Gold-Mining Pollution Exposure, Health Effects and Private Healthcare Expenditure in Tanzania

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Abstract

This article examines an important externality that polluting industries may impose on peoples' health in their proximities. To ascertain the actual health outcomes and expenditure associated with mining pollution, this study (on a gold mine in Tanzania) used the Coarsened Exact Matching (CEM) approach, which matches the social, economic, and environmental risk-factor characteristics of households in treated and control groups. It also used a linear and logistics regression using CEM Weight to obtain robust treatment effects.

The results show that health outcomes (proxied by stunting rate) were significant within 10km of the nearby mine. The probability of a child in the treated group being stunted was 0.226 greater than for a child with similar social, economic and environmental risk factors in the control group. Moreover, the OLS regression suggested similarly that the children in the treated group had height-for-age Z-scores (HAZ06) of 0.827 less than for similar children in the control group. Further regression of HAZ06 on the distance from the mine provided robust evidence that health scores (HAZ06) among children increased statistically by 0.0212 for every kilometre they were further away from the mining site. These findings suggest that the less a person is exposed to mining pollutions (i.e., the further from the mine), the less the health impact.

Furthermore, the results showed that households within 10 km of the mine are spending 55 202 Tanzanian shillings (TZS) more on health per person per year than those further than 10km away. The regression of per-capita health expenditure on distance provides more evidence that healthcare expenditure per capita decreases by TZS 712 for every 1km increase in the average distance from the residence to the mining site. Drawing intuition from the hedonic theory, we further interpreted the results in terms of 'willingness to accept' (WTA); it was found that on average, the households staying within 10km of the mine (i.e., the victims of mining pollution) are willing to accept (WTA) minimum per-capita compensation for health expenditure of TZS 55 202 per annum (equivalent to USD 24.75). The minimum WTA increases closer to the mine site and decreases further away.

These findings have an important implication for environmental and industrial policies. They suggest environmental regulations should be tightened, to ensure that the pollution emitted by mines is within acceptable limits for health as laid down by the WHO. Moreover, there is a need for a thorough review of industrial policies (especially in terms of local content) to ensure that compensation policies and local multiplier effects are adequate to offset the negative health and income effects.

JEL Codes : I15, Q13, Q53, Q56

Keywords: Mining pollution, health effects, willingness to accept

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1. Introduction

The mining sector is one of the main economic sectors, with important linkages to the rest of the economy, both direct and indirect. Mining creates employment for local communities, generates revenue for governments, and contributes to economic growth and development. While positive effects such as employment and community development are vital, the negative impacts on local communities cannot be ignored, and they may be experienced long after mining activities end. The positive and negative effects of mining cannot be disputed; hence the two categories of mining externalities: positive externalities (desirable outputs) and negative externalities (undesirable outputs). Desirable outputs include the mineral product, the impact on GDP through the labour market, sectoral linkages, and local multiplier effects. Undesirable outputs include air, water and land pollution through carbon dioxide (CO_2) and sulphur dioxide (SO_2) emissions as well as other pollutants, which cause serious damage to health, environment and ecology.

The challenge for policymakers considering the severe negative externalities due to mining activity is to create an environment in which mining can become more sustainable (i.e., cause minimal negative externalities). In developing regions such as sub-Saharan Africa, the negative effects of mining are potentially more severe than elsewhere, due in part to poor regulation. Considering mining is a primary source of direct foreign investment in developing countries, a better understanding of its negative effects is key to improving regulation and moving closer to sustainable mining.

1.2 Statement of the problem

Valuable mineral deposits in developing countries can create nearly as many problems as they solve, since environmental and industrial regulations are lax in most developing countries. Modern mining activities in developing countries (including Tanzania) take place in close proximity to local communities, and thus health issues are a major concern. Over the years there have been repeated fatal incidents reported in the vicinity of the large gold mines, associated with the seeping of toxic chemicals into water sources used by the local communities. In the empirical literature, the levels of these chemicals and heavy metals are reported to be higher than the allowed thresholds recommended by the WHO. The levels observed are associated with significant health impacts, especially to children.

In most empirical studies, stunting rate[5] (in children below 59 months) is used as a measure of health outcomes. In Tanzania, children's health-risk indicators are way above the WHO threshold; in 2016, for instance, 34% of children under five years old were stunted, while 5% suffered from acute malnutrition in terms of wasting or low weight for height (USAID, 2018). The 2019 country profile report on nutrition and child stunting trends shows that in Tanzania there are over three million children under five years who are stunted. The estimated number of stunted children increased from 3.319 million in 2012 to 3.415 million in 2015 and is expected to rise to 3.569 million by 2025[6]. Though the country has targeted a stunting rate of 28% by 2021, it is projected that the target may not be realised by 2025. Among other things, differences in environmental amenities and poverty have been suggested as two of the culprits believed to contribute to poor health. Thus, controlling pollution from polluting industries and taking advantage of the mining local multiplier to reduce poverty would support efforts to reduce stunting rates and improve health outcomes in Tanzania.

Cunha and Heckman (2007) provided a capacity formation framework which shows that childhood health has significant effects on future health, educational attainment and labour market outcomes, through dynamic complementarities and cross-productivity with the development of cognitive and non-cognitive skills. In addition, Currie (2008) and Almond and Currie (2011) found that parents' socio-economic status is strongly linked to child health; the link suggests that parts of the intergenerational persistence of inequality are due to differences in childhood health conditions. Thus, addressing children's health issues has potential economic benefits, ranging from improving the labour market to reducing income inequality. In this paper, we focus on quantifying exposure to mining pollution impact on children’s health outcomes in the large gold mines surrounding communities in Tanzania. Moreover, from an environmental policy point of view, we estimate the economic costs associated with pollution on household health expenditure. We define this cost as the minimum amount of money households

[5] Failing to grow along the optimum trajectory set out in the WHO Child Growth Standards (WHO, 2016) is known as ‘stunting’, a term given to impaired linear growth (length/height for age) in the early years of life, which results in failure to reach by adulthood the height implied by genetic potential.

[6] See https://ec.europa.eu/europeaid/sites/devco/files/nutrition-graphs-tanzania-2016_en.pdf

exposed to mining pollution are willing to accept as compensation for lower environmental quality. Establishing how much those in the vicinity of the mine will accept as compensation for improvements in environmental quality may guide policies regarding pollution control in the mining zone.

1.3 Contribution

The empirical literature shows pollution can affect not only human health but also welfare, with effects on everything from health expenditure to housing prices, wages, agriculture, and labour productivity losses. Though health effects and welfare loss associated with pollution are highly interlinked, most empirical studies have analysed them separately. This study's first contribution was to link these two dimensions, first by establishing the existence and extent of health effects in terms of coverage in Tanzania, which in turn informed the calculation of the threshold distance separating the treated group and the control group – unlike other studies, which have established their threshold based on findings from other studies. This study also used the hedonic pricing approach to estimate welfare loss because of health expenditure as a defensive investment due to exposure to mining pollution. This contributes to the scant empirical evidence quantifying the costs of mining externalities, especially in Africa.

The second contribution of this study is that in addition to the socio-economic household characteristics considered in most empirical studies, we have also controlled household environmental risk factors (housing floor material, latrine type, drinking water source, cooking fuel type, sold waste disposal and hygiene). Vilcins, Sly and Jagals (2018) showed that environmental risk factors work independently of nutrition intake and socio-economic attributes to affect health outcomes, and ultimately health expenditure. Ignoring household environmental risk factors may over- or underestimate the actual effects. Thus, we have extended the studies of Von der Goltz and Barnwal (2019) and Akpalu and Normanyo (2017) by controlling household environmental risk factors, in addition to the commonly used socio-economic characteristics, to provide more robust estimates of effects and costs.

This study contributes to addressing this policy relevance of actual health outcomes due to mining operations. The results highlight the importance of introducing stricter environmental policies and regulations to control pollution from mining activities; as well as the importance of enforcing local content industrial policy to ensure higher local multipliers, which eventually translates into better health.

1.5 Organisation of the paper

The rest of the paper is structured as follows: Section 2 presents an overview of the mining pollution and health nexus. Section 3 is an overview of stunting and mining proximity. Section 4 demonstrates the empirical methodology adopted in the study, which includes the source of the data, the variables used, how they were measured, and the data analysis process. Section 5 provides the empirical results, and a discussion of the findings. Section 6 concludes the paper, discussing the main findings and recommendations of this study and outlining future research opportunities.

2.1 Mining pollution and health overview

Gold mines, in addition to emitting PPM and gases, are known to produce hazardous pollutants and heavy metals such as arsenic, cadmium, zinc, lead, copper, manganese and cyanide. (In low concentrations, these pollutants are dispersed and absorbed by the environment. In large concentrations, however, they can deposit on the ground in the form of acid rain, and are mostly dispersed through surface water, resulting in long-term cumulative effects.) They are also a source of noise, mainly from blasting explosives. Studies have shown that gold extraction and processing can significantly degrade natural environments (including reducing the quality of soil and sediments, water, and air), and thus human health and livelihoods (Akpalu and Normanyo, 2017; Hilson, 2000; Akpalu and Parks, 2007; Obiri, 2007; Leder et al., 2012; Saldarriaga-Isaza et al., 2013; Ako et al., 2014; Ansa-Asare et al., 2015). Pollution mainly occurs during gold extraction and processing, which includes carbon-in-leach, heap leaching with cyanide, and biological oxidation and roasting (Hilson, 2002; Leder et al., 2012).

Several studies in developing countries have examined the presence of pollutants and heavy metals near gold mines; they found mining to be a major cause of high concentrations of hazardous substance in several African countries (Ahoulé et al., 2015). Different approaches were used to establish toxicological profiles, including examining samples of soil, drinking water, air and food, as well as satellite images. Developing countries have been the setting for evaluation studies on soil samples (Mora et al., 2019: Kamunda et al., 2016; Palapa and Maramis, 2015; Rashed, 2010; Ogola, Mitullah and Omulo, 2002); drinking water samples (Gomezulu, Mwakaje and Katima, 2018; O'Sullivan, Mwalwiba, Purcell, Turner and Mtalo, 2016; Bortey-Sam et al., 2015; Almås and Manoko, 2012), air samples (Shenoy, 2018; Bi et al., 2018) and food samples (Bortey-Sam et al., 2015; Thompson and Darwish, 2019). More recently, using satellite images to evaluate the concentration of different pollutants has been a popular approach; such studies include Von der Goltz and Barnwal (2019) and Akpalu and Normanyo (2017). These studies concluded that the concentrations of pollutants and toxic metals near gold mines were significantly higher than the limits deemed acceptable by the WHO.

