CESifo WORKING PAPERS

9916
2022

August 2022

The Health Burden of E-Waste: The Impact of E-Waste Dumping Sites on Child Mortality

Stefania Lovo, Samantha B. Rawlings

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 9916*

The Health Burden of E-Waste: The Impact of E-Waste Dumping Sites on Child Mortality

Abstract

This paper examines the effect of e-waste dumping sites on early child health. We focus on two major dumping sites in West Africa, in Ghana and Nigeria. We observe children born before and after the creation of these dumps, and estimate a difference-in-difference specification in which we compare outcomes of those born within the vicinity of the dump to those farther away, before and after e-waste sites were created. We find that the e-waste sites increase neonatal and infant mortality, for children living in the proximity of the site. Event studies suggest that the negative effects emerge 2-3 years after the existence of the sites, consistent with the gradual and systematic build up of contaminants in the environment. By exploring routes of exposure, we find that the contamination of water and urban farming produce are among the drivers of the observed effects.

JEL-Codes: I100, Q530, Q560, O100.

Keywords: E-waste, health, infant mortality, dumping sites, West Africa.

Stefania Lovo
Department of Economics
University of Reading / United Kingdom
s.lovo@reading.ac.uk

Samantha B. Rawlings
Department of Economics
University of Reading / United Kingdom
s.b.rawlings@reading.ac.uk

August 23, 2022
We thank Sonia Bhalotra and Jorge Garcia Hombrados for valuable discussion and feedback. We also thank seminar participants at the University of Reading, the University of Bristol, the 2021 RES Conference, 2021 BREAD conference on the economics of Africa and the 2021 CREB Applied Development Economics Conference.

1 Introduction

E-waste refers to waste made up of electrical and electronic equipment (EEE), and is classified as hazardous waste, due to the presence of toxic materials in many electrical components (Bakhiyi et al., 2018). It is one of the fastest growing waste streams, with 53 million metric tons (Mt) of e-waste generated globally in 2019 estimated to rise to 74 Mt by 2030 (Lundgren (2012), Forti et al. (2020)). An important aspect of e-waste is that it is often inappropriately managed, especially in developing countries.

E-waste in developing countries originates both from domestic and international sources. Internationally, a vast share of e-waste imports is comprised of working or repairable electronic equipment that domestic consumers discard, because although often usable, imported second-hand equipment has a short life span (Heacock et al., 2016; Davis et al., 2019). Indeed, many e-waste dumping sites originate from or in the proximity of second-hand markets (Manhart et al., 2011). Evidence also indicates the existence of a non-negligible international flow of e-waste that enters developing countries illegally (Kellenberg, 2010). A significant share of the international flow is also generated within regions rather than transferred between regions (Lepawsky and McNabb, 2010). In West Africa, Ghana and Nigeria serve as the main trade hubs for both regional and international trade in EEE and e-waste (Schluep et al., 2011).

E-waste contains significant amounts of precious metals and other valuable materials. It is estimated, for example, that 7% of the world's gold is currently contained in e-waste (UNEP et al., 2019). This results in a market for salvage, as e-waste is typically transported to dump sites or workshops where it is stripped of valuable materials. In most African countries, e-waste management is predominantly performed by those in the informal sector. The stripping of components is done manually, and, after salvage, the unwanted components are burned or discarded in open dumpsites (Kellenberg, 2010).[1] This is of concern because e-waste consists of a number of environmental contaminants that pose a number of risks to health. Potential routes of exposure include ingestion, inhalation and dermal contact.[2] Children and the young are particularly at risk, due to additional routes of exposure such as breastfeeding and placental exposure and through behaviours such as persistent hand to mouth activities (Grant et al., 2013). Children are also at increased risk due to physiological differences from adults including higher

[1]The size of this informal economy is large, with recent estimates suggesting that 100,000 people work in the informal e-waste sector in Nigeria (ILO, 2019).

[2]These include organic pollutants such as polychlorinated biphenyls, which are components of e-waste and are known endocrine disruptors (Bergman et al., 2013), potentially hazardous chemical elements in electrical components that are known to have developmental effects on children such as lead, cadmium and arsenic (Chen et al., 2010), and carcinogenic polycyclic aromatic hydrocarbons (PAH) formed and released into the environment during burning of e-waste materials (Wang et al., 2012).

intakes of air, water, and food per body weight, and a lessened ability to eliminate toxins, particularly amongst infants (Pronczuk-Garbino et al., 2007).

A significant body of literature within economics has investigated the short- and long-run effects of early-life exposure to poor environmental quality on health outcomes at birth, childhood, and beyond (see Currie et al., 2014, for a review). Studies have focused on, for example, the effect of air pollution (see for example Currie and Neidell, 2005; Jayachandran, 2009; Greenstone and Hanna, 2014; Arceo et al., 2012; Luechinger, 2014; Tanaka, 2015; Currie and Neidell, 2005; Currie et al., 2009; Currie and Walker, 2011), water quality (Greenstone and Hanna, 2014; He and Perloff, 2016), and proximity to mining operations (von der Goltz and Barnwal, 2019) on health, yet the impact of waste has received little attention. An exception is Currie et al. (2011), who investigate the impact of toxic waste dumps in the US on infant health, exploiting the introduction of the Comprehensive Environmental Response, Compensation, and Liability Act (known as Superfund), which led to clean-ups of dangerous hazardous waste sites in the US. They find that clean-ups of hazardous waste sites reduce the incidence of congenital anomalies by roughly 20-25 percent, with no statistically significant effects on outcomes such as low birth weight, prematurity, or infant death. A more recent work by Gennaioli and Narciso (2017) investigates the impact of illegal dumping of (non-specified) hazardous waste in Ethiopia on infant health. Given the absence of information on locations of illegal waste sites, the study relies on predictions based on road construction. The premise underlying the paper is that road construction facilitates disposal of toxic waste. It finds that an additional road within a 5-kilometer radius is associated with an increase in infant mortality by 3 percentage points. Yet, specifically on e-waste, the evidence relies mostly on observational studies.[3]

This paper investigates how exposure to e-waste sites impacts infant and neonatal mortality employing a difference-in-difference approach. We exploit a household's distance to the dumping site to define intensity of exposure to pollution at birth or in the womb. Our identification strategy relies on the comparison of children born before and after the existence of the dump, and distance to the dump. We are able to address concerns about potential dump-induced residential sorting by focusing on non-migrant households and by comparing siblings born before and after the creation of the dump. To our knowledge, this is the first study to quantify the causal impact of e-waste dumping sites on early childhood health. This is particularly important given their extensive

[3]For example, a number of small-sample observational studies in China suggest negative associations between exposure to-e-waste and health outcomes. Children born near e-waste sites have reduced birthweights, whilst higher chemical pollutants are found in the cord blood of pregnant women residing near such sites, and increases in pregnancy miscarriage and premature births are observed, compared to women and children in control areas (see Grant et al., 2013, and references therein).

presence in developing countries, including a number of African and Central Asian countries and China (Forti et al., 2020). We find large and statistically significant effects of proximity to e-waste sites on neonatal and infant mortality. One additional kilometre away from the dumping sites reduces neonatal mortality by 6 deaths per 1,000 births and infant mortality by 7 deaths per thousand births after the creation of the dumping site. Event study analysis is used to understand the dynamics of the relationship and suggests that these effects emerge 2-3 years after the existence of the site, suggesting that effects emerge once contaminants have had time to build up in the environment. Finally, we present suggestive evidence that the effects are at least in part explained by the contamination of water, consumed directly for cooking and cleaning, and the consumption of locally sourced animal products.

The rest of the paper proceeds as follows. We give an overview of background and context regarding e-waste and the sites used in the analysis in section 2. Section 3 outlines the data used, section 4 outlines our empirical specifications, whilst section 5 presents our results. We discuss potential mechanisms underlying our results in 6 and robustness checks in section 7. Finally, section 8 concludes.

2 Background and Context

2.1 International Conventions on Exporting Hazardous Waste

In response to increasing exports of hazardous waste to countries in the developing world and the resulting international outcry, the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal was opened for signatures on 22 March 1989, and entered into force on May 5, 1992 (Kitt, 1994; Andrews, 2009). The convention did not ban the export of hazardous waste, but regulated it, based on the principle of prior informed consent (PIC), in which exporting parties would need to have explicit consent from a competent authority in the importing state for the trade to occur (Krueger, 1998). The intention was to strike a balance between free trade and environmental protection (Lucier and Gareau, 2016). The convention did not classify e-waste as hazardous waste under the Basel convention until 1998. A weakness of the 1989 Convention was that it defined waste only as objects for disposal i.e.'scrap', leading to the so-called 'recycling loophole' which allowed for the stated intention of exports to be recycling of raw materials when in effect waste was either dumped, burned, or recycled in such a way as to pose a risk to local inhabitants (Andrews, 2009). A 1995 Basel Ban Amendment attempted to address this, by extending the ban to include export of hazardous waste that was intended for recycling, but this was not ratified into international law until 2019. Despite these attempts to regulate e-waste trade, large amounts of e-waste have continued to be shipped illegally, in part due to the complex and fragmentary regulatory environments which have hindered enforcement of international and national law (UNEP et al., 2019).

In addition, the export of electronic equipment labelled as 'for re-use' is still permitted (UNEP, 1989). This has led to significant levels of imported used EEE into African countries which ultimately ended up discarded, either because of a short life-span, or for being illegally labelled as for re-use while effectively being end-of-life equipment (Heacock et al. (2016),Kellenberg (2010)).[4] In 2016, an estimated 44.7 Mt of E-waste was generated, approximately 6 kg per person on the planet, leading to the UN describing a 'tsunami of waste' (UNEP et al., 2019).[5]

2.2 E-waste sites

We focus on two major e-waste sites: Agbogbloshie in Ghana and Solous (2) in Nigeria. The choice of these two sites was determined by the following criteria: the site was established after e-waste became a significant waste flow in the late 1990s (Grant and Oteng-Ababio, 2012; Forti et al., 2018) and there is availability of sufficient data on birth outcomes (see section 3 for details on the data used).[6]

Agbogbloshie is a dumping site established in 2001 in Accra, Ghana, that deals exclusively with e-waste; in 2014 it was estimated to have a size of 10.6 hectares, and to receive 192,000 tonnes of e-waste every year (Waste Atlas Partnership, 2014). It is the second largest e-waste processing site in West Africa (Bernhardt and Gysi, 2013), and is situated in a densely populated area, with an estimated population within 10 km of the site of 2,350,000 (Waste Atlas Partnership, 2014). It has received intense media reporting

[4]In 2012 the Basel Secretariat, acknowledging difficulties associated with identification of genuine export of electrical equipment from e-waste intended for scrap, issued guidance on transboundary movements of e-waste in an attempt to aid in the distinction between waste and non-waste (Ogunseitan, 2013).

[5]This estimated figure has subsequently risen to 53 Mt in 2019 (Forti et al., 2020).

[6]Our search for sites was guided by the 2014 Waste Atlas Report on the world's 50 biggest dumpsites (Waste Atlas Partnership, 2014). The site coverage in the report was determined by (physical) size and spread of the site, estimated amount of waste disposed of, number of people potentially influenced by the site, and risks posed by the site to environmental and health. Inclusion in the report is conditional on data on site being available including the exact longitude and latitude location; data on sites was taken from both official data, and so-called 'grey' literature, e.g. news/media. The Waste Atlas Report also details of the types of waste handled at sites, including e-waste. Other categories of waste include municipal waste and hazardous waste. Of the 50 sites in the Waste Atlas Report, just 7 deal with e-waste. We excluded three other sites due to their opening date pre-dating the influx of e-waste so that date of treatment was uncertain, and two more recent sites (Tibar, in Timor-Leste, and Pugu-Kinyamwezi in Tanzania) because they also dealt with medical and hazardous waste rather than predominantely e-waste.

regarding the scale of the problem, and is notorious amongst NGOS such as Greenpeace.[7] In 2004, the Government of Ghana reduced the import duty on used computers to zero, leading to a large increase in shipments to Ghana (Grant and Oteng-Ababio, 2012).

Solous is a dumping site established in 2006 in Lagos, Nigeria, receiving a large amount of waste, both municipal and e-waste. For example, estimates suggest that it received 428,728 metric tonnes of waste in the first two quarters of 2009 (Balogun and Adegun, 2016).[8] An estimated 4 million people live within 10 km of the site, and the nearest settlement to the site is 200 m away (Waste Atlas Partnership, 2014). In addition, a road runs through the middle of the site, establishing it as a trade route and business centre (Ife-Adediran and Isabota, 2018). It has been described as "an entire human community on its own, where buying, selling, eating, drinking, playing, visiting and other normal activities take place daily" (p.710 Ife-Adediran and Isabota, 2018). A complication of the inclusion of this site into the study is the existence of an older, large dumpsite 14 km away, known as the Olusosun/Olushosun waste site. The Olusosun site also deals with e-waste, but was established as an ordinary waste site in 1992 before e-waste flows were a significant problem. This precludes us from having a clean 'before' and 'after' period of exposure to e-waste, and is, therefore, not include it in our main analysis.[9] In analysing the Solous site, we exclude all households living within 5km distance of Olusosun (further details are discussed in section 3).

3 Data

We use data from the Demographic Health Surveys (DHS) for Ghana (1998, 2003, 2008) and Nigeria (2003, 2008, 2013). These are nationally representative surveys, using standardised questionnaires that are comparable across countries. The DHS collects complete fertility histories from women aged 18-49, including information on all births and any deaths of children respondents have ever had. Women are also asked a range of questions on health and socioeconomic status, and a household questionnaire collects information on characteristics of the household. The DHS also contains a GPS dataset containing the latitude and longitude location of the cluster within which the household is placed.[10]

[7] See for example https://www.theguardian.com/environment/gallery/2014/feb/27/agbogbloshie-worlds-largest-e-waste-dump-in-pictures.

[8] There are no estimates separately for e-waste vs. municipal waste.

[9] We have conducted a separate analysis for Olusosun. In particular, we can argue, based on e-waste trade data, that the dumping of e-waste started in 1998. Based on this assumption, we found results consistent with our main findings, but more imprecise. Given the lack of a clean research design for this site, we omit Olusosun from our analysis. Results are however available in a previous version of this study, and are available on request.

