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Housing conditions and respiratory health in children in mining communities: An analysis of data from 27 countries in sub-Saharan Africa

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A R T I C L E I N F O

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A B S T R A C T

Background: Poor housing conditions, such as poor building materials and weak structures as well as high levels of indoor air pollution, are important risk factors for a broad range of diseases, including acute respiratory infections (ARI). In mining areas, research on the determinants of respiratory health predominantly focuses on exposures to outdoor air pollutants deriving from mining operations. However, mining projects also influence the socioeconomic status of households, which, in turn, affect housing quality and individual behaviors and, thus, housing quality and levels of indoor air pollution. In this study, we aimed to determine how proximity to an industrial mining project impacts housing quality, sources of indoor air pollution, and prevalence of ARI.
Methods: We merged data from 131 Demographic and Health Surveys (DHS) with georeferenced data on mining projects in sub-Saharan Africa (SSA) to determine associations between housing quality, indoor air pollution sources, and child respiratory health. Spatial differences in selected indicators were explored using descriptive cross-sectional analyses. Furthermore, we applied a quasi-experimental difference-in-differences (DiD) approach using generalized linear mixed-effects models to compare temporal changes in household and child health indicators at different operational phases of mining projects and as a function of distance to mines.
Results: For cross-sectional analyses, data of 183,466 households and 141,384 children from 27 countries in SSA were used, while 41,648 households and 34,406 children from 23 SSA countries were included in the DiD analyses. The increase in the share of houses being built from finished building materials after mine opening was more than 4-fold higher (odds ratio (OR): 4.32, 95% confidence interval (CI): 2.98–6.24) in close proximity to mining sites (i.e., $\leq$ 10 km) compared to areas further away (i.e., 10–50 km). However, these benefits were not equally distributed across socioeconomic strata, with considerably weaker effects observed among poorer households. Increases in indoor tobacco smoking rates in close proximity to operating mines were twice as high as in comparison areas (OR: 2.06, 95% CI: 1.15–3.68). The cross-sectional analyses revealed that traditional cooking fuels (e.g., charcoal, dung, and wood) were less frequently used (OR: 0.27, 95% CI: 0.23–0.31) in areas located in close proximity to mines than in comparison areas. Overall, no statistically significant association between mining operations and the prevalence of symptoms related to ARI in children under the age of 5 years was observed (OR: 0.78, 95% CI: 0.29–2.07).
Conclusions: Mines impact known risk factors for ARI through diverse pathways. The absence of significant changes in ARI symptoms among children is likely the result of counteracting effects between improvements in housing infrastructure and increased exposures to air pollutants from outdoor sources and tobacco smoking. For mining projects to unfold their full potential for community development, we recommend that impact assessments move beyond the mere appraisal of mining-related pollution emissions and try to include a more comprehensive set of pathways through which mines can affect ARI in exposed communities.

Abbreviations: ARI, acute respiratory infection; CI, confidence interval; DHS, Demographic and Health Survey; DiD, difference-in-differences; HH, household; IRR, incidence rate ratio; OR, odds ratio; PCA, principal component analysis; SSA, sub-Saharan Africa.

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1. Introduction

Housing conditions that promote health and wellbeing need to provide shelter, protect from environmental pollution, encompass access to essential services (e.g., clean water, improved sanitation, and electricity), and support healthy life-styles (e.g., access to green spaces and public transport options) (WHO, 2018). Poor housing conditions have been shown to hamper child development and are important risk factors for a broad range of communicable and non-communicable diseases, such as diarrhea, malaria, respiratory diseases, and cardiovascular diseases (Tusting et al., 2015, 2020; WHO, 2018).

A key aspect in the housing environment is indoor air quality (WHO, 2018). Most household air pollutants originate from indoor waste burning, cooking, and heating with traditional fuels (e.g., charcoal, dung, and wood) (Shupler et al., 2020; Tielsch et al., 2009; Zhou et al., 2014). In addition, indoor tobacco smoking can further deteriorate the quality of indoor air (Tielsch et al., 2009). Exposure to in-house air pollutants is attributable to a considerable burden of disease (Gordon et al., 2014). Indeed, globally, indoor air pollution from solid cooking fuels accounts for more than 2.5 million deaths every year (Gakidou et al., 2017). It is estimated that more than 600,000 deaths worldwide were caused by exposure to second-hand tobacco smoke (Öberg et al., 2011).

Around a quarter of the deaths due to indoor air pollution stem from acute respiratory infections (ARI), such as pneumonia and bronchitis (Gakidou et al., 2017). Children are particularly at risk for ARI from indoor air pollution, firstly due to their higher sensibility to exposures to air pollutants and secondly because they spend a large part of their time in and around the household, and are thus exposed to air pollutants from cooking facilities (Landrigan et al., 2017; Wright et al., 2020). Furthermore, inadequate housing conditions, such as overcrowded settlements, contribute to the high burden of ARI in low- and middle-income countries (Kristensen and Olsen, 2006; Nkosi et al., 2019).

Particularly in sub-Saharan Africa (SSA), predominantly solid fuels are used for food preparation and the associated health burden from ARI remains high (Chafe et al., 2014; Zulu and Richardson, 2013). As a region characterized by high urbanization rates and relatively small increases in income levels, the provision of adequate housing remains a challenge (World Bank Group, 2015). Wealth gains through economic development, such as the establishment of large resource extraction projects in the mining, oil, and gas sector, hold promise to boost local economies, and hence, improve housing conditions in underserved areas (Cawood et al., 2006; von der Goltz and Barnwal, 2019). On the other hand, the prospect of livelihood opportunities in mining areas can trigger rapid in-migration, which can lead to the formation of informal settlements and slums (Jackson, 2018; Marais et al., 2018, 2020). These settlements are usually characterized by makeshift low quality housing infrastructures, reduced service availability, and overcrowding (Contreras et al., 2019; Pelders and Nelson, 2018). Alongside exposures to air pollutants from the mines, poor housing conditions can negatively affect respiratory health of people living in mining communities (Hendryx and Luo, 2014; Nkosi et al., 2015).