Empirical studies in Tanzania include Gomezulu, Mwakaje and Katima (2018), in villages surrounding Buzwagi gold mine; O'Sullivan, Mwalwiba, Purcell, Turner and Mtalo (2016) and Almås and Manoko (2012), conducted at Geita gold mines and North Mara gold mines; and Nkuli (2012), at Bulyanhulu gold mine. Like other studies in developing countries, they found higher concentrations than normal of heavy metals and cyanide in soil samples and in the water in mining vicinities. In addition to the empirical findings, there have been several fatal incidents reported in Tanzania: for instance, in May 2009 an environmental incident occurred at the North Mara mine, when toxic chemicals leaked from a mine rock storage facility into the Tigithe River. Thirty people and 300 cows died from the pollution[7]. The same mine was ordered to close a pit refuse facility at North Mara in 2009, due to toxic leaks that contaminated local water sources[8]. Similar have been reported at other mines, such as Geita[9] and Bulyanhulu[10].

Such reports highlight the fact that in developing countries, often the existing laws fail to regulate the gold mining industry effectively, leading to excessive environmental degradation (Hilson, 2000). These lapses in regulatory oversight and enforcement have led to high levels of pollution, as gold mines routinely discharge toxic chemicals such as mercury (typically used by small-scale miners), cyanide and arsenic and their harmful compounds into water bodies, exposing workers and residents to a range of health risks (Akpalu and Normanyo, 2017). For a detailed analysis of heavy metals and their associated health risks, see Fashola, Ngole-Jeme and Babalola (2016).

2.2 Theoretical literature review

The relationship between exposure to pollution and health risks has been widely explored in toxicological and epidemiological studies. Toxicology studies explore pollution exposure to better understand the underlying mechanisms that affect health outcomes (Oberdörster, Oberdörster and Oberdörster, 2005; Stone et al., 2017). Indeed, pollutants can enter the human body via several routes, e.g., inhalation, absorption from the digestive tract, and injection for nanomedical applications (three exposure pathways include ingestion, inhalation and dermal contact). Regarding potential adverse impacts on the brain, uptake and retrograde axonal transport of pollutants via the olfactory nerve has been demonstrated in rodent inhalation studies (Oberdorster et al., 2004; Elder et al., 2006). Epidemiological studies are based on the dose-response theory (or exposure-response relationship). The dose-response function shows that the more a person (or other organism) is exposed to pollutants, drugs, foods and other substances beyond a particular threshold, the greater the chance of adverse health effects including death (WHO, 2016).

Epidemiological studies have reported numerous detrimental health consequences associated with mining pollutants, notably pathological respiratory and cardiovascular conditions (Brunekreef and Burdorf, 2018; Schultz, Litonjua and Melén, 2017; Barnes, Mathee, Thomas and Bruce, 2009; Dherani, Pope, Mascarenhas, Smith, Weber and Bruce, 2008). Pollution may increase the risk of premature mortality and morbidity, as per the global burden of disease report; for instance, it's estimated that worldwide in 2016, exposure to PM2.5 contributed to 4.1 million deaths from heart disease and stroke, lung cancer, chronic lung disease, and respiratory infections (Shupler at el., 2018; Heft-Nealet al., 2018) There is a growing number of empirical works on the effects of pollution on stunting rate, specifically regarding the presence of heavy metals (that potentially hinder growth) in mining vicinities (Von der Goltz and Barnwal, 2019; Vilcins, Sly and Jagals, 2018; Goyal and Canning, 2018; Machisa et al., 2013; Fenske et al., 2013; Mishra and Retherford, 2007).

Apart from the health effects of pollution (some of which are irreversible) evaluated in public health studies, in the economic literature pollution is considered to generate costs for third parties if not properly internalised. Pollution costs are quantified in the literature of non-market valuation of externality. Traditional frameworks for evaluating pollution abatement policy provide guidance on how to

[7] See http://protestbarrick.net/downloads/Beyond_barrick.pdf
[8] See http://protestbarrick.net/article.php@id=852.html
[9] See http://www.ipsnews.net/2001/05/environment-tanzania-farmers-link-deaths-to-gold-mine-pollution/
[10] See https://www.cyanidecode.org/sites/default/files/pdf/AcaciaBulyanhuluSAR2019.pdf

achieve the public objective of protecting the health of those of the population most at risk from polluting industries such as mining. The economic concept of marginal cost versus marginal benefit establishes a link between health outcomes, environmental regulations and pollution emission (Kolstad, 2011).

Therefore, the framework presents the underlying assumption that high levels of pollution are associated with high health expenditure. Thus, in our analysis it is acceptable to assume that people in a highly polluted area are more likely to have higher medical expenditure.

2.3 Empirical literature review

The empirical studies use several strategies to evaluate pollution costs, based on a willingness-to-pay approach. The two most used are: (1) defensive expenditures are used to proxy the costs; health expenditure is used most often, the argument being that it is highly likely that the risk of pollution-related sicknesses will necessitate increasingly high healthcare expenditure in affected communities. Empirical studies in this area include Zhang and Mu, 2018; Akpalu and Normanyo, 2017; and Deschenes, Shapiro and Greenstone, 2012. (2) willingness to pay for housing to avoid pollution is used. Empirical studies taking this approach include He and Collins, 2020; Chen and Jin, 2019; Currie et al., 2015; Chay and Greenstone, 2005; Smith and Huang, 1993. However, in developing countries such studies are implicitly limited; poor infrastructure and inflexible housing markets commonly make it impracticable to account for pollution. In addition to these two traditional approaches to measuring pollution costs, a few studies (Leitão, 2018; Aragón and Rud, 2016) have used agriculture productivity, while Lichter, Pestel and Sommer (2017), Chang, Graff Zivin, Gross and Neidell (2016) and Graff Zivin and Neidell (2012) all use labour productivity loss as a proxy for pollution cost[11].

The empirical literature shows pollution can affect human health as well as welfare, with issues ranging from health outcomes to health expenditure, housing prices and productivity losses. However, such damages are rarely internalised by the mines. Given the failure to internalise pollution cost by the mining and mineral processing industry (they are large polluters), it has been argued that the benefits of mining, in terms of revenue, foreign exchange and employment as a source of government revenue, has weakened such governments, dissuading them from passing and enforcing stringent mining-related environmental regulations (Akpalu and Normanyo, 2017; Greenstone and Hanna, 2014; McMahon, 2011). Therefore, mining pollution continues to cause damage to health, welfare and ecosystems.

Several studies have been undertaken on the health impacts of gold extraction (see e.g., Von der Goltz and Barnwal, 2019; Akpalu and Normanyo, 2017; Currie et al., 2014; Graff Zivin and Neidell, 2013). This study is similar to Von der Goltz and Barnwal (2019) in that we follow the same set-up of the treatment and control groups (we use distance to the nearest mine as a proxy for exposure to environmental pollution. The choice of a distance cut-off to define the treated group is therefore crucial[12].) However, Von der Goltz and Barnwal (2019) used information from different studies to establish the threshold at which the mining impacts are considered significant and to assign the treatment and control groups. In this study we estimate the threshold from the stunting data and use this threshold to establish our treatment and control groups. Moreover, Von der Goltz and Barnwal (2019) assumed that the health effects (on stunting) are entirely due to mining pollution; but in the literature there are several environmental risk factors. Vilcins, Sly and Jagals (2018) included sanitation, hygiene, access to and quality

[11] Recent studies on pollution explored the wealth and health trade-off associated with exposure to mining pollution (Von der Goltz and Barnwal, 2019: Aragón and Rud, 2013), while others evaluated pollution regulations and improved health outcomes (Cheung, He and Pan, 2020; Burns, Boogaard, Polus, Pfadenhauer, Rohwer, Van Erp and Rehfuess, 2020; Gehrsitz, 2017).

[12] Different studies have used different thresholds: Goltz and Barnwal (2018) used the distribution of lead around smelters to define the high-exposure level, which was at 5km (5-20km control) – this choice was in line with the definition of high exposure used by Geen et al., (2012). Wilson (2012) used a cut-off of 10km, while Aragón and Rud (2015, 2013) and Kotsadam and Tolonen (2016) used a baseline cut-off of 20km to 200km (based on the transport cost assumption). Shenoy et al (2018) used a cut-off of 10km when assessing the respirable dust concentration of mine tailings. Basu et al., (2010) used a cut-off of 7km, based on soil sample results, with sensitivity analysis for other choices. With perfect data, we might define closeness even more restrictively. However, in the context of available data, a tighter cut-off would risk introducing excessive noise, because we work with (imperfectly recorded) mine point locations as provided by USGS and business intelligence sources, while mining operations can measure several kilometres across.

of safe drinking water, solid waste disposal, housing, environmental enteropathy, intestinal parasites and air quality (regarding type of cooking fuel)[13].

In addition, health capital is determined genetically. Health can also be affected by investment in inputs ranging from medical care to personal behaviours such as consumption habits (smoking, drinking) and exercise (Wilson, 2002); our study focuses only on stunting rate, since children's health is less subject to personal behaviours.

Among the studies that have analysed the impact of exposure to pollution on stunting are Mishra and Retherford (2007); Machisa et al., (2013); Fenske et al., (2013); Goyal and Canning (2018); and Von der Goltz and Barnwal (2019). This channel associates the presence of heavy metals and pollutants with gold mines, showing how they affect the health outcomes of the people living nearby.

Historically, research into stunting has focused on dietary intake; yet a growing body of evidence has shown an important role for the natural and physical environment in child health (Vilcins, Sly and Jagals, 2018). We hypothesise that some environmental agents work independently of nutrition to negatively affect child growth. Therefore, in our analysis we control for other household environmental risk factors to ascertain the impact of mining pollution on health outcomes. We argue that the channel most plausible in explaining the different health outcomes between the treated and control groups when controlling for environmental risk factors (housing material, latrine type, drinking water source, cooking fuel type, solid waste disposal and hygiene) is through the presence of gold-mining-related pollution. The nutrition aspect (dietary intake) is proxied by the income and education of the household head; assuming that the higher the disposable income, the higher the consumption (consumption function), and the higher the education, the greater the concern over nutrition.

Moreover, there is little research quantifying the costs of mining externalities, especially in Africa. To help fill that gap, and similarly to the study by Akpalu and Normanyo (2017), we present a simple hedonic-type model that links private healthcare costs (both preventive and curative) to exposure to gold mining-related pollution. However, our analysis uses the coarsen exactly matching (CEM) approach to control for environmental risk factors and ensure similar comparisons between individuals in the same strata (exposed vs non-exposed) to establish the pollution Sample Average Treatment effect on the Treated (SATT), following the hypothesis that healthcare expenditure is higher the closer a household is to a mine.

3.1 Overview of stunting and mining proximity

There are 5 large gold mines in Tanzania, namely, Geita gold mine (GGM), Bulyanhulu gold mine, North Mara gold mine (NMGM), Buzwagi gold mine (BGM) and New Luika gold mine (NLGM), in respective of the year of starting operation. Table 1 shows the attribute of the mines.

Table 1: Gold mine production attributes[14].