[10] Cluster sizes are small, with approximately 25-30 houses per cluster. For privacy reasons, the locations of DHS clusters are randomly displaced by up to 2km in urban areas and up to 5km in rural

To increase sample size, we supplement our analysis with data from the Malaria Indicator Surveys for Nigeria (2010, 2015) which are also administered by the DHS programme.[11] These use identical questionnaires to the DHS, but collect information on a narrower range of outcomes, for children born in the last five years. Crucially, they still collect data on births, deaths, individual and households characteristics needed for our analysis, as well as GPS of cluster location.[12] Figure A.1 of the Appendix show the location of the two dumping sites and the distribution of survey clusters in the surrounding area of the site within the 20 km buffer zone.[13]

All women interviewed in the DHS are asked for the date of birth of each child and, if the child has died, their age at death.[14] Our measure of newborn and infant health is captured by measures of mortality in the first month (neonatal) and first year (infant) of life.[15] We construct dummy variables for neonatal and infant mortality that are equal to 1 if the child died before 30 days, or before 1 year, respectively.[16] We drop from our estimating sample those children who have not been fully exposed to the measure of mortality under study.[17] Our sample considers children born 20 km within the vicinity of the dumps five years before and after its establishment, leaving us with a sample of 3359 (3094) births in our neonatal (infant) mortality regressions, born to 1868 (1743) mothers.

Table 1 shows summary statistics for the births in our sample, for all households. Average neonatal (infant) mortality is 3.6% (5.7%), and these rates are broadly similar in Ghana (Panel B) and Nigeria (Panel C). The sample is primarily urban, with most individuals having secondary education. Country (i.e. dump) specific statistics show

areas. The majority of our clusters are urban (96% in Ghana and 97% in Nigeria), and our results are robust to exclusion of rural clusters that may have been displaced by larger amounts (results available on request). Displacement of location is random and there is no reason to believe that displacement varies systemically with either distance from the sites or over time. The result is that the resulting noise may lead to downward biased estimates so that, if anything, this displacement will make it harder to identify an effect.

[11] See `https://dhsprogram.com/What-We-Do/Survey-Types/MIS.cfm` for a further discussion of these data.

[12] Our results are robust to the exclusion of the MIS surveys.

[13] For Nigeria, we also show the location of the earlier established dumpsite, Olusosun, that is not included in our analysis for reasons discussed above. We also show the 5 km radius around Olusosun, to show which clusters are excluded from our analysis of the Solous dumpsite since they may also have been exposed to the Olososun site.

[14] This is reported as age in days if less than one month old at death, or age in months if older than one month at time of death.

[15] Evidence from developed nations commonly uses birth weight as a measure of newborn/in utero health (e.g. (Currie et al., 2011)); however, birth weight is often poorly recorded in the DHS surveys, and this is particularly the case in these surveys. Between 70-80% of observations are missing information on both reported weight at birth and a subjective measure of size at birth (i.e. whether the baby was small or large).

[16] Due to age heaping, we include the 30th day and 13th month in our definitions of neonatal and infant mortality.

[17] For example, if a child were only 2 months old at the date of the interview, they are not included in the infant mortality regressions since infant mortality is right censored for these individuals.

Table 1: Summary statistics

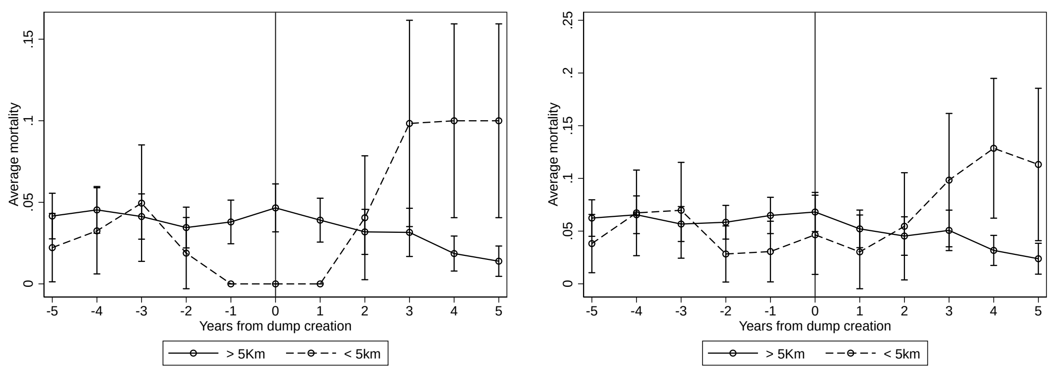
	N	Mean	Std. Dev.	Min.	Max.
All					
Neonatal Mortality	3359	.036	.187	0	1
Infant Mortality	3085	.054	.226	0	1
Mother < Primary schooling	3359	.069	.253	0	1
Mother Primary schooling	3359	.182	.386	0	1
Mother Secondary schooling	3359	.594	.491	0	1
Mother Higher education	3359	.155	.362	0	1
Spouse < primary schooling	2957	.041	.197	0	1
Spouse primary schooling	2957	.135	.341	0	1
Spouse secondary schooling	2957	.589	.492	0	1
Spouse higher schooling	2957	.235	.424	0	1
Urban	3359	.958	.201	0	1
Mother age at birth	3359	27.985	5.557	14	48
Male birth	3359	.509	.5	0	1
Multiple birth	3359	.036	.186	0	1
Ghana					
Neonatal Mortality	805	.03	.17	0	1
Infant Mortality	727	.051	.22	0	1
Mother < Primary schooling	805	.125	.331	0	1
Mother Primary schooling	805	.214	.41	0	1
Mother Secondary schooling	805	.607	.489	0	1
Mother Higher education	805	.053	.225	0	1
Spouse < primary schooling	710	.097	.296	0	1
Spouse primary schooling	710	.032	.177	0	1
Spouse secondary schooling	710	.725	.447	0	1
Spouse higher schooling	710	.145	.352	0	1
Urban	805	.932	.252	0	1
Mother age at birth	805	27.352	6.035	14	45
Male birth	805	.513	.5	0	1
Multiple birth	805	.037	.19	0	1
Nigeria					
Neonatal Mortality	2554	.038	.192	0	1
Infant Mortality	2358	.055	.227	0	1
Mother < Primary schooling	2554	.051	.22	0	1
Mother Primary schooling	2554	.172	.378	0	1
Mother Secondary schooling	2554	.589	.492	0	1
Mother Higher education	2554	.188	.39	0	1
Spouse < primary schooling	2247	.023	.149	0	1
Spouse primary schooling	2247	.167	.373	0	1
Spouse secondary schooling	2247	.547	.498	0	1
Spouse higher schooling	2247	.264	.441	0	1
Urban	2554	.966	.18	0	1
Mother age at birth	2554	28.185	5.383	14	48
Male birth	2554	.508	.5	0	1
Multiple birth	2554	.036	.185	0	1

Source: Authors calculations based on DHS data.

broadly similar patterns across the two dumpsites, with the exception of education; whilst the proportions of primary and secondary education are similar, the Nigerian sample has fewer individuals without primary education, and more with higher education. Appendix Tables A.1-A.3 tests differences in the compositions of birth between children born within 5 km of the dump and those farther away, before and after e-waste sites were established. The choice of 5 km is only for descriptive purposes, as our main analysis use a continuous measure of distance. There are some statistically significant differences in the levels of education, particularly spousal education, between areas near to (within 5 km) and further away (5 - 20 km), but these differences are stable over time (columns (IX) and (X)). *Within* these zones, there also appears to be very little change in the compositions of births before and after the e-waste sites were opened, and changes tend to be broadly similar across the two zones. For example, there is some (weak) evidence that spousal education was higher amongst births occurring after e-waste sites were established, in both areas relatively near and further away from the dump sites, but these differences are only statistically significant at the 10% level. Thus, table A.1 shows little evidence that compositions of births changed differentially over time for treatment and control areas.

Figure 1: Average neonatal (left) and infant (right) over time

(a) Neonatal mortality (b) Infant mortality



Authors' calculation based on DHS data for Ghana and Nigeria. For consistency, we consider a common number of years (5) before and after the dump for both countries. The plots are created by computing rolling 2-year averages of infant and neonatal mortality.

Figure 1 plots average mortality rates over time for households in the proximity of the site (5 km) and those farther away (5-20 km). Though the small sample size implies some noise, we see that, prior to the establishment of the e-waste sites, neonatal and infant mortality rates roughly co-moved for those living within and outside the vicinity of the e-waste sites. In the post-site period instead, we see a divergence in trends and a sharp increase in mortality rates amongst those living in the vicinity of e-waste sites. This effect persists and strengthens over time; for example, the (2 year) rolling-average of neonatal (infant) mortality within the vicinity of the sites rises from 20 (50) deaths per 1,000 children in the year of creation to more than 90 (110) deaths per 1,000 children 5 years after - an almost twofold increase in mortality in a five-year period. The rise is not immediate, and appears 2-3 years after the dump was created, consistent with the gradual accumulation of pollutants in the environment. It is worth noting, however, that the purpose of these graphs is only descriptive. For example, while we observe some differences in mortality in the pre-dump period, appropriate testing for pre-trends will be provided below.

4 Empirical Specification

Our main identification strategy is based on a difference-in-differences specification that uses the date of creation of a dumping site to determine treatment, and compares children located close to the site to those farther away, effectively considering the distance from e-waste site as a measure of treatment intensity of exposure to pollution from the site. We estimate the following equation:

$$Y_{ijt} = \beta DIST_{ij} + \gamma Post_t \times DIST_{ij} + \nu_t + \theta_d + \epsilon_{ijt} \tag{1}$$

where i indicates a child born in year t from mother j. $Post_t$ is an indicator variable which equals one if a child was born after the local dump was created, $DIST_{ij}$ is the continuous distance variable (0 km $\leq DIST_{ij} \leq$ 20 km). Lastly, ν_t is a vector of child year of birth fixed effects and θ_d are dump-specific fixed effects.[18] Our dependent variable Y_{ijt} is either neonatal mortality (1 = died before 30 days, 0 otherwise) or infant mortality (1 = died before 13 months, 0 otherwise), so that a worsening of infant health is represented by a positive coefficient for γ. Standard errors are clustered at DHS cluster level; there are 180 clusters in our analysis. In a robustness check, we control for dump-specific time trends ($\theta_d \times T$), mother and child characteristics X_{ijt}, interview year, and cohort dummies interacted with pre-dump local characteristics of clusters to account for differential evolution over time in local development associated with mortality (see section 7). In equation 1, we expect distance to the e-waste site to have no effect on health outcomes for children born before the creation of the site ($\beta = 0$), while a negative effect in the post-dump period would imply that the health conditions of children born in the proximity of the

[18] Note that the inclusion of ν_t means that, in practice, $Post_t$ drops out of the estimating analysis. The choice of omitted category in our dump-specific fixed effects is arbitrary and in our analysis, it is the Ghana dump, Agbogbloshie.

site have worsened relatively to those farther away.

To gain more insight into the dynamics of the relationship and how it evolves in the post-dump period, we extend the analysis given in equation 1, and perform an event study analysis, estimating the following specification:

$$Y_{ijt} = \beta_0 + \beta_1 DIST_{ij} + \sum_{k=-5}^{k=5} \gamma_k 1\{K_{it} = k\} + \sum_{k=-5}^{k=5} \gamma_k 1\{K_{it} = k\} \times DIST_{ij} + \theta_d + \epsilon_{ijt}, \quad (2)$$

Here, we replace our dummy $Post_t$ from equation 1, with a more flexible specification in which we include dummies for lags and leads relative to the creation of the dump, the omitted category being the year prior to the creation of the dump. In all other respects, equation 2 mirrors equation 1. As an additional specification, we also show results where we use a dichotomous measure of treatment, where we identify treated children as those living within 5 km from the site.

For all specifications, we show results both by pooling data from the two sites and for each dumpsite individually. Although dumps are created in different years in the two countries, when we pool the data across the sites we stack and align the two events. This is equivalent to a setting where the events happen contemporaneously, as is the case in our site-specific regressions. Hence, our setting does not suffer from the bias due to heterogeneous treatment effects that affects staggered treatment designs (Goodman-Bacon, 2021).

4.1 Identification Issues

The validity of our empirical strategy relies on the assumption that the polluting effects of the dumping site decline with distance, and that the evolution of health outcomes in areas near and far from the site would have been similar in the absence of the dumping site. While the common trends assumption cannot be tested, the event study analysis above allows us to test for differences in pre-dump trends in health outcomes for children living close and far from the site location. Following the latest developments in the difference in differences literature, we also implement the Doubly Robust estimator of Callaway and Sant'Anna (2021) to test for pre-trends conditional on covariates.

Yet, other unobserved time-varying factors correlated with the creation of the dump and affecting differently areas closer and farther from the site could challenge the validity of our results. In particular, one concern might be dump-induced migration. Specifically, if families in relatively worse/better health conditions had moved in the proximity of the site this would bias our results. Similarly, bias could be induced by the potential displacement of households caused by the dump. In section 7 we investigate whether this is a concern in two ways; first, by comparing the characteristics of women in our sample interviewed before and after the e-waste sites were established, and second by estimating the relationship for non-migrant households only. A caveat to the second approach is that there is limited information on years of residence in these particular DHS surveys,[19] and we are only able to perform the latter robustness check for Ghana. In addition, since we are able to observe children born from the same mother before and after the creation of the dump, in a further robustness check we are able to show a specification including mother fixed effects. This allows us to mitigate the concerns about unobserved heterogeneity in residential sorting. On the other hand, however, it does considerably restrict our sample and, therefore, requires further considerations that will be discussed below.

5 Main results

Regression results from the difference-in-difference specification in equation 1 are reported in table 2. Results show that the effect of distance becomes negative and significant only after the e-waste sites were opened. This is consistent with distance capturing exposure to pollution from the site and suggests an increase in mortality for children born in the proximity of the dump relatively to those farther away. The estimated effect of distance (which captures the pre-dump effect) indicates that, if anything, mortality prior to the establishment of the waste site was higher in areas away from the sites, though this relationship is weak, and not statistically significant for neonatal mortality. The effects indicate that, after the dump has been opened, moving one additional km away from the dump decreases neonatal and infant mortality by 4 and 5 deaths per 1,000 births, respectively. In appendix table A.4 we show estimates separately for each site in Ghana and Nigeria, and we find similar results, with effect sizes broadly similar, particularly for neonatal mortality.[20]

Results of the event study analysis (equation (2)) are reported in Figure 2 and confirm that the distance to the dumping site did not play any significant role in explaining neonatal and infant mortality of children born before the creation of the dump. We reach similar conclusions when testing parallel trends using a dichotomous treatment variable, where we define treated those children living within 5 km from the site (see Figure A.2). The negative effect of distance in the post-dump period confirms that children born in the

[19] Although in DHS survey rounds V and VII information on years of residency were collected, in DHS rounds VI, which make up the bulk of our surveys, this information was not collected. We therefore have no information on residency in the surveys for Nigeria conducted in 2010, 2013 and 2015, so that we have very limited information on residency in the post-dump period.

