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By

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Toxic Effects of Lead Disposal in Water: An Analysis of TRI Facility Releases[1]

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Abstract

Using county-level TRI data from 2003 to 2016, I find evidence that lead emissions in water adversely affect birth weights within the emitting county, especially with respect to the percentage of births considered low birth weight within that county (less than 2,500 grams). I find that a one percent increase in lead emissions per square mile increases the proportion of low birth weights by 0.27 percentage points. For a county with an average number of births in a particular year, this one percent increase in lead per square mile translates to an additional $475,000 in hospitalization costs from complications with delivery and perinatal care alone. My results show that lead emissions create a substantial negative externality even at relatively small quantities and may have more significant effects for those living in poverty.

I. Introduction

Elemental lead (Pb) was a standard, even luxury, input in paint and infrastructure until recent history. Its benefits with respect to painting were known to the Roman Empire, which explains the well-preserved paint on ruins. Lead is known to prevent issues with mildew and exposure to sunlight, which may otherwise accelerate the deterioration of paint or piping. Because of these benefits, lead became a commonality in the typical household, especially on painted materials and in piping (Rabin, 1989; Lessler, 1988).

In the beginning of the twentieth century, some researchers began to postulate that household usage of lead was leading to widespread lead poisoning in children. The wider scientific and global community did not reach a full consensus until the 1920s and 1930s, when it was banned for use indoors in several countries (Rabin, 1989). Lead would be classified as a probable carcinogen in 1981 (NTP, 2016). Despite knowledge of lead's toxicity, firms are still able to obtain authorization to release lead into bodies of water, such as streams, rivers, lakes, and oceans if a firm has a permit to do so.

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Due to the Emergency Planning and Community Right-to-Know Act (ECPRA), firms are required to report these emissions. Passed in 1986, it mandates annual reporting of numerous chemicals by firms in certain sectors, such as manufacturing. This reporting is released as public information in the form of the Toxics Release Inventory (TRI).

Using county-level TRI data from 2003 to 2016, I find evidence that lead emissions in water adversely affect birth weights within the emitting county, especially with respect to the percentage of births considered low birth weight within that county (less than 2,500 grams). These findings are robust to demographic controls, county fixed effects, and year fixed effects. In addition, these findings are consistent with the scientific literature that describes the negative health effects of lead, and this paper's main contribution is the estimation of this relationship. I find that a one percent increase in lead emissions per square mile decreases average birth weight by almost 7 grams while increasing the proportion of low birth weights by 0.27 percentage points. For a county with an average number of births in a particular year, this one percent increase in lead per square mile translates to an additional $475,000 in hospitalization costs from complications with delivery and perinatal care alone. My results show that lead emissions create a substantial negative externality even at relatively small quantities and may have more significant effects for those living in poverty.

II. Background

Lead

Health effects

Due to its wide range of toxic effects, both carcinogenic and not, lead is considered a priority chemical among metals as well as among all chemicals more generally (Nedellec and Rabl, 2016a; Lim et al., 2010; Lim et al., 2011). Following prenatal lead exposure, newborns can experience both immediate pregnancy and birth complications as well as latent effects. These include low birth weight, anemia, hypertension, spontaneous abortion, stillbirth, and cognitive delay (Zhu et al., 2010; Papanikolaou et al., 2005; Goyer, 1996; Xie et al., 2013; Wani et al., 2015).

Despite the numerous effects exposure can have, lead is known primarily as a neurotoxin that affects the developing brain (Sanders et al., 2009; Zheng et al., 2003; Goyer, 1996). Exposure to lead in childhood is associated with delayed and impaired cognitive development (Lanphear et al., 2005; Mazumdar et al., 2011; Koller et al., 2004; Nedellec and Rabl, 2016b) as well as Autism Spectrum Disorder (Kalkbrenner et al., 2014; Windham et al., 2006).

Behavioral effects

In addition to both immediate and latent health effects, exposure to lead has also been associated with behavioral outcomes with economic consequences. Grönqvist et al. (2017) exploit the phase-out of leaded gasoline in Sweden in order to measure the effect of elevated blood-lead levels on school performance and criminal conviction. They find that lead exposure in childhood and adolescence is associated with increases in property and violent crime above a threshold of 5.7 µg/dL[2] and is associated with a decrease in the probability of high school completion above a threshold of 3.5 µg/dL. Wright et al. (2008) find a similar association with probability of arrest in early adulthood resulting from prenatal exposure.

