Small-Scale Mining (Galamsey) and Malaria: Impacts on Children in Ghana

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Abstract

This study examines the causal relationship between artisanal small-scale mining (ASM) activity and malaria incidence among children under five years old in Ghana, a country with high malaria prevalence and significant ASM activity. Using a difference-in-differences design, we leverage ASM expansions to compare areas that become near to footprint to areas that remain far, before and after the expansion. We find that newly-exposed areas have a higher probability of malaria infection among children by up to 30 percentage points. Our estimates are robust to alternative specifications, various proximity thresholds, and random simulated spatial displacements. These results highlight the health risks associated with ASM expansion and suggest the need for targeted interventions to reduce malaria transmission in mining-adjacent communities.

1 Introduction

Ghana is one of the top gold producers of the world and artisanal small-scale mines (ASMs) contribute almost one third of the nation's total gold production (Eduful et al, 2020). The term ASM typically refers to a temporary, low-technology, and labor-intensive operation that is extracting and processing minerals in areas less than 25 acres (McQuilken and Hilson, 2016). These ASM operations serve as a "means for survival" and an "engine for small business growth" in many communities (Wilson et al, 2015). However, the majority of ASMs in Ghana are operating informally and are largely considered illegal. These informal ASM operations are locally coined *galamsey*, a term derived from the phrase "gather them and sell". In some cases, informal ASMs have a "social license to operate" granted to them by local leaders (McQuilken and Hilson, 2016). However, the legal ambiguity surrounding property and mineral rights creates friction between state and local leadership surrounding ASM policy in Ghana (Abdulai, 2017).

Informal ASMs are a major source of economic support for millions of people in Ghana (McQuilken and Hilson, 2016) and a lucrative source of economic gains for the political, business and local elite (Abdulai, 2017). However, some have noted that occupational hazards and limited income growth associated with ASM employment can create a poverty trap for its workers (Hilson, 2012; Wilson et al, 2015). For example, epidemiological studies have documented elevated levels of malaria, malnutrition, respiratory issues, and physical injury among ASM workers (*e.g.*, see Emmanuel et al, 2018; Allan-Blitz et al, 2022). Informal ASMs in Ghana also negatively impact surrounding communities and the natural environment through mercury exposure, vegetation loss, and soil degradation (Famiyeh et al, 2020; Rajaee et al, 2015; Basu et al, 2015).

This study aims to establish a causal link between proximity to ASMs and malaria incidence among children under 5 years of age in Ghana. We use a difference in differences (DiD) strategy that takes advantage of the expansion of the ASM spatial footprint. For ASM expansion, we identify areas that have transitioned from far to near and compare those to areas that remain similarly far. As the ASM footprint expands, we find that transitioned areas have higher malaria infection rates after the transition compared to non-transition areas by up to 30 percentage points. These results highlight the health risks associated with ASM expansion and suggests the need for targeted interventions to reduce malaria transmission in mining-adjacent communities.

There are epidemiological studies that document a high burden of malaria in ASM communities in Ghana (*e.g.*, Dao et al, 2021; Asante et al, 2011) as well as other countries all over the world (*e.g.*, see Schwartz et al, 2021). However, these communities often have high malaria transmission even before mining begins (Dery et al, 2015). To the best of our knowledge, only two studies have shown evidence of a causal link between ASMs and malaria and they show this in other parts of the world. Rozo (2020) finds that illegal ASMs increase malaria prevalence in Colombian municipalities using preexisting geochemical anomalies as an instrumental variable for illegal gold mining. Specifically, the annual parasite index for malaria increases by 1.04 cases per 100,000 inhabitants for every additional hectare of illegal gold mining. Pagel (2022) exploits a major policy shift which encouraged the creation of new ASMs in the Philippines. The author uses a difference-in-differences strategy to show that after the policy change, provinces with gold deposits had 32% more malaria cases relative to provinces without gold deposits. These effects persisted for many years after the policy change.

The two mechanisms discussed in this literature are the uncovered pits and the transitory workforce. As miners relocate, they often leave the excavation pits uncovered which creates an ideal breeding ground for mosquitoes. This could plausibly increase malaria transmission in nearby communities. The transitory workforce can also increase malaria transmission. For example, previously uninfected migrants who do not have the protective antigens move into malaria endemic areas to work in the mines. These newly infected workers could propagate the disease locally and beyond as they migrate to other parts of the country. A couple of studies have shown that malaria incidence increased for Brazilian miners returning home after working in ASMs abroad (da Cruz Franco et al, 2019; Arisco et al, 2021). In Ghana, a significant portion of the ASM labor force will migrate from one mine to another (Nyame and Grant, 2014). These transitory workers are made up of both domestic and foreign migrants with most of the foreign migrant workers coming from China (Crawford and Botchwey, 2017). However, both Rozo (2020) and Pagel (2022) show evidence that the uncovered excavation pits are the main mechanism and not work-related migration. Furthermore, a recent survey of people from mining communities in Ghana showed that 62% of respondents perceived the uncovered mining pits as the main driver of increased malaria (Quarm et al, 2022).

Our study focuses on children in Ghana because Ghana is a global leader in ASM gold production (Eduful et al, 2020) and malaria is a significant public health concern. Ghana and other Sub-Saharan countries bear a disproportionately large burden of malaria cases and deaths. In 2022, a few Sub-Saharan countries accounted for about 94% of global malaria cases and 95% of global malaria deaths (World Health Organization, 2023). That is an estimated 230 million cases and more than a half million deaths in the region alone. Furthermore, out of all malaria-related deaths, 78% are estimated to occur in children under five years old (World Health Organization, 2023). Children are particularly vulnerable to malaria infections and those who manage to survive early-life infections will likely experience adverse health outcomes in adulthood (Hong, 2013; Chang et al, 2014; Chen et al, 2024). Ghana is an important setting to investigate the causal relationship between ASMs and malaria because these are critical concerns for the country.