[20] The effect sizes on neonatal (infant) mortality for the Ghanaian and Nigerian sites are 4 (7) and 3 (4) deaths per 1,000 births, respectively.

Table 2: The impact of e-waste sites on newborn and infant health

	(I)	(II)
Dependent variable:	Neonatal Mortality	Infant Mortality
Distance (km)	0.001	0.003**
	(0.001)	(0.001)
Post × Distance (km)	–0.004***	–0.005**
	(0.001)	(0.002)
Mean mortality	0.036	0.056
Observations	3359	3094
Dump FE	Yes	Yes
Year of Birth FE	Yes	Yes

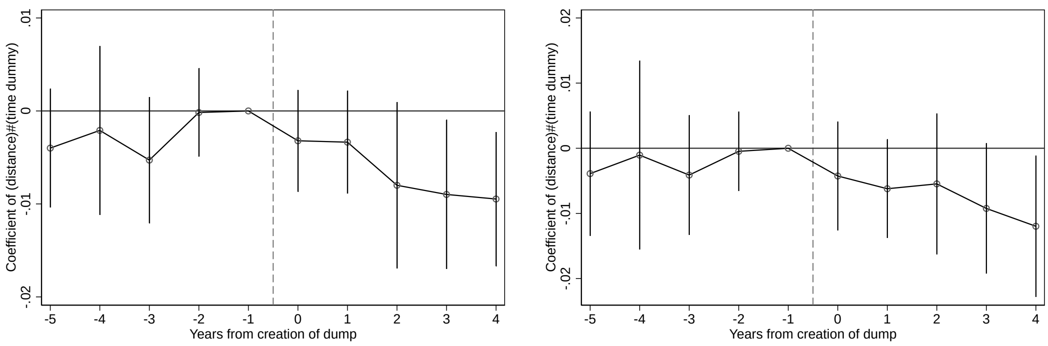
Standard errors (in parenthesis) are clustered at the DHS cluster level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%. Post is a dummy variable indicating a child was born after the creation of the dump site (For Ghana, t = 2001; for Nigeria, t = 2006). Children born between 5 years pre- and 5 years post are included in the analysis; for Ghana this is 1996-2006 and for Nigeria this is 2001-2011.

proximity of the site face greater chance of death than those living farther away. Results for individual dumps are shown in Figure A.3 and Figure A.4 of the Appendix and show consistent results for both countries.

Overall, evidence from estimates of equations (1) - (2) suggest that proximity to e-waste sites had a significantly negative impact on newborn and early life health, increasing the risk of mortality for those exposed to e-waste sites. This risk decreases with distance, and event-study analysis suggests the risk appears to emerge around 3 years after the creation of the e-waste sites. The effects are large, at around 10% of mean mortality in the sample. This is not unusual when we consider evidence from the wider literature on pollution and health. Most of the evidence on the effects of pollution on mortality focuses on intensity of exposure measured as unit reductions/increases in CO (Currie and Neidell, 2005), particulate matters (Knittel et al., 2016) or total suspended particles (Chay and Greenstone, 2003). For example, Alexander and Schwandt (2019) find that one additional emissions-cheating diesel car per 1,000 cars increases PM10 by 2.2 percent and led to a 1.7% increase in infant mortality in the US. In our case, the effect we find is the result of a large and sustained increase in the concentration of pollutants. While some pollutants are displaced, most are retained and have accumulated in the environment, in the soil, water and living things surrounding the area over the years. This is consistent with the effects materialising after 3 years from the creation of a dumping site. In what follows, we investigate these differing routes of exposure to pollution.

Figure 2: Event study for neonatal (left) and infant (right) mortality: intensity of treatment

(a) Neonatal mortality (b) Infant mortality



Authors' calculation based on the DHS data. Includes both e-waste sites. For consistency, we consider a common number of years (5) before and after the dump for both countries. The plots are created by a linear regression of mortality on a full set of event time indicators (years from dump) interacted with distance from the dump (in km) and controlling for country and birth year fixed effects. The vertical lines indicate 95% confidence intervals.

6 Underlying mechanisms

Our results point towards a substantial increase in mortality for children living in proximity of the two e-waste sites. Likely channels through which these sites can impact on child mortality include contamination of air, water and food (Grant et al., 2013). Such contamination has been investigated in the environmental and health literature, as described below. In this section, we aim at supplementing this literature using our data to provide evidence on the possible route of exposures that underlying our findings.

It is well documented that e-waste components are often inappropriately transported, stored or disposed of (Maphosa and Maphosa, 2020). Areas where components are discarded are frequently flooded by heavy rainfall or by the nearby river flooding, particularly in the case of Agbogbloshie, releasing hazardous chemicals (Brigden et al., 2008). The run-offs from dumping sites (known as lecheate) can reach local waterways and contaminate groundwater. Contaminated water is unlikely to be used directly for drinking as local residents largely rely on bottled water or water sachets, but can be used for cleaning and in the production of locally sourced crops and animal products. Of the two main sites we have considered above, the Agbogbloshie dump is the most studied in the medical and environmental literature. Studies have found evidence of increased levels of hazardous chemicals in the water, ground, as well as in human subjects. There is, for example, evidence of poisoning of the food chain, with eggs laid by free-range chickens from Agbogbloshie found to have elevated levels of hazardous chemicals; eggs sampled exceeded EU standards for some toxins by 171-fold (IPEN and BAN, 2019). Breast milk samples from women residing near Agbogbloshie have been found to contain abnormally high concentrations of PBDEs and similar contaminants (Daum et al., 2017).[21]

Whilst the Solous site has been less studied, evidence suggests that it has contributed to significant contamination of groundwater with excessively high levels of various heavy metals (Ofudje et al., 2014). These metals include Cadmium, which has been linked to adverse perinatal and neonatal outcomes (Grant et al., 2013). Lagos is a high-water table area, which increases the specific risk of contamination of water from the dumpsite (Osibanjo et al., 2017); this has led to nearby water that is unfit for human consumption (Adegun, 2013). Since the majority of the population of Lagos rely on boreholes and hand-dug wells for their water supply (Osibanjo et al., 2017), and evidence suggests that residents in the dump vicinity depend on groundwater as their source of domestic water supply (Balogun and Adegun, 2016),[22] such contamination may be a significant mechanism through which the health of individuals may be affected by proximity to the dumpsite.

To investigate water contamination, we first focus on the Agbogbloshie site where the Odaw river runs adjacent to the dumpsite and ends in the Korle Lagoon before entering the Gulf of Guinea; these water bodies form part of the major catchments in the Accra metropolis, and cover an area of $250km^2$ (Huang et al., 2014). Higher concentrations of copper, cadmium, lead, iron, and chromium have been found in the river (Huang et al., 2014), and significantly higher concentrations of PCBs have been found downstream from the waste site relative to upstream (Hosoda et al., 2014). Studies have found elevated levels of heavy metals and organic pollutants in the marine life, including fish, downstream and the city's coast (Bandowe et al., 2014; Hosoda et al., 2014). We can distinguish between children living upstream and downstream of the site.[23] In the analysis that follows, we restrict the treatment group to households living within 5 km

[21]Whilst it would be interesting to investigate whether breastfeeding is as a route of exposure, or whether, it acts as a protective measure, in our sample we have very little variation in breastfeeding status, with 95.9% of the entire sample having been ever breastfed. One might also wonder if women change their breastfeeding behaviour in response to perceived pollutants, as in Keskin et al. (2017). We investigated whether there were any effects of the dumpsites on breastfeeding behaviour, replacing mortality in equation 1 with an indicator for whether the child was ever breastfed. We found no effects, and no evidence of such behavioural changes. Results available on request.

[22]We confirm this using the DHS data; in our sample, 48% of individuals within 20 km of the dump use borewater or wells as their source of drinking water, with the remaining either using piped water (22%) or bottled/sachet water (22%). The DHS does not ask about sources of non-drinking water, but we may expect it to be significantly higher because people are unlikely to use bottled water for e.g. for cooking and bathing

[23]We cannot make use of the Solous site as there are no survey clusters located downstream of the nearest river, which runs at 1 kilometre from the site.

of the Odaw river. We then consider those living upstream and downstream as shown in Figure A.9 of the Appendix.[24] For this analysis we estimate both a difference in differences specification and event study, where the treatment group refers to downstream clusters, which are compared to upstream clusters. By comparing pre- and post-dump mortality rates for the two groups, we aim to provided suggestive evidence that the dumping site has increased mortality through increased water contamination. Note our assumption is that both groups are affected by the Agbogbloshie site, but we expect those living downstream to experience greater negative effects due to increased water contamination. One might argue that it is unlikely that many individuals drink directly from the water, since, due to water rationing and lack of piped water access, most citizens in the Accra area rely on sachet water for drinking (Stoler et al., 2012). However, due to price, households are unlikely to use such sachet water for other household activities such as cooking and bathing. A recent study in five slums in Accra, (Nima, Sabon Zongo, Chorkor, Jamestown, and Abokobi-Pantang) which includes slums both within our treatment area and downstream, found that groundwater was used for cooking (Ketadzo et al., 2021). Households who lack access to piped water may also lack access to personal bathing facilities; one study in Accra estimated that 18% of households who used sachets for drinking water used local rivers as their primary bathing facilities; a further 30% use 'open sources' (Stoler et al., 2012).

Any effects we find by comparing downstream vs. upstream households will reflect not only direct exposure to contaminated water via cooking and bathing, but also indirect exposure through contamination of urban crop and animal production. In later analysis, we investigate more closely this latter indirect route of exposure.

Results are shown in Table 3 while the event study is shown in Figure A.10 of the Appendix. Results show higher infant and neonatal mortality for children living downstream after the creating of the dumping site, although the coefficient is only statistically significant for neonatal mortality. The event study supports this analysis, and, although the coefficients are imprecisely estimated, they are suggestive of a greater impact for children living downstream, in particular for neonatal mortality. Overall, these results provide some (suggestive) evidence that one route of exposure is through contaminated water.

While the above analysis considers the specific case of contamination of the Odaw river, the mechanisms through which this may affect health are broad. One specific mechanism through which individuals may be affected is through contaminated water use in urban crop and animal production in both Ghana and Nigeria. In Ghana, urban

[24]To avoid the possibility of confounding downstream with distance to the dump, we exclude from the analysis clusters that are located more than 5 Km from the dump.

Table 3: The impact of dumping sites on newborn and infant health: downstream vs. upstream households

	(I) Neonatal Mortality	(II) Infant Mortality
Downstream	–0.043*	0.001
	(0.022)	(0.033)
Post × Downstream	0.109***	0.089
	(0.039)	(0.063)
Year of birth FE	Yes	Yes
Mean mortality	0.032	0.059
N	309	270

Standard errors (in parenthesis) are clustered at the DHS cluster level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%. Post is a dummy variable indicating a child was born after 2001. Downstream is a dummy variable for living downstream the river Odaw. Children born between 1996 (5 years pre) and 2006 (5 years post), and within 5 Km from the Agbogbloshie dump, are included in the analysis.

agriculture takes two main forms: backyard farming mostly for personal consumption and market-oriented open-space farming on larger plots (Lydecker and Drechsel, 2010). A study by Amoah et al. (2007), for example, finds contaminants in the lettuce produced at two urban cites in Ghana, one of which is located in our treatment area, downstream of the river Odaw. An estimated 90% of vegetables eaten in Accra are grown within the city, and urban agriculture depends primarily on untreated water for it's irrigation source (Keraita et al., 2008). Similarly, in Lagos, studies suggest that urban farming is fragmented, with smaller plots of land - frequently squatting rather than ownership or leasing of land (Lawal and Aliu, 2012) - utilising green disused space near roads and in the wetlands of Lagos, focusing on crops such as leafy vegetables and cassava, and small livestock such as poultry (Oludare et al., 2009; Lawal and Aliu, 2012). It is therefore inherently small scale and frequently no more than subsistence farming; one study found 70% of urban farmers in Lagos consumed their own produce in the household (Lawal and Aliu, 2012). In both study areas cattle, goats, and other small animals are raised for meat consumption and are likely to drink contaminated water.[25] In what follows, we investigate the effects of contaminated water through urban animal production.[26]

We compare mortality outcomes across clusters with different prevalence of urban animal farming. Unfortunately, information on household livestock holdings was not collected in earlier rounds of the Ghana or Nigeria datasets, therefore we determine

[25]This includes contaminated water transported from site to elsewhere but also, in the case of both dumping sites, livestock that grazes on the waste itself at the dumping sites (Alani et al., 2020; Daum et al., 2017).

[26]Whilst it would be of interest to investigate the effects of urban crop production, unfortunately data on this at the cluster level are not available.

the intensity of animal farming by using data from the Gridded Livestock of the World database (GLWD) (Robinson et al., 2014) which contains information on livestock density (heads of livestock per square kilometre) separately for sheep, goats, pigs, cattle and chicken at the cluster level.[27] GLWD data have been linked to DHS clusters via the DHS Spatial Covariate dataset.[28] We combine these measures of different types of livestock into an indicator variable *Livestock*, which equals one if the cluster livestock density measure is greater than zero for at least one type of livestock. In the 20km region around the dumpsite, 18.72% of clusters are classified as having livestock, whilst within the areas within 5 km of the dumping sites, 16.5% of clusters are classified as having livestock.

Results are shown in Table 4. Columns (I) and (II) show results when we simply add an indicator for livestock and it's interaction with *Post* in our analysis. We find no rise in mortality in livestock within the 20km zone around the dumpsites in the post dumpsite period. Columns (III) and (IV) however extend this specification to allow for variation by distance from the dumpsite in a triple difference framework which includes the interaction between an indicator for post-dump, an indicator for livestock, and distance from the dumpsite. We now find that households in higher-density livestock experience higher neonatal (infant) mortality after the creation of the dump, than those in areas without livestock. This effect, however, declines with distance from the site, with a negative and statistically significant effect on the triple interaction term. Thus, the mortality increases we observe in the post-dump period in livestock areas appear to be strongest in households near to the dump as opposed to far.

Due to the complexity of modelling a triple difference interaction in an event study framework, for simplicity we focus on areas within 5km of the sites and consider the effect of $Post \times Livestock$ (Appendix Table A.11). We see a clear jump in mortality for those living in areas with higher prevalence of livestock, after two years from the creation of the dump. This is again consistent with the gradual accumulation of contaminants in the surrounding environment.

Taken together these two sets of results suggest that contamination of water - both river and groundwater - by pollutants from the dump sites, contributes to the effect we find, through not only direct exposure to water through cooking and bathing but also through locally sourced farm products.

The widespread practice of burning plastic and cable coverings from electronic equip-

[27]Since data on household livestock holdings is available in the 2008 survey for Ghana, we have confirmed that households with livestock are more likely to be based in clusters with higher livestock density according to the GLWD.

