Mining Leaks: Water Pollution and Child Mortality in Africa*

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Abstract

In the midst of Africa's mining boom, communities downstream from industrial mines face increased exposure to toxic waste, yet the causal impact of mining-induced water pollution on local health remains unquantified at the continental scale. We construct a novel dataset of opening dates for 2,016 industrial mines and combine it with child health outcomes from the Demographic and Health Surveys spanning 1986 to 2018 across 26 African countries. Using a staggered difference-in-differences design comparing villages located downstream and upstream—based on hydrological networks—of

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mines before and after their opening, we find a 25% increase in 24-month mortality downstream after mine opening, relative to upstream areas where mortality rates remain stable. The effect is concentrated among children who were no longer breastfed after six months, consistent with the protective role of breastfeeding against heavy metal ingestion through contaminated water and with exposure to heavy metals rather than microbial contamination. Effects are stronger during active mine operation, at high international mineral prices, and in densely mined regions, and decrease with distance from the mine, consistent with higher mining intensity generating higher pollution levels. We rule out alternative mechanisms including changes in fertility behaviors, access to healthcare, in-migration, conflict, and income effects. These findings underscore the significant local health impacts of industrial mining and highlight the need for stronger environmental regulation and water quality monitoring in resource-rich developing countries.

Keywords: Industrial mining, Water pollution, Child mortality, Africa, Heavy metals

JEL: Q53, I15, O13, Q33, N57

Since the 2000s, the rise in commodity prices has led to a significant increase in industrial mining activity in Africa, raising alarming concerns about environmental degradation (Taylor et al., 2009; Edwards et al., 2013) and adverse health effects among local communities. While a mine can generate positive externalities through economic activity and local development, it also produces negative externalities. Ore extraction processes release harmful heavy metals — including arsenic, lead, mercury, and cadmium — generating waste stored in retention ponds that can leak into local water resources and pose serious risks to human health. Humans are at risk from direct exposure via metal-contaminated water and indirect exposure through food produced in contaminated soil. High blood metal levels in blood can cause a range of health issues, which are especially harmful to children at a stage of rapid biological development (Coelho et al., 2011; Dike et al., 2020; He et al., 2020). Metal mining contamination of rivers and floodplains already affects 23 million people worldwide (Macklin et al., 2023), and Sub-Saharan Africa is particularly vulnerable — only 24% of its population has access to safe drinking water (UNESCO, 2019). Yet the causal impact of industrial mining-induced water pollution on the health of local African communities remains unquantified, leaving a critical gap at the intersection of environmental economics and development policy.

This paper investigates the causal impact of industrial mining-induced water pollution on child mortality in Africa. We combine geocoded information on 2,016 industrial mines — for which we manually collected opening dates through intensive review of company reports and satellite imagery — with child health outcomes from the Demographic and Health Surveys spanning 1986 to 2018 across 26 African countries. Exploiting temporal and geospatial variations in mine openings, we implement a staggered difference-in-differences (DiD) approach comparing communities located upstream and downstream of industrial mines before and after their opening, using hydrological networks from the HydroSHEDS database to determine water flow direction between each mine and surrounding communities. This upstream-downstream design allows us to isolate water pollution as the primary exposure channel, departing from conventional distance-based proxies used in previous studies. We focus on infant mortality given the well-documented effects of pollutant exposure during early biological development (Coelho et al., 2011; Dike et al., 2020; He et al., 2020), though we also examine other child health outcomes including anthropometric measures and anemia.

The main finding of this paper shows that industrial mine openings significantly increase child mortality in downstream communities compared to upstream areas, consistent with greater exposure to mining-induced water pollution. Specifically, 24-month mortality for children born downstream increases from 8.7% to 10.9% after a mine opening, compared to stable mortality rates for those born upstream — a 2.2 percentage point (p.p.) increase representing a 25% higher mortality rate in downstream areas. Results reveal a greater impact in rural areas, which are more dependent on the agricultural sector and on surrounding water resources, with downstream mortality rising by 40%. We find no significant effects on acute health outcomes such as diarrhea, fever, or cough among surviving children — a pattern consistent with heavy metal contamination rather than microbial water pollution.

To further establish water pollution as the primary mechanism, we exploit heterogeneity in children's early-life characteristics and mining activity. First, the mortality increase is concentrated among children who were no longer breastfed after six months — consistent with the well-documented protective role of breastfeeding against heavy metal ingestion through contaminated water (VanDerSlice et al., 1994; Fängström et al., 2008) — while children who remained breastfed beyond six months show a smaller and less significant increase. This breastfeeding gradient provides suggestive evidence that contaminated water, rather than prenatal exposure or other channels, drives the observed increase in mortality. Further analysis of household characteristics reveals larger effects among households with lower wealth indices, in line with their greater exposure to the harmful effects of contaminated water. At the mine level, and consistent with more intensive extraction processes generating higher water pollution, the increase in downstream mortality is primarily driven by open-pit mines and those owned exclusively by foreign companies.

We further examine the intensive margin and dynamic effects of mine openings, finding that mortality effects scale with the intensity of mining activity, consistent with higher levels of water pollution. Effects increase with production intensity — proxied by international commodity prices — and occur mainly while mines are active, with downstream mortality reaching a 40% increase during periods of peak production. The mortality increase also rises with the density of surrounding mines and fades with distance from the mine site, in line with the expected attenuation of water pollution with distance from its source. Finally, the event study confirms that effects persist in the medium term, up to a decade after mine opening, in line with the chronic nature of heavy metal contamination.

To assess whether the observed mortality increase reflects water pollution rather than alternative channels, we systematically rule out confounding mechanisms. We find no differential changes in household wealth, women's fertility behaviors and health outcomes, access to infrastructure — including piped water, electricity, or health facilities — or conflict intensity between upstream and downstream areas following mine openings. Our results remain robust when controlling for in-migration, ruling out the possibility that selective migration from downstream to upstream areas drives the mortality differential. Taken together, these tests leave water pollution as the primary explanation for the observed downstream mortality increase.

Our findings are supported by a series of robustness checks. Results hold when using a balanced sub-sample of DHS repeated cross-sections and applying the de Chaisemartin and d'Haultfœuille (2020) estimator to address heterogeneous treatment effects in a staggered adoption design, when correcting for DHS random displacement and restricting to mines with precise coordinates, and when accounting for spatial correlation and conducting spatial and temporal randomization inference tests.

This paper makes two key contributions to the literature. First, it provides new quasi-experimental evidence on the adverse health externalities of industrial mining, contributing to the natural resource curse literature. Second, it sheds new light on mining's environmental externalities by indirectly identifying water pollution as a significant negative externality at the continental scale in Africa. It links industrial mining activity to higher child mortality, through an upstream-downstream design consistent with water pollution as the main channel. These contributions are made possible by (1) the creation of a new database detailing the opening dates of 2,016 industrial mines in Africa, compiled through intensive manual data collection from company reports and satellite imagery, and (2) the adoption of a continental-scale upstream-downstream quasi-experimental design (Duflo and Pande, 2007; Strobl and Strobl, 2011; Do et al., 2018; Garg et al., 2018) that departs from conventional distance-based proxies used in previous studies, enabling the isolation of water pollution's effects on child health outcomes.

The remainder of the paper is organized as follows. Section 1 reviews the literature, Sections 2-3 describe the data, the empirical strategy, and present main results, Sections 4-5 explore heterogeneity and dynamic effects, Section 6 rules out alternative channels, and Section 7 provides robustness checks. Section 8 discusses the limitations of the study and Section 9 concludes.

1. Existing Evidence and Conceptual Framework

Mining-induced pollution and health– This paper's primary contribution is to quantify the adverse health impacts of industrial mining by indirectly identifying water pollution as the main transmission channel. We implement a continental-scale upstream–downstream identification strategy that overcomes the limitations of distance-based designs, which cannot disentangle positive income effects from negative pollution externalities. Few studies have quantified the environmental externalities of industrial mining at scale. Bialetti et al. (2018) examine mining-driven deforestation in India, and Aragón and Rud (2016) link Ghanaian gold mining to declines in agricultural productivity through air pollution. Von der Goltz and Barnwal (2019) document adverse effects on anemia, plausibly through water contamination. Descriptive hydrological studies show contamination of drinking water with cadmium, arsenic, manganese, and nitrate (Cobbina et al., 2013). While some research has contrasted upstream and downstream communities in specific mining settings—for example, Romero and Saavedra (2016), who document worse newborn health outcomes for mothers living downstream from Colombian gold mines, or Parfitt (2024), who studies illegal small-scale gold mining and finds large increases in both infant and fetal mortality in Brazilian riverside communities exposed to mercury contamination transmitted downstream along the Madeira River Basin—these analyses focus on single river systems or localized contexts and do not map hydrological pathways systematically. This paper is the first, to our knowledge, to implement a continent-wide, upstream–downstream identification strategy across 2,016 industrial mines in 26 African countries, made possible by a novel database of mine opening dates compiled through intensive manual data collection and enabling large-scale inference on the health impacts of industrial mining through an indirect identification of the water pollution channel.

Mining and Health– This paper contributes to the literature on the health effects of mining by documenting higher infant mortality downstream of mines. Although prior work has examined the local health impacts of mining, findings remain mixed. Benshaul-Tolonen (2018) documents reductions in infant mortality within 10 km of operating mines, whereas Von der Goltz and Barnwal (2019) report both wealth gains and adverse health outcomes such as anemia and stunting. A key challenge in distance-based designs is that they capture both positive externalities (income, services, infrastructure) and negative externalities (pollution), which makes it difficult to isolate the underlying mechanisms. The upstream–downstream design used in this paper overcomes this limitation by separating pollution-driven exposure from other channels. When replicating a distance-based treatment, we recover results similar to Benshaul-Tolonen (2018) using both their original gold-mine sample and our extended gold-mine sample. However, these effects disappear when applied to a broader set of countries and mines, suggesting that earlier findings may be region-specific and may conflate positive and negative spillovers (see Section F.2 for more details). This helps explain why previous studies reached different conclusions: distance-based approaches may mask pollution externalities that propagate downstream. By indirectly identifying mining-induced water pollution as the main channel at scale, this paper helps clarify the mechanism behind the observed adverse health impacts.

Industrial Mining and Local Welfare — Mining activity generates a complex combination of positive and negative spillovers. Industrial mining can stimulate local development (Mamo et al., 2019) and improve welfare (Dietler et al., 2021), but it also produces externalities related to conflict (Berman et al., 2017), pollution (Aragón and Rud, 2016), and migration (Corno and de Walque, 2012), affecting health (Corno and de Walque, 2012; Romero and Saavedra, 2016; Parfitt, 2024) and child outcomes (Atkin, 2016; Ahlerup et al., 2020; Malpede, 2021). The natural resource curse literature shows persistent uncertainty regarding the net effect of mining (Van der Ploeg, 2011; Cust and Poelhekke, 2015; Venables, 2016). Most empirical work measures exposure using Euclidean distance. While this approach has yielded important insights, it cannot account for hydrological spillovers nor distinguish income effects from pollution effects, which can generate heterogeneous or contradictory findings in prior studies (e.g., Aragón and Rud (2016), Von der Goltz and Barnwal (2019), Benshaul-Tolonen (2018)). A contribution of this paper is to expand the empirical scope of existing studies by assembling a continental-scale database of 2,016 industrial mines across Africa, allowing exposure to be measured more comprehensively than in earlier work based on smaller or country-specific samples. Leveraging this expanded dataset, our framework shows that distance-based approaches can obscure pollution-driven impacts, and that accounting for hydrological pathways is important for indirectly identifying mining-induced water contamination as a transmission channel for health.[1]

2. Data and Context

2.1. Data

In this paper, we match socioeconomic data from Demographic Health Surveys to an industrial mining database provided by SNL Mining and Metals. The database we build covers 26 African countries from 1986 to 2018, and we construct a panel of sub-basins surrounding mines from 2016 during this period.

Health and socio-economic data – We use all available survey rounds from the Demographic Health Surveys that contain GPS coordinates, from 1986 to 2018, covering 36 of the 54 African countries. We then select all countries that have at least two survey waves[2], enabling us to implement a DiD strategy with sufficient pre- and post-treatment observation, resulting in 26 countries (listed in Table 10), 12,442 clusters and 240,431 children under five.

Table 10 in Appendix A.1 provides the DHS survey years and the list of countries used in the analysis. We construct the child mortality variables using the DHS child recode database, which contains information on the age and survival status of children under five, whose mothers are aged between

[1]Our focus is on industrial mining, excluding artisanal mining (ASM). While ASM presents health risks due to hazardous conditions and mercury use (Bazillier and Girard, 2020), industrial mining generally involves larger-scale extraction and more pervasive pollution with greater health implications.

[2]We consider that implementing a DiD strategy in countries with only one survey round— covering a maximum of five years—does not allow us to capture the longer-term effects of mining activity.

15 and 49. Our dependent variable is the probability of mortality before 12 and 24 months for each DHS cluster. For each child, we build a dummy equal to 1 if the child is alive and 0 if not, conditional on having reached 12 and 24 months, respectively. We also estimate the effects of mining activity on biomarker variables and other health indicators among young children —such as diarrhea, fever, and cough reported within two weeks prior to the interview. We extend our analysis to women's fertility behavior and health outcomes, including current pregnancy status, total lifetime fertility, miscarriage, and anemia. Finally, since the aim of this study is to isolate the mechanism of water pollution, we use DHS data on the main source of drinking water, the presence of flush toilets, electricity, and access to health facilities to control for households' sanitary and economic environment. Descriptive statistics of the main variables are presented in Table 12 in Appendix A.1.

Mineral resource exploitation data – Industrial mining variables come from the SNL Metals and Mining database, which is privately owned by S&P Global and licensed[3]. The SNL database provides the best available data on industrial mines, including the location of all mines, as well as opening and closing dates, commodity types, and production levels for a subsample. While not exhaustive, this dataset is the most comprehensive source available on the timing of industrial mining activity[4]. Widely used in the literature (Aragón and Rud, 2016; Berman et al., 2017; Kotsadam and Tolonen, 2016; Benshaul-Tolonen, 2018; Von der Goltz and Barnwal, 2019; Mamo et al., 2019), it covers 3,815 mines across Africa from 1981 to 2021. A key contribution of this paper is the creation of a new database that adds opening dates for mines missing from the SNL data. Out of the 3,815 mines in the SNL database, 2,016 are located within 100 km of a DHS cluster in

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[3]We are grateful to CEPREMAP, PjSE, EHESS, and the GPET thematic group of PSE, for their financial support and their help in purchasing the access to the data.

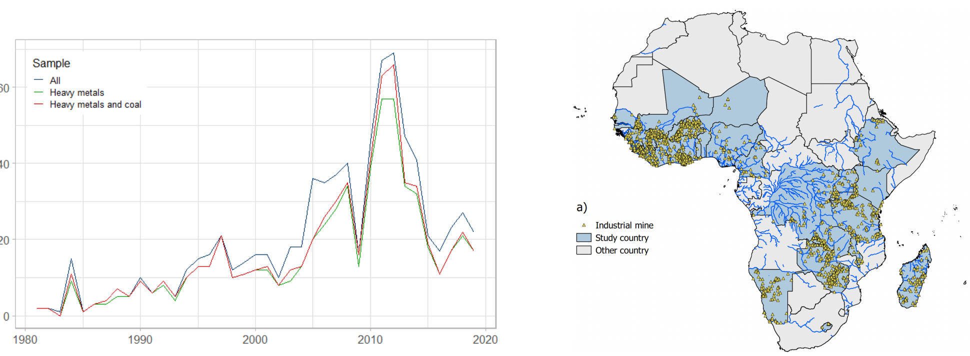
[4]We emphasize here that this paper focuses on the effects of industrial mining and that we do not include artisanal mining, which is not available in the SNL database.

countries with at least two survey rounds. While SNL provides opening years for 278 mines, we manually collected opening dates for an additional 1,738 mines using mining history information from the SNL database and mining company reports, complemented by extensive cross-checking with satellite imagery. We describe this intense data collection work in Appendix A.2. Using geocoded data and production start dates, we then create three main variables: (i) proximity (distance to the nearest mine); (ii) topographic position (upstream or downstream), and (iii) a mine status dummy (open or closed). Our analysis is restricted to heavy metal mines (metals with a density greater than 5g/cm^3) and also includes coal mines, given their association with toxic metals such as mercury and arsenic.