Our study supports other existing causal literature by providing causal evidence on the relationship between artisanal small-scale mining (ASM) activity and malaria incidence in Ghana. Ghana is particularly relevant setting for this research given the large burden of ASM activity and malaria prevalence. Unlike prior studies that primarily document correlations, our study leverages the changes in proximity to the ASM footprint to estimate the causal impact of ASM expansion on malaria incidence in children. We control for baseline malaria prevalence, climate, household wealth, and mother's education using detailed data from the Ghana Malaria Indicator Survey (GMIS) and the Demographic and Health Survey (DHS). Annual composites of the ASM footprint come from the Center for Remote Sensing and Geographic Information Services (CERSGIS) (2024), a research organization dedicated to providing geospatial services that help monitor ASM activities (and many other economic activities) from space.

2 Data and Background

2.1 Artisanal Small-Scale Mine (ASM) Footprints

Annual spatial footprints of ASM activity in Southern Ghana was provided by the Center for Remote Sensing and Geographic Information Services (CERSGIS) (2024). This organization is housed at the University of Ghana and provides a wide range of GIS and remote sensing services to decision-makers and planners. They are supported by USAID and NASA as part of the SERVIR West Africa Program. They use deep learning techniques on high-resolution satellite imagery to identify ASM activity. They integrate expert-generated ancillary data to ensure accuracy and usability of the classification results (Asare and Adjei-Sah, 2024). The resulting footprints have a resolution of 4.77 meters, allowing us to calculate precise distances from each survey cluster to the nearest footprint pixel.

The CERSGIS study area is focused on the forested southwestern regions of Ghana shown in Figure 1. CERSGIS data does not identify ASMs in the North despite known activity in this area (McQuilken and Hilson, 2016). Panel (a) shows the entire country of Ghana with our focus area shaded in dark blue and the extent of the ASM footprint outlined by the black rectangle. Figures 2 and A5 show the ASM footprint in 2016, 2019, and 2022. Figure 2c shows the changes in ASM activity from 2016 to 2019. Notice there are more areas expanding into ASM activity than contracting. Figure A5c shows the changes in ASM activity from 2019 to 2022. Notice there are more areas contracting from ASM activity and less areas expanding compared to the period 2019-2022. This is consistent with other sources showing a decrease in overall gold production in 2020 and 2021(Adranyi et al, 2024; The Ghana Chamber of Mines, 2021).

2.2 Survey data

We use detailed survey data from the 2016 and 2019 Ghana Malaria Indicator Survey (GMIS) which is collected by the Ghana Statistical Service in collaboration with the Demographic and Health Survey (DHS) Program. During the survey sampling procedure, the country is divided into survey regions based on existing administrative units. Enumeration areas, or survey clusters, are randomly and independently sampled in each survey year. These clusters typically contain 100-300 households of which 25-30 are randomly selected for the survey. The household questionnaire gathers basic information about the members of the household and the physical dwelling. Young women aged 15-49 are selected for more detailed interviews and information is gathered on their children. Children under the age of five years old are tested for malaria.

Both surveys collect two biomarkers for malaria infection: microscopy and rapid diagnostic tests (RDTs). Microscopy is the standard test for malaria diagnosis and serves as our outcome in our preferred specification. This requires a microscopic examination of a blood sample to visually identify the presence of the malaria-causing parasite. RDTs use an absorbing strip that changes color to indicate the presence of

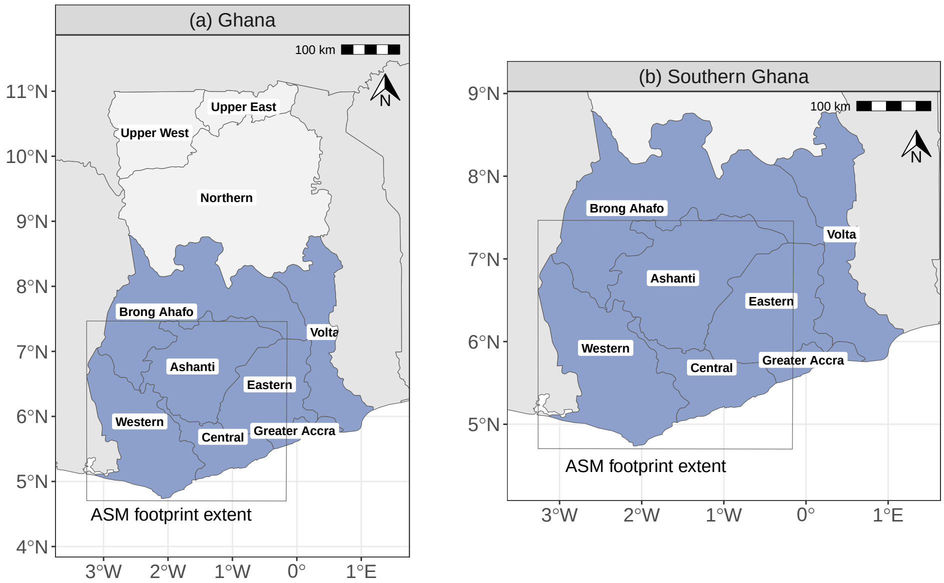

Fig. 1: Map of Ghana and Southern Ghana. Our study area is focused on Southern Ghana which is largely covered by the ASM footprint data.

malaria antigens. Unlike microscopy tests, RDTs do not require a skilled technician and the results are available in less than half an hour. However, RDTs identify the presence of malaria antigens and not the parasite itself. Therefore, individuals who have recently been cleared of the infection may test positive (The DHS Program, 2014). We report our results using microscopy in our preferred specification and show RDT outcomes as a robustness check.