As is apparent in the findings of Grönqvist et al. (2017), blood-lead levels below 10 µg/dL are associated with negative effects for those exposed. Until recent years, it was thought that 10 µg/dL was a safe threshold beyond which was considered a 'level of concern.' In 2012, following the growth of a literature describing adverse effects at subthreshold levels, the CDC declared that there is no evidence for a threshold of safety (CDC ACCLPP, 2012).

Benefits of Removal

Attempts have been made to quantify both medical costs and outcome-associated costs of exposure, such as falls in productivity. Using data from the National Health and Nutrition Examination Survey (NHANES), Trasande and Liu (2011) find that, in 2008, lead exposure produced cost \$50.9 billion in lost productivity due to cognitive impairment. They estimate that exposure cost an additional \$5.9 million in associated healthcare costs. Nedellec and Rabl (2016b) attempt to estimate the marginal social cost of lead emission resulting from healthcare cost using an impact pathway analysis model. They find that each kilogram emitted has an associated 29,343 $€_{2013}$ (≈\$16740.11 per pound adjusted for inflation) in medical costs.

Others attempt to quantify savings of lead removal with data from prior removal initiatives or proposed future projects. Using the decrease in blood-lead concentrations recorded by NHANES, from 1976 to 1999, Grosse et al. (2002) estimates at least \$110 billion in savings due to gains in worker productivity from lack of lead exposure. Gould (2009) estimates that lead hazard control for lead-based paint alone has the potential to produce net savings of at least \$181 billion.

As will be discussed further, lead exposure is more common in low-income and Black children, who are already at higher risk of having a low birth weight. The prospect of residential sorting is described in Zivin and Neidell (2013) as a family's decision between several locations based on the 'bundled amenities' of those areas. They cite a hypothetical example of an urban residence which provides good schools but poor air quality. As such, a choice must be made based on a family's preferences. However, rather than residential sorting, Christensen and Timmins (2018) find evidence of discriminatory steering of minorities. Using data from HUD's most recent housing study, they find realtors steer minorities toward neighborhoods with more crime, higher poverty rates, schools of lower quality, increased amounts of air toxics released,

[2] Micrograms per deciliter – the common measurement of blood lead concentrations.

and are in closer proximity to superfund sites when compared to white testers, while controlling for advertised house quality and observable preferences.

Low Birth Weight

While sometimes considered a proxy for infant malnutrition and poor infant health, low birth weight is also associated with poor health and economic outcomes. Recent studies use the method of twin- and sibling-matching to improve on the strength of evidence previously gathered through cross-sectional analysis. These studies find negative impacts on academic achievement, educational attainment, IQ, earnings, as well as increased welfare dependency resulting from low birth weight (Black et al., 2007; Oreopoulos et al., 2008; Almond and Currie, 2011). In addition to outcomes of predominantly economic importance, longitudinal studies have been conducted that connect low birth weights and increased risk of insulin resistance syndrome (Valdez et al., 1994), impaired glucose tolerance (Hales et al., 1991), high blood pressure (Poulter et al., 1999), coronary heart disease (Eriksson et al., 1999), hypertension, and diabetes (Curhan et al., 1996).

These effects of low birth weight could potentially affect subsequent generations. Using a dataset consisting of births in California, Currie and Moretti (2007) find evidence that, controlling for grandmother fixed effects, mothers born with low birth weights are more likely to have children with low birth weights as well. This risk is substantially greater for mothers living in high-poverty neighborhoods. This, in addition to the discriminatory steering found by Christensen and Timmins (2018), provide evidence for a theoretical mechanism through which environmental characteristics could add inertia to intergenerational immobility, especially among minorities, by reducing birth weight, which is then carried across generations (Bhattacharya and Mazunder, 2011).

Studying the Effects of Environmental Toxins

When attempting to study the effects of certain environmental toxins or variations in the environmental characteristics of a particular location (e.g. the construction of an oil well, the shutdown of a power plant), there are two common methodologies employed. Biomonitoring studies involve the collection of measurements, such as blood-lead concentration, from individuals in proximity to the emission source. These have the benefit of increased accuracy in measurement, but are costly due to the requirement of testing for each individual in the sample, which restricts sample sizes (for example, Kimbrough et al., 1995; Landrigan, 1996; Chaiklieng et al., 2015).

Epidemiological studies, while providing less individual-level precision, offer a better ability to generalize due to an increased sample size. These proximity studies are possible when data is collected in small areas, such as cities or counties. Outcome measures can then be studied in relation to the variation in the relevant toxin over time within the relevant region (for example, Neidell, 2004; Yang and Chou, 2015; Dickerson et al. 2015).