Research on the impacts of mines on housing conditions and associated health outcomes in children has mainly focused on case studies or on particular population groups, such as mine workers or slum dwellers (Marais et al., 2020; Pelders and Nelson, 2018). Furthermore, studies on air pollution exposures and associated health outcomes in mining areas predominantly look at direct exposure pathways to air pollutant emissions from mining operations, without consideration of impacts on other potential exposure pathways in the community, such as indoor air pollutants (Boyles et al., 2017; Herrera et al., 2016). Similarly, in impact assessments, an approach to anticipate and manage potential impacts of projects as part of the licensing process (Harris-Roxas et al., 2012), the assessment of risk factors for respiratory diseases has a strong focus on the direct impacts of air pollutants from the mines (Dietler et al., 2020c; Riley et al., 2020). In contrast, housing conditions and associated health outcomes have received less attention in impact assessment practice (Dietler et al., 2020c; Pham et al., 2018; Riley et al., 2020). A deeper understanding of such indirect impacts on housing in mining areas could provide valuable insights for guiding impact assessments practice of mining projects.

The purpose of this study was to identify associations between mines and housing conditions in mining communities of SSA, and to determine whether these affect respiratory health of children. To do so, we used a large pseudo-panel of georeferenced health data across SSA to compare healthy housing indicators cross-sectionally at different distances from mines, and also longitudinally over time within areas where data prior and after the opening of mines were available.

2. Material and methods

2.1. Data and study design

Data from all 131 Demographic and Health Surveys (DHS) conducted in SSA that were readily available in March 2020 were combined with a comprehensive dataset on mining projects (Standard & Poor's Global, 2020; USAID, 2020). The DHS data feature a large set of household and child indicators. From the mining dataset, the location of major mines in SSA and their operational activities since the early 1980s were extracted.

The opening year, and for some mines also the closure year, were determined using either the information on annual extraction and production volumes or the reported opening and closure year in the dataset. As opening year, the first year with reported extraction was set, unless an earlier opening year was specifically indicated. Similarly, as closure year, the last year with reported operation or the reported closure year was taken, whichever was later. If no information on closure of a mine was available and the project status was labelled as "active", operation until the end of the study period (i.e., 2019) was assumed. The mines were considered as "active" during all years between opening (i.e., the first year commodities were extracted) and closure (i.e., the last year with reported extraction). Before mine opening and after mine closure, the mines were classified as "pre-operational" or "closed", respectively.

For each level of analysis (household- and child-level), two types of datasets were constructed, as shown in Fig. 1. Firstly, a cross-sectional dataset comprising of all data within a distance of 100 km from mining projects that were active at the time of the survey was created. This dataset was used to derive descriptive statistics and explore associations between the Euclidian distance to the mine and the different household indicatory and symptoms of ARI in children under the age of 5 years. Secondly, a pseudo-panel dataset was created. Only data within a 50 km radius from isolated mines (i.e., mines that were at least 100 km away from other mines) were included, regardless of the activity status of the mines at the time of the survey. The resulting dataset comprised data collected at different operational phases of the mines, allowing for longitudinal analyses of changes over time.

From all datasets, data from households that were located within the boundaries of large cities (i.e., $\geq$ 100,000 inhabitants) were excluded. The size of the city boundaries were determined by a visual appraisal of satellite images of a random set of differently sized cities listed in a dataset from Natural Earth (Natural Earth, 2020). The resulting buffer sizes around the city centers were 5 km for cities with a population size of 0.1–0.5 million, 7.5 km for 0.5–1 million, 15 km for 1–5 million, and 40 km for $>$ 5 million. Merging of the datasets and exclusion of data within cities were done using ArcGIS Pro version 2.2.4 (Environmental Systems Research Institute; Redlands, CA, USA) and StataSE version 16 (StataCorp LLP; College Station, TX, USA).

2.2. Variables

2.2.1. Exposure variable

In the cross-sectional dataset, the Euclidian distance between the

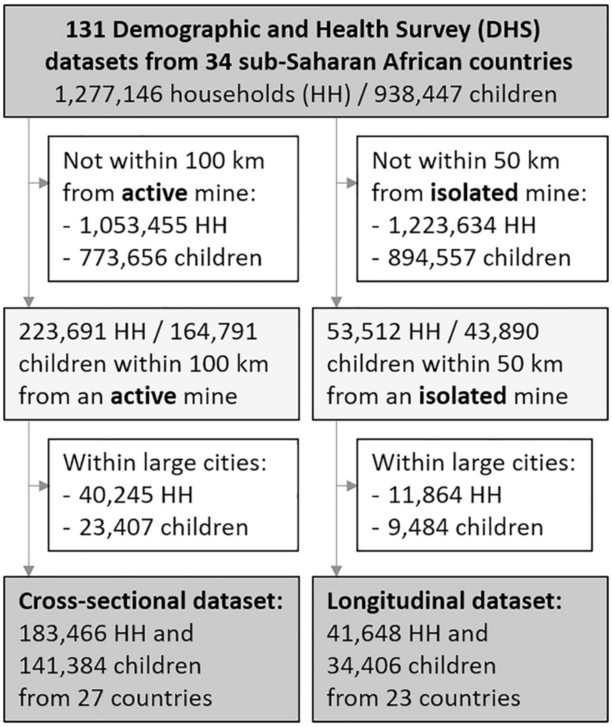

Fig. 1. Flowchart showing the selection of household (HH) and child data from within the proximity of mines and outside city boundaries.