The DHS provides geographic information on survey clusters but masks the true locations. We observe the centroid of the cluster from which households are sampled. However, centroids are spatially displaced according to a custom statistical algorithm that generates a random displacement (Burgert et al, 2013). For urban clusters, centroids are randomly displaced by up to 2 km. For rural clusters, centroids are randomly displaced by up to 5 km. In 1% of rural clusters, the random displacement can go up to 10 km. Our analysis relies only on urban clusters because of the smaller spatial displacement. We use the coordinates of the displaced centroids to calculate the distance from each survey cluster to the ASM footprint.

3 Empirical Strategy

ASMs in Ghana are typically located in impoverished areas that lack alternatives (Basu et al, 2015; Wilson et al, 2015). These areas often have high malaria transmission even before mining begins (Dery et al, 2015). A regression comparing malaria prevalence in areas near ASMs to areas far away from ASMs would be biased by unobservable characteristics that are related to ASMs and malaria prevalence. Instead, we use a

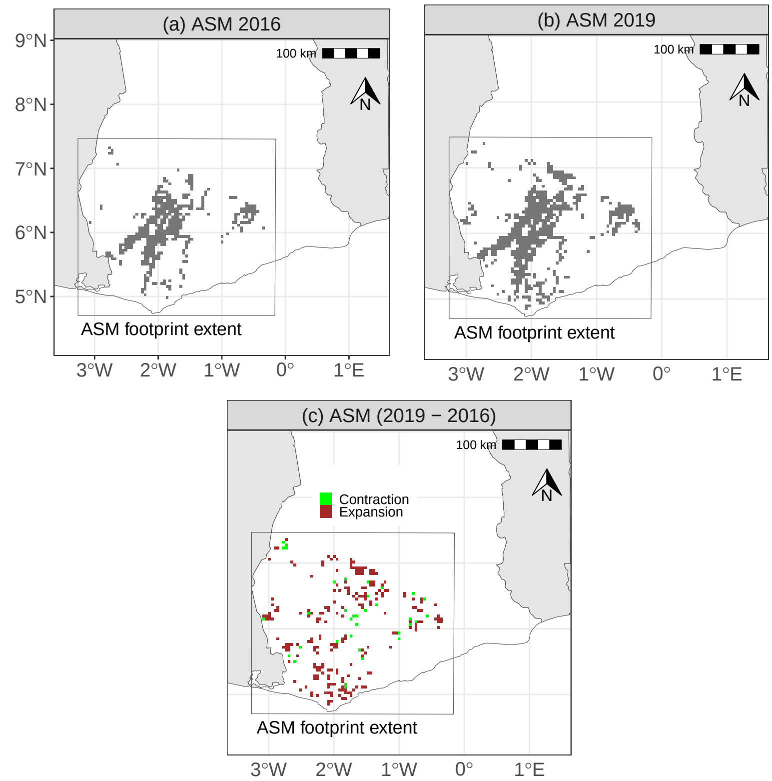

Fig. 2: ASM spatial footprint data from the Centre for Remote Sensing and Geographic Information Services (CERSGIS). We have reduced the resolution of this data for this figure to enhance visibility.

DiD strategy that compares malaria incidence in areas that transition to being near to ASM activity and areas that remain far from ASM activity before and after an expansion of the ASM footprint.

Figure 2 shows that ASM activity increased in many areas between the years 2016 and 2019. We use these ASM footprint expansions to identify clusters that transition to being near the ASM footprint and compare them to clusters that remain far during this time period. We use various thresholds to define what is near and far from the ASM footprint ranging from one to six kilometers. The general consensus is that mosquitoes typically do not travel past five kilometers (Huestis et al, 2019) and most remain within two kilometers from the breeding site Takken et al (2024). Therefore, we use a two kilometer threshold for defining near and far in our preferred specification.

The sample in our preferred specification is made up of children in survey clusters that are greater than 2 km from the ASM footprint in the year 2016. Our first difference comes from 2019 clusters that are currently less than 2 km from the ASM footprint (i.e., transition) and 2019 clusters that are currently greater than 2 km from the ASM footprint (i.e., non-transition). Our baseline difference in malaria incidence comes from

2016 clusters that will remain 2 km from the ASM footprint until 2019 (i.e., non-transition) and 2016 clusters that will be less than 2 km from the ASM footprint at some point between 2017 and 2019 (i.e., transition). We apply an additional restriction on maximum distance to ensure that the non-transition clusters begin similarly far from the ASM footprint in 2016 relative to transition clusters. In other words, we find the transition cluster with the greatest cluster-to-ASM distance in 2016 and only include non-transition clusters that are within that distance in 2016. We assume that this baseline difference in malaria incidence, controlling for observables, is an accurate representation of unobserved differences in clusters that tend to transition to be near the ASM footprint in 2019. Our setup is summarized in table 1.

Group	2016 survey clusters	2019 survey clusters
Transition (treated)	Clusters will be near in the future	Clusters were far and now near
Non-transition (control)	Clusters will always be far*	Clusters remain far*

Table 1: Simplified setup for DiD estimator for ASM footprint expansion. (*)We constrain the maximum distance to ensure all clusters begin similarly far.

We run the following Weighted Least Squares regression to estimate the effect of ASM expansion on malaria incidence:

$$\text{Malaria}_{ict} = \theta_1 \text{Transition}_c + \theta_2 \text{Post}_t + \theta_3(\text{Transition}_c \times \text{Post}_t) + \beta X'_{ict} + \epsilon_{ict} \quad (1)$$

Here, Malaria_{ict} is equal to one if child i in cluster c in survey year t has malaria and zero otherwise. We use RDTs and microscopy tests for malaria outcomes, separately. Transition_c is equal to 1 if cluster c transitioned in proximity at some point due to the expansion of the ASM footprint. The coefficient ρ will give us the difference in malaria outcomes between transition and non-transition clusters before ASM expansion. Post_t is equal to 1 for the treated year (i.e., the later year of the two). X_{ict} is a vector of controls including household wealth, mother's education level, whether the child sleeps under an insecticide-treated bed net, historical malaria prevalence at the survey cluster, and historical rainfall at the survey cluster.

