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Are donors targeting the greatest health needs? Evidence from mining sites in the D.R.Congo

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Abstract

I examine the effectiveness of donors in targeting the highest burden of malaria in the Democratic Republic of Congo when health information structure is fragmented. I exploit local variations in the burden of malaria induced by mining activities as well as financial and epidemiological data from health facilities to estimate how local aid is matching local health needs. Using a regression discontinuity design, I find significant but quantitatively small variations in aid to health facilities located within mining areas. Comparing local aid with the additional cost of treatment and prevention associated with the increased risk of malaria transmission, I find suggestive evidence that local populations with the highest burden of the disease receive a proportionately lower share of aid compared to neighbouring areas with reduced exposure to malaria infection. The evidence of disparities in the allocation of aid for malaria supports the view that donors may have inaccurate information about local population needs.

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1 Introduction

Identifying and reaching the populations who have the most pressing health needs is essential in countries with high disease burden and limited health care resources. Donors prioritise health interventions to achieve the highest reduction in disease burden along with health equity objectives (WHO, 2015a). Targeting the highest health needs requires donors to have complete and accurate information about the distribution and intensity of local needs to make optimal resource allocation decisions in the recipient country. However, barriers to the gathering and sharing of health information are commonplace in low-income countries and may pose a threat to narrow aid targeting.

In this article, I explore donors' ability to target the highest health needs at the community level by examining how local variations in the burden of malaria affect the amount of aid allocated locally. Some researchers have already emphasised the importance of aid allocation in maximising donors' intended outcomes along with the challenges related to the identification of the greatest needs.[1] In particular, aid re-allocation to the highest needs could lead to maximum welfare improvements when donors have full observability of the need in the country. To assess the efficiency of aid targeting, analyses have been done both across and within countries (Esser and Bench, 2011; Dieleman et al., 2014; Briggs, 2018). Although these studies provide innovative methodologies to track aid resources, 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 maximises the objective function of the donors (Collier and Dollar, 2002). Second, aid could potentially improve the welfare of the beneficiaries; simply matching aid resources to the distribution of the local needs could then lead to misleading findings. Third, 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). Fourth, the existence of various forms of aid support poses a challenge to the identification of donors' funding at the subnational level.[2] 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 donor funding 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 identified through the prevention, diagnosis

[1] See for example Ravallion and Chao (1989); Besley and Kanbur (1991); Bigman and Fofack (2000) and Collier and Dollar (2002).

[2] External funding can transit through the government budget (on-budget) or be directed to local interventions (off-budget); see Van de Sijpe (2013).

and treatment of malaria cases.[3] Thereby, I can link directly health needs related to malaria with aid allocated for the disease. Second, I exploit the presence of multiple mining areas in the eastern part of the Democratic Republic of Congo (DRC) to obtain spatial variations in the burden of malaria. The existence of a dramatic increase in the risk of malaria transmission within mining areas has been well documented in the tropical medicine literature (Gallup and Sachs, 2001; Moreno et al., 2007; Vittor et al., 2009; Knoblauch et al., 2014). The spatial variations in the disease pattern prevailing between mining and non-mining areas constitute a natural experiment to analyse the geographical distribution of aid for malaria. The fact that mining sites are characterised by having, locally, the highest risk of malaria transmission essentially means that they should receive comparatively the highest share of aid for malaria. 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 considerable financial support provided by the international community to tackle the humanitarian and health crisis created a disproportionately financed health system. A striking example is found with the National Malaria Control Programme for which 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. 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 leads to geographical areas with 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. The discontinuity in the exposure to intense malaria infection at the mining threshold 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 for the disease and consequently, inform about their ability to identify the highest health needs at the local community level.

I find no evidence that donors are targeting areas with the greatest burden of malaria. I first consider whether local aid for malaria increases within mining areas and find a significant but quantitatively small increase in local aid. To assess the magnitude of these estimates, I, next,

[3]The identification of the population with the highest burden of malaria should not be prone to different meanings among donors and local governments.

explore how the increase in local aid for malaria relates to the associated costs of the additional burden of malaria in mining areas. The results offer a contrasting picture of the initial finding.

