Beyond Hot Spots: Estimating Population Lead Exposure from Battery Recycling

Lee Crawfurd, James Hu, and Theodore Mitchell

Abstract

One in three children worldwide have harmfully high lead exposure. Lead-acid batteries are the main use of lead by weight, and many are recycled unsafely, but it is uncertain how much of human exposure can be traced to this recycling. In this paper, we provide new modelled estimates suggesting that around 33% of lead exposure in low- and lower-middle-income countries may come from battery recycling, although there remains significant uncertainty. The vast majority of harm comes from mass population low-level exposure, rather than localised hotspots. Previous studies have typically focused on small populations with high exposure living within hundreds of metres of polluted sites, but recent reduced-form quasi-experimental evidence demonstrates smaller negative effects for people living within much wider areas, affecting many more people. Our simulation model reconciles these approaches, and shows that expanding the area of concern around each recycling site increases the estimated share of global lead exposure attributable to battery recycling by an order of magnitude, from just 0.50% when considering only the high exposures within a few hundred metres of a site.

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Lee Crawfurd
Center for Global Development

James Hu
Coefficient Giving

Theodore Mitchell
Center for Global Development

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CENTER FOR GLOBAL DEVELOPMENT
2055 L Street, NW Fifth Floor
Washington, DC 20036
202.416.4000

1 Abbey Gardens
Great College Street
London
SW1P 3SE

www.cgdev.org

1 Introduction

One in three children worldwide have high blood lead levels. One important source of exposure is Used Lead-Acid Battery (ULAB) recycling. Around 86 percent of all lead by weight is used in these batteries (International Lead and Zinc Study Group, 2023), and informal unsafe recycling is inefficient, losing up to half of the lead content to the environment (Kinally et al., 2024). But the amount of human exposure that can be traced to this trade remains uncertain. Previous modelling suggests that only a small share of the total health burden of lead exposure is attributable to battery recycling (Ericson et al., 2016). However new evidence questions a critical assumption built into that modelling. The environmental literature suggests that pollution from recycling facilities is quite localised, and based on this Ericson et al. (2016) model exposure within a 300 metre radius of each site. By contrast recent reduced-form quasi-experimental studies have demonstrated negative causal effects of exposure to battery recycling sites over much broader areas, of a radius around 5,000 metres.

In this paper we ask what happens to the share of lead exposure burden that comes from battery recycling if we assume this activity exposes people over a much wider area. Our hypothesis is that a smaller impact per person over a much larger affected population could increase the overall share of the burden attributable to battery recycling by several multiples.

Our approach leans heavily on prior modelling approaches (Ericson et al., 2016; Kudymowa et al., 2025), but with new data and the critical new assumption about the geographic extent of exposure from each site. First we provide new estimates of the number of polluted sites due to battery recycling. Here we add data on new emerging electric vehicles. Second we provide new estimates of the geographic extent of lead exposure. The ideal dataset would have *blood* lead measurements at a wide range of distances from both formal and informal recyclers. The best available data is the Pure Earth Toxic Sites Identification Program (TSIP) dataset, which covers a large number of polluted sites but only has measures of soil lead. We convert this to blood lead using a standard biokinetic model, and also triangulate against other studies that do measure blood lead (but only around formal recyclers), and against the implied blood lead levels from quasi-experimental reduced-form studies on health and education outcomes. Third, we use the latest version of the TSIP dataset to estimate the average population at varying distances from polluted sites.

Overall we find consistent evidence that although exposure does fall steeply with immediate distance to a site, low-level exposures do in fact extend to a much wider radius around polluted sites. Environmental data is consistent with lead concentration falling in an inverse proportional manner, with rapid reductions in the immediate vicinity, but low-level exposure continuing over much greater distances. This is consistent with quasi-experimental reduced-form studies that estimate effects on educational and health outcomes (Berkhout et al., 2025; Ipapa, 2023; Litzow et al., 2024; Mahzab et al., 2024; Tanaka et al., 2022). At the extreme, lead has been shown to travel atmospherically over much wider distances, for instance from historic Roman smelters to ice in Greenland (Rosman et al., 1997) and across Western Europe (Schettler and Romer, 2006).

Armed with these new parameters on population exposure, we revisit the Ericson et al (2016) model on the burden of lead exposure attributable to battery recycling. Expanding the affected population near ULAB sites from 300 metres to 5,000 metres can increase the share of all lead exposure attributable to ULAB sites from around 0.5 to 33.28 percent. This compares to Ericson et al 2016 who estimated around 15 percent of the burden of lead exposure in low- and middle-income countries in 2013 could be attributed to battery recycling.[1] Our estimate is close to a more recent localised and more heavily data-driven estimate from Dhaka, Bangladesh, that 33 percent of lead exposure in that city can be attributed to battery recycling Forsyth et al. (2026).

Our estimates come with substantial uncertainty in almost all key parameters. We provide Monte Carlo simulations based on a beta-PERT distribution which suggest wide confidence intervals, but for which the lower bound excludes the central estimate of Ericson et al (2016).

Our estimates have important implications for policymakers interested in tackling lead exposure in low- and lower-middle-income countries. Used-lead-acid battery recycling shifts from being a marginal to a central contributor to the overall burden. Further, the majority of the harm comes from low-level exposure for large populations rather than high-exposure in small populations. We discuss potential policy solutions in more detail in Section 4.

[1] Specifically, they estimated that between 127,248 and 1,612,476 DALYs could be attributed to battery recycling in 2013 for the 90 countries for which they had data. The total lead burden from all sources in 2013 in the same 90 countries was estimated by the Global Burden of Disease study at 3.2 to 8.6 million DALYs. Taking the mean of both numerator and denominator gives a value of 14.7 percent. Taking the extremes of the two possible numerators and denominators gives a range of between 0.01 percent and 50 percent.

2 Modelling Lead Burden

Our model seeks to estimate the share of lead exposure in low- and lower-middle-income countries that can be attributed to battery recycling. We estimate this as the total burden of lead exposure due to battery recycling, measured in cumulative blood lead levels, as a share of total exposure from all sources (Fuller et al., 2025). We base our approach on that developed by Ericson et al 2016. We estimate the ULAB share for each country i as the product of the number of sites in each country contaminated by used lead-acid battery recycling (N_i); the level of lead-exposure around each polluted site ($\mathbb{E}$[BLL per person]); and the number of people exposed to contamination at each site (POP), all expressed as a share of total cumulative population blood lead levels ($cpBLL_i$). Cumulative population blood lead levels are the simple product of total population and mean blood lead levels (Fuller et al., 2025).

$$\text{ULAB share}_i \;=\; \frac{N_i \times \mathbb{E}[\text{BLL per person}] \times \text{POP}}{\text{cpBLL}_i} \tag{1}$$

We discuss the data used for each of these parameters in turn.

2.1 The number of polluted sites (N)

We follow Ericson et al. (2016) in using two alternative approaches to estimate the number of sites polluted by lead-acid recycling in each country. The first is based on the demand for lead-acid batteries implied by the quantity of vehicles in each country. The second is based on extrapolating from a unique census of polluted sites in Ghana.

Estimating polluted sites based on demand for lead

The first approach to estimating the number of polluted sites in a country is based on demand from vehicles. The main limitation to this approach is the requirement for data on vehicle usage. We start with the total number of vehicles estimated to be in use in each country. We use data on road vehicles from the International Road Federation and World Health Organization, on commercial vehicles from the International Organization of Motor Vehicle Manufacturers (OICA, 2024), and on motorbikes from a rental firm Riders Share (2023)[2]. We follow the approach of Kudymowa et al. (2025) in expanding the vehicle set to

[2]Note the vehicle data from the World Bank includes both private and commercial vehicles, so we subtract the OICA commercial vehicle data to get an estimate for private vehicles.

include electric three-wheelers, on which we obtain data from various sources (see Tables A.2 and A.3).

We then estimate the volume of lead produced from each vehicle. For passenger cars we assume that a car battery weighs 20 kg, of which 65% is lead, and lasts for two years, leading to 6.5 kg of lead produced per year (Table A.2). Using a similar approach each commercial vehicle is estimated to generate 32.5 kg of lead per year, each motorcycle 1.6 kg, each electric two-wheeler 26 kg, and each electric three-wheeler 78 kg (this last value is particularly large as these vehicles have four batteries). For electric two- and three-wheelers, we also assume the proportion that run on lead-acid (as opposed to lithium-ion) batteries for each country. From these inputs we calculate the total annual weight of lead generated by vehicle use for recycling.

Overall vehicles account for around 75 percent of all lead-acid battery use, with the rest coming from uses such as storage batteries for solar energy systems (Bonnifield and Mallory, 2026; Fortune Business Insights, 2025). We extrapolate from vehicle to total battery recycling assuming the share of lead generated by each lead-acid battery application equals its market share.

We make the simplifying assumption of no cross-border trade in batteries. 2023 UN Comtrade data suggest low- and lower-middle income (LMIC) countries are net importers of ULABs (see Figure A.1), meaning this is a conservative assumption for our estimation for the total share in LMICs. In this approach we also ignore legacy abandoned recycling sites that may still be causing harm, though these are accounted for in the second approach we discuss in the next section.