The DiD estimator θ_3 gives the effect that ASMs have on malaria incidence in adjacent communities. Our DiD estimator is a causal estimate assuming that the difference between transition clusters in the base year accurately captures important unobservable characteristics between transition clusters in the treated year. We use the wild cluster bootstrap to construct 95% confidence intervals and observations are weighted using DHS-provided weights.

We also randomly displace the survey clusters 20 times using the DHS algorithm in Burgert et al (2013). We run twenty-one regressions in a simulation-based robustness check. This helps us assess the stability of our distance-based estimates given the uncertainty introduced by the DHS random displacement. Our method provides a range of plausible estimates, which serves as a form of partial identification in the presence of spatial measurement error. Since we do not observe the true location, we instead characterize a neighborhood of plausible locations. By repeating the analysis across 21 different displacement realizations, we provide a range of plausible estimates given the uncertainty in cluster locations.

4 Results

Our results using survey years 2016 and 2019 show strong evidence that ASM expansion leads to higher malaria rates when measured by microscopy. Table 2 shows that transition clusters experience large increases in the probability of malaria infection by about 30 percentage points after ASM expansion relative to non-transition clusters. The unweighted specification without controls in the first column of Table 2 suggests an increase of roughly 20 percentage points. The unweighted specification with controls in the second column suggests an increase of 35 percentage points. The average malaria prevalence among children in our preferred specification is 8%. This suggests that on average ASM expansion can result in a malaria prevalence among children as high as 38%.

Figure 3a shows that our estimates decrease slightly as we increase the proximity threshold for the DHS-displaced clusters. The coefficients when using thresholds greater than 2 km range from 15 to 20 percentage points. Note that we cannot estimate a regression using a 1 km threshold because of insufficient observations. The results are similar for malaria infection determined by RDTs (see Figure A1). Recall that RDTs detect the presence of malaria antigens, so children who have cleared the disease can test positive. This is why malaria prevalence measured by RDT is higher in Table A1.

Figure 3b shows that our estimates are consistent when randomly displaced. Note that some regressions cannot be estimated because of insufficient observations. Additionally, we drop any results where there is only one cluster in any of the four DiD groups from Table 1. In Figure A2 we see that few clusters meet our definition of transition cluster. This figure shows the average number of clusters in each of the four DiD groups shown in Table 1 across different simulated displacements. We find that ASM expansion (i.e., clusters that were initially far from the ASM footprint become near) leads to significant increases in malaria infections among children under five years old. Increases in the probability of contracting the disease are as high as 30 percentage points but seem to bunch around 20 percentage points.

5 Discussion

5.1 The 2022 Standard DHS

The Standard 2022 DHS is much larger than the 2016 and 2019 GMIS. Both surveys collect malaria biomarkers but the Standard DHS is a longer survey that samples more survey clusters. We attempted to use the 2019 GMIS and the 2022 Standard DHS to look at the effect of ASM expansion during the 2019-2022 period.

Figure A3 shows that we are unable to produce estimates for the 2019-2022 period because of insufficient observations. Unfortunately, there are not enough clusters that

Table 2: The effect of ASM expansion on malaria incidence (microscopy)

	(1) Unweighted and no controls	(2) Unweighted with controls	(3) Preferred specification
Transition × Post	0.224	0.349	0.317
	(0.12)	(0.11)	(0.09)
Wild cluster bootstrap 95% CI	[-.04112, .5915]	[.09946, .7218]	[.09219, .6935]
Mean dep. var.	0.103	0.096	0.079
Survey weights			X
Controls		X	X
Observations	553	374	374

Notes: Robust clustered standard errors shown in parenthesis. Controls include historical malaria prevalence, historical rainfall, household wealth, mother's education, and whether the child uses an insecticide-treated bed net. Our preferred specification uses DHS survey weights. Malaria incidence comes from microscopy test results.

satisfy our definition of transition clusters in the 2019-2022 period. The simulation-based estimates suffer from the same issue. The few results we do have show no discernible relationship between ASM expansion and malaria incidence. There is much less expansion in ASM activity between the 2019-2022 period (see Figure A5) relative to the 2016-2019 period. Other sources also show a decrease in overall gold production in Ghana during 2020 and 2021(Adranyi et al, 2024; The Ghana Chamber of Mines, 2021).

5.2 ASM contraction

We are also interested in estimating the effects of ASM contraction on malaria incidence. ASM contraction happens when an area no longer has observable characteristics resembling current or former ASM activity. Both the ASM footprint data (see Figure A5) and anecdotal evidence suggest that contractions in this period are due to increasing efforts to restore degraded land and waterways (Modern Ghana, 2017; Citi Newsroom, 2021; MyJoyOnline, 2021).

For the contraction of the ASM footprint, our approach is analagous to the expansion method used for the main results. Our sample is made up of children in survey clusters that are within 2 km of the footprint in the base year. We use contractions in the ASM footprint to identify clusters that transition to being farther away. We then compare malaria incidence to non-transition clusters that remain near for the entire period. If there is a direct relationship between ASM contraction and malaria incidence, we would expect our estimates to be negative.