One of the richest datasets of toxin emissions available is the Toxics Release Inventory (TRI), which currently contains firm-level emissions data for 595 chemicals. Using EPA's TRACI (Tool for the Reduction and Assessment of Chemical and other environmental Impacts) to measure the potential toxicity of TRI-listed chemicals, Lim et al. (2010) finds that the distribution of toxicity potential is highly skewed. Lead and lead compounds account for more than 30 percent of non-cancer toxicity potential in both air and water emissions. In a follow-up study, they compare TRACI to the RSEI (Risk-Screening Environmental Indicator), a model with significantly different assessment methodology. Both label lead and lead compounds as a priority chemical type with respect to non-cancer toxicity (Lim et al., 2011).

The literature using TRI data to study variation in health outcomes has a diverse range of methodologies. In the environmental and public health literatures, it is common to collect TRI emissions data for several years and a measure of either total mortality or a disease-specific mortality from several years later, which is averaged across years as well. Despite the potential benefits of the instituted lag, using mortality may prove to be an outcome variable with poor specificity. As Agarwal et al. (2010) explains, the usage of mortality rate as an outcome cannot control for lifetime exposure, nor can it control for individuals moving in and out of the measured region. These issues led Agarwal et al. (2010) to use infant mortality. Infants are a particularly vulnerable subsection of the population, which allows for an increased ability to study immediate effects of exposure without the requirement of accounting for lifetime exposure. Further, pregnant women are highly unlikely to change counties during pregnancy, so any potential confounding issues due to moving across counties would be small and unlikely to alter results (Agarwal et al., 2010).

Although infant mortality provides a better means of studying the immediate effects of exposure to toxins when compared to general population mortality, it still lacks specificity. Infant health may be drastically affected by toxins within leading to an outcome of death. For example, as previously discussed, lead exposure prenatally and in infancy can have significant effects on development, but death due to environmental lead exposure appears to be a rarity in comparison to other outcomes (Currie and Schmieder, 2009). Because of this, using birth weight as a proxy for infant health allows for a more precise estimation of chemical.

III. Data Description

Data are collected from multiple sources to construct a dataset spanning years 2003 through 2016. Each primary dataset is described below and the locations of each dataset are available in the appendix.

Average birth weight, total births considered low birth weight, and total births were collected at the county level from the WONDER database provided by the CDC. The WONDER database limits queries to counties with populations of 100,000 or over, so our sample is restricted to populous areas.

Emissions data from water are from the TRI and aggregated at the county level.[3] Since the last TRI regulation to affect lead directly was passed in 2001, reporting requirements for lead stay consistent throughout the dataset (U.S. EPA, 2001b).

Since TRI reporting is only required for firms with at least 10 full-time employees and 100 pounds of lead emitted in a given year, non-reported emissions present a potential issue. Proportions of private employees and firms employed in manufacturing are collected to control for this.

I use $PM_{2.5}$[4] as a proxy to control for mobile source pollution. $PM_{2.5}$ is highly correlated with traffic itself (Bauldauf, 2012; Ferm and Sjöberg, 2011) as well as other traffic pollutants (Beckerman et al., 2008; Cyrys et al., 2003).

Socioeconomic and demographic control variables are gathered from various sources. Private employment, private firm, and unemployment data are collected from the BLS. Poverty rate and household income, as well as the measured area of each county, are collected from the US Census. Emissions data for particulate matter are collected from the CDC National Environmental Public Health Tracking Network.

Years	2003	2004	2005	2006	2007	2008	2009
Populous Counties							
Total Births	7150.26	7188.90	7234.88	7457.26	7545.86	7426.04	7221.44
	(572)	(572)	(572)	(572)	(572)	(572)	(572)
Total LBW Births	566.55	580.02	591.9	615.34	619.46	607.01	588.72
	(572)	(572)	(572)	(572)	(572)	(572)	(572)
Avg. Birth Weight (g)	3300.55	3291.19	3281.71	3274.76	3273.21	3273.93	3274.22
	(572)	(572)	(572)	(572)	(572)	(572)	(572)
Poverty Rate	11.49%	11.85%	12.49%	12.63%	12.17%	12.36%	13.54%
	(524)	(524)	(524)	(524)	(580)	(580)	(580)
Income	45571.56	46802	48613.75	50572.6	53041.96	54982.89	52875.85
	(524)	(524)	(524)	(524)	(580)	(580)	(580)
Unemployment	5.82%	5.43%	5.07%	4.64%	4.55%	5.69%	9.09%
	(524)	(524)	(521)	(521)	(580)	(580)	(580)
% Black	11.66%	11.76%	11.86%	11.99%	11.8%	11.89%	11.97%
	(524)	(524)	(524)	(524)	(580)	(580)	(580)
% Hispanic	10.33%	10.66%	11%	11.37%	11.37%	11.7%	11.7%
	(524)	(524)	(524)	(524)	(580)	(580)	(580)
Avg. $PM_{2.5}$ (mcg/m^3)	12.42	12.07	13.1	11.78	12.01	10.96	9.78
	(377)	(369)	(359)	(361)	(375)	(368)	(358)
Populous Counties w/ Lead							
Total Births	9795.88	10101.15	10072.66	10134.12	10353.23	10312.62	9608.8
	(261)	(256)	(259)	(257)	(265)	(265)	(264)
Total LBW Births	771.34	818.09	826.73	842.22	850.68	841.28	774.61
	(261)	(256)	(259)	(257)	(265)	(265)	(264)
Avg. Birth Weight (g)	3292.54	3282.07	3276.6	3270.32	3268.25	3267.05	3273.58
	(156)	(162)	(168)	(166)	(168)	(166)	(124)
Poverty Rate	11.75%	12.35%	13.01%	12.99%	12.6%	12.86%	13.85%