We don't distinguish between formal and informal recycling for several reasons. First there is evidence of harm from formal as well as informal recycling (Tanaka et al., 2022). Many formal recyclers are unsafe, and there is likely more of a gradient of harm than a binary distinction. Second, we only have limited data (for just seven low- and lower-middle-income countries) on formal recycling (estimated by the U.S. Geological Survey (2022)). For these countries formal recycling accounts for a relatively small share of all estimated lead production.

To infer the number of recycling operations from national recycled-lead volumes, we adapt the method introduced in Ericson et al. (2016). Their framework converts total recycled lead into site counts by assuming a distribution of operation sizes (estimates that are based on expert consultations). Applying their weights produces a single representative site throughput of around 375 t per year, which we use as the basis for estimating the number of informal sites in each country.

Estimating polluted sites based on population and economy

In addition to the vehicle-based approach in the previous section, Ericson et al. (2016) also propose a second method that estimates the number of battery recycling sites from a census of sites in Ghana (Dowling et al., 2016). Using the site census data we can calculate how many recycling sites operate per capita in Ghana, and extrapolate to other countries based on population size. The Ghana study found between 31 and 112 contaminated sites for every million residents, with 37% of these sites contaminated by lead. We start with the med-point of these two estimates, or 71.5. We assume 37% of these are contaminated by lead, and from the TSIP data we calculate that 52% of lead contaminated sites can be attributed to used lead-acid battery recycling, leaving us with 14 sites per million residents contaminated by lead from battery recycling.

For comparison two other more recent studies have attempted to exhaustively map polluted battery recycling sites. Forsyth et al. (2026) do this for Dhaka in Bangladesh. They identify 114 sites contaminated by lead in the city (through battery recycling, manufacturing, disassembly and repair, and lead ingot processing). Dhaka has a population of around 10 million people, so this is around 11 sites per million people. Zimba et al. (2025) finds 92 sites in four Malawian cities that have a combined population of around 2.5 million people, so 37 sites per million.

We proceed with 14 sites per million people as a basis for extrapolation to other countries. We follow Ericson et al 2016 in adjusting the initial estimate of the number of sites for country-level indicators that correlate with unsafe recycling. Specifically we compare each country to Ghana on (i) GDP (PPP) per capita, (ii) the relative size of the informal economy, (iii) the rate of urbanization, and (iv) the relative size of the mining, manufacturing, and utilities sector. Each variable is expressed relative to those of Ghana, such that Ghana's variables are all exactly 1. We then take a weighted average of these variables to produce an overall multiplier, in which GDP per capita receives the largest weight (0.75), followed by the informal economy size (0.1), urbanization rate (0.075), and mining and manufacrturing sector (0.075). Data on population is from the UN World Population Prospects, GDP per capita from the World Bank, on informality from Elgin et al. (2021), on urbanization from UNDP, and on manufacturing from the United Nations Statistics Division.

Comparing approaches

Using vehicle data we can produce estimates for 58 out of the 75 low- and lower-middle-income countries. With the top-down approach we can produce estimates for 74 countries. The correlation between the two estimates is 0.88 (see Figure A.1). For our main estimate we use the simple average of the two methods.

Ultimately we estimate a total of around 24,318 polluted sites. By comparison Ericson et al estimated between 10,599 and 29,241 depending on approach.

2.2 Average lead exposure around each site

How much lead is the average person living near a battery recycling site exposed to? Our main approach to estimating this is using data on soil lead levels at varying distances from recycling sites, and then using a biokinetic model to convert from soil to blood lead.

Data on soil lead from the Toxic Sites Identification Program

Direct measures of soil lead exposure around polluted sites are available from the Toxic Sites Identification Program (TSIP) run by the NGO Pure Earth (Caravanos et al., 2014; Ericson et al., 2013). This is a major global effort to identify the most dangerous polluted sites around the world. We have little understanding of the degree of representativeness of this dataset, as there is no single standardized approach to identifying sites, as each country establishes its own priorities and methods, but sources of information include requests or concerns from local authorities or national government agencies, reports of incidents or alerts from affected communities, findings from government agencies or academic research, and news or media coverage. The database includes both active and inactive legacy sites. We use the version of the database downloaded in January 2025. This is an updated version of the same source used in previous modelling efforts (Ericson et al., 2016). Prior efforts estimated the degree of environmental contamination from polluted sites based on 28 assessments from 12 countries. From the full database of 1,672 sites we retain only battery-recycling sites that have both soil lead measurements and GPS coordinates.[3] Because measurements from nearby sites can overlap spatially and confound distance-decay estimates, we further restrict the sample so that all included sites are at least 10 km apart. After applying these filters we analyse 5,189 measures from 599 sites in 14 countries. Of these, 82 percent of measures are within 165 metres of the centre of the polluted site. The mean lead measurement within 165 metres is 13,162 parts per million (ppm), compared to 6,526 for those outside 165 metres. 64 percent of measurements within 165 metres are above the 200 ppm regulatory threshold, and 57 percent of measurements outside of 165 metres are above this threshold.

To isolate contamination attributable to battery-related activities, we sub-

[3]Specifically, we keep sites in which the 'key pollutant' variable is 'lead' and in which the 'site industry' description contains 'Lead - Battery Recycling', 'Lead-acid battery manufacturing', or 'Lead Smelting'

tract a background soil lead level of 41.8 mg/kg, the median urban soil lead across 32 Indian cities from a country-wide study (Adimalla, 2020). We choose this value because India, Indonesia, and Bangladesh account for 32%, 25%, and 23% of the TSIP battery-site sample respectively and among these, India has the only representative soil measurements in a recent systematic review of lead in soil (Mishra et al., 2025). We then set non-positive values to a small positive constant (1×10^{-5}) to preserve observations while enabling log transformations.

We follow Ericson et al. (2016), in using this data to predict lead levels within various radii around sites. We first define a near ring as a radii of 165 m (this is the weighted average of the three rings used by Ericson et al, at 100 m, 200 m, and 300 m). We then add a second concentric ring, from 165–5,000 m. We use 5,000 m as the cut-off on the second ring for two reasons; first it is on the lower end of the quasi-experimental literature effect bandwidths, and second as our main fitted model of the TSIP data would reach 200 mg/kg (the US EPS recommended residential soil lead screening level) at around 5,800 meters when background lead is not subtracted. Our model asymptotes to background levels of 42 mg/kg at 170,000 meters. We model other radii as sensitivity in Appendix C.2.

Table 1: Data on distance to sites and environmental lead

	Lead				Log Lead			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance (m)	-22.7***				-0.0***			
	(8.5)				(0.0)			
Inverse distance (m)		28504.7***				2.3***		
		(4461.5)				(0.2)		
Log distance			-7637.1***	-6275.8**			-0.6***	-0.5***
			(1285.6)	(2628.9)			(0.0)	(0.1)
Obs.	5,172	5,172	5,172	1,288	5,172	5,172	5,172	1,288
R^2	0.20	0.21	0.22	0.20	0.63	0.64	0.66	0.64

Note: This table presents alternative specifications for estimating the relationship between measured environmental lead and distance to a battery recycling site. The outcome in columns (1)–(4) is soil lead parts-per-million (ppm), and the outcome in columns (5)–(8) the log of soil lead (where values of zero are replaced by 0.00001). Columns (4) and (8) restrict observations to those in which there is no other polluted site within 10,000 m. All models have site fixed effects. * p<0.1, ** p<0.05, *** p<0.01

Ericson et al. (2016) estimate the average lead concentration in soil within 165 m at 2,050 mg/kg. The updated TSIP database has extremely high lead values that would skew the mean, and the data is not evenly distributed across our radii categories. Therefore we choose to first fit a curve through the data to predict expected lead levels. We estimate various models with different functional forms, selecting the model with the best fit. The best fit is a log-log specification, including site fixed effects (Table 1) i.e. a power law:

$$\hat{y}(r) = \exp(\alpha)\, r^{\beta} \tag{2}$$

where $\hat{y}(r)$ is predicted soil lead (mg/kg) at distance r (metres) from the site centre; α is the estimated intercept (with site fixed effects); and β is the slope in the log–log regression. To translate from predicted values in logs back to levels we use Duan's smearing retransformation (Duan, 1983). Our average exposure for each zone is the *area-weighted* mean over a disk (see Appendix E for more detail).

