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Lead Exposure and Collective Violence: Evidence from Unsafe Battery Recycling in Africa

Lee Crawfurd

Abstract

Does lead exposure make places more violent? Lead impairs impulse control, and a large literature links it to individual crime in high-income countries. We ask whether it also raises collective violence where exposure is concentrated around industrial sites. We compare places within 5 km of unsafe battery recycling sites in Kenya, Ghana and Senegal with places near other contaminated industrial sites, before and after recycling intensified in 2007. The annual probability of a riot near battery sites rises by 19 percentage points more than near the other sites, from a base of 16 percent. Organised armed violence barely moves, so net of organised violence the effect is 13 percentage points. Peaceful protest rises almost as much as riots, and only 0.1 percent of riots concern pollution. The pattern fits impaired impulse control rather than anger at the sites, and suggests that cleaning up these sites could reduce conflict as well as improve health.

KEYWORDS
lead exposure, riots, collective violence, battery recycling, pollution, Africa

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1. Introduction

Does environmental lead exposure make societies more violent? Lead is among the most common environmental health threats in the world. An estimated 800 million children, one in three, have blood lead levels at or above 5 μg/dL (UNICEF and Pure Earth, 2020). Lead is a neurotoxin that impairs cognitive development (Lanphear et al., 2005), reduces impulse control and heightens aggression (Needleman, 2004). Causal studies from the United States link it to crime (Reyes, 2007; Aizer and Currie, 2019; Feigenbaum and Muller, 2016), and observational studies point the same way (Talayero et al., 2023).

We know little about whether lead also contributes to collective violence. The question matters most where exposure and conflict overlap. In 2024 sub-Saharan Africa recorded 50,129 deaths from battles, explosions and violence against civilians, 21% of the world total, with only 15% of world population. The region also has some of the highest levels of lead exposure in the world, much of it from the unsafe recycling of used lead-acid batteries.

Lead matters most for violence that depends on impulse control. It operates in the opposite way to cognitive behavioural therapy, which reduces violence by making people less likely to meet a situation with an automatic response (Blattman et al., 2017; Heller et al., 2017; Abdul-Razzak et al., 2026). If lead acts through impulse control, we should expect it to raise spontaneous, low-coordination violence such as riots far more than planned, organised violence such as battles.

In this paper we estimate the effect of exposure to unsafe lead-acid battery recycling sites on conflict in Africa. We combine data from the Pure Earth Toxic Sites Identification Program (TSIP), a geo-referenced registry of contaminated sites, with data on conflict events recorded from the Armed Conflict Location Event Database (ACLED). Our focus is on three countries, Kenya, Ghana, and Senegal, that contribute 67 of the 76 African battery sites recorded in the database. No other African country has more than 3 sites. Our outcome is whether a grid cell records any riot in a year, since between 95 and 99% of cell-years record none. We estimate a standard difference-in-differences model, asking whether the probability of conflict rises more after 2007 in cells within 5 km of a battery

site than in cells farther away. 2007 marks a documented intensification of recycling as motorisation and the global price of lead grew. Cells near the other contaminated sites in the same registry enter the same regression. These sites are also industrial but do not emit lead, so they let us net out the effect of living near any polluting industry.

We find that riots rise sharply near lead-acid battery sites after 2007. Within 5 km of a site, the annual probability of a riot rises by 30 percentage points relative to cells farther away. The rise near other contaminated sites is smaller, and netting it out leaves a lead-specific gap of 19 points. Organised violence also rises a little near battery sites, so we net that out too, giving a four-way headline difference of 13 percentage points. This is a large increase relative to the baseline riot probability in these dense urban cells before 2007 of 16% a year.

The increase is concentrated in spontaneous violence, and the coefficient for organised battles is close to zero. Peaceful protest also rises almost as much as riots, which we did not expect. This suggests the distinction that matters may be coordination and not violence. Generic urban confounders, such as faster growth or better event reporting near battery sites, would raise conflict of every kind.

Close to none of the riots are about the polluted sites themselves. We classify all 6,124 riots in the three countries by their reported trigger, and only 6 concern pollution or contamination. The most common trigger is mob justice, such as attacks on suspected thieves (33% of riots).

The pooled result is precise. Country by country, the lead-specific gap is positive in all three, and significant in Ghana and Senegal but not in Kenya on its own. It survives dropping any individual site or treated cell, across 94 estimates that are all significant at 5%. Our choice of 2007 as the onset of treatment is somewhat arbitrary - only the Kenyan sites have directly documented opening dates. But results hold when we vary the assumed onset year from 2004 to 2011, or when we replace the single date with a smooth, rising country-specific path. Pre-treatment trends are flat: a linear pre-trend is small and insignificant in each country and pooled. Across the cells within 5 km of a documented site, the four-way difference implies 69 additional place-years with a riot since 2007 (95% CI 20–119). It also implies 38 additional place-years with a riot death.

We contribute to three literatures. First, the causal evidence on lead and crime concerns individual offending, mostly from US exposure to leaded petrol and water pipes (Reyes, 2007; Aizer and Currie, 2019; Feigenbaum and Muller, 2016). A meta-analysis finds that lead does increase crime, but by less than published estimates suggest, and by more in studies of areas than of individuals (Higney et al., 2022). We show that the channel operates for collective violence, where effects that spread between people should matter most. We also test the mechanism directly through conflict type.

Second, evidence on lead from low- and middle-income countries is recent and thin. Du and Zhang (2024) use contaminated spices in Bangladesh to study conflict and fertility, and Berkhout et al. (2025) study cognitive skills in Indonesia. The closest African evidence links individual lead levels to aggression in South Africa, but it is correlational (Nkomo et al., 2017, 2018; Naicker et al., 2018; Tlotleng et al., 2022). To our knowledge this is the first causal evidence on lead and collective violence in sub-Saharan Africa, where unsafe recycling is most common.

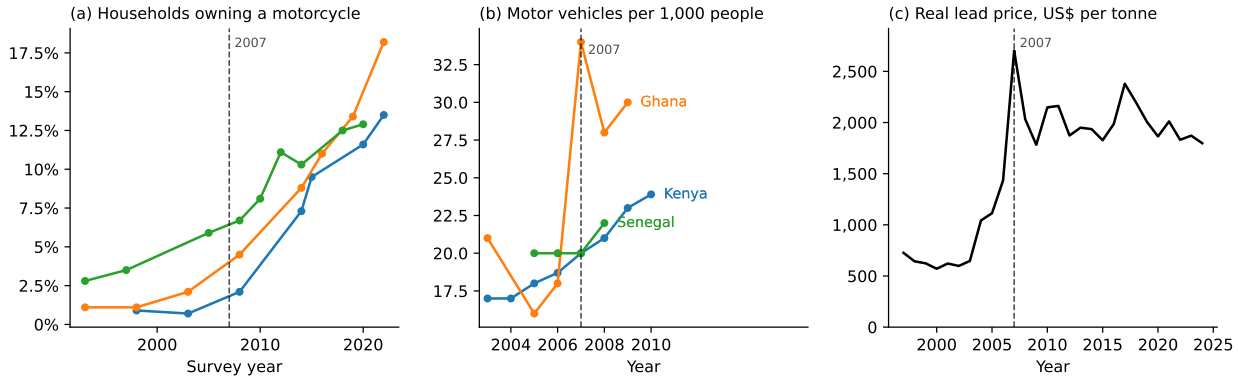
Third, the conflict literature has studied proximate triggers such as food prices and elections, and structural factors such as large youth cohorts and heat (Bellemare, 2015; Urdal, 2006; Hsiang et al., 2013). We add an environmental exposure that is widespread and measurable, and that can be cleaned up. Burden estimates for lead currently value its effect on conflict at zero (Larsen and Sánchez-Triana, 2023).

2. Context: lead exposure and battery recycling

Unsafe recycling of lead-acid batteries is one of the main sources of lead exposure in sub-Saharan Africa. It may account for a large share of all lead exposure in low- and lower-middle-income countries (Crawfurd et al., 2026). As the number of vehicles on the continent has grown, so has the number of batteries to be scrapped. Figure 1 shows the growth in the share of households that own a motorcycle in DHS surveys, and motor vehicles per 1,000 people from the World Bank development indicators. Safe formal recycling requires expensive capital equipment, and so both formal and informal operators often operate unsafely, melting used batteries without proper safety equipment or in open-

air furnaces. Smelters release lead dust and fumes into the surrounding neighbourhoods. Pure Earth's models suggest that millions of people in Africa are exposed to lead from unsafe battery recycling (Ericson et al., 2016).

Figure 1: Motorisation and the world lead price



Notes: Panel (a) shows the share of households owning a motorcycle or scooter, from DHS (StatCompiler indicator HC_TRNS_H_SCT). Panel (b) shows registered motor vehicles per 1,000 people, from the World Bank (IS.VEH.NVEH.P3), for countries with three or more observations. Colours denote the same countries in panels (a) and (b). Panel (c) shows the world lead price in US dollars per tonne at 2010 prices, from the World Bank Commodity Price Data (Pink Sheet), annual. The dashed line marks 2007.

Several studies document the harm of living near these sites. Ipapa (2026) finds battery recycling plants in Kenya in the Pure Earth database. Media reports put most of their openings in 2007, so he treats all plants as opening that year. Students near a plant score lower on the primary school leaving exam. Tanaka et al. (2022) and Litzow et al. (2026) study the move of US battery recycling to Mexico after US environmental rules tightened. They find effects on birth weight and on test scores, respectively. Kundu et al. (2026) use Bangladesh's 2015 barriers to battery imports, which moved battery production and recycling into the country, to estimate the effect on terminated pregnancies near battery sites.

The conflict-type prediction in the introduction rests on well-documented neuroscience. Besides impairing impulse control in general, lead causes a dose-dependent loss of grey matter in the prefrontal cortex. The loss is concentrated in the ventrolateral prefrontal cortex and the anterior cingulate cortex, the regions that govern impulse control and decision-making (Cecil et al., 2008). Cognitive behavioural therapy works on the same behavioural margin from the other direction. It makes people less likely to meet provoca-

tion with an automatic response (Blattman et al., 2017; Heller et al., 2017; Abdul-Razzak et al., 2026). The evidence that it does this by changing an underlying capacity is weak, and Heller et al. (2017) find no support for self-control as the channel. The contrast our design tests is therefore between impulsive, low-coordination violence and planned, hierarchically organised violence. The kinds of conflict that lead amplifies should mirror those that CBT reduces. The neuroscience speaks most directly to reactive aggression. Whether the same margin governs joining a peaceful crowd is less clear, and we return to it in Section 5.5.

Other explanations for riots emphasise social identity and grievance. Simon and Klandermans (2001) and van Zomeren et al. (2008) argue that collective action arises when a group perceives itself as disadvantaged, and is more likely when the group has a strong shared identity. Stott et al. (2017) and Drury et al. (2020) emphasise the role of police in triggering riots, arguing that heavy-handed policing can escalate tensions and provoke collective violence. We do not dispute this account of how riots ignite and spread. Our argument is that lead shifts the underlying propensity for an individual to engage in impulsive action, so familiar triggers are more likely to tip into spontaneous violence more often. In other settings, individual dispositions toward aggression and disruption predict support for political violence (Kalmoe, 2014; Landry et al., 2024). This links individual impulse control to collective violence, though the evidence is mostly on attitudes and from high-income democracies. The two accounts differ in which kinds of conflict they predict. Grievance and identity organise both spontaneous riots and sustained armed conflict. Impaired impulse control should raise the former far more than the latter. Our conflict-type contrast tests this difference.

Battery recycling exposes people to lead in a different way to leaded petrol. In the US literature, leaded petrol works through exposure in childhood, with lags of 15–20 years to adult crime. Battery recycling exposes adults as well as children to lead dust from open-air smelting, and the exposure is acute and ongoing. Our post-2007 effects can therefore work through current exposure as well as through early development. Adults near active sites breathe in lead dust every day. The toxicology literature documents immediate neurobehavioural effects at the blood lead levels found near ULAB sites. Shih

et al. (2007) review adult studies that measured both blood and bone lead, and find that lead is associated with worse neurobehavioural performance. In occupational cohorts the dose that matters is recent blood lead, whilst in older general populations it is cumulative bone lead. Battery recycling workers in Italy show impaired executive function at 24–76 μg/dL (Fenga et al., 2016). At Thiaroye sur Mer, Haefliger et al. (2009) measure mean blood lead of 130 μg/dL (range 40–614) in children. Adults there were likely exposed to similar levels.

The rising post-2007 effect in our event study fits this channel. It also fits the cohort channel below, so the time profile alone cannot tell them apart. As motorisation grows, more batteries are recycled, and people nearby face rising acute exposure in place of a one-off step change. Evidence on air pollution also supports a contemporaneous pathway. Herrnstadt et al. (2021) use wind direction to isolate short-run variation in pollution in Chicago. Acute exposure to particulate matter and ozone raises violent crime within days, which suggests a rapid neurological effect of inhaled pollutants on behaviour. Lead's acute neurotoxicity likely works in a similar way, especially at the high concentrations near unsafe recycling sites. Finally, in the South African Birth to Twenty Plus cohort, blood lead at age 13 predicts physical violence and fighting in late adolescence (Nkomo et al., 2017). Risk is higher at BLLs of 5–10 μg/dL, and the association is stronger above 10 μg/dL. That is a much shorter path from exposure to behaviour than in the US petrol-lead studies, which link prenatal or early-childhood exposure to adult crime a decade or more later.

A cohort channel adds to the contemporaneous effect. Recycling at many of our sites began before 2007. Children exposed in the 1990s–2000s reach the peak ages for joining riots (about 18–30) during our post-treatment window. The 2007 treatment date thus marks the intensification of recycling as motorisation grew, and not the start of all lead exposure near these sites. The same mechanism predicts lower school performance near battery sites (Ipapa, 2026).

Battery recycling could also raise conflict through a channel that has nothing to do with lead. The sites create low-wage informal jobs that may attract child labour and depress school attendance, which lowers test scores. Through worse long-term labour market

outcomes, this could raise crime and conflict over time. This channel makes different predictions from the neurological one. Its effects should build up gradually over 15–20 years as affected cohorts age. Our effect also builds up over time, so timing alone cannot rule this channel out. The evidence against it comes from two comparisons. Other labour-intensive informal sites, such as artisanal mines and dumps, are in the comparison group. The channel also predicts more organised conflict, which we do not see. It should raise organised as well as spontaneous conflict, since exclusion from the labour market can motivate sustained collective action. It should also appear near *any* labour-intensive informal industry, and not only near lead-emitting ones. Our design does not fully separate these channels. The lead-specific gap for battles is however near zero (0.017, pooled), and battles are the event type most associated with sustained organised mobilisation. This is hard to square with labour-market exclusion, which predicts no such split between spontaneous collective action and strategic armed violence. We read our estimates as a combination of contemporaneous neurological effects and cohort accumulation, with the schooling channel possibly operating in parallel.

Riots have many causes, and lead is only one contributing risk factor. Proximate triggers are well studied and include food or fuel price spikes (Bellemare, 2015; Hendrix and Haggard, 2015), contested elections (Salehyan and Linebarger, 2015; Dercon and Gutiérrez-Romero, 2012), heavy-handed policing (Stott et al., 2017) and local economic shocks (Harari and La Ferrara, 2018). Underlying factors that make some places riot-prone include the share of young people in the population (Urdal, 2006), ethnic divisions (Horowitz, 2001), especially when politicians mobilise them to win elections (Wilkinson, 2004), and, most like lead exposure, high temperatures (Hsiang et al., 2013).