Serial No.	Name	Type	Started production	Production 2017/18
1	Geita Gold Mine	Opencast	2000	539 000 ounces
2	Bulyanhulu Gold Mine	Underground	2001	175 491 ounces
3	North Mara Gold Mine	Underground	2002	323 607 ounces
4	Buzwagi Gold Mine	Opencast	2009	268 785 ounces
5	New Luika Gold Mine	Underground	2012	87 713 ounces

Table 1 above shows the attributes of the mines, in terms of type of mining operation: GGM and BGM are opencast mines, while the rest are underground mines. All are in close proximity to local communities, as they are all recently established. The communities surrounding are engaged in artisanal mining and agriculture activities. Moreover, they depend on groundwater from boreholes as the only source of water

[13] The environmental risk factors studied to find an association with stunting were reviewed by Vilcins, Sly and Jagals (2018), including sanitation (measured by latrine ownership and type); hygiene (appropriate handwashing, and presence of soap and water near latrine); safe drinking water access (piped and non-piped) and quality (presence of arsenic); solid waste disposal (presence of adequate waste removal); housing (poorer-quality housing materials, specifically dirt floors); environmental enteropathy (children who consume soil); intestinal parasites (parasite infections); air quality (type of cooking fuel); and electromagnetic fields (children living within 50m of high-voltage power lines).

[14] The dataset was compiled from respective mining annual performance report 2017/2018

for domestic use; being close to the mine, borehole water is vulnerable to pollution from mining activities, especially heavy metals and cyanide. These pollutants, together with others found in polluted air, pose serious health risks to the people (especially the children, the most vulnerable group) surrounding the mines.

To conceptualize the relationship between health outcomes and proximity to mining, a hotspot analysis was conducted, showing the spatial distribution of stunting in the country over the period of study. A hotspot is an area or region that requires special attention, compared to others. Hotspot analysis is also known as Getis-Ord Gi* (G-I-star) and uses vectors to identify locations (hotspots and coldspots) from the dataset that are statistically significant. The analysis groups feature with similar high (hot) or low (cold) values into a cluster, by aggregating points of occurrence into polygons or converging points considered in proximity to one another based on a calculated distance (Parker and Asencio, 2009). The results of the hotspot analysis are presented in **Error! Reference source not found.** below.

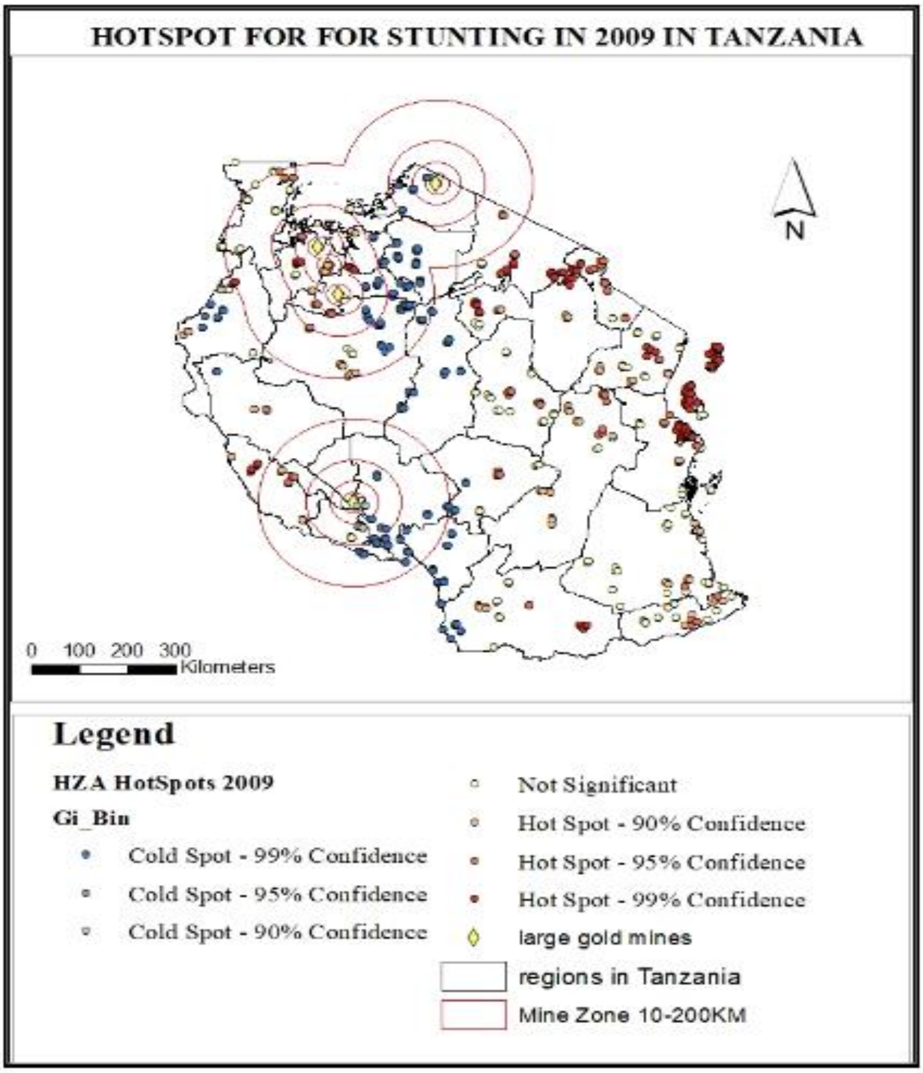

Figure 1: Hotspot analysis for Stunting

Error! Reference source not found. above shows the hotspot and coldspot areas for stunting based on the 2009 national panel survey (NPS). The coldspots are our major concern, as they represent the areas with significant low negative height for age Z-score (HAZ06), implying stunting (if less than -2) or severe stunting (if less than -3). The study used the global Moran's Index to test for the spatial cluster in the data; these results are presented in Figure 2 below.

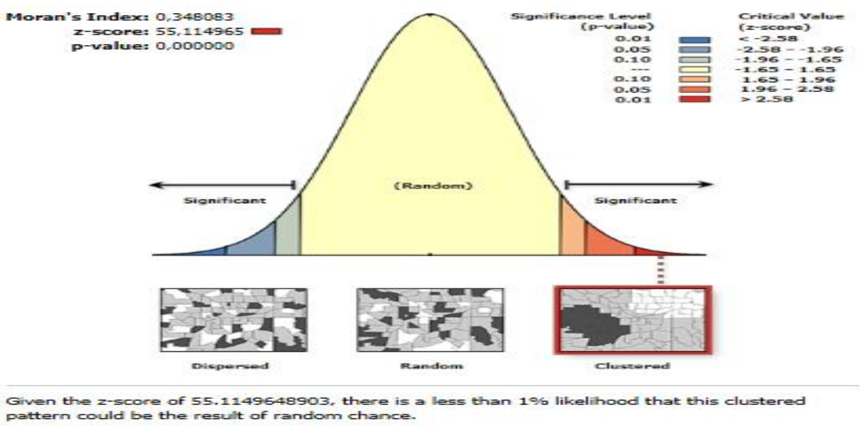

Figure 2: Global Moran's Index results

The global Moran's Index figures in Figure 2 show that there is a cluster with high levels of stunting in the proximity of the mines The p-value of 0.000 for a Z-core of 55.1 indicates that the results are statistically significant at the 1% level of significance; that is, we can reject the null hypothesis that the there is no high-cluster in the sample with a 99% confidence level. This implies that there is a less than 1% likelihood that this high-clustered pattern could be the result of random chance. Therefore, there is strong reason to assume a causal relationship between the stunting patterns we observe in locations in close proximity to mines, and mining activity.

Moreover, like similar studies, this study specifies a cut-off point for the control group. In our case, the control group could not exceed 100km distance from a mine, as beyond this threshold the mines intersect (see the map in Figure 3 below); this avoids the possibility that a person in the treatment group for one mine could be in the control group for the other mine. To avoid such a possibility, and to ensure homogeneity between the control and the treated groups, we maintained a cut-off distance of 50km.

To evaluate health outcomes from mining pollution exposure, the study specified the treated and control groups based on the findings of the stunting rate analysis. The results suggested that the mining zone (household located within 10km from a nearby mine) which in this study is categories based on the distance from the nearby large gold mine whereby the heath outcome was significant. The study design is presented in Figure 4 below.

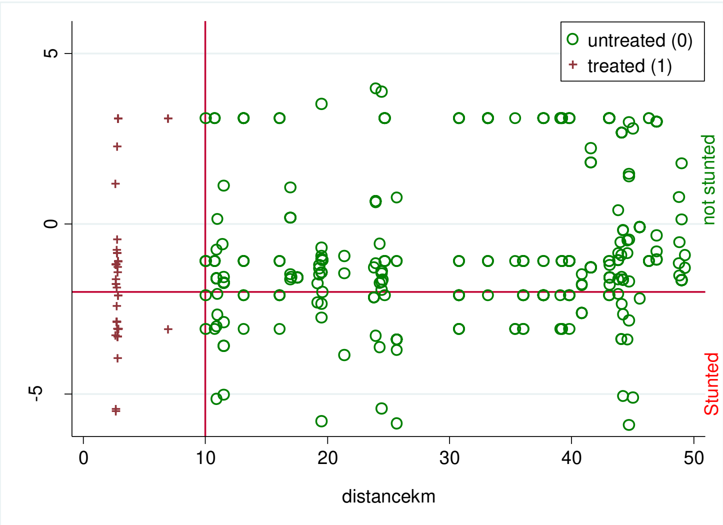

Figure 4: the study design

above shows the study design. People near a mine – i.e., within 10km – were categorised as being in the treated group (on the assumption that the closer an individual is to a mine, the more exposed he or she is to mining pollution). People further away (between 10km and 50km) were treated as the control (or untreated) group. The vertical axis indicates stunting status.

4.0 METHODOLOGY

4.1 Model specification

Building on the theoretical conceptualisation described above, we followed the avoidance expenditure model. The avoidance expenditure model derives its conceptualisation from revealed preference methods for evaluating environmental quality; it measures expenditure on market goods that compensate for lower levels of environmental quality (Moretti and Neidell, 2011; Neidell, 2009).

The study assumes a typical person with a utility function. Three variables enter the individual's utility function: health (H), air/soil/water pollution (A), and market goods (X). The individual produces health by combining medical care in the current period with pollution. Health is also influenced by the individual's predisposition to sickness and pollution exposure (living near mining). We can now say defensive expenditure on medical care (M) will depend on health (H), pollution and individual health records and experience (R).

$$M = f(H, A, R) \quad (1)$$

We followed Chang and Trivedi's (2003) model specification, which was extended and applied by Akpalu and Normanyo (2017); it assumes that health status depends on investment in health (M), which is a derived demand. Because of a number of exogenous environmental factors, the returns on such an investment are partly deterministic and partly stochastic. The stochastic component is assumed to have a one-sided distribution. Several factors could account for the uncertain health outcome, including misdiagnosis and reinfection resulting from repeated exposure to the emission of dangerous gases from the mines, or leakage of heavy metals into water that is later used domestically. As noted earlier, enormous amounts of inorganic mercury and high concentrations of arsenic are present in areas close to gold mines (see e.g., Smedley, 1996; Telmer and Veiga, 2009). We can then specify the general form of healthcare investment equation as:

$$M = f(h_0, B, z; A) \quad (2)$$

Thus, the stochastic component of the health outcome depends on exposure to mining externalities, such as cyanide spillage; as well as a vector of individual characteristics (A), where z is a vector of mining externalities (for example, nearness to the mining site, which is a proxy for exposure to pollution, or noise pollution from blasting, etc.). It is hypothesized that increased pollution decreases the expected returns to health expenditure. B is the budget in real terms. h0 is the initial or 'endowed' health status (long-term health).