DHS cluster and the closest active mine was the main exposure variable. The distance was categorized into 7 groups: $\leq$ 5 km, 5–10 km, 10–20 km, 20–30 km, 30–40 km, 40–50 km, and 50–100 km. The last group was used as reference in the analysis. In the longitudinal difference-in-differences (DiD) analysis, an interaction term between distance to and operational status of the mine at the time of the survey was created to assess the effect of a mine opening and closure at various distances from the mine. The distance variable was dichotomized, using $\leq$ 10 km as "close proximity" and 10–50 km as "comparison" area. The operational status was coded as pre-operational, active, and closed. The exposure definition was a combination of the distance ("close proximity" vs. "comparison") and activity status of the mine ("pre-operational" vs. "active" vs. "closed"), captured by a multiplicative interaction term "close proximity * operational" and "close proximity * closed", respectively.

2.2.2. Outcome variables

Household size

DHS data include information on the number of people residing in the household and the number of rooms used for sleeping. For our analysis, the number of *de jure* household members was used, indicating the number of people usually sleeping within the household. Households indicating zero *de jure* household members were excluded from analyses.

Housing infrastructures

The main construction materials used for flooring, walls, and roofing were categorized as finished or un-finished. Finished materials include, for example, cement, carpet, or parquet for floors; cement, bricks, or covered adobe for walls; and iron sheets, cement, or tiles for roofs. Households were considered as "built from finished materials" if at least two of the three structures were classified as finished (Tusting et al., 2019).

Indoor air pollution sources

Two indicators were used as a proxy for air pollution from indoor sources. Firstly, cooking fuels were categorized into clean and traditional sources. Clean sources include natural gas, biogas, electricity, and liquefied petroleum gas. All other sources were considered, including coal, wood, and other solid fuels, as traditional fuels. Households using unknown fuels or that did not prepare food in the house were excluded. Information on cooking fuels was only available since the beginning of DHS phase 4 in 1997.

As a second indicator, the prevalence of tobacco smoking indoors was used. All households that were characterized by at least one member smoking inside at least once a month, were considered polluted by tobacco smoke. The collection of smoking-related information only began in DHS phase 6 around 2008.

Acute respiratory infection

The definition of symptoms of ARI in children below the age of 5 years has changed over the course of the DHS program. Until the end of DHS phase 4 (around 2000) symptoms of ARI were defined as having cough accompanied by rapid breathing. In DHS carried out later on, information on whether symptoms were chest-related was also gathered and included in the definition. To allow comparison over time, the former definition was used.

2.2.3. Covariates

For each level of analysis, different variables were adjusted for. At the household-level, an indicator for household wealth was created. Since the wealth index included in the DHS data was built on some of the variables that were used as separate indicators in the analyses of this study, specific indexes that excluded these variables were created. Separately for each survey, a principal component analysis (PCA) was conducted to construct the index using information on water and sanitation infrastructures, access to electricity, ownership of a radio, television, telephone, fridge, bicycle, motorcycle, car, or bank account, and educational attainment of the household head. The first component of the PCA was used to create wealth quintiles (Filmer and Pritchett, 2001). Furthermore, the survey year and population density at the household location were included. At the child-level, the age and sex of the child (as categorical variables) were additionally included as covariates.

2.3. Statistical analysis

2.3.1. Cross-sectional analyses

The cross-sectional data were mainly used to explore the associations between the distance to mining sites and the different outcomes. For quantifying these associations, generalized linear mixed-effects models were employed. For the models with binary outcome variables (housing infrastructures, indoor air pollution sources, and ARI symptoms), logistic regression models, while for numeric outcomes (household size), negative binomial regression models were fitted. The models using household characteristics (e.g., housing infrastructures and indoor smoking) as outcome variables included population density, survey year, and household wealth as fixed effects. The models with symptoms of ARI as outcome were additionally adjusted for child age and sex. In all models, random intercept terms for the survey and region were included to account for clustering in the DHS data. The random intercept terms, child age and sex were included in the adjustment sets *a priori*. For population density and survey year terms, likelihood ratio tests were performed to assess their effect on model fit using cooking fuels as outcome (population density: $X^2(1) = 10{,}621$, $p < 0.001$; survey year: $X^2(1) = 805.36$, $p < 0.001$).

To compare impacts across socioeconomic groups, subgroup analyses were done for poorer households (lower two wealth quintiles) and wealthier households (upper two wealth quintiles). Because the motivation of the stratified analysis was to compare impacts among wealthier and poorer households, data from the middle wealth quintile as intermediary group were not further analyzed.

2.3.2. Longitudinal analyses

The repeated cross-sectional data allowed the extraction of data collected around the same mine at different points in time. Following a

DiD approach (Bärnighausen et al., 2017), we compared how the changes in our outcome variables across the different mining phases differed between areas in close proximity to the mines (i.e., ≤ 10 km from the mine) and comparison areas located further away (i.e., between 10 and 50 km). Hence, the main exposure variable was the multiplicative interaction term between distance and operational status of the mine. The same regression models, adjustment sets, and stratified analyses as for the cross-sectional analyses were performed, with the only difference that the regional-level random intercept term was replaced by mine-level random intercepts to account for the repeated cross-sectional structure of the data deriving from the different mining areas.

For all models, households or children with missing data were excluded from analyses. Where applicable, estimates are reported with their corresponding 95% confidence intervals (CIs). All statistical analyses were performed in R version 3.5.1 (R Core Team, 2018) using the lme4 package (Bates et al., 2015).

