest waterway in order to establish upstream and downstream relationships. Figure 4.5 shows the nearest point of contact along a waterway for a selection of *cluster centroids* (IDs #75-80) and mines (IDs #733-741).

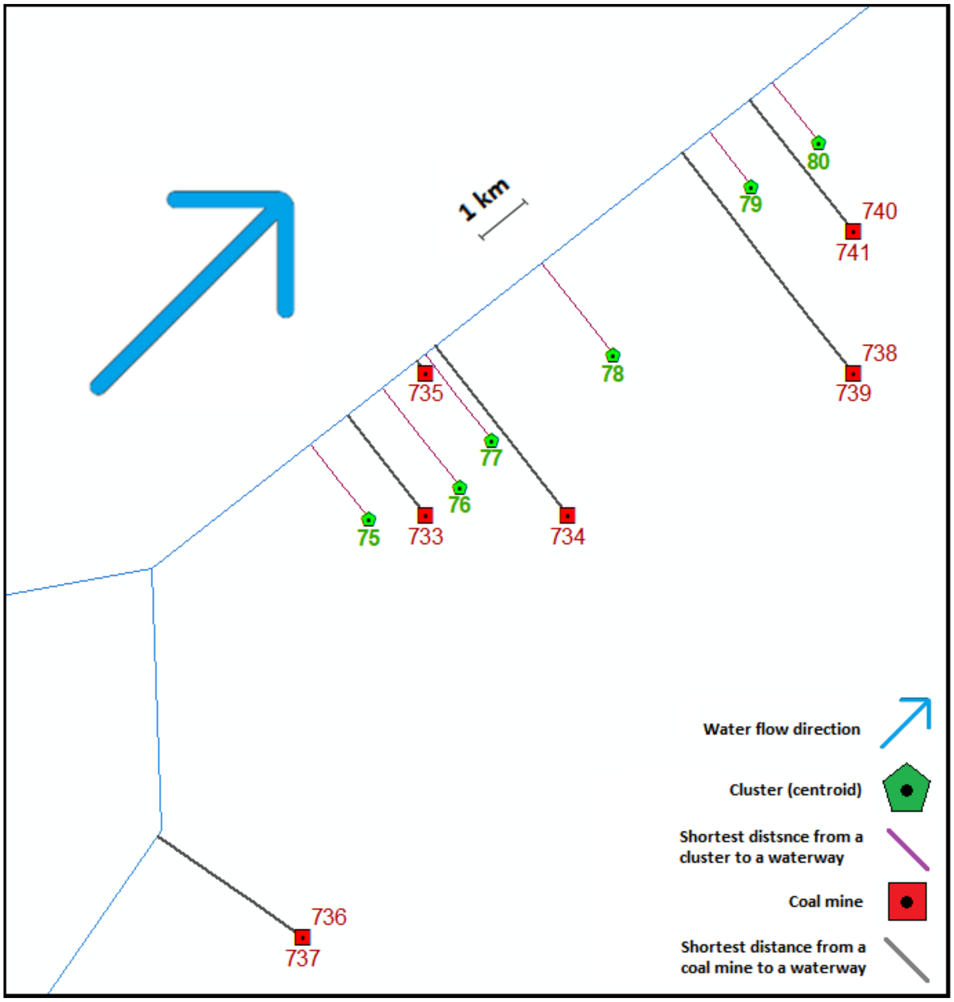

Figure 4.5 Finding the shortest linear distance of clusters and mines to waterways.

In establishing upstream and downstream relationships, there are resolution limitations in the dataset. Without a precise hydrological model around each coal mine, and only knowing a mine's location to the nearest square mile section, I cannot know the precise extent of water pollution exposure. While I do know, in a given area, the general elevation level and water flow direction, I do not know the exact path of water draining from a mine, as it may travel above or below ground based on unique watershed charactersitics (190). As a result, for each mine, I consider a gradient of potential exposure. I provide some examples in Figure 4.6, using mines #733-735. The orthogonal distance between a mine and the nearest waterway provides the first directional vector. The second directional vector follows the direction of water flow. The linear combination of these directional vectors forms a mine's expected maximum extent of water pollution, and any downstream *cluster centroid* whose own orthogonal distance to the nearest waterway crosses such an area is considered "potentially exposed" by my model. In the case of Figure 4.6, clusters #76-78 are exposed to mine #733, clusters #77-78 are exposed to mine #735, and cluster #78 is exposed to mine #734. Of course, there will be errors (e.g., it is possible that some postal codes designated as downstream may not truly be exposed due to micro-charactersitics of watersheds).[37] However, given the large scale of my investigation, errors on either side (i.e., downstream or upstream) will potentially cancel out, and be minor compared to the number of postal codes correctly assigned.

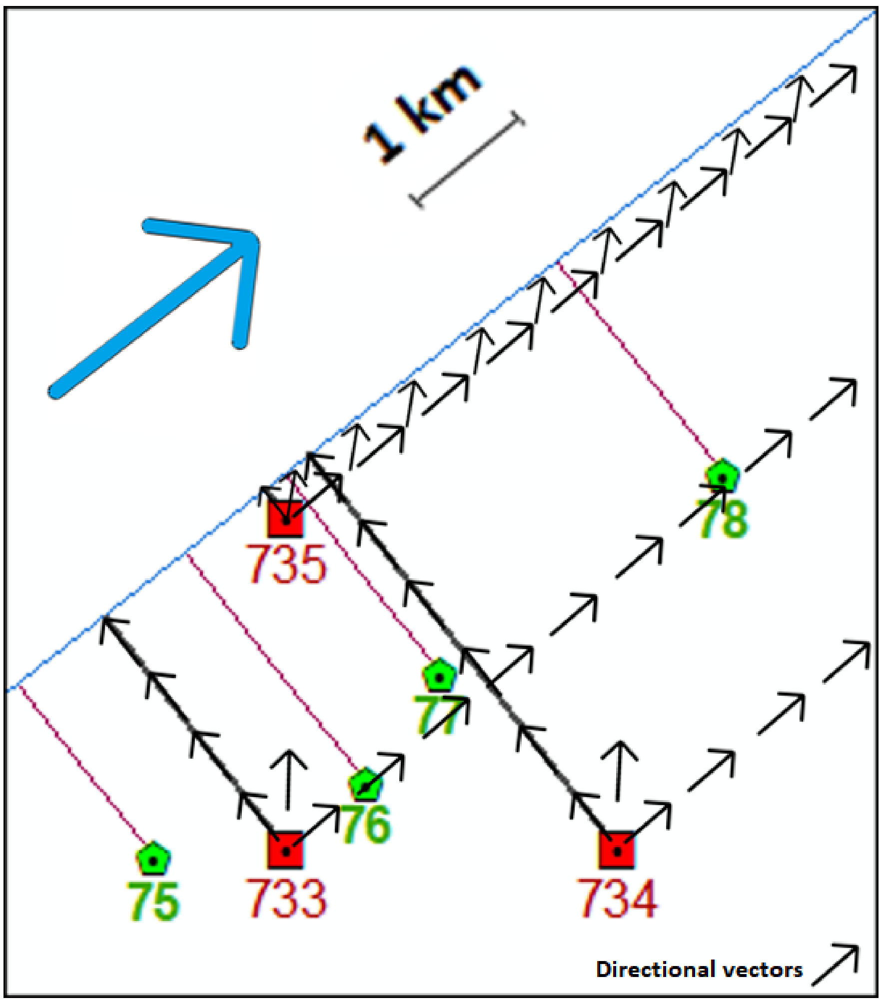

Figure 4.6 Stylized example of assumed extent of pollution impacts.

[37] Relationships are based off the assumed most likely points of contact, and interaction, between a mine (and its pollution) and youths living in the downstream clusters, and not the "closeness" to the waterway of each. For instance, youths in cluster #77 are classified as downstream from mine #735, even if the *cluster centroid* itself is "uphill" from mine #735.

In Figure 4.7, *cluster centroids* and mines are now established as *projected points* along the waterways. Given the direction of water flow, it is evident that cluster #80 is downstream from all mines in the area, while cluster #75 is only downstream from mines #736 & #737.

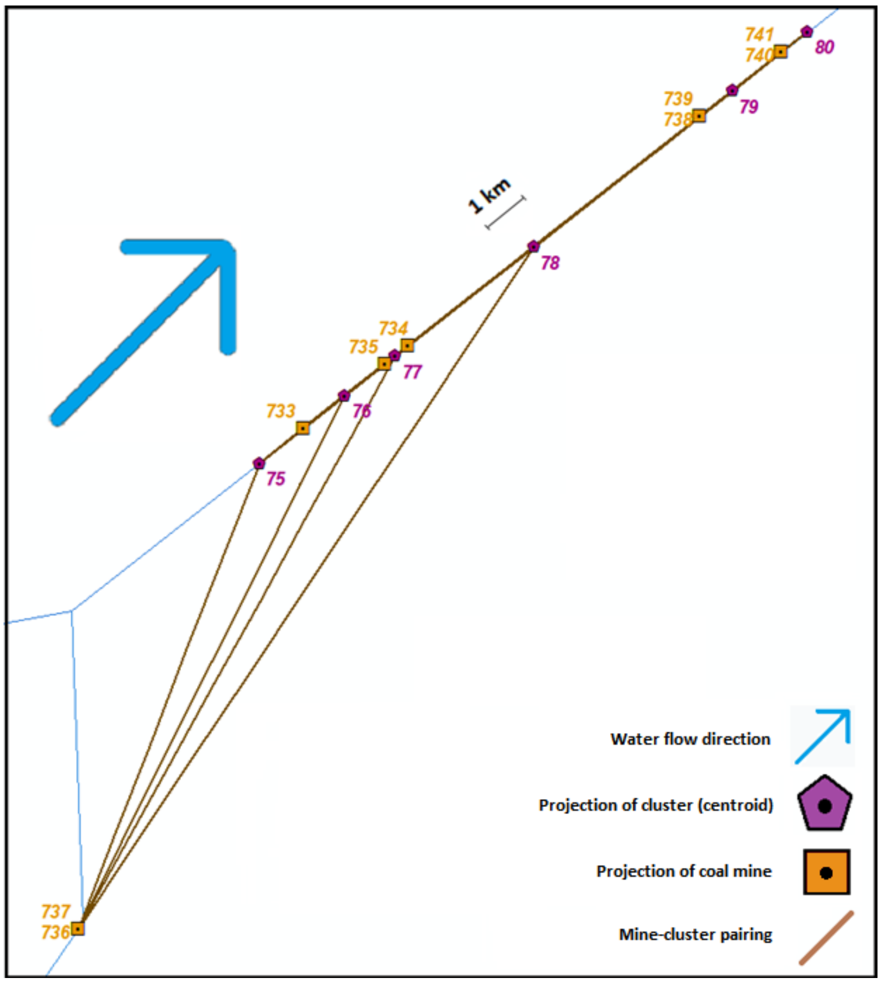

Figure 4.7 Finding the projection-based distance from each cluster to each coal mine.

The final step is to find the shortest linear distances between *projected points* of mines and *cluster centroids*. These distances, or *mine-cluster pairings*, are shown in Figure 4.7 as brown lines. Each of these pairings constitutes a unique observation for my modelling. Parings with distance greater than 10km are dropped. For example, one *mine-cluster pairing* is designated with the line from mine #736 to projected *cluster centroid* #75. Mine #736 is not paired with *cluster centroids* #79, for example, because the two points are farther than 10 km away. The *mine-cluster pairing* between mine #736 and cluster #75 is easy to see, as distances go over land because of changes in directions of waterways that cause paring distances to go over land.[38] However, there are also mine cluster pairings that are exclusively along waterways. These pairings are difficult to see because the lines overlap along waterways. I illustrate these relationships in Figure 4.8, using curved visual connections to avoid line overlaps. Figure 4.8 explicitly shows cluster #78's upstream and downstream relationships with nearby coal mines. Cluster #78 is downstream (i.e., treated observations, coloured red) from five mines (#733-737) and upstream (i.e., control group observations, coloured green) from four mines (#738-741).

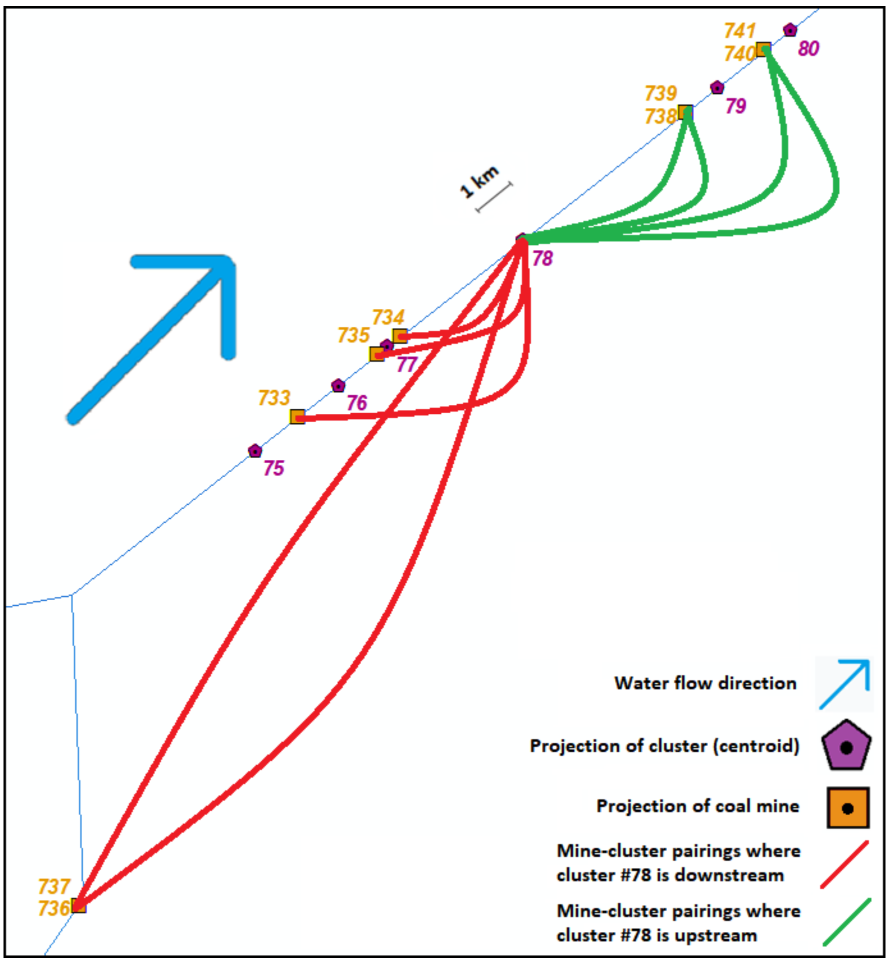

Figure 4.8 Stylized example of upstream and downstream mine-cluster pairings, using cluster #78.

[38] An alternative approach would be to restrict parings to be along waterways. The approach taken here avoids dropping a significant number of observations that would be farther away than 10 km if waterway distances were followed.

The approach in Figure 4.8 is the variation I use to estimate my models. For a given cluster entering the model, I construct i) a measure of health care demand (dependent variable), and ii) an indicator of being upstream or downstream from a specific coal mine (treatment indicator). In a given year, an observation will represent a mine-cluster pairing. Note that clusters and mines can and do enter the model multiple times. When a cluster has multiple nearby coal mines (up and/or down), then the cluster will participate in multiple observation pairings. Similarly, a mine may also enter the model in multiple pairings. This approach captures varying levels of potential exposure as clusters that are downstream from multiple mines enter the model through multiple observations.

4.3) Summary Statistics

Table 4.1 describes the mines in my sample. In total, I identified 749 historical sites of mining operations which which are sufficiently close to both waterways and residences of rural Alberta youth. Of these mines, the mean first year of operation is 1927.3, ranging from 1886 to 1993. The mean last (observed) year of operation is 1934, ranging from 1889 to 2014. The mean distance from a mine to a cluster, with a maximum allowed distance of 10 km, is about 4.5 km. I also observe that 58% of mines are upstream from clusters, placing just over half of the clusters in the treatment group.

Table 4.1 Summary statistics of mines, historical. N=749*

	Mean	St. Dev.	Min	Max
Mine characteristics				
Year the mine opened	1927.3	18.21	1886	1993
Year the mine operated to	1934.5	19.17	1889	2014
Mine-cluster relationships				
Distance* from mine to cluster (m)	4,532.2	2,881.9	0.0	9,992.4
Upstream from cluster (%)	0.58	0.49	0	1

*There are 749 unique mines in the model, whose locations are known to a resolution of one square mile. Distance statistics are based off of 2,358 unique mine-cluster relationships. A distance of 0.0 km indicates that the mine and the cluster fall within the same square mile. Distance is based off the relationship between *projected points* of mines and *cluster centroids*.

I measure the demand for health care as yearly averages per cluster across three separate indicators: 1) doctor visits[39], 2) emergency department (ED) visits[40], and 3) inpatient days[41] (187). After sorting youths into their respective clusters, I obtain the summary statistics found in Table 4.2. With 196 clusters over time, 2,368 observations result. For each cluster, mean yearly doctor visits, emergency department visits, and inpatient days are 2.73, 0.9, and 1.36, respectively. The mean age of youths is 3.6 years.

Table 4.2 Summary statistics of clusters of youths, 2002-2014. N=2,368*

	Mean	St. Dev.
Dependent Variables		
Doctor visits	2.73	1.52
ED visits	0.90	0.60
Inpatient days	1.36	2.03
Youth patient controls		
Female	0.48	0.16
Age	3.62	1.74

*While 13 years and 196 clusters would impute a total of 2,548 observations, I cannot observe a cluster until the first year at least one youth is born. This results in N=2,368 observations of cluster-years.

4.4) Model

My analysis tests whether there are observable differences in healthcare demand between two similar cohorts, with cohorts specifically referring to downstream/upstrem portions of the rural Alberta youth population living near waterway-proximate mining sites. By considering a small radius around each mine that captures both treatment (downstream) and control (upstream) cohorts, I expect profiles of neighbourhoods and residents alike to, on average, be similar between treatment and control. Moreover, I expect the decision for residents to reside upstream or downstream from a historical mining site to be orthogonal to both observable and unobservable determinants of health care demand. Together, this research design allows for the

[39] Also referred to as (general) physician, (general) practitioner, or office visits across health literature (191, 192, 193). This data comes from SPOR's Practitioner Claims dataset, with a new observation generated whenever a health service provider submits a claim for payment (after seeing a patient) under the Alberta Health Care Insurance Plan.
[40] Also referred to as emergency room, or ER, visits. This data comes from SPOR's National Ambulatory Care Reporting System (NACRS) dataset, with a new observation generated whenever a patient visits an emergency department in Alberta.
[41] This data comes from SPOR's Discharge Abstract Database (DAD), with a new observation generated whenever a patient's stay is longer than a day (i.e., overnight) at any Alberta hospital.

comparison of cohorts with similar characteristics and an exogenous source of variation (i.e., water flow direction), constituting a natural experiment. If mining indeed has a negative impact, I should see differences in the health outcomes of upstream versus downstream cohorts. Adverse health impacts experienced by individuals throughout a cohort, manifested in specific conditions or diseases (194), can be aggregated into more general measures of healthcare demand; i.e. doctor visits, emergency department visits, and inpatient days. For two similar cohorts living in the same area (e.g. rural Alberta youth), which differ significantly only by their relative position along a waterway, observable differences in the aggregate level of healthcare demanded as measured by any or all three of these measures may imply that the downstream cohort is being negatively impacted by something the upstream cohort is not exposed to; in my analysis, polluted water from coal mining.

Employing a fixed effects approach, the first empirical model is:

$$Y_{ijt} = \beta + \alpha M_{ij} + \lambda_j + \mu_t + \epsilon_{ijt} \quad (1)$$

where *Y* denotes one of three measures of average health care demand (i.e., doctor visits, emergency department visits, or inpatient days) for youths in the *mine-cluster pairing ij* (with *i* for cluster and *j* for mine*)* at year *t*. If mining pollutants are contaminating the water, I expect water contamination downstream to be higher than upstream, ceteris paribus. I therefore establish a binary indicator denoted *M* (i.e., a downstream exposure variable), which indicates whether the *mine-cluster pairing ij* is located upstream (=0) or downstream (=1) from a mining site. The value of coefficient α on *M* represents the association between being downstream from mining activity and average health care demand, i.e., while β captures the average health outcome *Y* of the upstream cohort, $\beta + \alpha$ captures the average health outcome *Y* of the downstream cohort. The terms λ and μ represent fixed effects of coal mines and clusters of youths, respectively. Fixed mine effects λ capture the effects (on health) of time-constant characteristics of the mine; for instance, thickness of coal seam mined (in metres), and whether a mine is above or below ground. Similarly, the parameter μ captures unobservable, time-specific determinants of the health outcome *Y*. The term ϵ is a random error representing idiosyncratic aspects of health.

I also estimate another specification that controls for youth observables, namely sex and age:

$$Y_{ijt} = \beta + \alpha M_{ij} + F_{ijt} + A_{ijt} + A_{ijt}^2 + A_{ijt}^3 + \lambda_j + \mu_t + \epsilon_{ijt} \quad (2)$$

where F and A are the proportion of female youths and the average age of youths in cluster i, respectively.