Water basins – To determine upstream and downstream relationships, we use HydroSHEDS data on HydroBASINS, which delineates basins based on the Pfafstetter coding system. According to this topological system, each sub-basin polygon has a unique flow direction and provides information on upstream and downstream connectivity. We use the finest Pfafstetter level (level 12 out of 12), where sub-basins average around 100 km^2 (see Figure 3a for an example). In our main analysis, the treatment group is defined as the three closest downstream sub-basins to each mine, based on their connectivity. Additionally, we control for the presence and intensity of river networks using the HydroRIVERS dataset, which provides a continuous variable based on catchment area and Strahler order, ranging from 3 to 10 in our sample.

2.2. Context

Mining in Africa – The African continent is richly endowed with mineral reserves, containing around 30% of the world's mineral reserves, and is estimated to have the largest reserves for strategically important metals such as cobalt, diamonds and uranium (Program, 2022). However, since the continent is made up of inhospitable terrains and lacks infrastructure, the geology of the continent remains largely unexplored (Taylor et al., 2009). Despite its rich geology, Africa's mineral production accounted for approximately 8% of global production in 2012 (AfricaBank, 2022), and represents an opportunity for mining investors. Thus, Africa has been facing a mining boom since the 2000s, attracting foreign investment mainly from China, Canada, Australia, Brazil, and Russia, raising concerns about environmental degradation on the continent (Taylor et al., 2009; Edwards et al., 2013). Human exposure to heavy metals through the consumption of contaminated water is a major concern in Africa and in Sub-Saharan Africa in particular, where only 24% of the population has access to safe drinking water (UNESCO, 2019).



(a) Mine Opening Over Time

(b) Geographic Distribution of Mines

Figure 1: Spatial and Temporal Distribution of Mines

Notes: Figure 1a shows the annual number of mine openings from 1981 to 2019, including all mines and heavy metal mines (coal included) from our sample. Figure 1b shows the stock of mines used in our sample across Africa, based on the SNL data and our manual data collection.
Source: Authors' elaboration on DHS, SNL, and HydroSheds data.

Figure 1a displays the annual number of mine openings in Africa from 1981 to 2019, based on the mines included in the main analysis. The data reveal a rising trend in openings since 2000 and show no significant differences in trends across different categories of mine. We also observe that the trends in mine openings align closely with the trend of industrial metal prices (as illustrated in a Figure in Supplementary Appendix), reflecting the mining boom since 2000 driven by rising metal prices, and a downturn in 2008–2009 due to the global financial crisis. The drop around 2016 corresponds to the fall in commodity prices in 2014 (Khan et al., 2016; Glöser et al., 2017). This pattern suggests that metal prices are strong instruments for mine opening dates, as shown in previous studies (Berman et al., 2017; Bazillier and Girard, 2020). In Section 5.1, we use metal prices as a proxy for production intensity. Figure 1b shows the number of mines across Africa in our sample. Major mining countries in the SNL database include Guinea, Sierra Leone, Ivory Coast, Ghana, Niger, Burkina Faso, Zimbabwe, Tanzania and Zambia. [5]

Health risks of industrial mining activity–Throughout each stage of a mine's life cycle, its activity can produce and release hazardous chemicals and minerals. Moreover, the water-intensive ore extraction processes can directly compete with the local demand, which is even more an issue in water-stressed areas. Mining activity consists mainly of extracting small concentrations of minerals from large volumes of rocks, creating a lot of waste that can be diluted in water. Waste stored in retention ponds can also leak into the local environment. These leaks can contaminate surrounding soil and water with toxic elements like arsenic, lead, mercury, and cadmium, posing long-term risks to ecosystems and human health. Although low concentration levels of heavy metals can be essential for human health, the abnormal amounts near mines can lead to serious health issues. Human health can be directly affected metal-contaminated soil and water through dermal contact, ingestion, inhalation, and absorption, and indirectly via contaminated food. Heavy metals have detrimental effects on human health and can be associated with neurological and cardiovascular diseases, organ dysfunction, a higher probability to develop cancer, infertility and miscarriages. Children are all the more vulnerable to heavy metals, even at low concentrations (Dike et al., 2020), due to their rapid development (in- and ex-utero) (Coelho et al., 2011), and high exposure to ingestion of soil and unclean water (He et al., 2020).

[5] South Africa is absent from our sample as we focused on countries with at least two DHS surveys.

Infant mortality in Africa– Africa faces high infant mortality rates, since the average 12 month mortality rate is 6.4 % and the average 24 months mortality rate is 8.3% according to the DHS data (cf. Table 12). Figure 2 maps both the spatial and temporal variation in 24-month mortality rates and shows the average rates for the three main periods of our DHS sample. We observe an overall reduction in mortality over time and across the distribution of DHS clusters.

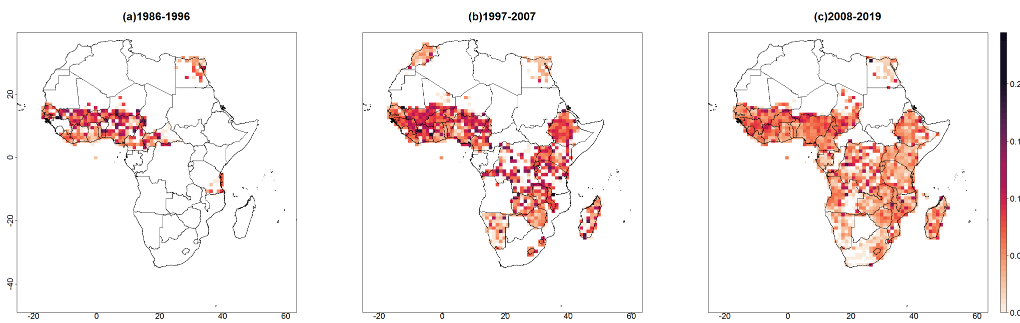


Figure 2: Spatiotemporal Variation of 24-Month Mortality Rates

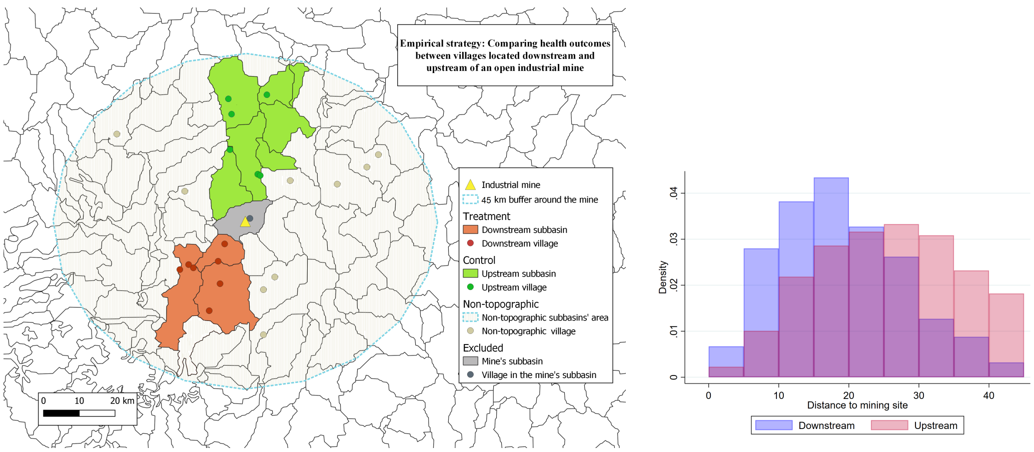
Notes: The figures represent the means of 24-month mortality rates averaged at the grid level over (a) 1986–1996, (b) 1997–2008, and (c) 2008–2019. Mortality rates are estimated excluding children who had not yet reached 24 months at the time of the survey.
Source: Authors' elaboration based on DHS data.

3. Empirical Strategy and Main Results

The main empirical strategy of this paper uses the relative topographic position of sub-basins as a proxy for exposure to water pollution from industrial mining activity. It compares the health outcomes of individuals living downstream to those living upstream of a mine, before and after the opening of at least one site. The analysis follows a staggered DiD approach, with fixed effects at the mine sub-basin and birth-year levels. This upstream–downstream framework is designed to isolate and identify water pollution as the primary mechanism driving the increase in child mortality.

3.1. Pairing strategy

Pairing DHS clusters with mines presents a methodological challenge due to the proximity of multiple industrial sites in major mining regions. To address potential endogeneity concerns and accurately measure exposure to water pollution, we implement the following three-step pairing strategy.



(a) Map of pairing strategy

(b) Mine Proximity Density

Figure 3: Pairing Strategy

Notes: Figure 3a illustrates the pairing strategy, showing the example of a mine, its main sub-basin, its three closest downstream and upstream sub-basins, and DHS clusters located in the treatment and control areas within 45 kilometers. Figure 3b plots the density of the distance (in km) to the mining site for DHS clusters across their upstream–downstream position.
Source: Authors' elaboration on DHS, SNL, and HydroSheds data.

First, we create a 100 km buffer around each DHS cluster and identify all mines within this radius, regardless of their activity status. Each cluster is then classified as downstream or upstream relative to a mine based on the topographic positions of their respective sub-basins. If a DHS cluster falls within the same sub-basin as a mine and its exact topographic position is unclear, we initially classify it as downstream. At this stage, some clusters may be paired with multiple mines, posing the challenge of selecting the most relevant mine. Second, we restrict downstream DHS clusters to those located within the three closest downstream sub-basins to focus on areas potentially more affected by water pollution. We then pair each cluster with a single mine: if a cluster is upstream of one mine and downstream of another, it is classified as downstream and paired with the mine downstream of which it lies, regardless of that mine's activity status. To further refine the sample and minimize potential misclassification caused by the random displacement of DHS cluster locations, we exclude any clusters located within the same sub-basin as their paired mine. This exclusion helps prevent misclassifying downstream clusters as upstream, and vice versa, due to the random displacement of DHS villages (see section 7 for further discussion). Finally, the control group is restricted to upstream clusters located within 45 km of the mine to ensure comparability between upstream and downstream villages. This distance corresponds to the average maximum distance between a mine and the farthest point in its third downstream sub-basin, which is 44.7 km. Figure 3b presents the distribution of distances to the mine for both upstream and downstream villages, showing that although downstream villages tend to be slightly closer, the two distributions remain comparable.

3.2. Identification Strategy

Main Estimation – The main analysis is based on a staggered DiD strategy that uses the topographic position of a DHS group relative to a mine to indirectly identify the effect of water pollution. We exploit variation in mine opening dates and their relative topographic positions by comparing individuals living in downstream sub-basins to those in upstream sub-basins, before and after a mine opens. Our specification includes sub-basin fixed effects and a linear birth-year trend for each mine to account for spatial and period-specific cofounders and trends. To isolate the water pollution mechanism, we construct treatment and control groups based on the upstream-downstream comparison. In the main estimation, we apply the pairing strategy described in section 3.1 and compare health outcomes in upstream and downstream areas, both before and after the paired mine's opening, estimating the following equation:

$$
\begin{aligned}
Death_{i,t,v,c,SB} = &\alpha_0 + \alpha_1 Opened_{t,i,v} + \alpha_2 Downstream_{v,SB} \\
&+ \alpha_3 Opened_{t,i,v} \times Downstream_{v,SB} + \alpha_4 X_i \\
&+ \gamma_{SB} + \gamma_{SB} \times t + \gamma_{c,t} + \epsilon_v
\end{aligned} \tag{1}
$$

With $Death_{i,t,v,c,SB}$ a dummy equal to one if child i, born in year t, from DHS village v of country c, has reached the n^{th} month and has died - n being 12 for the 12-month old mortality, same for 24 months [6]. $Opened_{t,i,v}$ is a dummy equal to 1 if the mine, which is located in sub-basin SB, has opened before child i's year of birth t. $Downstream_{v,SB}$ is a dummy of topographic position (equal to 1 if village DHS v is located in a sub-basin downstream of the mine sub-basin SB, and 0 if it is upstream). X_i is a vector of child, mother, and household-level controls, including the child's birth order, mother's age and age squared, mother's years of education, urban status of the DHS cluster, a continuous variable indicating the presence and order of rivers, and the number of open mines within 45 km of the DHS cluster. Finally, γ_{SB} is a mine sub-basin fixed effect, $\gamma_{SB} \times t$ a mine sub-basin linear birthyear trend and $\gamma_{c,t}$ a country-birthyear fixed effect. This analysis is a staggered design as the treatment shock (mine opening) does not occur at the same time for each DHS cluster.

Identification assumption –The key assumption of the DiD is that, in the absence of mine openings, downstream areas would have followed the same time trends as upstream areas. While we cannot directly test this counterfactual, Section 5 examines the common trends assumption using pre-treatment data. However, parallel pre-treatment trends are neither a

[6]We focus on mortality before 24 months because estimating effects at older ages would require restricting the sample to children who have already reached ages 3, 4, or 5 at the time of the survey, which substantially reduces the sample size and alters the composition of cohorts. This creates inconsistencies in exposure windows and leads to a loss of statistical power. For this reason, the main analysis focuses on a fully comparable sample of children observed from birth to age 24 months.

necessary nor sufficient condition for identification. Past trends may coincide, yet the upstream group could still be subject to a group-specific shock during the treatment period. The identification strategy of this paper relies on using the upstream–downstream comparison as a proxy for exposure to water pollution. The major identifying assumption is that mine openings affect downstream and upstream areas differently solely through changes in water quality. Throughout the paper, we address concerns about unobservable factors that might not be orthogonal to our treatment. Another threat to identification is the possibility that mine openings are correlated with unobservable factors that influence both health outcomes and water pollution, potentially affecting downstream and upstream areas differently. Table 13 and 14 in Appendix C replicates the main estimation using control variables, such as household characteristics (including access to infrastructure such as electricity and piped water, household wealth index, percentage of urban households, and exposure to conflict), early life characteristics (breastfeeding) as well as mother's characteristics (age, education and migration) and fertility. Section 8 presents a final, general discussion of potential threats to the identifying assumption and how they have been solved in the analysis.

Table 1: Balance Table

	Before Mine Opening					After Mine Opening					Within Up.	Within Dwn.	Within
	Upstream		Downstream		Diff	Upstream		Downstream		Diff			
	N	Mean /(SD)	N	Mean /(SD)	(4-2) /(p.v)	N	Mean /(SD)	N	Mean /(SD)	(9-7) /(p.v)	(7-2) /(p.v)	(9-4) /(p.v)	(12-11) /(p.v)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dth<12													
All	23,547	0.073	7,875	0.074	0.001	12,319	0.055	4,738	0.051	-0.004	-0.018	-0.023	-0.005
		(0.261)		(0.262)	(0.83)		(0.228)		(0.219)	(0.256)	(0)	(0)	(0.468)
Mines	244		237			179		183					
Dth<24													
All	17,726	0.096	5,928	0.098	0.002	8,664	0.068	3,330	0.072	0.004	-0.028	-0.026	0.002
		(0.294)		(0.297)	(0.618)		(0.252)		(0.259)	(0.428)	(0)	(0)	(0.671)
Mines	244		236			168		168					

Notes: Standard errors and p-values in parentheses. Descriptive statistics of 12- and 24-month mortality outcomes for villages located upstream and downstream of mining sites, for individuals born before and after the opening of the mine.
Source: Author's computations from DHS and SNL datasets.