Equation (2) is a hedonic-type equation, in which the economic cost of healthcare (both preventive and curative) depends on the level of environmental hazard to which an individual is exposed (z), after controlling for other social, economic and biophysical characteristics.

We used the hedonic pricing theory to establish how much households are willing to accept as compensation for improvements in environmental quality in the vicinity of a mine and use this as a guide to developing policy regarding pollution control in mining zones. The basic idea behind this method is that we could choose houses in neighbourhoods that currently experience different levels of environmental quality and compare their prices. The premium on prices in the high-air-quality neighbourhood should give us an indication of willingness to pay (WTP) (Currie et al., 2015).

But in developing countries, the housing market is less developed; thus, housing prices are used less often in empirical studies, and even then, usually as a substate. More often, empirical strategies have used other proxies such as agriculture productivity loss, defensive expenditure, and medical expenses (see Akpalu and Normanyo, 2017; Deschenes, Shapiro and Greenstone, 2012) to establish willingness to pay (for improved environmental quality) or willingness to accept (WTA) as compensation for the individual to accept lower environmental quality. In line with defensive-expenditure empirical studies we employ the hedonic type of equation – similar to what was done in Akpalu and Normanyo (2017) to establish the WTA. In our analysis we compared the health expenditure of households close to a mine (exposed to mining pollution) with similar households away from the mine, controlling for social, economic, and environmental characteristics.

However, instead of writing an expression that gives defensive expenditure as a function of H, A and R), we can write a health production function as:

$$HAZO6 = f(P, A, H) \quad (3)$$
$$Stunting = f(P, A, H) \quad (4)$$

where HAZO6-height for age Z-score (Health indicator) is a function of environmental amenities (A), parental awareness avoidance behaviour (P), and baseline child health (H). P, A and H can be viewed as functions of parents' income and/or education. (A similar approach was adopted in Nilsson, 2009; Currie, 2008; and Jans, Johansson and Nilsson, 2018.) This is simply another way of writing defensive expenditure.

4.2 Model estimation

Selection bias: in most cases, we do not observe the same individual in both situations/scenarios; that is, we observe Y_{1i} for individuals exposed to the mining pollution, and Y_{0i} for individuals observed in the non-mining zone. We seek the average (Y_{1i} -Y_{0i}), an average causal effect involving everyone's Y_{1i} and everyone's Y_{0i} (Angrist and Pischke, 2014). If we assume that living in the polluted area reduces everyone's health by a constant amount k. the constant effect assumption allows us to write:

$$Y_{1i} - Y_{0i} = k \text{ or } Y_{1i} = Y_{0i} + k \tag{5}$$

If we substitute the constant effect assumption for the average means difference ($avg_n[Y_{1i} - Y_{0i}]$),:

$$\begin{aligned} avg_n[Y_{1i}|D_i=1] - avg_n[Y_{0i}|D_i=0] &= \{k + avg_n[Y_{0i}|D_i=1]\} - avg_n[Y_{0i}|D_i=0] \\ &= k + \{avg_n[Y_{0i}|D_i=1] - avg_n[Y_{0i}|D_i=0]\} \end{aligned} \tag{6}$$

Difference in group means = average causal effect + selection bias,

whereby selection bias is defined as the difference in average Y_{0i} between groups compared, average causal effects in the treatment effects context are the average treatment effect (ATE), E [$Y_{1i} - Y0i$], and the average treatment effect on the treated (ATET), E [$Y_{1i} - Y_{0i}|\ D_i = 1$]. Note that the ATET can be rewritten as

$$E\,[Y_{1i} - Y_{0i}|\ D_i = 1] = E[Y_{1i}|D_i=1] - E[Y_{0i}|D_i=1] \tag{7}$$

This expression highlights the counter-factual nature of a causal effect. The first term is the average health outcome/health expenditure in the treated (exposed to pollution) population, a potentially observable quantity. The second term is the average health outcome/health expenditure had they not been treated. This cannot be observed, though we may have a control group or econometric modelling strategy that provides a consistent estimate. Thus, simply comparing those who are and are not treated may provide a misleading estimate of a treatment effect. Since the omitted-variables problem is unrelated to sampling variance or statistical inference, but rather is concerned with population quantities, it too can be efficiently described by using mathematical expectation notation to denote population averages.

Since in most cases we observe only $E[Y_{0i}|D_i=0]$ and not $E[Y_{0i}|D_i=1]$, most social experiments are subject to the selection bias problem. The selection bias is resolved by introducing random assignment, which ensures that the potential average health outcome (or health expenditure, had the subject not been treated) – an unobservable quantity – is well-represented by the randomly selected control group. Because randomly assigned treatment and control groups come from the same underlying population, they are the same in every way, including their expected Y_{0i}; that is, $E[Y_{0i}|D_i=1] = E[Y_{0i}|D_i=0]$. When Di is randomly assigned, the selection bias is eliminated, and the difference in expectations by treatment status captures the causal effect of treatment as follows:

$$\begin{aligned} E[Y_{1i}|D_i=1] - E[Y_{0i}|D_i=0] &= E[Y_{1i}|D_i=1]\} - E[Y_{0i}|D_i=0] \\ &= E\,[Y_{0i} + k|D_i=1]\} - E[Y_{0i}|D_i=0] \\ &= k + E[Y_{0i}|D_i=1]\} - E[Y_{0i}|D_i=0] \\ &\text{Since } E[Y_{0i}|D_i=1] = E[Y_{0i}|D_i=0], \\ &= k \end{aligned} \tag{8}$$

The solution is easily achieved with a randomised trial, where the experiments are set to estimate treatment effect. However, most of the research in economics uses observational data, prone to omitted variable bias or selection bias. In the absence of experiments, several statistical strategies or techniques have been put in place, including regression, matching, instrumental variables, and recently, a combination of matching with other methods such as regression.

In regression analysis, the omitted variable or selection bias is assumed to originate from a vector of observed covariates Xi, which correlates with the treatment dummy Di. However, sample regression (through a linear model) coefficients provide consistent population coefficients depending on their adherence to the law of large numbers.

The matching approach makes the same assumption as the regression, that the source of selection bias is the vector of covariate Xi, that may correlate with Di. Unlike regression, however, the construction of the treatment effect differs: in the regression analysis, the treatment effect is constructed by running a linear model, while in matching it is constructed by matching individuals with the same covariates (Rosenbaum and Rubin, 1983).

Matching is a nonparametric method for pre-processing data by pruning observations from the data to reduce the imbalance between the treated and control groups, making the covariate's (Xi) empirical distributions between groups more similar, and thus controlling for some or all of the confounding influence of pre-treatment control variables in observational data (Iacus et al., 2012; 2019). After pre-processing (matching), further analysis can be carried out, estimating causal effect by applying methods that would have been used without matching. In cases where the matching exactly balances the data, a simple difference in mean technique can be used, as there is no need to control further for X (because it is unrelated to the treatment variable). In cases where matching could not balance exactly but only approximately, other statistical tools are required to control for X (e.g., a parametric model must be used to control for the differences in the covariates across the treated and control groups. This may be a linear regression, a maximum likelihood estimator, or some other estimator). Applying data after matching to the model reduces statistical bias and model dependence; therefore, the only inferences are those relatively close to the data (Ho et al., 2007; Iacus et al., 2012; 2019). Further complications in the analysis of matched data occur when there is a mismatch between the number of treated and control units within strata. To overcome this problem, Lucas, King and Porro (2008) suggest the use of estimators, which weight observations based on their strata size.

There are several matching methods. The most common involve finding, for each treated unit, at least one control unit that is 'similar' on the covariates. What distinguishes the methods is how this similarity is defined. For example, propensity-score matching (PSM) imputes the missing potential outcome for each subject by using an average of the outcomes of similar subjects that receive the other treatment level (which is simply the probability of being treated, conditional on the covariates). Similarity between subjects is based on estimated treatment probabilities, known as propensity scores. The average treatment effect (ATE) is computed by taking the average of the difference between the observed and potential outcomes for each subject (Abadie and Imbens, 2006; 2008; 2011; 2012). Coarsened exact matching (CEM) simply matches a treated unit to all the control units with the same covariate values. It works by first sorting all the observations into strata, each of which has identical values for all the coarsened pre-treatment covariates, and then discarding all observations within any stratum that does not have at least one observation for each unique value of the treatment variable (Blackwell et al., 2009).

The application of matching estimators is backed up in statistical inference theories by the axiom of simple random sampling, whereby everyone in the population has an equal chance of being treated (Abadie and Imbens, 2006). This property is appropriate when we have exactly matching conditions, meaning empirical distributions between groups are the same or have the same propensity score. However, applied researchers most often work with continuous variables (that are featured by natural meaningful breakpoints well known to data analysts) and finite data; in such situations, the exactly matching condition is most unlikely to be attained (the application of 'exactly matching' would drop most of if not all the available observations).

In practice, empirical analyses face the approximate matching (not exactly matching) situation; and accordingly, various statistical strategies are put in place as approximate matching estimators (e.g., nearest neighbour matching, radius matching, kernel matching, etc.). Unfortunately, such approaches regularly violate the 'exactly matching' requirement, as they operate a simple random sampling by stratifying the sample ex-post on the initial covariate space or based on the propensity score or on the distance metric space (Iacus et al., 2019). In practice, these methodologies approximate matching within each stratum as if it were an exact matching. The Mahalanobis distance and propensity-score matching methods are

subject to the same trap: they require the user to set the size of the matching solution ex ante, and then check for balance ex post. Thus, analysts must check for balance after the algorithm is finished and then respecify a matching model and recheck balance, etc. This process repeats until the user obtains an acceptable amount of balance.
To overcome this problem Iacus et al., (2012; 2019) proposed a theory which allowed the replacement of simple with stratified sampling, ensuring the matching methodologies are coherent with the theoretical axiom suggested by the theories of inference statistics. They included ex-ante stratification of the data assumption, which formulates an alternative axiom on the data-generating process, based on a stratified sampling framework. Their proposition allowed all strata to be defined ex ante and working with the original variables, instead of doing this ex-post on more complicated variables which are retrieved from the matching procedure.
Recently, increasingly the CEM approach has been applied as a new method for improving the estimation of causal effects by reducing the imbalance in covariates between treated and control groups, since it adheres to the proposed theory of Iacus et al., (2012; 2019; 2020), which is based on ex-ante stratification of the data assumption. CEM bounds the degree of model dependence and causal effect estimation error by ex-ante user choice, is monotonic imbalance-bounding (so that reducing the maximum imbalance on one variable has no effect on others), does not require a separate procedure to restrict data to common support, meets the congruence principle, is approximately invariant to measurement error, balances all nonlinearities and interactions in sample (i.e., not merely in expectation), and works with multiply-imputed datasets. It is faster, easier to use and understand, requires fewer assumptions, and is more easily automated. Unfortunately, because of the richness of the covariates in many settings, this method often produces very few matches. A whole host of approximate-matching methods specify a metric to find control units that are close to the treated unit.

