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Does Aid for Malaria Increase with Exposure to Malaria Risk? Evidence from Mining Sites in the D.R.Congo*

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Abstract

I examine the ability of donors to target the highest exposure to malaria risk when the health information structure is fragmented. I exploit local variations in the risk of malaria transmission induced by mining activities in the Democratic Republic of Congo as well as financial and epidemiological data from health facilities to estimate how local aid is matching the local malaria burden. Using fine-grained data on mines and health infrastructure in a regression discontinuity design, I find no evidence that local populations exposed to the highest risk of malaria transmission receive a proportionately higher share of aid compared to neighbouring areas with reduced exposure to malaria risk.

I. Introduction

Identifying and reaching the populations with the most pressing health needs is essential in countries with high disease burdens and limited healthcare resources. Donors prioritize health interventions to achieve the highest reduction in disease burden along with health equity objectives (WHO, 2015a). To attain these objectives, donors must have complete and accurate information about the distribution and intensity of the needs in the recipient country. However, numerous barriers may prevent the gathering and sharing of health information in low-income countries and ultimately undermine the impact of aid.

JEL Classification numbers: D61, H42, H75, I14, I18, O12.

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To date, there is limited empirical evidence about the ability of donors to attain their objective, although this condition is crucial to maximizing the effects of aid (Ravallion and Chao, 1989; Besley and Kanbur, 1991; Bigman and Fofack, 2000; Collier and Dollar, 2002). With health interventions, reallocating aid to areas with the highest disease burdens could lead to maximum welfare improvements when donors have full observability. Identifying and targeting these locations is crucial to contain the risk of transmission and eliminate the disease.

Previous studies have examined aid targeting both across and within countries (Esser and Bench, 2011; Dieleman *et al*., 2014; Briggs, 2018) and provided innovative methodologies to track aid resources. However, few can relate the findings to the efficiency of aid targeting. First, the efficiency of aid should be determined by analysing how the observed aid allocation differs from the optimal allocation that maximizes the objective function of the donors (Collier and Dollar, 2002). Second, needs are often defined in general terms that could be measured through multiple potential outcomes (Alatas *et al*., 2012). Divergences in identifying the key outcomes of interest translate into unclear objectives of aid: the multifaceted relationship between health, education and poverty implies that aid resources can serve many purposes and the estimated outcomes can capture various types of aid (Qian, 2015). Moreover, need-based targeting might not necessarily be optimal for donors if the targeted areas have the least favourable conditions for aid effectiveness. Third, the existence of various forms of aid support poses a challenge to the identification of donors' funding at the subnational level. Especially, it is practically impossible to distinguish external resources from domestic spending at the local level since a significant part of aid may transit through the government budget. Altogether, these combined factors pose a clear threat to the identification and disaggregation of aid effects.

This paper addresses these identification issues in several ways. First, I focus the analysis on foreign aid for malaria to obtain distinct and measurable outcomes of donors' objectives. The high burden of the disease has attracted important external funding in sub-Saharan Africa and the strategies for malaria elimination are well-known, encompassing effective actions for the prevention, diagnosis and treatment of malaria cases.[1] Thereby, I can rely on the global health funders' common objective of malaria elimination, which cannot be restricted to the poorest populations, to have a precise measurement of the outcome by directly linking it to aid allocated for the disease.[2] Second, I utilize the presence of multiple artisanal mining sites in the eastern provinces of the Democratic Republic of Congo (DRC) to obtain spatial variations in the burden of malaria. The dramatic increase in the risk of malaria transmission around mines has been well documented in the tropical medicine literature (Gallup and Sachs, 2001; Vittor *et al*., 2009; Knoblauch *et al*., 2014). While mining areas provide higher employment opportunities, miners remain severely exposed to poverty and catastrophic healthcare expenditures (D'Souza, 2007; Brier *et al*., 2020). The comparatively higher

[1]The definition of the population with the highest burden of malaria should not be prone to different interpretations between donors and local governments, as opposed to the concept of poverty.

[2]Donors need to encompass a comprehensive approach that accounts for local variations in the risk exposure to achieve the long-term objective of malaria elimination (WHO, 2018).

income of miners is therefore unlikely to offset the increased risk of malaria transmission and the associated costs for treatment and prevention in mining areas. Locally, the higher risk exposure to malaria essentially means that these locations should receive locally the highest share of aid for malaria to successfully reduce the disease burden. Therefore, the setting provides a natural framework to compare the amount of aid received between high- and low-risk exposure.

Third, I exploit the unique health financing situation of the DRC to estimate aid for malaria at the community level. The disease is highly endemic in the DRC and several years of civil wars have extensively weakened the health system of the country. The proportionately huge financial support provided by the international community to tackle the humanitarian and health crisis led to an unequally financed health system that largely relies on donors. The National Malaria Control Programme of the DRC offers one striking example, where external aid accounts for more than 95% of its overall funding (MSP, 2017). Taking advantage of a novel dataset with detailed information on key financial and health indicators at the health facility level, I argue that the stock value of antimalarial commodities can approximate total aid for malaria at the local community level.

To ensure the validity of this assumption, I select health facilities located in a similar geographic area in the Eastern DRC and which should bear similar costs. I define a mining area as the catchment area of a mine characterized by a high risk of malaria transmission which does not decay with distance. The varying distances of health facilities to their closest mines form two distinct groups that correspond to the treatment (mining area) and control (non-mining area) groups. The presence of mosquito breeding sites within mines creates geographical areas with a high risk of malaria transmission (Bousema *et al*., 2012), and the mining threshold corresponds to the maximum travelling distance of miner patients to health facilities. Consistent with the related literature (Carter, Mendis and Roberts, 2000; Kaufmann and Briegel, 2004), I find a sharp discontinuity in the malaria risk exposure at the mining threshold. Importantly, I argue that this discontinuity should translate into a change in the pattern of donor's behaviour if the latter is accurately targeting the highest burden of malaria.

The estimation strategy relies on a regression discontinuity (RD) design to compare the allocation of malaria funding for health facilities in the two groups, and thus, identify the contribution of mining areas on local aid for malaria. To my knowledge, this is the first study to exploit the stock value of antimalarial commodities to obtain direct tracking of donors' funding for malaria to health facilities. Importantly, these estimates can document the precision of donors' targeting of the disease and their ability to identify the highest risk of malaria transmission at the local community level. The regression discontinuity estimates demonstrate that health facilities in mining areas do not receive higher aid for malaria than facilities in non-mining areas. Both quantities and stock values of antimalarial commodities funded by the donors are unaffected by mining areas while I document a discontinuous change in malaria risk of approximately 10% points across the mining threshold. Further results show that consumption of antimalarial medicines increases in mining areas, while both mining and non-mining areas experience similar frequency in the stock-out of health commodities. The lack of aid responsiveness suggests that health facilities exposed to high malaria risk might have very limited

capacity to respond to any increase in demand for healthcare services. I finally estimate the amount of aid that would provide similar healthcare services between areas with high and low malaria risk when accounting for prevention, diagnosis and treatment of the disease. The findings resonate with Brier *et al.* (2020) and suggest that the costs associated with the increased risk of malaria transmission may considerably increase the risk of catastrophic healthcare expenditures of miners when accounting for other healthcare costs related to mining health hazards (Akpalu and Normanyo, 2017). The RD estimates are robust to a number of sensitivity checks, including different polynomial orders and various bandwidth selections. These findings provide evidence consistent with studies showing the unequal allocation of donors' funds towards the need at sub-national levels (Borghi *et al.*, 2017; Kotsadam *et al.*, 2018; Briggs, 2018). Overall, these findings provide some suggestive evidence that donors may have limited ability to target aid to beneficiaries with the greatest health needs and challenge the assumption that donors possess adequate information about local needs to make optimal aid allocation decisions.

The remainder of the paper is organized as follows. Section II provides background on the financial and epidemiological situation in the DRC. Section III describes the data and the geographical analysis. Section IV presents the empirical analysis related to the impact of mines on aid for malaria to health facilities and introduces the regression discontinuity setting. Section V describes the results and section VI discusses policy implications and concludes.

II. Background

Malaria situation and artisanal small-scale mining

Malaria Situation—Malaria in the DRC is mostly caused by *Plasmodium falciparum*, a parasite transmitted through the bite of mosquitoes, and the disease constitutes a critical public health challenge in the DRC. Almost the entire country is at high risk of malaria transmission where the disease is among the leading cause of mortality and morbidity (WHO, 2015b). In 2015, the DRC accounts for 7.1% of the global total of estimated malaria deaths, ranking second in the world (WHO, 2015b).

Mining Sites—Artisanal and small-scale mining (ASM) refers to informal mining work involving minimum use of mechanical tools. The activity is estimated to be responsible for 90% of the total mineral production in the DRC (Radley, 2020). Owing to its informal nature, artisanal mining poses significant health and safety hazards. Furthermore, mining activities rely on the use of abundant water to filter the extracted minerals, leaving multiple open pits with stagnant water. As a consequence, mines provide favourable environments for mosquitoes' breeding habitats, ultimately translating into a high risk of malaria transmission for the surrounding populations (Staedke *et al.*, 2003; Vittor *et al.*, 2009; Knoblauch *et al.*, 2014).

Health funding landscape in the DRC

Health Sector—The Congolese public health sector is divided into three decentralized levels: a central level for the management of national health programmes and general

hospitals; an intermediate level composed of 26 provincial health divisions with provincial-level hospitals, laboratories and pharmaceutical warehouses; a health district level divided into 516 health zones across the country, where each health zone has at least one hospital. Health zones are then further divided into health areas which include one health centre for about 10,000 inhabitants. Access to quality healthcare services is a major health issue. Basic treatment services are not covering an estimated 60% of children under five in the DRC (Barroy *et al*., 2014).