Balance Table – Table 1 compares changes in infant mortality before and after the opening of a mine, for location upstream *vs* downstream of the mining site, based on the pairing strategy. It also displays the number of individuals and paired mines in each analysis group. On average, there are no significant differences in 12- and 24-month mortality rates between upstream and downstream areas (columns 5 and 10). For both upstream and downstream clusters, mine openings are associated with a significant decrease in mortality rates (columns 11 and 12), which aligns with the general decline in infant mortality rates over time in Africa, as trends are not included (Figure 2). Table 1 shows that the reduction in under-24-month mortality is slightly larger in upstream areas than in downstream areas (by 0.002), whereas the opposite is observed for under-12-month mortality, with a slightly greater reduction downstream (by 0.005). However, these differences are not statistically significant (column 13).

3.3. Main results

Child mortality–This section presents the main findings on child mortality, based on estimates from equation 1 for both the 12-month and 24-month mortality rates. Table 2 summarizes the key results. Columns (1) to (4) report results for the 12-month mortality rate, while columns (5) to (8) present results for the 24-month mortality rate. Columns (1), (2), (5), and (6) present estimates for the total population, while columns (3), (4), (7), and (8) focus specifically on the rural population. Control variables include birth order, mother's age, mother's age squared, mother's years of education, urban residence, and river network intensity. Additionally, even-numbered columns include the number of open mines within 45 km of the DHS cluster as a control for mining density. The results indicate that being downstream of an open mine increases the 24-month mortality rate by 2.16 percentage points (p.p) [7]. This represents a 25% increase, with the average 24-month mortality

[7] 95% Confidence interval: [0.000595; 0.042993]

Table 2: Effects of Industrial Mine Openings on Child Mortality

	12-month mortality				24-month mortality			
	Total Population		Rural Population		Total Population		Rural Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream × Open	-0.00361	-0.00513	0.00502	0.00498	0.0229**	0.0216**	0.0374***	0.0374***
	(0.00820)	(0.00828)	(0.0102)	(0.0101)	(0.0105)	(0.0108)	(0.0130)	(0.0130)
Downstream	-0.0140**	-0.0151**	-0.0201***	-0.0202***	-0.0202***	-0.0211***	-0.0285***	-0.0282***
	(0.00655)	(0.00665)	(0.00744)	(0.00763)	(0.00730)	(0.00738)	(0.00793)	(0.00808)
Open	0.0122*	0.00972	0.0108	0.0105	-0.00296	-0.00494	-0.00618	-0.00555
	(0.00722)	(0.00753)	(0.00859)	(0.00952)	(0.00987)	(0.0101)	(0.0115)	(0.0122)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb open mines	No	Yes	No	Yes	No	Yes	No	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48,472	48,472	33,231	33,231	35,638	35,638	24,544	24,544
R2	0.0373	0.0373	0.0469	0.0469	0.0504	0.0504	0.0623	0.0623
Outcome Mean	0.0666	0.0666	0.0716	0.0716	0.0873	0.0873	0.0945	0.0945

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All controls include mother's age, age squared, years of education, urban residency, and a continuous variable indicating the presence of rivers and their order. Columns (2), (4), (6), and (8) control for the number of open mines within 45 km. The estimation includes fixed effects for birthmonth, country-birthyear, mine sub-basin, and commodity, along with a mine sub-basin birthyear trend. The variables Downstream and Open are dummies that indicate whether an individual lives in a village downstream of at least one mining site and whether the site opened before the year of birth. Each DHS village is paired to only one mining site so that each individual appears only once in the regression. Columns (1)–(2) and (5)–(6) report results for the total population, while columns (3)–(4) and (7)–(8) report results for rural villages. *Source:* Author's calculations using DHS and SNL data.

rate rising from 8.73% to 10.89%. The effect is even larger in rural areas, where being downstream of an open mine increases the 24-month mortality rate by 3.74 p.p, corresponding to a 40% increase (from 9.45% to 13.19%). This is consistent with the fact that rural populations have limited access to infrastructure and are more exposed to unsafe water. No significant effect is observed for the 12-month mortality rate, with results very close to zero, indicating no difference between individuals living upstream and downstream. The delayed effect of water pollution on child health may be explained by the higher likelihood of children under 12 months being breastfed compared to those under 24 months, which reduces their exposure to contaminated water and limits direct ingestion (VanDerSlice et al., 1994; Fängström et al., 2008). This mechanism, which helps explain the different results for 12-month vs. 24-month mortality, is further explored in Section 4.1.

Other health effects– Table 3 presents the effects of industrial mine open-

Table 3: Effects of Industrial Mine Openings on Child Health Outcomes

	Surviving children							All births	
	Stunting	Underweight	Wasting	Anemia	Diarrhea	Cough	Fever	Low birth weight	Small at birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Downstream × Open	-0.0158	-0.0382**	-0.00474	-0.0274	0.00174	-0.00829	-0.00223	-0.00875	-0.00345
	(0.0201)	(0.0169)	(0.0109)	(0.0276)	(0.0130)	(0.0175)	(0.0154)	(0.0180)	(0.0120)
Downstream	-0.0122	-0.00276	0.00348	0.0426**	0.00281	-0.0113	0.0142	-0.0101	0.00673
	(0.0173)	(0.0153)	(0.00897)	(0.0188)	(0.0108)	(0.0138)	(0.0144)	(0.0164)	(0.0107)
Open	-0.00558	0.0260*	0.00555	0.00592	-0.00572	0.00561	-0.00588	0.0192	0.00750
	(0.0163)	(0.0147)	(0.00953)	(0.0246)	(0.0111)	(0.0124)	(0.0127)	(0.0159)	(0.0106)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,393	37,043	37,903	19,331	55,162	54,958	54,955	29,162	58,338
R2	0.149	0.122	0.0892	0.215	0.0899	0.104	0.111	0.0601	0.0528
Outcome mean	0.308	0.246	0.0893	0.660	0.165	0.237	0.246	0.171	0.157

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Columns (1-3) focus only on surviving children (due to variable construction in DHS), while the others encompass all children, including those who died before the survey. The same sample, controls, fixed effects and trends as Table 2 Column 2 apply. All controls include mother's age, age squared, years of education, urban residency,rivers presence and intensity, and the number of open mines within 45km. The estimation includes fixed effects for birthmonth, country-birthyear, mine sub-basin, and commodity, along with a mine sub-basin birthyear trend.
Source: Author's calculations using DHS and SNL data.

ings on downstream child health outcomes besides mortality. Columns (1) to (3) show results for anthropometric measures among children alive at the time of the survey. Column (4) reports effects on anemia, columns (5) to (7) present effects on gastrointestinal and respiratory outcomes measured over the two weeks preceding the survey. Columns (8) and (9) report effects on birth weight and reported size at birth. We find no significant effects on acute health outcomes among living children — including diarrhea, cough, and fever — nor on low birth weight or reported size at birth. The absence of effects on gastrointestinal outcomes such as diarrhea is consistent with heavy metal contamination (Briffa et al., 2020), which tends to generate chronic developmental toxicity rather than the acute gastrointestinal illnesses typically associated with microbial water pollution. This pattern is consistent with contamination by heavy metals released by industrial mining processes, for instance through leakages from tailings storage facilities and retention ponds. We also find no significant effects on anemia, stunting[8],

[8]A child is considered stunted if their height-for-age z-score is more than two standard

or wasting, suggesting that the impacts of mining activity on child health in our setting appear to operate more through mortality than through measurable changes in anthropometric outcomes among surviving children. The coefficient on underweight (column 2) is significantly negative, which could reflect survival selection whereby the most vulnerable children may be more likely to die following mine opening, leaving a surviving population that is on average healthier. However, this estimate is not robust to corrections for multiple hypothesis testing (Table 18 in Appendix D), which shows that no outcome — including underweight — remains significant after applying the Benjamini-Hochberg correction, consistent with mine openings affecting child health primarily through mortality.

4. Heterogeneity and Mechanisms

This section examines whether the observed mortality effects are consistent with exposure to mining-induced water pollution by analyzing heterogeneity across early-life characteristics, household vulnerability, and mine extraction methods. If water pollution is the main transmission channel, the effects should be larger among children more exposed to contaminated water or more vulnerable to its health consequences. In particular, we would expect larger effects among children who are no longer breastfed, those living in rural areas or in poorer households that rely more heavily on local water resources, and in areas surrounding mines using more intensive extraction methods that generate higher levels of water pollution.

4.1. Early life characteristics

Breastfeeding – Table 4 explores heterogeneity in the effect of mine-induced water contamination by breastfeeding practices using a triple-interaction

deviations below the mean, according to the World Health Organization Child Growth Standards. The same definition applies to underweight (weight-for-age) and wasting (weight-for-height).

specification. We focus on the six-month cutoff because WHO guidelines recommend exclusive breastfeeding for the first six months of life (World Health Organization, 2003; Organization, 2023), after which infants transition to water and complementary foods that become key vectors for heavy metal ingestion (Signes-Pastor et al., 2018). Consistent with this mechanism, Table 4 shows that the increase in mortality is concentrated among children who were no longer breastfed after six months.

Table 4: Effects of Industrial Mine Openings - Early Life Characteristics

	Breastfeeding						Child's access to health care			
Var.	No longer breastfed		Ever breastfed		Breastfeed months		No prenatal care		Ever vaccinated	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortality outcome	(6,12)	(6,24)	12m	24m	12m	24m	12m	24m	12m	24m
Down.× Open × Var.	0.0709	0.105*	0.00107	-0.0445	0.000988	0.00108	0.0164	0.0289	0.0110	0.0125
	(0.0532)	(0.0635)	(0.0516)	(0.0479)	(0.00177)	(0.00210)	(0.0272)	(0.0402)	(0.0190)	(0.0231)
Down.×Open	0.00206	0.0142**	0.00365	0.0693	-0.0193	-0.00183	-0.0116	-0.000821	-0.0120	-0.0102
	(0.00480)	(0.00700)	(0.0520)	(0.0486)	(0.0374)	(0.0516)	(0.00822)	(0.0120)	(0.0178)	(0.0212)
Down.	-0.00168	-0.00646	-0.00997	-0.0155	-0.0123	-0.0286	-0.0140**	-0.0201**	0.0114	0.00250
	(0.00375)	(0.00551)	(0.0250)	(0.0304)	(0.0238)	(0.0300)	(0.00612)	(0.00868)	(0.0127)	(0.0126)
Open	-0.0126***	-0.0227***	0.0183	0.0179	-0.0819***	-0.133***	0.00852	0.000467	0.00427	0.00913
	(0.00438)	(0.00640)	(0.0265)	(0.0344)	(0.0232)	(0.0324)	(0.00771)	(0.0117)	(0.0105)	(0.0175)
Var.	0.0471**	0.0527*	-0.920***	-0.880***	-0.0177***	-0.0201***	0.0302***	0.0399***	-0.0202***	-0.0257***
	(0.0227)	(0.0275)	(0.0114)	(0.0133)	(0.000591)	(0.000657)	(0.00773)	(0.0110)	(0.00730)	(0.00829)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	43,628	33,666	45,168	33,022	29,015	18,323	31,656	19,543	17,372	13,638
R2	0.0379	0.0464	0.208	0.174	0.326	0.354	0.0553	0.0813	0.238	0.304

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects and trends as Table 2 Column 2 apply.
Source: Author's calculations using DHS and SNL data.

In Table 4 columns (1) and (2), interacting the DiD estimator with an indicator for having stopped breastfeeding by month 6 reveals a large downstream effect after mine opening for 24-month mortality. While column (1) shows no significant effect among children who stopped breastfeeding by month 6 at the 12-month horizon — consistent with the limited exposure window between weaning at six months and the 12-month mortality cutoff — column (2) shows a 10.5 p.p increase in mortality between 6 and 24 months for children no longer breastfed, compared to a smaller 1.4 p.p significant effect among breastfed children. This is consistent with breastfeeding providing partial rather than complete protection against heavy metal ingestion, as documented in the literature on heavy metal transfer to breast milk (Ettinger et al., 2004; Rebelo and Caldas, 2016). This timing aligns with evidence that arsenic exposure increases substantially during the weaning transition, particularly through rice-based products, fruits, and vegetables commonly introduced at this age (Signes-Pastor et al., 2017, 2018). Heavy metals transfer to breast milk at low rates relative to maternal intake—breast milk lead concentrations remain very low relative to maternal blood lead levels (Ettinger et al., 2004), and arsenic and cadmium concentrations remain low even in highly exposed populations (Fängström et al., 2008; Rebelo and Caldas, 2016). This reduced exposure through breastfeeding appears sufficient to protect against mortality at the contamination levels in our study area. Moreover, infants not on breast milk may receive additional metal exposure through contaminated formula powder (Carignan et al., 2015) and the water used to reconstitute it. This heavy metal mechanism is further supported by the absence of significant effects on diarrheal incidence (Table 3), ruling out pathogen-mediated water contamination and consistent with heavy metal exposure primarily causing developmental rather than acute gastrointestinal toxicity.

Moreover, Table 13 in Appendix C indicates that the interaction between being downstream and a mine opening has no effect on breastfeeding beyond six months or on breastfeeding duration. This rules out behavioral adjustments in breastfeeding as a confounding mechanism and reinforces the interpretation that the estimated effects operate through differential exposure to heavy-metal contamination.

Finally, we do not find heterogeneity by ever-breastfed status or breastfeeding duration (columns 3–6), likely because breastfeeding initiation is nearly universal in the sample (98% of children were breastfed at some point).

Access to healthcare– We find no differential effects of mine openings on downstream children mortality based on access to healthcare. In Table 4, none of the triple interactions related to healthcare access show significant results. Our findings remain consistent across factors such as prenatal care (columns 7 and 8) and the child's vaccination status (columns 9 and 10).

4.2. Individual and household characteristics

Table 5: Effects of Industrial Mine Openings - Gender and Wealth Index

Outcome	24-month mortality							
	Gender				Wealth Index			
Sample	All		Rural		All		Rural	
	Girls	Boys	Girls	Boys				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Down.× Open × WIndex						-0.0673*		-0.0631
						(0.0348)		(0.0386)
Down.× Open	0.0125	0.0329*	0.0208	0.0661***	0.0217*	0.0834**	0.0307**	0.0865**
	(0.0150)	(0.0168)	(0.0185)	(0.0200)	(0.0116)	(0.0332)	(0.0150)	(0.0369)
Down.	-0.0202*	-0.0204*	-0.0290**	-0.0291**	-0.0238***	-0.0511***	-0.0328***	-0.0395*
	(0.0114)	(0.0110)	(0.0126)	(0.0116)	(0.00772)	(0.0191)	(0.00847)	(0.0203)
Open	0.00321	-0.0178	0.00391	-0.0187	-0.00427	0.00358	-0.00605	0.0136
	(0.0155)	(0.0143)	(0.0186)	(0.0182)	(0.0109)	(0.0219)	(0.0131)	(0.0236)
WIndex					-0.00449	-0.00986	-0.00625*	0.00376
					(0.00295)	(0.0136)	(0.00334)	(0.0139)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17,452	18,142	12,009	12,481	27,956	27,956	19,124	19,124
R2	0.0751	0.0750	0.0932	0.0950	0.0462	0.0463	0.0586	0.0587
Outcome mean	0.0805	0.0938	0.0883	0.101	0.0763	0.0763	0.0821	0.0821

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Same sample, controls, fixed effects and trends as Table 2 Column 2. Odd columns (5) and (7) control for the continuous wealth index; even columns (6) and (8) interact with a dummy equal to 1 if wealth index > 2. Rural sample in columns (3), (4), (7), and (8).
Source: Author's calculations using DHS and SNL data.