From the number of reported malaria cases at the facility level, the risk of malaria transmission increases, at least, by 7 percent in mining area. The estimated costs per capita of providing prevention, diagnosis and treatment for the additional burden of malaria are then compared to the increased aid for malaria in mining areas. I find that more than one third of the costs required to address the additional burden of malaria transmission are not financed by donors, suggesting that local aid is disproportionately distributed among health facilities across mining areas and non-mining areas. The estimates are robust to a number of sensitivity checks, including different RD 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 (Odokonyero et al., 2015; Borghi et al., 2017; Kotsadam et al., 2018; Briggs, 2018).

Furthermore, the decomposition of aid allocation between curative treatment, prevention and diagnosis reveals disproportionate funding patterns. A malaria-preventive commodity mostly drives the increase in local aid for malaria within mining areas for pregnant women, whilst aid for other commodities is either small or unchanged. Overall, these findings provide some suggestive evidence that donors have limited capacity to target aid to beneficiaries with the highest health needs.

This analysis contributes foremost to the literature on resource allocation and aid effectiveness. Donors' imperfect observability of local needs is a well-known problem for aid targeting (Besley and Kanbur, 1991) that has been addressed either by using a proxy based on a set of observable household characteristics for the unobservable outcome (proxy-means testing) or by delegating the identification process directly to local community leaders when essential information is missing (Coady et al., 2004; Galasso and Ravallion, 2005; Alatas et al., 2012). My work complements these studies by offering an innovative approach that exploits the geographic location of mines to determine locally the highest health needs and evaluate the precision of aid targeting.

My research also provides a novel contribution to the theoretical literature on aid effectiveness as it offers a unique opportunity to test empirically one of its main assumptions. Specifically, since aid ineffectiveness is widely seen as the consequence of agency problems between the donor and the recipient (Azam and Laffont, 2003), one solution consists of implementing an aid contract that incentivises the recipient to comply with the donor's poverty reduction objectives. This theoretical setting hypothesises that the donor has perfect information about the needs in the country. My results challenge this assumption by arguing that donors might only have limited capacity to collect local health information due to factors hampering the circulation of information from local communities to the central government and donors.[4]

[4]These findings are consistent with the recent experimental literature on the imperfect observability of local needs to donors, which also exploits location-specific data. See BenYishay and Parks (2019) for an excellent review of these studies.

The remainder of the paper is organised as follows. Section 2 provides background on the financial and epidemiological situation in the DRC. Section 3 describes the data and the geographical analysis. Section 4 presents the empirical analysis related to the impact of mines on aid for malaria to health facilities and introduces the regression discontinuity setting. Section 5 describes the results and section 6 discusses policy implications and concludes.

2 Background

2.1 Malaria situation and Artisanal Small-scale Mining

Malaria Situation - Malaria represents a critical public health challenge in the DRC. Almost the entire country is under 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). Malaria is mostly caused by *Plasmodium falciparum* in the country, a parasite transmitted through the bite of mosquitoes. National strategies to control and reduce the spread of the disease consists of 1) prevention through the use of insecticide-treated mosquito nets (ITNs), Indoor Residual Spraying (IRS) and sulfadoxine-pyrimethamine (SP), a chemoprevention administered to pregnant women and children less than five years old ; 2) identification of malaria cases through light microscopy or rapid diagnostic tests (RDTs)[5]; 3) antimalarial treatment with artemisinin-based combination therapy (ACT), the recommended first-line treatment for uncomplicated malaria cases.[6]