4.5) Results & Discussion

4.5.1) Main findings

Table 4.3 presents my main findings from model (1), estimated with three dependent variables (i.e., doctor visits, emergency department visits, and inpatient days). Overall, I find evidence of historical coal mining activity negatively associated with health. While youths in upstream clusters make an average of 2.4 doctor visits per year, downstream youths make, approximately, an additional 0.09 trips per year (p<0.01), or a 3.75% increase.[42] I also find statistically significant results for inpatient days. While upstream youths spent an average of 1.25 inpatient days per year, downstream youths spent about 0.23 days more (p<0.01), or an 18.4% increase. The downstream coefficient is also positive for the ED visits model, albeit close to zero and not statistically significant.

Table 4.3 Model (1) estimates

Dep. Var.	Doctor visits	ED visits	Inpatient days
Downstream	0.0887***	0.0083	0.2309***
	(0.0292)	(0.0122)	(0.0291)
Constant	2.3989***	0.9619***	1.2500***
	(0.0172)	(0.0072)	(0.0171)
Observations	29,542	29,542	29,542
R-squared	0.4278	0.4613	0.3054

Notes: All models include mine and year fixed effects.
Mine-clustered standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4.4 shows the results of models that add controls for average age and gender per cluster (model 2). Results are similar to those reported in Table 4.3. I observe significant

[42] The baseline number of doctor visits in my analysis (2.4) is corroborated by another study, which found that children under 18 made 233 visits per 100 population (2.33) in 2012 (195).

downstream coefficients in two models, i.e., increased health care demand in the form of doctor visits and inpatient days, but not emergency department visits. The effect of age varies across outcomes. From ages 0 to 7.5, doctor visits decrease with age, and increase from 7.5 to 13; emergency department visits initially decrease with age, then begin to increase around 8.8 years old; and inpatient days decrease with age. As for sex, male youths make more emergency department visits and have more inpatient days. These age and sex effects are corroborated by a report of youth doctor visits in the US (195) and a study of hospital admissions of youths in Korea (196).

Table 4.4 Model (2) estimates

Dep. Var.	Doctor visits	ED visits	Inpatient days
Downstream	0.0770***	0.0052	0.2139***
	(0.0286)	(0.0124)	(0.0289)
Female	0.6935***	-0.1484***	-0.6100***
	(0.0908)	(0.0218)	(0.1084)
Age	-0.3829***	0.0386	-2.8125***
	(0.1188)	(0.0412)	(0.1734)
Age^2	0.0106	-0.0238***	0.3860***
	(0.0200)	(0.0071)	(0.0325)
Age^3	0.0014	0.0017***	-0.0176***
	(0.0012)	(0.0004)	(0.0021)
Constant	3.1721***	1.368***	6.9479***
	(0.2000)	(0.0687)	(0.3064)
Observations	29,542	29,542	29,542
R-squared	0.4417	0.4668	0.3550

Notes: All models include mine and year fixed effects.
Mine-clustered standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.5.2) Evidence from Matching

As a robustness check, I compare the previous results to those obtained from two types of nearest neighbour matching (NNM) analyses. In both cases, each treated cluster is matched to the nearest neighbour cluster in the control group. The associations between mining and health outcomes are obtained by computing the average difference in outcomes of control (upstream) and treatment (downstream) groups. The matching is based on age and sex (197). The first type of matching

(Table 4.5) uses the Mahalanobis[43] distance to find the closest control cluster to each treated cluster, and vice-versa, which maintains the highest number of observations (198). The second type of NNM (Table 4.6) requires exact matching on the mine and, as such, it is more restrictive (199). In my case, this approach reduces observations from 29,542 to 14,634. But while fewer observations may reduce statistical power, the restrictive assumptions may improve precision of the estimates by comparing groups that are more similar (200).

Table 4.5 NNM estimates

Dep. Var.	Doctor visits	ED visits	Inpatient days
Downstream	0.1104***	0.0038	0.0433***
	(0.0113)	(0.0045)	(0.0107)
Observations	29,542	29,542	29,542

Notes: estimating treatment effects from observational data by nearest-neighbour matching. Mine-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In both matching models, the coefficient on doctor visits increases, from 0.09 (Table 4.3) to 0.11 (Table 4.5) with NNM and 0.13 (Table 4.6) with exact matching. In contrast, the coefficient on inpatient days decreases with matching, from 0.21 to 0.04, but increases with exact matching to 0.26. Estimates all remain significant at the 1% level. Perhaps most interesting, however, is that, unlike the other estimations, exact matching (Table 4.6) suggests a small yet significant (5% level) coefficient on emergency department visits, with downstream clusters going 0.017 more times per year on average. Moreover, I expect my estimates to be a lower bound due to limitations of only observing youths at the cluster level, and only as long as they stay within the clusters. Exact matching results suggest that mining pollution may indeed be associated with emergency department demand, but at a level that requires greater resolution than my study design permits.

[43] Matching weights are based on the inverse of the covariates' variance-covariance matrix.

Table 4.6 NNM estimates with exact matching

Dep. Var.	Doctor visits	ED visits	Inpatient days
Downstream	0.1277***	0.0169**	0.2644***
	(0.0231)	(0.0084)	(0.0339)
Observations	14,634	14,634	14,634

Notes: estimating treatment effects from observational data by nearest-neighbour exact matching. Mine-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.5.3) Health Care Demand Heterogeneity by Temporal Mine Characterstics

I also explore how legacy associations between mining and health care demand vary when only including subsamples of mines in model (1) by i) their most recent period of operation, and ii) the total number of years in which they operated. Though this approach reduces the number of observations, it allows me to investigate the hypothesis of whether mines operating closer to the present day, and mines operating for longer periods of time, have greater potential for adverse effects on human health.

Figure 4.9 displays results from 10 subsamples based on the most recent period of operation. These operation periods were chosen by working backwards from the first year of health data (2002). As one decade earlier (1992) did not provide a large enough sample, 1982 is the first period, followed by each subsequent decade until the first mining record of 1886.[44] Observations drastically increase towards the earliest operating year (from 575 in 1982 to 29,542 in 1886), illustrating the proliferation of mining in the past and its consolidation over time. While the coefficient on inpatient days remains relatively constant over time, it appears that the coefficient on doctor visits increases as older mines are removed from the sample. Furthermore, there is evidence of a small yet statistically significant association between mining and emergency department visits, which becomes larger and more significant alongside the coefficient on doctor visits.

[44] As the difference in the number of mines operating between 1886 and 1892 is insignificant, I omit 1892.

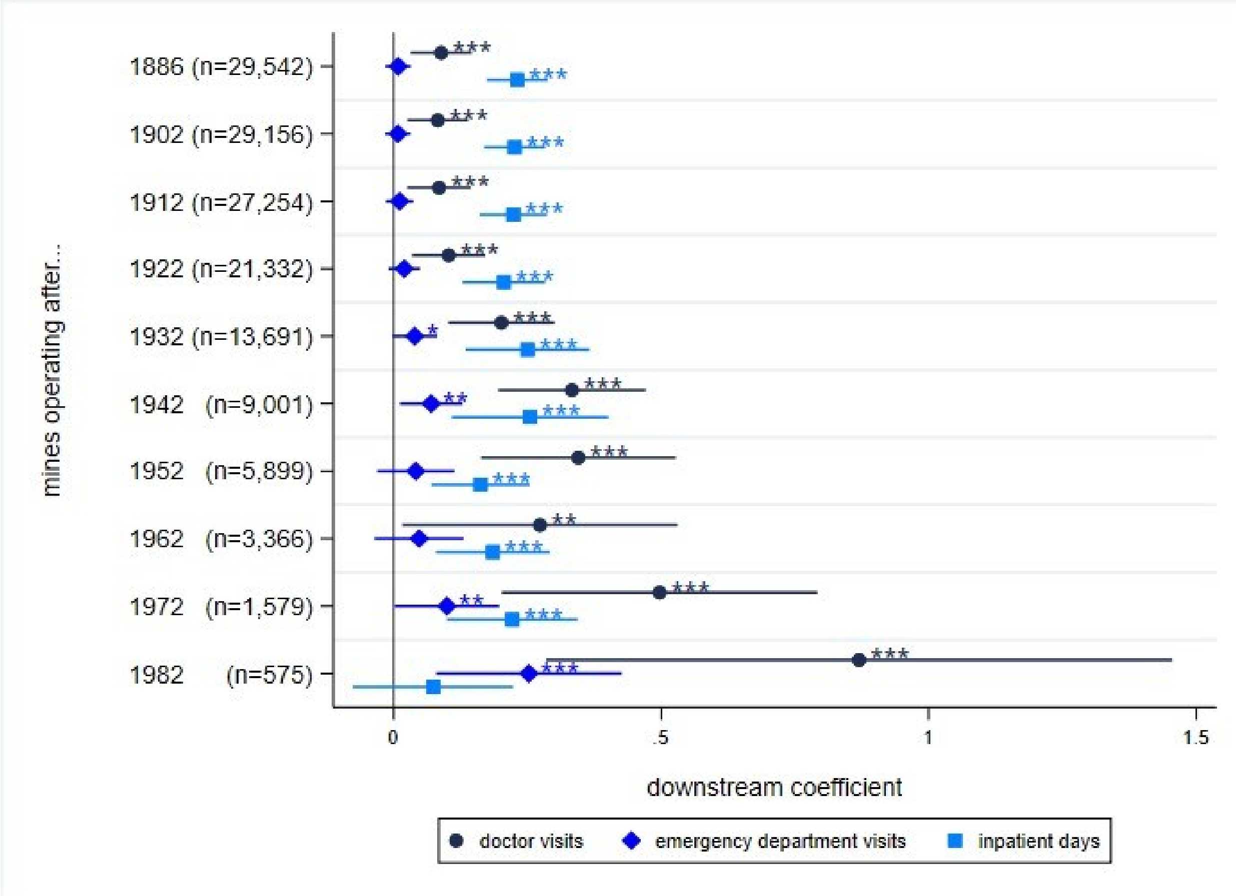

Figure 4.9 Downstream coefficient, by most recent year of mining operations.

In my second evaluation of heterogeneity (Figure 4.10), I consider 12 subsamples based on duration of mining operations, regardless of opening and closing years. These durations range from at least one year to at least 50 years, with most mines having a duration under five years. The coefficients on emergency department visits are insignificant in all cases, while the coefficients on doctor visits and inpatient days are conflicting. As the minimum number of years operating increases, the coefficient on inpatient days decreases, albeit slightly, while the coefficient on doctor visits increases. Significant associations observed at the upper end of operating years (as well as the most recent decade in Figure 4.9) must be evaluated with caution given the limited sample size and larger confidence intervals. However, as the overall pattern of associations remain relatively stable, I believe the results from Figures 4.9 and 4.10 corroborate my main findings.

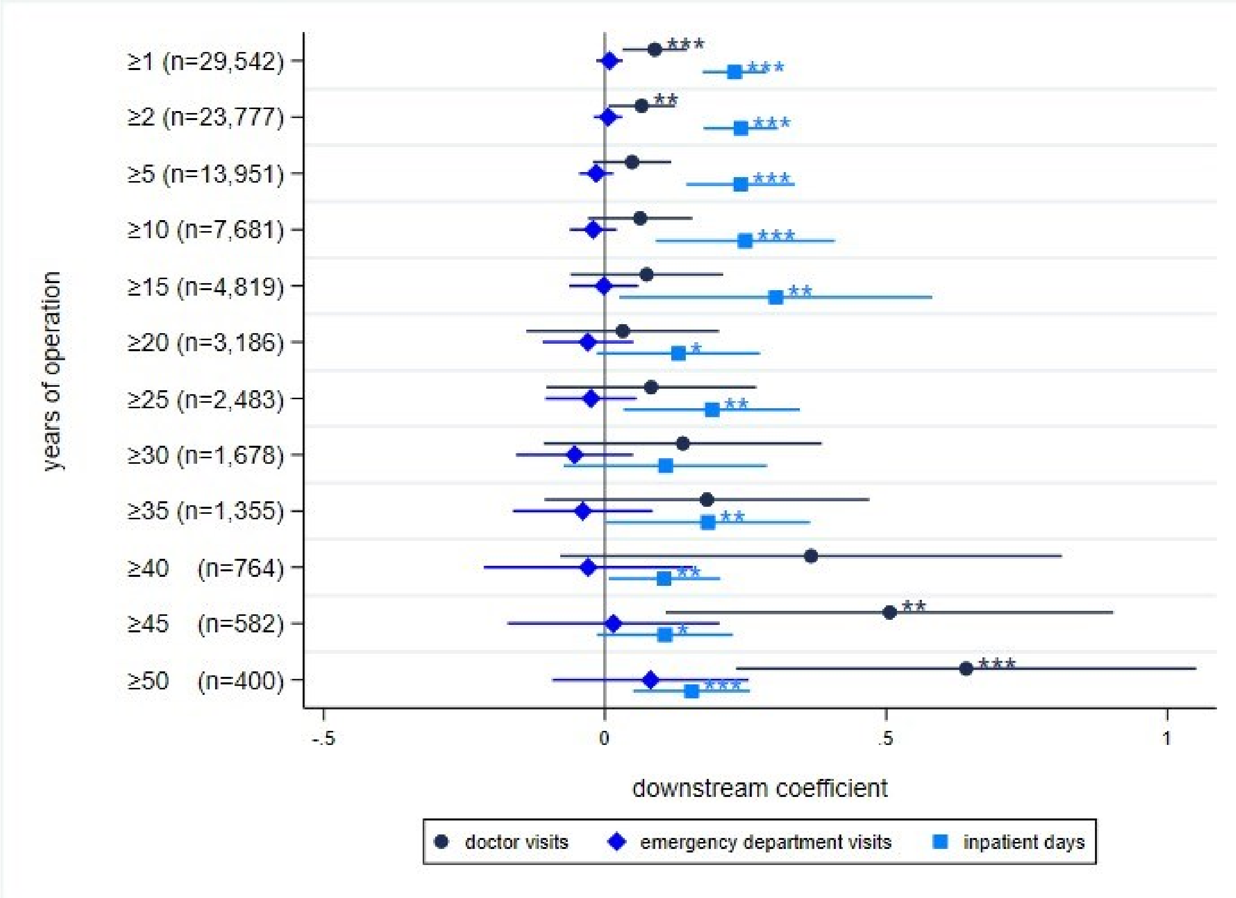

Figure 4.10 Downstream coefficient, by duration of mining operations.

4.6) Conclusions

My analysis suggests health care demand levels are higher for individuals living downstream from legacy coal mining activity, compared to their upstream counterparts. By restricting my sample of individuals to youths (aged 13 and under) born in (and remaining in) the study area during the time window (2002-2014), I avoid potential comparison biases from unknown levels of previous exposures to pollution. Over the entire sample, the yearly average number of doctor visits and inpatient days are higher for downstream youths by 3.75% and 16.8%, respectively. As this study focused on predominantly rural areas, these results lead me to advise for further water quality testing in rural Alberta. I also explore heterogeneity within the sample of coal mines and find statistically significant associations between mining and yearly average emergency department visits when restricting the sample to mines operating closer to the present day. This seems to imply that, compared to past mines, living downstream from contemporary mines may pose greater potential for health impacts. A future analysis consisting of a contemporary mines-only sample may be warranted, with a revised empirical strategy to capture more of these mines in relation to waterways.

To attain these results, I make use of empirical methods based on a natural experiment to spatially sort youths into clusters relative to their positions near coal mines and waterways. Despite these strengths in my analysis, a number of limitations arise. There are spatial limitations of my data due to the resolution of coordinates of both coal mines and population density-weighted rural postal codes; design limitations to protect anonymity (i.e., clusters of youths), and assumptions necessary to designate clusters as downstream or upstream based on elevation, water flow direction, and likely points of contact along waterways. Moreover, due to time constraints and the overall scope of my study, I elect to use general indicators of health demand rather than conditions or diseases which may be linked to specific heavy metals found in water pollution. If I can obtain this health data in future, an extension in this disease specific direction may be possible. However, the fact that significant associations were found with more-general health demand indicators suggest the possibility of negative pollution or AMD effects.

The results suggest that the associated health care costs due to pollution can be surprisingly high. For instance, Alberta doctor visits cost between $41-59 in 2020 (201), while the average hospital stay (0.99 inpatient days) was estimated to cost about $9,172 between 2021-2022 (202). Using the estimates from Table 4.3, each youth living downstream from a mine costs the province (annually) an additional $3.28 in doctor visits and $2,100 in inpatient days. With a mean of 232 youths per cluster, and 165 downstream clusters, these values amount to annual health care costs of $125,558 and $80,388,000, respectively. I acknowledge that this back-of – the-envelope calculation is a simplistic approach and that the cost of supplying health services is only one component of the total cost of pollution.

The cost of water pollution is multifaceted (e.g., environmental, health), with impacts that may be more widespread than initially expected, both temporally and spatially. While this research largely concerned coal mines from the past, the present day and future impacts of coal mining in are also being heavily discussed. Water quality concerns surrounding a possible expansion of an active Alberta coal mine were raised at the 27^{th} annual United Nations climate conference near the end of 2022 (203). The scope of water pollution from Alberta coal mines is not limited to the province, either, as drainage from the eastern slopes of the Rocky Mountains, an area of significant mining activity, also reaches the eastern Prairie Provinces of Saskatchewan and Manitoba (204). Certainly, water pollution mitigation efforts are in the best interest of current and future generations alike, both in the immediate vicinity and beyond.

Chapter 5 Conclusion

The three studies comprising my thesis, while each distinct, share a common goal of illuminating pollution-related externalities of resource development on local populations. They also share several traits, including a focus on younger cohorts, identification strategies rooted in spatial analysis, and utilizing non-survey data from government or government-adjacent sources. Focusing on these traits help identify causal effects in my models in a number of ways. First, as discussed throughout, youths (e.g., infants or children) are expected to be more sensitive to pollution impacts (e.g., birthweight, test scores, doctor visits) than the general population, and these impacts may have further ramifications to future health and earnings outcomes. Second, I identify samples based on proximity (e.g., of place of birth, school, or postal code) to resource sites, avoiding potential selection biases that may arise from other sampling techniques. Third, as I use secondary data from reputable sources (e.g., number of doctor visits recorded by the health provider), concerns of self-reporting errors (e.g., a survey relying on a patient's memory of the number of doctor visits) are eliminated.

In the first study (Chapter 2), I find negative effects of illegal gold mining on birthweights in municipalities of the Brazilian Amazon, specifically for indigenous infants. Moreover, the impacts are heterogeneous, with illegal mining disproportionately impacts births to single (versus married) indigenous mothers, lowering birthweight and increasing both premature and low Apgar score incidence within the subgroup. Births to young or lower educated indigenous mothers, or those living in municipalities with reserves, are also more likely to be underweight due to illegal mining. Indigenous births in municipalities with no reserves are less likely to be premature or exhibit low Apgar score. I do not find similar effects with respect to legal gold mining, suggesting that regulating the mining industry seems to work in terms of reducing health risks.

In the second study (Chapter 3), I find evidence of a causal relationship between the presence of nearby (i.e., within 4 km) oil wells and lower test scores in math and science in Alberta. Moreover, I identified significant variation in impacts by well life cycle stage.

Abandoned wells are, on average, the most harmful individually, followed by *Active* and *Suspended*. However, when considering the mean number of each type of nearby well, *Active* wells overall have the greatest impact on mean test scores. *Reclaimed* wells, however, do not have a significant impact. Additionally, when I alter the sample size by excluding schools in cities with larger populations, I find that while the marginal effect per well decreases in more-rural samples, the corresponding total effect increases, given a relatively higher mean number of nearby wells in more-rural samples.

In the third study (Chapter 4), I find higher health care demand levels for individuals living downstream from legacy coal mining activity, compared to their upstream counterparts. By restricting my sample of individuals to youths born in the study area during the time window, I avoid potential biases from unknown levels of previous exposures to pollution. Over the entire sample, the yearly average number of doctor visits and inpatient days are higher for downstream youths. I also explore heterogeneity within the sample of coal mines and find significant effects on yearly average emergency department visits when restricting the sample to mines operating closer to the present day.

All else equal, the findings of each study may seem to imply that stricter regulations or enhanced clean-up efforts would be advised to improve social well-being. For instance, cleaning up the substantial number of old oil wells across Alberta may improve student outcomes today, which, in turn, may subsequently result in higher productivity and earnings as adults in the future. But do these future earnings outweigh the cost of well clean-up? Moreover, the impacts (or conversely, the benefits of addressing a problem) can vary widely between population subgroups, as in the case of illegal gold mining and indigenous communities in the Brazilian Amazon. My hope is that these findings can assist policymakers who are in charge of making these cost-benefit decisions. Even as societies gradually move toward cleaner energy sources such as wind and solar, I believe it is important to remain cognisant of the potential legacy effects of past and present non-renewable resource extraction.