From environmental to human exposure

To estimate the blood lead levels from soil lead exposure, we employ the All-ages Lead Model (AALMv3), from U.S. EPA, which estimates BLLs based on environmental exposures. One important adjustment is that we expect ingestion rates to be higher in low- and middle-income countries than in the United States, as children may be less likely to have improved flooring inside, and spend more time outside with fewer solid surfaces. Ericson et al. (2016) multiplied the U.S. EPA defaults by three for children and by four for adults to reflect this. They cite evidence of greater hand-to-mouth behaviour in Native American tribes (Harris and Harper, 2004) that predicted soil ingestion values to be around 400 mg/day for children and adults in rural LMICs as an upper bound of the US EPA standards of the time. Since then, EPA defaults have been updated to incorporate newer empirical data showing substantially lower age-specific soil and dust ingestion in the US, about 60 percent of the original defaults (U.S. Environmental Protection Agency, 2021).[4]

Because our goal is to represent LMIC exposures, we multiply the AALMv3 soil ingestion defaults by three. Recent field data indicate that even this tripling is conservative: Yang et al. (2022) measured median soil ingestion of about 150 mg/day for children in an e-waste community in China, while Kwong et al. (2021) reported geometric-mean intakes of roughly 160–230 mg/day for toddlers in rural Bangladesh. Our threefold adjustment therefore errs on the side of caution yet remains within the range of empirically observed LMIC exposures. Our chosen ingestion rates are shown in Appendix A.5, along with a comparison

[4] These new estimates are in the U.S. EPA Integrated Exposure Uptake Biokinetic (IEUBK) model (U.S. Environmental Protection Agency, 2021). The All-Ages Lead Model (AALMv3) also adopts these more recent, lower baseline ingestion rates.

of previous default EPA rates and Ericson et al. (2016). We test sensitivity of ingestion rates in Appendix C.2.

We assume that soil accounts for 50% of the exposure caused by a site, with other known pathways such as water, air and food contamination combining to cause the other half of exposure. This assumption comes from taking a midpoint of limited heterogeneous evidence. Studies near lead-polluting sites report mixed pathway shares: some find soil and dust ingestion to be the primary contributor to lead exposure (Giubilato et al., 2025; Zhang et al., 2016), others observe roughly equal contributions from soil and food (Qu et al., 2012), and some identify food as the primary pathway (Gao et al., 2023; Cao et al., 2015). Given this assumption, we double the AALMv3 lifetime BLL estimate to capture total pathway exposure. We test sensitivity of this assumption in Appendix C.2.

Table 2: Population, Soil Lead, and Predicted Blood Lead by Distance from Recycling Sites

	Ericson et al. (2016)			This study		
Radii (m)	Pop	Soil (mg/kg)	BLL (µg/dL)	Pop	Soil (mg/kg)	BLL (µg/dL)
0–165	750	2,050	21–31	491	1,684	13.20
165–5000	–	–	–	335,600	206	1.7

Note: This table presents differences in key parameters between our study and Ericson et al. (2016). For Ericson et al. (2016) BLLs are a geometric mean of 21.2µg/dL for adults and 31.15 µg/dL for children. Soil is calculated by multiplying the soil concentration of their three modelled bands (850 mg/kg, 2500 mg/kg, and 5000 mg/kg) with their stated relative frequencies (0.5, 0.35, and 0.15 respectively). We calculate their average population by multiplying the population of their three modelled site sizes (200, 1000, 2000) with their stated relative frequencies (0.5, 0.35, and 0.15 respectively). Whilst Ericson et al don't express their results in terms of cumulative population blood lead levels (cpBLL), we can approximate this by multiplying their mean population exposure of (6,094,463 + 16,814,100)/2 = 11 million by their mean blood lead levels of 26µg/dL (the simple mean of child and adult levels), so 11 x 26 = 286 million cpBLL.

Comparing to other data sources

There are two ways we can benchmark our estimates. First, we review studies that do directly measure blood lead near polluted sites. Second, we calculate the blood lead level implied by quasi-experimental reduced-form estimates on test scores.

Forsyth et al. (2026) found that blood lead of children in Dhaka was 50% higher for those living within 1 km, and 24% higher for those within 1–2 km, of a battery recycling or lead industry site, compared to children living more than 5 km away. Differences beyond 2 km were not statistically significant, though this may reflect limited statistical power to detect smaller effects at greater distances. Other studies of battery recycling sites have focused primarily on populations living very close to emission sources, often within a few hundred metres (Chowdhury et al., 2021; Etiang et al., 2018; Irawati et al., 2022; Lumumba et al., 2024), and therefore provide limited information about impacts at larger distances. Chowdhury et al. (2021) find median soil concentrations of 1400 mg/kg and median blood lead levels of 21.3 µg/dL within 200 m of an abandoned informal used lead acid battery recycling site in Bangladesh. Irawati et al. (2022) find average blood lead levels in a village in Indonesia with ULAB recycling of 17 µg/dL. Every sample taken in one study in the heavily polluted village of Dong Mai in Vietnam was above 10 µg/dL (Daniell et al., 2015). Machmud et al. (2025) found that 61% of children living within 200 m of a recycling site in Indonesia had BLLs above 10 µg/dL, compared with 31% among those 200–250 m away. Similarly, Zhang et al. (2016) observed a decrease from 15 to 7 µg/dL between 250 m and 1 km in China. These studies demonstrate steep exposure gradients near battery recycling operations but provide little evidence regarding effects beyond approximately 1–2 km.

Several studies estimate the relationship between blood lead and distance to other types of lead industry such as mines and large formal smelters (Garcia-Vargas et al., 2014; Hegde et al., 2010; Paoliello et al., 2002; Willmore et al., 2006; Mandić-Rajčević et al., 2018). Paoliello et al. (2002) for example find blood lead within 2 km of a refinery in Brazil is 11.25 µg/dL, and 4.4 µg/dL in surrounding urban areas within 50 km.

We can also compare to the blood lead levels implied by observed test score impacts in reduced-form studies. These studies measured effects at distances of 2–10 km away. Here we use the estimated relationship between test scores (T) and blood lead (B) from Crawfurd et al. (2024), who find a meta-analytic effect (β) of 0.12 standard deviations per log unit increase in blood lead level.

$$T = \alpha + \beta \ln B, \quad \beta = -0.12 \tag{3}$$

Combined with estimates of mean blood lead level ($\overline{BLL}$) from IHME, we can calculate the implied change in blood lead (ΔBLL) associated with the estimated test score impacts from the quasi-experimental reduced-form studies (ΔT), as follows:

$$\Delta BLL = \overline{BLL}\left(\exp(\Delta T/\beta) - 1\right). \tag{4}$$

This works out as around 3 µg/dL for Berkhout et al. (2025), 0.6–1.1 µg/dL for Ipapa (2023), and 1.7–1.9 µg/dL for Litzow et al. (2024) (Table D.1), all close to our main estimate of 1.7 µg/dL.

2.3 Estimating population around each site (POP)

To estimate the number of people living in proximity to lead-acid battery recycling sites, we overlay observed site coordinates from the TSIP database on high-resolution gridded population data (CIESIN, 2018). For each site we construct concentric buffer zones at varying radii and sum the resident population within each zone. As we are missing data on the location of most sites, we estimate here the average population around each site and multiply this figure by the estimated number of sites in each country. One complication is that buffers around nearby sites overlap. We assume that exposures are additive, which aligns with our main outcome being cumulative population blood lead levels. Additivity can be assumed because the relationship between soil lead concentration and blood lead level is approximately linear over the relevant range of soil concentrations-up to ten times our study average (Appendix A.2).

But we are also interested in the number of unique people affected by battery recycling operations. In order to count the number of unique people we can construct the union of sites and count population within this. But this is further complicated because our dataset includes only a fraction of all existing sites in each country, requiring us to adjust for both observed and unobserved overlap. For the inner ring of 165 m there is minimal overlap between sites as these rings are sufficiently small. For the outer-most ring of 165–5000 m there is substantial overlap between the rings around different sites. To extrapolate population exposure beyond the observed sites, we need to estimate the location of the unobserved sites. We use an inhomogeneous Poisson point process with intensity proportional to local population. For each country, we (i) build a study domain around the observed points (convex hull + buffer, clipped to the national boundary); (ii) convert gridded population density to people-per-cell; (iii) keep the observed sites fixed; and (iv) simulate additional sites up to the country's estimated total number, by sampling grid cells with probability proportional to population. For each simulation we rasterize the 165–5000 m ring around all (observed + simulated) sites onto the population grid and sum unique population in the ring. Repeating this Monte Carlo step yields the expected unique population covered in the wide ring. This estimator reflects urban concentration better than a homogeneous Poisson rarefaction and avoids the downward bias from treating observed clusters as a random sample. Key assumptions are that population is a reasonable proxy for site intensity and that the domain captures where unobserved sites can plausibly occur.

3 Results

As there are a large number of assumptions and uncertainty that go into our model, we assess the impact of this parameter uncertainty using a Monte Carlo approach with a Beta-PERT distribution. This approach is widely used in cost-benefit and risk analysis, and provides a representation of uncertainty based on intuitive subjective inputs: the minimum, most likely, and maximum values of each parameter. We sample values for each parameter independently.

Here we present sensitivity to adjustments in our four main parameters. In the numerator, cumulative population blood lead levels (cpBLL) are the product of the number of sites, average blood lead increases due to each site, and the number of people affected by each site. The denominator is the cpBLL attributable to all sources.

First, for the number of sites, we use the global total across the 75 low and lower-middle income countries for which we have estimates, which is 24,318 sites. We show sensitivity to increasing or decreasing this amount by 50%.