Mining Sites - Artisanal and small-scale mining (ASM) refers to informal mining work involving minimum use of mechanical tools (Hentschel et al., 2002). The activity is estimated to be responsible for 90 % of the total mineral production in the DRC (Andrews et al., 2008). Owing to its informal nature, artisanal mining poses significant health and safety hazards. The use of mercury for gold extraction and the presence of dust and fine particles in the air surrounding mines expose miners to unsafe working conditions. Furthermore, mining activities rely on the use of abundant water to filter the extracted minerals, leaving multiple open pits with stagnant water. Consequently, mines provide extensive breeding sites for mosquitoes which could increase the risk of malaria transmission among populations living and working in proximity to mines (Staedke et al., 2003). Multiple evidence of an increased malaria prevalence within mining areas and around mosquito breeding sites, in general, supports this fact (Moreno et al., 2007; Vittor et al., 2009; Knoblauch et al., 2014).

[5]The malaria diagnosis relies on two possible tests: a microscopic identification of the malaria parasite and a Rapid Diagnostic Test (RDT). The former test requires extensive expertise and is usually done in clinical centres and hospitals. On the other hand, RDTs exist in kit forms and do not require extensive expertise to perform the test and interpret the results. It is therefore mostly used across health facilities in the DRC.

[6]In 2005, the DRC adopted artesunate and amodiaquine (ASAQ) as the first line treatment for uncomplicated malaria cases, and the combination of artemether and lumefantrine as the second line treatment (MSP, 2011).

2.2 Health funding landscape in the DRC

Health Sector - The Congolese public health sector is divided in three decentralised 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 and laboratories as well as 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 health care in the DRC is low in the public health sector, with a utilisation rate of health services of 30% (World Bank, 2015).

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 aid to finance the provision of health care services.[7] The presence of multiple donors affects disproportionately the financing of the health sector, with some disease programmes almost entirely funded by the international community (such as HIV, Tuberculosis or Malaria). 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). The three major donors for malaria control activities in the DRC are the Global Fund to Fight AIDS, Tuberculosis and Malaria, 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.[8]

According to national guidelines, prevention, diagnosis and malaria treatment in public health facilities is free of charge for patients. But due to low salary and frequent disruptions in salary payments, health workers charge, in practice, small user fees on malaria patients.[9]

2.3 Evidence of Local Malaria Funding

This section presents the proposed strategy to locally estimate foreign aid allocated to the Malaria Control programme.

Lack of information about donors' funding at the local level is a major barrier to quantify the amount of foreign aid that is allocated to each health facility. One reason behind this data limitation issue is that donors choose either to allocate funds to national disease programmes

[7] 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).

[8] Other partners for the malaria control programme include the World Bank, the World Health Organisation and UNICEF whose funds correspond to more general support for the health system of the country.

[9] Consultation fees represent about 30% of out-of-pocket expenditures for Congolese patients, whilst the average total medical cost for outpatient care is approximately $7 (Laokri et al., 2018). 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. These fees also tend to increase in urban areas and with the size of health facilities (Bertone et al., 2016).

that transit through the government budget or to directly target health interventions at subnational levels (through the support of local implementing partners). It is, therefore, practically impossible to distinguish external aid from domestic spending at the health facility level. However, the financing of the health system of the DRC offers a unique setting to circumvent this identification problem. The Malaria Control Programme is almost entirely funded by donors (see figure 1) which implies that antimalarial commodities in public health facilities are almost exclusively provided by external resources.[10]

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 (whilst 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.[11]

However, I restrict the data sample to observations that are located within a short distance of the mining threshold and I argue 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 (governmental payment distributed to all health workers) to health workers are provided by the government (mostly through donors' support) based on a salary scale.[12] 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.[13] Second, all health commodities are centrally procured by a national organisation that manages and coordinates the pool procurement of pharmaceuticals, their distribution and storage in regional warehouses, and their supply to health facilities.[14] The expenditures related to the transport and storage of health commodities are therefore closely tied to the geographic location of the health facility. Since my data sample spans health facilities over a

[10]The low contribution of government spending to the malaria control programme (figure 1) is mostly dedicated to cover management operations at the central level (MSP, 2017), and so its contribution to the local provision of commodities should be minimal. The proportionately low government spending also avoids the risk that donors may adapt their aid allocation to specific areas in response to government health investments or *vice versa* (Öhler et al., 2017). Another concern is that no information is available on patients' purchase of antimalarial medicines through retail drug stores. These expenditures may come from antimalarial medicines bought from the illegal pharmaceutical market ((Björkman Nyqvist et al., 2012);Cohen et al., 2015). However, I argue that the access to health products on illegal markets should not systematically differ in mining and non-mining areas, so its omission should not systematically bias the results.