Gender and Location–We conduct a heterogeneity analysis based on children's location and gender (Table 5). Results from Table 2 indicate that being downstream of an open mine has a more significant impact in rural areas (Column 4), where it increases the 24-month mortality rate by 3.74 p.p, corresponding to a 40% increase in mortality. The heterogeneity analysis by gender reveals that the effects are mainly driven by male mortality (Table 5 Columns 3 and 6), with this pattern remaining consistent in rural areas.

Household's wealth– Table 5 shows that the effects of mine openings on 24-month child mortality rates remain stable when controlling for the household wealth index, with larger effects observed among households with lower wealth indices. Columns (5) and (6) from Table 5 present the results for the full sample, while columns (7) and (8) focus on rural areas. Columns (5) and (7) include a triple interaction with a dummy variable that equals 1 if the household wealth index is above 2 (out of the 5 wealth quintiles) and 0 otherwise, while columns (6) and (8) control for the continuous household wealth index. The results of the triple interaction in columns (5) and (7) reveal larger effects for households with lower wealth indices. Households with a wealth index below 2 experience an 8.34 p.p increase in 24-month child mortality downstream, while households with a wealth index above 2 see a 1.6 p.p increase in mortality.

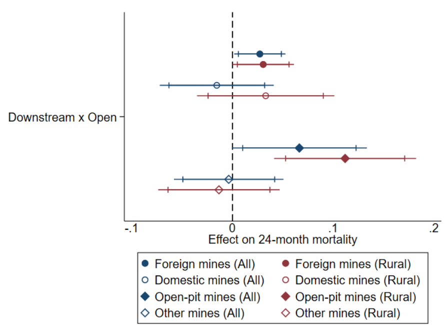
4.3. Mining activity's characteristics

Extraction methods–We further examine the heterogeneity of the effects across mine ownership and extraction methods. A mine is classified as domestic if at least one of its own companies is located in the same country as the mine site, which accounts for 17.8% of our mine sample. Figure 4 shows the results of DiD estimation for different samples based on mine characteristics. We find no effect of mine opening on downstream 24-month mortality rates when restricting the sample to domestic mines, while the results remain significant when focusing on foreign-owned mines (in blue). This pattern is consistent with two complementary explanations. First, domestic mines may be smaller in scale and subject to greater community oversight, resulting in lower levels of water contamination. Second, given that domestic mines represent a minority of our sample, statistical power to detect effects in this subgroup may be limited. We then investigate the impact of open-pit mining, which accounts for 21.6% of our mine sample. The results hold when restricted to open pit mines, but not when restricted to other mining methods such as underground, placer, and in-situ leach (in red). This is consistent with the fact that open pit mines are the most polluting mines due to the large amount of waste generated and stored in tailings dams, releasing heavy metals into surrounding waterways, while underground and in-situ extraction methods generate comparatively less surface contamination.

Regional Heterogeneity– Table 6 gives the results of the DiD estimation for different African subregions, revealing that the results are mainly driven by West Africa, with significant effects also observed in East Africa. [9]

Taken together, these heterogeneity patterns are consistent with water pollution exposure as the main mechanism linking mine openings to increased child mortality.

Figure 4: Heterogeneity Across Mines' Characteristics



Notes: This figure plots the DiD estimator for different mine characteristics. Blue coefficients correspond to foreign-owned versus domestically owned mines, and red coefficients correspond to open-pit versus other extraction methods (underground, placer, and in-situ leach). The specification includes the same controls and fixed effects as in the baseline regression. Vertical bars represent 95% confidence intervals.
Source: Author's calculations using DHS and SNL data.

Table 6: Effects of Industrial Mine Opening Across Regions

	24-month mortality	
	Western Africa	Eastern Africa
	(1)	(2)
Downstream×Open	0.0440**	0.0295*
	(0.0175)	(0.0154)
Downstream	-0.0153	-0.0368***
	(0.00942)	(0.0117)
Open	0.00527	-0.0142
	(0.0133)	(0.0158)
All Controls	Yes	Yes
All Fixed Effects	Yes	Yes
N	21,006	13,484
R^2	0.0512	0.0447
Outcome mean	0.0981	0.0712

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The sample is split by subregions of Africa. All regressions include the same controls, fixed effects, and trends as in the baseline specification.
Source: Author's calculations using DHS and SNL data.

5. Pollution Intensity and Dynamic Effects

This section provides additional evidence that the observed mortality effects are consistent with water pollution exposure by examining how the

[9]Results for Central and Southern Africa are not reported as these regions include only a small number of countries with limited mining activity near DHS clusters, yielding imprecise estimates

effects vary with pollution intensity and over time. In line with water pollution being the main mechanism, we observe larger effects in areas with higher exposure intensity and effects that evolve over time following mine openings. We examine these patterns using spatial exposure gradients, mine density, production intensity, and the dynamic effects of mine openings.

5.1. Intensive Margin

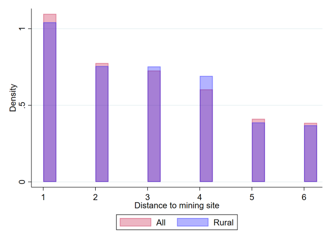


Figure 5: Distance to the Nearest Mine

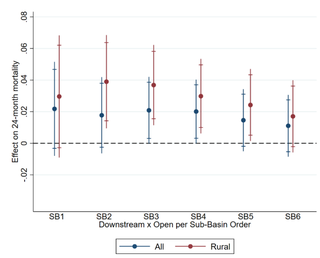


Figure 6: DiD estimator by Sub-Basin Order

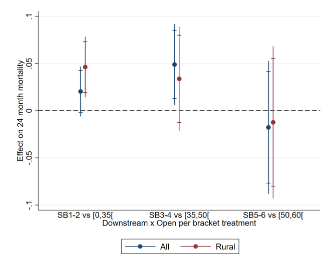


Figure 7: DiD estimator by Distance

Notes: Figure 5 plots the distribution of downstream DHS village distances to the nearest mine by sub-basin order. Figure 6 plots the DiD estimator when varying the treatment group: SB1 includes control villages up to the first sub-basin, SB2 up to the second, and so on, with SB3 corresponding to the main specification. Figure 7 plots the interaction term on 24-month mortality across distance brackets, comparing individuals in specific sub-basins to upstream villages within a given distance range, where distances are based on the mean distance from the mine to the edge of each sub-basin.
Source: Authors' elaboration on DHS and SNL data.

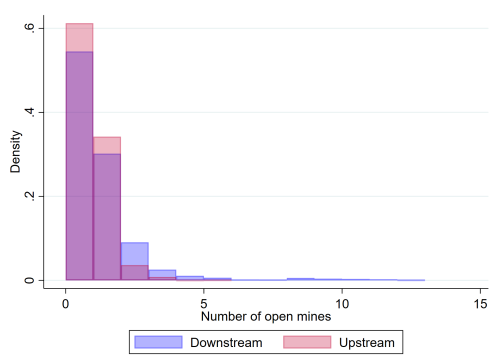
Spatial Intensive Margin—This section tests the effect of mine openings across different downstream sub-basin orders and distances. Figure 6 plots the coefficient on *Downstream* × *Open* for six models, varying the treatment group from the first to the sixth downstream sub-basin. SB3 corresponds to the main results in Table 2. The estimated effect decreases as more distant downstream sub-basins are included, consistent with pollution dilution along the hydrological network. Results are statistically significant at the 5% level up to the third sub-basin for the full sample, and up to the fourth for rural areas. The non-significance for the first sub-basins likely reflects lower statistical power due to smaller sample sizes. Figure 7 examines the effect by distance brackets, comparing individuals living downstream of the first two sub-basins to those within 35 kilometers of the mine, and so on for the next sub-basins. This analysis shows the strongest effect in the third and fourth sub-basins, particularly in rural areas, highlighting the greater impact closer to the mine where pollution levels are highest.[10] This spatial gradient is consistent with a water pollution exposure mechanism rather than alternative channels that would not vary systematically along the river network.

Mine density–This section explores the intensive margin of our results in relation to mine density. Figure 11b in Appendix A.3 shows the distribution of the distances between mines, with an average of 31km between each mine and its closest neighbor. The right-skewed distribution indicates that most mines are clustered in high-density areas, while a few are isolated. This underscores the need to control for mine density in the main analysis (Table 2) and examine heterogeneous effects. Figure 8a displays the frequency of open mines in both upstream and downstream areas within 45 km and the third sub-basin. We further analyze the DiD estimator differences when being downstream of one, two, or more mines in Figure 8b. For the full sample, being downstream of one mine increases 24-month mortality by 2 p.p., with the effect rising to 6 p.p. for those downstream of more than two mines. This pattern is in line with a water pollution exposure mechanism, as a higher number of nearby mines likely increases cumulative pollution exposure through the hydrological network.

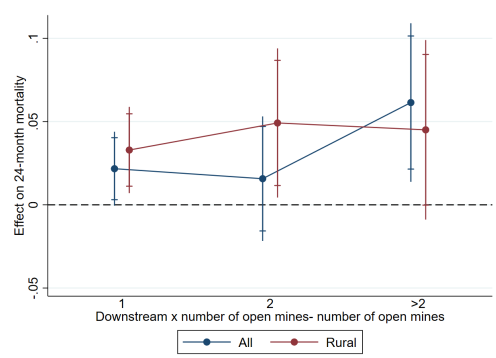
Production intensive margin–We proxy mine production intensity using the global price of each mine's primary commodity, following Berman et al. (2017) and Girard et al. (2022). Higher prices are assumed to reflect higher production intensity. Annual prices for coal, gold, lead, nickel, platinum,

[10]The discrepancy between the full and rural samples may be due to lower precision for mines near urban areas (see Table 20 and Section 7).

silver, and zinc are sourced from SNL data, while copper prices come from the World Bank Pink Sheet. For each commodity, we calculate the average price over 1971-2021, then compute the standardized difference and Z-score. The triple interaction with both price variables - standardized difference in column (1) and Z-score in column (2) - shows a positive and significant effect (Table 7). We then plot the coefficients of the interaction term for being downstream of an open mine across the quartiles of the Z-score change (Figure 9). For both total and rural samples, we observe that an increase in prices (from the second to the third quartile) amplifies the effect of industrial mining on downstream 24-month mortality. This pattern is consistent with a pollution exposure mechanism, as higher commodity prices likely increase mining production and associated pollution discharge into the hydrological network.



(a)

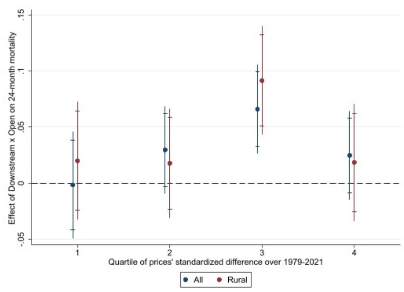


(b)

Figure 8: Effect of the number of mine openings on 24-month mortality

Notes: Figure 8a plots the distribution of the number of open mines across downstream and upstream villages. Figure 8b plots the interaction variable on 24-month mortality rates. It reports the average treatment effects of the number of mines open on 24-month mortality.
Source: Authors' elaboration on DHS, SNL, and HydroSheds data.

Figure 9: Heterogeneity by Commodity Price Changes



Notes: This graph shows the coefficients for being downstream of an open mine across quartiles of each commodity's standardized price deviation from the 1979–2021 mean.
Source: Authors' elaboration on DHS and SNL data.

Table 7: Effect of Industrial Mine Openings Across Commodity Price Changes

Outcome	24-month mortality	
	(1)	(2)
Var:	Standardized difference	Z-score
Down. × Open× Var.	0.0160*	0.0101**
	(0.00823)	(0.00463)
Down.	-0.00244	0.00102
	(0.0104)	(0.0110)
All Controls	Yes	Yes
All Fixed Effects	Yes	Yes
N	31,517	31,517
R2	0.0509	0.0509
Outcome mean	0.0907	0.0907

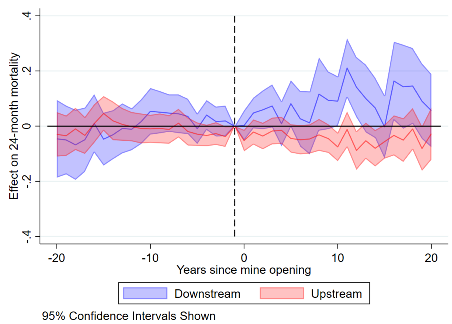
Notes: Standard errors clustered at the DHS village level. Standardized difference and Z-score of each commodity's price are calculated over 1979–2021. The same sample, controls and fixed effects as Table 2 Column 2 apply.
Source: Author's computations from DHS and SNL datasets.

5.2. Dynamic effects

This section examines the dynamic effects of industrial mine openings, focusing on pre-trends and the timing of their impact on 24-month mortality, both in the short and long term, as well as during the mining activity.

Pre-trends and Event Study– Figure 10 presents an event-study analysis of the effect of mine opening on 24-month mortality for both downstream and upstream villages, using the same controls and fixed effects as in the main specification (Table 2). The coefficients in the pre-treatment periods are small and not statistically different from zero, providing no evidence of differential pre-trends between upstream and downstream locations prior to mine opening. A joint F-test of the pre-treatment coefficients over the twenty years preceding mine opening fails to reject the null hypothesis of no pre-trends ($F(19, 816) = 1.06$, $p = 0.39$), providing formal support for the parallel trends assumption. Following mine opening, mortality increases downstream, with the effect gradually emerging over time and becoming statistically significant in the medium term, roughly a decade after the start of mining activity. Upstream locations show no comparable increase in mortality. The timing and gradual emergence of the effects, combined with the absence of differential pre-trends, are consistent with a causal effect of mine openings on downstream mortality through pollution exposure rather than pre-existing trends.

Figure 10: Event Study – 24-Month Mortality



Notes: This figure plots event-study estimates of the effect of mine opening on child mortality for downstream and upstream DHS villages, from 10 years before to 10 years after mine opening. The year immediately preceding mine opening ($t = -1$) is used as the reference period. The specification includes the same controls and fixed effects as in the baseline regression. Vertical bars represent 95% confidence intervals.
Source: Author's calculations using DHS and SNL data.

Table 8: Effects of Industrial Mine Activity

	12-month mortality		24-month mortality	
	All	Rural	All	Rural
	(1)	(2)	(3)	(4)
Downstream × Active	0.00960	0.0298	0.0368	0.0411*
	(0.0221)	(0.0255)	(0.0249)	(0.0245)
Downstream	-0.0264*	-0.0440**	0.00926	-0.00607
	(0.0137)	(0.0179)	(0.0143)	(0.0180)
Active	0.00184	0.00580	-0.00637	0.000501
	(0.0139)	(0.0173)	(0.0172)	(0.0192)
All Controls	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes
N	7,231	5,589	5,270	4,082
R^2	0.0879	0.0936	0.0952	0.104
Outcome mean	0.0756	0.0825	0.0981	0.104

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The variables *Downstream* and *Active* are indicators for whether a DHS village is located downstream of at least one mining site and whether the mine is active in the year of birth. All regressions include the same controls, fixed effects, and trends as in the baseline specification.
Source: Author's calculations using DHS and SNL data.