Health Funding Landscape—Several years of civil wars and continuing lack of government financing have drastically undermined the health system in the DRC. As a result, the country extensively relies on out-of-pocket expenditures and external assistance to finance the provision of healthcare services.[3] The presence of multiple donors affects disproportionately the financing of the health sector, with some disease programmes almost entirely funded by the international community. This observation is particularly salient with the National Malaria Control Programme where more than 95% of its overall funding comes from external aid (MSP, 2017).[4]

According to national guidelines, prevention, diagnosis and malaria treatment in public health facilities are free of charge for patients. But due to low salary and frequent disruptions in salary payments, health workers charge, in practice, user fees on malaria patients (Bertone, Lurton and Mutombo, 2016).[5]

Evidence of local malaria funding

Lack of information about donors' funding at the local level is a major barrier to quantifying the amount of foreign aid that is allocated to each health facility. The main reason behind this limitation is that donors choose to allocate funds that transit, at least partly, through the government budget. As a result, it becomes practically impossible to locally distinguish external aid from domestic spending. However, health financing in the DRC offers a unique setting to circumvent this challenge. An estimated 95% of the Malaria Control Programme is funded by donors in 2017 (Figure 1) which implies that the total resources for malaria in public health facilities are almost exclusively provided by external resources.[6] In this specific case where domestic spending is negligible, the distinction between domestic and external resources becomes unnecessary. Locally, the observed malaria funding can therefore be mostly attributed to international assistance. Unfortunately, no information is available on patients' purchase of antimalarial medicines through retail drug stores. These expenditures may

[3]In the DRC, the major source of health financing comes from household funds (45%) followed by external donors (40%) and government expenditures (15%) (MSP, 2017).

[4]The three major donors for malaria control activities in the DRC are the Global Fund to Fight AIDS, Tuberculosis and Malaria (Global Fund), the United States Government (U.S. Agency for International Development, USAID) and the United Kingdom Government (Department for International Development, DFID) which together account for 92% of total aid for the malaria programme in 2017.

[5]Patient user fees for diseases funded by external donors (such as malaria) are lowered due to the reduction in the cost of medicine and drug but still include fees to health workers (Laokri, Soelaeman and Hotchkiss, 2018).

[6]The low domestic spending on the malaria control programme is mostly dedicated to covering management operations at the central level (MSP, 2017). The lack of public domestic investments also avoids the risk that donors adjust their aid allocation to government health investments or *vice versa* (Öhler *et al*., 2017).

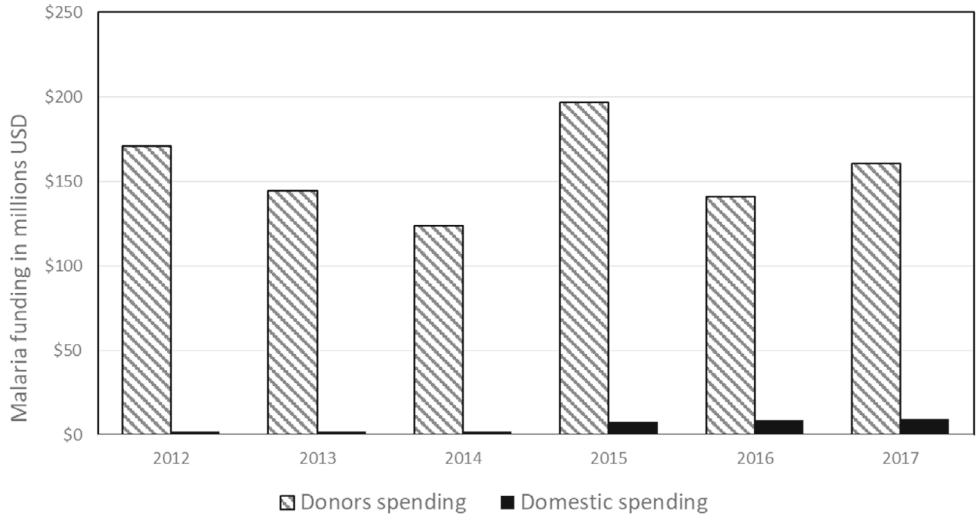


Figure 1. Share of donors and domestic spending in total malaria investment
Notes: The above figure documents the evolution of the contributions of external aid and government spending to the national malaria programme. External aid and government spending amount respectively to $160 million and $9 million in 2017.
Source: National Health Accounts of the DRC, 2015.

come from antimalarial medicines bought from the illegal pharmaceutical market (Cohen, Dupas and Schaner, 2015). However, I argue that the access to health products on illegal markets should not systematically differ between mining and non-mining areas, so its omission should not significantly bias the results. Furthermore, alternative ways to malaria treatment in the illegal market, which miners may be tempted to adopt, often correspond to substandard and falsified antimalarials, increasing the risk of drug resistance and resulting in higher mortality and morbidity (Newton, Hanson and Goodman, 2017; Mpanya, Tshefu and Likwela, 2017). Hence, better access conditions to illegal markets should not necessarily translate into increased access to healthcare services that lead to higher health outcomes.

Donors' role in the allocation of resources—In most stable countries, donors transfer aid for malaria through budget support to the governments. But in cases of fragile states where high corruption and lack of institutional capacity prevail, such as the DRC, donors need to adjust their strategies.[7] They can choose to directly run the programmes (such as in the case of humanitarian relief) or contract out the provision of health commodities. For example, the Global Fund, the largest donor for malaria control activities in the country, selects partners to exploit the existing network of the national logistics system for the procurement, storage and distribution of health commodities.[8] These partners are national and international Non-Governmental Organisations (NGOs) that receive by far the highest share of the Global Fund's

[7]The country ranked 161 of 180 in the 2017 Corruption Perceptions Index established by Transparency international (https://www.transparency.org/en/countries/democratic-republic-of-the-congo).
[8]Donors also financially support the national logistics system of health commodities (The Global Fund, 2018).

funding and are in charge of the programmatic distribution of resources across the health facilities of the country.[9] The local partners, or principal recipients, can also resort to contracting out other local NGOs that already have an established distribution network between regional warehouses and health centres in some provinces of the country (The Global Fund, 2016). In this case, the principal recipients are in charge of supervising the activities of local NGOs, while the Global Fund monitor and evaluate the overall implementation of the funded activities. Under these circumstances, malaria control operations are largely seen to be the responsibility of donors (Hershey *et al*., 2017).

The stock value of antimalarial commodities should then be a valid proxy for local external aid if it represents the major source of variations in local funding (while all other expenditures related to external aid for malaria remain constant). In general, this assumption would raise concerns as other malaria-related costs, namely human resource costs, transportation and storage, are expected to vary significantly across the country.[10]

However, I restrict the data sample to observations that are located within a short distance of the mining threshold (less than 20 Km). The rationale is that, apart from the provision cost of antimalarial commodities, all other malaria-related costs should remain relatively constant across health facilities in the sample. First, salaries and risk allowances to health workers are provided by the government (mostly through donors' support) based on a salary scale. It is then unlikely that two health facilities, located in a common (rural) area, experience significant disparities in governmental payments for a given qualification of health workers. Second, all health commodities are centrally procured by a national organization that manages and coordinates the pooled procurement of pharmaceuticals, their distribution and storage in regional warehouses, and their supply to health facilities.[11] The expenditures related to the transport and storage of health commodities are therefore closely tied to the geographic location of health facilities. Since my data sample spans health facilities over a relatively small geographic area compared to the country size (Figures 2 and 3), most health facilities are supplied by a common regional warehouse, and should, therefore, share identical costs of storage. Lastly, transportation costs from the regional warehouse to health facilities are likely to differ, depending on the location and accessibility of the health facility. Nonetheless, these transportation costs represent only 7% of the overall expenditures related to the malaria programme (The Global Fund, 2016), so these variations should only have a minimal impact on the local allocation of aid.

[9]The national logistics system is divided into three structures which comprise (i) the National Essential Medicine Supply Programme, (ii) a national organization for the centralization of pharmaceutical procurement (*Fédération des Centrales d'Achat des Médicaments Essentiels, FEDECAME*) and (iii) a decentralized warehousing and distribution system (*Centrales de Distribution Régionale, CDR*).

[10]According to the 2016 audit report in the DRC, 53% of total malaria funding is for the procurement of antimalarial commodities, 27% for expenditures related to human resources and 11% is attributed to transport and storage of commodities. A remaining 9% is dedicated to the management and organization of the malaria programme (The Global Fund, 2016).

[11]The FEDECAME works in close collaboration with the Global Fund to obtain negotiated prices of health commodities with manufacturers.