[3] Lead emissions from the TRI do not include lead emissions due to mass exposures due to human error, such as the Flint water crisis. TRI records planned emissions by firms.
[4] Particulate matter with a diameter under 2.5 micrometers.

	(213)	(208)	(211)	(209)	(234)	(237)	(249)
Income	4496.33	45706.86	47870.73	50225.45	52280.28	53964.49	52549.98
	(213)	(208)	(211)	(209)	(234)	(237)	(249)
Unemployment	5.94%	5.57%	5.18%	4.72%	4.56%	5.75%	9.08%
	(213)	(208)	(211)	(209)	(234)	(237)	(249)
% Black	12.13%	12.71%	12.86%	13.23%	12.65%	12.38%	11.42%
	(213)	(208)	(211)	(209)	(234)	(237)	(249)
% Hispanic	10.38%	10.77%	10.72%	10.78%	11.2%	11.94%	12.95%
	(213)	(208)	(211)	(209)	(234)	(237)	(249)
Avg. $PM_{2.5}$ (mcg/m^3)	12.79	12.54	13.68	12.21	12.14	11.08	9.85
	(155)	(147)	(148)	(146)	(156)	(157)	(140)

Table 1(a): Summary Statistics – Years 2010-2016

Years	2010	2011	2012	2013	2014	2015	2016
Populous Counties							
Total Births	6991.93	6911.87	6910.56	6874.44	6370.73	6355.43	6303.32
	(572)	(572)	(572)	(572)	(626)	(626)	(626)
Total LBW Births	569.17	558.94	551.94	550.87	509.34	512.57	514.12
	(572)	(572)	(572)	(572)	(626)	(626)	(626)
Avg. Birth Weight (g)	3273.39	3277.67	3282.05	3283.14	3285.32	3283.47	3279.12
	(572)	(572)	(572)	(572)	(626)	(626)	(626)
Poverty Rate	14.54%	15.05%	15.04%	15.01%	14.69%	14.02%	13.33%
	(580)	(580)	(580)	(580)	(580)	(580)	(580)
Income	52333.31	52910.82	54044.32	55135.02	56484.07	58351.13	60470.61
	(580)	(580)	(580)	(580)	(580)	(580)	(580)
Unemployment	9.43%	8.75%	7.93%	7.27%	6.1%	5.28%	4.88%
	(580)	(580)	(580)	(580)	(580)	(580)	(580)
% Black	12.03%	12.09%	12.15%	12.22%	12.3%	12.38%	12.46%
	(580)	(580)	(580)	(580)	(580)	(580)	(580)
% Hispanic	12.25%	12.44%	12.62%	12.8%	12.99%	13.19%	13.42%
	(580)	(580)	(580)	(580)	(580)	(580)	(580)
Avg. $PM_{2.5}$ (mcg/m^3)	9.9	9.85	9.25	9.02	8.95	8.9	8.1
	(351)	(335)	(326)	(326)	(309)	(369)	(374)
Populous Counties w/ Lead							
Total Births	9359.38	9478.13	9565.58	10175.22	9006.96	8935.39	8674.02
	(265)	(261)	(247)	(236)	(254)	(253)	(268)
Total LBW Births	757.01	760.4	753.07	813.04	711.56	714.6	700.06
	(265)	(261)	(247)	(236)	(254)	(253)	(268)
Avg. Birth Weight (g)	3267.55	3274.61	3281.43	3277.07	3280.73	3277.28	3275.32
	(171)	(172)	(157)	(152)	(159)	(160)	(166)
Poverty Rate	14.73%	15.38%	15.28%	14.97%	14.73%	14.03%	13.29%
	(242)	(233)	(217)	(205)	(208)	(207)	(222)
Income	52251.25	52698.73	54085.78	56133.01	57085.69	58636.09	61111.14
	(242)	(233)	(217)	(205)	(208)	(207)	(222)
Unemployment	9.25%	8.72%	7.89%	7.2%	5.99%	5.18%	4.85%
	(242)	(233)	(217)	(205)	(208)	(207)	(222)
% Black	12.02%	12.06%	11.86%	12.29%	11.8%	11.8%	12.12%
	(242)	(233)	(217)	(205)	(208)	(207)	(222)
% Hispanic	12.3%	12.6%	13.48%	13.66%	13.34%	13.63%	14.47%
	(242)	(233)	(217)	(205)	(208)	(207)	(222)