3. Results

Data from almost 1.3 million households with more than 900,000 children under the age of 5 years were obtained for the period 1990–2019 and were combined with information on 711 mines in 34 SSA countries (Fig. 1). In the cross-sectional datasets, the countries included Angola, Burkina Faso, Burundi, Côte d'Ivoire, Democratic Republic of the Congo, Eswatini, Ethiopia, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mozambique, Namibia, Niger, Namibia, Senegal, Sierra Leone, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe. No data from close to isolated mines for the longitudinal datasets from Côte d'Ivoire, Eswatini, Lesotho, and Senegal were available. Overall, 52 of the mines were considered as isolated and used as the pseudo-panels in the longitudinal dataset. After selecting observations in close proximity to mining sites and excluding data collected within the boundaries of large cities, the cross-sectional datasets comprised of 183,466 households and 141,384 children, while the longitudinal datasets included 34,406 children from 41,648 households (Fig. 1).

The basic characteristics of the different datasets are summarized in Table 1. The percentage of wealthy and poor households are shown in Table 2. The percentage of wealthy households in close proximity to mining sites increased from the pre-operational to the active phase of the mine. It further increased after closure of mines. Among households located further away, this percentage remained relatively stable over time. The inverse pattern was seen for the percentage of poor households in close proximity to the mining sites.

3.1. Housing conditions and ARI at different distances from mines

The average household within 5 km from a mine comprised of 2.0 rooms for sleeping and housed 4.2 people (Fig. 2). At a distance of 50–100 km, 5.0 people slept in 2.2 rooms on average. Hence, on average, households close to the mines housed 2.1 people per room, while further away, 2.3 people shared one room for sleeping.

Overall, household structures improved closer to the mines. In particular, finished building materials were more commonly used in close proximity to mining sites. The stratified analyses revealed that among the poorer households, the positive associations between the presence of a mine within 5 km and housing materials was not seen (odds ratio (OR): 1.14, 95% CI: 0.90–1.46), but slightly improved further away (e.g., OR at 5–10 km: 1.23, 95% CI: 1.05–1.43; Fig. *A*1). Among wealthier households, much stronger positive associations were seen in the area closest to the mines (OR: 2.28, 95% CI: 1.70–3.05), but not further away.

Households in close proximity to mines relied much less on

Table 1
Summary of household and child indicators in the cross-sectional and longitudinal datasets. The datasets comprise a selection of data from 131 Demographic and Health Surveys (DHS) collected within 100 km from active mines (cross-sectional datasets) and 50 km from isolated mines (longitudinal datasets), respectively. The household dataset includes information from all households. The indicators presented for the child dataset only comprise data from households with at least one child. The surveys were conducted between 1990 and 2019.

	Household data		Child data	
	Cross-sectional dataset (N = 183,466)	Longitudinal dataset (N = 41,648)	Cross-sectional dataset (N = 141,384)	Longitudinal dataset (N = 34,406)
Distance to mine				
≤ 5 km	2812 (1.5%)	n.a.	1756 (1.2%)	n.a.
5–10 km	5506 (3.0%)	n.a.	3615 (2.6%)	n.a.
10–20 km	12,809 (7.0%)	n.a.	8919 (6.3%)	n.a.
20–30 km	15,593 (8.5%)	n.a.	12,113 (8.6%)	n.a.
30–40 km	19,541 (10.7%)	n.a.	14,468 (10.2%)	n.a.
40–50 km	20,447 (11.1%)	n.a.	15,513 (11.0%)	n.a.
50–100 km	106,758 (58.2%)	n.a.	85,000 (60.1%)	n.a.
Mine near (≤ 10 km)	n.a.	2857 (6.8%)	n.a.	2016 (5.9%)
Mine status				
Pre-operational	n.a.	21,143 (54.9%)	n.a.	18,889 (59.0%)
Operational	n.a.	8873 (23.0%)	n.a.	7023 (21.9%)
Closed	n.a.	8517 (22.1%)	n.a.	6086 (19.0%)
Household members (median)	4	5	6	6
Sleeping rooms (median)	2	2	2	2
Finished building materials	100,603 (65.1%)	20,252 (57.8%)	71,867 (59.8%)	15,408 (54.9%)
Use traditional cooking fuels	147,468 (85.5%)	36,047 (95.2%)	122,537 (91.7%)	30,663 (97.7%)
Indoor smoking	19,784 (22.5%)	4635 (22.4%)	17,032 (24.8%)	3659 (21.2%)
Wealth quintile				
Poorest	36,001 (19.6%)	8652 (20.8%)	29,420 (20.8%)	7333 (21.3%)
Poor	41,066 (22.4%)	8330 (20.0%)	33,519 (23.7%)	7013 (20.4%)
Middle	41,887 (22.8%)	9295 (22.3%)	34,019 (24.1%)	8023 (23.3%)
Rich	37,349 (20.4%)	8993 (21.6%)	27,686 (19.6%)	7492 (21.8%)
Richest	27,163 (14.8%)	6378 (15.3%)	16,740 (11.8%)	4545 (13.2%)
Symptoms of ARI	n.a.	n.a.	9828 (9.3%)	3064 (12.1%)
Age (mean) in years	n.a.	n.a.	1.9	1.9
Female	n.a.	n.a.	69,785 (49.4%)	16,934 (49.2%)

Denominators for the calculation of the percentages included only cases with non-missing information
ARI = acute respiratory infection; n.a. = not applicable.

Table 2
Percentage of households (N = 41,648) classified as wealthy (upper two wealth quintiles) and poor (lower two wealth quintiles) by distance to the closest mine and mining phase. The data stem from 131 Demographic and Health Surveys (DHS) collected within 50 km from isolated mines, respectively. The surveys were conducted between 1990 and 2019.