In short, our empirical analysis is based on the use of CEM to assess the causal effect of mining pollution on health outcomes and health expenditure. Unlike other matching approaches, CEM has properties that are consistent and coherent with theoretical axioms on stratified sampling suggested by theories of inference statistics, as proven by Iacus et al., (2019). Thus, the use of CEM gives further reliability and credibility to our empirical analysis.

The CEM matching health outcome equation:

$$\text{CEM } X_i, \text{ treatment(treated)} \tag{9}$$

where X_i is the matching covariates, including marital status, matching variables marital status, drinking water, waste disposal, cooking fuel, latrine type, household floor, total household expenditure per capita, education of household head[15], while 'treated' (dummy variable 0=untreated or distance ≤q km, 1=treated or distance>q km) captured the treatment threshold (q), ranging from 5km (treat5) to 20km (treat20). The different threshold (q) estimations are saved as a sensitivity analysis of the threshold as well. To estimate the model for health outcomes, we followed the approach for sample splitting and threshold estimation suggested by Hansen (2000), and estimated treatment effects equation (10) using two approaches: logit and OLS regression.

$$Y_i = \beta_{1i} treat + \varepsilon_{i,} [\text{weight} = \text{ cem\_weights }] \tag{10}$$

Equation (10) was estimated as the logit regression when the independent variable was stunting (taking a value of 0 for not stunted and 1 for stunted). While the robust check was done by re-estimating the equation using a linear regression model (absorbing specific-mine fixed effect; this was done to ensure we compared people from the same mine) in which health was measured by height for age Z-score (continuous variable). In both cases the CEM weights were used as specified in equation (9). Several options for distance from mine (ranging from 5-20km) were used one at a time; the threshold was chosen as the point (distance) at which treatment effects were no longer significant.
When we analysed health expenditure, the data had to be resampled, as in the same localities there could be households which could not be considered under health outcomes (e.g., if there was no child or

[15] Age and gender of child could not be used, as they were incorporated in the calculation of HAZ06.

children under the age of 59 months). Moreover, the covaries had to be re-matched (CEM), as it was a new sample. Hence, the matching for health expenditure equation:

$$\text{Cem } X_i, \text{ treatment(treat10)} \tag{11}$$

where X_i is the matching covariates, including marital status, gender of the household head, drinking water, waste disposal, cooking fuel, latrine type, household floor, total household expenditure per capita, and education of household head, while treat10 (dummy variable, 0=untreated or distance≤10km, 1=treated or distance>10km) captured the treatment threshold at 10km (as established based on health outcome estimations).

To estimate the model for health expenditure effects, the treatment effects model is presented in equation (12):

$$Y_i = \beta_{1i} treat + \varepsilon_i, [\text{weight} = \text{ cem\_weights }] \tag{12}$$

The dependent variable is health expenditure per capita, and β_{1i} is the estimated coefficient which captures the treatment effect. The weights in this model were obtained for CEM equation (11). The model was estimated using OLS regression, while absorbing the nearest-mine fixed effect.

We further use the hedonic pricing theory intuition to establish how much the households in the mining neighbourhood are willing to accept as compensation for the health effects of mining pollution.

4.3 Data

This study used a secondary dataset, the National Panel Survey (NPS), collected by the National Bureau of Statistics (NBS) of Tanzania. NPS is a series of nationally representative household panel surveys that collect information on a wide range of topics including agricultural production, non-farm income-generating activities, consumption expenditure and wealth, among other socioeconomic characteristics. As an integrated survey covering several different socioeconomic factors, it complements other more narrowly focused survey efforts, such as the Demographic and Health Survey (DHS) on health, the Integrated Labour Force Survey (ILFS) on labour markets, the Household Budget Survey (HBS) on expenditure, and the National Sample Census of Agriculture (NSCA). In NPS, the same households are revisited over time (the first wave was done in 2008 and repeated every two years after that). We had all four waves available so far: Wave 1 – NPS 2008-2009; Wave 2 – NPS 2010-2011; Wave 3 – NPS 2012-2013; and Wave 4 – NPS 2014-2015.

4.4 Variable measurement

1) **HAZ06 and stunting:** the standard anthropometric measures are many, and they have different applications, implications and interpretations. The most used include height for age (H/A), weight for age (W/A), body mass index (BMI) and height for weight (W/H). Among others, Height for age (H/A) reflects cumulative linear growth. H/A deficits indicate past inadequate nutrition, and/or chronic/frequent illness. It does not measure short-term changes. Low scores for H/A imply 'shortness'; extremely low (<-2) implies 'stunting'; and <-3 implies extreme stunting. This variable has been widely used in empirical pollution studies, such as Goltz and Barnwal (2018), Akombi et al., (2017) and Charade et al. (2015). Mainly, this indicator is used as a population indicator, not for individual monitoring. H/A is appropriate for this study, since the percentage of children with low height for age (stunting) reflects the cumulative effects of undernutrition and infections since and even before birth. This measure can therefore be interpreted as an indication of poor environmental conditions or long-term restriction of a child's growth potential (WHO, 2010). Moreover, measuring health outcomes for children controls for other confounding factors that could influence health outcomes, 'lifestyle' among others.
   The z-scores could be generated using the 2000 US Centres for Disease Control and Prevention Growth Reference (US standard) and the 1990 British Growth Reference (UK standard). See the empirical application in STATA of the UK and US standards (Vidmarm, Carlin, Hesketh and Cole, 2004; Vidmar, Cole and Pan, 2013). Moreover, despite the country-specific standards, we used the general standards developed by the WHO in 1995 and revised in 2006 that are applicable worldwide.

The 2006 WHO new growth standards for 0-5 years, based on the Multi-Centre Growth Reference Study (see De Onis, Onyango, Borghi, Garza and Yang, 2006; Garza and De Onis, 2004) are used in this study, as they are the generally accepted standard worldwide. The anthropometric measures that were used to calculate Ha06 scores (range: -6 to 6) are height measured in centimetres, age measured in months, and gender a dummy 1 for males and 0 for females. Stunting rate is a dummy variable, value 1 for stunted and 0 for non-stunted, while HAZ06 is the continuous variable (range: -6 to 6).

2) **Treatment (treat)** is the threshold distance of the individual household from the nearby gold mine, measured in kilometres, used to categorise both the treated group and the control group. Various studies have used it in the same manner (Branson and Byker, 2018; Hanna and Oliva, 2015; Dinkelman, 2011; Oreopoulos, 2006; Finkelstein et al., 2012; Abadie, Angrist and Imbens, 2002). The assumption is that the closer an individual is to the mine, the more exposed to pollution he or she is. In this study we used the health outcome (stunting rate) to establish the threshold distance. The distance up to which the stunting rate was significant (10km) was considered treated, and that where stunting was insignificant was considered the control area. However, the control group had a cut-off point at 50km, to ensure the homogeneity of the group (similarity in terms of the food they access, the medical treatments, the culture, the market they access, and geographical, climatic and other physical features). Thus, treatment is a dummy variable, with 1=treated sample (distance≤10km) and 0=control group (10km> distance ≤50km).
3) **Distance (distancekm)** is the distance of the individual household from the nearby gold mine, measured in kilometres. ArcGIS 10.6 software was used to calculate the distances, using the GPS locations of the households and the mines.
4) **Health expenditure (Health_exp)** is the continuous variable that captures the total household out-of-pocket (OOP) health expenditure (no health insurance); this amount of money is measured in Tanzanian shillings (TZS). OOP costs are the direct costs a person pays for healthcare, which affects households differently depending on the source, whether from savings or consumption – a reduction in consumption to finance health expenditures can lead households further into poverty (Ssewanyana and Kasirye, 2020). On average, OOP costs make up 36% of health expenditure in sub-Saharan Africa (World Health Organisation, 2017). Tanzania allocates 7.3% of its GDP (a relatively large share of its resources) to healthcare expenditure, compared to an average of 5.3% in other low-income countries (Health Financing Profile: Tanzania – health policy project 2018 report,by Haazen, 2012). OOP accounted for an estimated 23% of total health expenditure in 2018. The low OOP in Tanzania was due to policy initiatives: in 1994, the public health facilities introduced user fees, with exemptions for some illnesses and demographic groups (children aged under five years and adults over 60 years). In 2001 the country started a National Health Insurance Fund (NHIF), funded by mandatory contributions from formal-sector employees and voluntary contributions from informal-sector workers. At least 9% of adults in Tanzania are covered by health insurance, mainly community-based mutual insurance (Ssewanyana and Kasirye, 2020).
5) **Health expenditure per capita (Health_exp_l)** is a continuous variable that captures annual OOP health expenditure per person in a household. It is calculated as household health expenditure divided by number of people in the household (household size) and is measured in TZS.
6) **Total household expenditure (totalexpend)** is a continuous variable that captures annual total household expenditure, measured in TZS; it is a proxy for disposable income. We hypothesised that all things being equal, higher income-earning households spend more on healthcare. Moreover, empirical studies in Africa, such as Murthy and Okunade (2009) and Ssewanyana and Kasirye (2020), confirmed the positive relationship between healthcare spending and real income.
7) **Total household expenditure per capita (totalexpend_l)** is a continuous variable that captures the annual total household expenditure per person in the household, measured in TZS. It is calculated by dividing total household expenditure by number of people in the household (household size).
8) **Household size (house_size)** is a continuous variable – the total number of people in a household.
9) **Household floor (floor)** is a discrete variable to capture the material used to make the floor of the main dwelling. It takes a value of 1 for earth, and 2 for concrete, cement, tiles or timber.
10) **Drinking water (drinking)** is a discrete variable that captures a household's main source of drinking water. It takes a value of 1 for piped water, 2 for water from boreholes and wells, 3 for bottled water, 4 for surface water (river, dam, lake, pond), and 5 for other sources.

11) **Waste disposal (waste)** is a discrete variable that captures how the household disposes of its garbage. It takes a value of 1 for collected by firm or government, 2 for a government bin, 3 for disposal within compound, 4 for none or unauthorised heap, and 5 for other.
12) **Latrine type (latrine)** is a discrete variable to capture the main toilet facilities used in the household. It takes a value of 1 for no toilet, 2 for open pit without slab, 3 for open pit with slab, 4 for pour flush, 5 for flush toilet, 6 for VIP toilet, and 7 for other.
13) **Cooking fuel (cooking)** is a discrete variable that captures the fuel used most for cooking in the household. It takes a value of 1 for firewood, 2 for animal residual, 3 for paraffin, 4 for charcoal, 5 for gas, 6 for electricity and 7 for other.
14) **Gender of the household (gender)** is a dummy variable, taking a value of 1 for male and 0 for female.
15) **Marital status** is a discrete variable taking the value 1 for single, 2 for married and 3 for divorced.
16) **Education of the household (education)** is a discrete variable, taking a value of 1 for no school, 2 for primary school, 3 for secondary school, and 4 for tertiary education.