References

Chapter 2 references

1. B. L. Perry, B. Aronson, B. A. Pescosolido, Pandemic precarity: COVID-19 is exposing and exacerbating inequalities in the American heartland. *Proc. Natl. Acad. Sci.* 118, 1–6 (2021).
2. J. Currie, Health disparities and gaps in school readiness. *Futur. Child.* 15, 117–138 (2005).
3. R. O'Brien, T. Neman, N. Seltzer, L. Evans, A. Venkataramani, Structural racism, economic opportunity and racial health disparities: Evidence from U.S. counties. SSM - Popul. Heal. 11, 1–6 (2020).
4. M. W. Kraus, J. M. Rucker, J. A. Richeson, Americans misperceive racial economic equality. Proc. Natl. Acad. Sci. U. S. A. 114, 10324–10331 (2017).
5. Z. Obermeyer, B. Powers, C. Vogeli, S. Mullainathan, Dissecting racial bias in an algorithm used to manage the health of populations. Science. 366, 447–453 (2019).
6. A. Young, Inequality, the urban-rural gap, and migration. *Q. J. Econ.* 128, 1727–1786 (2013).
7. A. E. Nigra, Environmental racism and the need for private well protections. *Proc. Natl. Acad. Sci. U. S. A.* 117, 17476–17478 (2020).
8. R. V. Santos, G. M. Borges, M. B. de Campos, L. Queiroz, C. E. A. Coimbra Jr., J. R. Welch, Indigenous children and adolescent mortality inequity in Brazil: What can I learn from the 2010 National Demographic Census? *SSM - Popul. Heal.* 10, 100537 (2020).
9. S. V Kildea, Y. Gao, M. Rolfe, J. Boyle, S. Tracy, L. M. Barclay, Risk factors for preterm, low birthweight and small for gestational age births among Aboriginal women from remote communities in Northern Australia. *Women and Birth*. 30, 398–405 (2017).
10. C. O'Callaghan-gordo, J. A. Flores, P. Lizárraga, T. Okamoto, D. M. Papoulias, F. Barclay, M. Orta-martínez, M. Kogevinas, J. Astete, Oil extraction in the Amazon basin and exposure to metals in indigenous populations. *Environ. Res.* 162, 226–230 (2018).
11. Thomas Hentschel, F. Hruschka, M. Priester, The Mining, Minerals and Sustainable Development (MMSD) Project: Global Report on Artisanal & Small-Scale Mining. *Int. Inst. Environ. Dev.* (2002)

12. B. F. M. Aragón, J. P. Rud, Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine. Am. Econ. Assoc. 5, 1–25 (2013).
13. R. Muggah, "Brazil's illegal gold rush is fueling corruption, violent crime and deforestation." News.mongabay.com (Jan. 14, 2022). https://news.mongabay.com/2022/01/brazils-illegal-gold-rush-is-fueling-corruption-violent-crime-and-deforestation/
14. G. P. Asner, W. Llactayo, R. Tupayachi, E. R. Luna, Elevated rates of gold mining in the Amazon revealed through high-resolution monitoring. Proc. Natl. Acad. Sci. U. S. A. 110, 18454–18459 (2013).
15. S. Scarr, A. Boadle, "Amazon gold rush: illegal mining threatens Brazil's last major isolated tribe." Retuers.com (June 25, 2020). https://www.reuters.com/article/us-brazil-indigenous-mining-insight-idUSKBN23W2W0
16. IWGIA, "Brazil." Iwgia.org (last accessed Feb. 2023). https://www.iwgia.org/en/brazil.html
17. R. Fuge, N. J. G. Pearce, W. T. Perkins, Mercury and gold pollution. Nature. 357, 369 (1992).
18. A. Hoppe, Mining in the Amazonian rainforests. Nature. 355, 593–594 (1992).
19. P. J. T. Leonard, Mercury in Brazil. Nature. 369, 613–614 (1994).
20. M. Balzino, J. Seccatore, T. Marin, G. De Tomi, M. M. Veiga, Gold losses and mercury recovery in artisanal gold mining on the Madeira River, Brazil. *J. Clean. Prod.* 102, 370–377 (2015).
21. M. H. D. Pestana, M. L. L. Formoso, Mercury contamination in Lavras do Sul, south Brazil: a legacy from past and recent gold mining. *Sci. Total Environ.* 307, 125–140 (2003).
22. Bussalleu, A., Di-Liberto, A., Carcamo, C., Carrasco-Escobar, G., Zavaleta-Cortijo, C., King, M., Berrang-Ford, L., Maurtua, D., Llanos-Cuentas, A., Garcia, P., Harper, S. L., Edge, V., Ford, J., Lwasa, S., & Namanya, D. B. (2020). Cultural Values and the Coliform Bacterial Load of "Masato," an Amazon Indigenous Beverage. *EcoHealth*, *17*(3), 370–380. https://doi.org/10.1007/s10393-020-01498-5
23. W. Akpalu, A. K. Normanyo, Gold Mining Pollution and the Cost of Private Healthcare: The Case of Ghana. *Ecol. Econ.* 142, 104–112 (2017).
24. F. M. Aragón, J. P. Rud, Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana. *Econ. J.* 126, 1980–2011 (2016)

25. Gyamfi, P. B. Sorenson, G. Darko, E. Ansah, J. L. Bak, Human health risk assessment of exposure to indoor mercury vapour in a Ghanaian artisanal small-scale gold mining community. *Chemosphere*. 241 (2020), doi:10.1016/j.chemosphere.2019.125014.
26. S. V. Rozo, Unintended effects of illegal economic activities: Illegal gold mining and malaria. *World Dev.* 136, 105119 (2020).
27. J. Currie, Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. *J. Econ. Lit.*, 87–122 (2009).
28. F. Campbell, G. Conti, J. J. Heckman, S. H. Moon, R. Pinto, E. Pungello, Y. Pan, Early childhood investments substantially boost adult health. Science 343, 1478–1485 (2014).
29. S. E. Black, P. J. Devereux, K. G. Salvanes, From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes. Q. J. Econ. 122, 409–439 (2007).
30. da Silva Júnior, F. M. R., Tavella, R. A., Fernandes, C. L. F., Soares, M. C. F., de Almeida, K. A., Garcia, E. M., da Silva Pinto, E. A., & Baisch, A. L. M. (2018). Genotoxicity in Brazilian coal miners and its associated factors. *Human and Experimental Toxicology*, *37*(9), 891–900. https://doi.org/10.1177/0960327117745692
31. Souza, T. P., van Tongeren, M., & Monteiro, I. (2021). Respiratory health and silicosis in artisanal mine workers in southern Brazil. *American Journal of Industrial Medicine*, *64*(6), 511–518. https://doi.org/10.1002/ajim.23242
32. Santos, A. P. R., Silva, L. Z., Freire, B. M., da Silva Faria, M. C., Batista, B. L., Rocha, B. A., Barbosa, F., & Rodrigues, J. L. (2023). Artisanal Gem Mining in Brazil: A Source of Genotoxicity and Exposure to Toxic Elements. *International Journal of Environmental Research and Public Health*, *20*(3). https://doi.org/10.3390/ijerph20032510
33. S. Bose-O'Reilly, B. Lettmeier, R. Matteucci Gothe, C. Beinhoff, U. Siebert, G. Drasch, Mercury as a serious health hazard for children in gold mining areas. Environ. Res. 107, 89–97 (2008).
34. P. Grandjean, R. F. White, A. Nielsen, D. Cleary, E. C. De Oliveira Santos, Methylmercury neurotoxicity in Amazonian children downstream from gold mining. Environ. Health Perspect. 107, 587–591 (1999).
35. C. I. R. Froes Asmus, V. M. Camara, P. J. Landrigan, L. Claudio, A Systematic Review of Children's Environmental Health in Brazil. Ann. Glob. Heal. 82, 132–148 (2016).

36. H. Gibb, K. G. O'Leary, Mercury exposure and health impacts among individuals in the artisanal and small-scale gold mining community: A comprehensive review. Environ. Health Perspect. 122, 667–672 (2014).
37. F. B. Ono, L. R. G. Guilherme, E. S. Penido, G. S. Carvalho, B. Hale, R. Toujaguez, J. Bundschuh, Arsenic bioaccessibility in a gold mining area: A health risk assessment for children. Environ. Geochem. Health. 34, 457–465 (2012).
38. E. S. de Souza, R. A. Texeira, H. S. C. da Costa, F. J. Oliveira, L. C. A. Melo, K. do Carmo Freitas Faial, A. R. Fernandes, Assessment of risk to human health from simultaneous exposure to multiple contaminants in an artisanal gold mine in Serra Pelada, Pará, Brazil. Sci. Total Environ. 576, 683–695 (2017).
39. O. Malm, Gold mining as a source of mercury exposure in the Brazilian Amazon. Environ. Res. 77, 73–78 (1998).
40. H. Akagi, A. Naganuma, Human Exposure to Mercury and the Accumulation of Methylmercury that is Associated with Gold Mining in the Amazon Basin, Brazil. J. Heal. Sci. 46, 323–328 (2000).
41. C. E. P. Corbett, M. El Khouri, A. N. Costa, J. V. Gyuricza, J. F. Corbett, R. Frizzarini, D. C. de Araújo Andrade, Q. Cordeiro, A. Stravogiannis, C. A. Chassot, J. L. F. Vieira, M. da C. Pinheiro, Health Evaluation of Gold Miners Living in a Mercury-Contaminated Village in Serra Pelada, Pará, Brazil. Arch. Environ. Occup. Heal. 62, 121–128 (2007).
42. E. C. Nyanza, F. P. Bernier, J. W. Martin, M. Manyama, J. Hatfield, D. Dewey, Effects of prenatal exposure and co-exposure to metallic or metalloid elements on early infant neurodevelopmental outcomes in areas with small-scale gold mining activities in Northern Tanzania. Environ. Int. 149, 106104 (2021).
43. M. Romero, S. Saavedra, The Effects of Gold Mining on Newborns' Health. *Work. Pap.* (2017).
44. J. von der Goltz, P. Barnwal, Mines: the local wealth and health effects of mineral mining in developing countries. J. Dev. Econ. 139, 1–16 (2019).
45. A. Childebayeva, J. M. Goodrich, N. Chesterman, F. Leon-Velarde, M. Rivera-Ch, M. Kiyamu, T. D. Brutsaert, A. W. Bigham, D. C. Dolinoy, Blood lead levels in Peruvian adults

are associated with proximity to mining and DNA methylation. Environ. Int. 155, 106587 (2021).

46. S. Farag, R. Das, W. H. J. Strosnider, R. T. Wilson, Possible health effects of living in proximity to mining sites near Potosí, Bolivia. J. Occup. Environ. Med. 57, 543–551 (2015).
47. M. Hendryx, M. M. Ahern, Relations between health indicators and residential proximity to coal mining in West Virginia. Am. J. Public Health. 98, 669–671 (2008).
48. Brazil Live Birth Information System (SINASC). Gov.br (last accessed Feb. 2023). https://svs.aids.gov.br/daent/cgiae/sinasc/
49. Amazonian Network of Georeferenced Socio-Environmental Information (RAISG). "About." Raisg.org (last accessed Feb. 2023). https://www.raisg.org/en/about/
50. Amazonian Network of Georeferenced Socio-Environmental Information (RAISG). "Maps." Raisg.org (last accessed Feb. 2023). https://www.raisg.org/en/maps/
51. M. Pasquali, "Legal Amazon area in Brazil as of 2021, by state." Statista.com (Feb. 8, 2023). https://www.statista.com/statistics/1043947/brazil-legal-amazon-area-state/
52. G. Lino, "10 hard facts that everybody (including investors) should know about the Amazon Rainforest." Msiainforma.org (June 26, 2020). https://msiainforma.org/10-hard-facts-that-everybody-including-investors-should-know-about-the-amazon-rainforest/
53. J. Siqueira-Gay, B. Soares-Filho, L. E. Sanchez, A. Oviedo, L. J. Sonter, Proposed Legislation to Mine Brazil's Indigenous Lands Will Threaten Amazon Forests and Their Valuable Ecosystem Services. One Earth. 3(3), 356–362 (2020).
54. Esri Inc. ArcMap (Version 10.6.1). Software. 2018. Available from https://desktop.arcgis.com/en/arcmap/
55. C. E. Pedreira, F. A. Pinto, S. P. Pereira, E. S. Costa, Birth weight patterns by gestational age in Brazil. *Ann. Brazilian Acad. Sci.* 83, 619–625 (2011).
56. P. A. Cavazos-Rehg, M. J. Krauss, E. L. Spitznagel, K. Bommarito, T. Madden, M. A. Olsen, H. Subramaniam, J. F. Peipert, L. J. Bierut, Maternal Age and Risk of Labor and Delivery Complications. Matern. Child Health J. 19, 1202–1211 (2015).
57. V. Shrestha, Maternal education and infant health gradient: New answers to old questions. Econ. Hum. Biol. 39, 100894 (2020).

58. E. Rauscher, D. E. Rangel, Rising inequality of infant health in the U.S. SSM - Popul. Heal. 12, 100698 (2020).
59. J. Currie, M. Neidell, Air Pollution and Infant Health: What Can I Learn from California's Recent Experience? Q. J. Econ. 120, 1003–1030 (2005).
60. Beam, A. L., Fried, I., Palmer, N., Agniel, D., Brat, G., Fox, K., Kohane, I., Sinaiko, A., Zupancic, J. A. F., & Armstrong, J. (2020). Estimates of healthcare spending for preterm and low-birthweight infants in a commercially insured population: 2008–2016. *Journal of Perinatology*, *40*(7), 1091–1099. https://doi.org/10.1038/s41372-020-0635-z
61. D. Almond, A. E. Kowalski, J. J. Doyle, H. Williams, E. Glaeser, M. Greenstone, J. Gruber, G. Imbens, L. Katz, M. Kremer, D. Lee, D. Neal, J. Newhouse, J. Poterba, J. Rothstein, A. Chandra, J. Currie, D. Cutler, D. Fetter, Estimating marginal returns to medical care: evidence from at-risk newborns. Q. J. Econ. 125, 591–634 (2010).
62. S. The, Q. Journal, N. Aug, D. Almond, K. Y. Chay, D. S. Lee, The Costs of Low Birth Weight. Q. J. Econ. 120, 1031–1083 (2005).

Chapter 3 references

63. K. Vohra, A. Vodonos, J. Schwartz, E. A. Marais, M. P. Sulprizio, L. J. Mickley, Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem. Environ. Res. 195, 110754 (2021).
64. X. Li, Y. Qiao, L. Shi, The aggregate effect of air pollution regulation on CO2 mitigation in China's manufacturing industry: an econometric analysis. J. Clean. Prod. 142, 976–984 (2017).
65. Q. Zhou, X. Zhang, Q. Shao, X. Wang, The non-linear effect of environmental regulation on haze pollution: Empirical evidence for 277 Chinese cities during 2002–2010. J. Environ. Manage. 248, 109274 (2019).
66. M. Zhang, X. Sun, W. Wang, Study on the effect of environmental regulations and industrial structure on haze pollution in China from the dual perspective of independence and linkage. J. Clean. Prod. 256, 120748 (2020).

67. J. Yang, Y. Zhao, J. Cao, C. P. Nielsen, Co-benefits of carbon and pollution control policies on air quality and health till 2030 in China. Environ. Int. 152, 106482 (2021).
68. R. A. Broome, N. Fann, T. J. N. Cristina, C. Fulcher, H. Duc, G. G. Morgan, The health benefits of reducing air pollution in Sydney, Australia. Environ. Res. 143, 19–25 (2015).
69. L. Li, T. Du, C. Zhang, The impact of air pollution on healthcare expenditure for respiratory diseases: Evidence from the People's Republic of China. Risk Manag. Healthc. Policy. 13, 1723–1738 (2020).
70. UN Environment Programme, "Young and old, air pollution affects the most vulnerable" Unep.org (Oct. 16, 2018). https://www.unep.org/news-and-stories/blogpost/young-and-old-air-pollution-affects-most-vulnerable#:~:text=While%20this%20impacts%20people%20of,of%20children%20around%20the%20world.
71. Z. Zhang, B. Dong, G. Chen, Y. Song, S. Li, Z. Yang, Y. Dong, Z. Wang, J. Ma, Y. Guo, Ambient air pollution and obesity in school-aged children and adolescents: A multicenter study in China. Sci. Total Environ. 771, 144583 (2021).
72. W. Austin, G. Heutel, D. Kreisman, School bus emissions, student health and academic performance. *Econ. Educ. Rev.* 70, 109–126 (2019).
73. F. Fionda, M. Sheldon, M. Hartshorn, "Map: Alberta littered with inactive oil and gas wells." Globalnews.ca (Oct. 28, 2015). https://globalnews.ca/news/2301432/map-shows-nearly-every-corner-of-alberta-littered-with-inactive-oil-and-gas-wells/
74. N. Groom, "Special Report: Millions of abandoned oil wells are leaking methane, a climate menace." Reuters.com (June 16, 2020). https://www.reuters.com/article/us-usa-drilling-abandoned-specialreport-idUSKBN23N1NL
75. C. Bussewitz, "Why it's so hard and expensive to plug an abandoned well." Apnews.com (July 29, 2021). https://apnews.com/article/business-environment-and-nature-climate-change-7392636504b2763de07ff4b3fe78710e
76. The Conversation, "Urban Oil Wells Linked to Asthma and Other Health Problems in Los Angeles." Usnews.com (June 2, 2021). https://www.usnews.com/news/cities/articles/2021-06-02/urban-oil-wells-linked-to-asthma-and-other-health-problems-in-los-angeles

77. J. E. Johnston, T. Enebish, S. P. Eckel, S. Navarro, B. Shamasunder, Respiratory health, pulmonary function and local engagement in urban communities near oil development. Environ. Res. 197, 1–25 (2021).
78. Z. Matthew, "4 Oil Wells Hidden in Plain Sight in L.A." Lamag.com (Feb. 5, 2018). https://www.lamag.com/citythinkblog/hidden-oil-wells/
79. E. D. Czolowski, R. L. Santoro, T. Srebotnjak, S. B. C. Shonkoff, Toward consistent methodology to quantify populations in proximity to oil and gas development: A national spatial analysis and review. Environ. Health Perspect. 125, 1–11 (2017).
80. J. Proville, K. A. Roberts, A. Peltz, L. Watkins, E. Trask, D. Wiersma, The demographic characteristics of populations living near oil and gas wells in the USA. Popul. Environ. (2022), doi:10.1007/s11111-022-00403-2.
81. B. Weber, "$1B orphaned oil and gas well cleanup bill estimate leaves out 'most expensive part,' critics say." Cbc.ca (Jan. 25, 2022). https://www.cbc.ca/news/canada/calgary/orphaned-wells-liability-alberta-1.6326942
82. Alberta Energy Regulation, "Orphan Well Association." Aer.ca (last accessed Feb. 2023). https://www.aer.ca/regulating-development/project-closure/liability-management-programs-and-processes/orphan-well-association
83. H. de Beer, Alberta's end-of-life Oil and Gas Liabilities (Unpublished master's thesis). University of Calgary, Calgary, AB. (2016). https://prism.ucalgary.ca/bitstream/handle/1880/51698/de%20Beer,%20Helena%20Maria%20Elisabeth.pdf?sequence=1#page=27
84. C. Clancy, "Cost estimates to clean up oil and gas wells lack transparency, says advocacy group." Edmontonjournal.com (July 18, 2019). https://edmontonjournal.com/news/politics/cost-estimates-to-clean-up-oil-and-gas-wells-lack-transparency-says-advocacy-group
85. N. Bowlin, "Interior devotes billions to plugging old oil wells. Is it enough?" Hcn.org (Jan. 19, 2022). https://www.hcn.org/articles/south-department-of-interior-devotes-billions-to-plugging-old-oil-wells-is-it-enough
86. P. Mohai, B. S. Kweon, S. Lee, K. Ard, Air pollution around schools is linked to poorer student health and academic performance. *Health Aff.* 30, 852–862 (2011).

87. C. L. Persico, J. Venator, The Effects Of Local Industrial Pollution On Students And Schools. *J. Hum. Resour.* 56, 406–445 (2021).
88. U. Balakrishnan, M. Tsaneva, Air pollution and academic performance: Evidence from India. *World Dev.* 146, 105553 (2021).
89. N. J. Sanders, What doesn't kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *J. Hum. Resour.* 47, 826–850 (2012).
90. Graff Zivin, N. Matthew, The Impact of Pollution on Worker Productivity. *Am. Econ. Rev.* 102, 3652–3673 (2012).
91. J. Currie, Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *J. Econ. Lit.* 47, 87–122 (2009).
92. S. Chen, C. Guo, X. Huang, Air Pollution, Student Health, and School Absences: Evidence from China. *J. Environ. Econ. Manage.* 92, 465–497 (2018).
93. J. Currie, E. A. Hanushek, E. M. Kahn, M. Neidell, S. G. Rivkin, Does Pollution Increase School Absences? *Rev. Econ. Stat.* 91, 682–694 (2009).
94. Alberta Energy Regulator, "Upstream Petroleum Industry Emissions Report." Aer.ca (Jan. 2022). https://static.aer.ca/prd/documents/sts/ST60B-2021.pdf
95. Environmental Protection Agency, "Importance of Methane." Epa.gov (June 9, 2022). https://www.epa.gov/gmi/importance-methane#:~:text=Methane%20is%20the%20second%20most,trapping%20heat%20in%20the%20atmosphere.
96. Public Health England, "Methane: General Information." Gov.uk/government/organisations/public-health-england (January 2019). https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/769766/Methane_PHE_general_information__070119.pdf
97. C. Wang, Q. Lin, Y. Qiu, Productivity loss amid invisible pollution. J. Environ. Econ. Manage. 112, 102638 (2022).
98. D. A. Garcia-Gonzales, O. Popoola, V. B. Bright, S. E. Paulson, Y. Wang, R. L. Jones, M. Jerrett, Associations among particulate matter, hazardous air pollutants and methane emissions from the Aliso Canyon natural gas storage facility during the 2015 blowout.