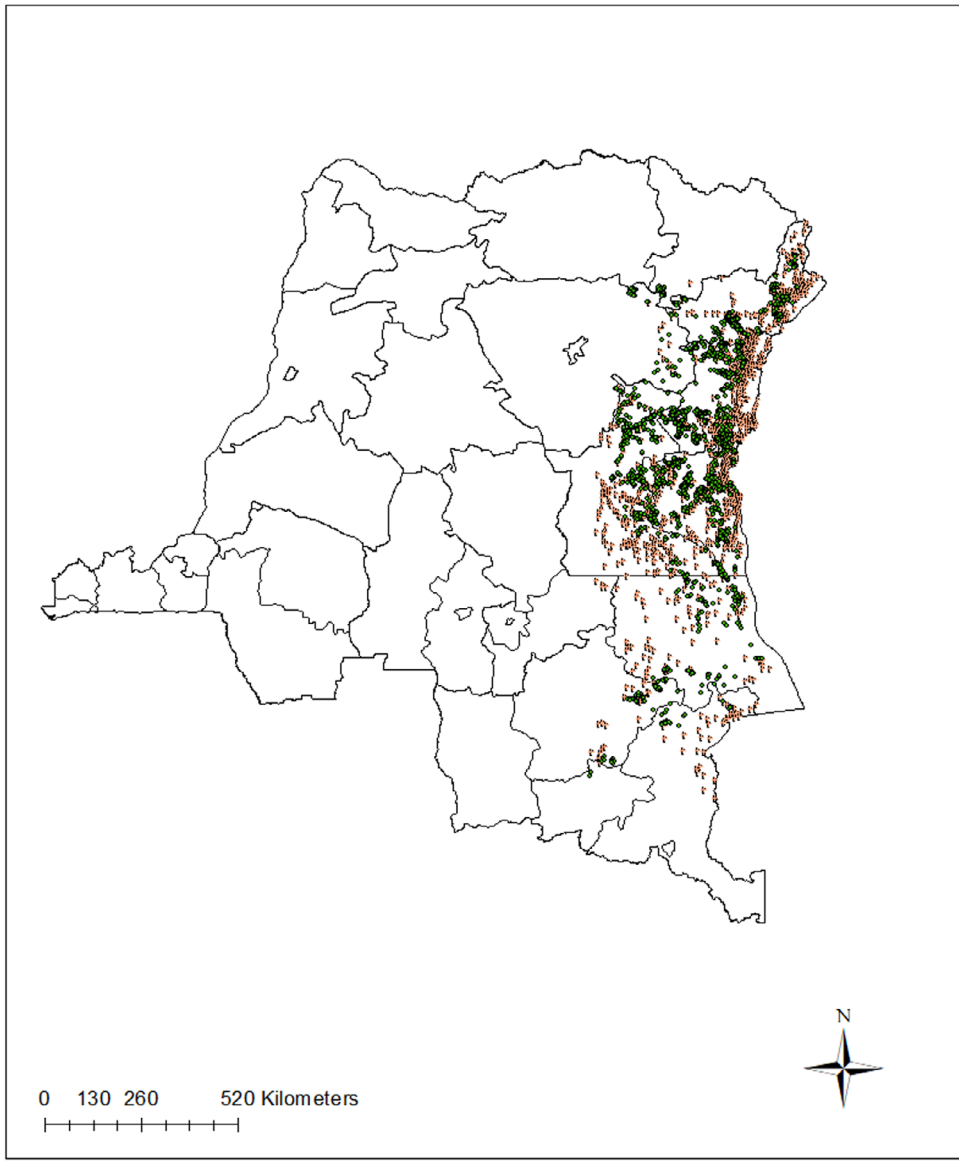


Figure 2. Mapping of the full sample of health facilities and mines in the DRC
Notes: The map shows the geolocation of the mines and the health facilities in the Eastern DRC along with provincial-level boundaries.

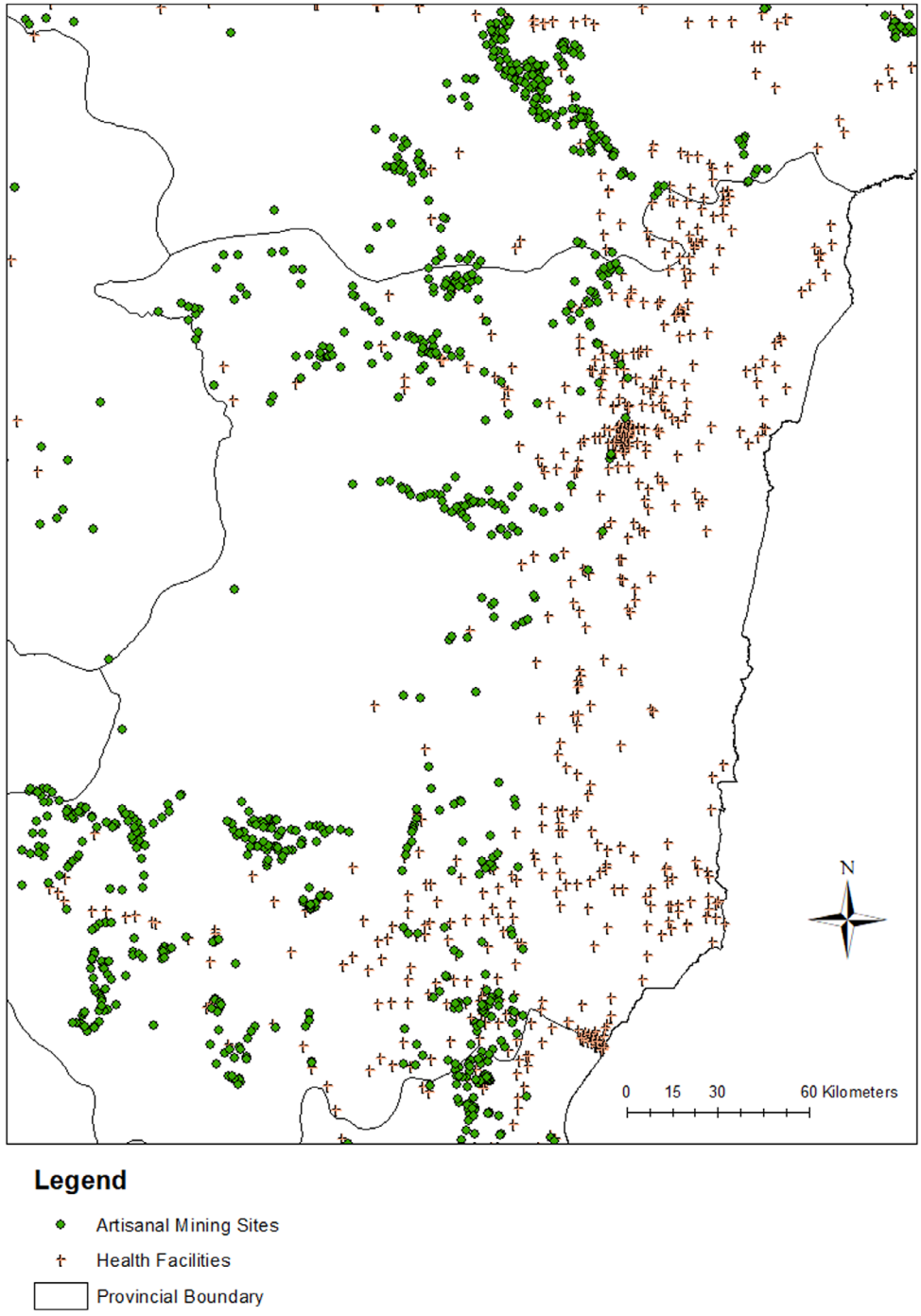


Figure 3. Mapping of health facilities and mines in North Kivu
Notes: The map shows the exact geolocation of the mines and the health facilities in the North Kivu province.

Mining threshold

The conducive conditions for the proliferation of mosquitoes around mines create high-risk areas of malaria transmission (Vittor *et al*., 2009). Locally, the high density of mosquitoes causes an increased risk of malaria transmission in the mining sites and their surroundings. In these 'hotspot' areas, the disease is endemic (Carter *et al*., 2000) and the malaria risk remains constant overtime (Bautista *et al*., 2006). As a consequence, mining areas exhibit a unique spatial–temporal pattern of a high risk of malaria transmission where surrounding populations of mining sites are locally exposed to the highest malaria risk.

I define a mining area as the catchment area of a mine characterized by a high risk of malaria transmission which does not decay with distance. The exposure to the disease is typically highest between 2 and 5 km from mosquito breeding sites (Carter *et al*., 2000; Kaufmann and Briegel, 2004). However, in the case of mines, this distance is considerably increased by the mobility of miners. Once infected by Plasmodium parasites, miners indirectly contribute to the spread of the parasites among their household members through new bites of mosquitoes, which in turn, get infected and pass the parasite to new people. Dibwe (2008) examines working conditions in artisanal mining sites in the Katanga province of the DRC and finds that more than 97% of miners are living within 7 km from the mines. In the same vein, Faber, Krause and Sánchez de la Sierra (2017) exploit data on miners from a random sample of 150 mining areas in the DRC and show that the average travelling distance of miners from their household is 7 km.[12] As a result, exposure to malaria should remain high within an average distance of 10 km from mining sites. The last element to consider is the travelling distance to health centres. Noor *et al*. (2003) find that the median travelling distance to health facilities in Kenya is 8 km in rural areas. Likewise, the Demographic Health Survey (DHS) conducted in 2007 and 2013 in the DRC reveals that the patient's travelling to a health facility is less than 2 hours for 75% of the rural population—which would represent a distance ranging from 6 to 8 km at the average human walking speed ranging from 3 to 4 km per hour.[13] To be considered part of a mining area (with high malaria risk), a health facility should then be located at a distance from a mine that does not exceed 15–18 km, accounting for the possibility that a health facility and a mine are located in the opposite direction from a patient's residence.

What is the spatial distribution of malaria risk beyond the mining area? The related literature indicates that the number of malaria cases decreases exponentially with distance from the hotspot (Bousema *et al*., 2012; Barros and Honório, 2015). I would therefore expect that malaria risk drops significantly beyond the mining area.

[12]Faber *et al*. (2017) also find that the median travelling distance of miners is 3 km, which suggests the presence of outliers with potentially far greater distances. However, the quasi absence of a road network in the Eastern DRC, where the analysis is focusing on, should reduce the risk of having a large travelling distance among miners.

[13]Note that the limited paved road network in eastern DRC may further reduce the ability to travel large distances.