Mine closure–In the main analysis, we focus on mine openings without considering closure dates, as this information is more difficult to obtain. In this section, we examine a restricted subsample of mines for which the SNL database provides closure dates to assess whether mine closure drives our main results. Figure 11a shows the distribution of mine lifespan based on this restricted subsample. On average, mines last 16 years, but the distribution is right-skewed, with most mines closing before 10 years.[11] Table 8 examines

[11]Note that the closure dates in the SNL database are not exact, as mines may be

the effects of being downstream of a mine that was active during the year of birth of the child. Columns (1) and (2) show no effect on 12-month mortality, while columns (3) and (4) reveal a 4 p.p. increase in the mortality rate for those downstream of an active mine, corresponding to a 40% increase. This suggests that the harmful effects of mining are concentrated during periods of active extraction, in line with a pollution exposure mechanism, as pollution is likely to be highest when mines are actively operating.

6. Ruling Out Alternative Channels

The main identification strategy relies on the assumption that upstream and downstream communities would have followed similar trends in the absence of pollution exposure. This section provides evidence supporting this assumption by testing whether mine openings lead to differential changes between upstream and downstream areas through channels other than water pollution—such as fertility, migration, access to infrastructure, conflict, or local economic conditions—and by controlling for these factors in the main specification.

Effect of mine opening on household and early life characteristics – Table 13 in Appendix C tests whether mine openings affect breastfeeding practices and other child and household characteristics. We find no effects of being downstream of an open mine on the probability of breastfeeding after 6 months, the duration of breastfeeding, or other characteristics such as plain water consumption or vaccination status. These results rule out the concern that our mortality findings are driven by endogenous changes in breastfeeding behavior induced by mine operations. We conduct the same analysis on household characteristics. We observe no statistical differences in terms of access to piped water and electricity. Column (4) of Table 13 shows no differential change in the wealth index between downstream and upstream areas

temporarily suspended for political or economic reasons.

after a mine opens. This suggests that income effects are unlikely to drive the mortality results, and that local wealth is not endogenous to either mining activity or downstream location. Table 13 shows that the share of urban households increases by 13 p.p., and Table 14 shows that the share of migrant mothers increases by 8.8 p.p. after a mine opens in downstream areas. These compositional changes are unlikely to drive the mortality results: we control for urban residency in all specifications, and the effects are primarily concentrated among rural households. Furthermore, Table 7 in Appendix C shows that the results hold when controlling for migration status, suggesting that in-migration does not drive the main findings.

Women's outcomes– We ensure that the results on child mortality are not confounded by changes in mother characteristics such as age or years of education, or changes in maternal fertility and health.[12] Table 14 in Appendix C shows no significant effects of industrial mining on maternal age, education, or fertility outcomes—including whether women have ever had a child (column 4), the total number of children (column 5), or current pregnancy status (column 6). We also find no effects on the occurrence of miscarriages or anemia status.

Households' access to water and facilities– We further investigate whether the observed effects on child mortality are due to water pollution downstream of mines, rather than improvements in water, sanitation, or facilities upstream. Table 13 in Appendix C explores the DiD estimator using access to piped water and electricity as dependent variables, showing no significant differences between upstream and downstream villages after mine openings. The 24-month mortality rate remains significantly higher by 2 p.p. when adding a triple interaction with several facility variables: whether a household has piped water as the main drinking source (Column 1), a flush toilet (column 2), access to electricity (column 3), and whether the mother visited a

[12]The analysis uses the DHS Women Recode, which includes women aged 15-49 years.

health facility in the 12 months preceding the survey (column 4). We find no significant heterogeneity across the four facilities, suggesting that the results are not driven by upstream facility improvements [13].

Migration– The results are robust to controlling for in-migration. Migration information — indicating whether mothers have migrated to their current residence — is available for 60% of our sample. Table 16 in Appendix C reports the main coefficient with and without controlling for migrant status, for both the full and rural samples. The results hold when controlling for migration, with coefficients remaining positive and significant across all specifications, suggesting that in-migration does not drive the mortality increase.

Conflicts–The main results remain robust when controlling for conflicts, as measured using the ACLED data. Table 17 in Appendix C controls for the number of conflicts reported in the ACLED data, distinguishing between the number of conflicts within the mine sub-basin and the DHS village sub-basin.

Income– First, Column (4) of Table 13 in Appendix C shows no differential change in the wealth index between downstream and upstream areas after a mine opens. This result complements existing studies documenting income gains after a mine opens (Kotsadam and Tolonen, 2016; Mamo et al., 2019) by showing that, in our setting, such effects do not differ between upstream and downstream areas, making it unlikely that income dynamics drive the mortality patterns we identify. The main results are also stable when controlling for household wealth using the DHS wealth index (see Table 5 in Section 4.2). Table 5 further indicates that the effects are stronger for households with a lower wealth index. Finally, in Section 7.4, we show that including non-topographic sub-basins in the control group—capturing income and labor market effects—does not alter the results. Taken together, these findings suggest that income- and labor-related channels do not drive the main effects.

[13] These results challenge the findings of Dietler et al. (2021)

Other controls– Finally, Table S1 in Supplementary Appendix shows that the main result remains robust when including additional controls such as rainfall (measured using CHIRPS), changes in population (measured using WorldPop (Tatem, 2017)), tree cover(measured using the Hansen et al. (2013) dataset), and the percentage of cultivated area.

Taken together, these results suggest that the estimated mortality effects in downstream areas are unlikely to be explained by endogenous changes in fertility, migration, infrastructure, conflict, or local economic conditions, supporting the interpretation that they reflect water pollution exposure.

7. Robustness checks

7.1. Balanced sample and Heterogeneous treatment effects

A key challenge with DHS data is dealing with repetitive cross-sections rather than a true panel. To address this, we demonstrate that our results remain consistent when using a balanced sample. This approach allows us to test for heterogeneous treatment effects with two-way fixed effects, showing even stronger results (Table 19). The definition of the balanced sample and its impact on treatment effects are detailed in Appendix D. By expanding the mine sample size and creating a new dataset with opening dates, we make it possible to restrict the analysis to this balanced sample, underscoring the value of our contribution in increasing the sample size of mines.

7.2. Measurement errors

In this section, we address measurement errors arising from the nature of the data, including random displacement of DHS villages, and test the robustness of our results based on the precision of mine location.

DHS random displacement– DHS randomly displaces village GPS coordinates to protect respondent confidentiality which introduces measurement errors, particularly as treatment depends on a village's location relative to the mine. To address this, we simulate 1,000 random displacements per village and adjust treatment status based on the new sub-basin's relation to the mine. Results show that 25% of initially treated villages are excluded from the sample, and Figure 14 visualizes the DiD estimator for these displacements. More details are provided in Section D.

Accuracy of mine location– We test for potential measurement errors by looking at the precision of the mines' location in Table 20. The SNL database provides information on the accuracy levels of each mine's GPS coordinates, enabling us to restrict the analysis to mines with exact coordinates, precise at 1 km. Our main results are positive, but no longer significant when restricting to the mines with exact coordinates, but remain comparable and significant when focusing on rural households (column 3). This suggests a higher effect of industrial mining activity on child mortality among rural households and a lack of precision in the location of mines close to urban areas.

7.3. Placebo tests

Randomization inference–To make sure that the assignment of each village to its topographic position relative to the mine is indeed what drives our result on child mortality, we run randomization inference tests. We draw randomly 1,500 permutations of the "Downstream" variable without changing the start-up year and 1,500 permutations of the *Open* variable without changing the downstream position [14]. The simulations show that the distribution of treatment effects (Downstream × Open) are shifted around zero (Figure 15). The red line represents the initial treatment effect using our main specification: we are sure at the 1 percent level that our main model is not misspecified.

Placebo diseases– We conduct a placebo test to determine whether diseases unrelated to water pollution are differentially affected in downstream

[14] The randomization inference of the *Downstream* and *Open* treatment are within the sub-basin level, and are clustered at the DHS village level.

versus upstream areas following a mine opening. We find no significant effect of the opening of the industrial mine on the incidence of sexually transmitted diseases among women living downstream (Table 21, column 1) or on the awareness of tuberculosis (column 2). The lack of differential health outcomes related to placebo diseases between upstream and downstream villages supports the the conclusion that the main results are mainly driven by water pollution.

7.4. Sensitivity analysis

Including non-topographic sub-basins–We replicate the main analysis from Table 2, adding individuals from sub-basins with no topographic relation to the mine within 45 kilometers to the control group. This test helps isolate the water pollution channel more precisely, excluding income effects and other mechanisms linked to mining. Villages in these sub-basins with no topographic relation to the mine are assumed to be less exposed to mining-induced water pollution but equally exposed to income, labor effects, conflicts, or migration effects. However, this approach may also compare villages with different water resources, potentially blurring the interpretation. For example, activities like agriculture or livestock farming, which could generate pollution, may be concentrated around the mining site, confounding our analysis. If these activities are located in sub-basins unrelated to the mine, the comparison may reflect both types of pollution, leading to a downward bias. Additionally, as mining activity is water intensive, the location of these activities might also be endogenous to the location of the mine, and this could induce an even larger downward bias. Table 9 shows that including non-topographic sub-basins in the control group leads to a downward bias in the 24-month mortality rate results, with significance only at the 10% level for rural populations.

Spatial correlation– As an additional robustness check, we run the main specification accounting for the spatial correlation of DHS clusters. Standard errors are estimated using a spatial HAC correction, following Conley (1999)

Table 9: Effects of Industrial Mine Openings on Child Mortality - Including DHS with Non-Topographic Relationship

	12-month mortality				24-month mortality			
	Total Population		Rural Population		Total Population		Rural Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream × Open	-0.00255	-0.00216	0.00352	0.00392	0.00771	0.00828	0.0173*	0.0167*
	(0.00542)	(0.00543)	(0.00631)	(0.00631)	(0.00751)	(0.00752)	(0.00887)	(0.00887)
Downstream	-0.00490	-0.00473	-0.00901*	-0.00881*	-0.00498	-0.00468	-0.0103	-0.0107*
	(0.00445)	(0.00446)	(0.00506)	(0.00507)	(0.00561)	(0.00560)	(0.00636)	(0.00636)
Open	0.00361	0.00484	0.00320	0.00467	0.00102	0.00293	0.00274	0.000169
	(0.00292)	(0.00302)	(0.00345)	(0.00359)	(0.00377)	(0.00391)	(0.00457)	(0.00440)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb open mines	No	Yes	No	Yes	No	Yes	No	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168,931	168,931	123,413	123,413	124,670	124,670	91,395	91,395
R2	0.0211	0.0211	0.0248	0.0248	0.0301	0.0301	0.0351	0.0350
Outcome Mean	0.0638	0.0638	0.0670	0.0670	0.0824	0.0824	0.0872	0.0872

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All controls include mother's age, age squared, years of education, urban residency, birth order, and a continuous variable indicating the presence of rivers and their order. Columns (2), (4), (6), and (8) control for the number of open mines within 45 km. The estimation includes fixed effects for birth month, country-by-birth-year, mine sub-basin, and commodity, along with a mine sub-basin birth-year trend. The sample includes individuals living in non-topographic sub-basins within 45 km.
Source: Author's calculations using DHS and SNL data.

and implemented in Stata by (Colella et al., 2019). Table 23 confirms the stability of our results across different spatial correlation cut-offs (20 km to 200 km) [15]. Table 23 presents results with only mine-subbasin and country-birthyear fixed effects.

Other tests– Other sensitivity tests are presented in Section E and in Supplementary Appendix. Table 22 confirms the stability of the results when accounting for manual data collection quality, showing that the results remain stable when controlling for a dummy indicating whether the mine's opening year was manually retrieved or directly provided in the SNL database (column (2)). In Supplementary Appendix, we show the stability of the results when removing fixed effects and trends sequentially, and when dropping individually one by one countries and metals.

[15] We did not use the Conley (1999) test in the main analysis due to its incompatibility with multiple fixed effects

8. Discussion

Threats to identification–A major threat to identification is that the opening of a mine may not be orthogonal to unobservable factors that affect health and water quality, in different ways for downstream and upstream areas. First, migration is a major methodological concern, as we show in Table 13 that migrants significantly settle downstream after a mine opening. Section 6 shows that our main result is robust when controlling for in-migration. A main violation of the identifying assumption would be if downstream villages anticipate the mine opening and strategically out-migrate within upstream areas to avoid pollution. In this case, there would be a selection bias, as the individuals surveyed downstream after the mine opening would be those that were not able to migrate or anticipate the pollution. Controlling for in-migration in DHS villages, we show that our result is robust to this specific strategic behavior. However, we cannot control for strategic out-migration outside of the study area, meaning individuals out-migrating to avoid pollution elsewhere than the upstream area. To address this concern, we control for population changes using WorldPop data (Table in the Supplementary Appendix), which leaves our main results unchanged and provides reassurance that large-scale out-migration is not driving our findings. [16] Accordingly, a potential threat to our identification could be differing improvements in infrastructure access between upstream and downstream areas following a mine opening. However, Table 13 shows no difference in access to electricity and piped water between downstream and upstream areas after a mine opening, and Section 6 confirms the robustness of our results when controlling for infrastructure changes. Similarly, conflicts and violence around mining areas (Berman et al., 2017) could introduce an upward bias if they occur more frequently downstream. Yet, Table 13 shows no systematic difference, and

[16] In this paper, we made the choice not to use mother fixed-effects and retrospective questions on birth history, to limit endogenous selection due to out-migration, and to account for children born up to five years prior to the year of the survey.

Table 17 affirms that our results remain stable when controlling for conflicts using the ACLED data. We also rule out differential income effects: Table 13 shows no change in wealth index between upstream and downstream areas after a mine opening, and Section 6 confirms the robustness of our results when controlling for wealth. An other potential threat to identification is if other industries, correlated with the mine's topographic position, contribute to the pollution.

Selection issues– Our study uses the most comprehensive available data on mining and child health across Africa, though it is not exhaustive or fully representative of the continent. By limiting our sample to countries with at least two DHS waves, we excluded several, including South Africa, despite its significant mining activity. The 26 countries in our sample account for about two-thirds of Africa's population. Additionally, our mining data only covers industrial sites, excluding artisanal and small-scale mining due to data limitations. Although the mechanisms for industrial and artisanal mining pollution differ, we cannot rule out the possibility that some of our results may capture pollution from artisanal mining. However, given the higher intensity of industrial mining production, we argue that this is primarily driving our results. One remaining concern is the exhaustiveness of the SNL data and the heterogeneity in sampling across countries. Although the SNL dataset is one of the most comprehensive available, assessing quality differences between countries is challenging. We acknowledge this limitation, but since dropping countries one by one does not significantly affect the results (as shown in the Supplementary Appendix), we consider this issue to be of limited concern.

Other pollutant vectors– This study focuses on water pollution transmitted through hydrological networks while controlling for rivers and surface water exposure, and does not investigate heterogeneity in groundwater pollution. Air pollution is unlikely to drive the main results for two reasons. First, the upstream–downstream comparison provides a natural control, as wind direction is less systematically related to a village's topographic position than hydrological flow. Second, we exclude the mine's own sub-basin from the analysis, which reduces direct exposure to local air pollution affecting mine workers and nearby residents. In addition, the inclusion of sub-basins with no topographic relation to the mine — which would only be exposed to air pollution — as an additional control group further supports this interpretation (Table 9). To the extent that some air pollution effects remain, our estimates are likely conservative and understate the total health costs of industrial mining.