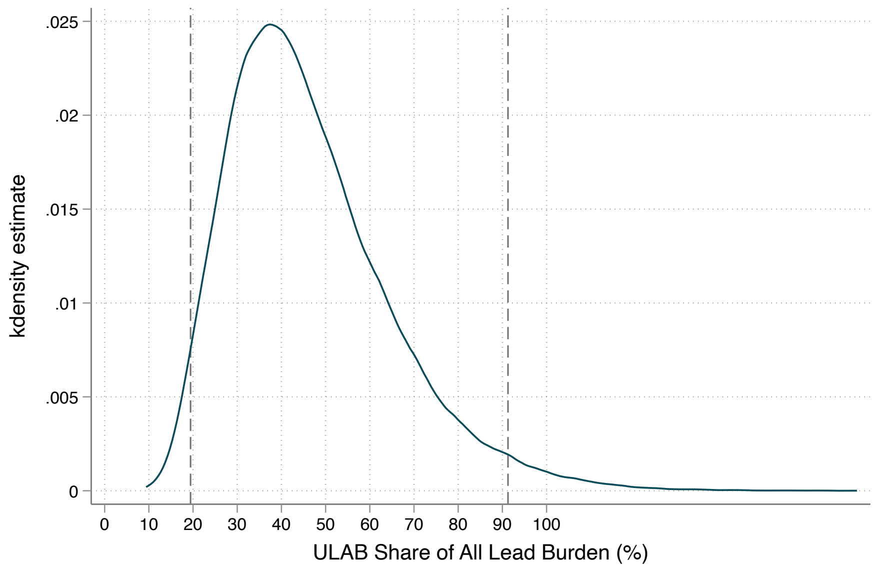
Second, for blood lead levels, our baseline estimate uses an average exposure level within 5km of 1.7µg/dL. Here we again present scenarios increasing or decreasing this amount by 50%.

Third, our baseline population estimate is that 335,600 people live within 5 kilometres of the average site. One point of comparison here is Forsyth et al. (2026) who find that 5 million people live within 2km of the 71 sites in Dhaka, or 70,000 per site (assuming no overlap). We again present estimates varying this by $\pm 50\%$.

Fourth, for the total cpBLL attributable to all sources we use the total for low- and lower-middle income countries from the IHME Global Burden of Disease (GBD) Study (GBD, 2025). This is a slight update to the GBD 2021 numbers used by Fuller et al. (2025). There is substantial structural uncertainty here given sparse underlying data from LMICs, so we again vary this amount by $\pm 50\%$ relative to the central estimate.

Figure 1 shows the distribution of estimates of the share of lead exposure attributable to lead-acid battery recycling. Whilst there is substantial uncertainty, the lower bound of the 95 percent confidence interval around our central estimate is above the earlier estimates from Ericson et al. (2016) The modal estimate is around 33.28 percent of the burden. 80 percent of our estimates fall within 26–71 percent of the burden.

Figure 1: Estimated share of lead exposure attributable to used lead-acid battery (ULAB) recycling



Note: This figure presents the distribution of estimates across 50,000 simulations with varying independent draws for each of the four key parameters. Vertical dashed lines indicate the 95% confidence interval.

In Table 3 we show the breakdown of our central estimates by world region. We show the total estimated number of sites, unique number of exposed people, total cumulative population blood lead levels (cpBLL) attributable to ULABs for the inner close ring (0–165 m), and the wider ring (0–5000 m), and the total estimated cpBLL from all sources. Overall we see an increase by two orders of magnitude in estimated lead exposure from battery recycling by widening the radius of exposure, from 0.50 % to 33 % . The region with the largest exposure from battery recycling is sub-Saharan Africa, with over 3 billion cpBLLs, accounting for over half of all lead exposure in the region. The share of the burden is also over half for South Asia, and for other regions is between a quarter and a third.

Table 3: Main results

Region	Sites	Exposed People (Unique)		cpBLL (Million, additive)			Shares (%)	
		0–165m	165–5000m	0–165m	0–5000m	All Sources	0–165m	0–5000m
Central Asia	341	159,513	5,589,208	2.2	97.1	274.9	0.8	35.3
East Asia and Pacific	3,174	1,485,781	71,887,207	20.6	1,239.7	1,974.6	1.0	62.8
Latin America and Caribbean	318	148,920	7,096,333	2.1	122.4	370.6	0.6	33.0
Middle East and North Africa	2,414	1,129,890	55,652,101	15.7	959.3	3,283.3	0.5	29.2
South Asia	10,294	4,818,257	306,102,983	66.8	5,253.1	16,565.7	0.4	31.7
Sub-Saharan Africa	7,777	3,639,930	158,021,988	50.5	2,731.3	8,785.9	0.6	31.1
Total	24,318	11,382,292	604,349,820	157.8	10,402.9	31,255.0	0.5	33.3

Note: This table presents estimates by region of the number of polluted sites, total unique exposed people within two rings, cumulative population blood lead levels, and the estimate share of all blood lead levels attributable to used lead-acid battery recycling (ULAB) sites. Shares use the denominator of cpBLL from all sources shown in column (6). Estimates reflect only LMIC countries within each region.

Table 4: Main Inputs Comparison

	Ericson et al. (2016) (0–165 m) (lower estimate)	Ericson et al. (2016) (0–165 m) (higher estimate)	This study (0–165 m)	This study (165–5000 m)
Number of sites	10,599	29,241	24,318	24,318
Average BLL per site	21	21	13.2	1.7
Population exposed per site	750	750	491	335,600
Cumulative BLL	166,934,250	460,545,750	157,761,710	10,487,724,403
% share of lead poisoning*	0.53	1.53	0.5	33.28

*Shares are calculated using a denominator cpBLL of 30,100,000,000.

In Table 4 we show the comparison of our inputs to the main equation with those of Ericson et al. (2016).

We can also express the total number of 10 billion cumulative population blood lead levels from battery recycling in terms of health and education impacts. The IHME estimate that 19 million disability-adjusted life years (DALYS) are attributable to lead exposure in low- and lower-middle income countries. A 33.28 percent share of this is equal to 8 million DALYs. Larsen and Sánchez-Triana (2023) estimate 2.4 million annual deaths from cardiovascular disease and 543 million IQ points lost due to lead exposure in low- and lower-middle-income countries. A 33.28 percent share of this due to battery recycling is equal to 807,471 annual deaths, and 181 million IQ points lost, or millions of learning-adjusted years of school (Angrist et al., 2025).

4 Policy solutions

These new estimates of the share of the burden of lead exposure attributable to ULAB recycling implies a higher priority for policy efforts to tackle this source of exposure vis-a-vis other common sources. The challenge with battery recycling is that unlike with many consumer products in which bans and enforcement are the obvious policy routes, battery recycling is highly economically valuable. Specific remediation efforts have been shown to be feasible at cleaning up the most contaminated sites (Chowdhury et al., 2021; Ericson et al., 2018), but the much broader spread of small effects imply a different set of solutions.

4.1 National action

The main priority for action is by national governments. Brazil has been hailed as one potential role model on action to address unsafe lead-acid battery recycling. Through a series of reforms implemented between 2008 and 2019 Brazil transitioned from an unsafe informal industry to a formal and safer one. The heart of this was a mandate for firms to buy-back or collect and recycle sold batteries. This was accompanied by eliminating taxes to make the formal sector more competitive with the informal sector (for more detail see Smith (2024)). The tax reduction seems to have been important, as a buy-back policy in India without the tax reduction did not seem to be effective (Pawar, 2025). More evidence is needed on the effectiveness of other 'extended producer responsibility' schemes. Further investigation of other models may also be needed in smaller countries that don't have domestic battery production. In many countries regulation already exists on safe recycling practices, and so increased enforcement against unsafe industry could play a useful role. Kundu et al. (2025) show information asymmetries in the market for batteries that policy could usefully address.

4.2 International action

International buyers of lead can potentially play a complementary role. Millions of dollars of lead are purchased annually by firms in the United States from West Africa. Improved due diligence rules could require larger buyers to map out supply chains, including auditing smelters and only purchasing from suppliers that meet existing international guidelines (such as the United Nations Basel convention). International actors might also provide technical assistance to governments on better regulation, or directly to large formal recyclers to encourage safer practices.

Beyond the battery recycling industry, improved public health monitoring, including critically more blood lead testing, can empower individuals to avoid lead exposure and demand safer practices.

5 Conclusion

In this paper we revisit previous estimates of the burden of lead exposure in low and lower-middle-income countries that is attributable to used lead-acid battery recycling. Updating prior modelling with new data on the extent of dispersion of lead suggests that the contribution of battery recycling could be significantly higher than previously thought. Though our central estimate is around a third of all exposure, we are unable to provide a very precise estimate due to the number of uncertain factors. Nonetheless evidence increasingly suggests that used lead-acid battery recycling affects massive numbers of people.

Our estimates have several limitations. Many of the key parameters are unknown. We don't know exactly how many battery recycling sites there are, how many people are exposed to lead at each site and by how much.