Mining phase	% wealthy households		% poorer households	
	Close (≤ 10 km)	Comparison (10–50 km)	Close (≤ 10 km)	Comparison (10–50 km)
Pre-operational	26.2	33.5	54.5	44.4
Active	59.1	29.8	32.2	49.4
Closed	71.9	39.0	10.8	39.5

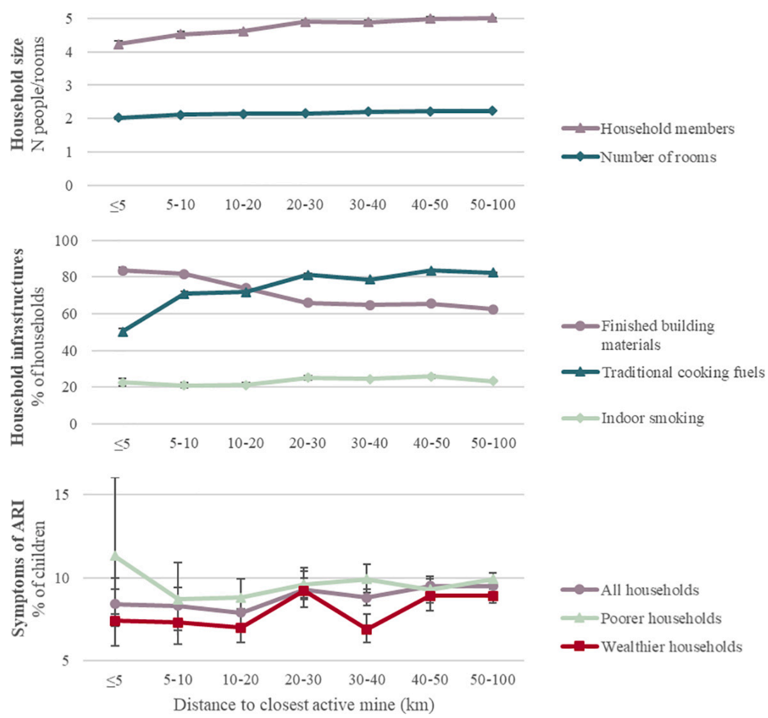

Fig. 2. Household indicators and prevalence of acute respiratory infection (ARI) symptoms in children below the age of 5 years at different distances from mines. For ARI symptoms, the dataset was stratified into children from poorer (lower two wealth quintiles) and wealthier (upper two wealth quintiles) households.

traditional cooking fuels. More specifically, 50.2% of households closest to the mines (i.e., ≤ 5 km) used traditional cooking fuels, compared to 82.3% of households located furthest away (i.e., 50–100 km; Fig. 2). The results from the regression models showed a similar pattern. There were marked differences between wealthier and poorer households. The reduction in the use of traditional cooking fuels in close proximity to the mines was largely attributable to the wealthier households. Among them, the OR for the use of traditional cooking fuel adjusted for survey year, population density, country, and regional-level differences was 0.42 (95% CI: 0.35–0.50) and 0.83 (95% CI: 0.72–0.97) within a ≤ 5 km and 5–10 km radius, respectively. Among the poorer households, these associations were not seen at ≤ 5 km distance (OR at ≤ 5 km: 1.10, 95% CI: 0.70–1.73) and use of traditional cooking fuels was even higher in poor households at 5–10 km (OR: 1.71, 95% CI: 1.27–2.29; Fig. *A*1). No clear trends in smoking rates were seen.

No marked differences in symptoms of ARI at different distances from the mine were evident (Fig. 2). Still, a statistically significant reduction in ARI prevalence at medium distances (i.e., between 10 and 20 km and between 30 and 40 km) compared to children below the age of 5 years living at a distance of 50–100 km from the closest mine was found (Fig. *A*1). Among children living in poorer households, there was a sharp increase in ARI symptoms in close proximity to the mines (≤ 5 km). However, this pattern was not statistically significant.

3.2. Changes in healthy housing indicators and ARI after mine opening

The size of the households is largely the same among the different distances (Fig. 3). Larger differences were seen in the percentage of households being built from finished materials. While in the years before mine opening these shares were similar, the percentage of households built from finished materials continued to rise after mine opening in areas in close proximity (i.e., ≤ 10 km) to the mine, while it remained relatively stable in areas further away (i.e., 10–50 km). Indoor smoking prevalence decreased in comparison areas from 25.0% prior to mine opening to 22.8% during the operational phase. Contrarily, in impacted areas, indoor smoking became more frequent, rising from 21.0% to 26.9%. For the percentage of children showing ARI symptoms in the 2 weeks prior to the survey, no clear temporal trend was observed. Before mine opening, households relied almost entirely on traditional fuels for cooking. Fitting of the models looking at temporal trends in use of cooking fuels was not possible. Therefore, this outcome was excluded from the longitudinal analyses.

The results from the regression analyses incorporating an interaction term capturing the impact of having a mine in close proximity during the different operational phases are depicted in Fig. 4 and listed in Table 3. Overall, no statistically significant impacts of the opening of a mine on household sizes were seen, though wealthier households in close proximity to the mine during the operational phase showed a slight reduction in the number of people per household (incidence rate ratio (IRR): 0.84,