We find some weak evidence that ASM contraction (i.e., clusters that were initially near to the ASM footprint become far) leads to lower malaria rates. These estimates suggest a decrease ranging from 10 to 30 percentage points in clusters that experienced a contraction in the ASM footprint relative to clusters that did not. The estimates for the 2016-2019 period are shown in Figure A4 and estimates for the 2019-2022 period are shown in Figure 4. The DHS-displaced estimates are small, negative, and statistically insignificant. Only one out of six regressions could be estimated for 2016-2019 (see Figure A4a) and three out of six could be estimated for 2019-2022 (see Figure 4a). However, our simulation-displaced estimates suggest that there could be some effects

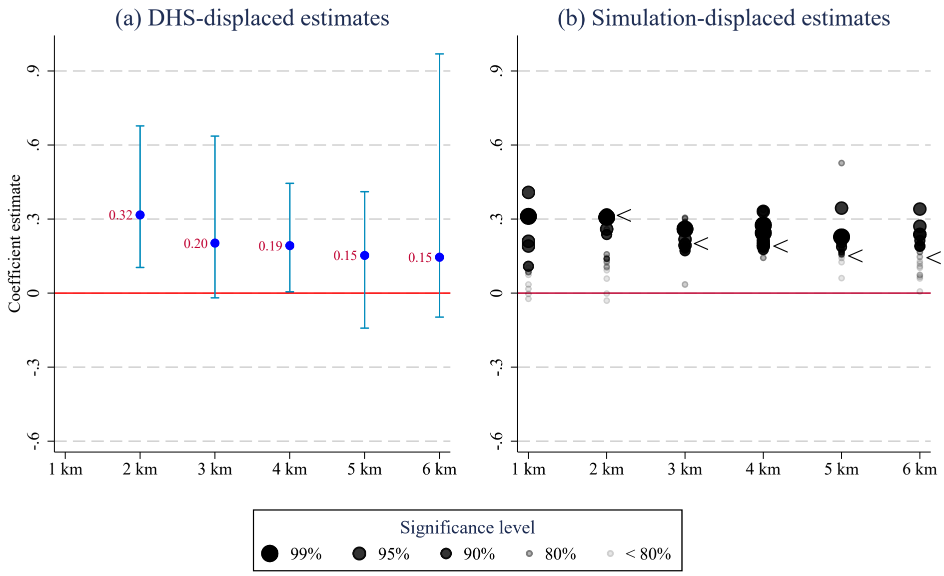

Fig. 3: The effect of ASM expansion on malaria incidence (microscopy) for different proximity thresholds and simulated displacements for the 2016-2019 period. DHS-displaced estimates use the original geographic coordinates from the DHS survey. Simulation-displaced estimates repeat regressions that displace survey clusters according to the DHS algorithm. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

that are attenuated by the DHS random spatial displacement. Our simulation-based regressions allow us to estimate five out of six regressions for 2016-2019 (see Figure A4b) and all six could be estimated for 2019-2022 (see Figure 4b). The result is a range of plausible estimates suggesting that ASM contraction (i.e., remediating uncovered mining pits) could at least partially offset the increases in malaria incidence after ASM expansion. However, more evidence is needed to fully understand the benefits of remediating uncovered mining pits.

5.3 Malaria Vaccine

Since 2019, Ghana, Malawi, and Kenya have delivered 2 million doses of the world's first malaria vaccine to children in select areas through the Malaria Vaccine Implementation Program (MVIP) recommended by the World Health Organization (WHO) (World Health Organization, 2024). In Ghana, the malaria vaccine was introduced in seven regions. These were Brong Ahafo, Central, Volta, Upper East region. The selection criteria favored regions with a rural/urban mix, a high malaria burden, and a significant number of children under five years old. Within those seven regions, 42 districts were targeted by the pilot program (Adjei et al, 2023). In Figure 5, we show the districts that were targeted by the vaccination program and overlay the 2019 DHS

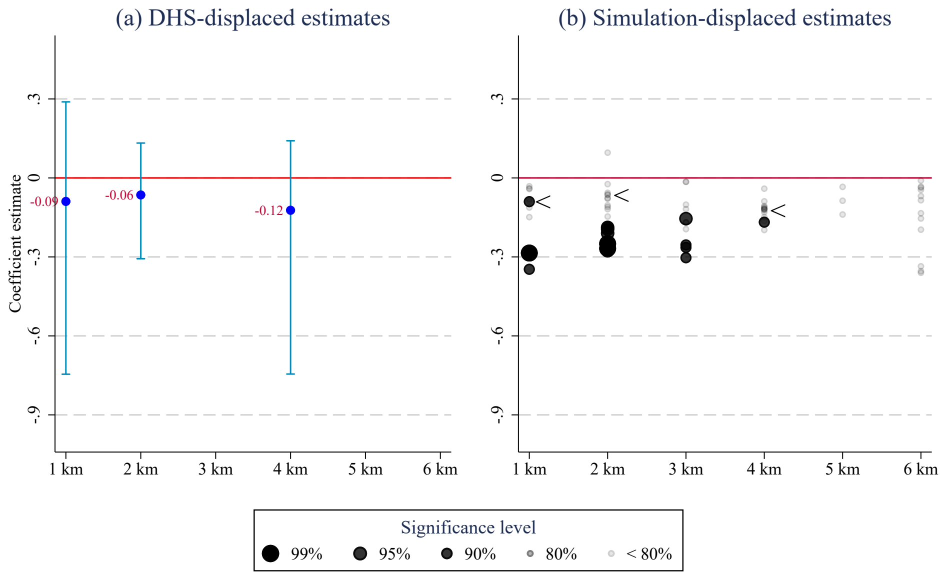

Fig. 4: The effect of ASM contraction on malaria incidence for different proximity thresholds and simulated displacements. DHS-displaced estimates use the original geographic coordinates from the DHS survey. Simulation-displaced estimates repeat regressions that displace survey clusters according to the DHS algorithm. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

survey clusters in Southern Ghana. The districts that were chosen tend to be far from the ASM footprint. None of the 12 clusters that are within 2 km of the ASM footprint within a district that was targeted by the vaccine. In 2022, 8 out of 44 districts within 2 km of the ASM footprint were in a district that received the vaccine. Future vaccine distributions could mitigate the burden of malaria in mining-adjacent communities if access is expanded to these areas.