[28]The measure reported in the Spatial Covariate dataset is the average livestock density within 2 km of clusters. Livestock density is calculated as within 10 km for rural clusters, but note that 96% the clusters in our sample are classified as urban. See the DHS Program Geospatial Covariate Datasets Manual (Mayala et al., 2018) for more detail and information.

Table 4: The impact of dumping sites on newborn and infant health through urban farming

	(I) Neonatal Mortality	(II) Infant Mortality	(III) Neonatal Mortality	(IV) Infant Mortality
Post × Distance (km)	–0.004***	–0.005**	–0.001	–0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Post × Livestock	0.022	0.021	0.140***	0.161***
	(0.015)	(0.021)	(0.029)	(0.056)
Post × Livestock × Distance (km)			–0.011***	–0.013***
			(0.003)	(0.004)
Livestock	–0.015	–0.012	–0.014	0.030
	(0.010)	(0.012)	(0.018)	(0.032)
Distance (km)	0.002	0.003**	0.002	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance (km) × Livestock			–0.000	–0.004
			(0.002)	(0.003)
Mean	0.036	0.056	0.248	0.250
N	3359	3094	3359	3094

Standard errors (in parenthesis) are clustered at the DHS cluster level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%. Regressions include only clusters within 5 km from the dumping site. Post is a dummy variable indicating a child was born after the creation of the dump. Livestock is a dummy variable for being in a cluster with livestock density greater than 0. Children born between 5 years pre- and 5 years post are included in the analysis; for Ghana this is 1996-2006 and for Nigeria this is 2001-2011.

ment in open grounds releases toxins and other dangerous compounds (Mudge et al., 2019), which can have damaging effects on adults and children health. For the Agbogbloshie site, for example, Kwarteng et al. (2020) finds exceptionally high concentrations of particulate matters attributed to burning of e-waste. Similarly, at the Solous site in Lagos, fires have been reported to smoulder from weeks to months at a time (Aderemi and Falade, 2012). Airborne particulate matter are vectors for contaminant and have the potential for long-range transport. Yet, most of the empirical evidence focuses on on-site measurements, while less is known about the effects on the surrounding communities. A few recent studies based on the Agbogbloshie site find evidence of e-waste related airborne contaminants in upwind areas (East and North-East) at 2 km from the edge of cite (Fujimori et al. (2016), Kwarteng et al. (2020)). Unfortunately, we are unable to provide additional empirical evidence on this mechanism, given the lack of sufficiently detailed data on air pollution. Ground level monitoring of ambient air quality is still very limited, and satellite-based data, for the period of the analysis, are not available at a sufficient level of spatial desegregation to allow us to disentangle variations in urban air quality.[29]

[29]Ambient air monitoring in Accra started in few sites around 2006. As of 2019, there are no operational air quality monitoring stations in Lagos.

7 Robustness checks

The results presented so far suggest that exposure to an e-waste dumping site causes an increase in both neonatal and infant mortality. In this section we provide further support to our results by providing a set of robustness checks with the aim of a) controlling for potential confounding effects, b) investigating alternative samples and c) considering whether alternative explanations other than the presence of e-waste sites might drive our results.

7.1 Inclusion of additional controls

Though we find limited evidence of differences in compositions of births between areas (see section 3), we investigate the robustness of our results to the inclusion of a set of additional control variables. These include a vector of control variables at both child and household level, as well as country (i.e. dump-specific) time trends. We include urban status, mother's age at birth, mother and father's educational level, mother age at birth, the child's gender and whether the birth was a multiple birth.[30]

There are two other concerns with regard to the locations of the dumpsites. The first is potential endogenous selection of dumpsite location, with the decision to locate a dumping site in a particular location being determined by characteristics of the surrounding area, where such characteristics also affect mortality. This would violate our identification assumption that there are no time-varying or cluster-specific effects correlated with the dump site location that also determine mortality. Our estimate could then confound the effect of the dump with changes in other characteristics of the area that also affect mortality. The second concern might be that our estimates may simply be picking up differences in peri-urban areas over time, particularly in the case of Accra where the observations closest to the site are in the city and the observations further away are more sub-urban.[31]

To address these concerns, we investigate the inclusion of interactions between cohort dummies and variables that capture urbanisation extent and local economic activity at the cluster level prior to the existence of the dump sites. This allows for differential variation in our outcome variable based on pre-existing differences between the characteristics of

[30] Father's education level is not available for the Nigeria MIS-DHS surveys, so that these surveys are not included in this analysis. Our results are robust to dropping controls for father's education and including MIS-DHS surveys in the following robustness checks (results available on request). The DHS data collects information on the wealth index of households, but we do not include this in our vector of household controls since it may be affected by the presence of the dumping sites and therefore a "bad control".

[31] Note that this is less of a concern for Nigeria since the dumpsite itself is located in a peri-urban area outside of the centre of Lagos city.

our clusters.

To capture urbanisation extent, we use data provided in the DHS spatial co-variates file on the built-up index of a cluster.[32] For local economic activity, we use nightlight data as a proxy for local economic activity, sourced from the National Oceanic and Atmospheric Administration (NOAA).[33] Figures A.5 and A.6 show variation in nightlight data in 1995, 2000, 2005 and 2010 for Ghana and Nigeria and demonstrate that, over the time period we consider, both areas have become more developed, with increases in nightlight intensity. They also show that, in 1995, areas nearer the dump sites were those where more economic activity was observed. We therefore calculate the average 1995 nightlight value for the area within the 2 km buffer of our clusters, and include this in the analysis.[34]

Our results are robust to the inclusion of additional control variables, and to the interaction of cohort dummies with built-up extent in 1990 and local economic activity in 1995 (Table A.5). Our main coefficients of interest remain similar in magnitude and precision across all the proposed specifications. We also use the same controls to implement the Doubly Robust (DR) estimator proposed by Callaway and Sant'Anna (2021) using a binary treatment indicating whether a household lives within 5 Km from the site.[35] This approach combines the outcome regression approach (Heckman et al., 1997) and the propensity score weighting approach (Abadie, 2005) to estimate the causal effect of exposure, conditional on pre-treatment covariates. Results are shown in Figure A.12 and confirm the absence of pre-trends and provide average treatment estimates of comparable magnitudes to our main findings for this specification as presented in Figure A.2.

7.2 Slum and location effects in Ghana

Related to the issues discussed above, in the case of the Agbogbloshie site in Ghana, an additional concern is that the estimated effect of the dumping site could be confounded by its proximity to slum areas, which are characterised by poorer living conditions. It could be argued that the location of the dumping site coincide with a high densely populated area, while farther away households are located in suburban and less densely

[32]This is an index ranging from 0 (extremely rural) to 1 (extremely urban) for the area within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster location. In our sample, just 7 of the 180 clusters are classified as rural by the DHS. It is available for either 1990 or 2000, and we use 1990, which is prior to both the Ghanaian and Nigerian sample time frames.

[33]We use the DMSP-OLS Nighttime Lights Time Series which is available from 1992-2013. This has been used by a number of recent studies to consider economic activity at a localised level; see Donaldson and Storeygard (2016) for a discussion of the uses of this data in economics.

[34]Average nightlight values within the 2 km buffer were calculated by the Authors in ArcGIS Pro, through overlaying the gridded nightlights data over the cluster locations and computing zonal statistics within 2 km buffers of the cluster points.

[35]We use this binary treatment since it is currently not possible to implement the DR estimator in the case of a continuous treatment as in our main specification.

populated areas. The Agbogbloshie site is located near three major slum areas (Figure A.7). In particular, it is contiguous to one of the largest slums in Accra: Old Fadama, also known as Sodom and Gomorrah. This slum area was estimated to host about 30,000 residents in 2004 and is classified as one of the four major extralegal settlements in Ghana (Oppong et al. (2020), Paller (2015)).[36] While we are not aware of specific interventions or shocks affecting the livelihood of slum residents during the period of analysis, we are still concerned about the possible confounding effects of deteriorating living conditions in the slum areas surrounding the site. Indeed, evidence suggests that the health of children living in slums is poorer than that of other urban children (Fink et al., 2014).

Table 5: Placebo analysis: Adoabo slum

	(I) Neonatal Infant	(II) Mortality Mortality
Distance (km)	–0.003**	–0.004**
	(0.001)	(0.002)
Post × Distance (km)	0.002	0.001
	(0.002)	(0.004)
Year of birth FE	Yes	Yes
Mean mortality	0.042	0.071
N	755	691

Standard errors (in parenthesis) are clustered at the DHS cluster level. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$. Post is a dummy variable indicating a child was born after 2001. Distance is measured from the Adoabo slum. Children born between 1996 (5 years pre) and 2006 (5 years post) are included in the analysis.

To investigate whether the effects we find for the Agbogbloshie site in Ghana might reflect location-related effects, we estimate a placebo regression using a similar-size slum area in Kumasi, the second-largest city in Ghana. The Aboabo settlement in Kumasi is an extralegal slum that hosted about 34,000 residents in 2000 (Dakpallah, 2011) and is also located within a high densely populated urban centre. Figure A.8 shows the location of the DHS clusters used in the placebo analysis. We re-estimate equation 1, using distance from the centre of the Adoabo slum as a placebo treatment, but maintain the treatment year as 2001. Table 5 shows the results. Whilst mortality is higher in general for households closer to the slum (and declines with distance from the slum), there is no differential effect in the post e-waste site period. Thus, results from this placebo analysis exclude the possibility that changes that might have occurred in slums

[36] Settlements in Ghana can be classified according to three types: indigenous (landlords are indigenous and local customs dominate local politics), purchased (when neighbourhoods formed historically when settlers purchased plots of land from authorities), and extralegal. Only indigenous settlements are recognised by the government, and extralegal settlements in particular are associated with poor quality housing such as shacks and kiosks (Paller, 2015).

or in high densely populated urban centres in Ghana at the time the e-waste site was established are driving our main results. We do not conduct a similar analysis for Nigeria as the site is located in the outskirts of Lagos and major slums are located near Lagos Mainland, which is located about 15 Km from the dumping site, and so do not pose threats to our identification strategy.

7.3 Residential sorting and employment effects of the dump

We next focus on two concerns regarding potential changes to the characteristics of households before and after dump creation that may affect our estimated results. The first concern is that of the potential residential sorting induced by the creation of the dump i.e. the possibility that families in relatively worse/better health conditions have been attracted or displaced by the creation of the dump. The second concern is that the dumpsites may have changed the employment prospects of households nearby so that there may be possible mitigating effects of dumpsite creation if it leads to higher income amongst households, which may itself lead to dump-induced migration.

As described in section 3, our sample of women is drawn from surveys carried out in Ghana between the years 1998-2008, whilst for Nigeria we have surveys from 2003-2013. Thus, we observe women interviewed before and after the e-waste sites were established. To investigate whether changes in the composition of households before and after dump sites drives our results, we proceed in two ways. First, we focus on the individual (woman) level data, as opposed to the child (birth level) data, and regress household characteristics (Z) on treatment indicators as follows:

$$Z_{ijs} = \delta DIST_{ij} + \eta Post_s \times DIST_{ij} + \nu_s + \theta_d + \epsilon_{ijs} \tag{3}$$

Here, $Post_s$ is an indicator equal to one if a woman interviewed in survey round s was interviewed after the e-waste site was established. Thus we compare characteristics of women before and after e-waste site creation in areas near and far from the sites.

Our second approach to investigating potential residential sorting is to re-consider the child level data and estimate equation 1 for non-migrant families only, as well as investigating the inclusion of mother-fixed effects in the analysis.

Table A.6 reports results from estimating equation 3 for a range of demographic indicators including education and employment of both the woman and her spouse. For spousal indicators, the sample size is smaller due to this not always being collected in the surveys. Country-specific estimates are given in tables A.7 and A.8. There is very little evidence of changes in the composition of households living near as opposed to far (as measured by distance in km) to e-waste sites either before or after the e-waste sites were opened.[37] Of interest is the fact that employment rates do not seem to be affected by the dumpsite creation.[38]

Nonetheless, to further address any concerns regarding residential sorting we re-estimate equation 1, by restricting the sample to non-migrant households, i.e. households that were living in the same location prior to the creation of the dumping site, hence excluding possible inward migrants. We are only able to do this for Ghana since residency information is not collected in the 2010 or 2013 surveys for Nigeria.[39] From our original sample, we lose 2,554 observations due to dropping Nigeria from the analysis, and a further 268 by removing inward migrants, who make up 33.3% of our original Ghana sample. As we might expect, the majority (198) of observations that we lose occurs in the 2008 survey, since our restriction here implies that they must have been living in the area since 2000 (8 years). Regression results are given in Table 6, and the event study analysis is presented in Figure 3. These results confirm our previous findings and indicate a negative effect of the Agbogbloshie dump site on infant mortality for non-migrant households. The effects for non-migrants (column (IV)) are even larger when compared to the full Ghanaian sample (column (III)).

Table 6: The impact of dumping sites on newborn and infant health: non-migrants only, Ghana

	(I)	(II)	(III)	(IV)
	Neonatal Mortality		Infant Mortality	
	All	Non-migrants	All	Non-migrants
Distance (km)	0.001	–0.001	0.002**	0.001
	(0.000)	(0.002)	(0.001)	(0.003)
Post × Distance (km)	–0.004***	–0.003	–0.007***	–0.011**
	(0.001)	(0.003)	(0.001)	(0.005)
Year of Birth FE	Yes	Yes	Yes	Yes
Mean mortality	0.030	0.028	0.051	0.049
N	805	537	727	469

Standard errors (in parenthesis) are clustered at DHS cluster level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Post is a dummy variable indicating a child was born after the creation of the Agbogbloshie site (t = 2001). Children born between 1996 (5 years pre) and 2006 (5 years post) are included in the analysis. Non-migrants refers to the restricted sample where the mother has been resident in the household prior to the creation of the Agbogbloshie dump site.

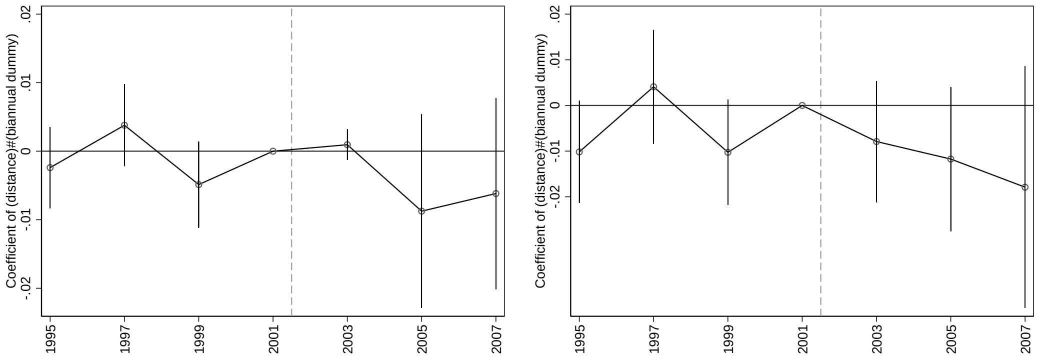
[37] The one exception is the proportion of spouses with no education, which falls with distance prior to dumpsites being created and rises with distance afterwards. This would imply that, if anything, spousal education improved nearer dumpsites after their creation, so that it cannot explain our results. This statistically significant effect is only found in the pooled sample, and not in the country-specific regressions.