Environ. Int. 132, 104855 (2019).C. Wang, Q. Lin, Y. Qiu, Productivity loss amid invisible pollution. J. Environ. Econ. Manage. 112, 102638 (2022).

99. H. Elser, R. Morello-Frosch, A. Jacobson, A. Pressman, M. A. Kioumourtzoglou, R. Reimer, J. A. Casey, Air pollution, methane super-emitters, and oil and gas wells in Northern California: the relationship with migraine headache prevalence and exacerbation (Environmental Health, (2021), 20, 1, (45), 10.1186/s12940-021-00727-w). Environ. Heal. A Glob. Access Sci. Source. 20, 1–14 (2021).

100. Y. Cao, Q. Wang, D. Zhou, Does air pollution inhibit manufacturing productivity in Yangtze River Delta, China? Moderating effects of temperature. J. Environ. Manage. 306, 114492 (2022).

101. S. Chen, D. Zhang, Impact of air pollution on labor productivity: Evidence from prison factory data. China Econ. Q. Int. 1, 148–159 (2021).

102. A. Lichter, N. Pestel, E. Sommer, Productivity effects of air pollution: Evidence from professional soccer. Labour Econ. 48, 54–66 (2017).

103. K. El Hachem, M. Kang, Methane and hydrogen sulfide emissions from abandoned, active, and marginally producing oil and gas wells in Ontario, Canada. Sci. Total Environ. 823, 153491 (2022).

104. M. Omara, D. Zavala-Araiza, D. R. Lyon, B. Hmiel, K. A. Roberts, S. P. Hamburg, Methane emissions from me low production oil and natural gas well sites. Nat. Commun. 13, 1–10 (2022).

105. A. Townsend-small, T. W. Ferrara, D. R. Lyon, A. E. Fries, B. K. Lamb, Emissions of coalbed and natural gas methane from abandoned oil and gas wells in the United States. *Geophys. Res. Lett.*, 2283–2290 (2016).

106. J. P. Williams, A. Regehr, M. Kang, Methane Emissions from Abandoned Oil and Gas Wells in Canada and the United States. *Environ. Sci. Technol.* 55, 563–570 (2021).

107. D. J. X. Gonzalez, C. K. Francis, G. M. Shaw, M. R. Cullen, M. Baiocchi, M. Burke, Upstream oil and gas production and ambient air pollution in California. *Sci. Total Environ.* 806, 150298 (2022).

108. A. Townsend-Small, J. Hoschouer, Direct measurements from shut-in and other abandoned wells in the Permian Basin of Texas indicate some wells are a major source of

methane emissions and produced water. Environ. Res. Lett. 16 (2021), doi:10.1088/1748-9326/abf06f.

109. The Canadian Association of Petroleum Producers, “Life Cycle of a Well.” Capp.ca (last accessed Feb. 2023). https://www.capp.ca/explore/life cycle-of-a-well/

110. Alberta Energy Regulator, “How are wells suspended?” Aer.ca (last accessed Feb. 2023). https://www.aer.ca/regulating-development/project-closure/suspension-and-abandonment/how-are-wells-suspended

111. N. Way, M. Simpson-Marran, “Landowners' Primer: What you need to know about unreclaimed oil and gas wells.” Pembina.org (Nov. 21, 2019). https://www.pembina.org/pub/landowners-primer-what-you-need-know-about-unreclaimed-oil-and-gas-wells

112. Alberta Energy Regulator, “Reclamation Certificate Application Submissions.” Aer.ca (last accessed Feb. 2023). https://www.aer.ca/regulating-development/project-closure/reclamation/oil-and-gas-site-reclamation-requirements/reclamation-certificate-application-submissions

113. Orphan Well Association, “Orphan Inventory.” Orphanwell.ca (last accessed Feb. 2023). https://orphanwell.ca/about/orphan-inventory/

114. L. Muehlenbachs, 80,000 Inactive Oil Wells: A Blessing or a Curse? Sch. Public Policy Publ. 10, 1–16 (2017).

115. Government of Alberta, “Provincial Achievement Tests.” Alberta.ca (last accessed Feb. 2023). https://www.alberta.ca/provincial-achievement-tests.aspx

116. CTV News Edmonton, “Both Edmonton Public and Catholic schools cancel provincial achievement tests.” Edmonton.ctvnews.ca (Oct. 23, 2020). https://edmonton.ctvnews.ca/both-edmonton-public-and-catholic-schools-cancel-provincial-achievement-tests-1.5157915

117. Government of Alberta, “Achievement Exam Results (School).” Open.alberta.ca (Apr. 15, 2021). https://open.alberta.ca/opendata/achievement-exam-results-school

118. Government of Alberta, “Guidelines for Interpreting Achievement Test Multiyear Reports.” Open.alberta.ca (Sept. 1, 2018). https://open.alberta.ca/publications/guidelines-for-interpreting-the-achievement-test-multiyear-reports

119. Government of Alberta, “Class size by school year, jurisdiction, and grade, Alberta.” Open.alberta.ca (Oct. 18, 2019). https://open.alberta.ca/opendata/class-size-by-school-year-jurisdiction-and-grade-alberta

120. Government of Alberta, “Education annual report.” Open.alberta.ca (June 28, 2022). https://open.alberta.ca/publications/1918-2864

121. Alberta Energy Regulator, “ST37: List of Wells in Alberta.” Aer.ca (last accessed Feb. 2023). https://www1.aer.ca/ProductCatalogue/10.html

122. Statistics Canada, “Dictionary, Census of Population, 2016: Forward Sortation Area (FSA).” Statcan.gc.ca (Nov. 16, 2016). https://www12.statcan.gc.ca/census-recensement/2016/ref/dict/geo036-eng.cfm

123. Statistics Canada, “Download, Census Profile, 2016 Census.” Statcan.gc.ca (Aug. 25, 2017). https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/download-telecharger/comp/page_dl-tc.cfm?Lang=E

124. Cylus, J., & al Tayara, L. (2021). Health, an ageing labour force, and the economy: Does health moderate the relationship between population age-structure and economic growth? *Social Science and Medicine*, *287*. https://doi.org/10.1016/j.socscimed.2021.114353

125. T. Jeffrey, “School Spending Up, Test Scores Down.” Dailysignal.com (Oct. 22, 2021). https://www.dailysignal.com/2021/10/22/school-spending-up-test-scores-down/

126. C. Wigfall, “Is there a link between school spending & student achievement?” Americanexperiment.org (June 30, 2017). https://www.americanexperiment.org/is-there-a-link-between-school-spending-student-achievement/

127. V. Joecks, “Analysis shows little to no correlation between education spending and student achievement.” Npri.org (May 17, 2012). https://www.npri.org/commentary/analysis-shows-little-to-no-correlation-between-education-spending-and-student-achievement/

128. J. Coulson, State Education Trends: Academic Performance and Spending over the Past 40 Years. Cato Inst. Policy Anal. 746, 1–60 (2014).

129. B. Degrow, E. C. Hoang, School Spending and Student Achievement in Michigan: What’s the Relationship? The Mackinac Center for Public Policy. (2016). https://files.eric.ed.gov/fulltext/ED568658.pdf

130. C. J. Matz, D. M. Stieb, O. Brion, Urban-rural differences in daily time-activity patterns, occupational activity and housing characteristics. Environ Health. 14 (2015), doi:10.1186/s12940-015-0075-y.

131. K. v. Tran, J. A. Casey, L. J. Cushing, R. Morello-Frosch, Residential proximity to oil and gas development and birth outcomes in California: A retrospective cohort study of 2006–2015 births. Environ Health Perspect. 128 (2020), doi:10.1289/EHP5842.

132. Government of Alberta, "List of Urban and Rural Communities (2016 Census)" Open.alberta.ca (last accessed Feb. 2023). https://open.alberta.ca/dataset/899c9cca-8ce7-40d2-8d2d-c9c369884d9a/resource/035d1e0d-595b-43aa-8d57-d7e3f7e11625/download/listofurbanandruralcommunitiesinalberta.pdf

133. Government of Alberta, "Guide for Petroleum and Natural Gas (PNG) Agreement Sales." Open.alberta.ca (last updated April 2020). https://training.energy.gov.ab.ca/Guides/GuideForSalesBranded.pdf

134. Government of Alberta, "Tenure – Overview." Alberta.ca (last accessed Feb. 2023). https://www.alberta.ca/tenure-overview.aspx#:~:text=Related-,Introduction,for%20the%20benefit%20of%20Albertans.

135. A. G. C. Boef, O. M. Dekkers, J. P. Vandenbroucke, S. Le Cessie, Sample size importantly limits the usefulness of instrumental variable methods, depending on instrument strength and level of confounding. J. Clin. Epidemiol. 67, 1258–1264 (2014).

136. Watts, T. W. (2020). Academic Achievement and Economic Attainment: Reexamining Associations Between Test Scores and Long-Run Earnings. *AERA Open*, *6*(2), 233285842092898. https://doi.org/10.1177/2332858420928985

137. B. Weber, "Budget officer finds $1B oil and gas orphan well liability by 2025; critics claim underestimate." Globalnews.ca (last accessed June 20, 2023). https://globalnews.ca/news/8536571/alberta-saskatchewan-orphan-well-cleanup-cost/

138. Alberta Energy Regulator, "Methane Reduction." Aer.ca (last accessed Feb. 2023). https://www.aer.ca/protecting-what-matters/protecting-the-environment/methane-reduction

Chapter 4 references

139. Maina, N. M., Murray, J., & McKenzie, M. (2020). Climate change and the fossil fuel divestment movement in Canadian higher education: The mobilities of actions, actors, and tactics. *Journal of Cleaner Production*, *253*. https://doi.org/10.1016/j.jclepro.2019.119874
140. Wood, N., & Roelich, K. (2019). Tensions, capabilities, and justice in climate change mitigation of fossil fuels. *Energy Research and Social Science*, *52*, 114–122. https://doi.org/10.1016/j.erss.2019.02.014
141. Megura, M., & Gunderson, R. (2022). Better poison is the cure? Critically examining fossil fuel companies, climate change framing, and corporate sustainability reports. *Energy Research and Social Science*, *85*. https://doi.org/10.1016/j.erss.2021.102388
142. Yu, B., Liu, J., Lyu, T., Li, Z., Wang, M., & Yang, W. (2022). A new detection method to assess the influence of human activities and climate change of CO2 emissions in coal field. *Ecological Indicators*, *143*. https://doi.org/10.1016/j.ecolind.2022.109417
143. Walk, P., & Stognief, N. (2022). From coal phase-out to net zero: Driving factors of UK climate policy. *Environmental Science and Policy*, *138*, 76–84. https://doi.org/10.1016/j.envsci.2022.09.019
144. Curran, G. (2021). Coal, climate and change: The narrative drivers of Australia's coal economy. *Energy Research and Social Science*, *74*. https://doi.org/10.1016/j.erss.2021.101955
145. Burke, A., & Fishel, S. (2020). A coal elimination treaty 2030: Fast tracking climate change mitigation, global health and security. *Earth System Governance*, *3*. https://doi.org/10.1016/j.esg.2020.100046
146. Adekoya, O. B., Kenku, O. T., Oliyide, J. A., & Al-Faryan, M. A. S. (2023). On the COP26 and coal's phase-out agenda: Striking a balance among the environmental, economic, and health impacts of coal consumption. *Journal of Environmental Management*, *328*. https://doi.org/10.1016/j.jenvman.2022.116872
147. Markard, J., Rinscheid, A., & Widdel, L. (2021). Analyzing transitions through the lens of discourse networks: Coal phase-out in Germany. *Environmental Innovation and Societal Transitions*, *40*, 315–331. https://doi.org/10.1016/j.eist.2021.08.001

148. Lanzi, E., Dellink, R., & Chateau, J. (2018). The sectoral and regional economic consequences of outdoor air pollution to 2060. *Energy Economics*, *71*, 89–113. https://doi.org/10.1016/j.eneco.2018.01.014

149. Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(32), 12936–12941. https://doi.org/10.1073/pnas.1300018110

150. Hendryx, M., & Ahern, M. M. (2008). Relations between health indicators and residential proximity to coal mining in West Virginia. *American Journal of Public Health*, *98*(4), 669–671. https://doi.org/10.2105/AJPH.2007.113472

151. Fernández-Navarro, P., García-Pérez, J., Ramis, R., Boldo, E., & López-Abente, G. (2012). Proximity to mining industry and cancer mortality. *Science of the Total Environment*, *435–436*, 66–73. https://doi.org/10.1016/j.scitotenv.2012.07.019

152. Jha, A., & Muller, N. Z. (2018). The local air pollution cost of coal storage and handling: Evidence from U.S. power plants. *Journal of Environmental Economics and Management*, *92*, 360–396. https://doi.org/10.1016/j.jeem.2018.09.005

153. Fitzpatrick, L. G. (2018). Surface Coal Mining and Human Health: Evidence from West Virginia. *Southern Economic Journal*, *84*(4), 1109–1128. https://doi.org/10.1002/soej.12260

154. Roy, R., & Braathen, N. A. (2017). The Rising Cost of Ambient Air Pollution thus far in the 21st Century: Results from the BRIICS and the OECD Countries. *OECD Environment Working Papers*, *124*. https://doi.org/10.1787/d1b2b844-en

155. Zhang, X., Zhang, X., & Chen, X. (2017). Valuing Air Quality Using Happiness Data: The Case of China. *Ecological Economics*, *137*, 29–36. https://doi.org/10.1016/j.ecolecon.2017.02.020

156. Chen, S., Guo, C., & Huang, X. (2018). Air Pollution, Student Health, and School Absences: Evidence from China. *Journal of Environmental Economics and Management*, *92*, 465–497. https://doi.org/10.1016/j.jeem.2018.10.002

157. Marove, C. A., Sotozono, R., Tangviroon, P., Tabelin, C. B., & Igarashi, T. (2022). Assessment of soil, sediment and water contaminations around open-pit coal mines in

Moatize, Tete province, Mozambique. *Environmental Advances*, *8*. https://doi.org/10.1016/j.envadv.2022.100215

158. Tozsin, G., Arol, A. I., Duzgun, S., Soydan, H., & Torun, A. (2022). Effects of abandoned coal mine on the water quality. *International Journal of Coal Preparation and Utilization*. https://doi.org/10.1080/19392699.2022.2044320

159. Government of Canada, "Coal Facts." natural-resources.canada.ca (last updated Apr. 5, 2022). https://www.nrcan.gc.ca/our-natural-resources/minerals-mining/minerals-metals-facts/coal-facts/20071

160. E. Karampela, "Global coal production to grow by a marginal 0.9% in 2022." Mining Technology. mining-technology.com (Sept. 13, 2022). https://www.mining-technology.com/comment/global-coal-production/

161. B. Hill, "Why Canada could be burning coal well beyond the 2030 deadline set by the Liberals." globalnews.ca (Sept. 2, 2021). https://globalnews.ca/news/8162207/canada-coal-thermal-deadline-2030-liberal/

162. A. Husser, "Canada is weaning itself off thermal coal but keeps shipping it elsewhere." cbc.ca (Nov. 4, 2021). https://www.cbc.ca/news/science/thermal-coal-canada-ban-exports-1.6236441

163. Alberta Energy Regulator, "ST45: Operating and Abandoned Coal Mines in Alberta." aer.ca (last accessed Feb. 2023). https://www.aer.ca/providing-information/data-and-reports/statistical-reports/st45

164. Alberta Energy Regulator, "Mine Reclamation Requirements." aer.ca (last accessed Feb. 2023). https://www.aer.ca/regulating-development/project-closure/reclamation/mine-reclamation-requirements

165. B. Weber, "Contaminant from coal mines already high in some Alberta rivers: unreported data." cbc.ca (Jan. 25, 2021). https://www.cbc.ca/news/canada/edmonton/selenium-alberta-coal-mines-contamination-1.5886293

166. B. Weber, "Alberta to extend pause on Rocky Mountain coal mines." cbc.ca (Mar. 4, 2021). https://globalnews.ca/news/8658813/alberta-rocky-mountain-coal-mining-reports/

167. B. Weber, “Alberta coal mine supporters hope for change under premier Smith.” calgary.citynews.ca (Oct. 19, 2022). https://calgary.citynews.ca/2022/10/19/coal-mine-alberta-premier/

168. Chen, B., Wang, M., Duan, M., Ma, X., Hong, J., Xie, F., Zhang, R., & Li, X. (2019). In search of key: Protecting human health and the ecosystem from water pollution in China. *Journal of Cleaner Production*, *228*, 101–111. https://doi.org/10.1016/j.jclepro.2019.04.228

169. Hendryx, M. (2015). The public health impacts of surface coal mining. In *Extractive Industries and Society* (Vol. 2, Issue 4, pp. 820–826). Elsevier Ltd. https://doi.org/10.1016/j.exis.2015.08.006

170. United States Environmental Protection Agency, “Abandoned Mine Drainage.” epa.gov (last updated Dec. 22, 2022). https://www.epa.gov/nps/abandoned-mine-drainage

171. Gaikwad, R. W., & Gupta, D. v. (2008). Review on removal of heavy metals from acid mine drainage. In *Applied Ecology and Environmental Research* (Vol. 6, Issue 3, pp. 79–96). Corvinus University of Budapest. https://doi.org/10.15666/aeer/0603_081098

172. Fernández-Caliani, J. C., Giráldez, M. I., & Barba-Brioso, C. (2019). Oral bioaccessibility and human health risk assessment of trace elements in agricultural soils impacted by acid mine drainage. *Chemosphere*, *237*. https://doi.org/10.1016/j.chemosphere.2019.124441

173. Farag, S., Das, R., Strosnider, W. H. J., & Wilson, R. T. (2015). Possible health effects of living in proximity to mining sites near Potosí, Bolivia. *Journal of Occupational and Environmental Medicine*, *57*(5), 543–551. https://doi.org/10.1097/JOM.0000000000000401

174. W. Allan, “Healthcare in Canada: Is it Really Free?” mdccanada.ca (Mar. 1, 2023). https://mdccanada.ca/news/live-in-canada/healthcare-in-canada--is-it-really-free-

175. Yabe, J., Nakayama, S. M. M., Ikenaka, Y., Yohannes, Y. B., Bortey-Sam, N., Oroszlany, B., Muzandu, K., Choongo, K., Kabalo, A. N., Ntapisha, J., Mweene, A., Umemura, T., & Ishizuka, M. (2015). Lead poisoning in children from townships in the vicinity of a lead-zinc mine in Kabwe, Zambia. *Chemosphere*, *119*, 941–947. https://doi.org/10.1016/j.chemosphere.2014.09.028

176. Varrica, D., Tamburo, E., Milia, N., Vallascas, E., Cortimiglia, V., de Giudici, G., Dongarrà, G., Sanna, E., Monna, F., & Losno, R. (2014). Metals and metalloids in hair

samples of children living near the abandoned mine sites of Sulcis-Inglesiente (Sardinia, Italy). *Environmental Research*, *134*, 366–374. https://doi.org/10.1016/j.envres.2014.08.013

177. Herrera, R., Radon, K., von Ehrenstein, O. S., Cifuentes, S., Muñoz, D. M., & Berger, U. (2016). Proximity to mining industry and respiratory diseases in children in a community in Northern Chile: A cross-sectional study. *Environmental Health: A Global Access Science Source*, *15*(1). https://doi.org/10.1186/s12940-016-0149-5

178. Bello, O., Naidu, R., Rahman, M. M., Liu, Y., & Dong, Z. (2016). Lead concentration in the blood of the general population living near a lead-zinc mine site, Nigeria: Exposure pathways. *Science of the Total Environment*, *542*, 908–914. https://doi.org/10.1016/j.scitotenv.2015.10.143

179. Lee, M., Lee, H., Warren, J. R., & Herd, P. (2022). Effect of childhood proximity to lead mining on late life cognition. *SSM - Population Health*, *17*. https://doi.org/10.1016/j.ssmph.2022.101037

180. ArcGIS, "What is ArcMap?" desktop.arcgis.com (last accessed Feb. 2023). https://desktop.arcgis.com/en/arcmap/latest/map/main/what-is-arcmap-.htm

181. Government of Alberta, "Alberta Township Survey System." alberta.ca (last accessed Feb. 2023). https://www.alberta.ca/alberta-township-survey-system.aspx

182. von der Goltz, J., & Barnwal, P. (2019). Mines: the local wealth and health effects of mineral mining in developing countries. *Journal of Development Economics*, *139*, 1–16. https://doi.org/10.1016/j.jdeveco.2018.05.005

183. Alberta Wilderness Association, "Map of Alberta Coal Mines and ISCG Pilot Projects." Albertawilderness.ca (Sept. 26, 2013). https://albertawilderness.ca/2013-09-26-map-of-alberta-coal-mines-and-iscg-pilot-projects/

184. Statistics Canada. *Postal Code^{OM} Conversion File Plus (PCCF+) Version 6C, Reference Guide*. August 2015 Postal Codes. Statistics Canada Catalogue no. 82-E0086-XDB. Ottawa, Minister of Industry, 2016.