9. Conclusion

This paper identifies a significant negative externality of industrial mining on local populations in Africa. Using a novel dataset of 2,016 industrial mine openings combined with household health surveys across 26 African countries, and exploiting an upstream-downstream quasi-experimental design, we find that industrial mine openings increase 24-month child mortality by 25% in downstream communities, in line with exposure to mining-related water pollution. This paper provides new continental-scale causal evidence on the effects of industrial mining on child health in Sub-Saharan Africa, using an upstream–downstream design based on hydrological networks to identify exposure to mining-related water pollution.

Additional results and heterogeneity analysis further support the water pollution mechanism. We find no significant effects on other health outcomes such as diarrhea, fever, or cough, a pattern in line with heavy metal rather than microbial contamination. The heterogeneity across breastfeeding practices shows that the results are mainly driven by children who were no longer breastfed after 6 months, which is consistent with the protective role of breastfeeding against heavy metal ingestion through contaminated water. In an additional heterogeneity analysis, we find that the effects are even more pronounced in rural areas, for open-pit and foreign-owned mines, and in places with a high density of mines. We also find that the effects increase with production intensity (proxied by international commodity prices), and occur mainly during active mine operation. These results form a coherent set of evidence consistent with a water pollution exposure mechanism: the effects are strongest among populations most exposed to contaminated water and when mining activity — and therefore pollution — is more intense.

We exploit the variation in industrial mine openings and show that our results are not driven by changes in women's fertility behavior, differential access to piped water, electricity, or health facilities, income shocks, in-migration, or conflict between upstream and downstream areas after mine opening. We run a battery of robustness checks and find that our results hold when restricting to a balanced sample. Our results are also robust to the heterogeneous treatment effects estimator of de Chaisemartin and d'Haultfœuille (2020), to measurement error corrections, a battery of placebo tests and spatial and temporal randomization inference tests. The absence of differential changes in these alternative channels, combined with the robustness of the results across specifications, supports the interpretation that the observed mortality effects are driven by water pollution exposure rather than other local economic or demographic changes induced by mining activity.

This paper provides a quantitative foundation for policy recommendations aimed at promoting sustainable mining in resource-rich developing countries. Through a back-of-the-envelope calculation (Appendix F.1), we estimate that over 9,200 deaths per year are associated with industrial mine openings in downstream communities across 26 African countries, highlighting the significant public health burden of mining-induced water pollution. Since this effect holds even for countries participating in the Extractive Industries Transparency Initiative (EITI) (Appendix F.1), these results suggest the need for more stringent public policies to mitigate the adverse impacts of water pollution. These findings highlight that the local environmental and health impacts of natural resource extraction can be large and highly spatially concentrated, underscoring the importance of environmental regulation and monitoring around mining sites.

APPENDIX

A. Data and Context

A.1. Descriptive Statistics

Table 10 provides a detailed overview of the DHS data used in our main analysis. It lists each country included in our sample, along with the corresponding survey years, the total number of DHS clusters, and the number of children under five living within 100 km of an industrial mine at any point during the study period. The DHS dataset covers 36 African countries from 1986 to 2018.

Tables 12 display the descriptive statistics of all the variables in the sample used in the main empirical strategy, that is, for the sample of all individuals living within 45 km of an industrial mine, regardless of their topographic position, in the 26 countries of Sub-Saharan Africa with at least 2 waves of DHS and for heavy metals and coal mines.

Table 11 lists the number of mines by commodity type and indicates whether each commodity is classified as a heavy metal. Our main regression analysis includes heavy metals and coal mines, to capture the negative externalities linked to the most toxic mines.

A.2. Data collection of Mines's opening dates

Our manual data collection work consisted of reviewing the available company reports (comments and work history) in the SNL database and browsing the available aerial images on the SNL platform, which provided exact GPS coordinates and main location labels. We complemented this information with online research, including press releases, mining companies' websites, and specialized websites on global mining activities. We also used Google Maps and Google Timelapse satellite imagery. A mine opening corresponds

Table 10: DHS – Under 5 Sample Description

Countries	Years	Nb. Clusters	Nb. < 5	% Sample
Burkina Faso	1993, 1999 2003, 2010	694	23,846	64.9
Benin	2001, 2012 2017	62	1,911	6.0
Burundi	2010, 2016	317	8,280	39.8
Democratic Republic of the Congo	2007, 2013	82	5,092	18.6
Côte d'Ivoire	1994, 1998 2012	196	4,838	39.6
Cameroon	1991, 2004 2011, 2018	90	2,513	8.0
Ethiopia	2000, 2005 2010, 2016	100	2,956	7.0
Ghana	1993, 1998 2003, 2008 2014	1,217	12,074	67.3
Guinea	1999, 2005 2012, 2018	360	11,775	44.3
Kenya	2003, 2008 2014	233	4,130	12.8
Liberia	1986, 2007 2013	190	7,537	46.5
Lesotho	2004, 2009 2014	336	2,810	27.4
Madagascar	1997, 2008	131	3,301	20.7
Mali	1996, 2001 2006, 2012 2018	570	19,147	36.1
Malawi	2000, 2004 2010, 2015	207	6,651	11.7
Nigeria	1990, 2003 2008, 2013 2018	105	3,993	3.7
Niger	1992, 1998	40	1,105	9.7
Namibia	2000, 2006 2013	138	2,175	16.0
Rwanda	2005, 2008 2010, 2014	713	14,615	66.6
Sierra Leone	2008, 2013	377	13,717	78.4
Senegal	1993, 1997 2005, 2010 2012, 2014 2015, 2016 2017	363	10,111	13.8
Togo	1988, 1998 2013	104	2,187	15.8
Tanzania	1999, 2010 2015	325	6,866	33.5
Uganda	2000, 2006 2011, 2016	305	9,031	24.0
Zambia	2007, 2013 2018	364	10,966	37.7
Zimbabwe	1999, 2005 2010, 2015	468	8,307	41.8

Notes: This table gives the sample size of children under five years old that are in our main analysis, defined as those within 100 km of an industrial mine.
Source: Author's computations from DHS and SNL datasets.

Table 11: SNL Dataset: Sample Description

Metals	Nb.	% of Total Mines
Heavy Metals		
Gold	581	41.88
Copper	89	5.03
Iron ore	54	8.72
U308	36	1.60
Nickel	25	5.06
Platinum	21	0.43
Zinc	19	2.46
Chromite	16	0.57
Ilmenite	14	3.67
Lanthanides	13	1.95
Manganese	12	0.62
Tin	10	4.87
Cobalt	7	0.56
Tungsten	6	1.06
Tantalum	5	0.15
Vanadium	4	0.04
Niobium	3	0.39
Heavy Mineral Sands	3	0.16
Silver	1	0.00
Lead	1	0.06
Non-Heavy Metals		
Diamonds	115	11.73
Coal	55	2.19
Bauxite	23	1.94
Graphite	21	0.82
Phosphate	14	2.78
Lithium	14	0.80
Rutile	2	0.29
Potash (Salt)	1	0.17

Notes: This table lists metals, the number of mines within 100 km of a DHS cluster, and the percentage of children under five associated with these mines.
Source: Author's computations from SNL dataset.

Table 12: Descriptive Statistics of Children's Outcomes

	Mean	Standard deviation	Median	Min	Max	Observations
A. Children's characteristics						
Mortality rates						
12-month mortality	0.064	0.244	0	0	1	189,181
24-month mortality	0.083	0.275	0	0	1	139,683
Control variables						
Birth order number	3.655	2.421	3	1	18	240,431
Male	0.508	0.500	1	0	1	240,431
Anthropometric measures						
Stunting	0.319	0.466	0	0	1	137,834
Underweight	0.234	0.423	0	0	1	136,043
Wasting	0.077	0.267	0	0	1	138,222
Weight and size at birth						
Less than 2.5 kg	0.164	0.370	0	0	1	117,651
Small or very small size	0.161	0.367	0	0	1	226,796
Measured anemia level						
Any anemia	0.633	0.482	1	0	1	67,567
Illness in the last 2 weeks						
Diarrhea	0.168	0.374	0	0	1	216,097
Cough	0.260	0.439	0	0	1	214,940
Fever	0.265	0.441	0	0	1	214,913
Nutrition						
Given plain water	0.187	0.390	0	0	1	122,915
Ever breastfed	0.980	0.140	1	0	1	223,039
Months breastfed	14.788	8.917	15	0	59	156,011
Health access						
No prenatal care	0.101	0.301	0	0	1	169,268
Ever vaccinated	0.788	0.409	1	0	1	82,082
B. Mine's characteristics						
Domestic mine	0.177	0.381	0	0	1	240,431
Open-pit mine	0.676	0.468	1	0	1	103,667
C. Mothers' characteristics						
Mother's age	28.918	6.979	28	15	49	240,431
Years of education	3.985	4.226	3	0	22	240,332
Urban	0.287	0.452	0	0	1	236,966
Migrant	0.594	0.491	1	0	1	161,292
Access to sanitation and health facilities						
Piped water as main drinking water source	0.261	0.439	0	0	1	240,431
Has flush toilet	0.086	0.280	0	0	1	239,773
Has electricity	0.218	0.413	0	0	1	236,692
Visited health facility in the last 12 months	0.623	0.485	1	0	1	218,053
D. Women's characteristics						
Ever had a child	0.736	0.441	1	0	1	330,889
Total lifetime fertility	2.890	2.785	2	0	18	330,889
Currently pregnant	0.091	0.288	0	0	1	330,744
Ever had a miscarriage	0.127	0.333	0	0	1	296,235
Any anemia	0.378	0.485	0	0	1	115,481
Placebo disease						
Any STD	0.049	0.216	0	0	1	276,924
Heard of tuberculosis	0.935	0.246	1	0	1	88,438

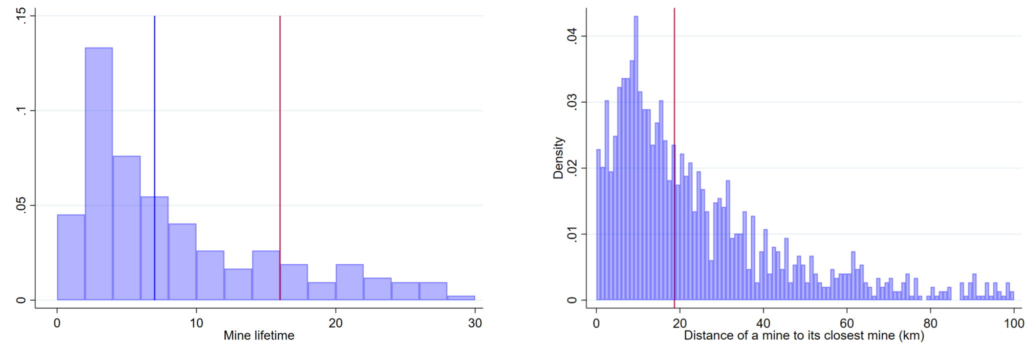
Notes: This table presents descriptive statistics for the main outcomes, the mortality rates at n months, conditionally on having reached n months. Descriptive statistics for other variables are also presented for the entire sample of children (A), mines (B), mothers (C), and women (D) in the main strategy sample who live within 45 km of an industrial mine, regardless of their topographic location.
Source: Author's calculations using DHS and SNL data.

to the beginning of production. The exact start year could not be determined for 18% of our sample, so these mines were excluded from our regressions. In total, we manually verified 83% of the mines located within 100 km of a DHS cluster.[17] Among the mines with a recorded start year, 83.2% opened after 1981, the earliest year covered by the DHS child surveys. The Supplementary Appendix includes a figure showing the percentage of mines that were manually verified and the percentage that ultimately had a start-up year, thus being included in our study, out of the full sample of 2,016 mines. Approximately half of the sample consists of gold mining sites. Ownership information is available for 65% of the mines, with the primary owners headquartered in the United States, the United Kingdom, Canada, Australia, and China. Additional figures in the Supplementary Appendix illustrate the distribution of mines—both overall and those from manual data collection—by primary commodity and country.

A.3. Context

Mining in Africa – Figure 11a displays the distribution of the duration of a mine life for the subsample with known closing dates, showing an average lifetime of 16 years. A Figure in the supplemetary Appendix shows the evolution of international commodity prices in our sample. A figure from Supplementary Appendix illustrates the distribution of mines opened within 100 km upstream or within the 3 closest downstream sub-basins during each child's birth year, revealing the countries with the highest and lowest densities of mines near DHS clusters between 1986 and 2018. Ghana, Zimbabwe, Tanzania, Zambia, Guinea, and Sierra Leone have the highest mine density, while Benin, Burundi, Cameroon, Lesotho, and Niger have the lowest. This figure also shows the variation in mine openings by country from the first

[17]We also investigated their closure dates and current activity status—whether the mining sites appeared active or inactive. However, since this information was more difficult to obtain, our analysis focuses on the opening dates.



(a) Distribution of a mine lifetime

(b) Distance of mines to each other

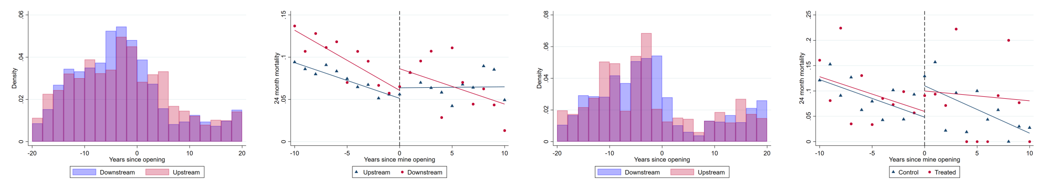
Figure 11: Descriptive statistics on mine characteristics

Notes: Figure 11a shows the distribution of mine lifetimes (mean: 16 years, red line; median: 7 years, blue line; max: 138 years). Figure 11b shows the distribution of distances between each mine and its closest other mining industrial site (median: 18 km, red line). Distances are shown for values below 100 km (max: 474 km).
Source: Authors' elaboration based on SNL and DHS data.

to the last year of surveys, reflecting changes in industrial mining activity over the period. Notably, Ghana, Tanzania, Guinea, Mali, and Burkina Faso experienced the highest number of mine openings between 1986 and 2018.

B. Pre-Trends

Pre-trends– The key assumption of the DiD strategy is that the 24-month mortality trend would have followed the same trajectory in both upstream and downstream areas in the absence of mine openings. Although the common trends assumption cannot be directly tested, we examine pretreatment data to observe the evolution of mortality rates before each mine opening. Figure 12b plots the linear trends of 24-month mortality, distinguishing between upstream and downstream DHS clusters before and after the mine opening, showing the average rates over the sample without controls or fixed effects. Figure 12a shows the distribution of years before and after the mine opening. Figure 12b suggests that mortality rates in both areas followed a



(a) All (b) All (c) Balanced (d) Balanced

Figure 12: Linear trends of 24-month mortality

Notes: Figures 12a and 12c show the distribution of the number of observations by mine opening year. Figures 12b and 12d plot trends in 24-month mortality rates relative to the year of mine opening. Figure 12b presents the full sample, while Figure 12d shows the balanced sample defined in Section 7. None of the figures include control variables or fixed effects. The reference period is -1, the year preceding mine opening. *Source:* Authors' elaboration based on DHS and SNL data.

similar decreasing pattern before the mine opened. Figure 12c and 12d plot the descriptive parallel trends for the balanced sample (cf Section D). This trend is likely driven by temporal factors, as recent years tend to show lower mortality rates, which are corrected in Figure 10 that shows no parallel trend.