Future research would be valuable in improving our certainty, by providing new data on several of the parameters in this model. Our estimate of the number of polluted sites in many countries is based in part on just one exhaustive census (Dowling et al., 2016). More similar studies would allow us to increase our confidence in those estimates, as would better data on demand for lead from vehicles.

Our estimate of the average lead burden from recycling sites comes primarily from the Toxic Site Identification Program (TSIP), which includes data from just 13 countries. This database may be biased towards more visible and therefore larger polluting sites. The method for collecting soil may bias towards finding samples with higher lead concentrations—the TSIP Investigator Handbook (Pure Earth, 2017) mentions targeting "sampling at suspected 'hotspots' such as residential areas adjacent to a contamination source". Data on the location of more sites would also increase our confidence in the average population exposed to sites. We also rely on very uncertain estimates of the background level of soil lead in developing countries, based on just one study, and on the level of ingestion of soil in developing countries, based on just two studies.

Our model relies on soil lead data, converted to blood lead via the All-Ages Lead Model (AALM) biokinetic model. We assume soil ingestion accounts for roughly half of the total exposure from a site. The relative contribution of each exposure pathway remains understudied.

Future research should also look further at other avenues to address the lead source apportionment question, such as isotopic fingerprinting, combining natural experiments with direct lead measurement (such as bone lead which provides estimates of cumulative exposure), and randomized remediation interventions.

Above all more evidence is needed on what policies and actions are most effective and cost-effective in improving the safety of lead battery recycling, and reducing lead exposure.

What is clear is that battery recycling is a significantly larger problem than previously thought. This has implications for actors focused on reducing lead exposure, who might want to update at the margin and reallocate some part of their portfolio towards developing solutions for battery recycling, despite the remaining uncertainty in the overall share of the burden.

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A Additional Tables and Figures

A.1 Tables

Table A.1: Trade Balance of ULAB-Related Products for LIC/LMICs

Product	Exports to LIC/LMICs	Exports to UMIC/HICs	Imports to UMIC/HICs	Net Imp.
Waste batteries (HS 854810)	147,738.1	11,639.9	275,936.4	116,558.4
Lead waste & scrap (HS 780200)	18,583.5	9,327.2	128,033.2	100,122.5

Note: Net imports = imports from UMIC/HICs minus total exports. Positive values indicate LIC/LMICs are net importers. The data is from 2023 UN Comtrade (Smith, 2025).

Table A.2: Lead generated per vehicle

Vehicle type	Battery weight (kg)	Batteries per vehi- cle	Service life (years)	Lead per year (kg)	Source
Passenger car	20	1	2	6.5	Tür et al. (2016)
Commercial vehicle	50	2	2	32.5	Tür et al. (2016)
Motorcycle	5	1	2	1.6	Two Tyres (2024)
Electric two-wheeler	40	1	1	26	Tran et al. (2023)
Electric three-wheeler	30	4	1	78	Table A.3

Note: We assume for all vehicle types that the lead content by weight of each battery is 65 percent. Our estimate of battery life for electric three-wheelers is supported by recent research from Bangladesh (Kundu et al., 2025).

Table A.3: Data sources for electric three-wheeler battery weight

Source	Weight per battery
https://www.zunaxenergy.in/electric-rickshaw-batteries.html	25–30 kg
https://www.thesupermexx.com/product/intelligent-e-rickshaw-battery/	25.6 kg (46.5 kg for a whole pack at 40–50% of weight of lead-acid equivalent, meaning 103 kg for 4 lead-acid batteries)
http://www.getekbatteries.com/heavy-e-rickshaw-battery-3552243.html	10–25 kg
https://www.ujalapowers.com/ups-12000-electric-rickshaw-batteries-1954218.html	38 kg
https://www.tradeindia.com/products/80-ah-acid-lead-e-rickshaw-battery-with-9-5-kg-weight-8256648.html	9.5 kg
https://www.indiamart.com/proddetail/140ah-e-rickshaw-battery-16258649291.html	33.3 kg
https://www.ujalapowers.com/er-13000-electric-rickshaw-batteries-6884489.html	31 kg

Table A.4: Distance-Decay Function by Country

	(1) Bangladesh	(2) Georgia	(3) India	(4) Indonesia	(5) Other	(6) All	(7) All
lndist	-0.879***	-1.144*	-0.466***	-0.606***	-0.121**	-0.377***	-0.614***
	(0.0520)	(0.587)	(0.0691)	(0.162)	(0.00534)	(0.0985)	(0.0495)
Obs.	1,493	308	1,382	1,329	59	601	5,172
R^2	0.60	0.36	0.71	0.59	0.16	0.61	0.66

Note: This table presents estimates of the relationship between log distance and log soil lead by country. We pool together countries with fewer than 100 data points each (these are Brazil, Colombia, Ghana, Kenya, Kyrgyzstan, Madagascar, Mongolia, Philippines, and Senegal). Alternative specifications for the full sample are shown in Table 1. All models have site fixed effects and standard errors clustered by sites.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

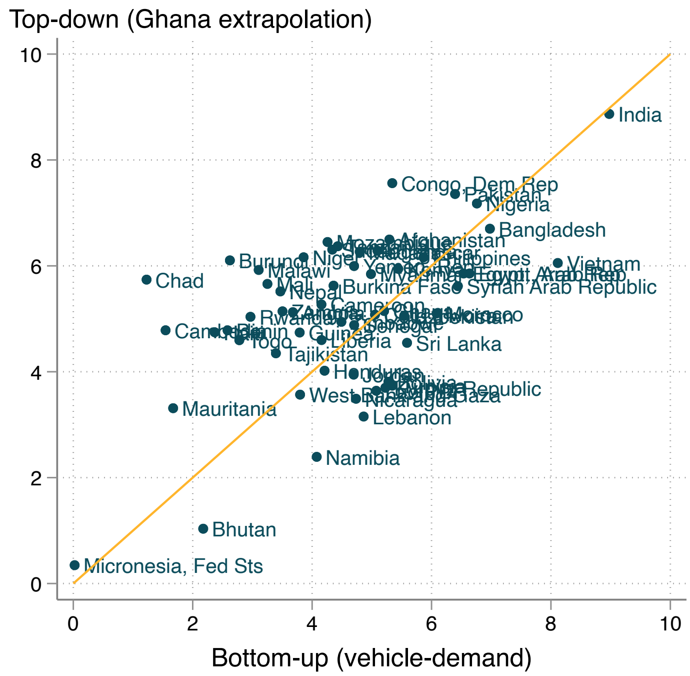
Table A.5: Comparison of Soil Ingestion Assumptions: Ericson et al. (2016) vs. This Study

	Ericson et al. (2016)		This Study	
Age group	Default	LMIC Adjusted	Default	LMIC Adjusted
From 0 years	38.75	255	—	—
From 1 year	60.75	405	—	—
From 2 years	60.75	405	—	—
From 3 years	60.75	405	—	—
From 4 years	45.00	300	—	—
From 5 years	40.50	270	—	—
From 6 years	38.25	255	—	—
Adults (17+)	50	200	—	—
From 0 years	—	—	18	54
From 0.25 years	—	—	32	96
From 1 year	—	—	41	123
From 5 years	—	—	36	108
From 10 years	—	—	27	81
From 15 years	—	—	14	42

Notes: Ingestion units are mg/day. Default refers to the default soil ingestion values in the model used. Ericson et al. (2016) used the IEUBK version 1 for children aged 0–7 and ALM version 1 for adults aged 17–64. Our study used the AALMv3 for all ages (0–64). Ericson et al. (2016) state that the IEUBK average soil ingestion is 85–135 mg/day, but this is in fact referring to a combined ingestion of soil and dust.

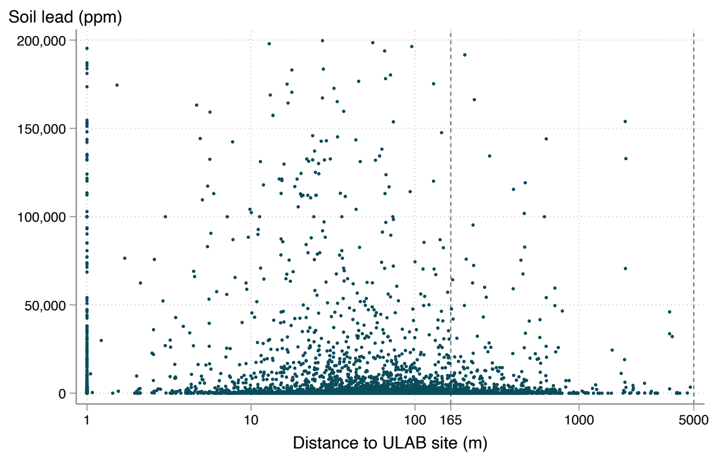
A.2 Figures

Figure A.1: Comparison between alternative methods for estimating number of polluted sites per country



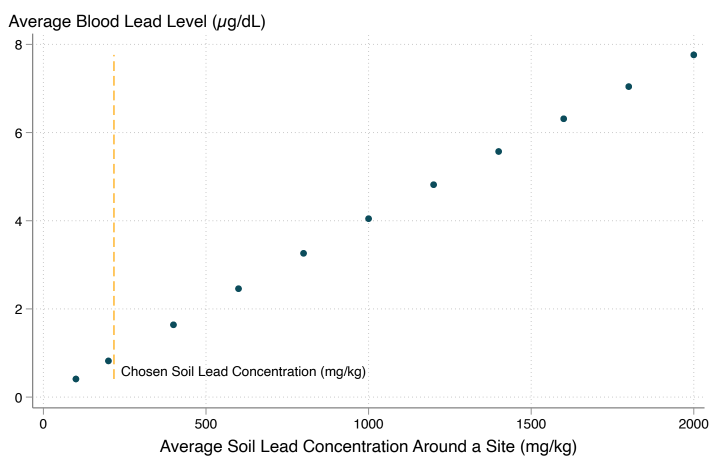
Note: This figure shows the log number of sites estimated for each of the 57 countries for which we have data by two alternative approaches, a top-down approach on the y-axis and a bottom-up approach on the x-axis. The correlation between raw numbers is 0.88. The yellow line is the line of equality.