[38] Note that we only look at female employment rates here, because spousal employment is missing for nearly 70% of observations.

[39] Although residency information is collected in 2008, this only gives us information on deaths in the 1-2 year period post dump.

Figure 3: Event studies for neonatal (left) and infant (right) mortality: non-migrant households (Ghana only)

(a) Neonatal: distance from dump (b) Infant: distance from dump



Authors' calculation based on the DHS data for Ghana. Biannual time indicators are used due to small sample sizes to increase precision, and children born 6 years after dump creation are included in the analysis. Results are obtained by interacting the biannual time indicator with distance from the dump (in Km). The vertical lines indicate 95% confidence interval.

Next, we re-estimate equation (1) for non-migrants, and include mother fixed effects, to compare outcomes between siblings born before and after the creation of the Agbogbloshie e-waste site. Compared to the results in Table 6, the coefficients for infant mortality are of larger magnitude: one additional kilometre from the dump decreases infant mortality by 15 deaths per 1,000 births (Table 7). When we consider neonatal mortality however, we do not find evidence of statistically significant differences between children born to the same mothers before and after the e-waste site creation.

Overall, taken together, tables A.6-A.8, 6 and 7 suggest that residential sorting arising as a result of the establishment of the dump sites does not drive our main results.

8 Conclusions

This paper estimates the health impacts of e-waste dumping sites on newborn and infant health in Ghana and Nigeria, which are major hubs in terms of trade and disposal of e-waste (Schluep et al., 2011). We find that proximity to an e-waste site increases neonatal and infant mortality. One additional kilometre from the dumping site decreases neonatal mortality by 6 deaths per 1,000 births and infant mortality by 7 deaths per 1,000 births. These effects are large relative to the mean, and reflect sharp observed increases in mortality in communities near to e-waste sites in the post-site period. We continue to find negative effects on health when we restrict the analysis to non-migrants, and when we consider sibling fixed effects, but data restrictions lead to substantial losses in sample size

Table 7: The impact of dumping sites on newborn and infant health: mother FE, non-migrants only

	(I) Neonatal Mortality	(II) Infant Mortality
Post × Distance (km)	–0.002	–0.015**
	(0.004)	(0.007)
Mother FE	Yes	Yes
Year of Birth FE	Yes	Yes
Mean Mortality	0.027	0.046
N	521	455

Standard errors (in parenthesis) are clustered at mother level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Post is a dummy variable indicating a child was born after the creation of the Agbogbloshie site (t = 2001). Children born between 1996 (5 years pre) and 2006 (5 years post) are included in the analysis. Non-migrants refers to the restricted sample where the mother has been resident in the household prior to the creation of the Agbogbloshie dump site.

which affect our ability to precisely estimate effects in these specifications. Additional evidence is suggestive of contamination of water and of locally sourced farm products as possible routes of exposure. Air pollution caused by the burning of plastic and other components is also another possible mechanism, although the lack of data prevent us from directly testing this hypothesis on our sample.

Our work has implications for the appropriate management of e-waste dumping sites, in a context in which there is growing concern about both the illegal flow of e-waste, and the export of near end of life electronics, which end up soon discarded in the destination country. Our results reveal the catastrophic impacts that the inappropriate management of e-waste has had on local communities and highlight the importance of growing efforts to re-visit and strengthen the rules on the trade and management of e-waste.

References

Abadie, A. (2005), 'Semiparametric difference-in-differences estimators', *The Review of Economic Studies* **72**(1), 1–19.

Adegun, O. (2013), 'Variation of leachate characteristics from selected dumpsites in Lagos, Nigeria', *Journal of Applied Sciences in Environmental Sanitation* **8**(4).

Aderemi, A. and Falade, T. (2012), 'Environmental and health concerns associated with the open dumping of municipal solid waste: A lagos, Nigeria experience', *American journal of environmental engineering* **2**(6), 160–165.

Alani, R., Ogunbanmwo, A., Nwude, D. and Ogbaje, M. (2020), 'Evaluation of the environmental impacts of electronic-waste management in lagos using alaba international market and ikeja computer village as case studies', *Evaluation* **4**(2), 283–297.

Alexander, D. and Schwandt, H. (2019), 'The impact of car pollution on infant and child health: Evidence from emissions cheating'.

Amoah, P., Drechsel, P., Henseler, M. and Abaidoo, R. (2007), 'Irrigated urban vegetable production in ghana: microbiological contamination in farms and markets and associated consumer risk groups', *Journal of water and health* **5**(3), 455–466.

Andrews, A. (2009), 'Beyond the ban-can the basel convention adequately safeguard the interests of the world's poor in the international trade of hazardous waste', *Law Env't & Dev. J.* **5**, 167.

Arceo, E., Hanna, R. and Oliva, P. (2012), 'Does the effect of pollution on infant mortality differ between developing and developed countries? evidence from Mexico City', *The Economic Journal* **126**(591), 257–280.

Bakhiyi, B., Gravel, S., Ceballos, D., Flynn, M. A. and Zayed, J. (2018), 'Has the question of e-waste opened a pandora's box? an overview of unpredictable issues and challenges', *Environment international* **110**, 173–192.

Balogun, I. and Adegun, B. (2016), 'Variability of groundwater quality around selected dumpsites in the lagos metropolis', *Ife Research Publications in Geography* **11**(1), 42–51.

Bandowe, B. A. M., Bigalke, M., Boamah, L., Nyarko, E., Saalia, F. K. and Wilcke, W. (2014), 'Polycyclic aromatic compounds (pahs and oxygenated pahs) and trace metals in fish species from ghana (west africa): bioaccumulation and health risk assessment', *Environment international* **65**, 135–146.

Bergman, Å., Heindel, J. J., Jobling, S., Kidd, K., Zoeller, T. R., Organization, W. H. et al. (2013), *State of the science of endocrine disrupting chemicals 2012*, World Health Organization.

Bernhardt, A. and Gysi, N. (2013), 'The world's worst 2013: The top ten toxic threats', *Blacksmith Institute and Green Cross Switzerland* .

Brigden, K., Labunska, I., Santillo, D. and Johnston, P. (2008), 'Chemical contamination at e-waste recycling and disposal sites in accra and korforidua, ghana'.

Callaway, B. and Sant'Anna, P. H. (2021), 'Difference-in-differences with multiple time periods', *Journal of Econometrics* **225**(2), 200–230.

Chay, K. Y. and Greenstone, M. (2003), 'The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession', *The quarterly journal of economics* **118**(3), 1121–1167.

Chen, A., Dietrich, K. N., Huo, X. and Ho, S.-m. (2010), 'Developmental neurotoxicants in e-waste: an emerging health concern', *Environmental health perspectives* **119**(4), 431–438.

Currie, J., Greenstone, M. and Moretti, E. (2011), 'Superfund cleanups and infant health', *American Economic Review* **101**(3), 435–41.

Currie, J. and Neidell, M. (2005), 'Air pollution and infant health: what can we learn from california's recent experience?', *The Quarterly Journal of Economics* **120**(3), 1003–1030.

Currie, J., Neidell, M. and Schmieder, J. F. (2009), 'Air pollution and infant health: Lessons from new jersey', *Journal of Health Economics* **28**(3), 688 – 703.

Currie, J. and Walker, R. (2011), 'Traffic congestion and infant health: Evidence from e-zpass', *American Economic Journal: Applied Economics* **3**(1), 65–90.

Currie, J., Zivin, J. G., Mullins, J. and Neidell, M. (2014), 'What do we know about short- and long-term effects of early-life exposure to pollution?', *Annual Review of Resource Economics* **6**(1), 217–247.

Dakpallah, T. A. G. (2011), Slum improvement in Ghana: The study of Aboabo and Asawase in Kumasi, PhD thesis, Kwame Nkrumah University of Science and Technology, Kumasi.

Daum, K., Stoler, J. and Grant, R. J. (2017), 'Toward a more sustainable trajectory for e-waste policy: a review of a decade of e-waste research in accra, ghana', *International journal of environmental research and public health* **14**(2), 135.

Davis, J.-M., Akese, G. and Garb, Y. (2019), 'Beyond the pollution haven hypothesis: Where and why do e-waste hubs emerge and what does this mean for policies and interventions?', *Geoforum* **98**, 36–45.

Donaldson, D. and Storeygard, A. (2016), 'The view from above: Applications of satellite data in economics', *Journal of Economic Perspectives* **30**(4), 171–98.

Fink, G., Günther, I. and Hill, K. (2014), 'Slum residence and child health in developing countries', *Demography* **51**(4), 1175–1197.

Forti, V., Balde, C. P., Kuehr, R. and Bel, G. (2020), 'The global e-waste monitor 2020: Quantities, flows and the circular economy potential'.

Forti, V., Baldé, K. and Kuehr, R. (2018), 'E-waste statistics: Guidelines on classifications, reporting and indicators'.

Fujimori, T., Itai, T., Goto, A., Asante, K. A., Otsuka, M., Takahashi, S. and Tanabe, S. (2016), 'Interplay of metals and bromine with dioxin-related compounds concentrated in e-waste open burning soil from agbogbloshie in accra, Ghana', *Environmental Pollution* **209**, 155–163.

Gennaioli, C. and Narciso, G. (2017), Toxic roads: Unearthing hazardous waste dumping, CGR Working Papers 82, Queen Mary, University of London, School of Business and Management, Centre for Globatlisation Research.

Goodman-Bacon, A. (2021), 'Difference-in-differences with variation in treatment timing', *Journal of Econometrics* .

Grant, K., Goldizen, F. C., Sly, P. D., Brune, M.-N., Neira, M., van den Berg, M. and Norman, R. E. (2013), 'Health consequences of exposure to e-waste: a systematic review', *The lancet global health* **1**(6), e350–e361.

Grant, R. and Oteng-Ababio, M. (2012), 'Mapping the invisible and real African economy: urban e-waste circuitry', *Urban Geography* **33**(1), 1–21.

Greenstone, M. and Hanna, R. (2014), 'Environmental regulations, air and water pollution, and infant mortality in India', *American Economic Review* **104**(10), 3038–72.

He, G. and Perloff, J. M. (2016), 'Surface water quality and infant mortality in China', *Economic Development and Cultural Change* **65**(1), 119–139.

Heacock, M., Kelly, C. B., Asante, K. A., Birnbaum, L. S., Bergman, Å. L., Bruné, M.-N., Buka, I., Carpenter, D. O., Chen, A., Huo, X. et al. (2016), 'E-waste and harm to vulnerable populations: a growing global problem', *Environmental health perspectives* **124**(5), 550–555.

Heckman, J. J., Ichimura, H. and Todd, P. E. (1997), 'Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme', *The review of economic studies* **64**(4), 605–654.

Hosoda, J., Ofosu-Anim, J., Sabi, E. B., Akita, L. G., Onwona-Agyeman, S., Yamashita, R. and Takada, H. (2014), 'Monitoring of organic micropollutants in ghana by combination of pellet watch with sediment analysis: E-waste as a source of pcbs', *Marine pollution bulletin* **86**(1-2), 575–581.

Huang, J., Nkrumah, P. N., Anim, D. O. and Mensah, E. (2014), E-waste disposal effects on the aquatic environment: Accra, ghana, *in* 'Reviews of environmental contamination and toxicology', Springer, pp. 19–34.

Ife-Adediran, O. and Isabota, O. (2018), 'Gamma dose profile and risk to scavengers and occupants near waste dumpsites in coastal Nigeria', *International Journal of Environmental Studies* **75**(5), 708–718.

ILO (2019), Decent work in the management of electrical and electronic waste (e-waste), Issues paper for the global dialogue forum on decent work in the management of electrical and electronic waste (e-waste) (geneva, 9-11 april 2019), International Labour Office, Sectoral Policies Department, Geneva, ILO, 2019.

IPEN and BAN (2019), 'Weak controls: European e-waste poisons Africa's food chain'.

Jayachandran, S. (2009), 'Air quality and early-life mortality: Evidence from Indonesia's wildfires', *The Journal of Human Resources* **44**(4), 916–954.

Kellenberg, D. (2010), 'Consumer waste, backhauling, and pollution havens', *Journal of Applied Economics* **13**(2), 283–304.

Keraita, B., Drechsel, P. and Konradsen, F. (2008), 'Perceptions of farmers on health risks and risk reduction measures in wastewater-irrigated urban vegetable farming in ghana', *Journal of Risk Research* **11**(8), 1047–1061.

Keskin, P., Shastry, G. K. and Willis, H. (2017), 'Water quality awareness and breast-feeding: Evidence of health behavior change in bangladesh', *Review of Economics and Statistics* **99**(2), 265–280.

Ketadzo, J. A., Nkongolo, N. V. and Akrofi, M. M. (2021), 'Empirical analysis of the impact of urbanization on groundwater quality within the slums of accra, ghana', *World Water Policy* **7**(1), 112–131.

Kitt, J. R. (1994), 'Waste exports to the developing world: A global response', *Geo. Int'l Envtl. L. Rev.* **7**, 485.

Knittel, C. R., Miller, D. L. and Sanders, N. J. (2016), 'Caution, drivers! children present: Traffic, pollution, and infant health', *Review of Economics and Statistics* **98**(2), 350–366.

Krueger, J. (1998), 'Prior informed consent and the basel convention: the hazards of what isn't known', *The Journal of Environment & Development* **7**(2), 115–137.

Kwarteng, L., Baiden, E. A., Fobil, J., Arko-Mensah, J., Robins, T. and Batterman, S. (2020), 'Air quality impacts at an e-waste site in ghana using flexible, moderate-cost and quality-assured measurements', *GeoHealth* **4**(8), e2020GH000247.

Lawal, M. O. and Aliu, I. R. (2012), 'Operational pattern and contribution of urban farming in an emerging megacity: evidence from Lagos, Nigeria', *Bulletin of Geography. Socio-economic series* (17), 87–97.

Lepawsky, J. and McNabb, C. (2010), 'Mapping international flows of electronic waste', *The Canadian Geographer/Le Géographe canadien* **54**(2), 177–195.