3. Data: TSIP sites and ACLED conflict events

3.1 Toxic sites: TSIP database

We use the Pure Earth Toxic Sites Identification Program (TSIP) database, downloaded in March 2026. The database holds geo-referenced records of contaminated sites in low- and middle-income countries, with each site's main pollutant and industry type. Our

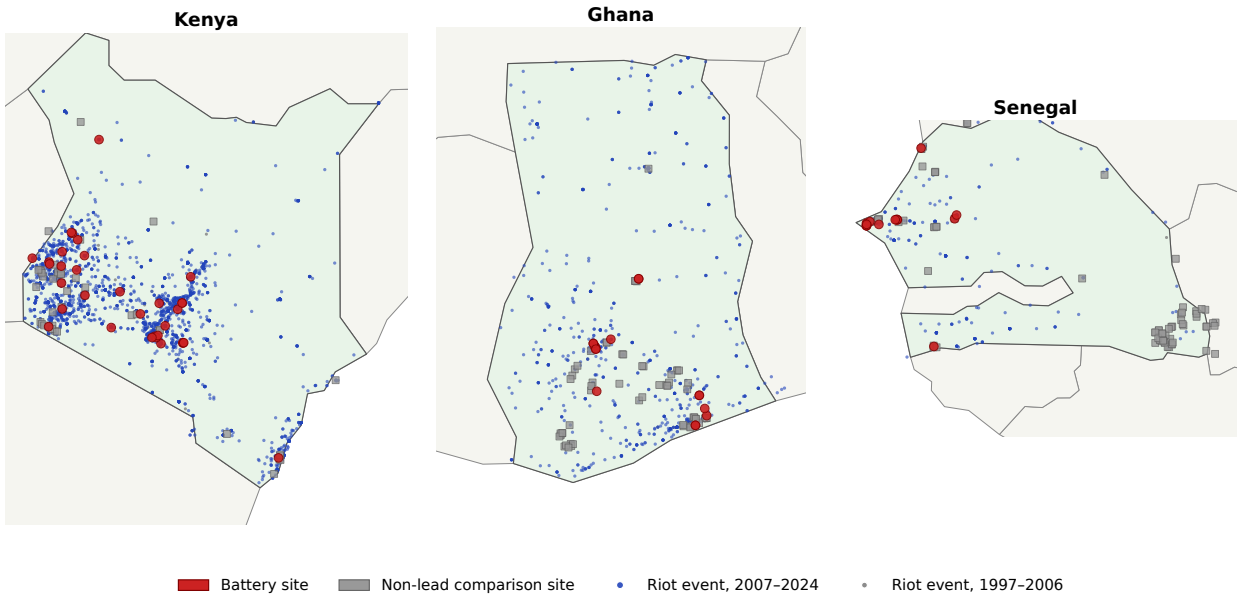
treatment sites are the 67 sites in the three countries whose TSIP industry involves batteries, which we call battery sites: 52 are classified as lead battery recycling, 13 as lead-acid battery manufacturing or repair, and 2 as recycling of other batteries. Battery sites include informal yards, where batteries are broken and melted in the open, and licensed smelters such as Metal Refinery (EPZ) at Owino Uhuru in Mombasa. Both kinds release lead into the surrounding area, so we treat them alike. Non-lead sites are the comparison group. In Kenya, Ghana and Senegal the largest category of non-lead TSIP sites is artisanal and small-scale gold and ore mining. These are heavily concentrated in southern Ghana's gold belt (Ashanti and Eastern regions) and in rural Senegal. Others are industrial and municipal dump sites (common in peri-urban Nairobi and Accra), e-waste and general recycling facilities, vehicle repair workshops (garages and mechanics), chemical manufacturing plants and petrochemical installations. Their main contaminants are arsenic, mercury, chromium and cyanide from mining, plus a range of persistent organic pollutants from industrial and waste sites. Table 1 summarises site coverage by country. Table 2 gives summary statistics for the cell-year panel, and Figure 2 maps the sites and riot events.

Table 1: Sample overview: TSIP sites and ACLED conflict events by country

	TSIP sites		ACLED events			
Country	Battery	Non-lead	Grid cells	Obs.	Riots	Protests
Kenya	33	45	1,319	36,932	4,218	4,658
Ghana	18	63	626	17,528	612	655
Senegal	16	72	1,050	29,400	492	710
Total	67	180	2,995	83,860	5,322	6,023

Notes: Battery sites are TSIP sites whose industry involves batteries (recycling, manufacturing or repair). Non-lead sites include all other pollutant types (arsenic, mercury, cadmium, etc.). We set treatment onset at 2007 in all countries. Grid cells are 0.1×0.1 degree cells within 50 km of any TSIP site (battery or non-lead). Cells with no recorded ACLED events are included with zero counts. Obs. is the number of cell×year observations. Riots and Protests are total event counts across all cells and years. ACLED coverage: 1997–2024.

Figure 2: Battery sites and riot events by country



Notes: Red circles are battery sites and grey squares are non-lead sites, both from TSIP. Dots are ACLED riots, blue for 2007–2024 and grey for 1997–2006.

3.2 Conflict data: ACLED

We use the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al., 2010), which provides geo-referenced records of political violence and protests from 1997 to the present. ACLED classifies events into six types: battles, explosions/remote violence, violence against civilians, riots, protests and strategic developments. Riots in ACLED are mob violence and violent demonstrations. Violence against civilians (VAC) covers attacks, abductions and sexual violence by armed groups. Battles are armed clashes between organised groups.

Riots and protests are our primary outcomes. We use battles and violence against civilians to test for differences by conflict type, as they are organised activities, and how often they occur depends on group capacity, hierarchy and strategic timing, and much less on whether individuals restrain themselves in a moment of provocation.

In our sample cells, 51% of battles and attacks on civilians kill at least one person, compared to 25% of riots (3,296 and 5,322 events, 1997–2024).

Table 2: Summary Statistics

	Kenya	Ghana	Senegal
Panel A: Sample Structure			
Grid cells	1,319	626	1,050
Cell×year obs.	36,932	17,528	29,400
Years covered	1997–2024	1997–2024	1997–2024
Battery recycling sites (TSIP)	33	18	16
Non-lead comparison sites (TSIP)	45	63	72
Panel B: Distance to Battery Sites and Clusters			
Cells within 5 km of battery site	20	4	6
Cells 5–10 km from battery site	49	18	14
Cells 10–20 km from battery site	179	49	47
Cells within 5 km of a non-lead site	26	18	32
Cells within 5 km of both	6	1	3
1° blocks (clusters)	33	16	28
of which contain a cell within 5 km of a battery site	11	3	4
Panel C: Pre-Period Means, 1997–2006 (per cell×year)			
Riots	0.023	0.001	0.002
Protests	0.018	0.002	0.003
Organised violence	0.046	0.003	0.016
Panel D: Post-Period Means, 2007–2024 (per cell×year)			
Riots	0.165	0.054	0.025
Protests	0.186	0.057	0.036
Organised violence	0.085	0.029	0.008
Panel E: Cell-Years with No Events			
Cell-years with zero riots	95.3%	98.0%	99.4%
Cell-years with zero protests	95.8%	98.4%	99.2%
Cell-years with zero organised violence	96.6%	98.7%	99.4%
Cells with no riot in any year	63.2%	75.2%	93.2%

Notes: Cells are 0.1° grid cells within 50 km of any TSIP site. Sites are from the Pure Earth Toxic Sites Identification Program (TSIP, March 2026), and events are from ACLED, 1997–2024. Pre- and post-period means are events per cell-year. Blocks are the 1°×1° squares on which standard errors are clustered.

3.3 Grid cell panel

Our unit of analysis is a 0.1×0.1 degree grid cell (about 11 × 11 km). We include all grid cells whose centroid lies within 50 km of any TSIP site (battery or non-lead). Cells with no recorded ACLED activity get zero event counts, so the sample is not selected on the outcome. We compute the distance from each cell centroid to the nearest battery site, and separately to the nearest non-lead site. A cell is treated if it lies within 5 km of a battery site, and a cell within 5 km of a non-lead site is near a comparison site.

4. Identification Strategy

We estimate a difference-in-differences model, comparing treated cells (close to a battery site) with comparison cells (close to a non-lead contaminated site) before and after 2007. The specification is:

$$Y_{ct} = \alpha_c + \delta_t + \beta\, B_c \cdot \mathbf{1}[t \geq T] + \gamma\, N_c \cdot \mathbf{1}[t \geq T] + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is an indicator equal to one if any event of the given type occurred in grid cell c in year t. This extensive margin is our primary outcome. Cell fixed effects α_c absorb all time-invariant characteristics, including baseline urbanisation, population and distance to sites. Year fixed effects δ_t absorb common trends. B_c is an indicator for cells within 5 km of a battery site, and N_c an indicator for cells within 5 km of another, non-lead, toxic site. $\mathbf{1}[t \geq T]$ marks the post-treatment period. The lead-specific gap is $\beta - \gamma$. A cell can be near both kinds of site, and then both indicators equal one. Of the 30 cells within 5 km of a battery site, 10 are also within 5 km of a non-lead site, and 76 cells in all are near a non-lead site.

We use 5 km because most exposure is close to the sites. Soil lead around battery recycling sites falls steeply within the first few hundred metres (Crawfurd et al., 2026). But studies of battery recycling find effects on children's test scores and health several kilometres away, some beyond 5 km (Ipapa, 2026; Berkhout et al., 2025; Litzow et al., 2026; Kundu et al., 2026). Appendix Figure A10 shows both. Cells beyond 5 km may therefore

be partly exposed, which would bias our estimates towards zero.

We use the extensive margin because, as Chen and Roth (2024) show, log(events + 1) and the inverse hyperbolic sine give effect sizes that depend on the units of the outcome and mix the extensive and intensive margins. The probability of any event does not depend on units. Appendix Figure A1 shows why this matters here. Between 95 and 99% of cell-years record no riot, and in more than 98.2% the count is zero or one, so for almost every observation the count and the indicator are the same. The rest of the distribution is a long, thin tail. Among cell-years with any riot, the top 10% account for 36–46% of all riot events. A log or count model therefore puts much of its weight on a few high-count urban cell-years. With an outcome this skewed, the transformations also target different estimands (Winkler et al., 2026). The extensive margin measures the change for the typical cell, which is whether it becomes more likely to record any riot. That is the margin the impulse-control mechanism speaks to. Count and Poisson models measure the change in total riots, which a few busy city cells dominate. We report log(events + 1) and raw counts in Appendix A.1 for comparison, but they estimate a different quantity.

We cluster standard errors on 1°×1° spatial blocks, about 110 km across, within each country (Bester et al., 2011). This allows any correlation between cells in the same block, including the clustering of treated cells around each site and conflict events that cross cell boundaries. The pooled sample has 77 blocks, 18 of which contain a cell within 5 km of a battery site. Because few blocks are treated, we also report wild cluster bootstrap p-values for the main estimates (Cameron et al., 2008; MacKinnon and Webb, 2017). Ghana and Senegal have only 3 and 4 treated blocks, so their bootstrap distributions have few distinct draws and their p-values are coarse. We therefore put most weight on the pooled estimate, and on randomisation inference across sites (Appendix Figure A2). Appendix Table A2 compares cell-clustered, block-clustered and Conley (1999) spatial standard errors.

Identification rests on parallel trends in the probability of any event. Absent treatment, $\Pr(Y_{ct}(0) = 1)$ would have followed the same trend in cells at different distances, conditional on cell and year fixed effects. In the pooled specification, which stacks all three countries, we replace δ_t with country×year fixed effects δ_{jt}. These absorb country-specific trends and keep only within-country variation in proximity. With country×year fixed

effects, parallel trends need only hold within countries. We test it with the event study (Figure 4 and Appendix Figure A3) and a test for a linear pre-trend (Appendix Table A4). With a binary treatment, β is a conventional average effect on the treated cells.

We also estimate a continuous version that replaces B_c with inverse distance $1/(d_c + 1)$, where d_c is the distance in kilometres to the nearest battery site (Appendix Table A10). Callaway et al. (2024) show that with a continuous dose the linear coefficient recovers a weighted average of causal responses only under a stronger parallel-trends condition. As an alternative, mutually exclusive distance rings (Figure 5) trace how the effect falls with distance without imposing a functional form, and the binned dose-response in Figure A14 is roughly linear.

The coefficient β measures whether cells within 5 km of a battery site see different changes in conflict after T, relative to cells farther away and to the pre-period. We set $T = 2007$, following the treatment timing in Ipapa (2026). In Kenya, the Owino Uhuru smelter in Mombasa is documented as opening in 2007, and is one of the largest operations documented by Pure Earth. Ipapa (2026) bases his date on media reports that most Kenyan plants opened in 2007, and finds flat test-score trends before that year. In Senegal, informal recycling in the Thiaroye sur Mer suburb of Dakar had been active since the mid-1990s, but intensified in late 2007, when residents began sieving soil for lead to sell, as world lead prices peaked (Figure 1). Several children died of lead poisoning between November 2007 and March 2008 (Haefliger et al., 2009). The real lead price peaked in 2007, rising 89% from \$1,434 to \$2,704 per tonne in 2010 dollars. This raised the return to collecting and recycling used batteries in that year. Appendix A.2 shows that this co-movement also stops us using commodity prices as independent variation in exposure, and uses food prices as a placebo instead.

For Ghana we have no site-specific opening dates, so we apply the same 2007 threshold. The rapid rise in motorisation in Figure 1 supports this date. Appendix Figure A6 varies the assumed onset across every year from 2004 to 2011. The battery riot effect is positive and significant in every year, in all three countries and pooled.

The non-lead sites enter equation (1) through N_c. The largest groups are artisanal mines and sites contaminated with mercury (Appendix Figure A8). They are harmful in their

own right and sit in broadly similar urban and peri-urban settings to battery sites, so the comparison does not assume they are inert. Any excess effect of battery sites over them nets out both urbanisation trends and the conflict effects of co-located non-lead industrial pollutants. It is a conservative lower bound on the lead-specific contribution. Non-lead and battery sites may still differ in the density of surrounding residential areas. Cell fixed effects absorb this if the difference is fixed over time, but not if urbanisation around battery sites grew faster after 2007.

These comparisons form a hierarchy of differences. The battery coefficient β_{battery} is a difference-in-differences across time and distance. Differencing it against the non-lead coefficient gives the lead-specific gap $\beta_{\text{battery}} - \beta_{\text{non-lead}}$. This triple difference nets out everything the two site types share. It is still exposed to anything that distinguishes battery from non-lead sites and correlates with conflict, such as faster urbanisation around them. Our central identifying test differences the gap once more, across conflict type. It compares the riot gap with the organised-violence gap in one stacked regression, in effect a quadruple difference across time, distance, site type and conflict type:

$$Y_{ctk} = \alpha_{ck} + \delta_{jtk} + \beta B_c P_t + \gamma N_c P_t + \beta^R B_c P_t R_k + \gamma^R N_c P_t R_k + \varepsilon_{ctk} \tag{2}$$

where k indexes riots and organised violence, R_k is one for riots, and $P_t = \mathbf{1}[t \geq T]$. The conflict-type contrast is $\beta^R - \gamma^R$. Both rows for a cell share its block cluster. A confounder that survives the triple difference would raise conflict of all types near a growing urban industrial site. Only a mechanism that acts on impulsive violence, and leaves coordinated violence alone, yields a gap that is large for riots and small for organised violence. Identification of the lead effect therefore rests on this selectivity by conflict type as much as on the triple difference.