C. Ruling Out Mechanisms

Table 13: Effects of Mine Openings on Child and Household Characteristics

	Child early-life characteristics				Household's characteristics			
	Breastfed after 6 months	Months breastfed	Given plain water	Ever vaccinated	% Urban households	Has piped water	Has electricity	Wealth Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream × Open	-0.00607	-0.134	0.0257	-0.0155	0.131***	0.0202	-0.00146	-0.0169
	(0.00892)	(0.349)	(0.0192)	(0.0227)	(0.0422)	(0.0277)	(0.0200)	(0.0623)
Downstream	-0.0127**	0.598**	-0.000278	0.0228	-0.0143	-0.0411*	0.00456	-0.0250
	(0.00615)	(0.232)	(0.0161)	(0.0185)	(0.0307)	(0.0239)	(0.0143)	(0.0554)
Open	0.0102	-0.200	-0.0143	0.00109	-0.0458	-0.00623	-0.0101	-0.0504
	(0.00761)	(0.257)	(0.0156)	(0.0199)	(0.0293)	(0.0209)	(0.0181)	(0.0510)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	61,690	41,302	29,371	21,071	61,690	61,690	61,179	47,227
R^2	0.384	0.525	0.275	0.346	0.608	0.489	0.547	0.573

Notes: Standard errors clustered at the DHS village level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All controls include mother's age, age squared, years of education, urban residency, presence and intensity of rivers, and the number of open mines within 45km. The estimation includes fixed effects for birth month, country-by-birth-year, mine sub-basin, and commodity, along with a mine sub-basin birth-year trend. *Source:* Author's calculations using DHS and SNL data.

Effect of mine opening on household, early life characteristics and Women's *outcomes* – Table 13 tests whether mine openings affect breastfeeding practices and other child and household characteristics. Table 14 tests whether the opening on industrial mines changes mother characteristics such as age or years of education, or changes in maternal fertility and health in downstream areas.

Table 14: Effects of Industrial Mine Openings on Women Outcomes

	Mother characteristics				Fertility		Health	
Outcome	Age	Years of education	% migrants	Ever had a child	Total lifetime fertility	Currently pregnant	Ever had a miscarriage	Anemia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream × Open	0.0455	-0.0119	0.0881***	0.0156	-0.0164	-0.0171	-0.00507	0.000806
	(0.162)	(0.144)	(0.0314)	(0.00977)	(0.0720)	(0.0111)	(0.0138)	(0.0261)
Downstream	-0.0811	-0.120	-0.0327	0.00886	0.0841	0.0160	0.00894	-0.00928
	(0.133)	(0.108)	(0.0272)	(0.00952)	(0.0731)	(0.0118)	(0.0134)	(0.0233)
Open	-0.131	-0.129	-0.0433*	-0.00161	0.0663	0.00607	-0.00136	-0.00417
	(0.136)	(0.112)	(0.023)	(0.00916)	(0.0595)	(0.00833)	(0.0119)	(0.0285)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	61,690	61,690	38,834	82,406	82,406	82,373	72,423	31,587
R2	0.681	0.463	0.185	0.510	0.659	0.0422	0.0906	0.122
Outcome mean	.	.	.	0.737	2.912	0.0939	0.136	0.396

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects, and trends as in Table 2 Column (2) are used.
Source: Author's calculations using DHS and SNL data.

Households' access to water and facilities– Table 13 explores the DiD estimator using access to piped water and electricity as dependent variables, showing no significant differences between upstream and downstream villages after mine openings. Table 15 adds a triple interaction with several facility variables: whether a household has piped water as the main drinking source (Table 15, column 1), a flush toilet (column 2), access to electricity (column 3), and whether the mother visited a health facility in the 12 months preceding the survey (column 4).

Migration– Table 16 reports the main coefficient with and without controlling for migrant status, for both the full and rural samples.

Conflicts–Table 17 controls for the number of conflicts reported in the ACLED data, distinguishing between the number of conflicts within the mine sub-basin and the DHS village sub-basin.

Other controls– Finally, Table S1 in Supplementary Appendix includes

Table 15: Effects of Industrial Mine Openings on Access to Water, Sanitation and Facilities

Outcome	24-month mortality			
Var.	Has piped water	Has flushed toilet	Has electricity	Visited health facilities
	(1)	(2)	(3)	(4)
Downstream × Open × Var.	0.000312	-0.0358	-0.0108	-0.0143
	(0.0194)	(0.0264)	(0.0189)	(0.0164)
Downstream × Open	0.0208*	0.0234**	0.0228**	0.0311**
	(0.0118)	(0.0110)	(0.0112)	(0.0156)
Var.	-0.00276	-0.0165*	-0.0179***	-0.00493
	(0.00639)	(0.00920)	(0.00631)	(0.00541)
Downstream	-0.0228***	-0.0214***	-0.0193***	-0.0163*
	(0.00769)	(0.00743)	(0.00732)	(0.00968)
Open	-0.00104	-0.00485	-0.00141	-0.00329
	(0.0103)	(0.0101)	(0.00962)	(0.0120)
All Controls	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes
N	35,638	35,536	38,611	32,018
R2	0.0505	0.0507	0.0482	0.0504
Outcome mean	0.0873	0.0873	0.0869	0.0857

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects, and trends as in Table 2 Column (2) are used.
Source: Author's calculations using DHS and SNL data.

Table 16: Effects of Industrial Mine Openings on Migration and Child Mortality

Outcome	Mortality under 24 months							
Spec.	Without migrant control		With migrant control		Migrant sample		Always lived here	
Sample	All	Rural	All	Rural	All	Rural	All	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream × Open	0.0216**	0.0374***	0.0293*	0.0380**	0.0313	0.0532	0.0298	0.0247
	(0.0108)	(0.0130)	(0.0158)	(0.0192)	(0.0273)	(0.0346)	(0.0214)	(0.0254)
Downstream	-0.0211***	-0.0282***	-0.0244**	-0.0327***	-0.0209	-0.0288	-0.0294**	-0.0412***
	(0.00738)	(0.00808)	(0.0105)	(0.0119)	(0.0190)	(0.0224)	(0.0140)	(0.0148)
Open	-0.00494	-0.00555	-0.0249	-0.0225	0.0150	0.0215	-0.0407**	-0.0410
	(0.0101)	(0.0122)	(0.0159)	(0.0193)	(0.0260)	(0.0333)	(0.0197)	(0.0255)
Migrant			0.00840*	0.00307				
			(0.00449)	(0.00593)				
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migrant Control	No	No	Yes	Yes	No	No	No	No
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35,638	24,544	22,231	15,060	8,658	6,007	13,503	8,982
R2	0.0504	0.0623	0.0625	0.0755	0.110	0.128	0.0785	0.106
Outcome mean	0.0873	0.0945	0.0946	0.104	0.0892	0.102	0.0983	0.107

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects, and trends as in Table 2 Column (2) are used. Columns (3) and (4) include a migrant dummy as an additional control. Columns (5) and (6) restrict the sample to migrant households, while Columns (7) and (8) restrict the sample to non-migrant households who always lived in the same location.
Source: Author's calculations using DHS and SNL data.

Table 17: Effects of Industrial Mine Openings - Conflicts

Outcome	Mortality under 24 months			
	All		Rural	
	Within Mine SB	Within DHS SB	Within Mine SB	Within DHS SB
	(1)	(2)	(3)	(4)
Downstream×Open	0.0225**	0.0234**	0.0369***	0.0376***
	(0.0105)	(0.0105)	(0.0130)	(0.0130)
Downstream	-0.0201***	-0.0203***	-0.0284***	-0.0285***
	(0.00730)	(0.00729)	(0.00794)	(0.00793)
Open	-0.00229	-0.00337	-0.00575	-0.00630
	(0.00993)	(0.00988)	(0.0115)	(0.0115)
All Controls	Yes	Yes	Yes	Yes
Control Conflicts within mine SB	Yes	No	Yes	No
Control Conflicts within DHS SB	No	Yes	No	Yes
All Fixed Effects	Yes	Yes	Yes	Yes
N	35,638	35,638	24,544	24,544
R2	0.0504	0.0504	0.0623	0.0623
Outcome mean	0.0873	0.0873	0.0945	0.0945

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects, and trends as in Table 2 Column (2) are used. Columns (1) and (3) control for the number of conflicts within the mine sub-basin, while Columns (2) and (4) control for the number of conflicts within the DHS village sub-basin.
Source: Author's calculations using DHS and SNL data.

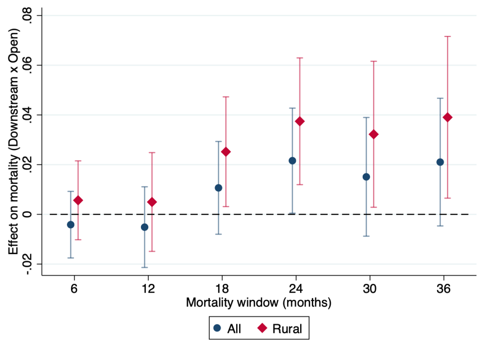
additional controls such as rainfall (measured using CHIRPS), changes in population (measured using WorldPop (Tatem, 2017)), tree cover(measured using the Hansen et al. (2013) dataset),and the percentage of cultivated area.

D. Robustness Checks

Age window—Figure 13 shows that the effects are robust across mortality windows from 18 to 36 months in the rural sample, consistent with gradual heavy metal exposure following the weaning transition, and significant at 24 months for the full sample.

Multiple Hypothesis Testing—Since Table 3 reports several secondary health outcomes, we address concerns related to multiple hypothesis testing by applying theBenjamini and Hochberg (1995) false discovery rate correction to the associated p-values. Table 18 reports the adjusted p-values and shows that none of the outcomes—including underweight—remains statistically significant after correction. This pattern is consistent with the interpretation

Figure 13: Effects of Industrial Mine Openings across Mortality Windows



Notes: This figure plots the DiD estimates across different mortality windows for the full sample and the rural sample. All specifications include the same controls, fixed effects, and trends as in the baseline specification. Vertical bars represent 95% confidence intervals.
Source: Author's calculations using DHS and SNL data.

Table 18: Multiple Hypothesis Testing for Secondary Child Health Outcomes

Outcome	Raw p-value	BH-adjusted p-value
Underweight	0.024	0.218
Anemia	0.322	0.893
Stunting	0.432	0.893
Wasting	0.627	0.893
Cough	0.637	0.893
Small at birth	0.663	0.893
Low birth weight	0.773	0.893
Fever	0.885	0.893
Diarrhea	0.893	0.893

Notes: This table reports raw and Benjamini–Hochberg (1995) adjusted p-values for the interaction term $Downstream \times Open$ across nine secondary child health outcomes. The Benjamini–Hochberg procedure controls the false discovery rate across multiple hypothesis tests.
Source: Author's calculations using DHS and SNL data.

that the effects of mine openings are concentrated on child mortality rather than on other health indicators.

Balanced sample– This section defines the balanced sample. The staggered DiD analysis compares mortality rate changes between observations that switch treatment status and those that do not. For the balanced sample, we define three groups: (1) *the switchers*, which includes areas where a mine opens between two survey years, changing the treatment from 0 to 1; (2) *the always treated*, areas where the mine has always been open and (3) *the never treated*, areas where the mine has not opened yet. Group 3 also includes areas where a mine is projected to open but has not been surveyed, or where no surveys were conducted post-opening. In the balanced sample, Group 1 (switchers) is the treatment group, and Groups 2 and 3 are controls. Group 1 is restricted to areas with DHS data both upstream and downstream, before and after mine opening, ensuring at least four observations. For Groups 2 and 3, we select areas with data either before (Group 3) or after (Group

2) the mine opened. A supplementary Appendix figure maps the groups of the balanced sample across Africa, highlighting key regions such as Western Africa, Zimbabwe, Western Kenya, Rwanda, Tanzania, and Madagascar, which align with the results in Table 6, showing that these regions drive the main findings. Additionally, a table provides statistics indicating that Group 1 consists of 13 mines, while the control groups (Groups 2 and 3) in the balanced sample include 75 mines.

Heterogeneous treatment effects– This paper's main result estimates the effect of being downstream of an open mine using standard DiD designs. However, recent developments in staggered adoption DiD estimators (Borusyak et al., 2024; Goodman-Bacon, 2018; Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfœuille, 2020) show that the Average Treatment on the Treated (ATT) is a weighted sum of different ATTs, with potentially negative weights. The negative weights are an issue when the treatment effect is heterogeneous between groups over time, as one could have the treatment coefficient in those regressions as negative while the treatment effect is positive in every group and time period. In our design, the effect on Group 1 (switchers) is compared to two control groups, Group 2 always treated and Group 3 never treated. Negative weights may arise from comparing Group 1 to Group 2, creating bias in the DiD estimator. To address this, we apply the de Chaisemartin and d'Haultfœuille (2020) estimator, which corrects for negative weights in a staggered adoption design. Table 19 compares the DiD estimator to the dCDH estimator (even columns). Columns (1-4) show results for 12-month mortality rates, and columns (5-8) for 24-month mortality rates. The DiD results are stable when applied to the balanced sample, representing 27% of the full sample. For the balanced sample, being downstream of an open mine increases 24-month mortality by 3.18 p.p, or 36%. Using the dCDH estimator, the effect rises to 11 p.p (126%), indicating stronger results when correcting for negative weights. Despite the higher magnitude, the direction and significance of the main effect remain consistent with the

DiD estimator. For 12-month mortality, the balanced sample shows a 2.8 p.p increase.

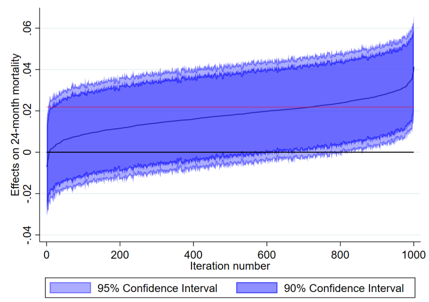
Table 19: Effects of Industrial Mine Openings - DiD and dCDH Estimator Comparison

	12-month mortality				24-month mortality			
	Whole Sample		Balanced Sample		Whole Sample		Balanced Sample	
	DiD est.	dCDH	DiD est.	dCDH	DiD est.	dCDH	DiD est.	dCDH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream×Open	-0.00513	0.0249	0.0284*	0.1457	0.0216**	0.1109**	0.0318**	0.1667***
	(0.00828)	(0.0345)	(0.0146)	(0.1291)	(0.0108)	(0.0468)	(0.0161)	(0.0630)
Downstream	-0.0151**		-0.0242***		-0.0211***		-0.0283**	
	(0.00665)		(0.00821)		(0.00738)		(0.00856)	
Open	0.00972		0.0356		-0.00494		0.0245	
	(0.00753)		(0.0319)		(0.0101)		(0.0347)	
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48, 472	48, 472	9, 606	9, 606	35, 638	35, 638	9, 606	9, 606
R2	0.0373		0.0507		0.0504		0.0583	

Notes: Standard errors clustered at the DHS village level. Column (1) gives the result of the main anlysis, the DiD estimator for the whole sample, while Column (2) gives the de Chaisemartin and d'Haultfœuille (2020) estimator. Columns (3) and (4) give the DiD estimator and de Chaisemartin and d'Haultfœuille (2020) estimators for the balanced sample.
Source: Author's computations from DHS and SNL datasets.

Measurement errors : DHS displacement– DHS randomly displaces village GPS coordinates to protect confidentiality, with urban locations displaced within 2 km and rural ones within 5 km within administrative units, while 1% of rural clusters are moved up to 10 km. These displacements introduce measurement errors, especially since treatment allocation depends on the village's position relative to the mine. To address this, we simulate 1,000 random displacements for each DHS village, considering a 2-km buffer for urban villages and 5-km for rural ones. After displacement, each village is assigned to a new sub-basin (which may or may not be the initial one) and its treatment status is re-determined following the pairing strategy. We shuffle only villages initially related to the mine, excluding those in sub-basins with no relation or beyond the fourth downstream. Figure from supplementary Appendix shows the probabilities of changing treatment status after 1,000 iterations, with 25% of initially treated villages excluded. A village

Figure 14: DHS Random Displacement – 1,000 Iterations



Notes: This figure plots the DiD estimator from 1,000 regressions, each estimated on a sample in which DHS GPS coordinates are randomly displaced. The red horizontal line corresponds to the coefficient from the baseline specification. Coefficients are ordered, and the shaded areas represent the 95% and 90% confidence intervals.
Source: Author's calculations using DHS and SNL data.