[11]Acoording 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 management and organisation of the malaria programme (The Global Fund, 2016).

[12]Note that health workers can also receive top-up payments from donors, and Bertone et al. (2016) find that they represent a relatively small share of total income of health workers in the DRC (an increase of $17 which represents about 10% of the total income of nurses who compose the vast majority of health workers in the sample).

[13]In the estimation results, I control for the number of health workers and their qualification (nurses vs. doctors)

[14]The Congolese organisation that controls the national procurement of drugs (*Federation of Central Procurement in Essential Medicines*) works in close collaboration with the Global Fund to obtain negotiated prices of health commodities with manufacturers (see Annexe 14).

relative small geographic area compared to the country size (as shown in 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 percent 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.

3 Data

The data used in this research is 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 resources information. The DHIS2 contains data on all health facilities in the DRC regardless of the type of structures (hospital, health centres and health posts) and includes both private and public health facilities, as well as faith-based facilities.[16] However, I restrict the data sample to rural health facilities located in the Eastern DRC, where information on mines is available. In total, there are 1,511 observations located in six provinces: North and South Kivu, Maniema, Ituri, Tshopo and Tanganyika (see figure 5).

Information on the stock level of commodities is reported at the beginning of each month (and thus before the consumption of commodities) from January to December 2017.[17] Due to inconsistent procurement of commodities to health facilities, I average monthly the stock level of commodities over the entire year of 2017.

Antimalarial commodities correspond to all malaria-related health products that are used for diagnosis (RDT), treatment (ACT) and prevention (SP and ITN). The estimated stock value is then calculated from the stock quantity of each antimalarial commodity at the facility level and its their prices. The latter is obtained from the reference pricing list of the Pooled Procurement mechanism established by the Global Fund (see Annexe 14).[18]

[15] The DHIS2 database is used by the Ministry of Health to monitor health service delivery, measure achievement and track health progress at the difference levels of health care 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] The earliest information on health facilities starts in 2015 with the initial implementation of the DHIS2; however, the complete coverage was only reached by the end of 2016.

[18] The Pooled Procurement mechanism set by the Global Fund aims to stabilise prices and ensure market sustainability of health commodities by pooling demand of countries that participate to the programme (The

Note that I provide in annexe 6 an extensive discussion on the data quality of DHIS2 in the DRC and provide evidence of its validity for this analysis.

Mining areas. Obtaining precise information on the burden of malaria at the local level is a challenging exercise. The Malaria Atlas Project provides a measure of the risk of malaria transmission based on the suitability of air temperature at national and regional levels (Hay and Snow, 2006). However, this information does not permit to identify the local needs at more granular levels, such as local communities. The finest source of information comes from the 2013 Demographic Health Survey (DHS) in the DRC, whereas information on local malaria funding is only available from January 2017. Furthermore, the GPS location provided in the DHS are randomised within a 5 km area for confidentiality purposes. This randomisation poses a risk of misidentification of the burden of disease when matched with the precise GPS position of health facilities. I adopt, therefore, a novel strategy that identifies the highest burden of malaria based on the presence of mines.

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.[19] The dataset contains information on the geo-location (longitude and latitude) of 3,687 mining sites artisanal mining sites in the entire provinces of North and South Kivu, as well as in the bordering health zones in the provinces of Maniema, Ituri, Tshopo and Tanganyika (figure 5).