Battery recycling is an urban activity, and this matters for parallel trends. Before 2007, cells near a battery site were more populous and brighter at night than cells near the non-lead comparison sites, and about 8 times more likely to record a riot. Organised violence was more common there too: 19% of cell-years within 5 km of a battery site recorded any, against 2% near non-lead sites. Satellite and household survey data suggest these places

did not change much differently in other ways (Appendix Table A8). Night lights did not grow faster near battery sites than near non-lead sites after 2007 (0.055 log points, $p = 0.46$). We also use Demographic and Health Surveys from all three countries, each with a round before 2007 (Kenya and Ghana 2003, Senegal 2005). Among 29,046 women in clusters near either kind of site, those within 5 km of a battery site did not become poorer or less schooled after 2007 than those near non-lead sites. Child health and school attendance did not change differently.

Identification does not require the two groups to be comparable in levels. Cell fixed effects absorb every time-invariant difference between them, so the estimate comes only from differential changes after 2007. It does require that the two groups would have trended together absent treatment. Two checks support this. First, riots near battery sites show no linear pre-trend in any country (Figure 4; Appendix Table A4), so treated and comparison cells were not already diverging. Second, we match cells within 5 km of a battery site to similar cells farther away on baseline riots, protests, population and nighttime lights. The battery coefficient stays positive and significant under both coarsened exact matching (0.199) and propensity-score matching (0.128), though both are smaller than the unmatched 0.273 (Appendix Table A6).

The 2007 threshold coincides with the global food-price crises of 2007–08 and 2011, which are themselves associated with riots. The poorer, more urban cells near battery sites may respond more strongly to food-price shocks. If so, that response, and not lead, could drive the rise after 2007. Country×year fixed effects already absorb national food-price waves. To absorb sub-national food-price and poverty dynamics as well, we add a coarse 1° macro-cell×year fixed effect. The lead-specific gap for riots barely moves, from 0.194 to 0.183 (both significant at 1%). Together with the timing sweep above, which keeps the effect positive and significant at every assumed onset year, this makes a food-price explanation unlikely.

We complement this with an event study:

$$Y_{ct} = \alpha_c + \delta_{jt} + \sum_{s \neq T-1} \beta_s \, B_c \cdot \mathbf{1}[t = s] + \sum_{s \neq T-1} \gamma_s \, N_c \cdot \mathbf{1}[t = s] + \varepsilon_{ct} \tag{3}$$

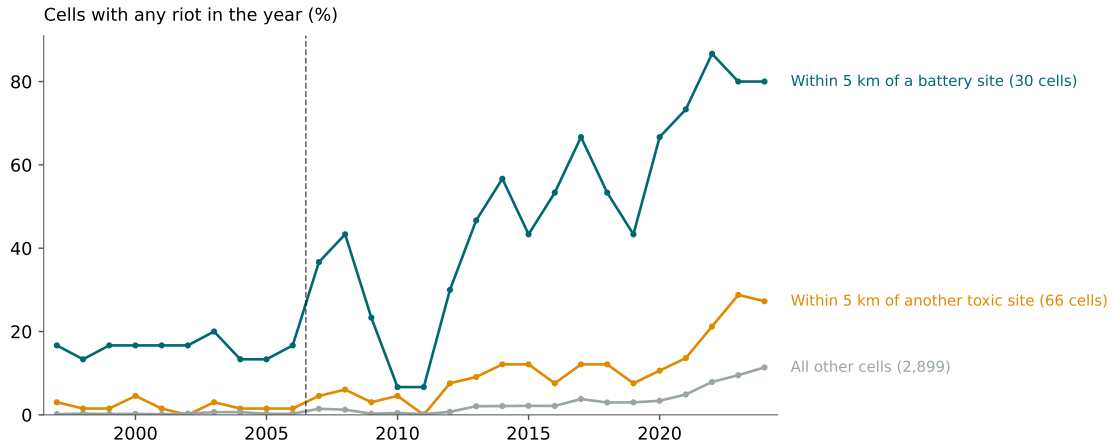
with $T-1$ as the omitted base year. Figure 4 plots $\hat{\beta}_s - \hat{\gamma}_s$ for the pooled sample. The country event studies in Appendix Figure A3 plot $\hat{\beta}_s$ alone, with year fixed effects in place of δ_{jt}.

5. Results

5.1 Main results

Figure 3 shows the raw data. Before 2007, cells near battery sites were already more likely than other cells to record a riot in a given year, but the gaps were stable. After 2007 the share near battery sites rose much faster than the share near other toxic sites or elsewhere. The rest of this section estimates that difference.

Figure 3: Share of Cells with Any Riot, by Proximity to a Contaminated Site



Notes: Each line is the share of 0.1° grid cells with any ACLED riot in the year, with Kenya, Ghana and Senegal pooled. Cells within 5 km of another toxic site exclude those also within 5 km of a battery site. The dashed line marks 2007.

Our main outcome is whether a cell records any event of a given type in a year, as 95 to 99% of cell-years record no event at all. Table 3 builds up the headline in three steps. First, the probability of any riot within 5 km of a battery site rises by 30 percentage points after 2007, relative to cells farther away. Second, we add cells near other contaminated industrial sites to the same regression. These share the urban growth and news coverage of battery sites but not the lead. The battery coefficient falls slightly, because 10 of the 30 battery cells are also near a non-lead site. Netting out the non-lead coefficient leaves a

lead-specific gap of 19 points. Third, we net out organised violence (battles and violence against civilians), which urban growth or better reporting would also raise. The riot gap is 13 points larger than the organised-violence gap. This four-way difference is our headline estimate. For comparison, the probability of a riot within 5 km of a battery site was around 16% a year before 2007.

Table 3: The Lead-Specific Riot Effect in Three Differences (Pooled, Extensive Margin)

	(1) DD Battery gradient	(2) DDD Lead-specific gap	(3) Conflict-type Conflict-type contrast
1[< 5 km] × Post (2007)	0.298***	0.194***	0.128**
	(0.040)	(0.051)	(0.046)
Wild bootstrap p	[0.000]	[0.002]	[0.011]
Difference across	time, distance	+ site type	+ conflict type
Removes	—	industrial proximity	conflict-neutral confounds
Treated cells (<5 km) / all cells		30 / 2,995	
Cell-years		83,860 (pooled KE + GH + SN)	

Notes: These are linear probability models, and the outcome is 1 if any riot occurred in the cell-year. Treatment is an indicator for a cell within 5 km of a battery site from 2007 onwards. DD is the battery coefficient from a regression without the non-lead indicator. DDD is the battery coefficient minus the non-lead coefficient, with both in one regression. The conflict-type contrast is the riot DDD minus the organised-violence DDD (battles and violence against civilians), from one stacked regression. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). Wild bootstrap p-values are from a restricted wild cluster bootstrap with Rademacher weights and 9,999 draws, clustered on the same blocks. Bracketed values are wild bootstrap p-values, and stars on estimates with a bracketed value use it. Other stars use the block-clustered t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 shows the same estimates by country and conflict type. For riots (Panel A), the battery coefficient is large and significant in all three countries, and 0.273 pooled. The non-lead coefficient is positive but much smaller (0.079 pooled). This suggests some effect of urbanisation and co-located pollutants near any industrial site, with a large excess near battery sites. The lead-specific gap is positive in all three countries: 0.117 in Kenya, 0.166 in Ghana and 0.299 in Senegal. It is significant in Ghana and Senegal (wild bootstrap p = 0.025 and 0.009), but not in Kenya on its own (p = 0.210). Protests (Panel B) show the same pattern, with a pooled gap of 0.168 (p = 0.001).

Organised violence (Panel C) is different. Its lead-specific gap is small in each country and not significant pooled (0.066, wild bootstrap p = 0.112). For battles alone, the most coordinated form of violence, it is 0.017 (Appendix Table A11). Panel D tests the difference

directly, in one stacked regression. The riot gap exceeds the organised-violence gap in every country (0.081 in Kenya, 0.089 in Ghana and 0.203 in Senegal), though no country is precise enough on its own. Pooled, the difference is 0.128 (wild bootstrap $p = 0.011$).

This contrast is the paper's main identification test. A confounder that survives the site comparison, such as faster urbanisation, better reporting or other economic activity near battery sites, would have to raise riots far more than organised violence to produce this pattern. Generic urban confounders should raise both. We do not read the organised-violence estimate as a zero, however. The test shows only that the gap is much smaller for organised violence than for riots, which is what impaired impulse control predicts. The non-lead sites are themselves contaminated with neurotoxicants such as mercury, arsenic and manganese, several with behavioural effects of their own. The gap is therefore best read as a lower bound on the effect of lead.

5.2 Timing

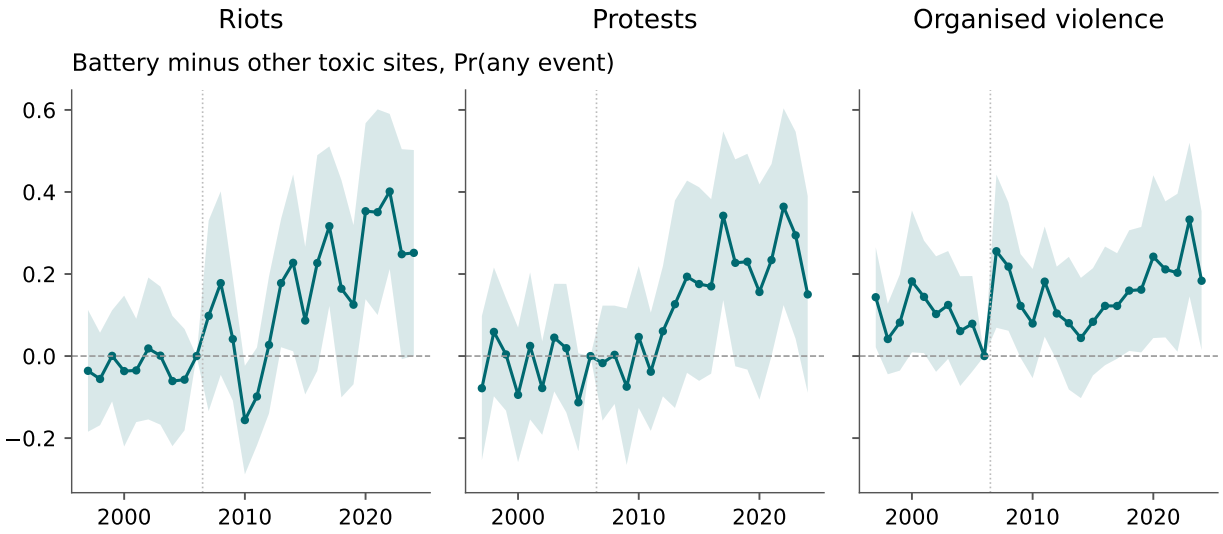
Figure 4 plots the lead-specific gap year by year: cells near battery sites minus cells near other toxic sites, pooled across the three countries. Before 2007 the riot gap is flat around zero. After 2007 it opens up and widens through the 2010s, which fits lead exposure building up as motorisation and battery recycling kept growing. Protests follow a similar path from around 2010. The organised-violence gap sits above zero in most years before 2007 as well as after, so it shows a level difference between the two kinds of site rather than a break in 2007. Appendix Figure A3 shows the event study for each country.

Table 4: Main results: riots, protests and organised violence within 5 km of a battery site

	Kenya		Ghana		Senegal		Pooled	
	Battery	Non-lead	Battery	Non-lead	Battery	Non-lead	Battery	Non-lead
Panel A: Riots								
1[< 5 km] × Post	0.252***	0.135***	0.228***	0.062**	0.341***	0.042*	0.273***	0.079***
	(0.052)	(0.036)	(0.068)	(0.026)	(0.057)	(0.021)	(0.038)	(0.020)
Lead-specific gap	0.117		0.166**		0.299***		0.194***	
	(0.079) [0.210]		(0.068) [0.025]		(0.071) [0.009]		(0.051) [0.002]	
Pre-2007 mean, battery cells	0.190		0.050		0.133		0.160	
Panel B: Protests								
1[< 5 km] × Post	0.236***	0.123***	0.172**	0.056**	0.283***	0.044*	0.243***	0.075***
	(0.055)	(0.027)	(0.073)	(0.022)	(0.033)	(0.023)	(0.039)	(0.017)
Lead-specific gap	0.113		0.115		0.239***		0.168***	
	(0.075) [0.200]		(0.070) [0.178]		(0.048) [0.009]		(0.047) [0.001]	
Pre-2007 mean, battery cells	0.150		0.100		0.233		0.160	
Panel C: Organised violence (battles + VAC)								
1[< 5 km] × Post	0.078*	0.042	0.103	0.026	0.100	0.004	0.088***	0.022*
	(0.039)	(0.026)	(0.071)	(0.026)	(0.083)	(0.013)	(0.031)	(0.012)
Lead-specific gap	0.036		0.077		0.096		0.066	
	(0.056) [0.557]		(0.058) [0.147]		(0.091) [0.648]		(0.037) [0.112]	
Pre-2007 mean, battery cells	0.210		0.125		0.150		0.187	
Panel D: Riots minus organised violence								
Riot gap − organised-violence gap	0.081		0.089*		0.203		0.128**	
	(0.055) [0.229]		(0.036) [0.081]		(0.158) [0.268]		(0.046) [0.011]	
Cells	1,319		626		1,050		2,995	
of which within 5 km of a battery site	20		4		6		30	
Cell-years	36,932		17,528		29,400		83,860	

Notes: These are linear probability models, and the outcome is 1 if any event of the given type occurred in the cell-year. Battery (non-lead) is an indicator for a cell within 5 km of a battery site (non-lead TSIP site) from 2007 onwards, and both enter one regression. The gap is the battery coefficient minus the non-lead coefficient. Organised violence is battles and violence against civilians. Panel D is the riot gap minus the organised-violence gap, from one stacked regression with cell×outcome and year×outcome fixed effects (country×year×outcome when pooled). The sample is all 0.1° cells within 50 km of any TSIP site, 1997–2024. Country columns include cell and year fixed effects, and pooled columns include cell and country×year fixed effects. The pre-2007 mean is the share of cell-years before 2007 with any event, among cells within 5 km of a battery site. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). Wild bootstrap p-values are from a restricted wild cluster bootstrap with Rademacher weights and 9,999 draws, clustered on the same blocks. Bracketed values are wild bootstrap p-values, and stars on estimates with a bracketed value use it. Other stars use the block-clustered t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 4: The Lead-Specific Gap by Year: Battery Sites minus Other Toxic Sites



Notes: Each point is the coefficient on an indicator for a cell within 5 km of a battery site interacted with year, minus the coefficient on an indicator for a cell within 5 km of a non-lead site interacted with year, from one regression. The outcome is 1 if any event of the given type occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Coefficients are relative to 2006, and the dotted line marks 2007. Shaded areas are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Pre-trends for riots are flat. We test for a linear pre-trend: the yearly change in the probability of a riot near battery sites relative to other cells, 1997–2006. It is 0.0024 a year in Kenya (wild bootstrap $p = 0.74$), −0.0151 in Ghana ($p = 0.53$), −0.0019 in Senegal ($p = 0.75$) and −0.0008 pooled ($p = 0.87$). We prefer this to a joint test of all nine pre-period coefficients, which is poorly sized with 11 treated blocks in Kenya and fewer elsewhere (Appendix Table A4). The joint test does not reject at 5% for riots. It does reject for protests and organised violence in Kenya, Senegal and pooled, though their linear pre-trends are also flat. Dropping Kenyan years before 2005 leaves a gap of 0.228 (Appendix Table A6). We also run a Rambachan and Roth (2023) sensitivity analysis for the average post-2007 event-study coefficient. For Kenya (Appendix Figure A4), under the relative-magnitudes restriction, the lower confidence bound is 0.115 under exact parallel trends, and it crosses zero once violations reach 0.08 times the largest pre-period deviation. The smoothness restriction is less informative here, because the variance matrix rests on 11 treated blocks and the interval collapses as soon as any deviation is allowed. For the pooled lead-specific gap (Appendix Figure A5), the lower bound is 0.030 under exact parallel trends and crosses

zero at 0.03 times the largest pre-period deviation. The pooled gap is therefore robust only to departures from parallel trends that are much smaller than the largest deviation seen before 2007.