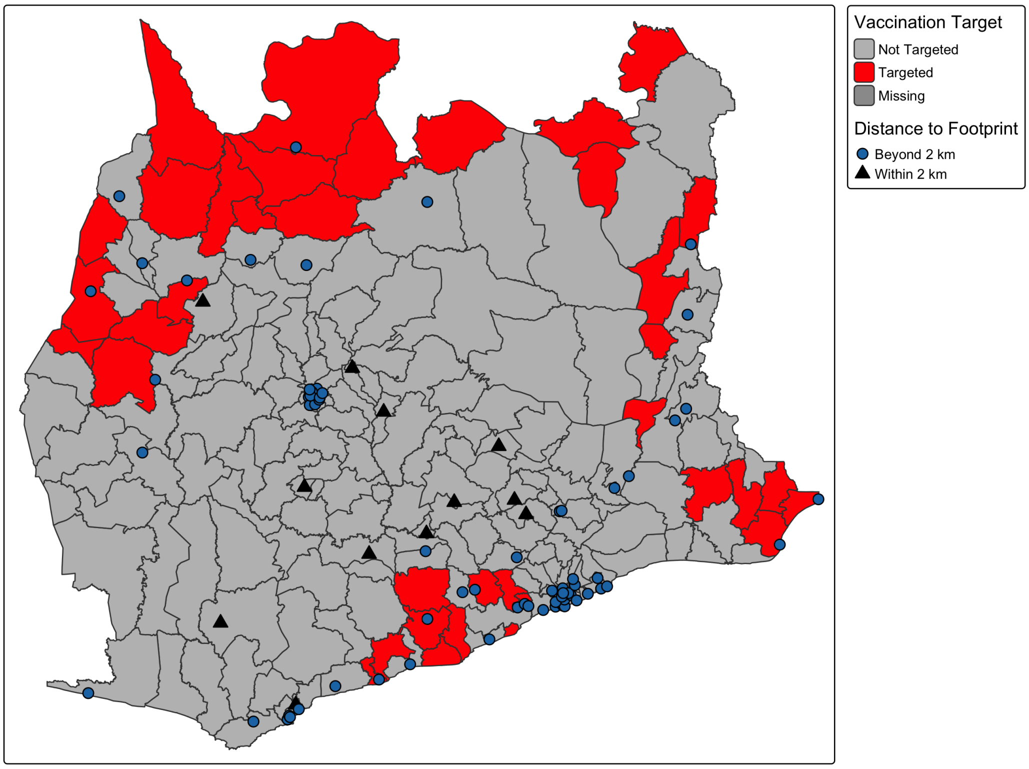

Fig. 5: Districts targeted by the 2019 Malaria Vaccination Implementation Program (MVIP) and 2019 DHS survey clusters. Red districts receive the vaccine in 2019 and other districts do not. Triangles represent survey clusters that are within 2 km of the ASM footprint.

6 Conclusion

We provide causal evidence that informal ASMs are increasing malaria incidence in Ghana by comparing incidence in children living in clusters that transitioned in proximity to the ASM footprint relative to children living in clusters that remained stationary. There is evidence that the formal large-scale mining sector in Ghana leads to economic growth, reduced infant mortality, and female empowerment (Benshaul-Tolonen, 2019, 2024). Informal ASMs, however, are associated with a wide range of negative impacts in Ghana and in other areas around the world. Despite these negative impacts, millions depend on this sector for economic sustenance. In response to this complex issue, some have called for the formalization of Ghana's ASM sector (McQuilken and Hilson, 2016; Bansah, 2023; Kumah, 2022; Hilson et al, 2017). However, as Pagel (2022) shows, increases in malaria prevalence can also occur in a formalized ASM sector.

Efforts to formalize the ASM sector in Ghana should be coupled with efforts to mitigate malaria impacts. For example, vaccine programs should consider proximity to ASM activity when determining distribution. Moreover, reclaiming mining wastelands and filling excavation pits are important actions to continue.

Acknowledgements

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Appendix A Additional tables and figures

Table A1: The effect of ASM expansion on malaria incidence (RDT)

	(1) Unweighted and no controls	(2) Unweighted with controls	(3) Preferred specification
Transition × Post	0.201	0.312	0.318
	(0.10)	(0.07)	(0.06)
Wild cluster bootstrap 95% CI	[-.08775, .5182]	[.1321, .4952]	[.1397, .5176]
Mean dep. var.	0.105	0.110	0.094
Survey weights			X
Controls		X	X
Observations	553	374	374

Notes: Robust clustered standard errors shown in parenthesis. Controls include historical malaria prevalence, historical rainfall, household wealth, mother's education, and whether the child uses an insecticide-treated bed net. Our preferred specification uses DHS survey weights. Malaria incidence comes from RDT results.

Group	**Base year**	**Treated year**
Transition (treated)	Clusters will be far in the future	Clusters were near and now far
Non-transition (control)	Clusters will always be near	Clusters remain near

Table A2: Simplified setup for DiD estimator for ASM footprint contraction.