185. Canada Post, "Addressing Guidelines." Canadapost-postescanada.ca (last updated Jan. 18, 2022). https://www.canadapost-postescanada.ca/cpc/en/support/articles/addressing-guidelines/postal-codes.page

186. Statistics Canada, “More information on Postal code.” Statcan.gc.ca (last updated Nov. 20, 2009). https://www12.statcan.gc.ca/census-recensement/2006/ref/dict/geo035a-eng.cfm
187. Alberrta SPOR SUPPORT Unit, “Alberta Health Services Data Set Availability.” absporu.ca (last accessed Feb. 25, 2023). https://absporu.ca/research-services/alberta-health-services-data-set-availability/
188. Romero, M., & Saavedra, S. (2017). The Effects of Gold Mining on Newborns’ Health. *Working Paper*.
189. ArcGIS Pro, “Identifying stream networks.” Pro.arcgis.com (last accessed Feb. 2023). https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/identifying-stream-networks.htm
190. National Ocean Service, “What is a watershed?” Oceanservice.noaa.gov (last updated Jan. 20, 2023). https://oceanservice.noaa.gov/facts/watershed.html
191. Mehra, M., Merchant, S., Gupta, S., & Potluri, R. C. (2014). Diabetic peripheral neuropathy: Resource utilization and burden of illness. *Journal of Medical Economics*, *17*(9), 637–645. https://doi.org/10.3111/13696998.2014.928639
192. Pulok, M. H., van Gool, K., & Hall, J. (2020). Inequity in physician visits: the case of the unregulated fee market in Australia. *Social Science and Medicine*, *255*. https://doi.org/10.1016/j.socscimed.2020.113004
193. Tran, M., Gannon, B., & Rose, C. (2023). The effect of housing wealth on older adults’ health care utilization: Evidence from fluctuations in the U.S. housing market. *Journal of Health Economics*, *88*. https://doi.org/10.1016/j.jhealeco.2023.102737
194. Fernández-Luqueño, F., López-Valdez, F., Gamero, P., & Luna, S. (2013). Heavy metal pollution in drinking water-a global risk for human health: A review. *African Journal of Environmental Science and Technology*, *7*, 567–584. https://doi.org/10.5897/AJEST12.197
195. P. Somnath. (2018). Health-Related Office Visits by Children and Adolescents. me *Pharm*. 43(5):12. https://www.uspharmacist.com/article/healthrelated-office-visits-by-children-and-adolescents
196. Kim, B. S., Kim, J. Y., Choi, S. H., & Yoon, Y. H. (2018). Understanding the characteristics of recurrent visits to the emergency department by paediatric patients: A

retrospective observational study conducted at three tertiary hospitals in Korea. *BMJ Open*, *8*(2). https://doi.org/10.1136/bmjopen-2017-018208

197. Stata, “teffects nnmatch – Nearest-neighbor matching.” Stata.com (last accessed Feb. 2023). www.stata.com/manuals13/teteffectsnnmatch.pdf

198. N. Greifer, “Matching Methods.” cran.r-project.org (Feb 22, 2023) https://cran.r-project.org/web/packages/MatchIt/vignettes/matching-methods.html

199. Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. In *Statistical Science* (Vol. 25, Issue 1, pp. 1–21). https://doi.org/10.1214/09-STS313

200. Snedecor, G.W., & Cochran, W.G. (1980). Statistical Methods. 7th Edition, Iowa State University Press, Ames, IA.

201. D. Bennett, “Alberta government extends deadline for changes to doctor fees.” Globalnews.ca (last updated Jan. 14, 2020). https://globalnews.ca/news/6411547/alberta-doctor-billing-patient-visits-changes/

202. Alberta Health Services, “2021-22 Alberta Health Services Annual Report.” Albertahealthservices.ca (last updated June 1, 2021). ahs-pub-pr-2021-22-q4.pdf (albertahealthservices.ca)

203. E. Blondeau, “Fight against coal mine expansion to be brought to UN climate change conference.” cbc.ca (last updated Nov. 5, 2022). https://www.cbc.ca/news/indigenous/vista-mine-cop27-keepers-water-1.6641300

204. N. Brubaker, “The effects of coal mining in Alberta would ripples throughout the prairies.” canadians.org (Apr. 27, 2021). https://canadians.org/analysis/effects-coal-mining-alberta-would-ripple-throughout-prairies/

Appendix A references

205. L. M. Diele-Viegas, E. Johnson, D. A. Leão, C. Frederico, D. Rocha, The new Brazilian gold rush: Is Amazonia at risk? *For. Policy Econ.* 119 (2020), doi:10.1016/j.forpol.2020.102270.

206. L. Ferrante, M. Gomes, P. M. Fearnside, Amazonian indigenous peoples are threatened by Brazil s Highway BR-319. *Land use policy*. 94, 104548 (2020).

207. R. Sousa, M. Veiga, D. Van Zyl, K. Telmer, S. Spiegel, J. Selder, Policies and regulations for Brazil's artisanal gold mining sector: Analysis and recommendations. *J. Clean. Prod.* 19, 742–750 (2011).

208. M. M. Veiga, O. Fadina, A review of the failed attempts to curb mercury use at artisanal gold mines and a proposed solution. *Extr. Ind. Soc.* 7, 1135–1146 (2020).

209. World Health Organization. 2007. "Exposure to Mercury: A Major Public Health Concern." https://www.who.int/phe/news/Mercury-flyer.pdf

210. Z. Castilhos, S. Rodrigues-Filho, R. Cesar, A. P. Rodrigues, R. Villas-Bôas, I. de Jesus, M. Lima, K. Faial, A. Miranda, E. Brabo, C. Beinhoff, E. Santos, Human exposure and risk assessment associated with mercury contamination in artisanal gold mining areas in the Brazilian Amazon. *Environ. Sci. Pollut. Res.* 22, 11255–11264 (2015).

211. E. C. D. O. Santos, I. M. De Jesus, E. Da Silva Brabo, E. C. Brito Loureiro, A. F. Da Silva Mascarenhas, J. Weirich, V. de M. Câmara, D. Cleary, Mercury exposures in riverside amazon communities in Para, Brazil. *Environ. Res.* 84, 100–107 (2000).

212. F. M. Rebelo, R. Leandro, P. D. Andrade, A. Walkimar, C. Junior, W. R. Bastos, E. D. Caldas, Mercury in breast milk from women in the Federal District, Brazil and dietary risk assessment for breastfed infants. *J. Trace Elem. Med. Biol.* 44, 99–103 (2017).

213. A. S. Lino, D. Kasper, Y. S. Guida, J. R. Thomaz, O. Malm, Mercury and selenium in fi shesfrom the Tapajós River in the Brazilian Amazon: An evaluation of human exposure. *J. Trace Elem. Med. Biol.* 48, 196–201 (2018).

214. F. B. Custódio, A. M. G. F. Andrade, L. R. Guidi, C. A. G. Leal, M. B. A. Gloria, Total mercury in commercial fishes and estimation of Brazilian dietary exposure to methylmercury. *J. Trace Elem. Med. Biol.* 62 (2020), doi:10.1016/j.jtemb.2020.126641.

215. R. C. Marques, J. V. E. Bernardi, J. G. Dó, Fish Consumption during Pregnancy, Mercury Transfer, and Birth Weight along the Madeira River Basin in Amazonia. *Int. J. Environ. Res. Public Health*, 2150–2163 (2013).

216. M. Ahern, M. Mullett, K. Mackay, Residence in Coal-Mining Areas and Low-Birth-Weight Outcomes. *Matern. Child Health J.*, 974–979 (2011).

217. H. J. F. Veloso, A. Augusto, H. Bettiol, M. Z. Goldani, F. L. Filho, V. Maria, F. Simões, R. Fernandes, L. Batista, M. A. Barbieri, Low birth weight in São Luís, northeastern Brazil: trends and associated factors. *BMC Pregnancy Childbirth*, 1–12 (2014).

218. D. S. Small, D. W. Firth, L. J. Keele, M. Huber, M. Passarella, S. A. Lorch, H. H. Burris, Surface mining and low birth weight in central appalachia. *Environ. Res.*, 110340 (2020).

219. A. Arrieta, J. Guillen, The birthweight toll of mining pollution: evidence from the most contaminated mine site in the Andean region. *BJOG an Int. J. Obstet. Gynaecol.*, 19–21 (2018).

220. J. R. Chrisman, I. E. Mattos, R. J. Koifman, S. Koifman, P. Moraes, M. Boccolini, A. Meyer, Prevalence of very low birthweight, malformation, and low Apgar score among newborns in Brazil according to maternal urban or rural residence at birth. *Obstet. Gynaecol. Res.* 42, 496–504 (2016).

221. M. Vigeh, E. Nishioka, K. Ohtani, Y. Omori, Prenatal mercury exposure and birth weight. *Reprod. Toxicol.* 76, 78–83 (2018).

222. L. Deroma, M. Parpinel, V. Tognin, L. Channoufi, J. Tratnik, M. Horvat, F. Valent, F. Barbone, Neuropsychological assessment at school-age and prenatal low-level exposure to mercury through fish consumption in an Italian birth cohort living near a contaminated site. *Int. J. Hyg. Environ. Health*. 216, 486–493 (2013).

223. R. T. Emeny, S. A. Korrick, Z. Li, K. Nadeau, J. Madan, B. Jackson, E. Baker, M. R. Karagas, Prenatal exposure to mercury in relation to infant infections and respiratory symptoms in the New Hampshire Birth Cohort Study. *Environ. Res.* 171, 523–529 (2019).

224. C. Santos-lima, D. De Souza, C. Ferreira, D. Carvalho, B. Souza-marques, C. M. Vega, R. Araújo, N. Argollo, J. A. Menezes-filho, N. Abreu, S. De Souza, Neuropsychological Effects of Mercury Exposure in Children and Adolescents of the Amazon Region, Brazil. *Neurotoxicology*. 79, 48–57 (2020).

225. S. Freitas, E. Maria, B. Lacerda, I. Christine, S. Martins, D. Rodrigues, D. Maria, O. Bonci, M. Izabel, T. Cortes, T. Cristina, O. Corvelo, D. Fix, L. Carlos, D. L. Silveira, C. Nascimento, S. Souza, Cross-sectional study to assess the association of colour vision with mercury hair concentration in children from Brazilian Amazonian riverine communities. *Neurotoxicology*. 65, 60–67 (2018).

226. J. C. Ng, V. Ciminelli, M. Gasparon, C. Caldeira, Health risk apportionment of arsenic from multiple exposure pathways in Paracatu, a gold mining town in Brazil. *Sci. Total Environ.* 673, 36–43 (2019).
227. B. C. Henn, A. S. Ettinger, M. R. Hopkins, R. Jim, C. Amarasiriwardena, D. C. Christiani, B. A. Coull, D. C. Bellinger, R. O. Wright, Prenatal Arsenic Exposure and Birth Outcomes among a Population Residing near a Mining-Related Superfund Site. *Environ. Health Perspect.* 1308, 1308–1315 (2016).
228. J. Currie, M. Neidell, Air Pollution and Infant Health: What Can I Learn from California's Recent Experience? Q. J. Econ. 120, 1003–1030 (2005).
229. D. Almond, A. E. Kowalski, J. J. Doyle, H. Williams, E. Glaeser, M. Greenstone, J. Gruber, G. Imbens, L. Katz, M. Kremer, D. Lee, D. Neal, J. Newhouse, J. Poterba, J. Rothstein, A. Chandra, J. Currie, D. Cutler, D. Fetter, Estimating marginal returns to medical care: evidence from at-risk newborns. Q. J. Econ. 125, 591–634 (2010).
230. S. The, Q. Journal, N. Aug, D. Almond, K. Y. Chay, D. S. Lee, The Costs of Low Birth Weight. Q. J. Econ. 120, 1031–1083 (2005).
231. K. S. Buckles, D. M. Hungerman, Season of birth and later outcomes: Old questions, new answers. *Rev. Econ. Stat.* 95, 711–724 (2013).
232. R. J. Waldmann, Income Distribution and Infant Mortality. Q. J. Econ. 107, 1283–1302 (1992).
233. G. R. Guedes, E. S. Brondízio, A. F. Barbieri, A. Resende, P.-F. Rodrigo, Á. O. D'Antona, Poverty and Inequality in the Rural Brazilian Amazon: A Multidimensional Approach. Hum Ecol Interdiscip J. 40, 41–57 (2012).
234. D. B. De Castro, R. C. Pinto, B. C. de Albuquerque, M. Sadahiro, J. U. Braga, The Socioeconomic Factors and the Indigenous Component of Tuberculosis in Amazonas. PLoS One, 1–10 (2016).
235. T. Andrasfay, N. Goldman, Reductions in 2020 me life expectancy due to COVID-19 and the disproportionate impact on the Black and Latino populations. *Proc. Natl. Acad. Sci. U. S. A.* 118, 1–6 (2021).
236. L. J. Marteleto, M. Dondero, Racial Inequality in Education in Brazil: A Twins Fixed-Effects Approach. *Demography*. 53, 1185–1205 (2016).

237. W. S. Walker, S. R. Gorelik, A. Baccini, J. L. Aragon-Osejo, C. Josse, C. Meyer, M. N. Macedo, C. Augusto, S. Rios, T. Katan, A. A. de Souza, S. Cuellar, A. Llanos, I. Zager, G. D. Mirabal, K. K. Solvik, M. K. Farina, P. Moutinho, S. Schwartzman, The role of forest conversion, degradation, and disturbance in the carbon dynamics of Amazon indigenous territories and protected areas. Proc. Natl. Acad. Sci. U. S. A. 117, 3015–3025 (2020).

238. D. Herrera, A. Pfaff, J. Robalino, Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian Amazon. Proc. Natl. Acad. Sci. U. S. A. 116, 14916–14925 (2019).

239. M. C. Castro, A. Massuda, G. Almeida, N. A. Menezes-Filho, M. V. Andrade, K. V. M. de Souza Noronha, R. Rocha, J. Macinko, T. Hone, R. Tasca, L. Giovanella, A. M. Malik, H. Werneck, L. A. Fachini, R. Atun, Brazil's unified health system: the first 30 years and prospects for the future. Lancet. 394, 345–356 (2019).

240. Columbia Public Health, "Comparative health policy library – Brazil summary." Publichealth.columbia.edu (Feb. 14, 2023). https://www.publichealth.columbia.edu/research/comparative-health-policy-library/brazil-summary

241. International Student Insurance, "Brazil student insurance – healthcare in Brazil." Internationalstudentinsurance.com (last accessed Feb. 2023). https://www.internationalstudentinsurance.com/brazil-student-insurance/healthcare-in-brazil.php

242. Aetna International, "Health and health care in Brazil." Aetnainternational.com (last accessed Feb. 2023). https://www.aetnainternational.com/en/individuals/destination-guides/expat-guide-to-brazil/health-and-health-care.html

243. J. Paim, C. Travassos, C. Almeida, L. Bahia, J. MacInko, The Brazilian health system: History, advances, and challenges. Lancet. 377, 1778–1797 (2011).

244. Institutional Repository for Information Sharing, World Health Organization (WHO). https://apps.who.int/iris/handle/10665/137005

245. R. Miranda, "Mining in Brazil: overview." uk.practicallaw.thomsonreuters.com (Nov. 1, 2017). https://uk.practicallaw.thomsonreuters.com/w-011-4019?transitionType=Default&contextData=(sc.Default)&firstPage=true

246. C. Jamasmie, “Brazil launches new mining agency days before Temer steps down.” Mining.com (Dec. 5, 2018). https://www.mining.com/brazil-opens-new-mining-agency-days-temers-govt-ends/
247. S. Advogados, “Spotlight: Mining in Brazil.” Lexology.com (Dec. 10, 2021). https://www.lexology.com/library/detail.aspx?g=c50722df-19e3-4d31-b0b1-d7d37f59b357
248. Sistema Único de Saúde Department of Informatics (DATASUS). Datasus.saude.gov.br (last accessed Feb. 2023). https://datasus.saude.gov.br/
249. World Bank, “Data Catalog.” Worldbank.org (last accessed Feb. 2023). https://datacatalog.worldbank.org/home
250. Brazilian Institute of Geography and Statistics (IBGE). Ibge.gov.br (last accessed Feb. 2023) https://ibge.gov.br/
251. National Indian Foundation (FUNAI), “About.” Survivalinternational.org (last accessed Feb. 2023). https://www.survivalinternational.org/about/funai
252. Pan American Health Organization (PAHO). Paho.org/en (last accessed Feb. 2023). https://www.paho.org/en

A. Chapter 2 Appendix

A.1 - Additional Literature Review

A.1.1) Political Factors

This study is pertinent to recent political activity in Brazil. Former President Bolsonaro planned to expand mining operations within Amazonian indigenous lands, despite concerns for socioeconomic and environmental impacts (205). Short-term economic growth is being prioritized at the expense of Amazonia. The potential for further devastation to the most remote and conserved parts of the Amazon is high and with widespread impacts. The possible reopening of Brazilian Highway BR-319 through the heart of the Amazon is just one example (206). There are many gaps in current policy regarding artisanal and small-scale (i.e., illegal) gold mining in Brazil and the government does not have the resources necessary to enforce regulations (207). Reviews of previous failed attempts to curb mercury use at artisanal gold mines, in Brazil or otherwise, demonstrate a lack of continuity in enforcement and misplaced objectives which have thwarted any such efforts (208).

A.1.2) Mercury

Human health effects of mining may be driven by air or water pollution, which I cannot discern at the level of resolution of municipal births. However, I suspect the primary cause of pollution to be mercury, as artisanal gold mining is heavily associated with its use. Mercury is mixed with mining material containing gold and other sediments to form a mercury-gold amalgam. This amalgam is then heated to vaporize the mercury and isolate the gold ore. Human health can be compromised by inhaling or ingesting high levels of mercury. From the World Health Organization, such effects include damage to the nervous, digestive, and immune systems, lungs, and kidneys (209). Fetuses are especially sensitive to mercury and may experience neurological symptoms after birth including vision and hearing loss, deficiencies in memory and motor skills, seizures, and language disorders. Risk assessments have established causal links between mining pollution and human health due to vapor inhalation and consuming contaminated fish, which can be measured in a variety of ways including dietary, hair, or breast milk samples (210-215).

Chief to my investigation is the impact of gold mining-borne mercury exposure on infant health outcomes. Previous investigations have identified impacts of mining and their respective pollution types on negative birthweight outcomes (216-221). Neurological and physiological impacts of mercury exposure in youth have also been well documented (222-225). Beyond mercury, there are also human health concerns for arsenic exposure in mining areas (226-227). Arsenic, a human carcinogen, naturally occurs in the environment and is often disturbed and released by mining activity.

A.1.3) Health Costs: Measurements and Complications

Societal efforts to protect human health can be framed positively (i.e., quality of life improvements or lives saved) or negatively (i.e., monetary costs). For instance, pollution abatement measures were estimated to have saved approximately 1,000 infant lives in California (228). Conversely, the cost of low birth weight has been estimated to be as much as $550,000 per statistical life (229). In any case, cross-sectional estimates on returns to low birth weight-prevention may be biased by omitted variables including genetics (230) and any proposed value should be scrutinized accordingly. Seasonality of birth is also associated with long-term outcomes, possibly explained by maternal characteristic variations; winter births are disproportionately characterized by teenage and unmarried mothers (231).

A.1.4) Disparities in Health

Unequal income distribution is linked to higher infant mortality rates and increasingly so as the rich get richer, possibly explained by relative access to health care or correlation with the relative effects of government policies on income brackets (232). Brazil as a country has relatively high levels of both poverty and inequality, higher still in the rural Brazilian Amazon (233). Limited health care services and poor socioeconomic conditions mean that otherwise preventable conditions such as Tuberculosis are still a concern to these populations (234).

Recently, COVID-19 has created a new dimension of health disparity among ethnic groups (235), with Brazil being one of the world's hardest hit countries by the pandemic. And beyond health, racial disparities in Brazilian education have also been identified (236). The wellbeing of indigenous communities in Brazil's Amazon is also central in discussions around climate change and deforestation, as their presence inhibits environmental degradation (237-*238*).

A.2 - Brazilian Public Health Care Systems

Brazil's publicly funded health care system, Sistema Único de Saúde (SUS), was implemented in 1990 following the creating of the new 1988 Brazilian Constitution which established health as a universal right (239). Covering every legal resident of Brazil, the goal of SUS was to improve health outcomes by reducing health care access inequalities. SUS is decentralized with administrative responsibilities at the federal, state, and municipal levels of government, and offers free services including primary, inpatient, and outpatient care (240).

While SUS provides free services to both Brazilians and foreigners, underfunding and overcrowding in the public system often lead to patients seeking private treatment if they can afford it (241). The public and private health sectors operate independently, and National Health Identification Cards, previously known as SUS cards, are required to access the healthcare system and provide mobility of medical records between services (242). This connectivity allows patients to access both private and public health care services across all three government subsectors (243). SUS is used exclusively by over 78% of the Brazilian population, making it an excellent source of health data, including birth records (244).

A.3 - Brazilian Mining Regulatory Scheme

Prior to 2017, the Brazilian mining sector was regulated by two authorities. The Ministry of Mines and Energy (Ministério de Minas e Energia), or MME, is responsible for making public policy covering various energy sectors, and The National Department of Mineral Production (Departamento Nacional de Produção), or DNPM, oversees mining activity throughout Brazil

(245). The National Mining Agency (Agência Nacional de Mineração), or ANM, has since replaced the DNPM as the regulatory agency of the mining sector, bringing stricter environmental regulations and expectations for reclamation of degraded areas (246).