For most sites we assume the 2007 onset and do not observe it. In Senegal, informal recycling at Ngagne Diaw began around 1995 (Haefliger et al., 2009), and for Ghana there are no documented opening dates at all. Two checks show the result does not depend on the date. First, the battery riot coefficient stays positive and significant for every assumed onset from 2004 to 2011, with a smallest t-statistic of 2.8 (Appendix Figure A6). Second, we replace the binary post-2007 indicator with a smooth country-specific path:

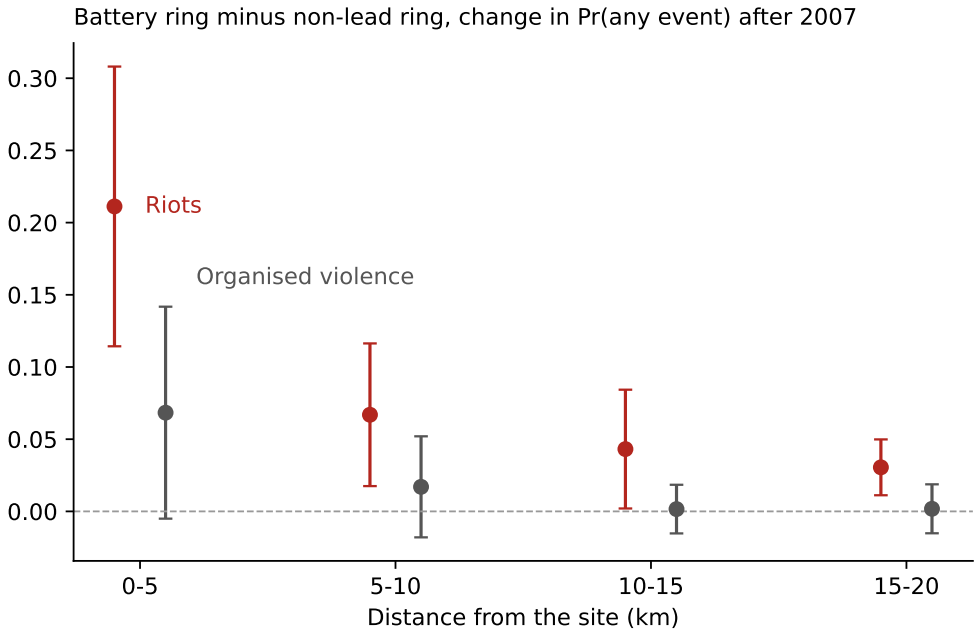
$$Y_{ct} = \alpha_c + \delta_{jt} + \beta\, B_c \cdot V_{jt} + \gamma\, N_c \cdot V_{jt} + \varepsilon_{ct} \tag{4}$$

where V_{jt} is cumulative new vehicle registrations per 1,000 persons in country j since 2005 (OICA), standardised within country, over 2005–2018. Because V_{jt} varies only by country and year, β is in effect identified from three national paths, so we read this as a check on the timing assumption, not as independent identification. It reproduces the escalating differences without any assumed treatment year: a lead-specific gap of 0.081 and a four-way difference of 0.083 (Appendix Table A5 and Figure A7).

5.3 Distance

Figure 5 replaces the single 5 km indicators with mutually exclusive distance rings around both battery and non-lead sites, pooled across the three countries and estimated in one regression. It plots each battery ring minus the same ring around non-lead sites. The riot gap is largest within 5 km and falls with distance. This fits the spatial footprint of airborne lead from open-air smelting. The organised-violence gap is small in every ring. Country estimates are in Appendix Figure A11, and Appendix Figure A12 shows flat pre-trends within each ring.

Figure 5: The Lead-Specific Gap by Distance from the Site



Notes: Each point is the coefficient on a distance ring around the nearest battery site minus the coefficient on the same ring around the nearest non-lead TSIP site, each interacted with an indicator for 2007 onwards, from one regression. Rings are 0–5, 5–10, 10–15 and 15–20 km, and the reference is cells more than 20 km from both kinds of site. The outcome is 1 if any event of the given type occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Bars are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Can we see the effect closer than 5 km? The grid cannot, because a 0.1° cell is about 11 km across. But ACLED gives each event its own coordinates, so we can measure the distance from each riot to each site directly. Appendix Figure A13 compares rings around the 67 battery sites with the same rings around the 180 non-lead sites, after 2007 against before. Per 100 km^2 of ring, riots rise by 2.9 at 1–2 km, 2.2 at 2–3 km and 0.3 at 3–5 km. Most of the effect is within 3 km. The 0–1 km estimate is larger but noisy (21.5). The 0–1 km estimate survives dropping the five most-used event locations in each country, which are city-centre points (6.0 riots per 100 km^2). We cannot go much finer than this. ACLED places an event at the centre of the town or neighbourhood it names, so the 721 riots within 1 km of a battery site sit at only 27 distinct points.

5.4 Robustness

The riot result survives several further checks. First, it holds with log(events + 1), the inverse hyperbolic sine and raw counts as the outcome (Appendix Table A1). Second, city×year fixed effects for Nairobi, Mombasa, Accra and Dakar leave the gap at 0.186 (Appendix Table A6), which rules out city-specific trends after 2007. Third, a placebo onset in 2002, estimated on 1997–2006 only, gives a pooled gap of 0.013 (wild bootstrap p = 0.560; Appendix Table A7). Fourth, its significance does not change with cell-clustered, block-clustered, 50 km Conley or 100 km Conley standard errors (Appendix Table A2). Fifth, identification rests on 30 treated cells, so we drop each country, each battery site and each treated cell in turn. Across all 94 estimates the lead-specific gap stays between 0.149 and 0.244 and is significant at the 5% level in every one (Appendix A.1). Finally, randomisation inference that reassigns the site-type labels among all toxic sites in each country gives one-sided p-values for the lead-specific gap of 0.059 in Kenya, 0.035 in Ghana and <0.001 in Senegal (Appendix Figure A2).

The composition of the comparison group could in principle survive even this contrast. Artisanal mining and ore processing make up 58% of the non-lead sites, and mining is linked to organised violence over rents (Berman et al., 2017; Sánchez de la Sierra, 2020). Mining sites are also more rural than battery sites, and riots are mostly urban. So a large riot contrast could reflect battery sites being more urban than a mining-heavy comparison group. We test this in two ways (Appendix Table A6). First, we drop all mining and ore-processing sites and compare against the remaining 76 non-lead sites. The riot gap is 0.177 (against 0.194 at baseline) and the conflict-type contrast 0.126, both still significant. Second, we keep only cells with above-median population before 2007, so urban battery cells are compared only with urban comparison cells. The gap is 0.151 and the contrast 0.097, both still significant. Neither mining nor urban composition explains the result.

Matching gives smaller but still significant effects. We match cells within 5 km of a battery site to similar cells 5–50 km away on pre-treatment riots, protests, population, nighttime lights and centroid, within each country. The pooled battery coefficient is 0.199 under coarsened exact matching (Iacus et al., 2012) and 0.128 under propensity-score

matching, against 0.273 without matching (Appendix Table A6).

5.5 Are the riots about the sites?

Does lead raise violence, or collective action more broadly? The lead-specific gap for peaceful protest alone is 0.157, close to the 0.194 for riots (Appendix Table A11 splits protests into sub-types). This fits the mechanism once it is stated carefully. Lead acts on how readily people respond automatically rather than deliberately, the same margin the CBT evidence in Section 2 works on, and that margin governs joining any spontaneous crowd, not only aggression. The contrast in the data is about coordination. The gap is large for low-coordination mobilisation, violent or not, and small for organised violence (0.066 pooled, and 0.017 for battles alone), which needs planning and hierarchy. We did not set out to test this distinction, so the peaceful-protest result is consistent with this account rather than evidence for it.

The contrast by conflict type rules out confounders that raise conflict of all kinds near a growing urban industrial site. It does not rule out a mechanism that raises spontaneous collective action about the site itself. Battery recycling is visibly dirty, and acute poisoning episodes near these sites have provoked local anger. Such a channel would reproduce our whole pattern, with more riots and protests near battery sites and no more organised armed conflict. It would have nothing to do with impaired impulse control.

The trigger of each riot tells the two accounts apart. Impaired inhibitory control raises spontaneous violence whatever the grievance that sets it off. Anger at a recycling site raises violence about pollution and about the site. We therefore classify every riot recorded in the three countries by its reported trigger, including riots outside the 50 km regression sample, using the ACLED `notes` field. We use deterministic keyword matching in a fixed priority order, and categories are mutually exclusive. Pollution and contamination are scored first, so any mention of contamination counts as a grievance event. This ordering tilts the classification in favour of the grievance reading. The replication files include the event-level assignments.

Two facts follow. First, riots triggered by pollution or contamination are almost absent: 6 of 6,124 riots, or 0.1%. Even if we attribute every one to the sites, a category this small

cannot generate a lead-specific gap of 19 percentage points. Second, the largest single category is mob justice, at 33% of all riots. These are lynchings of suspected thieves, reprisals for cattle theft and assaults after witchcraft accusations. All are spontaneous violence against individuals. A recycling site also creates something worth stealing, so some of this mob justice could be about theft from the sites themselves. Only 5 riots mention the theft of batteries or scrap metal, 2 of them within 5 km of a battery site. Keyword matching will miss thefts described in other words, so this counts explicit mentions only. Anger at a recycling site cannot explain why residents living near one are more likely to beat a suspected thief. Impaired inhibitory control can.

ACLED's notes show what these events look like. In Nairobi in 2023, "a mob beat up and injured a man . . . for allegedly being a thief, after a woman neighbor raised a false alarm." Political riots look different. In Thiaroye in 2023, "Pastef supporters demonstrated . . . after their party's leader was sentenced", and "1 demonstrator was shot and killed." Riots about pollution are rare. One, in Migori in 2022, was "a violent demonstration against a gold leaching firm . . . for allegedly polluting water sources." All three took place within 5 km of a battery recycling site.

Table 5 re-estimates the lead-specific gap separately by trigger. The gap is positive and significant in every category with enough positive cell-years to estimate it. It is largest for mob justice (0.150) and political riots (0.204). Political riots need the most care. A planned rally or a disputed result can turn into a spontaneous riot. Faster growth in urban political competition near battery sites would also raise them, and the conflict-type contrast would not net that out. Mob justice is the cleaner test, since it involves no organiser at all. Its gap barely changes when we drop mining sites from the comparison or keep only urban cells (Appendix Table A13). By country, the mob-justice gap is 0.122 in Kenya and 0.088 in Ghana. Senegal has too few positive cell-years to estimate it.

The pollution share does not change either. Pollution-triggered riots are 0.15% of riots within 5 km of a battery site and 0.19% within 5 km of a non-lead site. Peaceful protest, where an environmental grievance would more plausibly surface, shows the same pattern. Of all 7,009 protests in the three countries, 0.3% concern pollution: 0.33% within 5 km of a battery site and 0.26% near a non-lead site (Fisher exact $p = 1.00$). The overall mix of

Table 5: Lead-Specific Gap by Riot Trigger

Riot trigger	Events	Share (%)	Lead-specific gap
Pollution / contamination	6	0.1	—[a]
Mob justice (individuals)	2,040	33.3	0.150***
			(0.040)
Political / electoral	1,512	24.7	0.204***
			(0.040)
Services / infrastructure	923	15.1	0.102***
			(0.029)
Prices, wages, taxes	234	3.8	0.062***
			(0.019)
Policing and courts	69	1.1	0.030**
			(0.015)
Other / unspecified	1,340	21.9	0.057**
			(0.028)
All riots	6,124	100.0	0.194***
			(0.051)

Notes: Each row is the lead-specific gap (the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site from 2007 onwards), where the outcome is 1 if any riot of that trigger type occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Triggers are coded by keyword matching on ACLED event notes, in a fixed order with pollution first, and categories are mutually exclusive. Counts and shares cover all ACLED riots in Kenya, Ghana and Senegal, 1997–2024. The gap column uses the regression sample of cells within 50 km of a TSIP site. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[a] Too few cell-years with an event to estimate.

triggers does differ (χ^2 p <0.001). Political riots are a larger share near battery sites, by 6 percentage points (Appendix Table A12).

6. Discussion and Conclusion

Unsafe lead-acid battery recycling is a major source of environmental lead exposure in sub-Saharan Africa. Living near a contaminated site is associated with a differential rise in riots and violent demonstrations. This association remains when differencing across space, time, types of pollution, and types of conflict. These patterns fit the neurotoxicological mechanism, that lead exposure impairs inhibitory control and makes people more likely to join spontaneous collective violence, but has weaker effects on organised strategic violence that requires sustained coordination. The effect is similar in each of the three countries and in a pooled specification with country×year fixed effects.

Published effect sizes bracket our estimate, depending on how much blood lead rises near these sites. Using the decay of soil lead measured around the African sites, the estimate of Reyes (2007) implies a riot gap close to ours, and that of Aizer and Currie (2019) a larger one. Using the steeper decay estimated across all sites worldwide, both imply a smaller one. The meta-analytic estimate of Higney et al. (2022) implies a much smaller effect under either assumption, but covers a heterogeneous set of lead exposures. Collective outcomes may also respond more than individual ones, since lead-exposed children worsen their classmates' behaviour as well as their own (Gazze et al., 2024).

How large is this compared with other causes of riots? Shocks that pass within a year or two move riots much less. A one standard deviation rise in world food prices raises the probability of a riot or attack on civilians in a food-producing African grid cell by 15% of its mean (McGuirk and Burke, 2020). Across studies, a one standard deviation climate shock raises intergroup conflict by 14% (Hsiang et al., 2013). Our estimate is 81% of the riot probability that cells near battery sites would otherwise have. Permanent local changes produce effects closer to ours. The probability of protests or riots near a commercial mine roughly doubles once it starts producing (Christensen, 2019). Years of living next to an open-air smelter is a change of this second kind. The effect in percentage

points is larger than in these studies mainly because our cells are much smaller and more densely populated. The estimate can also be anchored to measured blood lead levels. Appendix A.4 sets out both checks.

This paper has two main limitations. First, for most sites the treatment date is assumed rather than known. If sites opened at different times, our 2007 threshold misclassifies some post-treatment years as pre-treatment, which attenuates estimates toward zero. In Senegal, informal ULAB recycling at Ngagne Diaw began around 1995 (Haefliger et al., 2009), more than a decade before our assumed onset. Our estimate for Senegal therefore captures only the marginal increase in exposure after 2007. Our effects are however robust to varying the assumed onset year, and to replacing the binary post-2007 indicator with a smooth country-specific path of new vehicle registrations. We also searched media, court and NGO records for dated closures, but found the exercise infeasible. Only four sites across the three countries have a documented date. Closures are also rarely permanent, and often reversed.

Second, non-lead TSIP sites are themselves contaminated with harmful pollutants such as arsenic, mercury and cadmium. These 'placebo' effects may therefore reflect a mix of confounding from general urban development, and conflict driven by these other sources of pollution. Our triple difference may therefore be a conservative lower bound on the lead-specific effect.