4.4 Data Analysis

The data analysis was done using two software packages, namely Stata 15 and ArcGIS 10.6; the data from the survey were merged to their household identification (hhi) and the individual in the household (id), then merged further to their corresponding GPS location (latitude and longitude). The HAZ06 scores were calculated using zscore06 in Stata. The data were input to ArcGIS to visualise and calculate the hotspot and spatial correlation. ArcGIS was also used to calculate the distances from nearby gold mines. The data were then imported into Stata for treatment effect estimations.

The estimations were done in two ways; first was the estimation of the health effects, in which the dependent variable was stunting/HAZ06; this estimation was used to establish the threshold distance at which the treatment (mining pollution) had significant impacts on health, thus defining the treated and control groups. Second was the analysis of the impacts of mining pollution on health expenditure, based on the threshold established in the health outcome estimations. To achieve the two estimations, the sample was taken in two ways; for the health outcome the same treatment and control group threshold were considered, but the analysis was based only on households with a child or children less than or equal to 59 months old. The the estimations for health expenditure included all available household in both the treated and the control groups.

In both cases the treatment effect model was specified and estimated using the matching weights from the CEM to get the robust treatment effects results. The estimations for the threshold were performed using the two estimation models (regression and logit) as a validation strategy. In addition, the specification for distance was changed (ranging from 5km to 20km) for sensitivity analysis.

5.0 EMPIRICAL FINDINGS

We start our analysis by presenting the descriptive statistics for stunting rate in Table 2 below. The variables of interest are described: total observations of all variables are 402, the age of the children observed is between 1 and 59 months, 54% of the children are female and 46% are male. The children that are observed live between 2.6km and 50km from their nearest gold mines. The sample in the treated group consists of 67 children; in the control group there are 335 children. Their height-for-age score (HAZ06) ranges between -5.92 and 5.63, which is within the WHO prescribed limit[16]. The overall average stunting rate of the children is 29% (43% in the treated group; the control group is 26% – see 'stunting by treatment', Appendix Table 1). Most (68%) households use concrete, cement, tiles and timber for the floor of the main dwelling, while 32% have the earth floor. The average of 3.164 for waste disposal suggests that most people dispose of their garbage in their compounds or use an unauthorised heap (or none at all). The latrine type average of 2.74 suggests that most households have toilets, ranging from open pit without a slab to VIP toilets. The main sources of cooking fuel, as suggested by the average of 1.68, are firewood and charcoal. The main source of drinking water is water from boreholes and wells.

[16] The children with HAZO6 scores above 6 or below -6 were eliminated from the sample, as they are either abnormal (which may be biologically impossible) or there were measurement errors.

Table 2:Descriptive Statistics for stunting

	All samples				Treat(0)	Treat(1)	Treat(0)	Treat(1)	
Variable	Obs	Mean	Min	Max	Obs.	Obs.	Mean	Mean	Dif
age_month	402	26.933	0	58	335	67	27.511	24.045	3.466
gender	402	1.535	0	1	335	67	1.484	1.791	-0.307***
Haz06	402	-0.741	-5.92	5.62	335	67	-0.6	-1.45	0.851***
stunting	402	0.289	0	1	335	67	0.26	0.433	-0.173***
house_size	402	4.699	2	13	335	67	7.213	10.017	-2.804***
totalexpen	402	5580000	407000	1.39e+07	335	67	3430000	4290000	-859000**
totalexpenl	402	509000	85466.23	2630000	335	67	514000	486000	27950.57
floor	402	1.314	1	2	335	67	1.224	1.164	0.059
wastedispo	402	3.164	1	5	335	67	4.122	4.373	-0.251***
latrine	402	2.749	1	7	335	67	2.869	2.15	0.72***
cooking	402	1.677	1	7	335	67	1.752	1.298	0.454**
drinking	402	2.833	1	5	335	67	2.546	4.268	-1.722***
distancekm	402	26.267	2.618	49.308	335	67	30.932	2.942	27.99***

Dif represents the t-test of equality of means (Covariate balance test at treatment=10km)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

As in most evaluation studies, we proceed by presenting the simple mean difference of the output variable (here, the health outcomes) between the treated and untreated groups (the treatment threshold distance of 10km was used to establish the table). The results from the t-test which allows the unequal variance between the group is presented in Table 2 above.
Table 2 above shows the average outcome for children in the households that are far away from the mining zone (not exposed to mining pollution) in column (8); and the average outcome for children in households that are exposed to mining pollution in column (9). Column (10) presents the difference between these quantities. These sample quantities estimate two parameters: (column 8) the average health outcome, had all households in the study group been exposed to mining pollution; (column 9) the average health outcome had none of the households in the study group been exposed to mining pollution; and (column 10) the difference between column (8) and column (9), that is, the average causal effect, which provides the simple comparison of sample means consistently estimates that causal effect of pollution exposure on health outcome. Galiani and Schargrosky (2004) refer to intention-to-treat analysis: children are compared based on whether they are exposed to mining pollution or not, not according to whether the household opted to be exposed to mining pollution or not.

This simple analysis shows evidence of pollution exposure on health outcomes, with a difference in means of the Haz06 Z-scores of 0.851 between households that were exposed to pollution and those that were not. Which implies that on average, the children in the treated area (exposed to mining pollution) have lower Haz06 (-1.45) than those in the control group (-0.6) with similar social, economic and environmental attributes. The difference is statistically significant, at a 5% level of significance. Moreover, the difference of -0.173 in stunting rate points in the same direction.
Furthermore, the balance test shows that the average household size in the treated group is greater than in the control group. On average, the people in the treated area (near mines) spend more than people in the control group. The household floor materials are much better in the treated than in the control group. Similarly, the treated group has good access to drinking water, proper toilet facilities, waste disposal facilities, and good (green) cooking fuels.
This simple comparison (as motivated and justified by the Neyman model) provides some evidence of the causal effect of exposure to pollution, and a simple and transparent way to estimate average causal effects in strong experiments (Dunning, 2012). However, it is prone to selection bias [see equation (6)] and does not include the confounders: the variables associated with assignment to the treatment of the control group that are also related to the potential

outcome. This is not the actual causal effect that we are interested in. Thus, simply comparing the mean value of y for the treated and untreated groups badly over- or underestimates the effect of treatment.

To address the selection bias problem, we employ CEM [see equation (9) above]. The results for threshold at 10km are presented in Table 3 below, while the quality of matching to other distance thresholds is presented in Appendix Table 2.

Table 3: CEM for stunting at 10km

	Untreated	Treated	Total
All	335	67	402
Matched	57	25	82
Unmatched	278	42	327
Share matched	16.1%	31.3%	18.7%
Multivariate $\mathcal{L}1$ distance			0.21470343

Table 3 above shows the number of observations matched and thus retained, as well as those that were pruned because they were not comparable between the treated and control groups. The overall imbalance is given by the $\mathcal{L}1$ statistic, introduced in Iacus, King, and Porro (2008) as a comprehensive measure of global imbalance which is interpreted as perfect global balance (up to coarsening) when $\mathcal{L}1=0$, while larger values indicate a larger imbalance between the groups, with a maximum of $\mathcal{L}1=1$, indicating complete separation. Thus, the $\mathcal{L}1$ statistic of 0.21 in our case implies a good matching solution. Moreover, the number of matched strata in the treated (25) and control groupa (57) is not the same; we don't have an exactly matching scenario, where simple mean difference could work perfectly. Thus, we employ a regression analysis to control for X, as suggested by Lucas, King and Porro (2008), using estimators which weight observations based on their strata size in such situations [equation (10)]. The results for the health outcome (stunting rate) treatment effects at different threshold distance are presented in Table 4 below.

Table 4: Threshold estimation using logit regression of health outcome (stunting rate)

	(1)		(2)		(3)		(4)	
VARIABLES	5km	MFX	7km	MFX	10km	MFX	11km	MFX
treat5	1.728***	0.282**						
	(0.641)	0.113						
treat10			1.728***	0.282**				
			(0.641)	0.113				
treat11					1.492**	0.226**		
					(0.610)	0.094		
treat12							0.357	0.069
							(0.442)	0.086
Constant	-2.213***		-2.213***		-2.234***		-1.226***	
	(0.457)		(0.457)		(0.474)		(0.294)	
Observations	75		75		82		110	

MFX stands for marginal fixed effect after logit regression.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The results in Table 4 show the health effects (stunting rate) where statistically significant (at 5% level of significance) to a distance up to 10km from the nearby gold mine. At 10km, the marginal fixed effects (MFX) show that the probability of a child being stunted in the treated area (near the mine) is 0.226 greater than in the control group, when social, economic and environmental characteristics are controlled. Moreover, the treatments were statistically insignificant at a threshold of 11km and above; thus, the results suggest that the health outcomes from exposure to mining pollution are significant only to distances 10km or less from the mine. Therefore, it is logical to place our threshold at 10km for distinguishing between the treated and untreated groups. The study used the OLS regression of health outcomes (HAZ06), running equation (10) for validation of threshold distance. The results are presented in Table 5 below.

Table 5: Threshold estimation using OLS of HAZ06

VARIABLES	(1) 5km	(2) 7km	(3) 10km	(4) 11km	(5) 12km
treat5	-1.042**				
	(0.396)				
Treat7		-1.042**			
		(0.396)			
treat10			-0.827**		
			(0.412)		
treat11				-0.447	
				(0.440)	
treat12					-0.447
					(0.440)
Constant	-0.706***	-0.706***	-0.762***	-1.253***	-1.253***
	(0.203)	(0.203)	(0.234)	(0.245)	(0.245)
Observations	75	75	82	110	110
R-squared	0.374	0.374	0.301	0.056	0.056

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regression results presented in Table 5 above show that the HAZ06 scores are statistically significant at a 5% level of significance for distances of up to 10km from the mine. The findings further reveal that as the distance from the mine increases, HAZ06 improves (from -1.042 to -0.447), which implies that health outcomes improve as pollution decreases. The study also tested the sensitivity of the results to change in threshold level, up to a threshold distance of 20km from the nearby gold mine (the results above 10km were all statistically insignificant). We assumed that being close to the mine would increase the treatment effect and being further away from the mine would reduce the effect. Guided by this assumption, the study used the regression of HAZ06 on distance, absorbing nearest mine fixed effects. The results are presented in Table 6 below.

Table 6: regression of HAZ06 on distance

VARIABLES	(1) HAZ06
distancekm	0.0212**
	(0.008)
Constant	-1.299***
	(0.24)
Observations	402
Mineid	5
R-squared	0.0622

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0

The results in Table 6 above support our hypothesis that distance to nearest major mining site, a proxy for exposure to pollution, is positively related to health outcomes; the coefficient of 0.0212 implies that as one moves away from the nearest gold mine, for each kilometre further, HAZ06 (the health outcome indicator) increases significantly by 0.0212. In other words, the less a person is exposed to mining pollution (i.e., the greater the distance from the mining site), the better the health outcomes.