Figure A.2: Soil lead and distance to polluted sites in the Pure Earth global database



Note: This figure plots data from the Toxic Sites Identification Programme downloaded in January 2025.

Figure A.3: Soil lead and Blood lead relationship in AALMv3



Note: This figure shows the AALMv3 output of average lifetime (ages 0-64) blood lead from soil lead input values up to 10 times the average soil used our the model. The linear relationship observed here is our justification for assuming additivity of exposure from multiple sites.

B Model Specification and Simplifying Assumptions

We make a number of adjustments and simplifying assumptions to the model developed by Ericson et al. (2016), which we list here.

B.1 Number of sites

In estimating the number of polluted sites based on vehicle demand, we add a common new vehicle type to those considered by Ericson et al. (2016)—electric three-wheelers. They estimate a total number of estimated sites at 10,599 from the vehicle demand method and 29,241 from the Ghana census-extrapolation method. We estimate a total of 57,774 (Table 3).

We model a single recycling site size rather than three different sizes. Ericson modelled three sizes of sites (outer exposure distance of 100m, 200m, 300m) with frequency ratios of 0.5, 0.35, 0.15 respectively. We modelled the average of this to be 165 m. This does not change the main results of the model.

B.2 Average exposure

We enter soil lead concentrations directly into the AALMv3 and use the model's single 0–64-year population average without applying any demographic weighting. For example, a soil lead level of 500 mg/kg gives an AALMv3 output of 0.684 µg/dL as the average blood-lead level across ages 0–64, and we assign that value to everyone in our exposure model. Because the AALMv3 already incorporates age-specific physiology before producing this mean, our approach captures children's higher biological uptake within the 0–64 average itself. However, it does not adjust for the younger age structure of low- and middle- income countries. By contrast, following Ericson et al. (2016) by splitting ages and using a soil lead level of 500 mg/kg would give AALMv3 age-group means of 2.0 µg/dL (0–6 years), 0.86 µg/dL (7–16 years), and 0.87 µg/dL (17+ years), then weighting them by typical LMIC demographics, 15 percent aged 0–6, 25 percent aged 7–16, and 60 percent aged 17+, would yield a weighted average of about 0.77 µg/dL. Our simpler method therefore underestimates the LMIC population-wide average by roughly 10%.

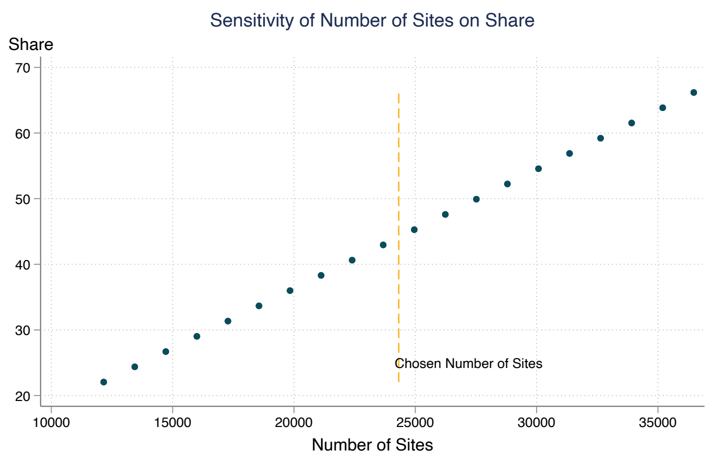
C Robustness

We make a number of adjustments and simplifying assumptions to the model developed by Ericson et al. (2016), which we list here.

C.1 Number of sites

In Figure C.1 we show the responsiveness of the estimated share of lead burden to changes in the estimated number of polluted sites, holding other parameters constant.

Figure C.1: Battery-recycling share of lead burden and number of polluted sites



Note: Holding the Average BLL (1.7) and the population exposed (335,600) constant. The x-axis range shows 50% above and below our preferred estimate.

C.2 Average exposure

Our average blood lead level input is generated using the AALMv3 model, which converts soil lead concentrations to average BLLs for ages 0–64. At the soil levels we model (0–2500 mg/kg), the AALM output scales linearly with soil ingestion rate, allowing us to express average BLL from soil as a product of three terms:

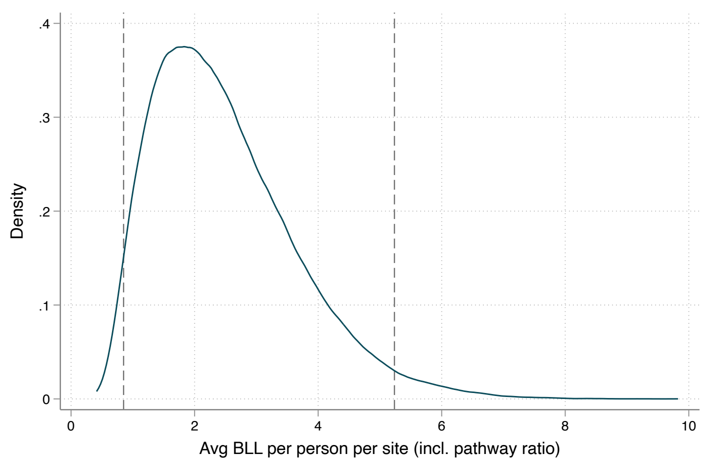
$$\text{Avg BLL}_{\text{soil}} = \text{Avg Soil Lead} \times \text{Avg Soil Ingestion Rate} \times \text{Conversion Factor}.$$

And we can express the BLL from all sources as:

$$\text{Avg BLL}_{\text{all}} = \text{Avg BLL}_{\text{soil}} \times \text{Soil Share of All Exposure Pathways.}$$

We conduct sensitivity analyses on each of these four underlying components, first using a probabilistic Monte Carlo method drawing each parameter from a distribution (as in Section 3). We then show how blood lead levels respond to each individual parameter whilst holding the others constant in a deterministic model. Figure C.2 shows the Monte Carlo results, Figure C.3 varies soil lead concentration, Figure C.4 varies soil ingestion rate, Figure C.5 varies the soil-to-BLL conversion factor, and Figure C.6 varies the share of total exposure attributed to soil ingestion.

Figure C.2: Estimated effect on blood lead levels within 5km of a polluted site



Note: This figure presents the distribution of estimates of blood lead levels across 50,000 simulations with varying independent draws for each of four underlying model parameters; (i) the soil lead level, (ii) the soil ingestion rate, (iii) the soil to blood lead conversion rate, and (iv) the soil share of all exposure pathways. Each parameter's possible minimum and maximum is the X-axis range in the four scatter graphs shown in Figures C.3, C.4, C.5, and C.6

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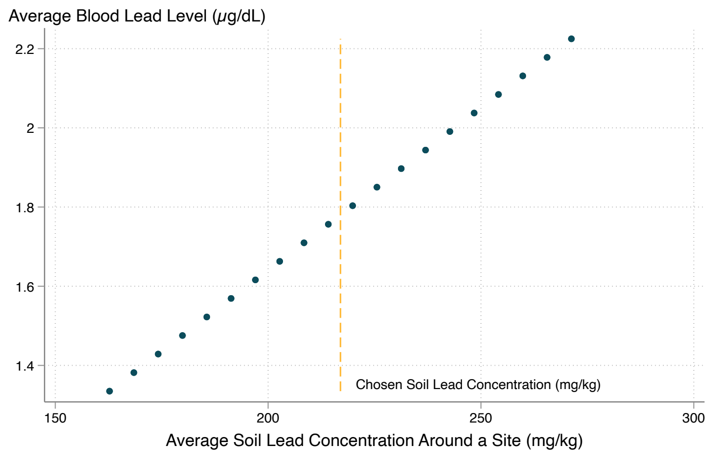
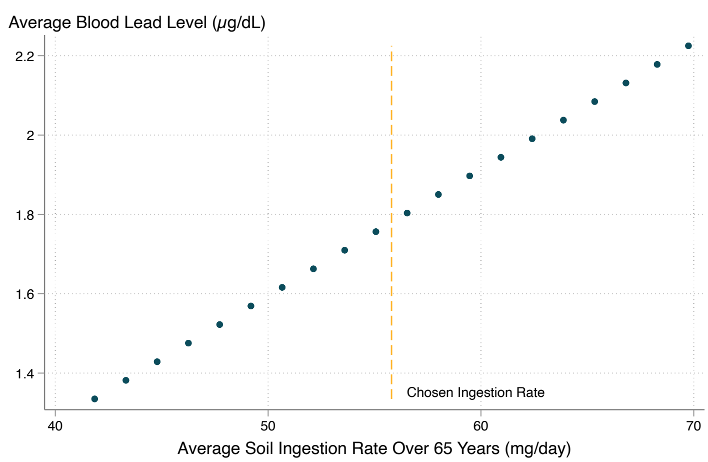
Figure C.3: Sensitivity of Soil Lead Concentration on Avg BLL