The magnitudes of our main effect are substantial. They therefore imply that a policymaker focused only on security and with no interest in health or education outcomes would still be justified in tackling unsafe battery recycling. Applied to every cell within 5 km of a documented battery site in each post-2007 year, the four-way difference implies 69 additional place-years with a riot across Kenya, Ghana and Senegal between 2007 and 2024 (95% CI 20–119). That is about 4 a year, and around 3% of all place-years with a riot recorded within 50 km of a documented toxic site over the period. The same four-way difference for any riot death is 0.070, which implies 38 additional place-years with a riot death.

Two comparisons put the magnitude in context. Higney et al. (2022) estimate that lower blood lead levels account for 7–28% of the *fall* in US homicide rates between 1976

and 2009. That is a share of the *reduction* in crime, not of its current level, so the two figures are not directly comparable. Both, however, point to lead as a material contributor to violence in very different settings. Larsen and Sánchez-Triana (2023) estimate the annual global economic cost of lead exposure at $6.0 trillion (6.9% of global GDP). This covers IQ-linked productivity losses and cardiovascular mortality but explicitly excludes crime and conflict. Published estimates of the cost of lead-linked crime (Gould, 2009) count individual offences, not collective violence. That is not the relevant cost when the outcome is riot deaths. We do not attempt a global figure, and we cannot say what the omitted channel is worth. What we can say is that the burden estimate values conflict at zero, and our results imply that this is the wrong value. Appendix A.4 turns the question round and asks what an averted riot would have to be worth for remediation to pay for itself on the conflict channel alone.

Our results imply that targeted soil remediation at battery recycling sites (Haefliger et al., 2009) might be justified by reductions in violence alone, in addition to the cognitive and health benefits. They also imply that targeted cognitive behavioural therapy might be a useful intervention for exposed individuals, in addition to the early-childhood interventions which reduce the later harms of lead exposure (Billings and Schnepel, 2018).

Future research could usefully improve on our assumed treatment timing with site-specific opening dates, where media archives or firm records have them. Extending the analysis to Indonesia (265 TSIP sites, 64 classified as battery recycling) or Latin America, where ACLED coverage and battery site documentation are improving, would test external validity beyond sub-Saharan Africa.

Data availability. Replication code and all data that may be redistributed are at `https://github.com/lcrawfurd/lead-collective-violence`. TSIP site data are shared with the permission of Pure Earth (`https://contaminatedsites.org`). ACLED conflict data (`https://acleddata.com`) and Demographic and Health Surveys (`https://dhsprogram.com`) cannot be redistributed and are free to download after registration.

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Declaration of competing interest

The author declares no competing interests.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used Claude (Anthropic; Claude Opus models, used through Claude Code in 2026) to write, debug and document the Python and R code in the replication package, to suggest edits to the wording and structure of the text, to check that cited works exist and support the statements they are cited for, and to check that every number in the text, tables and figures matches the code output. The research question, the empirical design and the interpretation of results are the author's. Every estimate in the paper is produced by deterministic scripts in the replication package, and a clean rerun from raw data reproduces all of them. The author reviewed and edited all output and takes full responsibility for the content of the publication.

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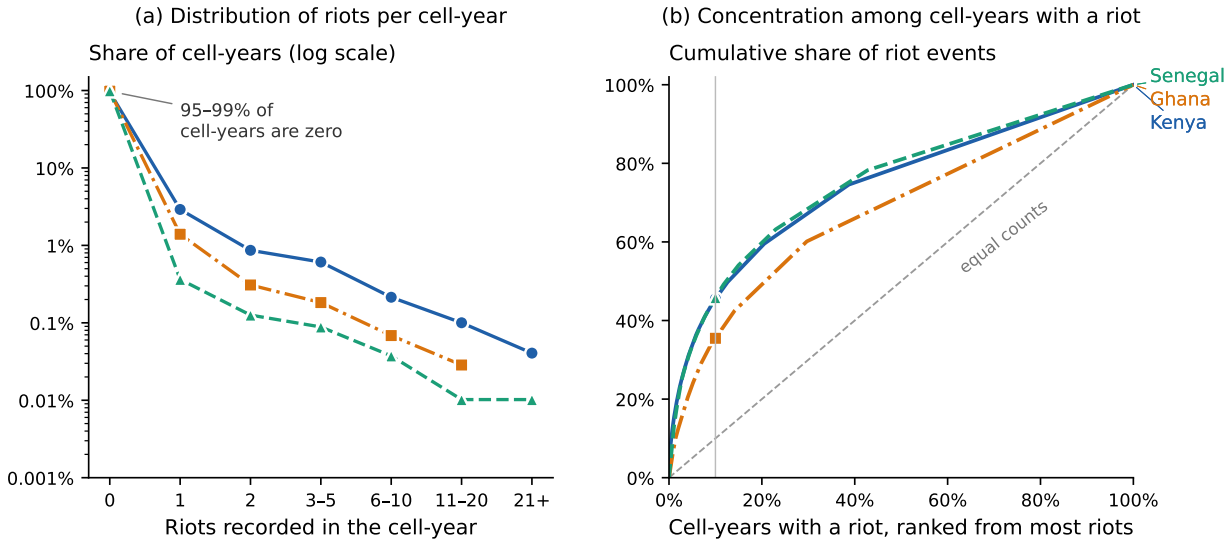
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Appendix

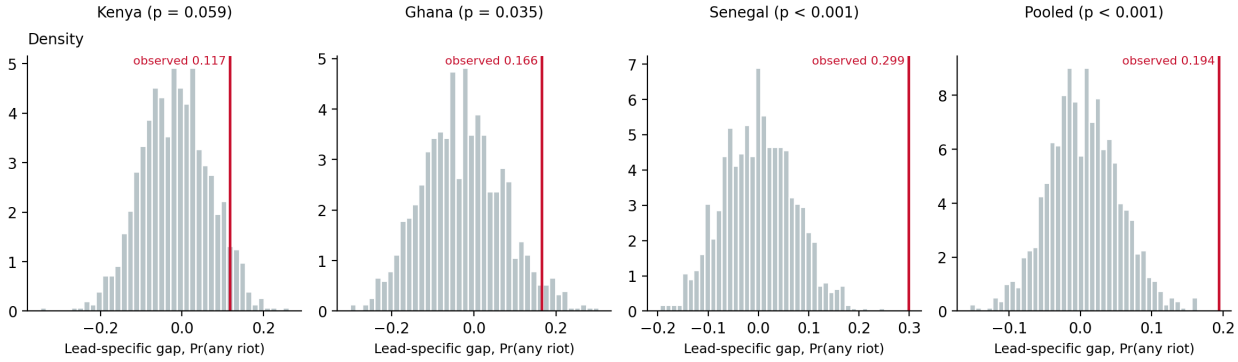
A.1 Outcome and inference

Figure A1: Riots per cell-year



Notes: Panel (a) shows the share of cell-years by the number of ACLED riots, on a log scale, with bins widening above two. Panel (b) shows cell-years with at least one riot.

Figure A2: Randomisation Inference: Observed vs Permuted Battery Site Locations



Notes: The statistic is the lead-specific gap: the coefficient on an indicator for a cell within 5 km of a battery site from 2007 onwards minus the same for non-lead TSIP sites, in one regression, where the outcome is 1 if any riot occurred in the cell-year. Country panels include cell and year fixed effects, and the pooled panel includes cell and country×year fixed effects. The grey histogram shows the gap from 1,000 permutations that reassign the site-type labels (battery, non-lead, other lead) among all TSIP sites within each country, keeping the number of each type. The red line is the observed gap. The one-sided p-value is the share of permuted gaps at or above the observed one.

Table A1: Robustness: Alternative Outcome Transformations (Lead-Specific Gap)

	$\log(y+1)$ (OLS)	Counts (OLS)	$\text{asinh}(y)$ (OLS)	$\mathbf{1}[y>0]$ (main outcome)
Riots				
Kenya	0.248*	1.591	0.313*	0.117
	(0.136)	(0.948)	(0.172)	(0.079)
Ghana	0.306	0.988	0.392	0.166**
	(0.204)	(0.828)	(0.259)	(0.068)
Senegal	0.579***	2.500**	0.730***	0.299***
	(0.088)	(0.948)	(0.102)	(0.071)
Pooled	0.389***	1.929***	0.491***	0.194***
	(0.090)	(0.614)	(0.113)	(0.051)
Organised violence				
Kenya	0.015	0.104	0.019	0.036
	(0.083)	(0.328)	(0.106)	(0.056)
Ghana	0.154	0.495	0.198	0.077
	(0.148)	(0.506)	(0.190)	(0.058)
Senegal	−0.018	−0.330	−0.020	0.096
	(0.151)	(0.528)	(0.192)	(0.091)
Pooled	0.048	0.136	0.062	0.066*
	(0.047)	(0.189)	(0.061)	(0.037)

Notes: Each cell is the lead-specific gap (the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site from 2007 onwards, in one regression), with the outcome transformed as in the column heading. y is the number of events in the cell-year. Country rows include cell and year fixed effects, and pooled rows include cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: Standard errors under different clustering choices

			Standard error			
		Coef.	1° block	Cell	Conley 50 km	Conley 100 km
Riots						
Kenya	Battery	0.252***	(0.052)	(0.050)	(0.048)	(0.042)
	Gap	0.117	(0.079)	(0.070)	(0.066)	(0.086)
Ghana	Battery	0.228***	(0.068)	(0.084)	(0.081)	(0.067)
	Gap	0.166**	(0.068)	(0.087)	(0.079)	(0.075)
Senegal	Battery	0.341***	(0.057)	(0.059)	(0.058)	(0.050)
	Gap	0.299***	(0.071)	(0.063)	(0.070)	(0.063)
Pooled	Battery	0.273***	(0.038)	(0.037)	(0.037)	(0.033)
	Gap	0.194***	(0.051)	(0.043)	(0.045)	(0.052)
Organised violence						
Kenya	Battery	0.078*	(0.039)	(0.035)	(0.031)	(0.024)
	Gap	0.036	(0.056)	(0.051)	(0.043)	(0.044)
Ghana	Battery	0.103	(0.071)	(0.073)	(0.069)	(0.069)
	Gap	0.077	(0.058)	(0.068)	(0.061)	(0.060)
Senegal	Battery	0.100	(0.083)	(0.088)	(0.077)	(0.057)
	Gap	0.096	(0.091)	(0.093)	(0.086)	(0.062)
Pooled	Battery	0.088***	(0.031)	(0.030)	(0.027)	(0.021)
	Gap	0.066*	(0.037)	(0.034)	(0.032)	(0.027)

Notes: These are linear probability models, and the outcome is 1 if any event of the given type occurred in the cell-year. Battery is an indicator for a cell within 5 km of a battery site from 2007 onwards. The gap is the battery minus the non-lead coefficient, both in one regression. Country rows include cell and year fixed effects, and pooled rows include cell and country×year fixed effects. The four standard error columns are for the same estimate: clustered on 1° blocks (as in the rest of the paper), clustered by cell, and Conley (1999) spatial HAC with 50 km and 100 km cutoffs. Stars use the block-clustered standard error. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

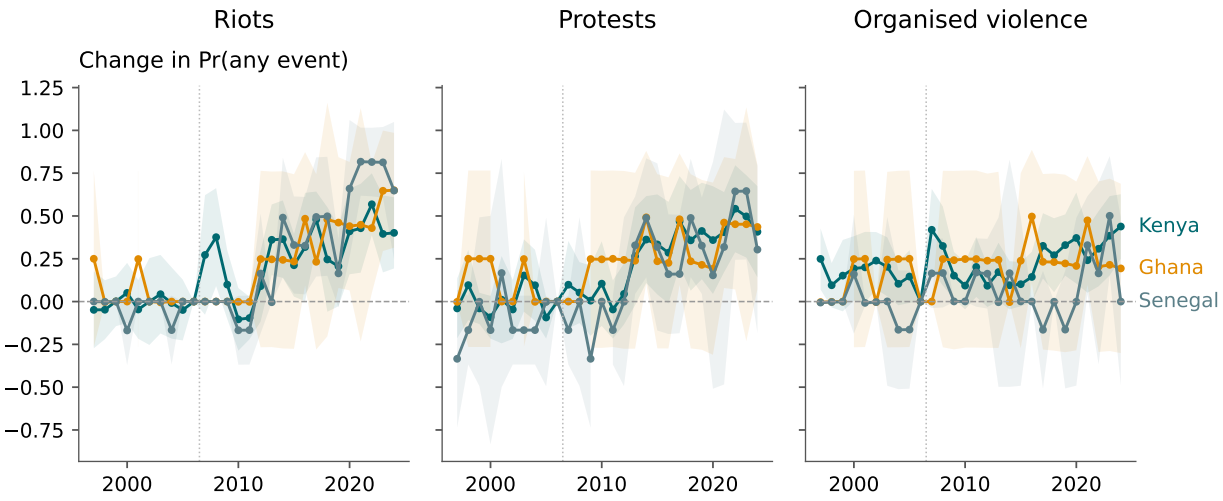
Table A3: Leave-One-Out: Lead-Specific Riot Gap

Unit dropped	Estimates	Min gap	Max gap	Sig. at 5%	Most influential
Country	3	0.149	0.244	3/3	Senegal
Nearest battery site	61	0.168	0.216	61/61	Se_15
Treated cell (<5 km)	30	0.180	0.207	30/30	Ke_0.35_34.45
Baseline (nothing dropped)	—	0.194***		(0.051)	—

Notes: Each row is the pooled lead-specific gap for riots (the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site from 2007 onwards, with outcome 1 if any riot occurred in the cell-year), dropping one unit. Nearest battery site drops every cell whose nearest battery site is that site, and is skipped if fewer than five treated cells remain. Treated cell drops one cell within 5 km of a battery site. All rows include cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2 Timing, placebos and the comparison group

Figure A3: Event Study by Country and Conflict Type



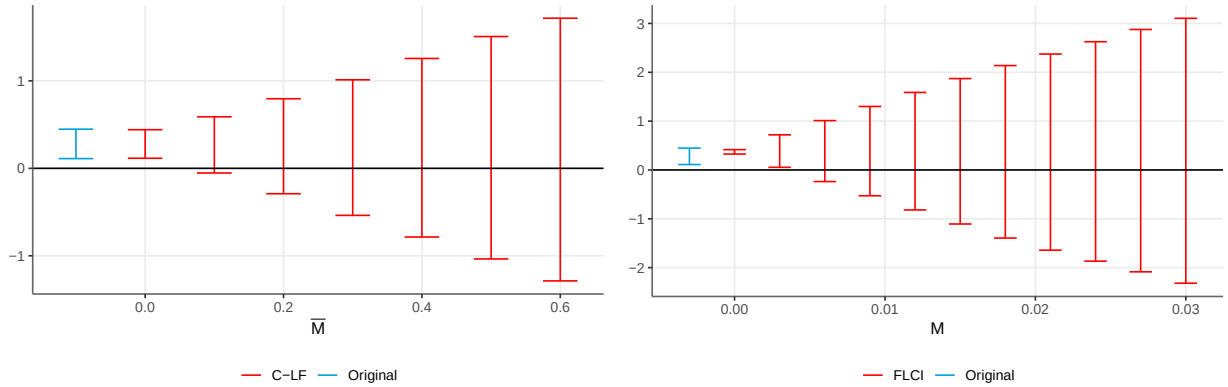
Notes: The figure shows coefficients on an indicator for a cell within 5 km of a battery site interacted with year, estimated separately by country and outcome. The outcome is 1 if any event of the given type occurred in the cell-year. All regressions include cell and year fixed effects, and 2006 is the base year. Coefficients are relative to 2006. Shaded areas are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Table A4: Pre-Trend Tests (Battery Sites, Main Design, 1997–2006)