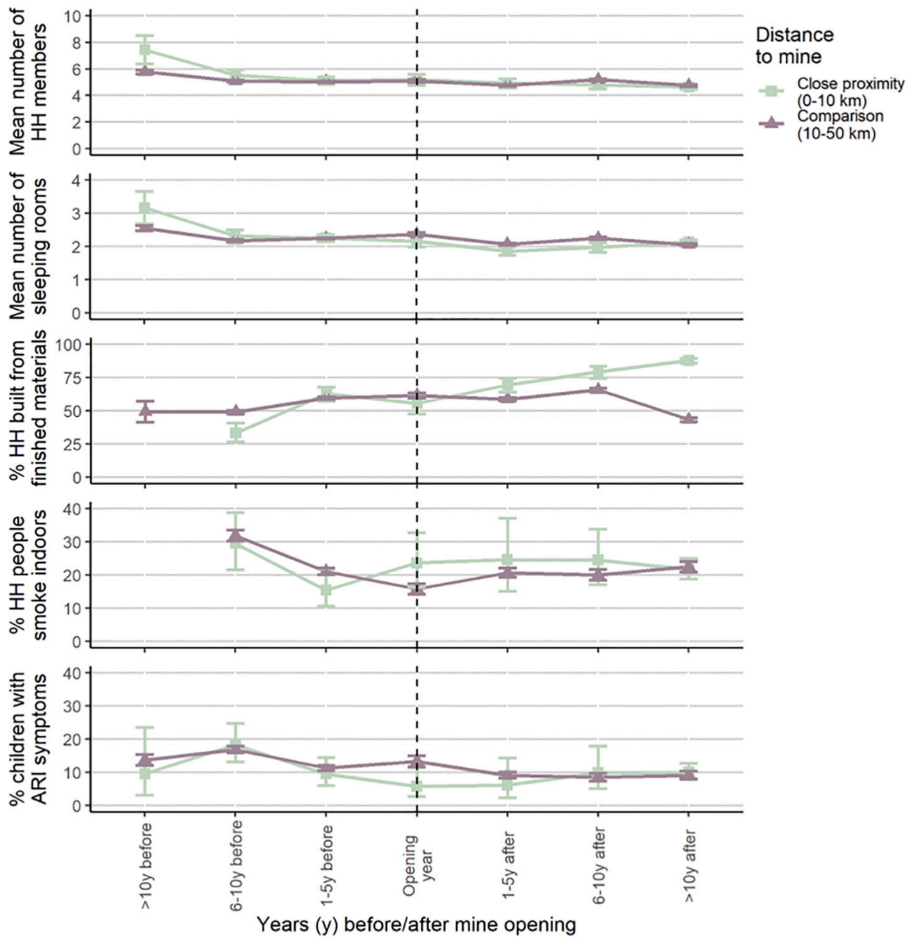

Fig. 3. Changes in household (HH) indicators and prevalence of acute respiratory infection (ARI) symptoms among children below the age of 5 years relative to the opening year of the closest mine at different distances from the mine (≤ 10 km vs. 10–50 km). The x-axis shows the difference between the survey year and the opening year of the mine. For housing materials, no data were available from mines more than 10 years before mine opening.

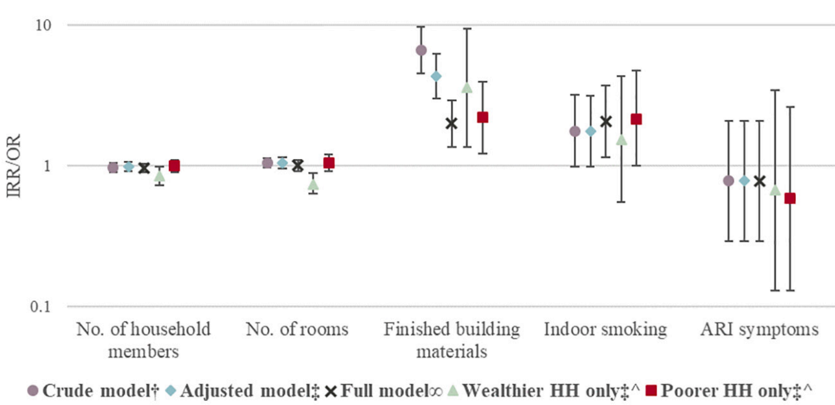

Fig. 4. Incidence rate ratios (IRR; for count data) and odds ratios (OR; for binary outcomes) for the effect of the interaction between the factor close proximity to a mine (i.e., ≤ 10 km compared to 10–50 km) and the mine being active (compared to pre-operation) on the different household indicators and symptoms of acute respiratory infections (ARI) in children under the age of 5 years using the longitudinal datasets. The estimates are plotted on a log-scale.
† Survey-level and mine-level random intercepts only.
‡ Additionally adjusted for survey year and population density (for household indicators); additionally adjusted for survey year, child age and sex (for ARI symptoms).
∞ Additionally adjusted for household (HH) wealth quintile (for household indicators); additionally adjusted for household wealth quintile, population density and household size (for ARI symptoms).
^ Stratified analyses using only data from the two lower wealth quintiles (poorer households) and the two upper wealth quintiles (wealthier households), respectively.

95% CI: 0.72–0.98) and rooms (IRR: 0.74, 95% CI: 0.63–0.88). Furthermore, building materials of houses in close proximity to mining sites improved upon mine opening (OR (full model): 1.98, 95% CI: 1.35–2.90; Fig. 4). This effect persisted after mine closure (Table 3).

Adjusting for all covariates, the share of households with indoor smokers doubled (OR: 2.06, 95% CI: 1.15–3.68) after mine opening close to the mines compared with comparison areas. Although only marginally significant, this effect was predominantly seen in poorer households.

During the operational phase, changes in the prevalence of symptoms of ARI did not differ between children living in close proximity and in comparison sites. After mine closure, however, children from wealthier households located in close proximity to mines showed increased odds of ARI symptoms, compared to the pre-operation phase.