The MME and ANM, both federal authorities, share most of Brazilian mining sector administrative functions, with no firm hierarchy established between them (247). As further described, the MME formulates mining policies, supervises implementation, and grants mining concessions, while the ANM is responsible for managing, regulating, and supervising mining activity, as well as granting exploration licences and mining titles beyond the MME's roles. According to Brazil's Federal Constitution, mineral deposits belong to the Federation and thus require titles to be explored or mined. Economic exploitation without such a concession is considered illegal. Permits are divided into two phases, exploration - guaranteeing the owner ability to research the area without extracting, and exploitation - granting the owner power to extract until exhaustion. Mineral licences, which grant rights to extract specific substances without prior research, as well as small-scale mining permits, which allow for immediate mineral use, are also available. Conditions to regulate resource exploration and extraction in indigenous areas are being formulated as part of the Federal Constitution but have not yet been implemented. Accordingly, no mineral activities are currently permitted in indigenous areas, and any such activity occurring is illegal.

A.4 - Additional Data Source Information

The infant health data comes from the Brazil Live Birth Information System (SINASC), which contains microdata on live births over numerous variables, including race, gender, place of birth, and mother characteristics. Data was collected for the years 2008-2017, with over 5 million birth records in the Brazilian Amazon. Municipality-level spending data was accessed from the SUS Department of Informatics, or DATASUS (248). Information on mines, both illegal and legal, comes from the Amazon Geo-Referenced Socio-Environmental Information Network (RAISG), a collaborative effort of numerous organizations from Amazon countries concerned with socio-environmental sustainability in the region. Capital city coordinates and federal highway system mapping come from The World Bank Data Catalog (249). Shapefiles for Brazil, its state and municipality borders, and population levels from the 2010 census are available online at The Brazilian Institute of Geography and Statistics, or IBGE (250). Indigenous land boundaries are from the National Indian Foundation, or FUNAI (251). GPS coordinates for ICU-equipped hospitals come from Pan American Health Organization, or PAHO (252).

Of these 742 municipalities, 28 contain at least 1 illegal mine, with a mode of 1, a maximum of 16, and a total of 62 (Figure A.1). This data structure provides me with a sizeable control group, i.e., 714 municipalities without illegal mines. With respect to legal gold mining, I observe a total of 1537 operating mines within 84 of the 742 municipalities, with a mode of 1 and a maximum of 695.

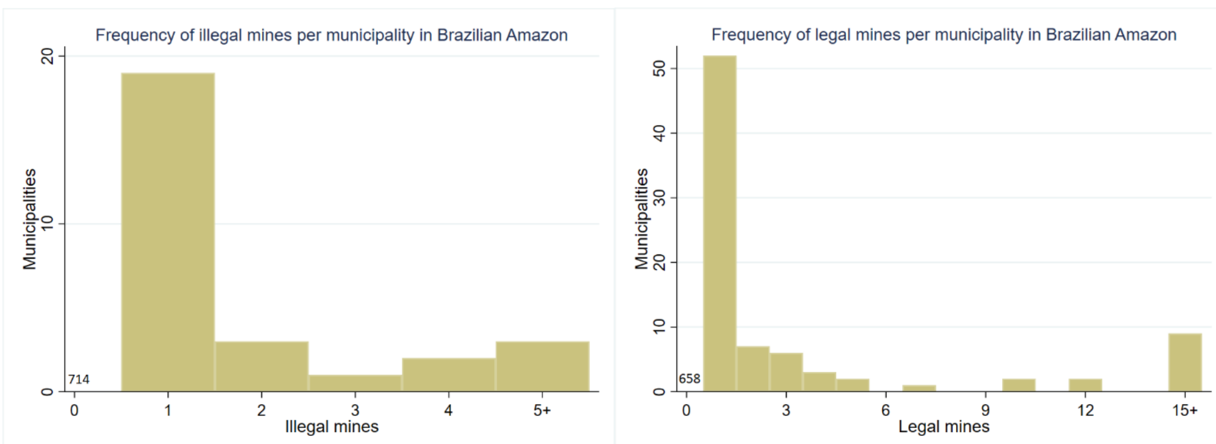

Figure A.1 Frequency of illegal and legal mines in municipalities of the Brazilian Amazon.

A.5 - Suppressed Regression Results for Table 2.2 and Figures 2.2-2.4

Table A.1 Main results – full models

Dep. Var.	Birthweight (g)	Premature Birth*100 (%)	Low Apgar Score*100 (%)
Model	(1)	(1)	(1)
Indigenous	-39.24***	3.63**	-0.001
	(13.20)	(1.46)	(0.98)
Illegal mine	1.91	0.28	-0.09
	(1.85)	(0.30)	(0.29)
Legal mine	0.05***	-0.0001	0.02***
	(0.02)	(0.002)	(0.002)
Indigenous*Illegal mine	-22.64***	-0.18	0.35
	(4.14)	(0.31)	(0.71)
Indigenous*Legal mine	0.03	0.01	-0.01
	(0.13)	(0.01)	(0.01)
Delivery age	8.22***	-0.16***	-0.08***
	(0.29)	(0.02)	(0.02)
Married (%)	32.47***	-1.30***	-0.40
	(4.04)	(0.31)	(0.49)
Education 2 (%)	100.96***	-2.59**	-0.91
	(17.16)	(1.01)	(0.88)
Education 3 (%)	132.47***	-4.13***	-2.05**
	(17.04)	(1.04)	(0.89)
Education 4 (%)	140.55***	-6.31***	-2.35**
	(17.28)	(1.07)	(0.94)
Education 5 (%)	104.74***	-6.56***	-2.94***
	(17.26)	(1.10)	(0.98)
GDP (R$/thousand people)	-0.55*	0.04**	0.01
	(0.29)	(0.02)	(0.04)
Health spending (per 1k)	-5.72	-2.12	-7.74***
	(19.35)	(1.82)	(2.82)
Education spending (R$/thousand people)	14.80	0.32	3.57**
	(13.53)	(0.83)	(1.74)
Bolsa spending (R$/thousand people)	-2.81	-0.70	0.91
	(26.44)	(1.85)	(4.00)
Population density (thousand people/km2)	-109.13***	1.75**	-7.50***
	(18.18)	(0.78)	(2.77)
ICU-equipped hospitals (#/thousand people)	234.51***	-3.57	13.03
	(66.29)	(5.63)	(10.11)
d2008	-	-	-
d2009	22.32	-	20.62***
	(29.37)		(1.80)
d2010	26.75*	91.80***	-1.00
	(13.96)	(0.87)	(1.69)
d2011	30.44**	-2.95***	-3.36
	(13.45)	(1.04)	(2.19)
d2012	-	-	-
d2013	-	-	-
d2014	26.81**	-4.93***	0.50
	(13.02)	(1.25)	(1.30)
d2015	-51.35***	8.90***	-1.73
	(8.77)	(0.89)	(1.43)
d2016	26.05	-6.55***	59.17***
	(15.99)	(1.72)	(1.84)
d2017	-	-	-
Constant	2,873.31***	23.06***	17.28***
	(23.00)	(1.58)	(2.60)
Observations	270,534	189,909	254,132
R-squared	0.0133	0.0064	0.0134

Notes: Birthweight is measured in grams. Premature birth is defined as occurring before 37 weeks. Low Apgar score indicates a value between 0-7 on a discrete scale between 0-10. Education attainment of the mother is categorized into 5 groups: 1 for 0 years, 2 for 1-3 years, 3 for 4-7 years, 4 for 8-11 years, and 5 for 12+ years. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2 Birthweight heterogeneity – full models

Dep. Var.	Birthweight		Birthweight		Birthweight		Birthweight	
Model	Single	Married	Young	Old	Low educ.	High educ.	Reserves: Yes	Reserves: No
Indigenous	-36.59***	-42.92**	-56.97***	-41.35	-72.08***	-34.47**	-50.22***	55.60
	(12.64)	(18.87)	(14.68)	(26.05)	(14.72)	(14.63)	(12.37)	(34.59)
Illegal mine	2.84	0.70	8.79***	7.26	8.14***	-1.60	1.26	-14.71
	(2.68)	(6.01)	(2.74)	(4.43)	(2.09)	(2.45)	(2.83)	(9.63)
Legal mine	0.03	0.06	0.03	0.06	-0.01	0.07***	-0.01	0.10
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.19)
Indigenous*Illegal mine	-27.10***	-1.36	-29.81***	-21.00***	-28.56***	-33.73***	-19.68***	39.69**
	(3.76)	(8.03)	(8.01)	(7.04)	(6.06)	(7.68)	(3.99)	(19.49)
Indigenous*Legal mine	0.31	-0.20	0.09	2.83**	-0.03	0.23**	0.01	-0.03
	(0.26)	(0.14)	(0.17)	(1.11)	(0.18)	(0.11)	(0.14)	(3.62)
Delivery age	9.57***	7.19***			7.88***	7.26***	8.99***	7.53***
	(0.39)	(0.36)			(0.37)	(0.35)	(0.41)	(0.39)
Married (%)			34.34***	24.09**	40.29***	28.10***	44.30***	22.98***
			(5.87)	(10.15)	(5.64)	(4.43)	(6.01)	(4.87)
Education 2 (%)	144.05***	60.67***	154.04***	53.58**			122.61***	60.24***
	(24.69)	(16.20)	(33.59)	(22.27)			(21.60)	(18.54)
Education 3 (%)	171.12***	95.17***	155.28***	103.91***			145.03***	100.70***
	(24.00)	(15.82)	(32.44)	(21.83)			(21.39)	(18.64)
Education 4 (%)	182.48***	101.07***	174.85***	90.87***			154.69***	109.46***
	(24.03)	(16.28)	(32.12)	(21.55)			(21.60)	(19.62)
Education 5 (%)	160.03***	62.53***	193.64***	67.85***			120.83***	73.08***
	(24.35)	(16.43)	(37.65)	(23.40)			(21.38)	(20.57)
GDP (R$/thousand people)	-0.49	-0.61*	-0.93**	-0.39	-0.73	-0.44	-0.38	-0.36
	(0.33)	(0.34)	(0.38)	(0.52)	(0.46)	(0.28)	(0.43)	(0.33)
Health spending (per 1k)	-19.92	5.49	-2.71	-14.79	33.20	-13.19	5.09	9.47
	(23.59)	(23.22)	(27.13)	(36.17)	(31.69)	(18.73)	(33.45)	(24.17)
Education spending (R$/thousand people)	22.19*	8.69	6.84	13.81	14.56	7.65	-32.59	20.96
	(13.32)	(16.28)	(15.73)	(23.64)	(18.98)	(13.57)	(21.96)	(13.80)
Bolsa spending (R$/thousand people)	2.24	-8.02	-31.22	56.72	-9.79	7.02	76.96	-11.19
	(26.69)	(33.46)	(32.87)	(49.94)	(30.96)	(28.79)	(46.71)	(27.56)
Population density (thousand people/km2)	-31.06*	-154.92***	-89.31***	-140.57***	-121.43***	-102.70***	-1,588.85***	-75.33***
	(18.47)	(23.65)	(19.83)	(27.57)	(34.98)	(15.37)	(440.92)	(14.40)
ICU-equipped hospitals (#/thousand people)	215.32***	245.63***	157.67*	351.27**	234.70**	227.51***	106.29	188.88***
	(80.17)	(79.51)	(92.96)	(143.68)	(103.88)	(68.42)	(110.52)	(70.96)
d2008	-	-	-	-	-	-	-	-
d2009	34.61	-7.81	12.30	60.62**	30.35	11.54	6.99	-
	(30.23)	(36.02)	(37.18)	(23.52)	(30.30)	(27.94)	(29.83)	
d2010	38.51**	16.66	-19.73	-139.71***	68.16***	-9.55	6.80	107.36***
	(17.67)	(15.13)	(21.38)	(33.82)	(18.26)	(13.10)	(11.70)	(14.06)
d2011	95.79***	12.27	28.09	71.60***	36.69	15.13	7.92	-
	(15.20)	(17.98)	(17.88)	(24.92)	(27.44)	(12.60)	(19.67)	
d2012	-	-	-	-	-	-	-	-
d2013	-	-	-	-	-	-	-	-
d2014	117.07***	-39.33	13.18	-290.54***	-12.74	77.93***	-	34.27***
	(11.96)	(25.16)	(19.32)	(21.70)	(14.16)	(14.85)		(12.07)
d2015	-72.83***	-42.90***	-53.10***	-45.91***	-129.18***	-33.67***	-68.94***	-
	(9.94)	(12.36)	(12.08)	(15.94)	(19.90)	(8.25)	(12.14)	
d2016	69.69***	-53.76**	32.21	118.45***	8.67	-66.54***	4.92	-
	(17.65)	(21.59)	(19.99)	(30.05)	(20.85)	(18.37)	(19.11)	
d2017	-	-	-	-	-	-	-	-
Constant	2,798.46***	2,973.10***	2,970.27***	3,141.31***	2,986.47***	3,041.50***	2,871.80***	2,905.76***
	(29.17)	(25.33)	(37.59)	(32.20)	(19.48)	(16.58)	(31.32)	(27.47)
Observations	113,312	157,222	70,359	21,499	83,590	192,287	127,869	142,665
R-squared	0.017	0.009	0.007	0.008	0.018	0.010	0.020	0.011

Notes: For Tables 2.4-2.6, Models 1 (a) & (b) compare births of single mothers to married mothers, Models 2 (a) & (b) compare young mother births (≤19) to old mother births (≥35), Models 3 (a) & (b) compare relatively low education level (≤7 years) to high (≥8 years), and Models 4 (a) & (b) compare municipalities with (>0%) and without (=0%) indigenous reserves. Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3 Premature birth heterogeneity – full models

Dep. Var.	Premature*100		Premature*100		Premature*100		Premature*100	
Model	Single	Married	Young	Old	Low educ.	High educ.	Reserves: Yes	Reserves: No
Indigenous	3.84**	3.42**	4.12***	4.95**	4.31***	4.23***	3.92***	-2.09
	(1.65)	(1.56)	(1.55)	(2.15)	(1.60)	(1.52)	(1.41)	(2.56)
Illegal mine	0.24	0.34	0.49	-0.41	-0.09	.42*	0.19	-0.66**
	(0.35)	(0.26)	(0.44)	(0.32)	(0.46)	(0.24)	(0.41)	(0.27)
Legal mine	-0.003	0.0005	-0.001	0.004	0.001	-0.0008	0.0006	0.05**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.02)
Indigenous*Illegal mine	-0.04	-0.65	0.04	-0.47	-0.17	1.03*	-0.29	-4.67***
	(0.28)	(0.57)	(0.76)	(0.34)	(0.36)	(0.60)	(0.30)	(1.28)
Indigenous*Legal mine	-0.03***	0.02**	-0.002	0.28*	0.01	-0.004	0.01	-0.45
	(0.01)	(0.01)	(0.01)	(0.16)	(0.01)	(0.01)	(0.01)	(0.28)
Delivery age	-0.23***	-0.11***			-0.18***	-0.13***	-0.18***	-0.14***
	(0.02)	(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
Married (%)			-1.69***	-0.49	-1.54***	-1.18***	-1.37***	-1.25***
			(0.45)	(0.73)	(0.50)	(0.32)	(0.53)	(0.36)
Education 2 (%)	0.04	-4.08***	-1.13	-2.22			-3.17**	-1.66
	(1.64)	(1.21)	(2.73)	(1.69)			(1.33)	(1.39)
Education 3 (%)	-1.80	-5.47***	-0.91	-3.35**			-5.07***	-2.94**
	(1.59)	(1.25)	(2.85)	(1.60)			(1.35)	(1.43)
Education 4 (%)	-4.17**	-7.51***	-4.04	-3.98**			-6.81***	-5.54***
	(1.62)	(1.27)	(2.90)	(1.60)			(1.40)	(1.43)
Education 5 (%)	-4.82***	-7.75***	-6.48**	-4.02**			-7.00***	-.580***
	(1.68)	(1.32)	(3.21)	(1.73)			(1.48)	(1.46)
GDP (R$/thousand people)	0.04*	0.04**	0.05*	0.06	0.02	0.05***	0.04	0.03*
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)
Health spending (per 1k)	-4.32*	-0.79	-2.86	-1.06	-2.02	-2.25	-3.63	-0.88
	(2.25)	(2.01)	(2.51)	(3.25)	(2.73)	(1.75)	(3.81)	(1.43)
Education spending (R$/thousand people)	0.64	0.22	0.54	-0.45	-0.03	0.59	2.10	-0.38
	(1.13)	(0.89)	(1.08)	(1.54)	(1.23)	(0.80)	(1.87)	(0.86)
Bolsa spending (R$/thousand people)	-1.21	-0.59	-0.25	-0.73	-0.30	-0.60	-6.03	2.13
	(2.45)	(2.07)	(2.75)	(3.29)	(2.52)	(1.80)	(4.19)	(1.64)
Population density (thousand people/km2)	-2.39**	3.73***	-1.80	0.39	0.76	1.79**	24.54	2.25***
	(1.06)	(1.08)	(1.54)	(1.71)	(1.94)	(0.75)	(41.64)	(0.64)
ICU-equipped hospitals (#/thousand people)	5.68	-9.55	5.27	-8.37	-2.87	-3.14	-6.48	-1.56
	(8.24)	(5.85)	(8.79)	(10.47)	(8.67)	(5.46)	(10.49)	(5.10)
d2008	-	-	-	-	-	-	-	-
d2009	-	-	-	-	-	-	-	-
d2010	90.14***					91.68***	91.74***	-
	(1.52)					(0.77)	(1.41)	
d2011	-1.60	-2.69**	-3.74**	-6.16***	-5.90***	0.56	-2.63	-
	(1.33)	(1.11)	(1.77)	(1.86)	(1.78)	(0.99)	(1.64)	
d2012	-	-	-	-	-	-	-	-
d2013	-	-	-	-	-	-	-	-
d2014	-5.16***	-3.98**	-18.18***	21.71***	-6.29***	-4.36***	-	-3.51***
	(1.26)	(1.54)	(1.31)	(1.46)	(2.38)	(0.92)		(0.53)
d2015	9.39***	8.86***	1.45	18.41***	10.09***	8.38***	9.41***	-
	(1.08)	(0.89)	(1.38)	(1.42)	(1.52)	(0.85)	(1.13)	
d2016	-6.45***	-7.15***	-11.25***	-4.39*	-12.08***	-6.85***	-6.09***	-
	(2.06)	(1.72)	(2.17)	(2.38)	(2.06)	(1.50)	(1.83)	
d2017	-	-	-	-	-	-	-	-
Constant	23.22***	21.41***	19.29***	17.96***	20.71***	15.38***	24.99***	20.99***
	(02.10)	(1.90)	(3.03)	(2.42)	(1.47)	(1.20)	(2.47)	(01.86)
Observations	75,919	113,990	50,000	14,660	56,970	136,372	85,126	104,783
R-squared	0.0071	0.0063	0.0062	0.0053	0.0048	0.0045	0.0097	0.0046

Notes: For Tables 2.4-2.6, Models 1 (a) & (b) compare births of single mothers to married mothers, Models 2 (a) & (b) compare young mother births (≤19) to old mother births (≥35), Models 3 (a) & (b) compare relatively low education level (≤7 years) to high (≥8 years), and Models 4 (a) & (b) compare municipalities with (>0%) and without (=0%) indigenous reserves. Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A.4 Low Apgar score heterogeneity – full models