	Riots			Protests			Organised violence		
	Slope	Wild p	Joint p	Slope	Wild p	Joint p	Slope	Wild p	Joint p
Kenya	0.0024	[0.74]	0.246	0.0023	[0.77]	0.000	−0.0125*	[0.12]	0.000
	(0.0063)			(0.0074)			(0.0068)		
Ghana	−0.0151	[0.53]	0.060	−0.0182	[0.55]	0.060	0.0168	[0.13]	0.312
	(0.0146)			(0.0177)			(0.0161)		
Senegal	−0.0019	[0.75]	0.191	0.0182	[0.50]	0.001	−0.0143	[0.53]	0.002
	(0.0012)			(0.0158)			(0.0167)		
Pooled	−0.0008	[0.87]	0.972	0.0028	[0.71]	0.005	−0.0089	[0.17]	0.016
	(0.0047)			(0.0070)			(0.0061)		

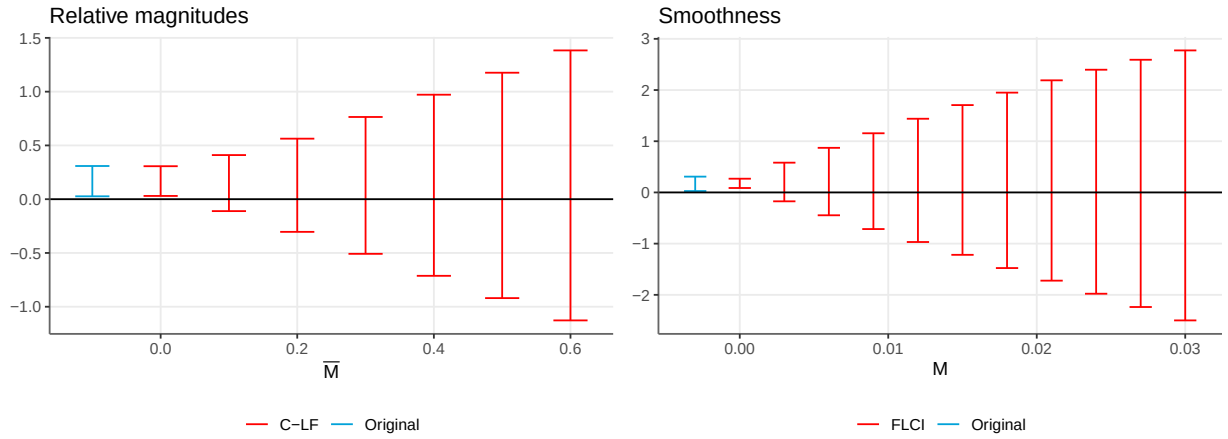
Notes: The outcome is 1 if any event of the given type occurred in the cell-year. Each row comes from the event study in Appendix Figure A3: coefficients on an indicator for a cell within 5 km of a battery site interacted with year, with 2006 as the base year. The slope is the yearly linear trend in the battery effect over 1997–2006, with its block-clustered standard error in parentheses and its wild bootstrap p-value in brackets. The joint p is from an F-test that all nine pre-2007 coefficients are zero. Country rows include cell and year fixed effects, and pooled rows include cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A4: Honest DiD Sensitivity for Kenya Riots: (a) Relative Magnitudes, (b) Smoothness



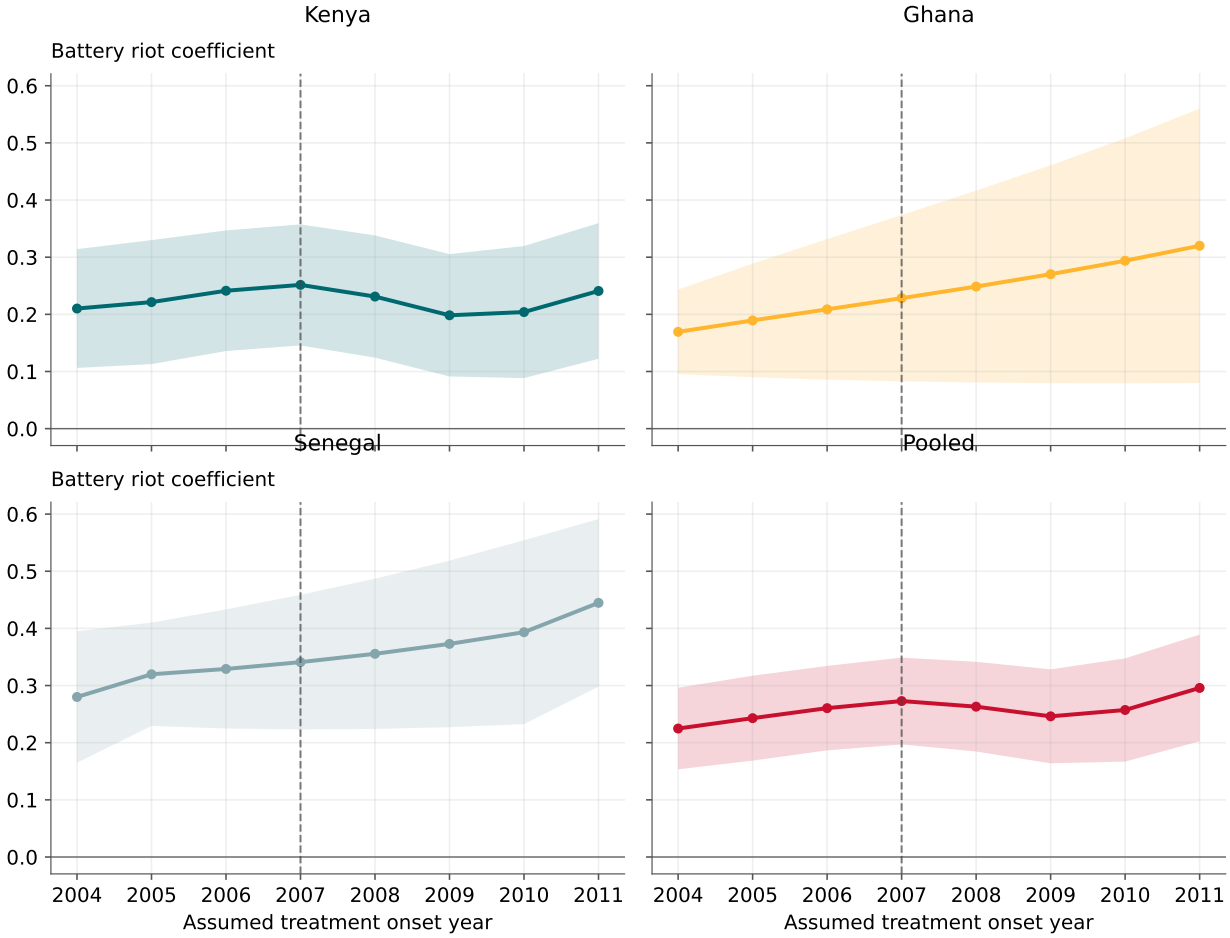
Notes: The figure shows Rambachan and Roth (2023) confidence intervals for the average post-2007 effect on Kenya riots (1 if any riot, cells within 5 km of a battery site). Panel (a) uses the relative-magnitudes restriction and the C-LF method; panel (b) uses the smoothness restriction, which bounds the change in the trend between adjacent periods, and the FLCI method. The blue bar is the conventional 95% confidence interval. Red bars are robust intervals for each $\bar{M}$, the permitted post-period deviation from parallel trends, as a multiple of the largest pre-period deviation in panel (a). Intervals use the block-clustered variance matrix.

Figure A5: Honest DiD Sensitivity for the Pooled Lead-Specific Gap



Notes: The figure shows Rambachan and Roth (2023) confidence intervals for the average post-2007 lead-specific gap for riots, from the event study in Figure 4. The left panel uses the relative-magnitudes restriction and the C-LF method, and the right panel uses the smoothness restriction and the FLCI method. The first bar in each panel is the conventional 95% confidence interval. The other bars are robust intervals for each $\bar{M}$ (left) or M (right). Intervals use the block-clustered variance matrix.

Figure A6: Treatment-timing sweep: battery riot coefficient by assumed onset year



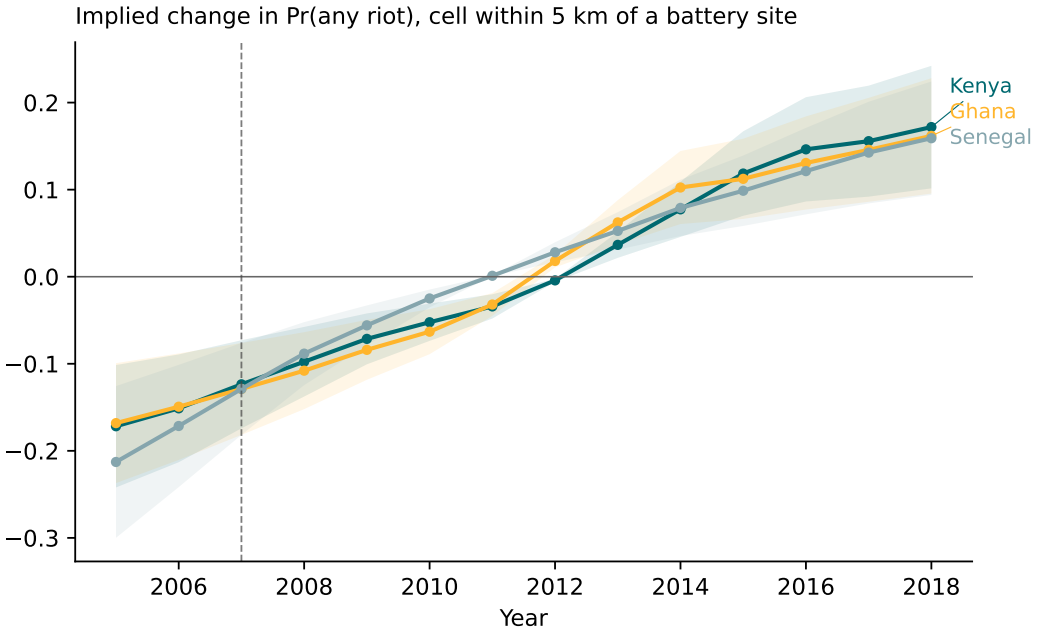
Notes: Each point is the coefficient on an indicator for a cell within 5 km of a battery site interacted with an indicator for years from the assumed onset, shown on the horizontal axis, with the non-lead indicator also included. The outcome is 1 if any riot occurred in the cell-year. Country panels include cell and year fixed effects, and the pooled panel includes cell and country×year fixed effects. Shaded areas are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). The dashed line marks 2007.

Table A5: Escalating Differences under a Continuous Vehicle-Dose Treatment (Pooled, Extensive Margin)

	(1) DD Battery gradient	(2) DDD Lead-specific gap	(3) Conflict-type Conflict-type contrast
$\mathbf{1}[< 5\,\text{km}] \times$ Vehicle dose	0.125*** (0.025)	0.081*** (0.027)	0.083*** (0.030)
Difference across	time, distance	+ site type	+ conflict type
Cell-years	41,930 (pooled KE + GH + SN, 2005–2018)		

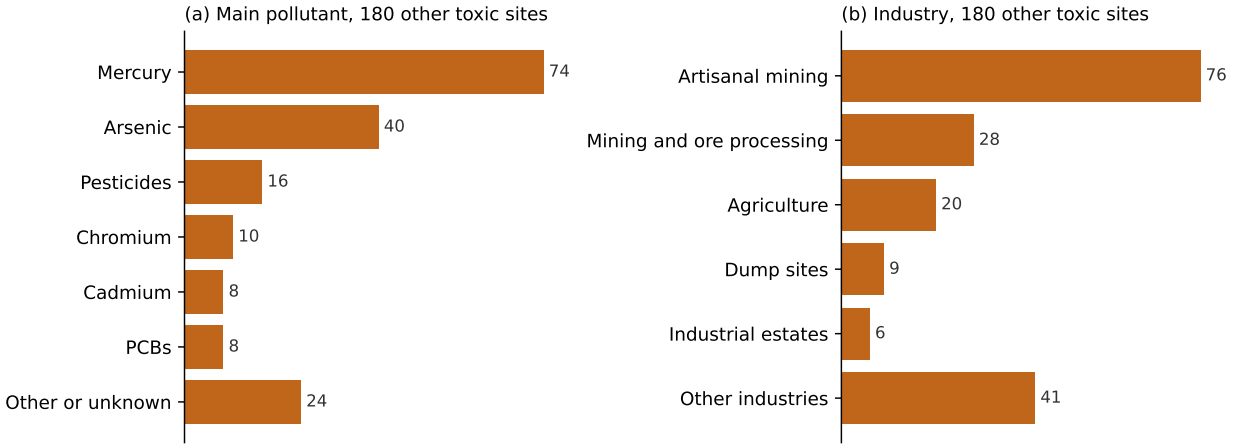
Notes: The outcome is 1 if any riot occurred in the cell-year. Treatment is an indicator for a cell within 5 km of a battery site times V_{jt}, where V_{jt} is cumulative new vehicle registrations per 1,000 people in country j (OICA), standardised within country, 2005–2018. Columns are defined as in Table 3. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A7: Implied Effect of Battery Site Proximity on Riots over Time



Notes: The figure shows $\hat{\beta}\, V_{jt}$ by country and year, from the pooled vehicle-dose specification (equation (4)). This is the implied change in the probability of any riot for a cell within 5 km of a battery site, relative to a cell near neither kind of site. V_{jt} is cumulative new vehicle registrations per 1,000 people, standardised within country, so values below zero are below the country mean. Shaded areas are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Figure A8: The Non-Lead Comparison Sites



Notes: The figure counts the non-lead TSIP sites in Kenya, Ghana and Senegal by main pollutant (panel a) and industry (panel b).