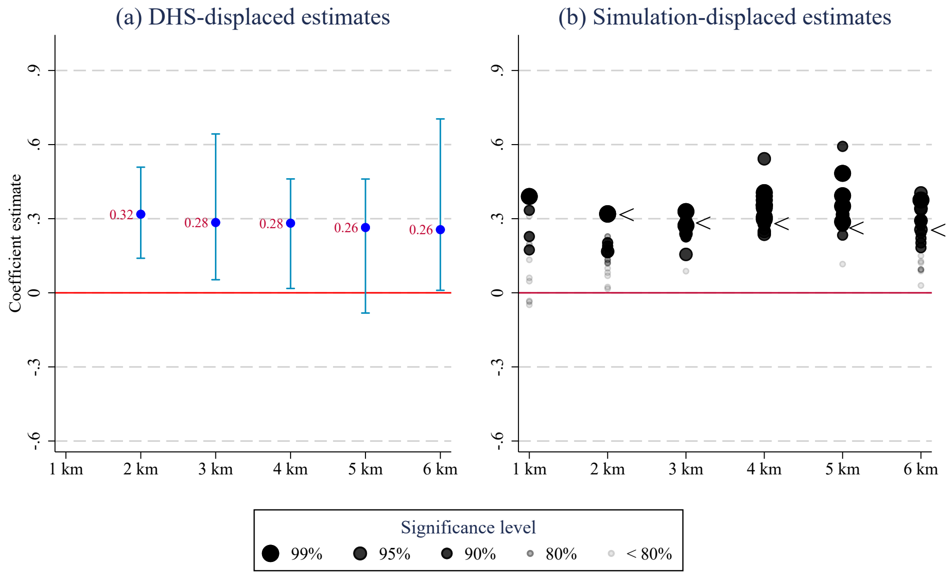

Fig. A1: The effect of ASM expansion on malaria incidence (RDT) for different proximity thresholds and simulated displacements for the 2016-2019 period. DHS-displaced estimates use the original geographic coordinates from the DHS survey. Simulation-displaced estimates repeat regressions that displace survey clusters according to the DHS algorithm. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

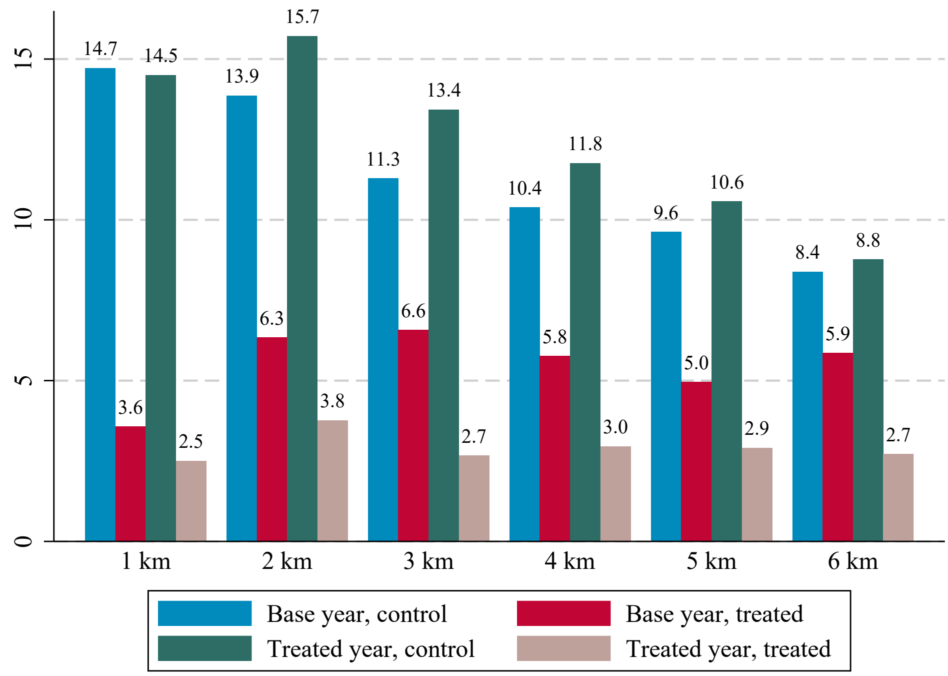

Fig. A2: The average number of clusters in each of the four DiD groups for different simulated-displacement regressions. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

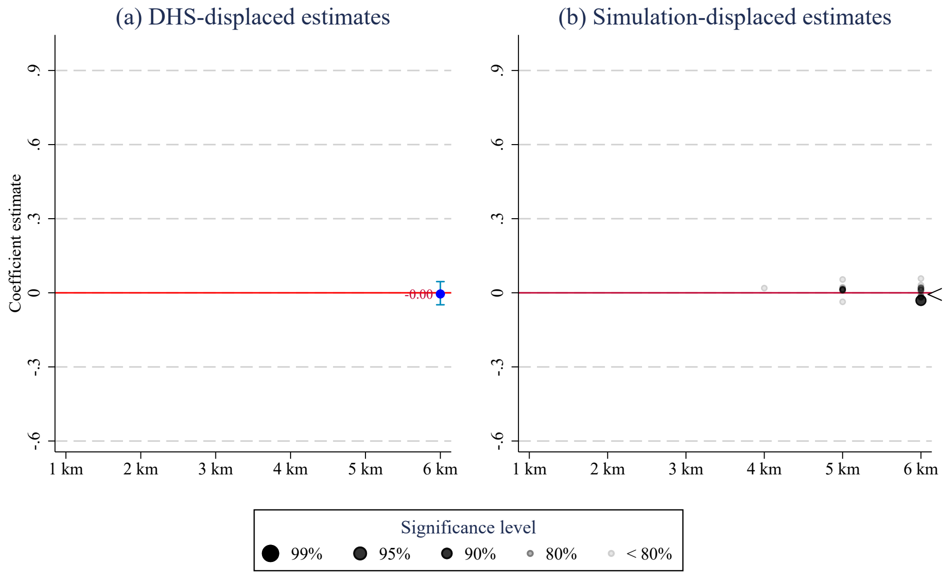

Fig. A3: The effect of ASM expansion on malaria incidence (microscopy) for different proximity thresholds and simulated displacements for the 2019-2022 period. DHS-displaced estimates use the original geographic coordinates from the DHS survey. Simulation-displaced estimates repeat regressions that displace survey clusters according to the DHS algorithm. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