Figure 4 provides a visual inspection of this setting with the data sample. I define the probability of malaria cases as the mean share of malaria cases reported by a health facility out of the total population of its catchment area. Panel A plots the distribution of the probability of malaria cases for each health centre in the sample (scatter dots) against the distance to its closest mine (in metres). Solid lines are quadratic fits separately estimated on both sides of the 15-km threshold. Panel B provides an analogous exercise and plots the maximum probability of malaria cases within a 1 km bin. The figure clearly illustrates a sharp shift in the malaria risk before and after 15 km from the mines. Moreover, the figure shows that malaria risk does not decay with distance within mining areas.

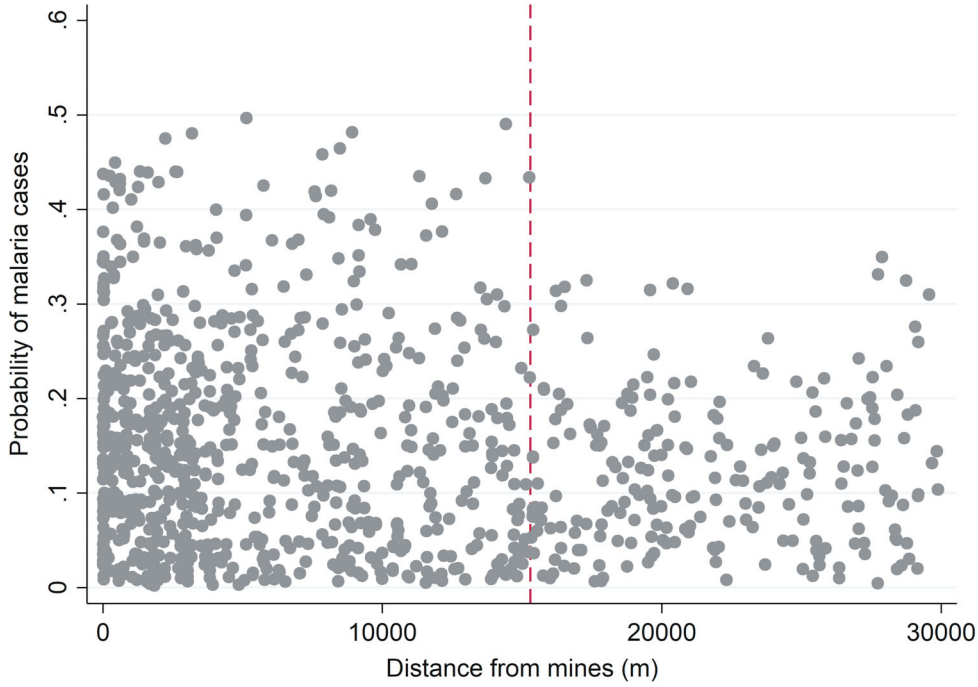
I provide further empirical evidence about the existence of a mining threshold by performing the Supremum Wald test for a structural break with unknown break distance proposed by Andrews (1993). The objective is to identify any abrupt changes in malaria incidence. The test uses the maximum value of the Wald test statistics obtained from a series of Wald tests over all possible break distances between 0 and 30 km.[14] For this exercise, I consider the maximum probability of malaria cases within a 1 km bin. Figure A1 in the online appendix plots the Wald test statistics that are used to calculate the Supremum Wald test with respect to the distance. The structural break test identifies one important shift with a spike in the Wald test statistics that reaches 117.5 at 15 km, above the critical value. We can therefore reject the null hypothesis of no structural break at the 5% level and interpret the shift in malaria incidence at 15 km as additional evidence for the existence of a mining threshold.

The distance of the mining threshold is remarkably consistent with the findings from the literature highlighted above. Yet, the reported probability of malaria cases could pose potential endogeneity concerns since it relies on the internal capacity of health facilities to detect and report malaria cases (such as the number of nurses or the availability of malaria diagnostic tests) which could be affected by foreign aid. I partially address this challenge in the Results section where I document insignificant effects on the number of stock-out days of RDTs between mining and non-mining areas. This essentially means that the number of detected cases should not be more constrained by the availability of RDTs in health facilities located in mining areas compared to those in non-mining areas.

Another concern is that the change in the risk of malaria transmission might be relatively smooth around the mining threshold. One might think that it would be preferable to estimate the effects of mining areas on local aid by a fuzzy RD design that uses the distance to mines as an instrument for exposure to the malaria burden. Yet, the reported number of malaria cases by health facilities would be a 'poor' instrument because it might not necessarily reflect the 'true' malaria risk: for instance, some facilities might report low numbers of malaria cases even though they are located in a malaria-endemic area. This is illustrated in graph A of Figure 4 where the probability of malaria cases differs significantly between health facilities that are

[14]Since the test has lower power at the borders of the sample (Andrews, 1993), the distances at the 15th and 85th percentiles are treated respectively as the first and last possible break distance.

(a) Distribution of malaria risk



(b) Maximum of malaria risk

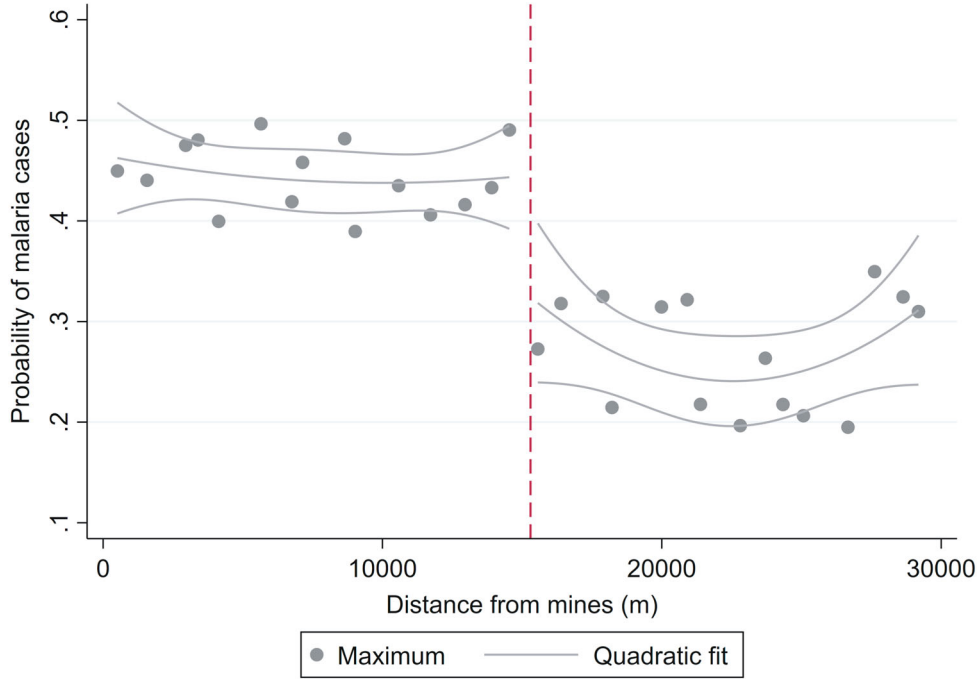


Figure 4. Malaria prevalence as a function of the distance to mines
Notes: Panel a presents the distribution of the probability of malaria cases with respect to the running variable of the RD design, the distance from mines. The probability of malaria is defined as the total number of malaria cases divided by the total population in the catchment area of each health facility. Panel b plots the maximum probability of malaria cases within a 1 km bin. The solid lines are quadratic fits separately estimated on both sides of the 15-km threshold, along with 95% confidence intervals. Scatter dots represent reported probabilities in panel a and maximums in panel b.

located within a similar distance from the mines, even when controlling for the population in the catchment area of the facility. Although I show that the stock of RDTs between mining and non-mining areas is not statistically different, the reported number of malaria cases might be influenced by other unobservable characteristics.

As a consequence, I consider a 'doughnut hole' approach which excludes the facilities that lie within 2 km from the threshold in the main analysis. This strategy should reduce the risk that miner (non-miner) patients cross the threshold and seek healthcare in the non-mining (mining) area. The cost of this approach is that it may also weaken the comparability of the units on each side of the threshold. However, I assess the sensitivity of the results to the gap selection and provide evidence of their robustness in the Results section.

III. Data

The data used in this research are drawn from two main sources: the District Health Information System and geographic locations of artisanal mining sites.

District Health Information System. Epidemiological and financial data on health facilities were extracted from the District Health Information System (DHIS2), a web-based health information system where health facilities report their routine administrative and clinical data.[15] Reports from health facilities are uploaded monthly to the system and include multiple epidemiological measures on disease burden, consumption and stock level of health commodities as well as financial and human resource information. DHIS2 contains data on all health facilities in the DRC regardless of the type of structures (hospital, health centres and health posts) and includes private, public and faith-based health facilities.[16] To ensure that all health facilities can report on DHIS2, VSAT (very small aperture terminal) satellites and solar panels were installed in health zones that did not have internet access or electricity.[17]

I restrict the data sample to rural health facilities located in the Eastern DRC, where information on mines is available. In these provinces, more than 89% of health facilities were submitting routine monthly reports using DHIS2 in 2017. In total, the

[15]DHIS2 is implemented by the Ministry of Public Health, with technical and financial assistance from donors, to monitor health service delivery, measure achievement and track health progress at the different levels of healthcare across the country.

[16]Uncomplicated malaria cases, diagnosis and prevention services can be provided in health posts but patients seeking clinical services are referred to health centres or hospitals. At the community level, unpaid health workers may also carry out health promotion activities but there is no information available on the service provided.

[17]A VSAT is an antenna with two terminals that transmits and receives data from satellites.

data sample spans 1,511 health facilities located in six provinces: North and South Kivu, Maniema, Ituri, Tshopo and Tanganyika (Figure A2 in the online appendix). The number of observations shrinks to 465 when the sample is restricted to a 10 km window around mining sites.