Lucier, C. A. and Gareau, B. J. (2016), 'Obstacles to preserving precaution and equity in global hazardous waste regulation: an analysis of contested knowledge in the basel convention', *International Environmental Agreements: Politics, Law and Economics* **16**(4), 493–508.

Luechinger, S. (2014), 'Air pollution and infant mortality: a natural experiment from power plant desulfurization', *Journal of health economics* **37**, 219–231.

Lundgren, K. (2012), *The global impact of e-waste: addressing the challenge*, International Labour Organization.

Lydecker, M. and Drechsel, P. (2010), 'Urban agriculture and sanitation services in accra, ghana: the overlooked contribution', *International Journal of Agricultural Sustainability* **8**(1-2), 94–103.

Manhart, A., Osibanjo, O., Aderinto, A. and Prakash, S. (2011), 'Informal e-waste management in Lagos, Nigeria. Socio-economic impacts and feasibility of international recycling co-operations', *Final report of component* **3**, 1–129.

Maphosa, V. and Maphosa, M. (2020), 'E-waste management in sub-saharan Africa: A systematic literature review', *Cogent Business & Management* **7**(1), 1814503.

Mayala, B., Fish, T. D., Eitelberg, D. and Dontamsetti, T. (2018), *The DHS program geospatial covariate datasets manual*, ICF, Rockville, Maryland, USA.

Mudge, S. M., Pfaffhuber, K. A., Fobil, J. N., Bouman, E. A., Uggerud, H. T. and Thorne, R. J. (2019), 'Using elemental analyses and multivariate statistics to identify the off-site dispersion from informal e-waste processing', *Environmental Science: Processes & Impacts* **21**(12), 2042–2057.

Ofudje, E., Alayande, S., Oladipo, G., Williams, O. and Akiode, O. (2014), 'Heavy metals concentration at electronic-waste dismantling sites and dumpsites in lagos, nigeria', *International Research Journal of Pure and Applied Chemistry* pp. 678–690.

Ogunseitan, O. A. (2013), 'The basel convention and e-waste: translation of scientific uncertainty to protective policy', *The Lancet Global Health* **1**(6), e313–e314.

Oludare, H. et al. (2009), 'Urban agriculture and urban land use planning: Need for a synthesis in metropolitan Lagos, Nigeria', *Journal of Geography and Regional planning* **2**(3), 043–050.

Oppong, B. E., Asomani-Boateng, R. and Fricano, R. J. (2020), 'Accra's Old Fadama/Agbogbloshie settlement. to what extent is this slum sustainable?', *African Geographical Review* pp. 1–19.

Osibanjo, O., Adeyi, A. A. and Majolagbe, A. O. (2017), 'Characterisation of groundwater quality around soluos dumpsite in Lagos, Nigeria', *International Journal of Water* **11**(1), 44–58.

Paller, J. W. (2015), 'Informal networks and access to power to obtain housing in urban slums in Ghana', *Africa Today* **62**(1), 31–55.

Pronczuk-Garbino, J. et al. (2007), 'Children's health and the environment. a global perspective', *Int J Public Health* **52**, 67–68.

Robinson, T. P., Wint, G. W., Conchedda, G., Van Boeckel, T. P., Ercoli, V., Palamara, E., Cinardi, G., D'Aietti, L., Hay, S. I. and Gilbert, M. (2014), 'Mapping the global distribution of livestock', *PloS one* **9**(5), e96084.

Schluep, M., Manhart, A., Osibanjo, O., Rochat, D., Isarin, N. and Mueller, E. (2011), Where are weee in Africa? findings from the basel convention e-waste Africa programme, *in* 'Published by the Secretariat of the Basel Convention'.

Stoler, J., Fink, G., Weeks, J. R., Otoo, R. A., Ampofo, J. A. and Hill, A. G. (2012), 'When urban taps run dry: Sachet water consumption and health effects in low income neighborhoods of accra, ghana', *Health & place* **18**(2), 250–262.

Tanaka, S. (2015), 'Environmental regulations on air pollution in China and their impact on infant mortality', *Journal of Health Economics* **42**, 90 – 103.

UNEP (1989), Basel convention on the control of transboundary movements of hazardous wastes and their disposal, Technical report, UNEP.

UNEP, P., ITU, I. and UNIDO, U. (2019), 'A new circular vision for electronics time for a global reboot'.

von der Goltz, J. and Barnwal, P. (2019), 'Mines: The local wealth and health effects of mineral mining in developing countries', *Journal of Development Economics* **139**, 1–16.

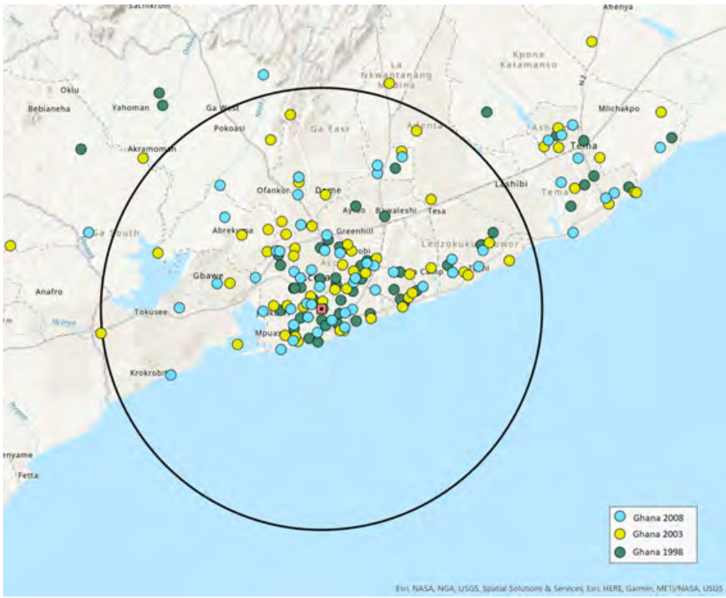
Wang, Y., Tian, Z., Zhu, H., Cheng, Z., Kang, M., Luo, C., Li, J. and Zhang, G. (2012), 'Polycyclic aromatic hydrocarbons (pahs) in soils and vegetation near an e-waste recycling site in south China: concentration, distribution, source, and risk assessment', *Science of the Total Environment* **439**, 187–193.

Waste Atlas Partnership (2014), 'The world's 50 biggest dumpsites'.

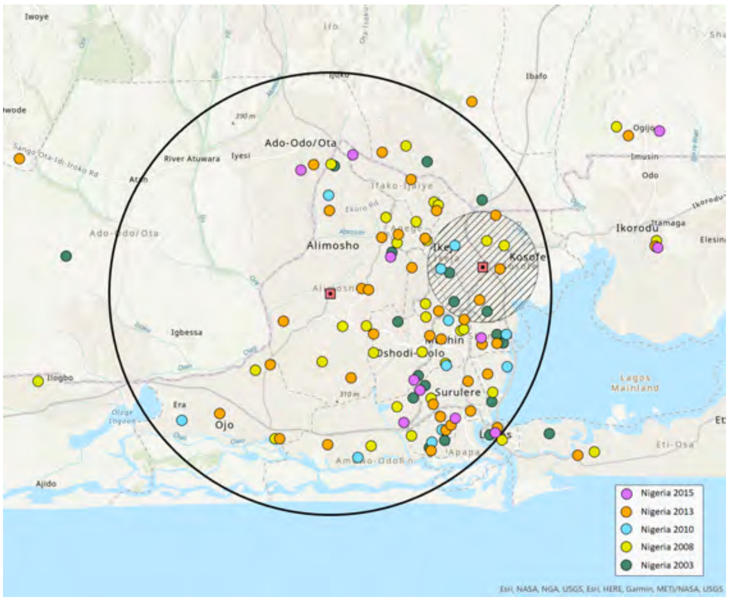
Appendix

Figure A.1: Dumping sites and households location

(a) Ghana



(b) Nigeria

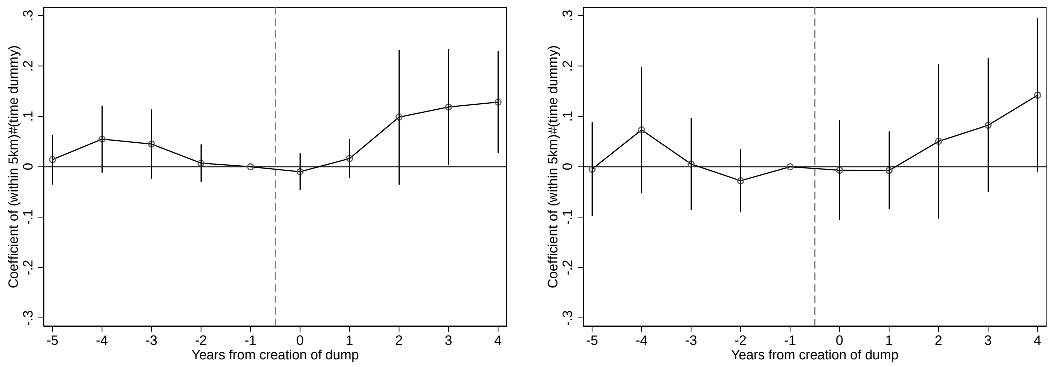


Maps plotting DHS data for Ghana and Nigeria. Dots represent DHS clusters and are colour coded for survey year. Dumpsite locations are given by the squared points. The black buffer represents 20km from the sites and inclusion into our sample. The hatched buffer area in Nigeria shows the existence of the older dump known as Olusoshun, not included in the analysis, and all clusters within this 5km buffer are excluded from our analysis.

Figure A.2: Event study for neonatal (left) and infant (right) mortality: binary treatment

(a) Neonatal mortality

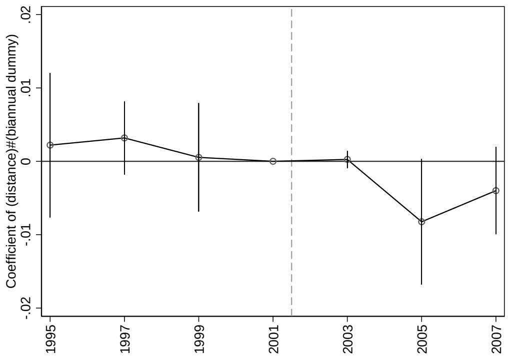
(b) Infant mortality



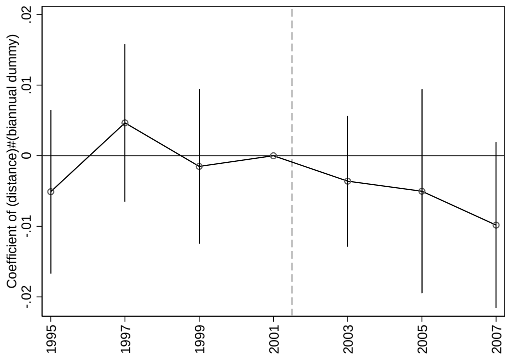
Authors' calculation based on the DHS data. Includes both e-waste sites. For consistency between the two countries we consider a common number of years (5) before and after the dump. The plots are created by a linear regression of mortality on a full set of event time indicators (years from dump) interacted with a dummy indicating whether the household lives within 5 Km from the site and controlling for country and birth year fixed effects. The vertical lines indicate 95% confidence intervals.

Figure A.3: Event study for neonatal (left) and infant (right) mortality: Ghana

(a) Neonatal: distance from dump



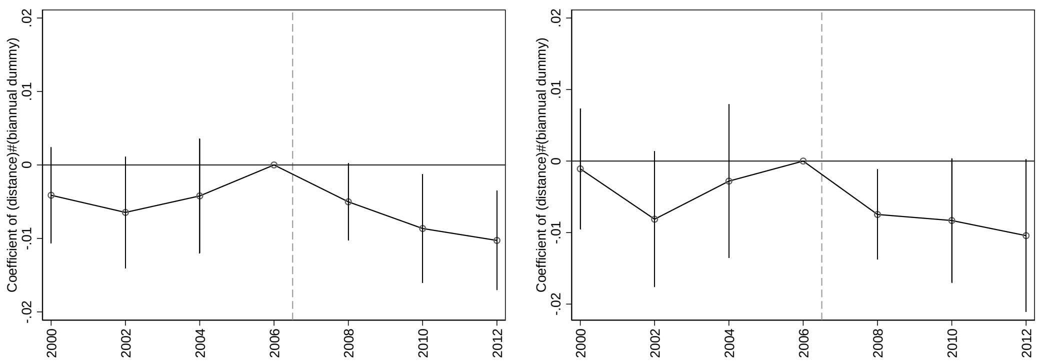
(b) Infant: distance from dump



Authors' calculation based on the DHS data for Ghana. The plots are created by a linear regression of mortality on a full set of event time indicators (biannual) for country and year fixed effects. Results are obtained by interacting the biannual time indicator with distance from the dump (in Km). The lines indicate 95% confidence interval.

Figure A.4: Event study for neonatal (left) and infant (right) mortality: Nigeria

(a) Neonatal: distance from dump (b) Infant: distance from dump



Authors' calculation based on the DHS data for Ghana. The plots are created by a linear regression of mortality on a full set of event time indicators (biannual) for country and year fixed effects. Results are obtained by interacting the biannual time indicator with distance from the dump (in Km). The lines indicate 95% confidence interval.

Figure A.5: Nightlights over time: Ghana

(a) 1995

(b) 2000

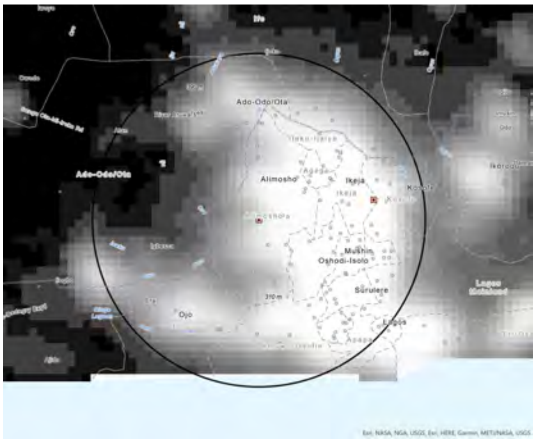
(c) 2005

(d) 2010

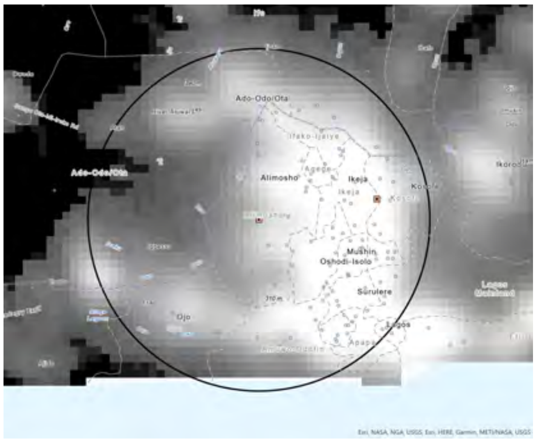
Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency. The squared point indicates the Agbogbloshie dumpsite. The black buffer represents 20km from the sites and inclusion into our sample; blue dots indicate DHS clusters.