Avg. $PM_{2.5}$ (mcg/m^3)	10.09	10.1	9.5	9.31	9.28	9.24	8.29
	(152)	(144)	(132)	(126)	(116)	(137)	(148)

Table 1(b): Summary Statistics – Years 2010-2016

Simple means of demographic, socioeconomic, and environmental variables in years 2003 to 2016. These are presented to facilitate comparison of lead-emitting counties to populous counties in general.

Tables 1 and 2 display simple means of birth weight, socioeconomic, and demographic data in all populous counties and in lead-emitting counties within each year of the data. These figures suggest that lead-emitting counties do not significantly differ from populous counties in general. Because of this, I consider the allocation of firms emitting lead as quasi-random.

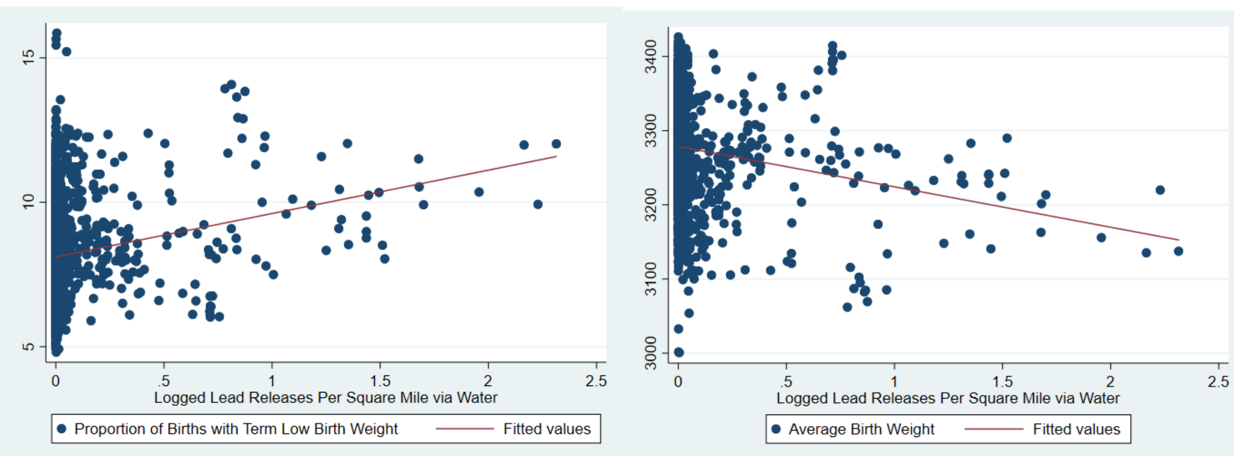

Figure 1: Correlations of nonzero lead emissions and outcome variables

Raw correlation between logged lead emissions via water adjusted for county area and the two response variables of percentage of low weight births (left) and average birth weight (right).

Figure 1 displays raw correlations between nonzero logged lead emissions adjusted for county area and the two outcome variables being studied, proportion of low birth weight births (left) and average birth weight (right). It is apparent from these graphs that lead emissions are highly skewed, with most values near to zero. Additionally, there is a high amount of noise in both graphs, implying that the relationship between emissions and health outcomes is modulated by other factors.

IV. Methodology

In order to attribute health effects to specific chemicals, I use a methodology similar to that of Currie and Schmieder (2009) by focusing on lead emissions in water. This has the added benefit of augmenting the results of Currie and Schmieder (2009), who only study the emissions of particular chemicals released in the air.