Antimalarial commodities correspond to all health products that are used for diagnosis (rapid diagnostic tests, RDT), antimalarial treatment (artemisinin-based combination therapy, ACT) and prevention (sulphadoxine–pyrimethamine, SP and insecticide-treated mosquito nets, ITN).[18] DHIS2 contains a malaria intervention module that is used in this exercise. Information on the stock level of commodities is reported monthly before the consumption of commodities from January to December 2017. Finally, I use the estimated population in the catchment area of each facility as reported in DHIS2 to account for variations in population density.

Mining areas. A comprehensive list of artisanal mining locations in the Eastern DRC was compiled by the International Peace Information Service (IPIS) through multiple data collection campaigns conducted between 2009 and December 2017. The dataset contains information on the geolocation (longitude and latitude) of 3,687 artisanal mining sites in Eastern DRC.

Geocoding of health facilities. The geographic locations of health facilities are only partially provided by DHIS2. To complete the geocoding of the remaining health facilities in the sample, I triangulate information from DHIS2 with two other sources of georeferenced data: ReliefWeb maps provided by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) and OpenStreetMap files.

In the online appendix, Table A1 presents summary statistics for key health facility characteristics in mining and non-mining areas and their difference in means for observations that fall within 10 km from the border of mining areas.

IV. Empirical framework and estimation

Spatial aid targeting

Spatial variations in the risk of malaria are common in endemic regions. Although malaria transmission is seasonal, malaria hotspots contribute to maintaining the transmission of the disease during seasons where the risk is low and accelerate it during high transmission seasons. Consequently, targeting these specific locations allows to efficiently reduce malaria transmission (Bousema *et al*., 2012). For the donors whose objective is to 'reduce and eliminate malaria' (WHO, 2015a), aid targeting to malaria hotspots should be prioritized if they have sufficient information to do so. In resource-limited settings, restricting aid to areas with intense malaria transmission can free up resources to make interventions more affordable while reaching the highest impact. Mining areas constitute one example of malaria hotspots: they are characterized by high malaria risk in the whole area while the risk sharply declines outside the area. I propose to exploit the natural discontinuity in the risk of

[18]ACT treatments are characterized by specific dosages which relate to four different age categories (below 1, between 1 and 5, between 6 and 13 and above 13).

malaria transmission at the border of mining areas to estimate the causal effect of malaria risk on local aid for malaria in a regression discontinuity (RD) design. The main advantage of this approach is that it offers a unique opportunity to compare clearly identified high and low health need areas without directly relying on the reported number of malaria cases. The latter is highly endogenous to the model with local aid, as aid can increase the capacity to detect more malaria cases. Second, the proximity of health facilities to the threshold ensures that health facilities are comparable and only differ in their exposure to malaria risk. For example, they should present similar access to the transportation of health products so that aid can equally reach the facilities on both sides of the threshold.

The discontinuity at the threshold, if observed by the donors, should translate into a different level of aid on each side of the threshold to adjust with the malaria risk.

Lastly, the malaria literature has documented that children are at a higher risk of malaria transmission than adults (Smith *et al*., 2007). This fact could pose a threat to the comparability of the treatment and control groups if mining areas are mostly deprived of children. Yet, recent evidence suggests that children in the DRC may often engage in mining activities, regardless of international labour standards on child labour. The Multiple Indicator Cluster Survey (MICS) conducted in the DRC in 2017 reveals that more than 60% of children in Eastern DRC are engaged in labour activities including mining. Likewise, Faber *et al*. (2017) find that about 13% of miners were aged below 18 in Eastern DRC.

Nonetheless, I discuss in the online appendix how the absence of meaningful socio-economic data at the individual (or household) level may limit the analysis. The results should therefore be interpreted with some caution as available data only allows to draw conclusions on the matching of aid with the risk of malaria. In the Results section, I discuss how the findings could relate to health needs.

Setting the RD design

Since mines are located where the exploitation of natural resources is feasible, their locations form a natural random selection framework where other local characteristics between mining and non-mining areas are unlikely to vary discontinuously at the boundary. The RD design evaluates the effect of mining areas on aid for malaria to health facilities, where local aid is captured by the stock value of antimalarial commodities. The border of the mining area constitutes a threshold that generates a discontinuous probability of getting infected with malaria. I hypothesize that the mining threshold should also cause a discontinuity in local aid for malaria if donors are responsive to the local needs related to the disease.

Estimation framework

The causal mining effect on local aid is estimated using the following specification

$$Y_{ip} = \alpha + \beta_1 mine_{ip} + g(\tilde{X}_{ip}) + \beta_2 z_{ip} + \mu_p + \varepsilon_{ip} \quad (1)$$

where Y_{ip} corresponds to aid for malaria per capita in facility i in province p, $\tilde{X}_{ip}$ denotes the distance to mine X_{ip} re-centred at threshold ($\tilde{X}_{ip} = X_{ip} - c$), $mine_{ip}$ is an indicator for mining area ($\tilde{X}_{ip} \leq 0$) and μ_p denotes province fixed effects. $g(\widetilde{X_{ip}})$ is the RD polynomial which controls for smooth functions of geographic distance from a mine to its closest health facility i.[19] Under the identifying assumption that health facilities in non-mining areas form a valid counterfactual, β_1 identifies the effects of mines on local aid for malaria. In other words, β_1 captures the effect on local aid from being exposed to a high risk of malaria, as a consequence of the health facility being located in a mining area, as opposed to not being exposed to a high malaria risk. The vector of covariates z_{ip} includes geographic characteristics for facility i in province p at the spatial resolution of 3 arc-second (approximately 90 metres): elevation, slope, ruggedness (standard deviation of elevation), distance to the closest regional distribution centre of health commodities, distance to armed conflicts[20] and the number of mines in the vicinity of the facility. In addition, most health facilities in the data sample are located in a mountainous region where the average altitude is about 1,300 meters (Table A1 in the online appendix); using chordal or relative Euclidean distances might then lead to misleading results.[21] I rely instead on a more realistic distance based on slope and surface elevation using information collected from NASA's Shuttle Radar Topography Mission (SRTM) satellite images (Figure A3 in the online appendix). Finally, health facilities report their activities within health zones, which are used by donors and government services to coordinate the delivery of healthcare services. Robust standard errors are therefore clustered at the health zone level to allow for arbitrary correlation of the error term (Bartalotti and Brummet, 2017).

Polynomial choice and bandwidth selection

In the following section, I report the baseline results with the local linear model and test their robustness with a quadratic polynomial in the online Appendix. I follow the methodology proposed by Calonico, Cattaneo and Titiunik (2014) to obtain robust confidence intervals by correcting for the bias introduced by the approximation of the RD local polynomial estimator. The procedure consists of augmenting the confidence intervals centred around the bias-corrected RD estimator and using a standard error that reflects the uncertainty introduced in the biased estimation. In the following section, I report the results of the RD treatment effect using this data-driven methodology, referred to as 'CCT'.

[19]The local linear regression is used in the baseline results, where $g(\tilde{X}_{ip}) = \delta_1 \widetilde{X}_{ip} + \delta_2 mine_{ip} \tilde{X}_{ip}$. The presence of the interaction terms allows for two different regression functions on each side of the threshold. To test the stability of the findings, I also report, in the online appendix, the results with a quadratic model that provides a more flexible form of the polynomial.

[20]I use data from Armed Conflict Location and Event Data Project (ACLED) which reports georeferenced information on political violence and protests between January and December 2017.

[21]The chordal distance is the distance between two points on a curve and accounts for the spherical shape of the Earth.

V. Results

I start by providing evidence of the plausibility of the two main identification assumptions of a valid RD design: continuity around the threshold (no self-selection) and random assignment.

Validity

The assumption of the RD design would be violated if health facilities can manipulate the geographic distance to their closest mine. However, this assignment does not leave much room for strategic behaviour as most of the artisanal mining activities should be more recent than the presence of health facilities.[22] Figure 5 presents a visualization of the density function of the running variable. Note that the running variable is centred at the threshold point, so negative and positive distance correspond respectively to mining and non-mining areas. The smoothness of the density suggests there is little scope for selective sorting of health facilities across the RD threshold.

I perform several density continuity tests of the running variable based on a data-driven procedure proposed by Cattaneo, Jansson and Ma (2020). Table 1 presents the results of the density test, where the null hypothesis corresponds to equal density functions of the treatment and the control group. The first two columns correspond to

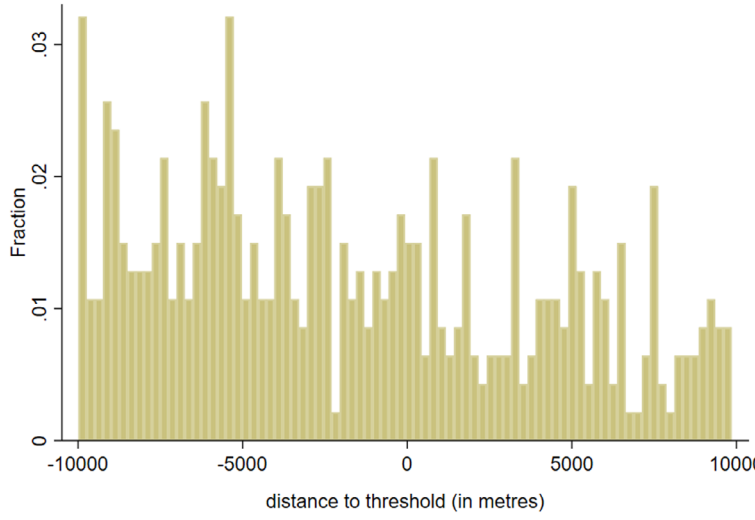


Figure 5. Density of the running variable
Notes: The figure shows the distribution of the running variable for health facilities in the sample. The running variable is the distance from the health facility to the mining threshold. The running variable is centred around the threshold, so distances are negative in the mining areas (left side of the threshold) and positive in non-mining areas (right side of the threshold). The *y*-axis shows the percentage of observations within each bin, where the latter represents a 250-m interval.