Figure A.6: Nightlights over time: Nigeria

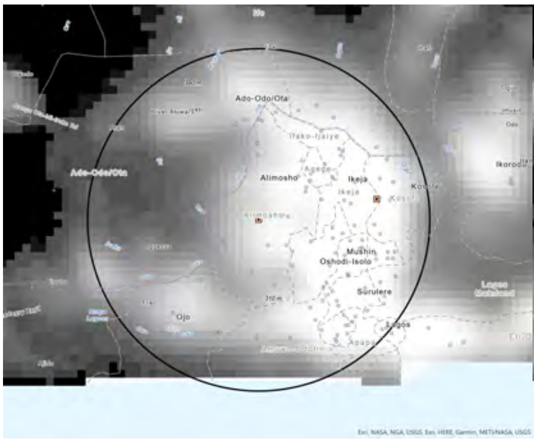
(a) 1995



(b) 2000



(c) 2005



(d) 2010

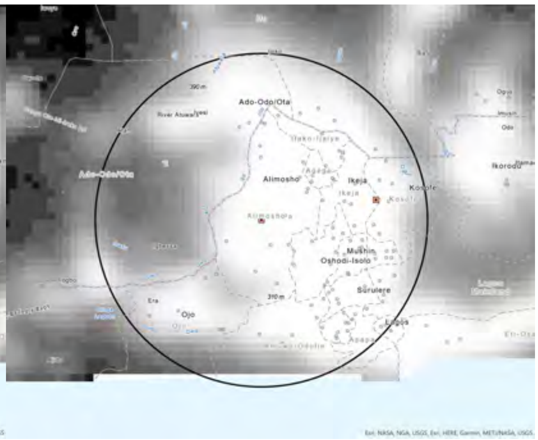
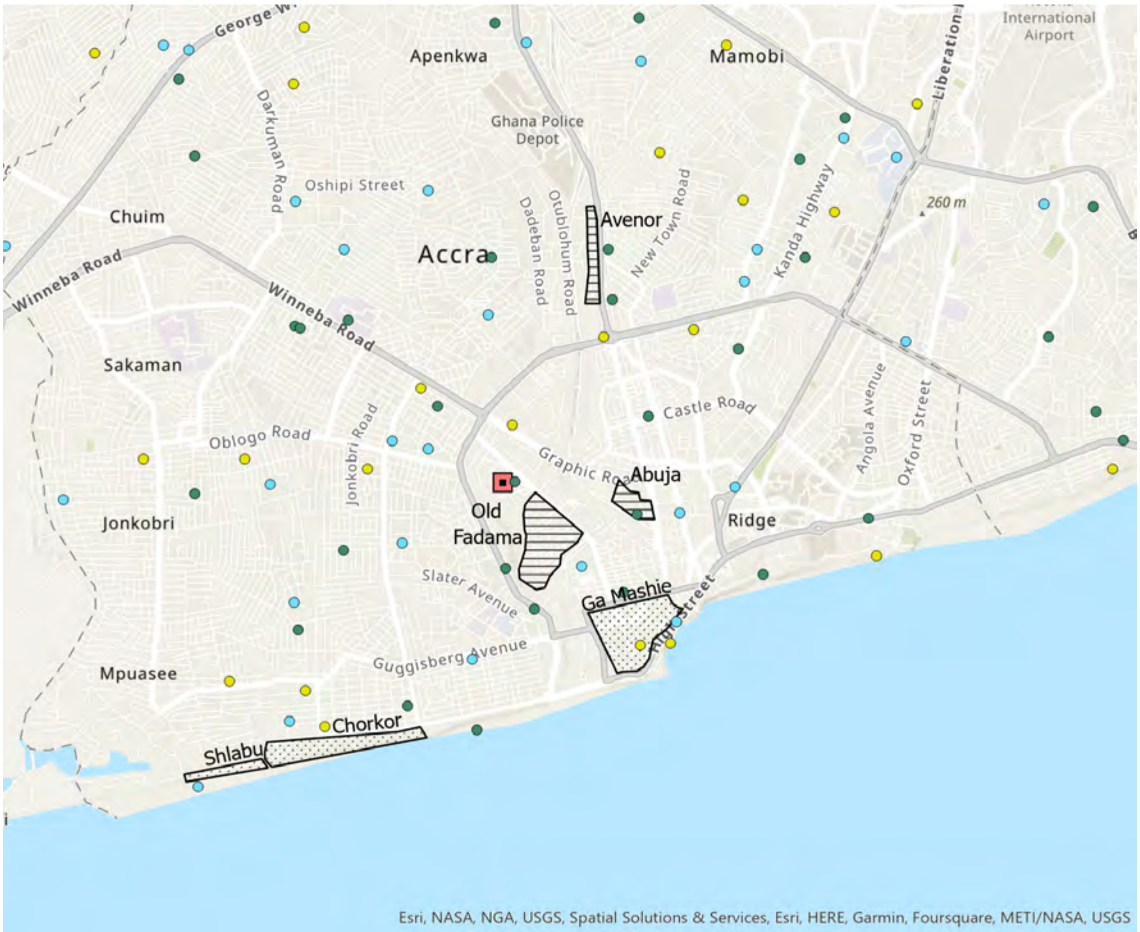


Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency. The squared points indicates the Solous and Olusoshun dump sites. The black buffer represents 20km from the Solous site and inclusion into our sample; blue dots indicate DHS clusters.

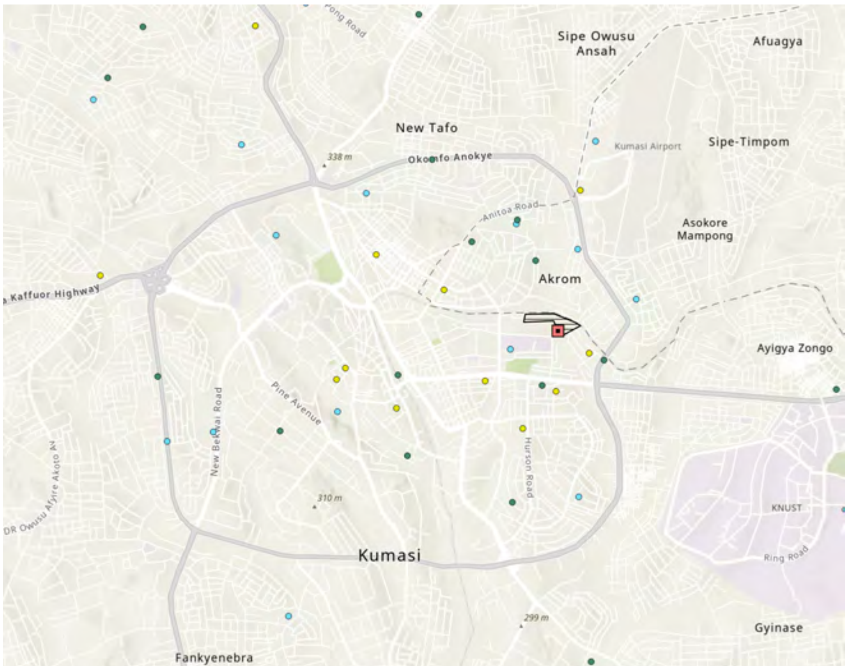
Figure A.7: Slum area in Accra - Ghana



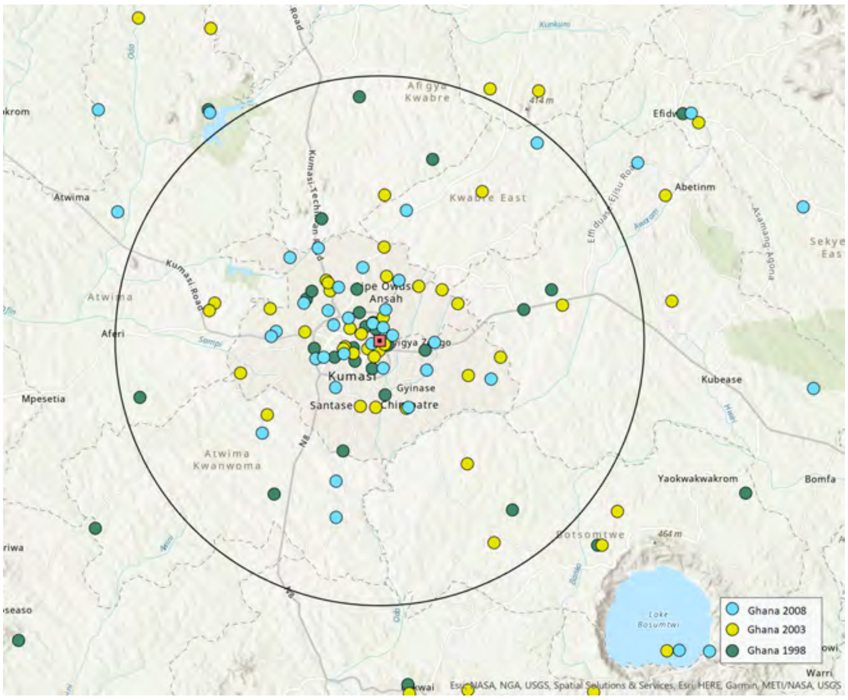
Map plotting DHS data for Ghana. Dots represent DHS clusters in the proximity of the e-waste site. The shaded areas represent slums locations. Striped areas are extralegal settlements, which in the postcolonial context, gathered previously marginalized communities to establish territorial authority (Paller, 2015).

Figure A.8: Aboabo slum in Kumasi - Ghana

(a) Location of Aboabo slum

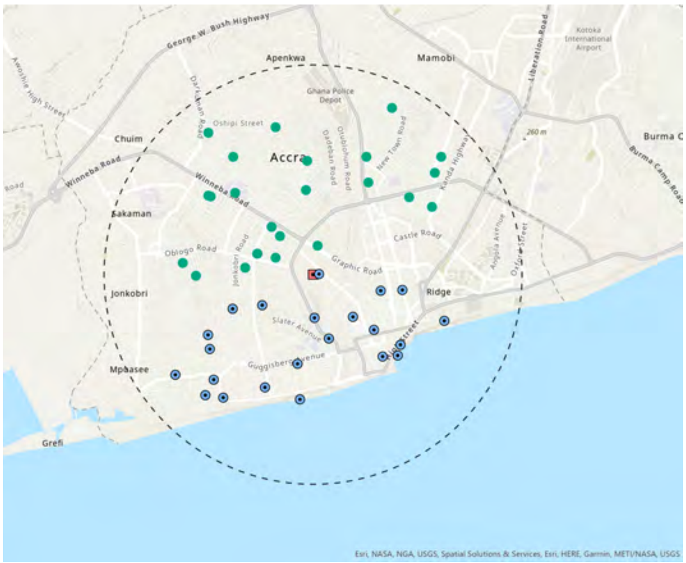


(b) DHS clusters in the proximity of Aboabo



Map plotting location of Aboabo slum in Kumasi, Ghana. Dots represent DHS clusters. The black buffer is drawn at 20km from the slum centre.

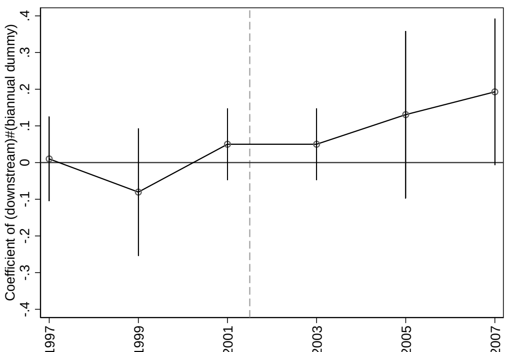
Figure A.9: Upstream and Downstream clusters in Ghana



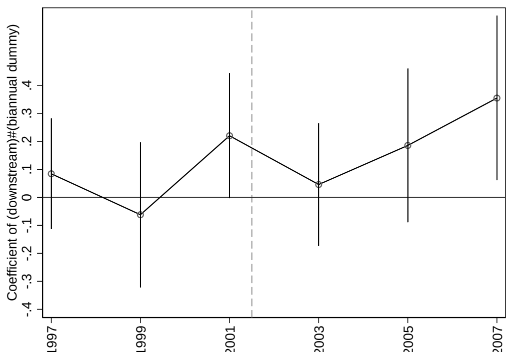
Maps plotting DHS data for Ghana. Dots represent DHS clusters. The dashed buffer indicates 5km from the e-waste site. Green dots are categorised as upstream, while those in blue are categorised as downstream.

Figure A.10: Event study for neonatal (left) and infant (right) mortality: downstream versus upstream households

(a) Neonatal mortality



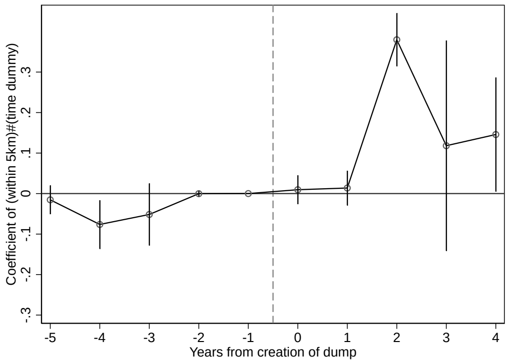
(b) Infant mortality



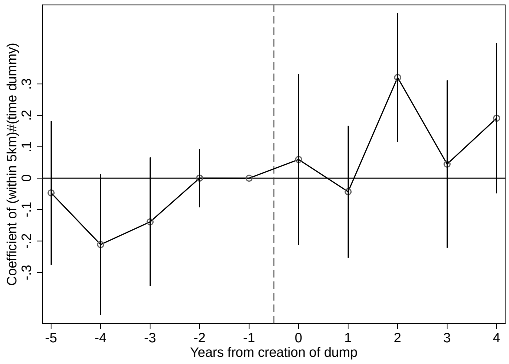
Authors' calculation based on the DHS data for Ghana. The plots are created by a linear regression of mortality on a full set of event biannual time indicators interacted with a dummy variable taking value one for downstream households and controlling for time fixed effects. We consider biannual time indicators rather than annual indicators due to the small sample sizes in this analysis. The vertical lines indicate 95% confidence interval.