Table A6: Robustness of the lead-specific riot effect (pooled, main design)

	(1) DD Battery	(2) DDD Lead-specific gap	(3) Conflict-type contrast	Treated cells
(1) Baseline	0.273***	0.194***	0.128**	30
	(0.038)	(0.051)	(0.046)	
		[0.002]	[0.011]	
(2) No mining or ore-processing sites in comparison	0.278***	0.177**	0.126*	30
	(0.042)	(0.068)	(0.063)	
		[0.030]	[0.065]	
(3) Above-median pre-2007 population cells	0.240***	0.151**	0.097*	30
	(0.038)	(0.054)	(0.049)	
		[0.015]	[0.058]	
(4) City × year FE (4 cities, 30 km)	0.262***	0.186***	0.129**	30
	(0.041)	(0.053)	(0.047)	
		[0.005]	[0.012]	
(5) Kenya from 2005 only	0.289***	0.228***	0.122*	30
	(0.036)	(0.044)	(0.062)	
		[0.000]	[0.083]	
(6) Coarsened exact matching	0.199***			30
	(0.042)			
(7) Propensity-score matching (1:3)	0.128**			30
	(0.047)			

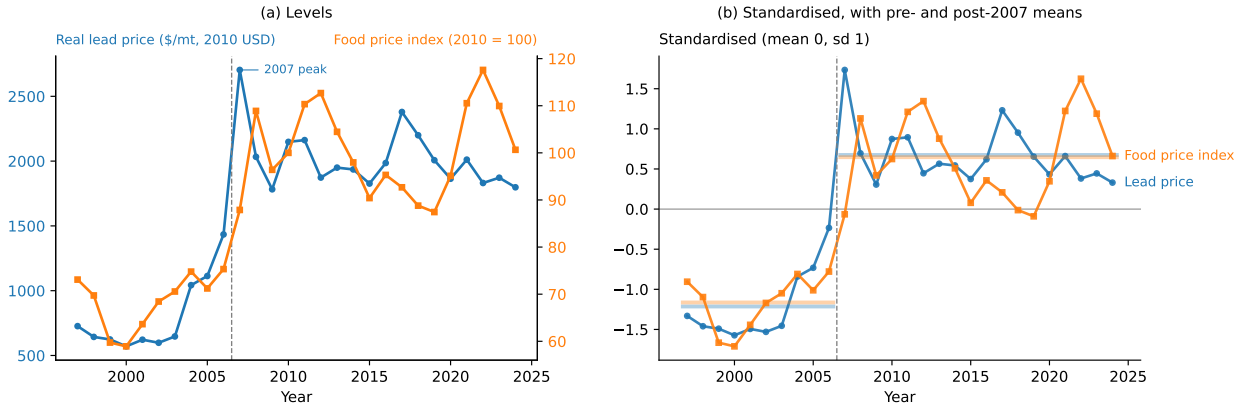
Notes: These are linear probability models, and the outcome is 1 if any riot occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Treatment is an indicator for a cell within 5 km of a battery site from 2007 onwards. DD is the battery coefficient. DDD is the battery minus the non-lead coefficient, from one regression. The conflict-type contrast is the riot DDD minus the organised-violence DDD, from one stacked regression. Row 2 drops artisanal mining and ore-processing sites from the non-lead comparison. Row 3 keeps cells with above-median population before 2007 (WorldPop). Row 4 adds city×year fixed effects for cells within 30 km of Nairobi, Mombasa, Accra and Dakar. Row 5 drops Kenyan years before 2005. Rows 6 and 7 match cells within 5 km of a battery site to cells 5–50 km away within each country, by coarsened exact matching (covariates in tertiles, weighted by inverse stratum size) and by nearest-neighbour propensity-score matching (1:3, with replacement), and regress the outcome on the battery indicator alone. The matching covariates are pre-2007 mean log(riots + 1) and log(protests + 1), log population (WorldPop 2000), pre-2007 mean log night lights (Li et al., 2020), and centroid latitude and longitude. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). Wild bootstrap p-values are from a restricted wild cluster bootstrap with Rademacher weights and 9,999 draws, clustered on the same blocks. Bracketed values are wild bootstrap p-values, and stars on estimates with a bracketed value use it. Other stars use the block-clustered t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: Placebo Test: Fake Onset in 2002 (Lead-Specific Gap, Main Design)

	Kenya	Ghana	Senegal	Pooled
Fake onset in 2002, pre-period only (1997–2006); any riot				
Lead-specific gap	0.048	−0.093	0.010	0.013
	(0.034)	(0.088)	(0.011)	(0.021)
Wild bootstrap p	[0.239]	[0.295]	[0.662]	[0.560]

Notes: Each cell is the lead-specific gap (the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site, in one regression). The sample is 1997–2006 only, with a placebo onset in 2002, and the outcome is 1 if any riot occurred in the cell-year. Country columns include cell and year fixed effects, and pooled columns include cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). Wild bootstrap p-values are from a restricted wild cluster bootstrap with Rademacher weights and 9,999 draws, clustered on the same blocks. Bracketed values are wild bootstrap p-values, and stars on estimates with a bracketed value use it. Other stars use the block-clustered t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A9: Real lead and food prices, 1997–2024



Notes: Prices are from the World Bank Commodity Price Data (Pink Sheet), annual, in real 2010 US dollars. Blue is lead in dollars per tonne, and orange is the food price index (2010 = 100). Panel (a) shows levels. Panel (b) shows standardised series, with horizontal bands at the means before and after 2007. The dashed line marks 2007.

Table A8: Changes in Other Outcomes near Battery Sites after 2007

	Battery × post	s.e.	N
Panel A: Satellite data, cell-years			
Log night lights	0.055	(0.075)	83,720
Panel B: DHS, women aged 15–49			
Wealth index (standardised)	0.035	(0.115)	29,046
Years of schooling	−0.050	(0.458)	29,039
Anaemic (Ghana and Senegal)	−0.020	(0.045)	5,582
Panel C: DHS, children and households			
Anaemic, 6–59 months (Ghana and Senegal)	−0.002	(0.070)	3,163
Haemoglobin, g/dl (Ghana and Senegal)	−0.164	(0.329)	3,268
Died before age 5	0.002	(0.018)	15,830
Stunted (post-2007 rounds only)	0.001	(0.015)	8,316
In school, ages 6–14	0.015	(0.042)	27,066

Notes: Each row compares places within 5 km of a battery site with places within 5 km of a non-lead TSIP site, after 2007 against before. In Panel A the unit is the grid cell-year and the outcome is log night lights. The row is the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site from 2007 onwards, from one regression with cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). Panels B and C use Demographic and Health Surveys for Kenya, Ghana and Senegal, with one round before 2007 in each. DHS clusters are assigned by distance from their GPS point, which DHS displaces by up to 2 km in urban areas. Each row is the coefficient on battery site × post-2007, with country-region-round fixed effects and an urban indicator, weighted by DHS sampling weights. Standard errors are clustered by DHS cluster. Stunting is measured only after 2007, so that row compares levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

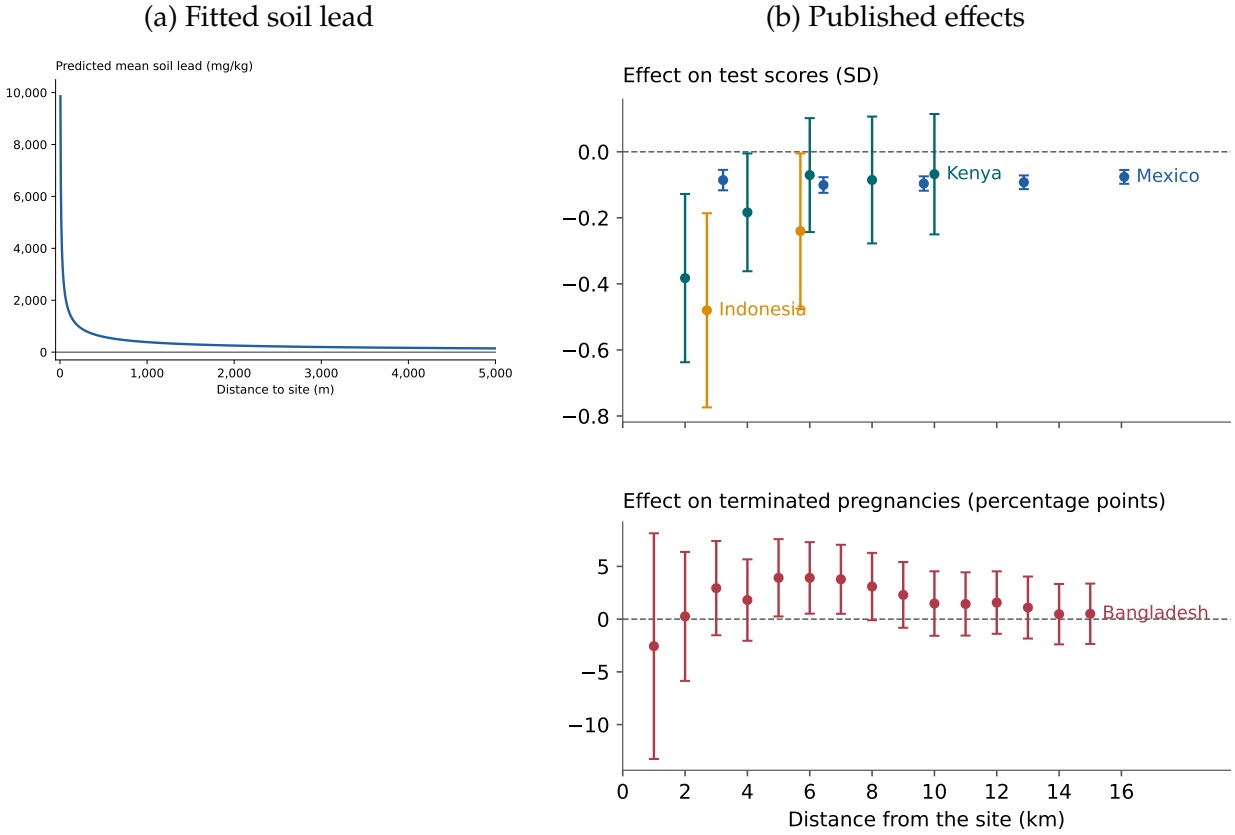
Table A9: Food and Lead Price Interactions: Lead-Specific Riot Gap

	Food price	Lead price
Raw prices		
Battery (within 5 km) × price	0.100***	0.032
	(0.021)	(0.022)
Non-lead (within 5 km) × price	0.030**	0.008
	(0.014)	(0.013)
Lead-specific gap	0.070**	0.024
	(0.028)	(0.029)
Within-period variation only		
Battery (within 5 km) × price	0.029	−0.073***
	(0.021)	(0.025)
Non-lead (within 5 km) × price	0.007	−0.025*
	(0.015)	(0.015)
Lead-specific gap	0.021	−0.048
	(0.028)	(0.031)
Cell-years	83,860	

Notes: Each column is the lead-specific gap (battery minus non-lead) on a real commodity price interacted with an indicator for a cell within 5 km of the site, from one regression with both prices and both proximity indicators. The outcome is 1 if any riot occurred in the cell-year. Prices are from the World Bank Pink Sheet, annual, in real 2010 US dollars, standardised. The upper panel uses raw prices, and the lower panel uses prices residualised on the post-2007 indicator. All columns include cell and country×year fixed effects. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

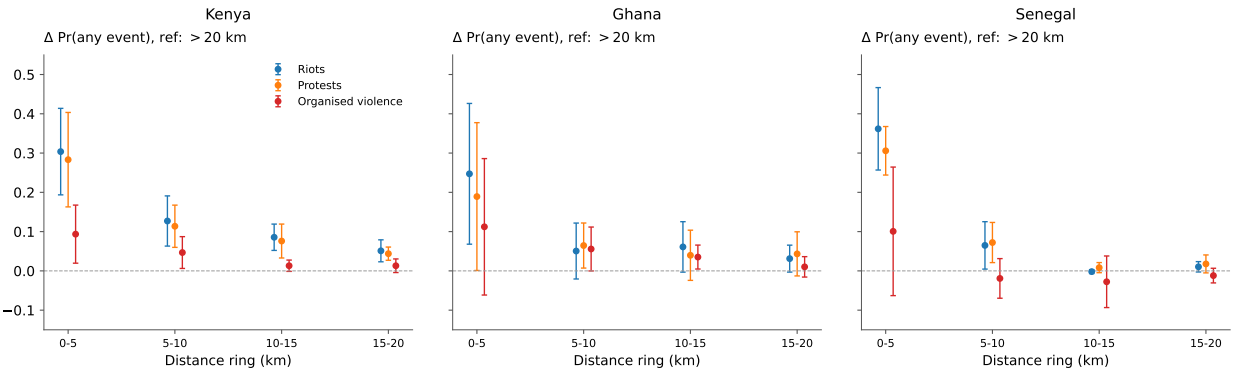
A.3 Distance and dose

Figure A10: Soil Lead and Published Effects by Distance from a Battery Recycling Site



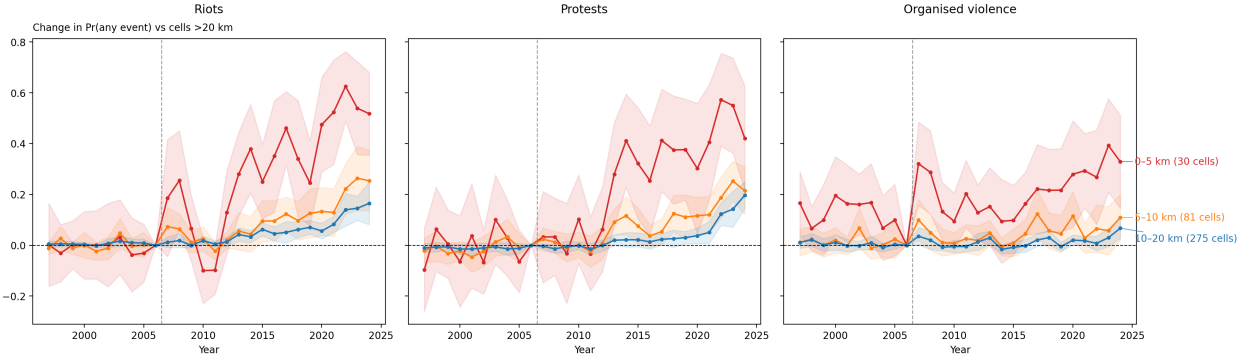
Notes: Panel (a) shows fitted soil lead by distance to a battery recycling site, from Pure Earth soil samples at all TSIP battery sites (Crawfurd et al., 2026). Panel (b) shows published estimates of the effect of living near a lead-acid battery site, plotted at the outer distance of each estimate's treated area. The top part shows effects on children's test scores in standard deviations. Kenya: schools within 2 to 10 km of a plant against schools 10–20 km away (Ipapa, 2026). Indonesia: numeracy within 0–3 and 3–6 km against beyond 6 km (Berkhout et al., 2025). Mexico: math in two-mile distance rings out to ten miles, each against schools 25–30 miles away (Litzow et al., 2026). The bottom part shows the effect on the probability of a terminated pregnancy in percentage points, for women within 1 to 15 km of a battery site in Bangladesh against women farther away (Kundu et al., 2026). The Mexico and Bangladesh estimates are read from the authors' figures. Bars are 95% confidence intervals.

Figure A11: The Effect by Distance from the Nearest Battery Site, by Country



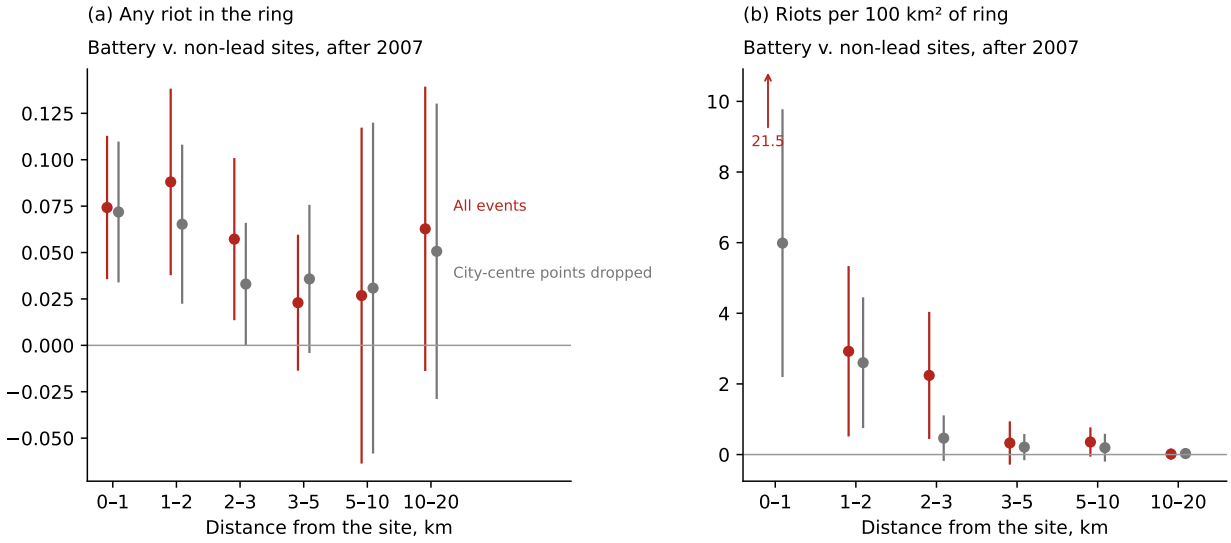
Notes: The figure shows coefficients on mutually exclusive distance rings around the nearest battery site, interacted with an indicator for 2007 onwards, from one regression. The reference is cells more than 20 km away. The outcome is 1 if any event of the given type occurred in the cell-year. All regressions include cell and year fixed effects. Bars are 95% confidence intervals, and some are clipped to the plotting range. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Figure A12: Event Study by Distance Band



Notes: The figure shows coefficients on distance bands (0–5, 5–10 and 10–20 km from the nearest battery site) interacted with year, relative to cells beyond 20 km, with 2006 as the base year. The outcome is 1 if any event of the given type occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. Shaded areas are 95% confidence intervals. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country).