[22]Revamping health infrastructures in the DRC is a well-recognized priority, so it is unlikely that the construction of health facilities preceded recent mining exploitations (MSP, 2017).

TABLE 1

Manipulation density tests

Density tests	*Mining areas*		*Non-mining areas*		
	(1) *Bandwidth*	*(2)* *Observations*	*(3)* *Bandwidth*	*(4)* *Observations*	*(5)* P-*value*
Separate MSE Optimal bandwidth	3,705	65	3,079	67	0.60
Restricted C.D.F	7,367	111	7,367	178	0.92

Notes: The table shows the results of the manipulation test based on the local polynomial density estimation technique (Cattaneo *et al*., 2020) where the density functions of the mining and non-mining areas are equal under the null hypothesis. The first two columns correspond to the choice of the bandwidth (in metres) on each side of the threshold and the number of observations assigned to mining areas, and columns (3) and (4) present the same results for the non-mining areas; the last column gives the *P*-value of the test. I perform the test using two different MSE optimal bandwidths on each side of the cutoff for which the results are reported in the first row. The second row corresponds to the density test where the Cumulative Distribution Functions (C.D.F.) of the running variable on each side of the cutoff are assumed to be equal, and the joint estimation relies on a common bandwidth.

the choice of the bandwidth (in metres) on each side of the threshold and the corresponding number of observations in mining areas, and columns (3) and (4) present the same results for the non-mining areas. The last column gives the *P*-value of the density test. I perform the test using two different MSE optimal bandwidths on each side of the threshold (Cattaneo *et al*., 2020) for which the results are reported in the first row. The second row corresponds to the density test which determines the possibility of equality of the two cumulative distribution functions of the running variable on each side of the threshold. In both cases, the tests fail to reject the null hypothesis of continuity.

The falsification test provides further evidence about the plausibility of the identification strategy. Placebo covariates are the predetermined covariates that should not be affected by the mining area under a valid RD design. Figure 6 provides a visual inspection of the effect of mining areas on the placebo covariates, where the running variable is the distance to mines centred around the threshold (mining and non-mining areas correspond respectively to the right and left-hand side of the threshold). The solid line plots quadratic fits on each side of the mining threshold using triangular kernel weights, and each point represents an average value within a 1 km spread bin. The absence of discontinuity between mining and non-mining areas is consistent with the randomization assumption.

Mining effect on local malaria funding

Figure 7 provides an analogous exercise for the stock quantity of antimalarial commodities. The graphs show a similar pattern for each commodity and suggest that aid for malaria remains constant on each side of the threshold. Table 2 reports the parametric (panel A) and non-parametric (panel B) estimates of the effect of mining on the outcome of interest and the placebo outcomes from equation (1). In panel A, columns (1) and (2) report the parametric results of the RD treatment effect on local aid for malaria using a linear model in distance. The corresponding window selection

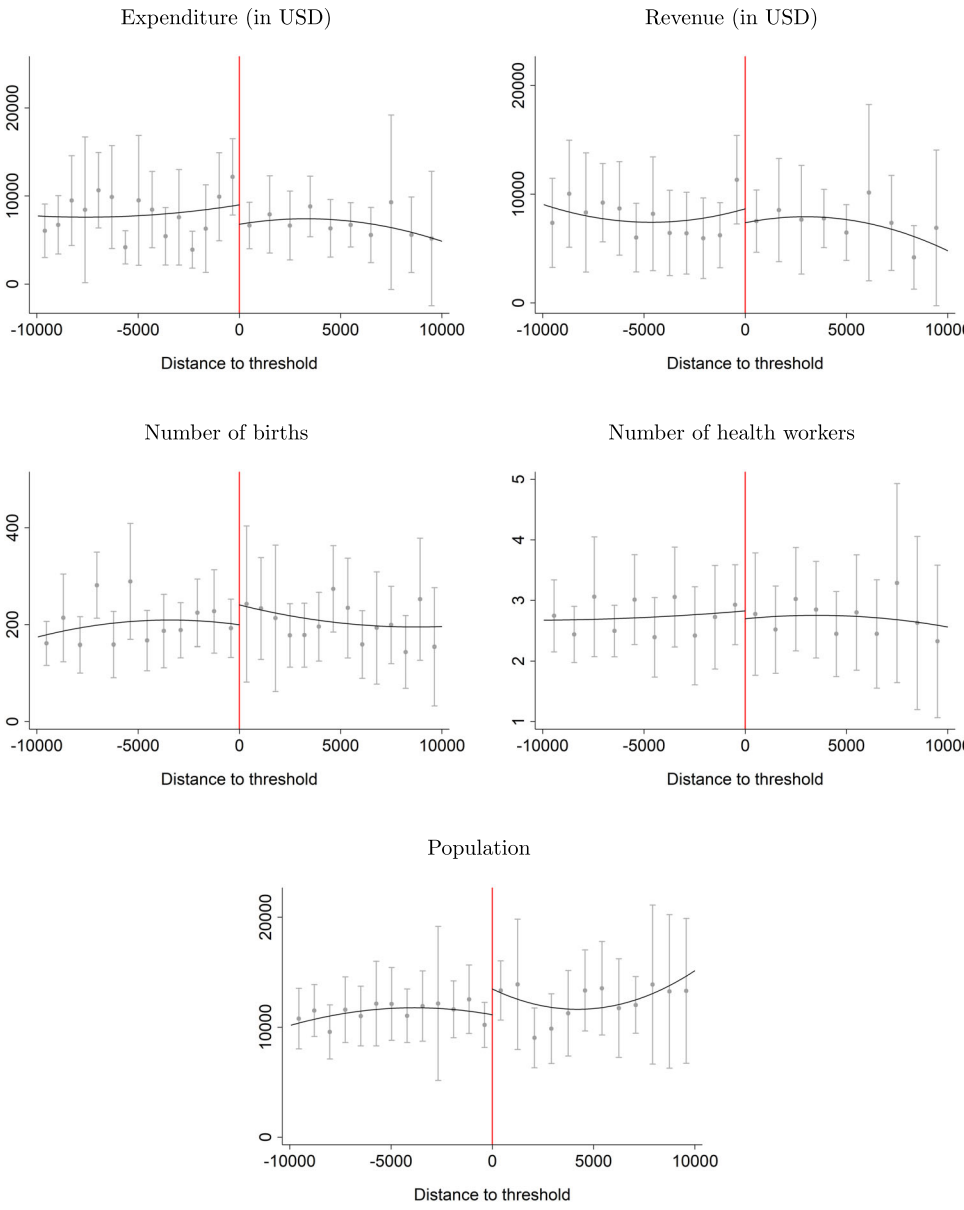


Figure 6. Evidence on continuity condition
Notes: Each point plots an average value within a bin conditional on the distance to the mining threshold. The distance is in metres and the solid lines plot quadratic fits on each side of the threshold using triangular kernel weights along with 95% confidence intervals.

restricts health facilities to be located within 6 km from the mining threshold. Column (2) explores the sensitivity of the results to the inclusion of baseline covariates. Panel B presents the non-parametric estimates using a triangular kernel function with a local linear regression. Following Calonico *et al*. (2014), the reported results are based on