Dep. Var.	Low Apgar*100		Low Apgar*100		Low Apgar*100		Low Apgar*100	
Model	Single	Married	Young	Old	Low educ.	High educ.	Reserves: Yes	Reserves: No
Indigenous	-0.51	0.51	0.37	-0.24	-0.07	0.89	-0.99	-0.34
	(1.31)	(1.13)	(1.18)	(1.67)	(1.13)	(1.10)	(1.11)	(2.43)
Illegal mine	-0.20	0.12	-0.31	-0.39	-0.16	-0.07	-0.12	1.58
	(0.18)	(0.56)	(0.33)	(0.27)	(0.37)	(0.27)	(0.31)	(2.72)
Legal mine	0.02***	0.01***	0.02***	0.02***	0.01***	0.02***	0.01***	-0.01
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.01)
Indigenous*Illegal mine	0.98*	-0.37	0.12	2.54***	0.84	-1.20	0.60	-7.11**
	(0.55)	(1.10)	(0.91)	(0.48)	(0.60)	(0.78)	(0.64)	(2.95)
Indigenous*Legal mine	-0.03*	0.004	-0.0007	-0.26	-0.002	-0.01	-0.01	-0.60***
	(0.02)	(0.01)	(0.009)	(0.17)	(0.01)	(0.01)	(0.01)	(0.19)
Delivery age	-0.13***	-0.04**			-0.03	-0.10***	-0.12***	-0.03
	(0.03)	(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
Married (%)			-0.77	0.28	-0.96	-0.13	-0.08	-0.50
			(0.65)	(0.64)	(0.59)	(0.48)	(0.74)	(0.57)
Education 2 (%)	-1.49	-0.54	-1.72	-0.41			-0.29	-2.09
	(1.35)	(1.16)	(2.34)	(1.68)			(1.08)	(1.44)
Education 3 (%)	-1.56	-2.39**	-2.54	-1.43			-1.50	-3.08**
	(1.28)	(1.21)	(2.29)	(1.65)			(1.12)	(1.41)
Education 4 (%)	-2.69**	-1.98	-2.95	-2.21			-1.13	-3.91***
	(1.31)	(1.27)	(2.28)	(1.56)			(1.16)	(1.46)
Education 5 (%)	-2.57*	-2.89**	-2.25	-4.42***			-1.98	-4.30***
	(1.38)	(1.29)	(2.50)	(1.64)			(1.22)	(1.54)
GDP (R$/thousand people)	0.02	0.01	-0.01	0.03	0.01	0.01	-0.01	0.08
	(0.06)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.07)
Health spending (per 1k)	-7.22*	-8.16***	-6.36*	-4.60*	-7.43**	-8.31***	-10.60**	-3.86
	(3.75)	(2.91)	(3.51)	(2.75)	(3.58)	(2.74)	(5.21)	(3.24)
Education spending (R$/thousand people)	3.39	3.60**	3.21	2.50	2.69	3.94**	4.52	1.75
	(2.29)	(1.72)	(2.06)	(1.62)	(2.07)	(1.68)	(3.90)	(1.76)
Bolsa spending (R$/thousand people)	-1.72	3.00	0.64	3.90	2.32	0.33	1.56	4.84
	(4.79)	(4.35)	(4.67)	(3.68)	(4.48)	(3.95)	(7.15)	(4.61)
Population density (thousand people/km2)	-8.83**	-6.21***	-9.43**	-4.98*	-9.83**	-7.41***	-46.31	-5.35**
	(3.66)	(2.34)	(3.68)	(2.91)	(4.16)	(2.49)	(50.83)	(2.38)
ICU-equipped hospitals (#/thousand people)	4.22	19.34**	14.02	4.26	13.67	12.14	30.72*	-5.38
	(14.38)	(9.75)	(12.54)	(10.54)	(12.96)	(9.58)	(17.07)	(12.95)
d2008	-	-	-	-	-	-	-	-
d2009	21.62***	15.72***	24.47***	17.67***	22.68***	19.36***	21.45***	-
	(2.35)	(1.67)	(2.51)	(2.59)	(2.36)	(1.64)	(2.82)	
d2010	2.22	-5.80***	1.96	-4.79	1.16	-2.78*	-2.60	-3.43
	(2.37)	(2.01)	(2.43)	(3.28)	(1.78)	(1.51)	(2.22)	(3.27)
d2011	-2.00	-4.39*	3.45	-2.24	-7.13***	-1.13	-7.81**	-
	(2.25)	(2.62)	(2.16)	(2.00)	(2.32)	(2.25)	(3.05)	
d2012	-	-	-	-	-	-	-	-
d2013	-	-	-	-	-	-	-	-
d2014	23.06***	-3.57	4.67***	11.56***	8.21***	-0.0489***	-	-1.70
	(1.31)	(2.69)	(1.48)	(2.33)	(1.63)	(0.0127)		(3.14)
d2015	-0.71	-2.49	6.73***	6.23***	-2.09	-0.0142	-4.80**	-
	(1.28)	(1.81)	(1.37)	(1.27)	(1.50)	(0.0145)	(1.91)	
d2016	5.381***	78.98***	70.61***	54.75***	63.88***	0.5846***	58.67***	-
	(02.30)	(1.97)	(2.24)	(2.19)	(2.14)	(0.0177)	(2.75)	
d2017	-	-	-	-	-	-	-	-
Constant	19.52***	15.06***	17.62***	13.74***	14.54***	15.64***	18.28***	15.21***
	(3.47)	(2.74)	(3.69)	(2.77)	(2.60)	(2.39)	(3.96)	(3.17)
Observations	104,989	149,143	65,774	19,996	75,607	183,084	120,175	133,957
R-squared	0.0203	0.0086	0.0149	0.0113	0.0145	0.0127	0.0264	0.0045

Notes: For Tables 2.4-2.6, Models 1 (a) & (b) compare births of single mothers to married mothers, Models 2 (a) & (b) compare young mother births (≤19) to old mother births (≥35), Models 3 (a) & (b) compare relatively low education level (≤7 years) to high (≥8 years), and Models 4 (a) & (b) compare municipalities with (>0%) and without (=0%) indigenous reserves. Cluster-robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.6 - Additional checks

A.6.1) Illegal Mine-only Municipalities and Legal Mine-only Municipalities

Model (1) is modified to estimate health effects in municipalities with only illegal gold mines (2) or only legal gold mines (3):

$$H_{ij} = \alpha R_i + \beta I_j + \delta(R_i \times I_j) + \sigma_m M_i + \sigma_d D_i + \sigma_J J_j + \lambda_s + \epsilon_{ij} \quad (2)$$

$$H_{ij} = \alpha R_i + \nu L_j + \rho(R_i \times L_j) + \sigma_m M_i + \sigma_d D_i + \sigma_J J_j + \lambda_s + \epsilon_{ij} \quad (3)$$

where $L = 0$ in (2) and $I = 0$ in (3), respectively. Model (2) estimates health outcomes during observations years for municipalities with illegal mining (test group) versus municipalities with no illegal mining (control group). Municipalities with legal mines, regardless of the presence of illegal mining, are excluded. The converse is true for model (3). In this way, I capture the explicit effect of mining regulatory schemes on infant health outcomes.

I compare illegal-only model (2) and legal-only model (3) results in Table A.5 (below) to the main model (1) results in Table A.1 (above). With respect to birthweight, the effect of *indigenous* in (3) is about the same as in (1), while the *indigenous* effect in (2) is smaller than in the other models, -34.5 g vs. -39 g, respectively. However, the interaction between *indigenous* and *legal mine*, while insignificant in (1), is now significant at the 1% level in (3), with indigenous infants weighing 4 g more per legal mine. Just one legal mine in a municipality makes up the difference in the *indigenous* estimates between models (2) and (3). The interaction between *indigenous* and *illegal mine* is about the same in magnitude between models (1) and (2), and significant at the 1% level in both.

For premature birth incidence, the effect of *indigenous* is smaller in (2) and (3) compared to (1) in both magnitude and significance (2.84% increase in indigenous premature birth incidence at 10% significance level versus 3.63% at 5% significance level, respectively). The effect of *legal mine* is now significant in (3), at the 5% level, increasing premature birth incidence among all births by 0.04% per mine. All other estimates remain insignificant.

As for low Apgar score incidence, the only significant estimate in (1) was *legal mine*, increasing low Apgar incidence among all births by 0.02% per mine, significant at the 1% level.

In the separate mine-type models, *legal mine* is no longer significant, while the interaction between *indigenous* and *legal mine* in (3) is now significant at the 1% level, increasing low Apgar score incidence by 0.24% per legal mine. This result likely stems from relatively more legal mining occurring in municipalities with less indigenous reserves; while mining regulation helps, protected areas help more for such vulnerable populations.

Table A.5 Effect of illegal-only and legal-only mines on infant health outcomes

Dep. Var.	Birthweight		Premature Birth*100		Low Apgar Score*100	
Model	(2)	(3)	(2)	(3)	(2)	(3)
Mine Type	illegal	Legal	illegal	legal	illegal	legal
Indigenous	-34.45**	-39.13***	2.84*	2.84*	-0.49	-0.22
	(13.89)	(13.92)	(1.46)	(1.61)	(0.91)	(0.97)
Illegal mine	1.00		0.19		-0.13	
	(1.73)		(0.25)		(0.28)	
Legal mine		0.21		0.04**		-0.01
		(0.35)		(0.02)		(0.03)
Indigenous*Illegal mine	-23.46***		-0.11		0.83	
	(3.74)		(0.26)		(0.56)	
Indigenous*Legal mine		4.03***		0.04		0.24***
		(0.61)		(0.15)		(0.06)
Delivery age	8.22***	8.00***	-0.16***	-0.15***	-0.08***	-0.07***
	(0.31)	(0.31)	(0.02)	(0.02)	(0.02)	(0.02)
Married (%)	32.29***	32.12***	-1.32***	-1.24***	-0.15	-0.34
	(4.24)	(4.05)	(0.33)	(0.31)	(0.52)	(0.49)
Education 2 (%)	111.55***	101.20***	-2.94***	-2.13**	-1.05	-0.86
	(17.49)	(16.34)	(1.04)	(1.01)	(0.90)	(0.89)
Education 3 (%)	143.83***	132.83***	-4.65***	-4.01***	-2.29**	-1.92**
	(17.14)	(16.03)	(1.08)	(1.04)	(0.92)	(0.90)
Education 4 (%)	151.31***	141.34***	-6.76***	-6.14***	-2.49***	-2.16**
	(17.33)	(16.34)	(1.12)	(1.07)	(0.96)	(0.94)
Education 5 (%)	113.71***	106.11***	-6.83***	-6.35***	-3.12***	-2.75***
	(17.42)	(16.47)	(1.16)	(1.09)	(1.01)	(0.99)
GDP (R$/thousand people)	-0.47	-0.48*	0.05**	0.05**	0.0006	0.005
	(0.29)	(0.28)	(0.02)	(0.02)	(0.05)	(0.04)
Health spending (per 1k)	-8.58	-11.22	-2.38	-2.54	-7.74***	-7.46***
	(18.94)	(18.50)	(1.83)	(1.82)	(2.87)	(2.81)
Education spending (R$/thousand people)	21.19	17.86	0.23	0.36	3.70**	3.55**
	(13.55)	(13.84)	(0.84)	(0.82)	(1.80)	(1.76)
Bolsa spending (R$/thousand people)	-6.52	-10.84	-0.88	-0.78	2.37	1.63
	(26.92)	(26.47)	(1.93)	(1.85)	(4.12)	(3.98)
Population density (thousand people/km2)	-102.02***	-112.33***	1.74**	1.85**	-7.54***	-7.33***
	(16.39)	(18.31)	(0.81)	(0.79)	(2.81)	(2.75)
ICU-equipped hospitals (#/thousand people)	253.07***	214.00***	-1.73	-3.68	13.04	11.83
	(67.27)	(65.27)	(5.85)	(5.50)	(10.81)	(10.25)
d2008	-	51.52***	-	-	-	4.31
		(12.44)				(6.65)
d2009	-	48.80***	-	-	-	-2.91
		(13.76)				(2.20)
d2010	27.78*	49.37***	91.65***	2.24	-1.57	22.86***
	(14.33)	(12.53)	(0.88)	(1.48)	(1.75)	(3.36)
d2011	36.24**	42.81***	-2.49**	0.88	-3.98	54.84***
	(15.19)	(11.93)	(1.21)	(0.93)	(2.59)	(2.02)
d2012	-	69.93***	-	2.21	-	1.71
		(19.72)		(1.37)		(5.97)
d2013	-	-57.57***	-	1.30	-	11.78***
		(11.78)		(0.91)		(1.97)
d2014	23.15*	-36.44***	-5.02***	5.40***	0.49	-0.70
	(13.86)	(9.89)	(1.50)	(0.82)	(1.09)	(1.79)
d2015	-47.23***	34.08	9.48***	-0.92	-2.20	-2.06
	(10.18)	(21.72)	(1.08)	(1.00)	(1.74)	(2.20)
d2016	29.52*	96.28***	-5.97***	-5.27***	59.98***	-1.95**
	(16.07)	(7.73)	(1.81)	(0.69)	(1.79)	(0.88)
d2017	-	-	-	-	-	-
Constant	2,856.65***	2,880.57***	23.75***	22.73***	16.98***	16.70***
	(23.27)	(22.09)	(1.66)	(1.55)	(2.74)	(2.61)
Observations	244,086	267,013	174,129	188,628	229,616	251,644
R-squared	0.0136	0.0125	0.0061	0.0062	0.0080	0.0081

Notes: Birthweight is measured in grams. Premature birth is defined as occurring before 37 weeks. Low Apgar score indicates a value between 0-7 on a discrete scale between 0-10. Education attainment of the mother is categorized into 5 groups: 1 for 0 years, 2 for 1-3 years, 3 for 4-7 years, 4 for 8-11 years, and 5 for 12+ years. All models include State-level fixed effects and employ Municipality-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.6.2) Instrumental Variables

To this point, I maintained the assumption that mines are exogenous from infant health measures. In the case that the number of illegal mines in a municipality is correlated with unobservable determinants of health, specifically birthweight, I consider several instrumental variable regressors. I derive 7 different instruments based on the average distance from a municipality's set of Illegal mines to the nearest (point distance) marker of a geographic category. These include i) the country border of Brazil, ii) Amazonian state borders, iii) Amazonian municipality borders, iv) capital cities, v) federal highways, vi) the sum of a municipality's neighbours' highway distances, and vii) both (v) and (vi). In essence, these instruments capture the "remoteness" of an illegal mine. My hypothesis is that miners in more remote areas may act more recklessly with less fear of detection and subsequently release more pollution into the surrounding environment. With respect to the strength of the instruments, it could be argued that remoteness affects birthweight via reduced health care access and is thus correlated with the error term. However, I already control for health care in my models in two ways: i) the amount of health spending per capita, and ii) the number of ICU-equipped hospitals per 1,000 people.

Table A.6 contains the estimates from my IV regressions. I observe two patterns across these models. First, the indigenous race indicator tends to be larger and significant when using broader definitions of remoteness (i.e., state and municipality borders) and the interaction term is smaller and insignificant. Second, when I scale the remoteness instrument down to the level of capital cities and federal highways, I find the indigenous indicator to have a smaller and often insignificant effect, while the coefficient on the interaction between indigenous and illegal mines become larger and more significant. Intuitively, the distance from a mine to a definitive location of activity (i.e., a city or a highway) may be a better indicator of remoteness than the arbitrary distance of a mine to the nearest border segment which could be completely uninhabited all the way across.

Table A.6 Birthweight outcomes using instrumental variables

Dep. Var.	Birthweight	Birthweight	Birthweight	Birthweight	Birthweight	Birthweight	Birthweight
IV	Country Border	State Borders	Municipality Borders	Capital Cities	Federal Highways	Neighbour Highways	Own & Neighbour Highways
Indigenous	-34.13	-48.61***	-35.46**	-28.44*	-27.88*	-18.76	-27.50*
	(21.44)	(15.34)	(16.54)	(14.94)	(15.38)	(24.39)	(15.38)
Illegal mine	11.77	10.20	-11.71	-6.84	6.96	185.19	5.58
	(8.95)	(9.60)	(15.64)	(8.94)	(9.35)	(133.65)	(9.32)
Legal mine	-0.02	-0.01	0.14	0.11*	0.01	-1.22	0.02
	(0.06)	(0.07)	(0.11)	(0.06)	(0.07)	(0.94)	(0.07)
Indigenous*Illegal mine	-45.08	1.47	-20.76	-46.87***	-60.47**	-242.01*	-60.47**
	(58.77)	(27.31)	(21.36)	(15.68)	(25.10)	(131.34)	(25.15)
Indigenous*Legal mine	0.18	-0.13	0.01	0.19	0.29**	1.58*	0.29*
	(0.34)	(0.21)	(0.18)	(0.13)	(0.14)	(0.94)	(0.15)
Delivery age	8.22***	8.23***	8.21***	8.21***	8.21***	8.28***	8.21***
	(0.29)	(0.30)	(0.29)	(0.29)	(0.29)	(0.30)	(0.29)
Married (%)	32.01***	32.33***	31.39***	31.35***	31.72***	36.47***	31.67***
	(4.04)	(4.03)	(4.05)	(4.03)	(4.00)	(5.04)	(4.00)
Education 2 (%)	100.81***	102.73***	101.03***	100.09***	99.99***	98.48***	99.95***
	(17.21)	(19.03)	(17.12)	(16.94)	(16.99)	(17.42)	(17.00)
Education 3 (%)	131.43***	135.53***	131.60***	129.65***	129.61***	128.62***	129.49***
	(17.84)	(18.93)	(17.30)	(16.92)	(17.06)	(17.10)	(17.056)
Education 4 (%)	139.41***	143.32***	139.45***	137.61***	137.65***	137.65***	137.53***
	(17.98)	(19.09)	(17.57)	(17.16)	(17.28)	(17.48)	(17.28)
Education 5 (%)	103.96***	107.74***	103.56***	101.86***	102.15***	105.46***	102.01***
	(17.99)	(19.08)	(17.56)	(17.15)	(17.28)	(18.49)	(17.28)
GDP (R$/thousand people)	-0.48*	-0.45*	-0.49*	-0.51*	-0.50*	-0.38	-0.50*
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.72)	(0.27)
Health spending (per 1k)	-11.54	-14.74	-7.37	-6.61	-9.11	-40.97	-8.75
	(18.03)	(18.13)	(18.66)	(18.47)	(17.76)	(61.72)	(17.81)
Education spending (R$/thousand people)	13.33	12.91	13.23	13.45	13.49	14.17	13.50
	(13.37)	(13.46)	(13.48)	(13.44)	(13.35)	(18.82)	(13.36)
Bolsa spending (R$/thousand people)	-4.91	-1.31	-12.07	-12.50	-8.23	46.38	-8.78
	(27.16)	(27.06)	(27.797)	(26.78)	(26.72)	(36.68)	(26.80)
Population density (thousand people/km2)	-110.28***	-109.69***	-114.46***	-114.00***	-111.53***	-79.78***	-111.81***
	(18.11)	(17.99)	(19.45)	(19.04)	(18.38)	(18.10)	(18.46)
ICU-equipped hospitals (#/thousand people)	229.75***	234.99***	245.84***	240.55***	231.16***	109.36	231.97***
	(65.86)	(65.68)	(67.53)	(67.01)	(65.79)	(125.07)	(65.82)
Observations	270,534	270,534	270,534	270,534	270,534	270,534	270,534
R-squared	0.0120	0.0118	0.0119	0.0117	0.0118	-0.0146	0.0118
Under-Ident. Test	6.632***	3.842**	8.209**	3.810*	5.072**	2.740*	6.740*
P-value	(0.010)	(0.050)	(0.0042)	(0.0510)	(0.0243)	(0.0979)	(0.0807)
Weak-Ident. Test	5788.1	25,000	7972.2	26,000	21,000	713.629	11,000
10% maximal IV size	(7.03)	(7.03)	(7.03)	(7.03)	(7.03)	(7.03)	(7.56)
Over-Ident. Test	0.000	0.000	0.000	0.000	0.000	0.000	6.447**
P-value	Eq. exactly ident.	Eq. exactly ident.	Eq. exactly ident.	Eq. exactly ident.	Eq. exactly ident.	Eq. exactly ident.	(0.0398)

Notes: All instruments are distanced-based and use the average distance of a municipality's set of Illegal mines to the nearest 1) Brazilian border, 2) State border, 3) Municipality border (own), 4) Capital city (anywhere), and 5) Federal highway (anywhere). The IV for model (6) is the average of (5) for all of a municipality's neighbours, and model (7) uses the IVs from (5) and (6). Cluster-robust standard errors in parentheses: Year dummies are omitted, as otherwise the estimated covariance matrix of moment conditions is not of full rank. *** p<0.01, ** p<0.05, * p<0.1.