Table 3
Exponentiated regression coefficients of the interaction between the factor close proximity to a mine (i.e., ≤ 10 km compared to 10–50 km) and activity status (top: active vs. pre-operational; bottom: closed vs. pre-operational).†, ‡, ∞, ^, *, **

Opera-tional status	Outcome	OR/IRR (95%CI) for interaction near*operational status				
		Crude model†	Adjusted model‡	Full model∞	Wealthier HH only‡^	Poorer HH only‡^
Active	Number of HH members	0.97 (0.90–1.05)	0.98 (0.91–1.06)	0.96 (0.89–1.03)	0.84 (0.72–0.98)*	0.99 (0.89–1.10)
	Number of sleeping rooms	1.04 (0.96–1.13)	1.04 (0.95–1.14)	1.00 (0.91–1.10)	0.74 (0.63–0.88)**	1.04 (0.91–1.19)
	Finished building materials	6.61 (4.53–9.64)**	4.32 (2.98–6.24)**	1.98 (1.35–2.90)*	3.57 (1.36–9.40)*	2.19 (1.22–3.92)*
	Indoor smoking	1.76 (0.98–3.16)	1.75 (0.98–3.13)	2.06 (1.15–3.68)*	1.53 (0.55–4.29)	2.15 (0.99–4.69)
	ARI symptoms	0.78 (0.29–2.08)	0.78 (0.29–2.07)	0.78 (0.29–2.06)	0.67 (0.13–3.45)	0.58 (0.13–2.61)
Closed	Number of HH members	0.92 (0.87–0.98)*	0.94 (0.89–1.00)	0.92 (0.87–0.98)*	0.84 (0.76–0.93)*	0.87 (0.78–0.97)*
	Number of sleeping rooms	0.96 (0.90–1.03)	0.97 (0.90–1.04)	0.94 (0.87–1.01)	0.85 (0.76–0.96)*	0.96 (0.84–1.10)
	Finished building materials	7.98 (6.16–10.33)**	3.73 (2.85–4.87)**	2.19 (1.66–2.90)**	2.81 (1.67–4.72)**	2.08 (1.31–3.32)*
	Indoor smoking	0.95 (0.64–1.40)	1.05 (0.71–1.55)	1.27 (0.85–1.88)	1.04 (0.54–2.01)	1.55 (0.77–3.11)
	ARI symptoms	1.30 (0.85–1.99)	1.31 (0.86–2.00)	1.42 (0.93–2.18)	2.06 (1.04–4.06)*	0.67 (0.13–3.45)

OR = odds ratio (for the binary outcomes building materials, smoking, and ARI symptoms); IRR = incidence rate ratio (for number of household (HH) members and sleeping rooms).

† Survey-level and mine-level random intercepts only.

‡ Additionally adjusted for survey year and population density (for household indicators); additionally adjusted for survey year, child age, and sex (for ARI symptoms).

∞ Additionally adjusted for household (HH) wealth quintile (for household indicators); additionally adjusted for household wealth quintile, population density, and household size (for ARI symptoms).

^ Stratified analyses using only data from the two lower wealth quintiles (poorer households) and the two upper wealth quintiles (wealthier households), respectively.

* $p < 0.05$

** $p < 0.001$

4. Discussion

Data from almost 1.3 million households were combined with information on 711 mines to create the largest available multi-national dataset on household and child characteristics in mining areas in SSA. We found that housing conditions, including the quality of construction materials and access to clean cooking fuels, improved over the course of mining activities, while household density did not change. The positive effects were less pronounced in poorer households. Furthermore, the potential reduction in indoor air pollution from traditional cooking fuels was offset by a higher rate of tobacco smoking within the households close to mining sites. Indoor tobacco smoking rates increased more than 2-times more after mine opening in households in close proximity to operational mining sites compared to households located further away. In our sample, these potential positive and negative impacts in indoor air pollution exposure in mining sites were not reflected by changes in symptoms of ARI in children under 5 years of age. Taken together, the positive impacts of mines on housing conditions are promising. However, the unequal distribution of these benefits within the mining communities and the absence of improvements in respiratory health warrant further scientific inquiry.

4.1. Improvements in housing conditions in mining areas

The marked improvements in housing conditions, both in terms of building materials and access to clean cooking fuels, underline the potential of mining projects to promote social and economic development in the surrounding of mining sites (United Nations Economic Commission for Africa, 2011; von der Goltz and Barnwal, 2019). Indeed, in our analyses, adjustment for household wealth explained a large part of the improvements in housing conditions. In addition, the longitudinal analyses revealed that the share of wealthier households in communities near mines is substantially larger when mines are operational. Our findings are in line with other studies that have shown positive effects of mining projects on household wealth and livelihoods (Bury, 2005; von der Goltz and Barnwal, 2019). For example, people living in close proximity to mining sites in Peru have been found to have increased economic resources, as well as improved access to financial services potentially fostering investments in housing infrastructures (Bury, 2005). Furthermore, a recent study in SSA showed that water and sanitation infrastructures improve after the development of a mining project in close proximity of the community (Dietler et al., 2020b).

4.2. Potential formation of informal settlements around mining sites

Overall, we found no evidence of overcrowding in household in mining areas. This finding is surprising, since many studies and international guidelines describe the potential for rapid migration and overcrowding effects upon mine development (IFC, 2009; Jackson, 2018; Nyame et al., 2009; Pelders and Nelson, 2018). Yet, other studies have found no differences in settlement growth between mining and non-mining areas (Dietler et al., 2020a). It is therefore possible that the overcrowding effect only affects very specific mining communities (e.g., village or town where recruitment is done by the mining project), which are not detected when using aggregated data. Parallel development in settlement structures, with formal and informal settlements being built up simultaneously, has been reported both in mining areas and around urbanizing centers in other parts of Africa (Bah et al., 2018; Gough et al., 2019). In our sample, the poor households within a 10 km radius with comparably little or no improvements in housing quality and reduced access to clean cooking fuels may be an indication of the development of informal settlements close to the mining sites. No or inadequate infrastructures in these settings can contribute to a high disease burden of informal settlement dwellers (Shortt and Hammett, 2013; Snyder et al., 2013). Our findings underline the importance of an equity focus in the management of mining-related impacts on communities (Leuenberger et al., 2019).