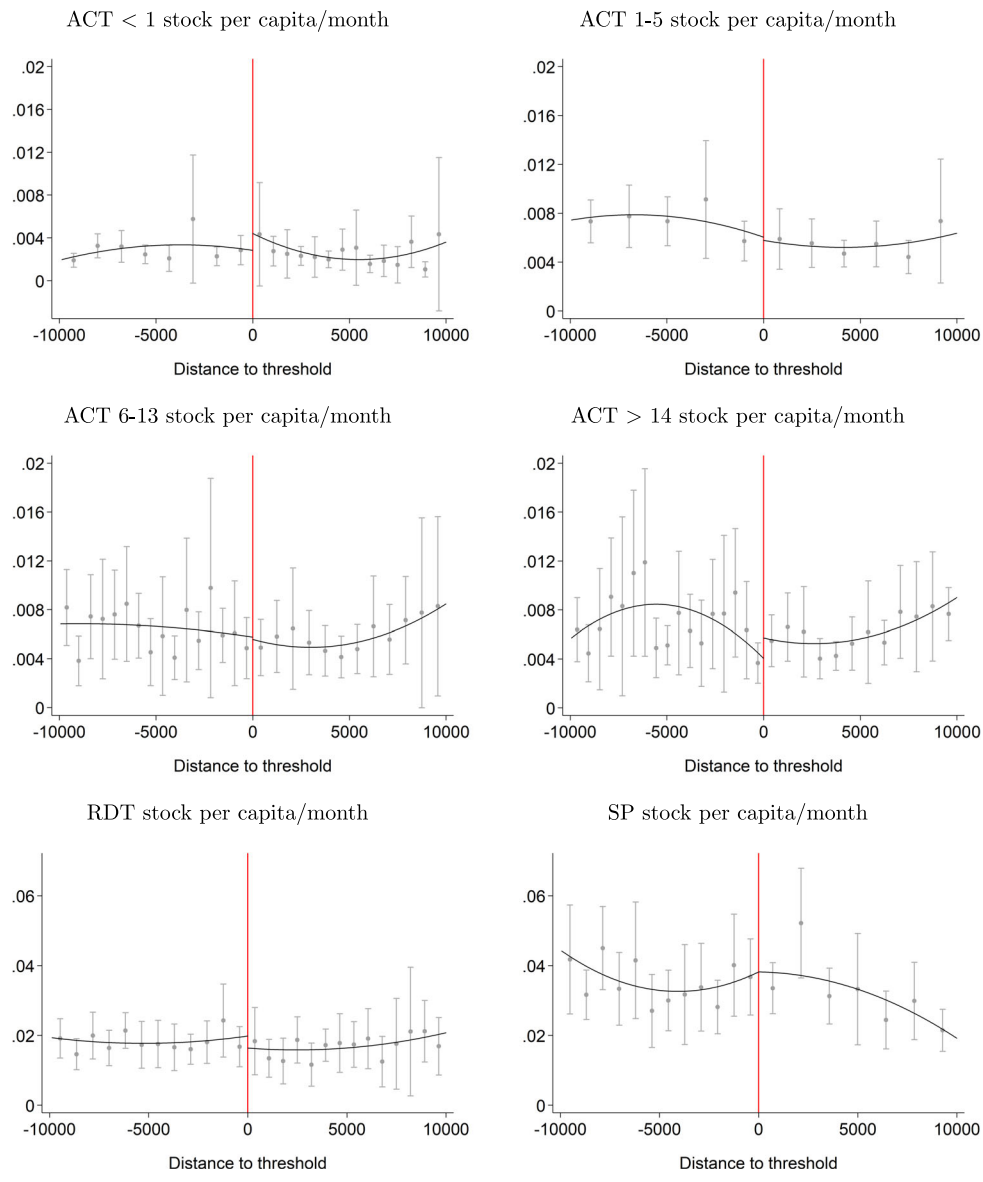


Figure 7. The effect of mining areas on the stock quantity of antimalarial commodities
Notes: Each point plots an average value within a bin conditional on the distance to the mining threshold. The distance is in metres and the solid lines plot quadratic fits on each side of the threshold using triangular kernel weights along with 95% confidence intervals.

cluster-robust confidence intervals and mean squared error (MSE)-optimal bandwidth.[23]

[23]The MSE-optimal bandwidth selection and point estimators are specifically chosen to include covariates and adjusted for clustering (Calonico *et al*., 2019).

TABLE 2

Effect of mining areas on local aid for malaria

Window selection	*6 km*	
*Control variables**	*No*	*Yes*
	(1)	*(2)*
Panel A. Parametric estimation		
Aid for malaria per capita		
RD Mining effect	−0.035	−0.038
s.e.	0.027	0.030
Standard *P*-value	0.195	0.206
Obs.	207	207
Placebo outcomes, standard *P*-values		
Expenditures	0.967	
Revenue	0.379	
No. of health workers	0.743	
No. of births	0.986	
*Control variables**	*No*	*Yes*
	(1)	*(2)*
Panel B. Non-parametric estimation		
Bandwidth h (in metres)**	6,498	5,557
Aid for malaria per capita		
RD Mining effect	−0.028	−0.030
Robust s.e.	0.021	0.019
Robust *P*-value	0.142	0.083
Obs.	294	261
Placebo outcomes, robust *P*-values		
Expenditures	0.346	
Revenue	0.306	
No. of health workers	0.351	
No. of births	0.898	

Notes: Panel A reports results of the parametric estimates based on specification (1). Columns 1–2 report the results using a linear model. Panel B reports results of non-parametric RD estimations with local linear regressions using triangular kernel weights. The bottom part of both panels A and B reports the robust *P*-values of the estimates of the mining effects on several predetermined covariates following the procedure described by Calonico *et al*. (2014). Robust standard errors are clustered at the health zone level. All specifications include province fixed effects.

*Control variables include elevation, slope, ruggedness, distance to regional medical stores, distance to conflict and distance to road blocks.

**The bandwidth selection follows the MSE-optimal procedure proposed by Calonico *et al*. (2014).

The results are robust across the parametric and non-parametric estimations and present a consistent picture of the absence of mining effect on local aid for malaria. The RD estimates are small, negative and statistically insignificant, which suggest that mining areas do not have causal effects on local aid for malaria. In the online appendix Table A2, I further show that these results are robust to alternative local polynomial orders by using a quadratic model for the non-parametric estimation, and a wider window selection (9 km) for the parametric estimation.

The bottom parts of panels A and B in Table 2 provide results of placebo tests which estimate the mining effect on the following predetermined covariates: total expenditures,

total revenue, number of health workers and number of births per health facility. These control variables could be causal factors for local aid targeting if donors are able to identify health facilities' characteristics, and would, in turn, invalidate the RD design. The reported *P*-values indicate no evidence of a mining effect on these placebo outcomes.

Robustness

I present additional robustness tests in the online Appendix. In Figure A4, I test the sensitivity of the results to the bandwidth selection and the polynomial order and report consistent estimates. I also explore in Figure A5 whether donors decide to target facilities closer to the mining sites, independent of health need consideration. The results present no evidence that donors provide exclusive targeting efforts to the closest health facilities to mining sites. Likewise, Figure A6 presents evidence that donors do not respond to the discontinuity in the malaria risk at the border of mining areas by smoothing their financial assistance. In particular, the figure highlights the scattered distribution of health facilities which is likely to prevent any smooth aid responses. Finally, I examine in Figures A7 and A8 whether the findings are driven by a lack of statistical power to detect an effect with the RD estimation strategy. The power analyses show that the study is underpowered with the local quadratic approximation, but they also suggest that the local linear model is sufficiently powered to detect small-sized effects. The stability of the coefficient estimates across specifications gives further confidence in the findings.

Decomposition by commodity and additional tests

Each commodity has a specific role in tackling the disease burden, which can be decomposed into three sub-categories: prevention, identification and curative treatment. To uncover more details about the effect of mining areas on aid for malaria, Table 3 examines how the burden of malaria affects the allocation of aid resources to each of these sub-categories. The table provides the non-parametric estimates from equation (1) where the outcomes of interests are the stock quantity of ACT for each age category (below 1, between 1 and 5, between 6 and 13 and above 14), SP, RDT and ITN. I further explore the 'doughnut' RDD sensitivity in columns 2 and 3 by increasing the excluding window around the mining threshold to 4 and 5 km respectively.

The coefficients are statistically insignificant across all antimalarial commodities and excluding windows. If the demographic characteristics are similar across the mining threshold, these results might suggest that even for the most vulnerable populations, children (ACT below 5) and pregnant women (SP), aid for malaria is unaffected by local changes in the burden of malaria. To further explore this assumption, I examine some mechanisms that could explain the unchanged provision of antimalarial medicines.

Disentangling the mining effects on local aid. First, health facilities within mining areas might be subject to systematically increased disruptions in the provision of health products for reasons inherent to the presence of mines. To assess this assumption, Table A3 in the online appendix documents the mining effects on the monthly number of stock-out days and consumption for each antimalarial commodity. Column 1 reports the estimates for SP and columns 2–5 decompose the mining effects for each age

TABLE 3

Sensitivity tests of the quantities of antimalarial commodities to the window exclusion around the threshold

Excluding window	*3 km (1)*	*4 km (2)*	*5 km (3)*
ACT < 1			
RD Mining effect	0.000	0.002	0.003
s.e.	0.001	0.001	0.003
Robust *P*-value	0.712	0.171	0.168
Bandwidth (metres)	3,323	3,843	4,437
Obs.	147	175	218
ACT 1–5			
RD Mining effect	0.002	0.004	0.003
s.e.	0.003	0.004	0.004
Robust *P*-value	0.476	0.368	0.338
Bandwidth (metres)	5,882	4,031	4,196
Obs.	271	194	206
ACT 6–13			
RD Mining effect	0.001	0.004	0.001
s.e.	0.003	0.005	0.003
Robust *P*-value	0.776	0.366	0.566
Bandwidth (metres)	3,609	3,150	3,106
Obs.	159	144	145
ACT > 14			
RD Mining effect	0.001	0.003	0.002
s.e.	0.003	0.003	0.002
Robust *P*-value	0.628	0.358	0.374
Bandwidth (metres)	3,340	3,002	4,010
Obs.	148	138	196
Sulphadoxine–pyrimethamine (SP)			
RD Mining effect	−0.026	0.001	0.001
s.e.	0.022	0.025	0.009
Robust *P*-value	0.145	0.924	0.937
Bandwidth (metres)	3,584	3,532	3,977
Obs.	141	147	172
Rapid diagnostic test (RDT)			
RD Mining effect	0.002	0.001	0.000
s.e.	0.004	0.004	0.004
Robust *P*-value	0.541	0.896	0.773
Bandwidth (metres)	4,570	4,444	4,169
Obs.	205	204	195
Insecticide-treated bed net (ITN)			
RD Mining effect	−0.003	−0.005	−0.003
s.e.	0.002	0.003	0.004
Robust *P*-value	0.157	0.094	0.307
Bandwidth (metres)	3,578	4,167	4,386
Obs.	131	168	176

Notes: The table reports the results from non-parametric estimations of specification (1) using a local linear model for each antimalarial commodity. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico *et al*. (2014), as well as the construction of cluster-robust standard errors and *P*-values. The smoothed distribution function used is the triangular kernel. The outcome is the quantity of each antimalarial commodity expressed as a share in the population catchment area of health facilities. All specifications include the baseline control variables and province fixed effects.

category of ACT treatment. The last two columns present the estimates of ITN and RDT respectively. The RD estimates of the monthly number of stock-out days are statistically insignificant for all commodities, except for antimalarial treatments for children below 1. As anticipated, monthly consumption of ACT increases for young adults (between 6 and 13) and adults (14 and above) across the mining threshold, but the consumption of all preventive antimalarial commodities remains unchanged.