I assume the relationship between lead emissions and birth weight outcomes is linear and can be represented as:

$$Y_{it} = \beta_0 + \beta_1 L_{it} + \beta_j \boldsymbol{X}_{jt} + \mu_{it} + \varepsilon_i$$

where Y represents the outcomes of low-weight birth percentage and average birth weight. L is the aggregated county-year emissions of lead reported in the TRI. I use this explanatory variable both in its original form and adjusted for county area. I use a vector of controls $\mathbf{X}_{jt}$ (where $j = 2, 3, \ldots, 9$) to account for variation in economic characteristics, demography, and pollution, which may affect birth weights. I also use the percentages of private firms and employees employed in manufacturing in order to attempt to control for non-reported emissions. Additionally, I use county and year fixed effects to control any time trends and differences across counties.

As of yet, it is not settled in the literature whether to cluster by state or by county when performing this type of analysis. Citing the desire to account for serial correlation, Currie and Schmieder (2009) cluster by county. In contrast, Agarwal et al. (2010) cluster by state in an attempt to control for pollution spillover effects across counties.

I cluster by county to account for potential issues arising from my sample, which is restricted to counties with populations of at least 100,000. As is argued by Abadie et al. (2017), clustering can be used as a means to correct for problems in sampling and assignment. There are potentially significant differences between counties with large populations and those with small populations, as well as potential differences in lead's effects due to compounding with intergenerational 'transmission' of low birth weight, as described above. Clustering by county is the best choice to account for such differences in sampling and treatment effects. In addition, as my results show, effects are sensitive to adjustment in county area. Since each individual county's area is significant in studying the health effects, it is likely that lead emissions via water do not disperse significantly. Since this is the case, there is little evidence of cross-county spillover.[5]

V. Results

	Avg. BW			**% LBW**		
Variable	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
ln(Lead)	-.522943	-.3580827	-.0747652	.0003114**	.000248*	.0001705
SE	.4939031	.4687346	.5921632	.0001564	.00015	.0001789
% Black		-220.3941*	-354.0805**		.0783193**	.0972043**
		126.4073	141.9106		.0384096	.0429667
% Hispanic		-179.9556**	-157.7001*		.034059	.0386148*
		87.87881	94.30129		.0260713	.0232801
% Firms		583.3438**	633.3314**		-.1775276**	-.1325388
		248.0216	310.1605		.0745168	.0842017
% Emp.		14.8461	77.20634		.0048867	-.0208436

[5] This argument cannot be generalized. Agarwal et al. (2010) are likely correct that some chemicals, especially those emitted via air, have the potential to have cross-county effects.

		62.78763	75.24088		.0233143	.0230499
Poverty Rate		2.978725	-41.25574		-.0125031	.0003936
		48.96413	55.56281		.0166231	.0181569
ln(Income)		9.605157	-4.413424		-.0079137	-.0057114
		17.5513	19.9316		.0048913	.0052806
Unemployment		29.14838	-13.6125		-.0143745	.00433
		54.01573	58.04075		.0186226	.0209735
Avg. $PM_{2.5}$			-.5855736			.0002303*
			.4149496			.0001309
Observations	2247	2231	1641	2247	2231	1641
Groups	288	288	226	288	288	226
Adj. R-Squared	.0370279	.645863	.6804394	.0360826	.6906978	.7300361

Table 3: Effects of Unadjusted Lead Emissions via Water

Results for regressions using unadjusted logged lead emissions via water on average birth weight and percentage of low weight births. * - p < .10; ** - p < .05; *** - p < .01.

Table 3 displays results for logged unadjusted lead emissions via water. Columns 1 and 2 contain estimations for the outcome variables of average birth weight and percentage of low weight births, respectively. In both columns, subcolumn (a) is a baseline estimation of the explanatory and response variables.

Subcolumn (b) controls for socioeconomic and demographic variation by including variables for the percentages of Black and Hispanic individuals, unemployment rate, and poverty rate. Additionally, I use percentages of private employees and private firms in the manufacturing sector to control for emissions from non-reporting firms.

Subcolumn (c) contains all controls from (b) in addition to daily average $PM_{2.5}$ as a proxy for mobile source pollution. The addition of this control variable is included as its own column because there are significantly fewer counties with monitors of $PM_{2.5}$. Significance is sparse in the outcome variables of interest, with only low weight birth percentage reaching slight significance, which disappears with the inclusion of particulate matter.