B. Chapter 3 Appendix

B.1 – Regression Results for a Progressively More Rural Sample

Table B.1 Regressions results with a progressively more rural sample, Model 1 - Math

Municipality type	Full sample (1)	Exclude 2 cities with largest pop. (1a)	Exclude 5 cities with largest pop. (1b)	Exclude 10 cities with largest pop. (1c)	Rural only (1d)
Wells (counts)					
All	-0.642***	-0.591***	-0.564***	-0.559***	-0.558***
	(0.172)	(0.179)	(0.186)	(0.188)	(0.194)
School					
School population	0.621**	0.313	0.589	0.779	0.827
	(0.240)	(0.361)	(0.414)	(0.598)	(0.711)
Average class size	-0.010	0.007	0.019	0.019	0.017
	(0.032)	(0.042)	(0.050)	(0.054)	(0.056)
Authority funding	-0.048*	-0.043	-0.061**	-0.062	-0.067*
	(0.025)	(0.027)	(0.030)	(0.039)	(0.040)
Constant	68.492***	69.321***	69.028***	70.637***	72.408***
	(3.705)	(4.975)	(5.470)	(6.608)	(7.018)
Observations	2,418	1,481	1,258	1,110	1,044
R-squared	0.815	0.770	0.763	0.758	0.755

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. ‘All’ wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.2 Regressions results with a progressively more rural sample, Model 1 - Science

Municipality type	Full sample (3)	Exclude 2 cities with largest pop. (3a)	Exclude 5 cities with largest pop. (3b)	Exclude 10 cities with largest pop. (3c)	Rural only (3d)
Wells (counts)					
All	-0.261*	-0.259*	-0.247	-0.253*	-0.254
	(0.151)	(0.153)	(0.156)	(0.152)	(0.154)
School					
School population	0.290	-0.026	-0.044	0.102	0.119
	(0.210)	(0.280)	(0.316)	(0.456)	(0.507)
Average class size	0.006	0.015	0.017	0.024	0.013
	(0.030)	(0.040)	(0.042)	(0.045)	(0.046)
Authority funding	-0.049**	-0.043*	-0.056**	-0.060*	-0.063*
	(0.022)	(0.024)	(0.026)	(0.035)	(0.035)
Constant	72.690***	74.175***	73.650***	73.789***	74.757***
	(3.104)	(4.131)	(4.434)	(5.565)	(5.854)
Observations	2,423	1,481	1,251	1,104	1,048
R-squared	0.805	0.758	0.739	0.739	0.738

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. ‘All’ wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.3 Mean wells by life cycle stage (Model 2) and total observations from a progressively rural sample of Alberta schools administering Provincial Achievement Tests in Math and Science, 2015-2019

	Math			Science		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Active Wells (# of wells within 4 km)						
Full sample	2,418	5.57	20.60	2,423	5.27	20.04
Exclude 2 cities with largest pop.	1,481	8.42	25.27	1,481	7.95	24.61
Exclude 5 cities with largest pop.	1,258	9.27	26.54	1,251	8.78	25.89
Exclude 10 cities with largest pop.	1,110	10.27	28.07	1,104	9.72	27.39
Rural only	1,044	10.47	28.49	1,048	10.15	28.03
Suspended Wells (# of wells within 4 km)						
Full sample	2,418	3.73	15.05	2,423	3.64	14.96
Exclude 2 cities with largest pop.	1,481	5.45	17.93	1,481	5.31	17.83
Exclude 5 cities with largest pop.	1,258	6.02	18.96	1,251	5.90	18.90
Exclude 10 cities with largest pop.	1,110	6.74	20.06	1,104	6.60	20.00
Rural only	1,044	7.00	20.60	1,048	6.89	20.47
Abandoned Wells (# of wells within 4 km)						
Full sample	2,418	2.59	9.58	2,423	2.53	9.46
Exclude 2 cities with largest pop.	1,481	3.47	11.28	1,481	3.37	11.14
Exclude 5 cities with largest pop.	1,258	3.82	12.06	1,251	3.72	11.94
Exclude 10 cities with largest pop.	1,110	4.21	12.77	1,104	4.10	12.64
Rural only	1,044	4.39	13.12	1,048	4.29	12.94
Reclaimed Wells (# of wells within 4 km)						
Full sample	2,418	2.21	8.70	2,423	2.15	8.55
Exclude 2 cities with largest pop.	1,481	2.93	10.41	1,481	2.83	10.23
Exclude 5 cities with largest pop.	1,258	3.14	11.18	1,251	3.01	11.01
Exclude 10 cities with largest pop.	1,110	3.42	11.86	1,104	3.27	11.67
Rural only	1,044	3.58	12.20	1,048	3.42	11.96

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.4 Regressions results with a progressively more rural sample, Model 2 - Math

Municipality type	Full sample (2)	Exclude 2 cities with largest pop. (2a)	Exclude 5 cities with largest pop. (2b)	Exclude 10 cities with largest pop. (2c)	Rural only (2d)
Wells (counts)					
Active	-0.693***	-0.655***	-0.643***	-0.637***	-0.639***
	(0.148)	(0.154)	(0.157)	(0.158)	(0.165)
Suspended	-0.642***	-0.609***	-0.615***	-0.603***	-0.609***
	(0.160)	(0.167)	(0.170)	(0.171)	(0.178)
Abandoned	-0.763***	-0.720***	-0.714***	-0.708***	-0.711***
	(0.151)	(0.159)	(0.162)	(0.163)	(0.170)
Reclaimed	-0.399	-0.315	-0.255	-0.242	-0.238
	(0.302)	(0.330)	(0.323)	(0.323)	(0.326)
School					
School population	0.616**	0.316	0.582	0.757	0.801
	(0.240)	(0.362)	(0.414)	(0.598)	(0.710)
Average class size	-0.009	0.008	0.021	0.021	0.019
	(0.032)	(0.042)	(0.050)	(0.054)	(0.056)
Authority funding	-0.047*	-0.041	-0.059**	-0.060	-0.065
	(0.025)	(0.027)	(0.030)	(0.039)	(0.041)
Constant	68.421***	69.321***	69.433***	71.117***	72.982***
	(3.478)	(4.553)	(4.915)	(6.080)	(6.463)
Observations	2,418	1,481	1,258	1,110	1,044
R-squared	0.816	0.770	0.764	0.759	0.756

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.5 Regressions results with a progressively more rural sample, Model 2 - Science

Municipality type	Full sample (4)	Exclude 2 cities with largest pop. (4a)	Exclude 5 cities with largest pop. (4b)	Exclude 10 cities with largest pop. (4c)	Rural only (4d)
Wells (counts)					
Active	-0.260*	-0.295**	-0.293**	-0.294**	-0.292*
	(0.151)	(0.148)	(0.147)	(0.145)	(0.149)
Suspended	-0.192	-0.234	-0.250	-0.244	-0.240
	(0.163)	(0.163)	(0.160)	(0.159)	(0.163)
Abandoned	-0.316**	-0.365**	-0.369**	-0.370**	-0.366**
	(0.155)	(0.151)	(0.151)	(0.149)	(0.153)
Reclaimed	-0.168	-0.054	-0.028	-0.034	-0.049
	(0.291)	(0.268)	(0.264)	(0.265)	(0.269)
School					
School population	0.287	-0.018	-0.046	0.090	0.103
	(0.210)	(0.281)	(0.316)	(0.455)	(0.507)
Average class size	0.007	0.017	0.020	0.027	0.016
	(0.030)	(0.040)	(0.042)	(0.045)	(0.046)
Authority funding	-0.048**	-0.042*	-0.054**	-0.058*	-0.060*
	(0.022)	(0.024)	(0.026)	(0.035)	(0.035)
Constant	72.287***	73.811***	73.619***	73.716***	74.652***
	(3.089)	(4.013)	(4.285)	(5.475)	(5.771)
Observations	2,423	1,481	1,251	1,104	1,048
R-squared	0.805	0.759	0.740	0.741	0.739

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B.2 – Robustness Checks 1: Instrumental Variables Regression

I begin by matching well locations with type of agreement. The Alberta government only maintains a database of currently active Agreements, so I am unable to match older wells with the Agreements they were once associated with. Therefore, I elect to only consider Agreements active during the years that match my test scores (2015-2019) with the goal of estimating nearby well activity in the current observation year. I formally define the instrument as the mean age of contemporary Agreements within 4 km of schools. This definition, unlike other structures of variables considered, accounts for both the extensive and intensive margins of oil well activity. Using counts or year-sums of Agreements would combine young leases with older leases, but one can reasonably expect i) a delay between an entity being granted a lease and the beginning of extraction activity, and ii) an increase in productivity up to some maximum extraction level. In contrast, the mean age of Agreements from 2015-2019 is strictly increasing, with greater weight given to leases which began closer to 2015 than 2019. In total, there are 793 PNG agreements and 18 OS agreements in my sample. Figure B.1 depicts a zoomed-in area from Figure 3.1, that shows Agreements of various sizes (depicted as purple areas with black boundaries) within the 4 km radius (depicted as a black circle) of a school. Note that any Agreement that falls at least partially within a given radius is included in the associated mean age calculation.

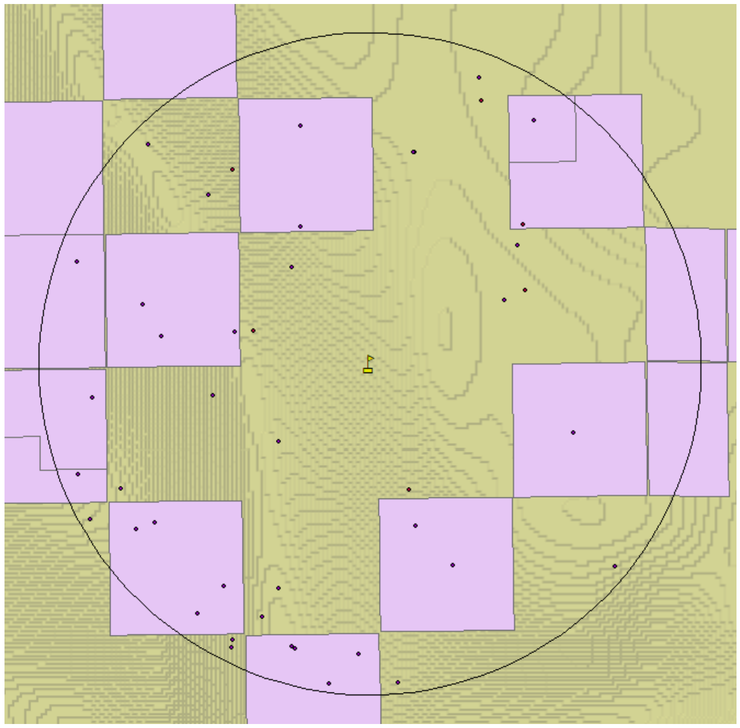

Figure B.1 An example of PNG and OS agreements, within 4 km of a school, used as an instrumental variable.

Table B.6 contains the estimates from IV estimation. As I only have one instrument, I can only use Model (1), with its singular oil well variable, for IV estimation. For math, the negative association of wells on test scores via IV estimation (column 1v), compared to OLS (1), is larger (-2.45 vs -0.64) but lower in significance (at the 5% level vs the 1% level). As previously stated in Section 3.5, I believe the OLS estimates to be closer to the true effect given my sample size. If, in future, I could obtain significantly more observations (e.g., more years or more schools), then I may reach a threshold where my IV outperforms OLS. As for science, the coefficient of *All* wells from IV estimation (column 3v) is similarly larger (-1.29 vs 0.26), but no longer significant. For both IV estimations, I can reject the nulls of under-identification and weak identification. That is, the instrumental variable chosen is not only relevant, but also not weakly correlated with the included endogenous variables. These results substantiate my earlier findings of mean test scores, math in particular, being negatively associated by the presence of oil wells.

Table B.6 IV regression - Math and Science

Subject Column	Math (1v)	Science (3v)
Wells (counts)		
All	-2.45**	-1.29
	(1.05)	(0.84)
School		
School population	0.62**	0.29
	(0.24)	(0.21)
Average class size	-0.01	0.01
	(0.03)	(0.03)
Authority funding	-0.07**	-0.06**
	(0.03)	(0.02)
Observations	2,418	2,423
Under-Ident. Test	16.50	15.98
P-value	0.0000	0.0001
Weak-Ident. Test	82.52	78.70
10% maximal IV size	16.54	16.20
Over-Ident. Test	0.000	0.000
P-value	Eq. exactly ident.	Eq. exactly ident.

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B.3 – Robustness Check 2: Controlling for Well Ages

Tables B.7 and B.8 contain well-age robustness check results for math and science, respectively. For the reader's convenience, I repeat the main results of the paper (reported in Section 3.4) in columns (1), (2), (3), and (4). For math, columns (1e) and (2e) include mean well age as an additional control variable (columns (3e) and (4e) for science), and columns (1f) and (2f) include oldest well age (columns (3f) and (4f) for science). While the coefficient for each age control variable is negative, neither is ever significant. By a small margin, well coefficients are uniformly larger when including mean well age and uniformly smaller when including oldest well age. Significance levels of well coefficients only vary for science, and only for i) *Active*, which increases from the 10% level in column (4) to the 5% level in column (4e), and ii) *Abandoned*, which decreases from the 5% level in column (4) to the 10% level in column (4f). As these differences are not economically significant, my findings appear robust to well ages.

Table B.7 Robustness Check: Well Age – Math

Well age Column	(1)	Well age: mean (1e)	Well age: oldest (1f)	(2)	Well age: mean (2e)	Well age: oldest (2f)
Wells (counts)						
All	-0.64***	-0.66***	-0.61***			
	(0.17)	(0.19)	(0.18)			
Active				-0.69***	-0.73***	-0.66***
				(0.15)	(0.17)	(0.15)
Suspended				-0.64***	-0.67***	-0.59***
				(0.16)	(0.18)	(0.16)
Abandoned				-0.76***	-0.80***	-0.72***
				(0.15)	(0.17)	(0.16)
Reclaimed				-0.40	-0.40	-0.32
				(0.30)	(0.30)	(0.30)
Well age						
Mean		-0.04			-0.07	
		(0.15)			(0.15)	
Oldest			-0.21			-0.25
			(0.19)			(0.19)
School						
School population	0.62**	0.62**	0.64***	0.62**	0.62**	0.64***
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Average class size	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Authority funding	-0.05*	-0.05*	-0.05*	-0.05*	-0.05*	-0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	68.49***	69.18***	72.06***	68.42***	69.91***	72.69***
	(3.71)	(4.80)	(4.81)	(3.48)	(4.56)	(4.68)
Observations	2,418	2,418	2,418	2,418	2,418	2,418
R-squared	0.82	0.82	0.82	0.82	0.82	0.82

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.8 Robustness Check: Well Age – Science

Well age Column	(3)	Well age: mean (3e)	Well age: oldest (3f)	(4)	Well age: mean (4e)	Well age: oldest (4f)
Wells (counts)						
All	-0.26*	-0.33*	-0.25*			
	(0.15)	(0.17)	(0.15)			
Active				-0.26*	-0.36**	-0.25*
				(0.15)	(0.16)	(0.15)
Suspended				-0.19	-0.28	-0.18
				(0.16)	(0.17)	(0.17)
Abandoned				-0.32**	-0.40**	-0.31*
				(0.15)	(0.16)	(0.16)
Reclaimed				-0.17	-0.18	-0.15
				(0.29)	(0.29)	(0.29)
Well age						
Mean		-0.04			-0.07	
		(0.15)			(0.15)	
Oldest			-0.21			-0.25
			(0.19)			(0.19)
School						
School population	0.30	0.29	0.29	0.30	0.29	0.30
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Average class size	0.01	0.01	0.01	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Authority funding	-0.05**	-0.05**	-0.05**	-0.05**	-0.05**	-0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	75.96***	73.56***	72.29***	76.10***	73.42***	75.96***
	(4.12)	(4.09)	(3.09)	(4.03)	(4.10)	(4.12)
Observations	2,423	2,423	2,423	2,423	2,423	2,423
R-squared	0.81	0.80	0.81	0.81	0.81	0.81

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B.4 – Robustness Check 3: Controlling for Test Attendance

Table B.9 contains test attendance robustness check results for math and science. Comparing results from columns (1-4) to columns (1g-4g), respectively, the percentage of students writing does not have a significant effect on test score outcomes for either subject.

Table B.9 Robustness Check: Controlling for Test Attendance - Math and Science

Subject	Math				Science			
Test Attendance		Attendance	l	Attendance		Attendance		Attendance
Column	(1)	(1g)	(2)	(2g)	(3)	(3g)	(4)	(4g)
Wells (counts)								
All	-0.64***	-0.64***			-0.26*	-0.26*		
	(0.17)	(0.17)			(0.15)	(0.15)		
Active			-0.69***	-0.69***			-0.26*	-0.26*
			(0.15)	(0.15)			(0.15)	(0.15)
Suspended			-0.64***	-0.64***			-0.19	-0.19
			(0.16)	(0.16)			(0.16)	(0.16)
Abandoned			-0.76***	-0.76***			-0.32**	-0.32**
			(0.15)	(0.15)			(0.15)	(0.15)
Reclaimed			-0.40	-0.39			-0.17	-0.17
			(0.30)	(0.30)			(0.29)	(0.29)
Test Attendance								
Percent of enrolled		-0.02		-0.03		0.01		0.01
		(0.04)		(0.04)		(0.03)		(0.03)
School								
School population	0.62**	0.61**	0.62**	0.61**	0.29	0.29	0.29	0.29
	(0.24)	(0.24)	(0.24)	(0.24)	(0.21)	(0.21)	(0.21)	(0.21)
Average class size	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Authority funding	-0.05*	-0.05*	-0.05*	-0.05*	-0.05**	-0.05**	-0.05**	-0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	68.49***	70.44***	68.42***	70.58***	72.69***	71.88***	72.29***	71.64***
	(3.71)	(4.95)	(3.48)	(4.78)	(3.10)	(4.02)	(3.09)	(4.02)
Observations	2,418	2,418	2,418	2,418	2,423	2,423	2,423	2,423
R-squared	0.82	0.82	0.82	0.82	0.80	0.80	0.81	0.81

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

B.5 – Robustness Check 4: Truncating Sample at Zero

Table B.10 contains results for the zero-truncated estimations (1h-4h). For math, total observations N decrease from 2,418 to 1,048 moving from the full sample to zero truncation. Coefficients for *All*, *Active*, S*uspended*, and *Abandoned* wells decrease by about 0.04 percentage points each, and all remain significant at the 1% level. The coefficient of school population, while still significant at the 5% level, increases from about 0.62 to 0.90 in the zero-truncated models, while authority funding is no longer significant.

With respect to science, observations decrease from 2,423 to 1,062. The coefficient for *All* wells marginally decreases from -0.26 in column (3) to -0.25 in column (3h), still significant at the 10% level. Similarly, *Active* and *Abandoned* well coefficients both marginally decrease in size (-0.26 to -0.25 and -0.32 to -0.30, respectively), as well as significance (10% level to insignificant and 5% level to 10% level, respectively). These findings indicate that the negative associations of wells with science test scores largely stems from whether a school has a nearby well or not, and not the number of wells. And similar to math, authority funding becomes insignificant to science test score outcomes when truncating at zero. Overall, while there are slight variations observed, my original results appear robust to zero-truncation.

Table B.10 Robustness Check: Truncating Sample at Zero - Math and Science

Subject	Math				Science			
No 0s		No 0s		No 0s		No 0s		No 0s
Model	(1)	(1h)	(2)	(2h)	(3)	(3h)	(4)	(4h)
Wells (counts)								
All	-0.64***	-0.59***			-0.26*	-0.25*		
	(0.17)	(0.17)			(0.15)	(0.15)		
Active			-0.69***	-0.65***			-0.26*	-0.25
			(0.15)	(0.15)			(0.15)	(0.15)
Suspended			-0.64***	-0.59***			-0.19	-0.16
			(0.16)	(0.16)			(0.16)	(0.17)
Abandoned			-0.76***	-0.72***			-0.32**	-0.30*
			(0.15)	(0.15)			(0.15)	(0.16)
Reclaimed			-0.40	-0.32			-0.17	-0.15
			(0.30)	(0.30)			(0.29)	(0.28)
School								
School population	0.62**	0.90**	0.62**	0.90**	0.29	0.20	0.29	0.20
	(0.24)	(0.37)	(0.24)	(0.37)	(0.21)	(0.34)	(0.21)	(0.34)
Average class size	-0.01	-0.02	-0.01	-0.02	0.01	0.01	0.01	0.01
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
Authority funding	-0.05*	0.00	-0.05*	0.01	-0.05**	-0.03	-0.05**	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	68.49***	72.26***	68.42***	71.89***	72.69***	75.53***	72.29***	74.40***
	(3.71)	(7.02)	(3.48)	(6.37)	(3.10)	(6.03)	(3.09)	(6.09)
Observations	2,418	1,048	2,418	1,048	2,423	1,062	2,423	1,062
R-squared	0.82	0.77	0.82	0.77	0.80	0.74	0.81	0.75

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B.6 – Robustness Check 5: Controlling for Average Well Distances

Table B.11 contains average well distance robustness check results for math and science. Comparing the previous results in columns (1h-4h) to the new results in respective columns (1i-4i), I do not observe a significant coefficient of average well distance for either mean test score regressions. This outcome may be caused by the fact that well pollution exposure is not limited to the time spent at school. The location of any given student's home (which I do not know) may be closer or farther away from any nearby well in the sample.

Table B.11 Robustness Check: Controlling for Average Well Distance in Sample Truncated at Zero - Math and Science

Subject	Math				Science			
Well distance	No 0s	No 0s: Avg. well dist.	No 0s	No 0s: Avg. well dist.	No 0s	No 0s: Avg. well dist.	No 0s	No 0s: Avg. well dist.
Model	(1h)	(1i)	(2h)	(2i)	(3h)	(3i)	(4h)	(4i)
Wells (counts)								
All	-0.59***	-0.58***			-0.25*	-0.24		
	(0.17)	(0.17)			(0.15)	(0.15)		
Active			-0.65***	-0.63***			-0.25	-0.24
			(0.15)	(0.14)			(0.15)	(0.16)
Suspended			-0.59***	-0.57***			-0.16	-0.16
			(0.16)	(0.16)			(0.17)	(0.17)
Abandoned			-0.72***	-0.70***			-0.30*	-0.29*
			(0.15)	(0.15)			(0.16)	(0.16)
Reclaimed			-0.32	-0.31			-0.15	-0.14
			(0.30)	(0.30)			(0.28)	(0.28)
Well Distance								
Average		-0.01		-0.01		-0.01		-0.01
		(0.01)		(0.01)		(0.01)		(0.01)
School								
School population	0.62**	0.61**	0.62**	0.61**	0.29	0.29	0.29	0.29
	(0.24)	(0.24)	(0.24)	(0.24)	(0.21)	(0.21)	(0.21)	(0.21)
Average class size	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Authority funding	-0.05*	-0.05*	-0.05*	-0.05*	-0.05**	-0.05**	-0.05**	-0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	68.49***	70.44***	68.42***	70.58***	72.69***	71.88***	72.29***	71.64***
	(3.71)	(4.95)	(3.48)	(4.78)	(3.10)	(4.02)	(3.09)	(4.02)
Observations	1,048	1,048	1,048	1,048	1,062	1,062	1,062	1,062
R-squared	0.82	0.82	0.82	0.82	0.80	0.80	0.81	0.81

Notes: Models include school year-level fixed effects and employ school-clustered standard errors. 'All' wells equal the sum of Active, Suspended, Abandoned, and Reclaimed wells. Cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.