Second, differences in demographic characteristics between mining and non-mining could naturally affect the stock of gender and age-specific commodities (such as SP for pregnant women and ACT treatment by age category). Unfortunately, data limitation prevents from exploring the distribution of age population in these areas (Table A4 in the online appendix). I can therefore only assume that the age distributions are similar on each side of the mining threshold. One concern with this assumption is that mining areas could have a lower rate of children due to the health and safety hazards of mines. However, as discussed in section IV, recent studies on child labour suggest that the presence of children should not be significantly lower within mining areas.

All pregnant women are administered a dose of SP during routine antenatal care (ANC) visits, regardless of whether women have malaria infection or not (WHO, 2018). Table 4 shows that the effect of mining areas on the number of prenatal visits is statistically insignificant, either with local (column 1) or quadratic RD polynomial (column 2). Likewise, populations in the catchment area of health centres are unaffected by the mining threshold. These results can reasonably be interpreted as equal distributions of pregnant women between mining and non-mining areas.

Another concern is that the geographic location of health facilities might affect their routine supply of health commodities. Table 4 explores the existence of discontinuities in exposure to conflict, distance to roadblocks set by rebels and distance to regional medical stores. Geographic coordinates of conflicts in 2017 are obtained from ACLED, and the coordinates of roadblocks for taxation purposes is reported by IPIS. The results indicate statistically similar distances across the mining threshold. Lastly, the bottom part of Table 4 documents a similar stock value per capita for all other drugs across the mining threshold.

Equity of local aid. I further document how the distribution of local aid for malaria should match the needs in relation to the exposure to malaria risk. The baseline results have shown that aid for malaria remains statistically unchanged across the mining threshold while malaria risk might increase by at least 10% points in mining areas (Figure 4).

To quantify the gap in aid for malaria in mining areas, I estimate the theoretical costs that should be borne at the health facility level for the prevention, diagnosis and treatment for an additional unit of risk of malaria transmission. Using the prices of antimalarial commodities from the Pooled Procurement mechanism of the Global Fund (Figure A9 in the online appendix), the total monthly estimated cost for providing malaria treatment and prevention per capita is \$1.25.[24] Reassuringly, this estimate is

[24]The total cost per capita is decomposed as follows: ACT \$0.7, SP \$0.09, RDT \$0.25 and ITN \$0.21. To calculate it, I rely on the decomposition of the Congolese population that was taken from the United Nations World Population Prospects: 57% of adults, 25% of children between 6 and 14 and 16% less than 5. The share of pregnant women and children is estimated to be 25% (MSP, 2017). The costs associated with the prevention, detection and treatment of malaria are substantially lower than the prices paid by Congolese on the private or illegal drug market (Laokri *et al*., 2018).

TABLE 4

Robustness tests for continuity of observables across the mining border

	Linear model (1)	*Quadratic model (2)*
No. of prenatal visits		
RD Mining effect	−6.8	−43.7
Robust s.e.	67.9	69.3
Robust *P*-value	0.942	0.555
Bandwidth h (in metres)*	4,576	9,419
Observations	205	414
Population		
RD Mining effect	3,415.9	3,506.2
Robust s.e.	2,681.5	2,644.8
Robust *P*-value	0.170	0.180
Bandwidth h (in metres)*	4,436	8,865
Observations	201	393
Distance to regional medical stores (in metres)		
RD Mining effect	−50,028	−47,118
Robust s.e.	38,198	33,986
Robust *P*-value	0.122	0.096
Bandwidth h (in metres)*	4,294	9,606
Observations	188	436
Distance to road blocks (in metres)		
RD Mining effect	9,717	10,200
Robust s.e.	10,638	10,508
Robust *P*-value	0.507	0.430
Bandwidth h (in metres)*	4,379	9,125
Observations	198	412
Distance to conflicts (in metres)		
RD mining effect	−6,740	−6,299
Robust s.e.	9,223	8,638
Robust *P*-value	0.352	0.391
Bandwidth h (in metres)*	4,767	10,134
Observations	222	471
Stock value of all other drugs per capita		
RD Mining effect	−0.154	−0.158
Robust s.e.	0.151	0.150
Robust *P*-value	0.252	0.235
Bandwidth h (in metres)*	5,115	9,950
Observations	237	460

Notes: The table reports the results from non-parametric estimations of specification (1) using local linear and quadratic regressions for each outcome. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico *et al*. (2014), as well as the construction of robust standard errors *P*-values. The smoothed distribution function used is the triangular kernel. All specifications include the baseline control variables and province fixed effects.

*The bandwidth selection follows the MSE-optimal procedure proposed by Calonico *et al*. (2014), as well as the construction of cluster standard errors *P*-values.

consistent with WHO's findings for the cost of curative treatment for malaria in sub-Saharan African countries (WHO, 2015a). With a 10% points increase in mining areas, it results that local aid should rise by a minimum of $0.125 (0.10×1.25) per capita to

health facilities in mining areas to fully meet the needs related to the increased malaria risk. In comparison, the baseline estimates range between −0.038 and −0.028 (Table 2). With an average population size of 11,000 in the catchment area of the facilities in mining areas (Table A1 in the online appendix), the minimum estimated gap in aid for malaria at the facility level is then approximately $1,700 ((0.125+0.033)×11000).

VI. Discussion and conclusion

Targeting health needs is central in low-income countries with high disease burdens and limited resources. Important health gains could be achieved through a more precise allocation of resources to areas with the greatest health challenges (Bigman and Fofack, 2000). In this study, I leverage natural variation in the burden of malaria between mining and non-mining areas to estimate the response of donors to local needs. I find no evidence that aid for malaria increases with exposure to malaria risk. The finding suggests that local populations with the highest burden of malaria do not receive the highest share of aid for malaria compared to those living in neighbouring areas with reduced exposure to malaria infection. I propose three main assumptions that could explain why aid remains unchanged in regions with a high malaria risk, and discuss their validity.

First, the results support the assumption that donors may lack the necessary information on where the greatest needs are located to implement effective targeting. This is the preferred explanation given the complex situation in the region under study: armed group presence and population displacement are likely to undermine the accurate collection of information on health needs. At the same time, aid is crucial in the region to reach those in urgent need and mitigate the humanitarian crisis. Appeals for humanitarian assistance might compel donors to allocate resources in the region while information of health needs is incomplete (Easterly, 2006).

Second, corruption and embezzlement could impair aid targeting and prevent donors from reaching those with the greatest needs. Yet the close monitoring of donors' aid disbursement, particularly in challenging environments such as the DRC, should limit the risk that a significant share of aid is systematically lost. For example, regular audits and investigations are carried by USAID and the Global Fund, the two largest donors for malaria, 'to prevent fraud and misuse of funds' and set 'safeguards to improve program implementation [..], supply chain management and financial controls' (The Global Fund, 2016). The regular oversight by donors of financial aid-related activities should then limit the scope for a systematic aid loss in corruption.[25] Furthermore, the RD estimates document that health facilities in mining and non-mining areas are located at a similar distance from roadblocks set by rebel groups. It suggests that both areas should have similar exposure to the risk of local capture of aid. Taken together, the risk of losing aid in local corruption and embezzlement and causing imperfect targeting appears limited.

[25]Between 2012 and 2019, the Global Fund identified an estimated US$10 million in losses in the DRC representing only 0.9% of its total contribution to the country during the same period (https://data.theglobalfund.org/investments/location/COD).

A third assumption relates to the limited capacity of country partners. When donors administer their funds to local NGOs, difficulties experienced by the latter in implementing the programmes could result in an apparent mistargeting. A typical example includes disruptions in the supply chain of health products leading to poor availability of medicines in health facilities (Yadav, 2015). However, the RD estimates demonstrate that the number of stock-out days for each antimalarial commodity does not systematically differ among areas with varying risks of malaria transmission. This finding partially rules out the role of the supply chain of health products in explaining the difference in the stock of antimalarial commodities between local areas with varying burdens of malaria.[26] Nonetheless, additional threats to targeting related to partners remain such as lack of coordination between actors or limited capacity to absorb donors' funds. Unfortunately, it was not possible to test these possibilities in my data. In such a case, the findings would challenge the donors' decision to use non-state actors in place of the national government as the most effective way to disburse aid (OECD, 2009).

The results of this research only apply to the malaria programme in Eastern DRC, and it would be speculative to draw general policy implications. Rather, the findings underscore important research questions in conflict-affected settings where the lack of necessary data and administration support to implement aid programmes might be important barriers to making substantial improvements. Although data limitation on patients' income and wealth prevent from drawing firm conclusions on aid targeting, the findings suggest that aid could be more closely tailored to the spatial variation of malaria, and potentially health needs, in the context of fragile states. Better allocation of aid could generate health efficiency gains and reduce inequities in treatment access for patients across areas with different burdens of malaria. In cases where health information is fragmented and difficult to collect, donors could seek the engagement of local community leaders in aid targeting decisions. More research on using non-state providers as opposed to the national or local governments is also needed to quantify the benefits of the contracting approach. Finally, this study has shown the critical importance of focusing on a disease-specific programme when documenting the distribution of health resource allocation. Further research on other highly financed diseases (such as HIV and AIDS) could help to uncover the root causes of targeting deficiencies.

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[26]I cannot completely rule out the possibility that the supply chain causes more frequent disruptions in the provision of medicines in health facilities located in areas with high disease burden without causing systematic stock-outs. However, this eventuality is highly improbable: the quantities of health commodities provided to facilities could hardly remain systematically low without causing frequent stock-outs.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix A. Construction of the stock variable.
Appendix B. Comparability of mining and non-mining areas.
Appendix C. Sensitivity analysis.
Appendix D. Evidence for RD design.
Appendix E. Power analysis.
Appendix F. Data.
Appendix G. Evidence of Data quality of DHIS2.