	Avg. BW			**% LBW**		
Variable	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
ln(Lead/mi^2)	-10.11264***	-8.445781**	-5.918679	.0033417**	.0029198**	.0026567**
	2.569914	2.553692	4.440227	.001069	.0011626	.0010867
% Black		-225.4304*	-349.5724**		.0830478**	.0987463**
		125.2744	140.7029		.0383755	.0428943
% Hispanic		-173.7718**	-151.7729		.0323884	.0369706
		87.46707	93.3561		.0259417	.0231308
% Firms		569.231**	612.2723**		-.1722321**	-.1216864
		246.9395	310.221		.0740926	.0839623
% Emp.		17.30896	80.80159		.0045299	-.0223604
		62.579	74.91889		.0233061	.0230744
Poverty Rate		3.756545	-40.88204		-.0129124	.0000479
		48.95923	55.39435		.0166214	.0181457
ln(Income)		8.889133	-4.455019		-.0076259	-.0055869
		17.50743	19.7975		.0048823	.0052451
Unemployment		27.67073	-12.18595		-.0144197	.0031101
		53.77927	57.98893		.0185278	.0209731
Avg. $PM_{2.5}$			-.555354			.0002181*
			.4144903			.0001288

Observations	2247	2231	1641	2247	2231	1641
Groups	288	288	226	288	288	226
Adj. R-Squared	.0360136	.6431272	.6818157	.0389582	.6887619	.7326382

Table 4: Effects of Lead Emissions via Water Adjusted for County Area

Results for regressions using logged lead emissions via water adjusted for county area on average birth weight and percentage of low weight births. * - p < .10; ** - p < .05; *** - p < .01.

Table 4 displays results for logged emissions via water when adjusted for county area. The columns and subcolumns have a similar structure to those in table 3. Significance and coefficients are markedly different from those in table 3. When adjusted for county area, lead emissions display markedly increased significance, especially in the percentage of low weight births. This suggests that the dispersal of lead is sensitive to the area over which it is dispersed, meaning that those closer to lead-emitting facilities may experience increased effects. This is lent further strength by the difference in significance between percentage of low weight births and average birth weight. While average birth weight may provide a more precise variable to track overall trends in birth weight, percentage of low weight births has a better ability to detect significant variation that occurs in a small number of births.[6] Since low weight birth percentage is a more consistently significant outcome variable, it implies that the changes in birth weight are not necessarily occurring in all births, but only in small subsection of them, providing further evidence for potentially small dispersal ranges and increased effects near lead-emitting facilities.

Column (1c)'s coefficients suggest that an increase of 1% in lead emissions per square mile results in a decrease of 5.9 grams in average birth weight, though this result is insignificant. More importantly, column (2c) suggests that a 1% increase results in an increase of 0.27% in low weight births. This means that, for an average lead-emitting county with 9681.59 births, a 1% increase in lead emissions per square mile would result in 26 additional low weight births. While this appears to be low, one must consider the costs involved. For instance, Russell et al. (2007) estimate that hospitalization costs associated with low weight birth are approximately $15,100 per birth (≈$18,267 per birth adjusted for inflation). This means that these 24 low weight births lead to approximately $475,000 in hospitalization costs for that county. If this increase in lead emissions occurred in all lead-emitting counties appearing within column (2c), resultant costs would be $107 million. This is in addition to productivity loss associated with complications due to low birth weight and lead exposure, such as decreased IQ and decreased educational attainment.[7]

[6] To give a simple example, there are two birth weights of 2000 grams and 3444.44 grams designated low and normal weights, respectively. The low weight birth percentage is 10%, so the average birth weight is 3300 grams. A 1% increase in low birth weights from 10% to 11% would lead to a new average of 3285.5 grams. Although the percentage of low weight births increased significantly, it did so only for a small number of births. Average birth weight may not function as an outcome variable that can accurately capture these large changes in a small percentage of births.

[7] An additional note concerning results: In both tables, the percentage of firms employed in manufacturing leads to significant positive outcomes for birth weights. This variable may be capturing how economic security leads to increased birth weights. It also calls into question whether or not effects of non-reporting firms are significant enough to warrant attempts to control for them, as neither proxy for them detects negative outcomes.

VI. Conclusions

Even though the emission of lead into water is regulated under the Clean Water Act and Safe Drinking Water Act (U.S. EPA, 2001a), health effects appear to exist. My analysis suggests that such emissions may cause harm equivalent to or greater than that of mobile source pollution. Although my results suggest that the number of individuals affected by an incremental increase is small, the potential costs associated with the effects remain large. These effects appear to be larger near lead-emitting facilities. Spatial analysis with further specificity and biomonitoring subjects near such facilities would allow for confirmation.

Furthermore, as discussed in the literature review, parents who were born with low birth weight are more likely to have children with low birth weight, a risk which is increased for parents living in high-poverty areas (Currie and Moretti, 2007). The effect I have found has the potential to augment this, leading to a larger risk of negative behavioral, economic, and health outcomes for children born with a low birth weight living in poverty. These effects, when considered together, further build the case for the theory of cyclical poverty due to environmental characteristics.