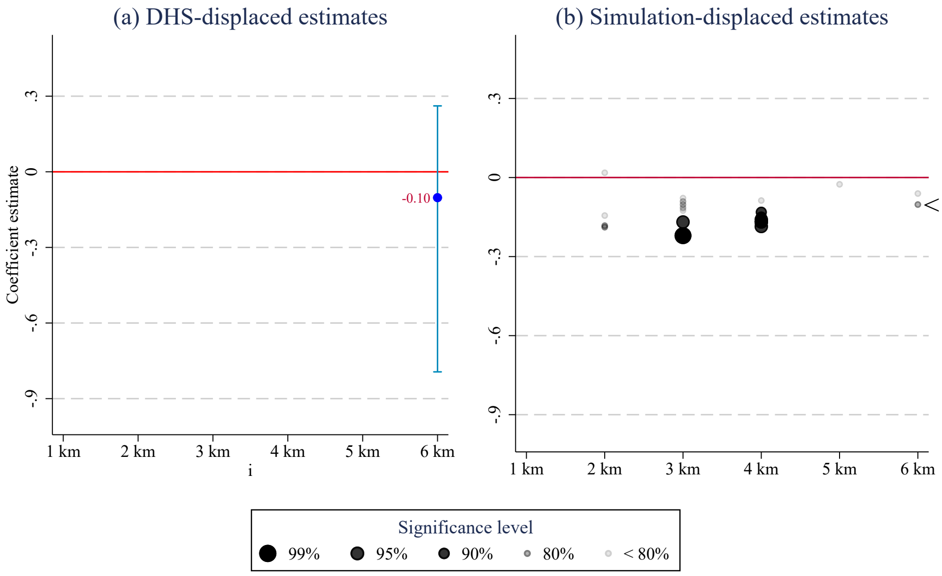

Fig. A4: The effect of ASM contraction on malaria incidence (microscopy) for different proximity thresholds and simulated displacements for the 2016-2019 period. DHS-displaced estimates use the original geographic coordinates from the DHS survey. Simulation-displaced estimates repeat regressions that displace survey clusters according to the DHS algorithm. Proximity thresholds on the x-axis represent what distance is considered to be near and far.

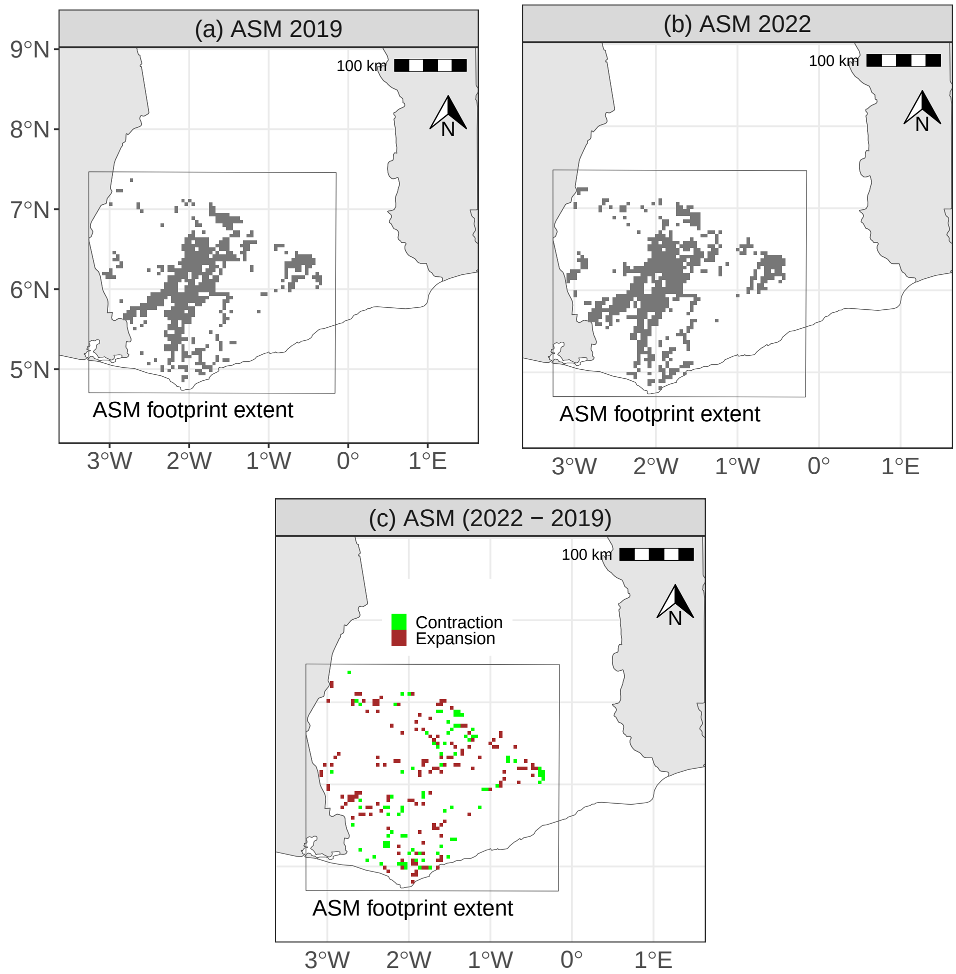

Fig. A5: ASM spatial footprint data for 2019 and 2022 from the Centre for Remote Sensing and Geographic Information Services (CERSGIS). We have reduced the resolution of this data for this figure to enhance visibility.

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