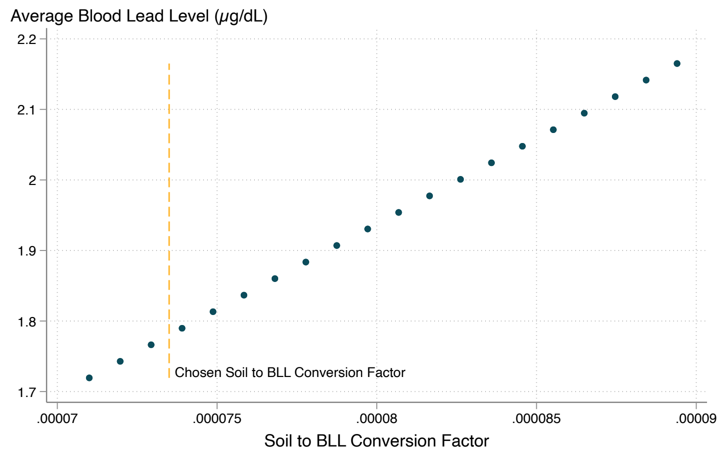
Note: Holding the average ingestion rate (55.8), soil-to-BLL conversion factor (.0000735), and the soil share of exposure (0.5) constant. The X-axis range is arbitrarily chosen at 25% higher and lower our preferred estimate.

Figure C.4: Sensitivity of Soil Ingestion Rate on Avg BLL



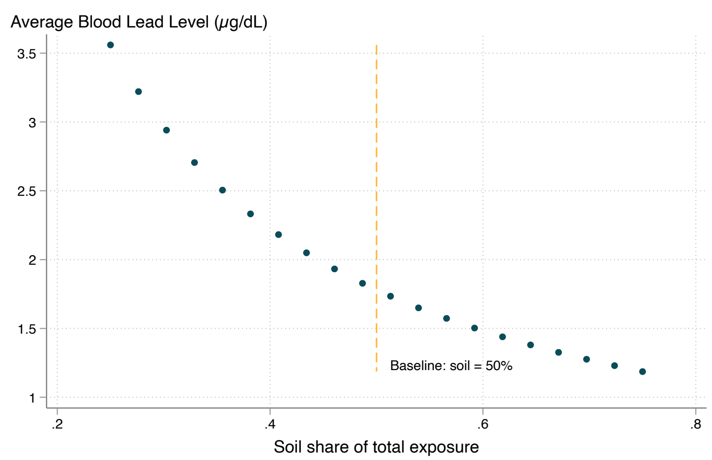
Note: Holding the soil lead concentration (217mg/kg), the soil-to-BLL conversion factor (0.0000735), and the and the soil share of exposure (0.5) constant. The X-axis range spans 1–10× of AALMv3 soil ingestion defaults, where 1x represents the soil ingestion in HICs, and 10x matches Ericson et al. (2017).

Figure C.5: Sensitivity of Soil-to-BLL Conversion Factor on Avg BLL



Note: Holding the soil lead concentration (217 mg/kg), the ingestion rate (55.8), and the soil share of exposure (0.5) constant. X-axis range reflects the lowest and highest conversion factors generated by AALMv3 across soil (0–2500 mg/kg) and average ingestion (18–170 mg/day) inputs.

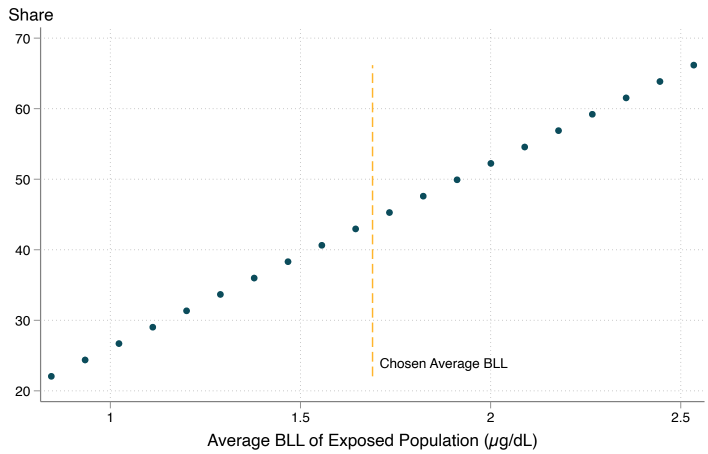
Figure C.6: Sensitivity of Soil Share of Exposure on Avg BLL



Note: Holding the number of sites (35,000), the soil lead concentration (217 mg/kg), and the population exposed (330,000) constant. The x-axis range was arbitrarily chosen at 50% above and below our preferred estimate.

In C.7 we show the sensitivity of the share of lead burden when changing the average blood lead level of the exposed population.

Figure C.7: Sensitivity of Avg BLL on Share

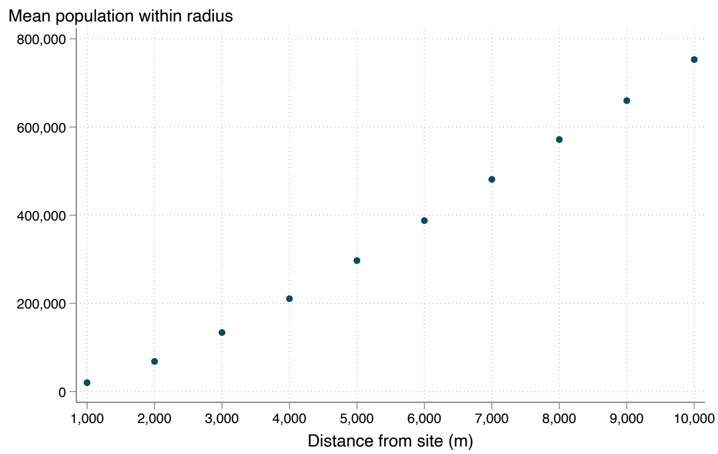


Note: Holding the number of sites (35,000), the population exposed (330,000), and the cumulative BLL from all sources (30,100,000,000) constant. The x-axis range was arbitrarily chosen at 50% above and below our preferred estimate.

C.3 Average population

For our calculation of the population around each site we use a somewhat arbitrary ring of 165–5,000 m. In Figure C.8 we show the simple mean across all sites of population within each specific ring from 165–1,000 m up to 165–10,000 m.

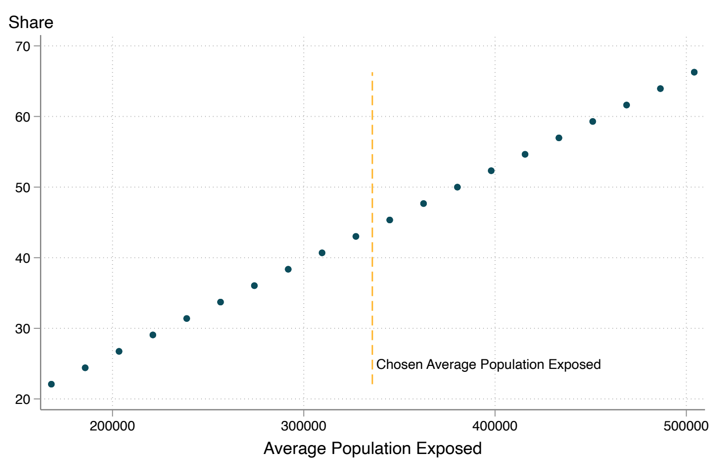
Figure C.8: Average population around polluted sites, by distance



Note: This figure shows the mean population around sites polluted by lead battery recycling in the Toxic Sites Identification Program (TSIP) database (Caravanos et al., 2014; Ericson et al., 2013).

In C.9 we show the sensitivity of the share of lead burden when changing the average exposed population.