Figure A.11: Event study comparing areas with high and low prevalence of livestock (within 5 km)

(a) Neonatal mortality



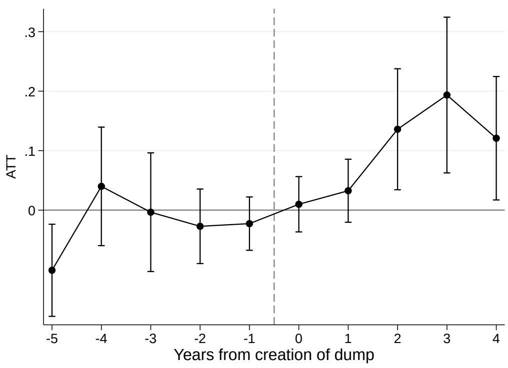
(b) Infant mortality



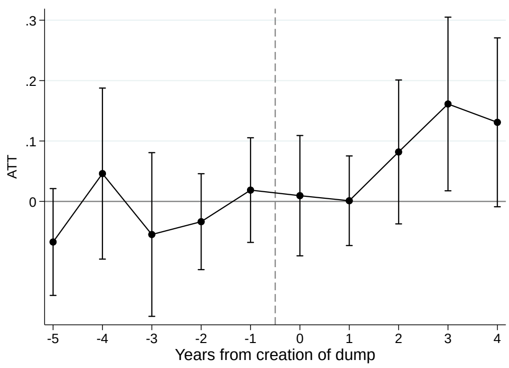
Authors' calculation based on the DHS data for Ghana and Nigeria. Includes both e-waste sites. For consistency between the two countries we consider a common number of years (5) before and after the dump. The plots are created by a linear regression of mortality on a full set of event time indicators (years from dump) interacted with a dummy indicating whether the cluster is considered to have livestock. We consider only cluster with 5 km from the dumping sites. The vertical lines indicate 95% confidence intervals.

Figure A.12: Event study estimates based on Doubly Robust estimator

(a) Neonatal mortaity



(b) Infant mortality



Results obtained implementing the Doubly Robust estimator by Callaway and Sant'Anna (2021), using a binary treatment indicating whether the household lives within 5 Km from the site. Data include both e-waste sites. For consistency between the two countries we consider a common number of years (5) before and after the dump. The lines indicate 95% confidence interval.

Table A.1: Compositions of births: differences in means; full sample

	$> 5km$					$\leq 5km$					$\leq 5km - > 5km$	
	I	II	III	N	IV	V	N	VI	VII	VIII	IX	X
	Before	N	After	N	Difference	Before	N	After	N	Difference	Before	After
Neonatal Mortality	0.041	1964	0.029	1374	-0.012*	0.025	397	0.057	227	0.032*	-0.016	0.028*
Infant Mortality	0.063	1906	0.043	1070	-0.020*	0.053	378	0.078	180	0.025	-0.012	0.032*
< primary schooling	0.079	1964	0.056	1374	-0.023*	0.088	397	0.035	227	-0.053*	0.009	-0.021
Primary schooling	0.190	1964	0.148	1374	-0.042*	0.239	397	0.194	227	-0.045	0.049*	0.045*
Secondary schooling	0.582	1964	0.603	1374	0.021	0.579	397	0.612	227	0.033	-0.003	0.010
Higher education	0.148	1964	0.193	1374	0.045*	0.093	397	0.159	227	0.065*	-0.055*	-0.034
Spouse < primary schooling	0.039	1788	0.024	1105	-0.014*	0.080	362	0.056	214	-0.024	0.042*	0.032*
Spouse primary schooling	0.158	1788	0.122	1105	-0.036*	0.083	362	0.084	214	0.001	-0.075*	-0.038
Spouse secondary schooling	0.574	1788	0.588	1105	0.014	0.657	362	0.631	214	-0.027	0.084*	0.043
Spouse higher education	0.230	1788	0.265	1105	0.035*	0.180	362	0.229	214	0.049	-0.050*	-0.036
Urban	0.944	1964	0.961	1374	0.017*	1.000	397	1.000	227	0.000	0.056*	0.039*
Male	0.504	1964	0.518	1374	0.014	0.476	397	0.480	227	0.004	-0.028	-0.038
Multiple birth	0.033	1964	0.035	1374	0.002	0.035	397	0.062	227	0.026	0.002	0.027*
Mother age at birth	27.485	1964	28.687	1374	1.202*	27.005	397	28.824	227	1.819*	-0.480	0.137

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table A.2: Compositions of births: differences in means; Ghana

			$> 5km$					$\leq 5km$			$\leq 5km - > 5km$	
	Before	N	After	N	Diff.	Before	N	After	N	Diff.	Before	After
Neonatal Mortality	0.034	385	0.021	191	-0.013	0.025	241	0.036	110	0.011	-0.009	0.015
Infant Mortality	0.049	366	0.036	165	-0.013	0.059	222	0.068	88	0.010	0.007	0.023
< primary schooling	0.151	385	0.105	191	-0.046	0.133	241	0.064	110	-0.069*	-0.018	-0.041
Primary schooling	0.190	385	0.204	191	0.015	0.245	241	0.245	110	0.001	0.055*	0.041
Secondary schooling	0.600	385	0.602	191	0.002	0.589	241	0.673	110	0.084	-0.011	0.071
Higher education	0.060	385	0.089	191	0.029	0.033	241	0.018	110	-0.015	-0.027	-0.071*
Spouse < primary schooling	0.091	342	0.056	162	-0.035	0.124	209	0.102	98	-0.022	0.034	0.046
Spouse primary schooling	0.023	342	0.025	162	0.001	0.043	209	0.051	98	0.008	0.020	0.026
Spouse secondary schooling	0.722	342	0.710	162	-0.012	0.742	209	0.765	98	0.024	0.019	0.055
Spouse higher education	0.164	342	0.210	162	0.046	0.091	209	0.082	98	-0.009	-0.073*	-0.128*
Urban	0.886	385	0.911	191	0.025	1.000	241	1.000	110	0.000	0.114*	0.089*
Male	0.525	385	0.492	191	-0.033	0.477	241	0.473	110	-0.004	-0.047	-0.019
Multiple birth	0.036	385	0.042	191	0.006	0.025	241	0.055	110	0.030	-0.011	0.013
Mother age at birth		385	27.686	191	0.478	26.461	241	28.291	110	1.830*	-0.747	0.605

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table A.3: Compositions of births: differences in means; Nigeria

	> $5km$					≤ $5km$					≤ $5km-$ > $5km$	
	Before	N	After	N	Diff.	Before	N	After	N	Diff.	Before	After
Neonatal Mortality	0.043	1579	0.030	1183	-0.013*	0.026	156	0.077	117	0.051	-0.017	0.046*
Infant Mortality	0.067	1540	0.044	905	-0.023*	0.045	156	0.087	92	0.042	-0.021	0.049*
< primary schooling	0.062	1579	0.048	1183	-0.014	0.019	156	0.009	117	-0.011	-0.043*	-0.040*
Primary schooling	0.191	1579	0.139	1183	-0.051*	0.231	156	0.145	117	-0.085*	0.040	0.006
Secondary schooling	0.578	1579	0.603	1183	0.025	0.564	156	0.556	117	-0.009	-0.013	-0.047
Higher education	0.170	1579	0.210	1183	0.040*	0.186	156	0.291	117	0.105*	0.016	0.081*
Spouse < primary schooling	0.026	1446	0.019	943	-0.007	0.020	153	0.017	116	-0.002	-0.007	-0.002
Spouse primary schooling	0.189	1446	0.139	943	-0.051*	0.137	153	0.112	116	-0.025	-0.052	-0.027
Spouse secondary schooling	0.539	1446	0.567	943	0.029	0.542	153	0.517	116	-0.025	0.004	-0.050
Spouse higher education	0.246	1446	0.275	943	0.029	0.301	153	0.353	116	0.053	0.055	0.079*
Urban	0.958	1579	0.970	1183	0.011	1.000	156	1.000	117	0.000	0.042*	0.030*
Male	0.499	1579	0.522	1183	0.023	0.474	156	0.487	117	0.013	-0.025	-0.035
Multiple birth	0.032	1579	0.034	1183	0.002	0.051	156	0.068	117	0.017	0.019	0.035*
Mother age at birth	27.552	1579	28.849	1183	1.296*	27.846	156	29.325	117	1.479*	0.294	0.476

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table A.4: The impact of e-waste sites on newborn and infant health: site specific analysis

	(I)	(II)	(III)	(IV)
	Ghana		Nigeria	
	Neonatal Mortality	Infant Mortality	Neonatal Mortality	Infant Mortality
Distance (km)	0.001	0.002	0.002*	0.004***
	(0.002)	(0.003)	(0.001)	(0.001)
Post × Distance (km)	–0.004*	–0.007*	–0.003**	–0.004*
	(0.002)	(0.004)	(0.001)	(0.002)
Mean mortality	0.030	0.051	0.038	0.057
N	805	727	2554	2367
Dump FE	Yes	Yes	Yes	Yes
Year of Birth FE	Yes	Yes	Yes	Yes

Standard errors (in parenthesis) are clustered at the DHS cluster level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%. Post is a dummy variable indicating a child was born after the creation of the dump site (For Ghana, t = 2001; for Nigeria, t = 2006). Children born between 5 years pre- and 5 years post are included in the analysis; for Ghana this is 1996-2006 and for Nigeria this is 2001-2011.

Table A.5: The impact of dumping sites on newborn and infant health: additional controls

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
			Neonatal Mortality					Infant Mortality		
B: Distance in km										
Distance (km)	0.001	0.001	0.002	0.002	0.002	0.003**	0.003*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post × Distance (km)	–0.003***	–0.004**	–0.004**	–0.004***	–0.004***	–0.005**	–0.005**	–0.004*	–0.004**	–0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mean	0.036	0.040	0.040	0.040	0.040	0.056	0.060	0.060	0.060	0.060
N	3359	2957	2957	2957	2957	3094	2733	2733	2733	2733
Dump FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dump-trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Nightlights	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Built-up Presence	No	No	No	Yes	Yes	No	No	No	Yes	Yes

Standard errors (in parenthesis) are clustered at the DHS cluster level. . *** p-value < 1%, ** p-value < 5%, * p-value < 10%. See notes to table 2. *X* Controls include urban status, mother's age at birth, mother and father's educational level, mother age at birth, and the child's gender and whether the birth was a multiple birth. 'Nightlights' refers to the interaction of cohort dummies with the average nightlight value in a 2km buffer around the cluster in 1995. 'Built-up Presence' refers to the interaction of cohort dummies with the DHS spatial variable indicating degree of urbanisation in a 2 (5) km buffer around urban (rural) clusters in 1990.

Table A.6: Effect of e-waste sites on household characteristics

	(I) Mother: No Schooling	(II) Mother: Primary	(III) Mother: Secondary	(IV) Mother: Higher	(V) Father: No Schooling	(VI) Father: Primary
Distance (km)	0.003	−0.007	0.005	−0.001	0.003	−0.007
	(0.009)	(0.008)	(0.010)	(0.004)	(0.008)	(0.005)
Post × Distance (km)	0.000	0.008	−0.007	−0.001	−0.004	0.008
	(0.009)	(0.009)	(0.010)	(0.005)	(0.008)	(0.006)
Mean	0.072	0.168	0.609	0.151	0.040	0.125
N	1868	1868	1868	1868	1598	1598
	Father: Secondary	Father: Higher	Urban	Mother: Age (first birth)	Mother: Employed	
Distance (km)	−0.000	0.004	−0.004	0.056	0.004	
	(0.011)	(0.008)	(0.004)	(0.058)	(0.008)	
Post × Distance (km)	0.000	−0.004	−0.008	−0.095	0.001	
	(0.012)	(0.009)	(0.006)	(0.069)	(0.008)	
Mean	0.592	0.243	0.961	22.686	0.834	
N	1598	1598	1868	1790	1701	
Dump FE	Yes	Yes	Yes	Yes	Yes	
YOB FE	Yes	Yes	Yes	Yes	Yes	

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table A.7: Effect of e-waste sites on household characteristics: Ghana

	(I) Mother: No Schooling	(II) Mother: Primary	(III) Mother: Secondary	(IV) Mother: Higher	(V) Father: No Schooling	(VI) Father: Primary
Distance (km)	0.005	–0.013	0.009	–0.001	0.005	–0.007
	(0.015)	(0.009)	(0.014)	(0.002)	(0.015)	(0.005)
Post × Distance (km)	–0.006	0.011	–0.012	0.008**	–0.010	0.006
	(0.015)	(0.011)	(0.015)	(0.004)	(0.015)	(0.005)
Mean	0.131	0.189	0.629	0.050	0.087	0.033
N	518	518	518	518	449	449
	Father: Secondary	Father: Higher	Urban	Mother: Age (first birth)	Mother: Employed	
Distance (km)	–0.008	0.010	–0.000	–0.003	0.005	
	(0.016)	(0.009)	(0.000)	(0.080)	(0.010)	
Post × Distance (km)	0.005	–0.001	–0.024***	0.037	0.001	
	(0.017)	(0.011)	(0.009)	(0.097)	(0.011)	
Mean	0.731	0.149	0.952	21.046	0.849	
N	449	449	518	518	518	
Dump FE	Yes	Yes	Yes	Yes	Yes	
YOB FE	Yes	Yes	Yes	Yes	Yes	

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table A.8: Effect of e-waste sites on household characteristics: Nigeria

	(I) Mother: No Schooling	(II) Mother: Primary	(III) Mother: Secondary	(IV) Mother: Higher	(V) Father: No Schooling	(VI) Father: Primary
Distance (km)	–0.001	0.002	–0.000	–0.001	0.001	–0.007
	(0.007)	(0.015)	(0.014)	(0.009)	(0.001)	(0.010)
Post × Distance (km)	0.005	0.001	–0.000	–0.006	0.000	0.009
	(0.007)	(0.016)	(0.014)	(0.010)	(0.002)	(0.010)
Mean	0.049	0.160	0.601	0.190	0.022	0.161
N	1350	1350	1350	1350	1149	1149
	Father: Secondary	Father: Higher	Urban	Mother: Age (first birth)	Mother: Employed	
Distance (km)	0.009	–0.003	–0.009	0.145**	0.003	
	(0.017)	(0.015)	(0.010)	(0.068)	(0.012)	
Post × Distance (km)	–0.008	–0.001	0.003	–0.219***	0.001	
	(0.018)	(0.015)	(0.011)	(0.082)	(0.012)	
Mean	0.538	0.279	0.965	23.354	0.827	
N	1149	1149	1350	1272	1183	
Dump FE	Yes	Yes	Yes	Yes	Yes	
YOB FE	Yes	Yes	Yes	Yes	Yes	

*** p-value < 1%, ** p-value < 5%, * p-value < 10%.