5.2 Estimating the health costs of pollution.

To analyse the health expenditure associated with mining operations, the study resampled the data based on the threshold determined by the health outcome results; thus, the available data for all households near mines were included (unlike the health outcomes analysis, where only households with children under five years old were considered). The descriptive statistics are presented in Table 7 below.

Table 7: Descriptive Statistics (health care expenditure)

	All sample				Treat(0)	Treat	Treat(0)	Treat(1)	
Variable	Obs	Mean	Min	Max	Obs.	Obs.	Mean	Mean	Dif
age_year	1301	39.671	20	97	1062	239	39.731	37.718	2.014
gender	1301	1.294	0	1	1062	239	1.293	1.333	-0.04
marital	1301	2.806	1	3	1062	239	2.813	2.588	0.225
education	1301	2.394	1	4	1062	239	2.402	2.118	0.284
house_size	1301	5.78	1	14	1062	239	5.723	7.516	-1.792**
floor	1301	1.285	1	2	1062	239	1.283	1.359	-0.076
wastedispo	1301	4.136	1	5	1062	239	3.126	3.462	-0.336***
latrine	1301	3.38	1	7	1062	239	3.376	3.513	-0.137
cooking	1301	1.882	1	7	1062	239	1.865	2.436	-0.572**
drinking	1301	3.253	1	5	1062	239	3.255	3.205	0.049
totalexpend	1301	5210000	119000	3.24e+07	1062	239	4160000	5710000	-1550000**
totalexpen~l	1301	685000	29725	1.08e+07	1062	239	683000	740000	-57600
health_exp	1301	324000	0	4280000	1062	239	217000	448000	-231000***
health_exp_l	1301	24812.3	0	1070000	1062	239	23445.83	66908.3	-43500**
distancekm	1301	61.4	2.618	49.394	1062	239	63.185	3.631	59.553***

Dif represents the t-test of equality of means (Covariate balance test at treatment=10km)
*** p<0.01, ** p<0.05, * p<0.1.

In Table 7 above, the new sample has a total observation count of 1 301, the age of the household head ranges between 20 and 97 years, 70% are male and 30% are female. The mean marital status of 2.8 implies that most (62.9%) household heads are either married or divorced. More than 40% of the household heads have secondary or higher education. The average household size is six people, and 71% of the households have earth floors while 29% have used concrete, cement, tiles, and/or timber. The average of 4.136 for waste disposal suggests that most people dispose of their garbage within their compounds (77.6%) or use no or unauthorised heaps (14.8%). The latrine-type average of 3.38 suggests that most households (84.7%) have toilets, ranging from open pit without slab to VIP toilets. The main source of cooking fuel, as suggested by the average of 1.882, is firewood (77.8%). The other mainly used source is charcoal (20.7%). The main source of drinking water is water from boreholes and wells (42.7%); surface water (rivers, dams, lakes, ponds) account for 31.7%. (For more details on variable frequencies and percentages for cooking fuel, household floors, waste disposal, latrine type and drinking water source, see Appendix Tables 3 through 7 respectively).

The study showed that on average, the households in the mining area spend an average of TZS 5 210 000 annually (equivalent to USD 2 265 in 2018). This amount is similar to the one presented in the 2017-18 Household Budget Survey (HBS) report published by the National Bureau of Statistics (NBS, 2018), which revealed that the average consumption per household per month was TZS 416 927 (TZS 5 003 124 annually). According to the 2017-18 household budget survey key indicator report, average monthly household consumption expenditure was higher in the urban areas (TZS 534 619) than in the rural areas (TZS 361 956) (NBS, 2018).

Average annual household out-of-pocket health expenditure was TZS 324 000 (equivalent to a 6.2% share of household income spent on health). Minimum health expenditure was zero; this could be attributed to the potential risk of impoverishment, which may lead to changes in health-seeking behaviour: due to unaffordable services, some vulnerable groups may avoid seeking the required health services (Russell, 2004; Ssewanyana and Kasirye, 2020).

The balanced test results further reveal that the treated group (near the mine) are younger (mean age of 37) than the control group (mean age 39). The treated group has more male and fewer educated people than its control counterpart, which could be because mining work is labour- and strength-intensive. Households in the treated group have higher incomes (proxied by total expenditure) and can afford more household members. They have better environments, in terms of better floors, better latrines, greener cooking fuels, and waste disposal away from their compounds. However, there is no significant difference between the treated and untreated groups in terms of source of drinking water. Moreover, the findings reveal that on average, a household in the treated group spends TZS 43 500 per capita more on health annually than a household in the control group.

These findings imply environmental quality plays an important role in health expenditure. Families located near mines stand to earn higher incomes; but contrary to the popular understanding – that high income implies the family can afford better food, housing and medication (Fichera and Savage, 2015) – high incomes in mining settings are achieved with poor environmental quality, which eventually compromises health outcomes. Or rather, the income effect is not sufficiently significant to compensate for the health damage from pollution.

This heterogeneity simply means there is no unique causal effect of pollution exposure, and that for some households the effect may deviate from those extensively documented. Individuals differ not only in background characteristics, but also in how they respond to treatment, intervention, or stimulation (Zhou and Xie, 2020). Responses to mining pollution exposure (and thus the treatment effects) probably differ from individual to individual. For example, high-immunity individuals are likely to have fewer health impacts than immune individuals and may therefore enjoy larger returns from mining pollution exposure. Children from disadvantaged backgrounds may lose more from exposure to mining pollution than children from advantaged backgrounds. Even though treatment effects are likely to be heterogeneous, previous empirical work on health outcomes has not paid much attention to heterogeneous treatment effects (see Von der Golt and Barnwal, 2019).

There are several realistic reasons to assume treatment effect heterogeneity. First, individuals can be heterogeneous in their untreated outcomes (Y_{0i}), reflecting differences in their health before mining operations, such as the quality of their immunity, family background, etc. The introduction of mining activities brings more differences in health, after which Y_{1i} would be more heterogeneous than Y_{0i} and individuals with higher outcomes in the untreated state would have fewer treatment effects. Alternatively, it could be that some individuals are more able to benefit from staying in the mining zone (perhaps because of the higher income they generate, or better-quality medical care); so, they would have a higher Y_{1i} even if Y_{0i} was similar to that of other individuals. A higher Y_{1i} for a given Y_{0i} could also result from variation in quality of treatment (the intensity of pollution exposure).

To control for background characteristics (heterogeneity) we use CEM on the covariates, as explained in equation (11); the results are presented in Table 8 below.

Table 8: CEM for health expenditure

	Untreated	Treated	Total
All	1 062	239	1 301
Matched	59	21	80
Unmatched	1 003	218	1 221
Share matched	5.6%	8.8%	6.14%
Multivariate $\mathcal{L}1$ distance			7.633e-17

Table 8 above shows the results from the CEM matching, based on the covariates specified in equation (11). The number of matched observations was 80, while the observations that did not match were 1 221. Even though most observations were pruned, the $\mathcal{L}1$ statistic of 7.633e-17 implies the quality of matching is very high. There is no exact match, as the number of strata in the treated group is 21, against 59 in the control group. Thus, a further model is required to control for covariates, as suggested by Lucas, King and Porro (2008); we used the OLS regression, absorbing the specific mine fixed effects, as expressed in equation (12). The results are presented in Table 9 below.

Table 9: Treatment effect on per capita health expenditure

VARIABLES	(1) 7km	(2) 10km	(3) 11km	(4) 13km	(5) 15km	(6) 20km
treat7	65,098					
	(51,815)					
treat10		55,202**				
		(26,847)				
treat11			46,957**			
			(20,367)			
treat13				33,018**		
				(14,221)		
Treat15					30,900**	
					(13,210)	
Treat20						27028*
						(11380)
Constant	9,586	16,734*	13,538	11,473	11853*	11211*
	(27,891)	(9,386)	(8,782)	(7,157)	(6660)	(5811)
Observations	35	80	82	89	96	118
R-squared	0.221	0.134	0.148	0.116	0.1116	0.1093

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.

Table 9 above shows health expenditure on per capita treatment effects at 7Km (in column 1), 10km (in column 2), 11km (in column 3), 13km (in column 4), 15km (column 5) and 20km (column 6). The results show that households located near mines (exposed to pollution) are spending more on health per capita than households far from mines. Households within 10km of a mine spend TZS 55 202 more on health per capita than those further than 10km away from the mine. This supports the hypothesis that distance to nearest major mining site – a proxy for exposure to pollution – is negatively related to healthcare expenditure. The linear regression of health expenditure per capita on distance absorbing mine fixed effects further verifies the hypothesis; the results are presented in *Table 10* below.

Table 10: Regression of health expenditure per capita on distance

VARIABLES	(1) Health expenditure per capita
distancekm	-712.46**
	(409.17)
Constant	50762.52***
	(12656.78)
Observations	1301
Mineid	5
R-squared	0.0490

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0

The distance coefficient (-712.46) in Table 10 above is statistically significant at a 5% level of significance. This implies that healthcare expenditure per capita decreases by TZS 712 for every 1km increase in average distance from residence to mining site. Equally, the marginal willingness to accept compensation for healthcare expenditure per capita because of exposure to pollution from mining activities, all else being equal, is higher for households that are closer to mining sites.

5.2 Willingness to Accept (WTA) Compensation for Mining Pollution

As noted in Table 9 above, and drawing from the intuitions of hedonic theory, households staying 10km or less from a mine (victims of mining pollution) are willing to accept (WTA) minimum compensation of an average per capita health expenditure of TZS 55 202 per annum.

The minimum WTA increases the closer one gets to the mine site, e.g., at 7km the average WTA was TZS 65 098. On average, households far (20km) from the mining zone are willing to accept a minimum of TZS 27 028 per capita household health expenditure per annum. The average minimum WTA per capita health expenditure for victims of mining pollution, at TZS 55 202, is equivalent to USD 24.75 – higher than the national average per capita out-of-pocket healthcare expenditure of USD 8.83 in 2018. The trade-off between minimum WTA and distance from the nearest mine is presented in

below.