Figure A13: Riots by Distance from the Site, Measured Event by Event



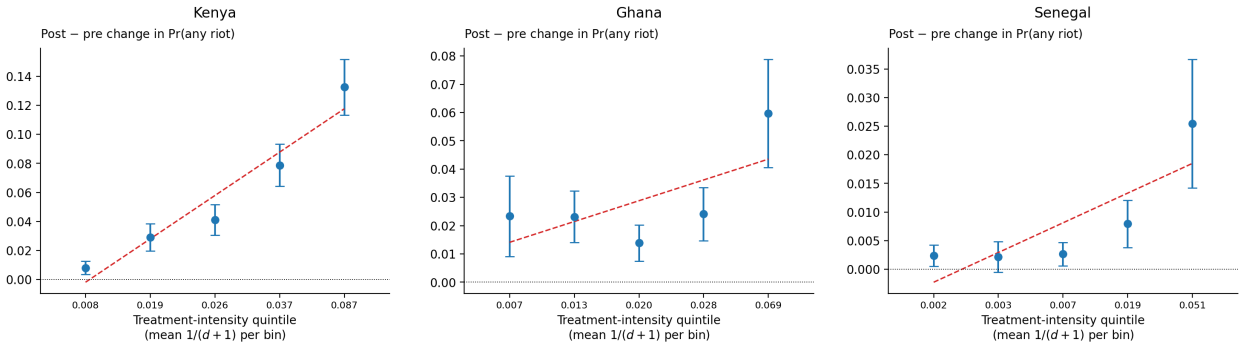
Notes: The unit is site × ring × year, for 67 battery recycling and 180 non-lead TSIP sites in Kenya, Ghana and Senegal, 1997–2024. Distances run from each ACLED riot's coordinates to each site, and a riot counts for every site whose ring it falls in. Each point is the coefficient on ring × battery site × post-2007, from one regression with site×ring and ring×country×year fixed effects. In panel (a) the outcome is 1 if any riot occurred in the ring; in panel (b) it is riots per 100 km^2 of ring. Red uses riots with ACLED's highest location precision, and grey drops the five most-used event coordinates in each country. The red 0–1 km point in panel (b), 21.5 (s.e. 11.6), is off the scale. Bars are 95% confidence intervals, with standard errors clustered by site group (sites within 10 km are chained; 95 groups).

Table A10: Continuous Proximity: Riots, Protests and Organised Violence by Inverse Distance to a Battery Site

	Kenya		Ghana		Senegal		Pooled	
	Battery	Non-lead	Battery	Non-lead	Battery	Non-lead	Battery	Non-lead
Panel A: Riots								
$\frac{1}{d+1} \times$ Post	1.199***	0.523***	0.742***	0.375**	0.887***	0.291**	1.053***	0.416***
	(0.217)	(0.103)	(0.176)	(0.138)	(0.076)	(0.127)	(0.128)	(0.075)
Lead-specific gap	0.740***		0.373*		0.599***		0.683***	
	(0.237)		(0.182)		(0.150)		(0.138)	
Pre-treatment mean	0.010		0.001		0.001		0.005	
Panel B: Protests								
$\frac{1}{d+1} \times$ Post	1.087***	0.473***	0.679***	0.341**	0.819***	0.272**	0.958***	0.379***
	(0.163)	(0.075)	(0.173)	(0.136)	(0.114)	(0.124)	(0.100)	(0.065)
Lead-specific gap	0.672***		0.346*		0.546***		0.620***	
	(0.162)		(0.166)		(0.163)		(0.103)	
Pre-treatment mean	0.010		0.001		0.002		0.005	
Panel C: Organised violence (battles + VAC)								
$\frac{1}{d+1} \times$ Post	0.339**	0.189**	0.466**	0.195	0.095	0.048	0.317***	0.142***
	(0.135)	(0.076)	(0.162)	(0.112)	(0.279)	(0.042)	(0.101)	(0.042)
Lead-specific gap	0.157		0.294*		0.036		0.183	
	(0.173)		(0.138)		(0.276)		(0.113)	
Pre-treatment mean	0.020		0.002		0.007		0.012	
Cells	1,319		626		1,050		2,995	
of which treated (<5 km)	20		4		6		30	
Cell-years	36,932		17,528		29,400		83,860	

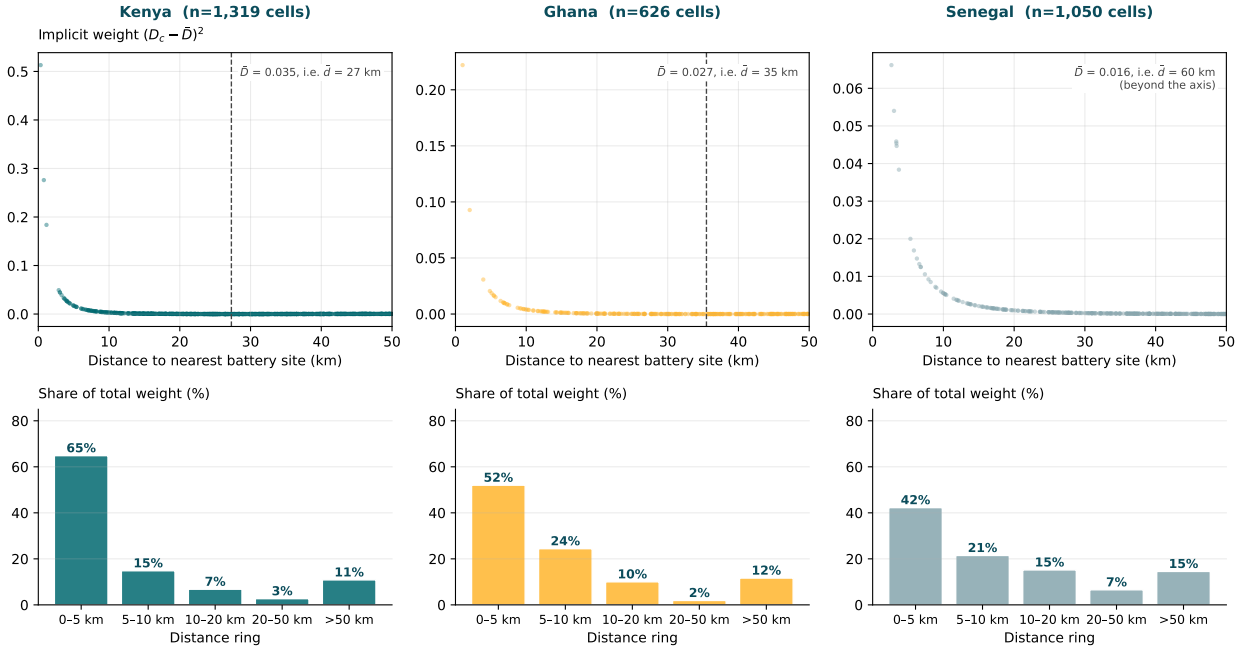
Notes: The outcome is 1 if any event of the given type occurred in the cell-year. Treatment is interaction between the inverse distance to a battery site and the post-treatment period, represented as $1/(d+1) \times$ Post. The gap is the battery coefficient minus the non-lead coefficient. The sample is all cells within 50 km of any TSIP site. Country columns include cell and year fixed effects, and pooled columns include cell and country×year fixed effects. The pre-treatment mean is the share of cell-years before 2007 with any event. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A14: Dose-Response: Change in the Probability of a Riot by Proximity Quintile



Notes: Cells are grouped into quintiles of $1/(d+1)$. Each point is a quintile's mean change in the share of years with any riot, 2007–2024 minus 1997–2006, plotted against its mean $1/(d+1)$. Bars are 95% confidence intervals, and the dashed line is an OLS fit.

Figure A15: Empirical TWFE Identifying Weights $(D_c - \bar{D})^2$ by Cell



Notes: The top row plots the implicit TWFE weight $(D_c - \bar{D})^2$ for each cell against its distance to the nearest battery site, where $D_c = 1/(d_c + 1)$ and $\bar{D}$ (the dashed line) is its mean. These are the weights implicit in a linear regression on a continuous dose. Callaway et al. (2024) show why they need not match the weights on causal responses. The bottom row shows the share of total weight by distance ring. Cells more than 50 km from a battery site are in the sample because they are within 50 km of a non-lead site.

A.4 Mechanism and magnitudes

Table A11: Riot, protest and organised-violence sub-types within 5 km of a battery site

	Battery	Non-lead	Lead-specific gap	Pre-2007 mean
Riots				
Mob violence	0.258***	0.059***	0.199***	0.063
	(0.038)	(0.017)	(0.046)	
Violent demonstration	0.207***	0.057***	0.150***	0.127
	(0.033)	(0.015)	(0.040)	
Protests				
Peaceful protest	0.231***	0.074***	0.157***	0.150
	(0.037)	(0.017)	(0.044)	
Protest with intervention	0.155***	0.018	0.137***	0.033
	(0.035)	(0.011)	(0.040)	
Organised violence				
Battles	0.019	0.002	0.017	0.120
	(0.025)	(0.010)	(0.026)	
VAC: attack	0.072**	0.028**	0.045	0.133
	(0.028)	(0.013)	(0.030)	
VAC: abduction	0.056**	0.006	0.050*	0.003
	(0.026)	(0.008)	(0.029)	
Fatalities				
Any riot death	0.173***	0.037**	0.136***	0.050
	(0.033)	(0.014)	(0.036)	

Notes: These are linear probability models, and the outcome is 1 if any event of the given ACLED sub-type occurred in the cell-year (any riot death in the last row). Battery (non-lead) is an indicator for a cell within 5 km of a battery site (non-lead TSIP site) from 2007 onwards, and both enter one regression. The gap is the battery coefficient minus the non-lead coefficient. Mob violence and violent demonstration are ACLED riot sub-types, and peaceful protest and protest with intervention are protest sub-types. Battles are organised-violence events other than violence against civilians. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. The pre-2007 mean is the share of cell-years before 2007 with any event, among cells within 5 km of a battery site. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A12: Riot Trigger Composition Near Battery and Non-Lead Sites

Riot trigger	Battery (%)	Non-lead (%)	Diff. (pp)
Pollution / contamination	0.15	0.19	−0.05
Mob justice (individuals)	25.62	26.46	−0.84
Political / electoral	29.44	22.96	+6.48
Services / infrastructure	12.34	14.79	−2.45
Prices, wages, taxes	4.66	2.53	+2.13
Policing and courts	1.83	0.39	+1.44
Other / unspecified	25.97	32.68	−6.72
Riots	2,018	514	
Fisher exact p, pollution share		1.00	
χ^2 p, all triggers		<0.001	
Protests			
Pollution-triggered share	0.33	0.26	+0.06
Protests	2,452	763	
Fisher exact p, pollution share		1.00	

Notes: The table shows the share of ACLED riots of each trigger type within 5 km of a battery site, and within 5 km of a non-lead TSIP site but not a battery site, 1997–2024. Distances are measured from each event's coordinates, and shares cover all events in the three countries. Triggers are coded as in Table 5. The lower panel covers protests. Fisher exact and χ^2 tests compare the two columns.

Table A13: Lead-Specific Gap by Riot Trigger: Comparison-Group Robustness

Riot trigger	Baseline	Non-mining comparison	Urban cells
Mob justice (individuals)	0.150***	0.143***	0.127***
	(0.040)	(0.049)	(0.042)
Political / electoral	0.204***	0.183***	0.186***
	(0.040)	(0.046)	(0.042)
Services / infrastructure	0.102***	0.081*	0.087***
	(0.029)	(0.042)	(0.032)
Prices, wages, taxes	0.062***	0.063***	0.058***
	(0.019)	(0.021)	(0.020)
Policing and courts	0.030**	0.026	0.029*
	(0.015)	(0.016)	(0.015)
Other / unspecified	0.057**	0.072*	0.038
	(0.028)	(0.041)	(0.028)
All riots	0.194***	0.177**	0.151***
	(0.051)	(0.068)	(0.054)
Cells	2,995	2,995	1,497

Notes: Each cell is the lead-specific gap (the battery minus the non-lead coefficient, each an indicator for a cell within 5 km of the site from 2007 onwards), where the outcome is 1 if any riot of that trigger type occurred in the cell-year. Kenya, Ghana and Senegal are pooled, with cell and country×year fixed effects. The non-mining column drops artisanal mining and ore-processing sites from the non-lead comparison. The urban column keeps cells with above-median population before 2007 (WorldPop). Triggers are coded as in Table 5. Standard errors are clustered on 1°×1° spatial blocks (about 110 km across, within country). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A14: Break-Even Value of an Averted Riot-Death Place-Year

Site in	Source	Cost (US$)	10 years	20 years
Bangladesh	Chowdhury et al. (2021)	40,300	127,899	63,950
Vietnam	Ericson et al. (2018)	118,750	376,875	188,438
Dominican Republic	Ericson et al. (2018)	430,000	1,364,684	682,342

Notes: Each cell is the remediation cost of one site divided by the riot-death place-years averted over the horizon in the column heading. Averted place-years per site per year are 0.057 with a riot and 0.032 with a riot death, from the aggregate estimates (69 and 38) spread over 67 sites and 2007–2024. Costs are not discounted.

Table A15: Effect-Size Plausibility

	Soil-lead distance decay	
	All TSIP sites	Kenya, Ghana, Senegal
Distance−decay elasticity	−0.61	−0.31
Blood lead increase within 5 km (μg/dL)	1.7	8.1
Ratio to background, r	1.29–1.39	2.38–2.81
Predicted within-5 km gap from published effect sizes (pp)		
Reyes (2007), $\varepsilon = 0.8$	4.6–6.0	18.2–22.5
Higney et al. (2022), $\varepsilon = 0.09$	0.5–0.6	1.7–2.0
Aizer and Currie (2019), individual dose-response	8.4	32.2
Estimated (pp)		
Lead-specific gap, riots (Table 4)	19.4	
Riots minus organised violence (Table 4)	12.8	

Notes: Each row converts a published estimate into our outcome. Lead multiplies the riot rate by r^{ε}, where ε is the elasticity and $r = (B + \Delta)/B$. B is the national mean blood lead level (IHME Global Burden of Disease 2023), from 4.5 to 5.8 μg/dL across the three countries. Δ is the population-weighted increase in blood lead over background within 5 km of a battery recycling site, following Crawfurd et al. (2026): soil lead is regressed on distance to the site (both in logs, with site fixed effects, after subtracting 41.8 mg/kg background), and soil lead is converted to blood lead with the AALM biokinetic model. The first column uses all TSIP battery sites, and the second uses the 47 sites in Kenya, Ghana and Senegal (320 soil samples, 8 of them more than 1 km from a site). The rate maps to the probability of any riot as $1 - e^{-\lambda}$, with a comparison-cell probability of 0.24, the pre-2007 riot probability near battery sites plus the post-2007 non-lead coefficient. Higney et al. (2022) is a meta-analysis of 542 estimates, corrected for publication bias. The Aizer–Currie row assumes the riot-prone population rises by 25% per μg/dL.