4.3. Changes in indoor air pollution sources in mining areas

Indoor air pollution in mining sites may change in both directions – they might improve due to the reduced use of traditional cooking fuels or worsen because of increased tobacco smoking. Studies on these sources in mining settings are rare, though some studies have described high smoking rates in mining communities (Hendryx, 2009; Rajaee et al., 2015). In Zambian mining areas, increased smoking prevalence was seen among people with lower educational attainment, which could explain the increased smoking rates, particularly among the poor (Zyaambo et al., 2013). Furthermore, increases in disposable income could be a potential reason for the increased uptake of tobacco smoking in mining settings (Ukuhor and Abdulwahab, 2018; Zyaambo et al., 2013).

Research on access to clean cooking fuels as a source of indoor air pollution is scarce. Contrary to our findings, access to electricity – a clean energy source potentially used for cooking – was found to be lower in close proximity to mining sites in Tanzania but not in Mali (Polat et al., 2014). The paucity of research warrants further investigation on the driving forces of these positive and negative changes in indoor air pollution sources in mining areas. Geospatial analyses, combining outdoor air pollution measurements with information on indoor air pollution sources, could help to better understand the changes of the diverse respiratory health risks in mining projects.

4.4. Impacts of mining projects on respiratory health

Respiratory health in mining areas can be impacted by a variety of factors, including indoor and outdoor air pollution and housing conditions (Gordon et al., 2014; Hendryx, 2015; Hendryx and Luo, 2014). The overall absence of positive or negative impacts on ARI symptoms may potentially be the result of the counteracting effects of reduced pollution from traditional cooking fuel and better construction materials on the one hand, and the increased pollution levels from indoor smoking and outdoor pollution from mining operations on the other hand (Asif et al., 2018; Gordon et al., 2014; Herrera et al., 2016; Öberg et al., 2011; Pless-Mulloli et al., 2000). Indeed, when focusing on poorer households, where the positive impacts on ARI risk factors were less pronounced or absent, a slight, statistically not significant increase in ARI symptoms at close proximity to the mines was observed. A study on respiratory diseases in a mining site found that respiratory health impacts are limited to an area up to 1.8 km distance from the mine (Herrera et al., 2016). The artificially introduced spatial errors in DHS data may have reduced statistical power and concealed potential impacts at a smaller scale (Elkies et al., 2015). Furthermore, the increased reporting rates of child health outcomes among better educated caregivers might explain the increased odds of ARI in wealthier households after mine closure (Manesh et al., 2007). Nevertheless, our results show the significance of alternative air pollution pathways to be considered for the management of potential health impacts of mines.

4.5. Addressing respiratory health risks in mining areas

Impact assessments commonly serve as foundations for predicting and managing such different direct and indirect impacts of mines on air pollution and respiratory health (Harris-Roxas et al., 2012; Winkler et al., 2020a). In this process, impacts of mining projects on outdoor air pollution are commonly assessed for the identification of mitigation strategies to reduce air pollution emissions and the subsequent monitoring of air quality impacts (Baumgart et al., 2018; Dietler et al., 2020c; Pham et al., 2018; Riley et al., 2018, 2020). However, other aspects such as smoking or housing infrastructures receive less attention in current impact assessment practice (Dietler et al., 2020c). Hence, the unequal distribution of benefits on housing infrastructures, the increases in smoking rates, and the absence of improvements in respiratory health in mining areas warrant a comprehensive assessment of potential impacts on the diverse determinants of respiratory health, with a particular focus on the most vulnerable population groups (Leuenberger et al., 2019; Quigley et al., 2006; Winkler et al., 2020b).

4.6. Strengths and limitations

While our study provides new insights into diverse impacts of mines on housing-related determinants of respiratory health using a large multi-national dataset, we acknowledge several limitations. Firstly, the data stem from cross-sectional surveys, which did not follow the same people over time. Using the DiD approach, we could adjust for some factors that changed over time, such as population density. However, the population composition is likely to have changed over the course of a mining project and populations may differ in the time they have resided in a mining area. Hence, it is conceivable that the changing population had different unmeasured characteristics that influenced our outcome variables. These changes may also include the composition of the different socioeconomic strata. Although the wealth index was created using the whole sample of households for the given survey, "being poor" could have a different meaning in operational mining areas. The poor in mining areas could, for example, include marginalized population groups living in informal settlements, comprising of migrants. Furthermore, respondents with higher educational attainment tend to more often report child health outcomes in DHS surveys (Manesh et al., 2007). Hence, the potentially higher reporting rates among wealthy households may be an explanation of the increases in ARI after mine closure. Lastly, the spatial offsets introduced in the global positioning system coordinates in DHS may have led to non-differential exposure misclassification. This random error is likely to have diverted the estimates towards the null (Elkies et al., 2015).

5. Conclusion

The findings from our continental analysis of a comprehensive multinational dataset on household and child health indicators in mining areas revealed an overall positive impact of mines on housing conditions, although poorer households generally benefitted less from these developments. We found no evidence of overcrowding upon mine opening, as previously described in the literature. While the risk of indoor air pollution from traditional cooking fuels is reduced in active mining sites, smoking rates increased after mine opening. Hence, considerable environmental health risks persist in some population groups in mining communities, although the resulting burden of respiratory disease among children under the age of 5 years remained unchanged. New research on how the changes in housing quality, including indoor air pollution sources, are impacting respiratory health in mining communities is needed. Finally, these diverse underlying pathways of respiratory health outcomes need to be comprehensively assessed in impact assessments of mining projects to attain an equal distribution of mining-related benefits and promote public health in mining communities.

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Declaration of Competing Interest

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

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