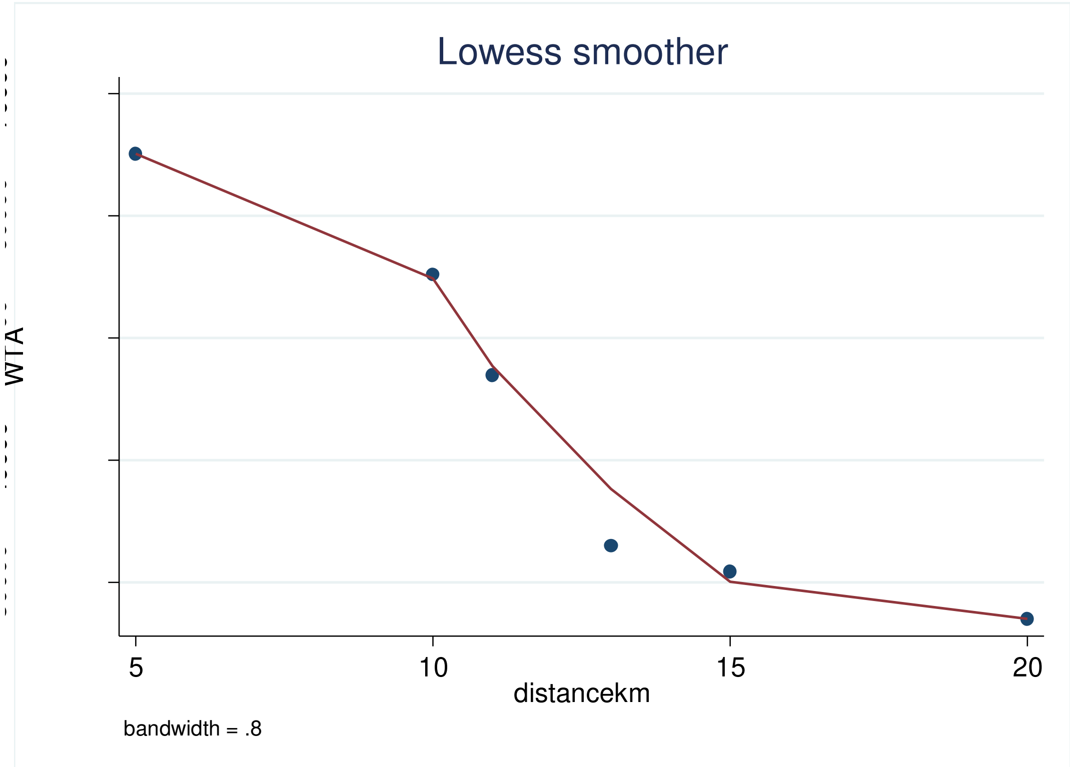

Figure 5: Willingness to accept compensation: the proximity-health expenditure trade-off.

Figure 5 above shows that the minimum compensation households closer to the mine are willing to accept is higher than for households far from the nearest mine. The slope at the nearer distance (less than 10km) is flatter, which implies the marginal willingness to accept is small (the difference in the WTA amount between persons living a kilometre from each other is small). After 10km the slope is steeper, indicating the marginal WTA is larger, and implying the WTA amount changes by a greater proportion between two people living a kilometre apart.

Conclusion

This article examines an important externality that a polluting industry may impose on the health of people living in close proximity to the industry. Most African countries, especially the mineral-rich countries (including Tanzania), have weak institutions and limited capacity to regulate the mining sector. Laxity in environmental policy, regulation and enforcement has resulted in the discharge of large quantities (beyond the WHO's suggested thresholds) of pollutants, toxic chemicals, and heavy metals into the environment, which exposes residents and workers to a range of health conditions. There is a limited number of empirical studies from developing countries that quantify this health damage and evaluate the effects of exposure to mining pollution on healthcare expenditure among residents of mining communities. To the best of our knowledge no study has controlled environmental risk factors in its analysis; however, empirical studies have shown that environmental risk factors work independently of other social and economic factors to affect health outcomes and hence health expenditure.

Thus, in order to ascertain the actual health outcomes and expenditure associated with mining pollution, this study used the CEM approach, which matches the social, economic and environmental risk factors and characteristics of households in the treated and control groups. Unlike other studies, we used data on stunting rate to establish the threshold distance for which health impacts are statistically significant, and used the threshold obtained to define the treated (victims of mining pollution) and control groups.

The results of both the logit model and OLS regression using the CEM weights for the threshold estimation showed that at distances up to 10km away from the nearest mine (after carrying out threshold sensitivity analysis), health effects are statistically significant at a 5% level of significance. At distances of more than 10km the health effects are statistically insignificant at a 5% level of significance; thus, the threshold distance of 10km was used to define the treated and control groups.

The result from the logit marginal fixed effects at 10km shows that the probability of a child from the treated group being stunted is 0.226 greater than for a child in the control group with similar social, economic and environmental risk factors. The OLS regression suggests a similar result: children in the treated group had HAZ06 0.827 less than similar children in the control group. Further regression of HAZ06 on distance from the mine provided robust evidence that statistically, health scores (HAZ06) among children increased by 0.0212 HAZ06 for every kilometre further away from the mining site. These findings suggest that the less a person is exposed to mining pollution (i.e., the further away from the mine they live), the smaller the health impact is.

Furthermore, the results from the OLS regression of per capita health expenditure on treatment showed that households within 10km of a mine spend TZS 55 202 more per capita on health than people who stay 10km or more from the mine. The regression of per capita health expenditure on distance provides more evidence: healthcare expenditure per capita decreases by TZS 712 for every 1km increase in average distance from the mining site. Drawing on the intuitions of the hedonic theory, the results were further interpreted in terms of willingness to accept (WTA); it was found that the households staying 10km from a mine (victims of mining pollution) are willing to accept minimum compensation per capita health expenditure of TZS 55 202 per annum on average, equivalent to USD 24.75. The minimum WTA increases as one get closer to the mine site: at 7km, average WTA was TZS 65 098, while households far (20km) from the mining zone are willing to accept a minimum of TZS 27 028 per capita household health expenditure per annum on average.

The balance test found that households in the treated group have higher income (proxied by total expenditure), could afford a larger number of household members, have a better environment in terms of better floors, better latrine types, greener cooking fuels, and waste disposal done outside of their compounds. Moreover, on average a household in the treated group spends TZS 1 550 000 more per annum than a household in the control group. These findings imply that environmental quality plays an important role in health expenditure. Households located near mines stand to gain higher income; but contrary to the popular understanding that high income implies the household can afford better food, housing and medication (Fichera and Savage, 2015, Kuehnle, 2014), high income in mining settings is achieved with poor environmental quality (high pollution levels), which eventually compromises health outcomes. Or rather, the income effects are not sufficient to compensate for health damage from pollution.

These findings have an important implication for environmental and industrial policies. They suggest environmental regulations should be tightened, to ensure that the pollution emitted by mines is below the identified required health thresholds. Moreover, proximity to a mine should be assessed and people evacuated from highly polluted zones. Regular environmental assessment should consider the impact of polluting industries on the actual health outcomes of surrounding communities.

Mining industries affect local economic conditions through many channels, which could create local demand (given an effective local-content policy), affect the provision of public goods, and change the scope of re-distributive policies. Similarly, mining can also generate negative local effects, such as increases in rent-seeking behaviour, conflict and political corruption. The household total-expenditure differences between the treated and control groups imply that the compensation policies and positive spill-overs from mines, if any, are insufficient to offset their negative health effects on surrounding communities. Thus, there is a need for a thorough review of industrial policies (especially concerning local content) to ensure that compensation policies and local multiplier effects are adequate to offset any negative effects.

The evaluation of health outcomes, especially for children, has significant social and economic implications: childhood health can generate significant effects on subsequent health, educational attainment, and labour market outcomes, through dynamic complementarities and cross-productivity with the development of cognitive and non-cognitive skills. Moreover, there is strong evidence in the literature for a link between parents' socioeconomic status and child health; a link that suggests that parts of the intergenerational persistence in inequality are due to differences in childhood health conditions. Thus, addressing children's health issues has potential economic benefits, ranging from labour market improvements to income inequality reduction.

The study was limited in two ways. We could not clearly establish the relative significance of each mechanism through which pollution could plausibly affect health outcomes, such as water pollution, air pollution and soil pollution, which all affect the food chain. Similarly, we could not examine the types of pollutants that significantly affect health outcomes.

The study also faced the same data challenge as most similar studies, in using the demographic health surveys (DHS), which are taken annually. However, most of the DHS for most of the previous years did not capture the GPS coordinates of the respondents; even those that did distorted the codes for individual households to approximate a radius of between 2km and 10km difference to the actual codes, for confidentiality's sake. The actual/precise-to-within-15m codes available are at cluster level, which is not appropriate for this study (Perez-Heydrich, Warren, Burgert and Emch, 2013; Burgert, Colston, Roy and Zachary, 2013). Thus, we could not use the DHS, as we required actual locations.

In addition, our dataset has the advantage of being a panel; however, we could not take advantage of panel regression. Instead, we used the repeated cross-sectional, because the HAZ06 measures growth rate to the age of 59 months. Since our data waves are collected at two-year intervals, the maximum tracing for a single individual would be for only two waves. While beyond the scope of this study, examination of these issues warrants further research.

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Appendix

Appendix Table 1: **Stunting rate by treatment**

		Treatment (10km)	
Stunting	**statistics**	0	1
0	Frequency	248	38
	Mean gender	1.472	1.684
	Mean age (months)	25.927	23.289
	Mean expenditure per capita	523000	585000
1	Frequency	87	29
	Mean gender	1.517	1.931
	Mean age (months)	32.023	25.034
	Mean expenditure per capita	487000	362000

Stunting in the untreated area is (87/335=0.26) 26%, while in the treated area it is (29/67=0.43) 43%.

Appendix Table 2: Matching summary (stunting)

	5km		10km		11km	
	Untreated	treated	untreated	treated	untreated	treated
All	335	67	335	67	312	90
Matched	54	21	54	21	51	31
Unmatched	281	46	281	46	261	59
Share matched	16.1%	31.3%	16.1%	31.3%	16.3%	34.4%
Multivariate $\mathcal{L}1$ distance	0.21470343		0.21470343		0.19354839	

Appendix Table 3: Cooking fuel

S/No.	Fuel source	Frequencies	Percentage
1	Animal residual	1	0.08
2	Firewood	1,014	77.8
3	Paraffin	5	0.3
4	Charcoal	267	20.7
5	Gas	6	0.5
6	Electricity	1	0.08
7	Others	7	0.54
	total	1301	

Appendix Table 4: Household floor

S/No.	The floor material	Frequencies	Percentage
1	Earth	932	71.5
2	Concrete, cement, tiles, timber	369	28.5
	Total	1301	

Appendix Table 5: Waste disposal

S/No	Dispose of its garbage	Frequencies	Percentage
1	Collected by government or private firm	35	2.7
2	Government bin	18	1.4
3	Disposal within compound	1,010	77.6
4	None or unauthorised heap	193	14.8
5	Other (specify)	45	3.5
	Total	1301	

Appendix Table 6: Latrine type

S/No	Main toilet facilities	Frequencies	Percentage
1	No toilet	199	15.3
2	Open pit without slab	376	28.9
3	Open pit with slab	344	26.4
4	Pour flush	230	17.7
5	Flush toilet	111	8.5
6	VIP	40	3.1
7	Other (specify)	1	0.08
	Total	1301	

Appendix Table 7: Drinking water

S/No	Main source of drinking water	Frequencies	Percentage
1	Piped water	101	7.8
2	borehole and wells	556	42.7
3	Bottled water	110	8.5
4	Surface water (river, dam, lake, pond,	412	31.7
5	Other, specify	122	9.3
	Total		