Table 20: Restriction to Mines with Exact Coordinates

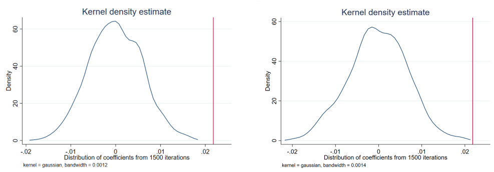
Outcome	24-month mortality	
Accuracy level	Exact coordinates	
Sample	Urban and rural	Rural
	(1)	(2)
Downstream×Open	0.0113	0.0285**
	(0.0115)	(0.0143)
Downstream	-0.0204**	-0.0236***
	(0.00805)	(0.00886)
Open	0.00509	0.00831
	(0.0104)	(0.0130)
All Controls	Yes	Yes
All Fixed Effects	Yes	Yes
N	29,195	20,172
R^2	0.0508	0.0614
Outcome mean	0.0858	0.0920

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The sample is restricted to mines with exact geographic coordinates. All regressions include the same controls and fixed effects as in the baseline specification.
Source: Author's calculations using DHS and SNL data.

initially downstream in the third sub-basin has a 70% chance of remaining downstream, 0.3% of becoming upstream, 24% of falling into an unassigned sub-basin, 3.5% of becoming part of the same sub-basin, and 2% of being excluded from the sample due to a displacement further downstream. Figure 14 plots the *Downstream* × *Open* DiD estimator for 1,000 random displacements of DHS GPS coordinates, with coefficients ordered and 95% and 90% confidence intervals shown. Since the reshuffling increases the likelihood of villages leaving the sample, the number of observations per iteration is typically smaller than in the main estimation.

Placebo tests - randomization inference– To ensure that the topographic assignment of villages drives our result on child mortality, we perform a randomization inference test with 1,500 permutations of the *Downstream* and *Open* variables in Figure 15, and find that the distribution of treatment effects is centered around zero, confirming the validity of our main model at the 1% level. Figure 15a represents 1,500 permutations of the *Downstream*

Figure 15: Randomization Inference Tests



(a) Downstream (b) Open

Notes: The figures show the distribution of the DiD estimator for under-24-month mortality obtained from 1,500 randomization inference permutations of the *Downstream* and *Open* indicators. The vertical line indicates the estimated coefficient from the baseline specification. *Source:* Author's calculations using DHS and SNL data.

Table 21: Placebo Diseases

Outcome	(1) Any sexually transmitted infection	(2) Heard of tuberculosis
Downstream × Open	0.00332	-0.0387
	(0.00923)	(0.0259)
Downstream	0.00751	0.0277
	(0.00772)	(0.0210)
Open	0.00766	0.00469
	(0.00913)	(0.0314)
All Controls	Yes	Yes
All Fixed Effects	Yes	Yes
N	66,653	14,750
R^2	0.0888	0.186
Outcome mean	0.0501	0.938

Notes: Standard errors clustered at the DHS village level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, and fixed effects as in the baseline specification are used. These outcomes serve as placebo tests and should not be affected by mining activity.
Source: Author's calculations using DHS and SNL data.

position for each DHS sub-basin, while Figure 15b shows 1,500 permutations of the *Open* variable. The red line indicates the initial treatment effect of our main specification.

E. Sensitivity

Results are unchanged when controlling for data quality in the measurement of mine opening dates (Table 22) and when correcting for spatial correlation using Conley standard errors (Table 23).

F. Discussion

F.1. Policy Discussion

Back-of-the-envelope calculation– We estimate the number of deaths attributable to water pollution from industrial mining in 26 African countries. Using a back-of-the-envelope calculation, we assess how many deaths could have been prevented if policies to limit water pollution had been implemented between 1981 and 2020. From the DHS data, we find that 28% of individuals

Table 22: Data Collection Quality

Outcome	24-month mortality			
Specification	Main result	Adding control	SNL database	Hand-collected
	(1)	(2)	(3)	(4)
Downstream × Open	0.0216**	0.0216**	0.0236	0.0342**
	(0.0108)	(0.0108)	(0.0347)	(0.0138)
HAND dummy		0.0271		
		(0.0336)		
Downstream	-0.0211***	-0.0211***	-0.0172	-0.0313***
	(0.00738)	(0.00738)	(0.0243)	(0.00839)
Open	-0.00494	-0.00487	-0.0210	-0.00943
	(0.0101)	(0.0101)	(0.0468)	(0.0126)
All Controls	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes
N	35,638	35,638	6,702	22,017
R2	0.0504	0.0504	0.0605	0.0630
Outcome mean	0.0873	0.0873	0.0727	0.0954

Notes: Standard errors clustered at the DHS village level. Columns (1) and (2) rely on the same sample and controls as Table 2 Column 2. Column (2) controls for the quality of the data collection, while Columns (3) and (4) split the samples.
Source: Author's calculations using DHS and SNL data.

Table 23: Spatial Correlation

Outcome	24-month mortality			
Conley spatial correction threshold	20 km	45 km	100 km	200 km
(1)	(2)	(3)	(4)	
Downstream × Open	0.0177*	0.0177*	0.0177*	0.0177*
	(0.0100)	(0.00999)	(0.00996)	(0.00916)
Downstream	-0.0219***	-0.0219***	-0.0219**	-0.0219**
	(0.00709)	(0.00746)	(0.00913)	(0.0106)
Open	-0.00466	-0.00466	-0.00466	-0.00466
	(0.00941)	(0.00932)	(0.00955)	(0.00938)
All Controls	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes
N	35,648	35,648	35,648	35,648
R2	0.00262	0.00262	0.00262	0.00262

Notes: Standard errors are corrected for spatial autocorrelation using Conley standard errors with different distance thresholds. All regressions include the same controls and fixed effects as in the main specification.
Source: Author's calculations using DHS and SNL data.

live within 45 kilometers of a mine, with 1.94% downstream, 5.25% upstream, 17.93% without topographic relation to the mine, and 2.92% in the same sub-basin as a mine. The DiD estimator indicates a 2.18% increase in mortality rates due to industrial mining-induced water pollution. Among the 9,258 individuals living downstream, 822 deaths are observed, leading to an estimated 202 additional deaths from mining pollution. Considering 880 million children aged 0-2 years from 1981-2020, we estimate that 17 million children lived within 45 km downstream of a mine, resulting in 370,600 deaths due to mining-induced water pollution, or 9,265 deaths per year, equivalent to 16 deaths per mine annually. This accounts for 1.1% of the number of births per country in our sample.

Policy Discussion–We examine whether the Extractive Industries Transparency Initiative (EITI), launched in 2002 and currently comprising 55 countries, influences the effect of industrial mining on child mortality. EITI member countries commit to disclosing information along the oil, gas, and mining production value chain and adhering to common governance standards. Out of the 26 countries in our sample, 18 have signed the EITI, representing 76% of our child sample. We compare results between EITI members and

Table 24: Effect of Industrial Mine Openings and EITI Membership

Outcome	24-month mortality					
Sample	All			Rural		
	Not EITI	EITI		Not EITI	EITI	
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream × Open	0.0176	0.0256**	0.0128	-0.0428	-0.0181	-0.0531
	(0.0210)	(0.0127)	(0.0189)	(0.0509)	(0.0415)	(0.0670)
Surveyed after joining EITI			0.0215			-0.0297
			(0.0301)			(0.0300)
Downstream × Open × After EITI			0.0249			0.0242
			(0.0234)			(0.0708)
Downstream	-0.0558***	-0.00928	-0.00425	-0.00366	0.0345	0.0118
	(0.0140)	(0.00875)	(0.0107)	(0.0482)	(0.0389)	(0.0650)
Open	-0.00765	-0.00563	-0.00632	-0.0525	-0.00327	-0.0111
	(0.0248)	(0.0112)	(0.0163)	(0.0632)	(0.0269)	(0.0440)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	8,434	26,810	26,810	2,251	8,685	8,685
R2	0.0341	0.0541	0.0542	0.0777	0.0665	0.0668
Outcome mean	0.0716	0.0920	0.0920	0.0604	0.0738	0.0738

Notes: Standard errors clustered at the DHS village level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The same sample, controls, fixed effects, and trends as in Table 2 are used. Columns (3) and (6) include an interaction capturing whether the survey took place after the country joined the Extractive Industries Transparency Initiative (EITI).
Source: Author's calculations using DHS and SNL data.

non-members and find that the effect of industrial mining on child mortality remains significant, even in countries with EITI commitments (Table 24). Additionally, we find no significant differences when comparing the timing of surveys relative to the countries' EITI membership (Columns (3) and (6)).

F.2. Replication of the Geographic Treatment

To assess the contribution of this study and compare the results with the existing literature, we replicate the analysis from (Benshaul-Tolonen, 2018), which finds a positive externality near mines, showing a decrease in infant mortality within 10 km of a mine compared to individuals living between 10-100 km, using a limited number of mines and countries in Africa. In Table 25, we replicate this analysis for the same sample and find similar results. In Table 26, we extend the sample using data from manual collection, including more countries, DHS waves, and mines. Our replication on the extended sample, however, fails to replicate the positive externalities, highlighting our paper's contribution in identifying negative externalities and improving the external validity of the results. This implies that the positive externalities identified in (Benshaul-Tolonen, 2018) may be influenced by selection bias and the specific choices made regarding countries and mines. Following (Benshaul-Tolonen, 2018), we estimate :

$$\begin{aligned} Death_{i,v,c,m,SB} = &\alpha_0 + \alpha_1 Opened_{birthyear,i,v} + \alpha_2 MineDeposit_{[0;10km]v} \\ &+ \alpha_3 Opened_{birthyear,i,v} \times MineDeposit_{[0;10km]v} + \alpha_4 X_i \\ &\gamma_d + \gamma_{d-bthtrend} + \gamma_{c,birthyear} + \epsilon_v \end{aligned} \quad (2)$$

With $Death_{i,v,c,d}$ is a dummy variable equal to 1 if child i from DHS village v in district d and country c has died by the n^{th} month (e.g., $n =$ 12 for 12-month mortality). $Opened_{birthyear,i,v}$ is a dummy equal to 1 if a mine within 10 km (treatment group) or 100 km (control group) opened before child i's birth year. $MineDeposit_{[0;10km]}v$ is a proximity dummy (1 if the village is within 10 km of a mine deposit, 0 if within 10-100 km). X_i is a vector of child and mother controls (mother's age, age squared, years of education, and urban status). γ_d is a district fixed effect, $\gamma_{d-bthtrend}$ is a district-birthyear linear trend, and $\gamma_{c,birthyear}$ is a country-birthyear fixed effect.

Table 25 replicates Benshaul-Tolonen (2018) Table 2 using the same sample of mines and DHS survey rounds. [18]. Our results show a 4.9 p.p. increase in infant mortality rates associated with a mine opening within 10 kilometers, compared to 5.5 p.p in Benshaul-Tolonen (2018). Following their method-

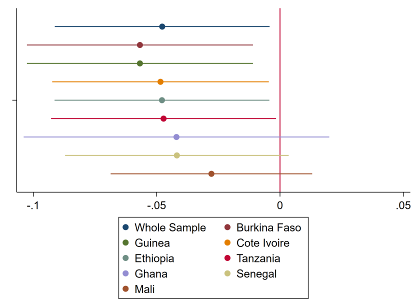
[18]We observe minor differences in sample size (37,365 children in (Benshaul-Tolonen, 2018) vs. 41,902 in ours), likely due to differences in how the 100 km buffer distance was calculated. The key distinction between our study and Benshaul-Tolonen (2018) is the shock variable: we use the opening of industrial mines, while they use mine activity status based on SNL production data, which includes interim years when production was on hold. In this section, we replicate this variable exactly for comparison purposes.

Table 25: Geographic Treatment

Dependent variable	12-month mortality rates	
	All	Drop spillover
	(1)	(2)
Indus. × deposit	-0.0494**	-0.0471*
	(0.0229)	(0.0244)
deposit [0;10km]	0.0394**	0.0587***
	(0.0179)	(0.0198)
All Controls	Yes	Yes
All Fixed Effects	Yes	Yes
Drop 10–30 km away	No	Yes
Drop investment phase	No	Yes
Mean of outcome	0.079	0.080
Mean(treatment, pre-treatment)	0.109	0.118
Observations	40,386	32,873

Notes: Standard errors clustered at the DHS cluster level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The variables *Deposit* [0–10 km] and *Industrial* × *Deposit* (at birth) replicate the specification from Benshaul-Tolonen (2018) and indicate whether the child was born within 10 km of at least one industrial mining site and whether this site was active at the time of birth. All regressions include the same controls and fixed effects as in the main specification.
Source: Author's calculations using DHS and SNL data.

Figure 16: Dropping One Country at a Time



Notes: The figure shows the estimated coefficient on Downstream × Open when dropping one country at a time from the sample. The specification includes the same controls and fixed effects as in the main regression. Vertical bars represent 95% confidence intervals.
Source: Author's calculations using DHS and SNL data.

Table 26: Geographic Treatment - Extended Sample

	12-month mortality rates				24-month mortality rates	
	All		Drop spillover		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Indus. × Deposit	-0.00259	-0.00823**	-0.00189	-0.00575	0.000248	-0.00264
	(0.00329)	(0.00418)	(0.00407)	(0.00537)	(0.00431)	(0.00535)
Deposit	0.00130	0.00374	0.00103	-0.000128	0.000627	0.00121
	(0.00252)	(0.00317)	(0.00392)	(0.00500)	(0.00321)	(0.00411)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes
Migrant Controls	No	Yes	No	Yes	No	Yes
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Drop 10–30 km	No	No	Yes	Yes	No	No
Drop t-2	No	No	Yes	Yes	No	No
N	359,219	243,645	236,573	165,202	265,735	179,729

Notes: Standard errors clustered at the DHS cluster level. The variables *Deposit* (0–10 km) and *Industrial* × *Deposit* (at birth) replicate the specification from Benshaul-Tolonen (2018) and indicate whether the child was born within 10 km of at least one industrial mining site and whether this site was active at the time of birth. All regressions control for mother's age, age squared, mother's education, and urban residence, and include district, birth month, and country-by-birth-year fixed effects.
Source: Author's calculations using DHS and SNL data.

ology, we exclude individuals born 10-30 kilometers from a mine and those born two years before its opening. Figure 16 replicates Benshaul-Tolonen (2018).Figure A6 shows that results are highly sensitive to the inclusion of Mali, Senegal, and Ghana, despite representing a small portion of the sample. Table 26 replicates their strategy using our full sample, covering both 12-month (columns 1-4) and 24-month mortality rates (columns 5-6). We find a significant reduction in 12-month mortality rates in Column (2) when controlling for migrants, but no significant results otherwise, highlighting the limitations of proximity as a proxy for mining exposure and emphasizing the value of our topographic-based estimation strategy.

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

During the preparation of this work the authors used Claude (Anthropic) and ChatGPT (OpenAI) in order to improve the clarity and language of sections written by the authors. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

DHS and HydroSHEDS data are publicly available online. Processed data and Stata/R codes will be shared upon acceptance. Mining data are proprietary (S&P license) and are under a confidentiality clause.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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