Figure C.9: Sensitivity of Population Exposed on Share

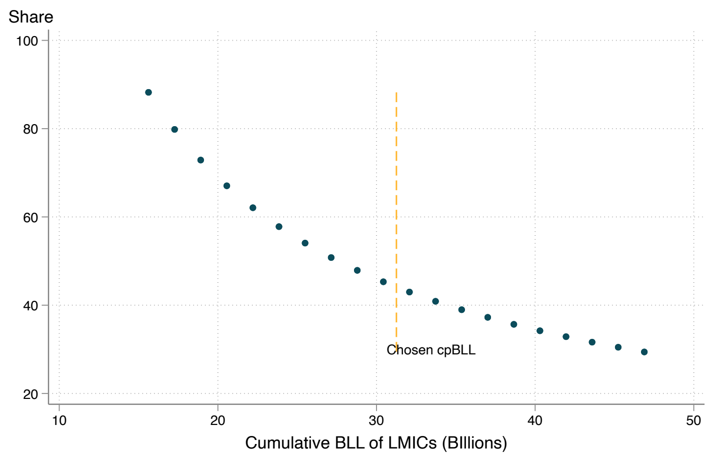


Note: Holding the number of sites (24,318), the Average BLL (1.7), and the cumulative BLL from all sources (30,100,000,000) constant. X-axis range arbitrarily chosen at 50% higher and lower our preferred estimate.

C.4 Total Lead Exposure

Fuller et al. (2025) mention data limitations when introducing their cumulative blood lead level country measure. We show the sensitivity of the share of lead burden to the cumulative lead burden in LMICs in Figure C.10.

Figure C.10: Sensitivity of the Total cpBLL on Share



Note: Holding the number of sites (24,318), the Average BLL (1.7), and the population exposed (335,600) constant. Total LMIC cpBLL range is arbitrarily chosen at 25% higher and lower the current estimate.

D “Reduced-form” studies on recycling impacts

Here we discuss the new quasi-experimental studies in the economics literature. These studies have used a larger radius around polluted sites in part due to practical data constraints. They rely on existing survey or administrative data that is not collected for the purpose of focusing on polluted sites, and so their geographical overlap with polluted sites is limited. Using a larger distance around sites increases the overlap with these data on outcomes. Despite this limitation, results are quite consistent across various distances from 1,000 metres to 10,000 metres (Figure D.1).

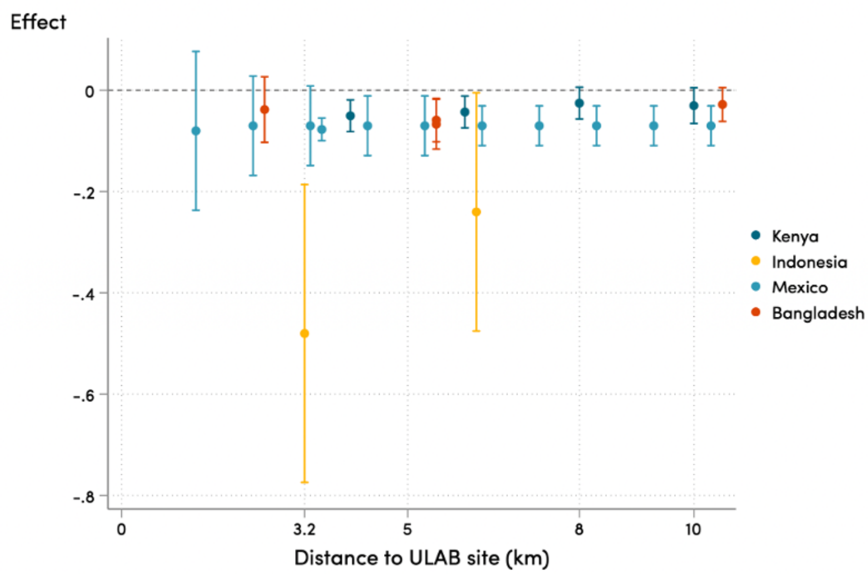
Tanaka et al. (2022) and Litzow et al. (2024) both use the same natural experiment to examine impacts on child birth weight and school test scores, respectively. They focus on the increase in battery recycling at existing plants in Mexico that occurred after regulations raised environmental standards in the United States. Both studies focus their main estimates on schools within 2 miles (3.2 km) of a formal recycling facility. Tanaka et al. (2022)motivate this choice by reference to data from the US that shows ambient lead levels that are similar within 1 mile and between 1–2 miles, before falling after 2+ miles. They show that US air quality regulation improved air quality within both a 1 and 2 mile radius of a recycling plant (with a larger improvement within 1 mile). Litzow et al. (2024) use a variety of distances as a robustness check, finding similar effects when looking within each mile between 1 and 10 miles away.

Ipapa (2023) estimates effects of new recycling operations in Kenya. In his main specification he finds negative effects for schools within 4 km of a recycling plant, and only slightly smaller negative effects for schools within 6, 8, and 10 km.

Mahzab et al. (2024) find negative effects on terminated pregnancies within a 5 km radius of recycling and smelting operations in Bangladesh. They vary this distance to either 2 km or 10 km, in this case finding results that are smaller and no longer statistically significant.

Berkhout et al. (2025) compare learning outcomes of children first exposed to newly opened ULAB sites before age seven with those first exposed at age seven or older, across distance bands. Relative to households 6–10 km away, early-life exposure within 0–3 km lowers numeracy and Raven scores. At 3–6 km, effects remain significant at about half the magnitude.

Figure D.1: Quasi-experimental effects of lead at alternative distances



Note: This figure reproduces estimates from Ipapa (2024, Kenya), Berkhout et al (2025, Indonesia), Litzow et al (2024, Mexico), and Mahzab et al (2024, Bangladesh). Estimates are reduced-form effects of potential exposure to lead from used battery recycling sites on test scores (in Kenya, Indonesia, and Mexico) and on child health (Bangladesh).

Table D.1: Quasi-experimental "reduced-form" studies

Study	**Country**	**Treated (km)**	**Comparison (km)**	**Main estimate**	**Standard error**	**Outcome**	**Mean National BLL**	**Implied BLL Increase**
Berkhout et al (2025)	Indonesia	0-3	6-10	-0.48	0.15	Learning	3	-2.95
Berkhout et al (2025)	Indonesia	3-6	6-10	-0.24	0.12	Learning	3	-2.59
Ipapa (2024)	Kenya	0-4	10-20	-0.0503	0.016	Learning	3.2	-1.10
Ipapa (2024)	Kenya	0-6	10-20	-0.0428	0.016	Learning	3.2	-0.96
Ipapa (2024)	Kenya	0-8	10-20	-0.0253	0.016	Learning	3.2	-0.61
Ipapa (2024)	Kenya	0-10	10-20	-0.0303	0.018	Learning	3.2	-0.71
Litzow et al (2024)	Mexico	0-3.2	3.2+	-0.0772	0.0114	Learning	3.8	-1.80
Litzow et al (2024)	Mexico	0-1	1+	-0.08	0.08	Learning	3.8	-1.85
Litzow et al (2024)	Mexico	0-2	2+	-0.07	0.05	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-3	3+	-0.07	0.04	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-4	4+	-0.07	0.03	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-5	5+	-0.07	0.03	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-6	6+	-0.07	0.02	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-7	7+	-0.07	0.02	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-8	8+	-0.07	0.02	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-9	9+	-0.07	0.02	Learning	3.8	-1.68
Litzow et al (2024)	Mexico	0-10	10+	-0.07	0.02	Learning	3.8	-1.68
Mahzab et al (2024)	Bangladesh	0-5	5+	0.0588	0.0219	Miscarriage		
Mahzab et al (2024)	Bangladesh	0-5	5-15	0.067	0.025	Miscarriage		
Mahzab et al (2024)	Bangladesh	0-2	2+	0.038	0.033	Miscarriage		
Mahzab et al (2024)	Bangladesh	0-10	10+	0.028	0.017	Miscarriage		
Tanaka et al (2022)	Mexico	0-3.2	3.2+	-38.5	16.3	Birthweight		

Note: Data for mean national Blood Lead Level (BLL) is from the Institute for Health Metrics and Evaluation (IHME). The implied log unit BLL change is calculated using the parameter for the lead-test scores relationship estimated by Crawfurd et al. (2024) of 0.12 standard deviations per log unit change in blood lead.

E Method for averaging exposures across a disk

For a circle of radius R:

$$\bar{y}(0,R) = \frac{2}{R^2}\int_0^R r\,\hat{y}(r)\,dr. \tag{5}$$

where $\bar{y}(0,R)$ is the area-average soil lead (mg/kg) inside radius R (metres); $\hat{y}(r)$ is the predicted soil lead at distance r. This is a standard polar-coordinate mean value formula (e.g., (Stewart, 2016), Sec. 15.3).

We compute the inner-zone mean as $\bar{y}(0,165)$. The mean for the 165–5,000 m ring is then obtained from the two disk means:

$$\bar{y}(165,5{,}000) = \frac{5{,}000^2\,\bar{y}(0,5{,}000) - 165^2\,\bar{y}(0,165)}{5{,}000^2 - 165^2}. \tag{6}$$

where the numerator subtracts the total "lead mass" (area × mean) of the inner disk from that of the larger disk, and the denominator is the ring area.