The effects I have found of lead on birth weights, as well as the risk of outcomes associated with both low birth weight and lead exposure, should be considered in the appraisal of regulation affecting lead emissions and the construction of lead-emitting facilities.

This chemical-specific analysis is necessary in order to determine which chemicals are of greatest importance when considering further regulation. I suggest that further research should be conducted with regard to the chemicals determined by Lim et al. (2010, 2011) to be high-priority. These include chemicals that are toxic to humans as well as to the environment. This presents potential research for the literatures of both environmental/ecological and public health research. These chemicals will be listed in the appendix.

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Appendix

Priority Chemicals

Lim et al. (2010) label priority chemicals by weighting total TRI emissions from the 2007 reporting year by toxicity potentials as calculated by TRACI. These weighted emissions are then used to calculate percentages of total toxicity-weighted emissions by chemical. The top six chemicals in each category are displayed in Table 5.

Lim et al. (2011) use TRI data from the 2006 reporting year to compare toxicity potentials as estimated by TRACI and RSEI, which use substantially different methodologies. Four chemical categories are labeled priorities using both tools. Table 6 displays these chemicals, their cancer toxicities, non-cancer toxicities, and ecotoxicities as determined by TRACI, as well as their risk scores as determined by RSEI. TRACI measures are converted to chemical-equivalents in order to easily compare toxicities between chemicals. RSEI risk scores are comparable between chemicals as well.

Cancer Potential			
Air	**Adj-%**	**Water**	**Adj-%**
Carbon Tetrachloride	62	Arsenic	59
Chromium	12	Hexachloro-benzene	21
Ethylene Oxide	4	Carbon Tetrachloride	8
Lead	4	Ethylene Oxide	2
Chloromethane	3	1,2,3-Trichloropropane	2
Benzene	3	Lead	1
Non-cancer Potential			
Air	**Adj-%**	**Water**	**Adj-%**
Lead	51	Mercury	51
Mercury	30	Lead	33
Aluminum	7	Copper	10
Hydrogen Cyanide	3	Arsenic	2
Copper	2	Vanadium	1
Phosgene	2	Cadmium	1
Ecotoxicity Potential			
Air	**Adj-%**	**Water**	**Adj-%**
Mercury	85	Formaldehyde	37
Benzo(g,h,i)Perylene	6	Benzo(g,h,i)Perylene	34
Copper	3	Vanadium	14
Thiram	1	Naphthalene	9
Nickel	1	Copper	5
Zinc	1	Carbon Disulfide	.3

Table 5: TRACI-Derived Priority Chemicals and Toxicity-adjusted Shares of Emissions

Priority chemicals as found by Lim et al. (2010) their shares of total emissions adjusted for the chemical's toxicity as estimated by TRACI.

	TRACI Potentials			
Substance	**Cancer**	**Non-Cancer**	**Ecotoxicity**	**RSEI Risk Score**
Chromium and Chromium Compounds	6.16E+07	2.34E+09	1.66E+07	4.66E+05
Lead and Lead Compounds	1.64E+07	6.96E+11	1.11E+07	2.78E+05
Manganese and Manganese Compounds	0	8.25E+09	0	3.16E+06
Nickel and Nickel Compounds	1.57E+06	3.59E+09	5.66E+07	7.52E+05

Table 6: TRACI- and RSEI-identified Priority Chemicals and Estimated Toxicities

Chemicals labeled by both TRACI and RSEI models as priorities and their respective estimated toxicities. TRACI potentials are measured as compared to the benchmark toxicities of benzene, toulene, and 2,4-Dichlorophenoxyacetic acid for cancer toxicity, non-cancer toxicity, and ecotoxicity, respectively. RSEI risk scores are ordinal in nature and are meant for comparison between each other.

Data Sources

For increased ease of replicability, data sources are listed in Table 7 with accompanying URLs. A do file and accompanying dataset will be available upon request.

Data	Source
Lead Emissions	Toxics Release Inventory Basic Data Files
Birth Weight Data	CDC WONDER Database
% Black, Hispanic	Census 2000-2010; Census 2010-2017
Poverty Rate, Median Income	Census Small Area Income and Poverty Estimates
% of Firms, Employees in Manufacturing	BLS QCEW
Unemployment	BLS Local Area Unemployment
Particulate Matter Levels	CDC National Environmental Public Health Tracking Network
Replication Files (zip)	Google Drive Link

Table 7: Data Sources

Links to primary data sources for easier reference. Note that percentage of Black and Hispanic data are found at two distinct URLs depending on which year span is of interest.