Geocoding of health facilities. The geographic locations of health facilities are only partially provided by the DHIS2. To complete the geocoding of the remaining health facilities in the sample, I triangulate information from the 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. ReliefWeb provides a list of geocoded health facilities in North and South Kivu related to OCHA's humanitarian activities and OpenStreetMap is an open database routinely enriched by field observations, satellite images and integrated datasets. Overall, the data sample comprises 1,511 health facilities, as shown in figure 2. Distances between health facilities and their closest mines are obtained from the use of geostatistical tools available in Geographic Information System (GIS) software.[20]

Furthermore, data on elevation and terrain features were obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images.[21] Elevation information is provided at a high spatial resolution (3 arc-second resolution or approximately 90 metres) which makes

Global Fund, 2018).

[19] IPIS research teams worked in collaboration with the Congolese Ministry of Mines, the Congolese Public Service for Assistance to Artisanal and Small-scale Mining, the Congolese Mining Register, the Provincial Mining Divisions and representatives from local civil society organisations. See Weyns et al. (2016) for a detailed description of the data and collection process.

[20] ArcGIS 10 and QGIS 2.8 have been used for this exercise.

[21] Terrain's elevation data is produced from radar interferometry technique where a satellite equipped with the instrument collects data to generate a digital elevation map of the Earth (see https://www2.jpl.nasa.gov/srtm/.

it possible to determine the precise geographical features of each observation in the sample. In particular, distances from mines to health facilities are calculated based on the elevation and surface features in order to obtain more realistic distance measures than the straight line Euclidean distance (see figure 4).[22]

Table 1 presents summary statistics for key health facility characteristics in mining and non-mining areas and their difference in means with the full sample. Tables 2 and 3 restrict the sample to observations that fall respectively within a 8 and 3 km window around the threshold. Columns (1-3) and (4-6) of each table show the number of observations, sample mean and robust standard deviations for non-mining and mining areas respectively. Columns (7-9) indicate the difference in means between non-mining and mining areas, the robust standard errors for the difference and the p-value of the test of equality of the mean coefficients between the mining and non-mining samples. Whilst the baseline characteristics present several statistically significant differences using the full sample of observations, these differences tend to disappear as the sample shrinks to smaller areas around the mining threshold. In particular, the difference of antimalarial stock value is highly significant with the largest window selection but it becomes insignificant as the sample reduces to closer distance from the mining area threshold. The variations in these differences-in-means with the window selection underline the importance of identifying a clear strategy to determine the causal effects of mining areas on local aid for malaria.

4 Empirical framework and estimation

4.1 Setting the RD design

To test whether local aid received by health facilities reflects the burden of malaria among the populations in their catchment areas, I rely on the stock value of antimalarial commodities. However, locally assessing the risk of malaria transmission is a challenging exercise. Despite the fact that health facilities report the monthly number of malaria cases that could be used to determine the location of the highest burden of the disease, the identification of malaria cases relies on the availability of RDTs that are financed by external funding. An increase in the reported number of malaria cases may therefore simply reflect a higher stock of RDTs in the health facility. Furthermore, there could also exist some inconsistencies in the reported number of malaria cases across health facilities that would affect the estimation of the distribution of the

[22]Satellite images of light density from the Suomi-NPP Visible Infrared Imaging Radiometer Suite (VIIRS) provides a useful source of information on local economic activity (see for examples Henderson et al., 2012; Michalopoulos and Papaioannou, 2013). The location of economic activity in the vicinity of mining areas could potentially correlate with lower disruptions in the provision of health commodities nearby health facilities through better road access or higher consumption of commodities if patients have higher incomes. However the resolution of the satellite images (approximately 1 km) provides a noisy estimate of the location of economic activity compared to the precise data-location of mines and health facilities collected in this study. Furthermore, all mines are located in rural areas where night light density is low, particularly in this region of Africa. Hence, using night light density might not bring a useful sense of the local variations in economic activity around mining sites and health facilities.

burden of malaria. To overcome these issues, I employ an instrument that correlates with the risk of malaria transmission without being caused by external funding or data quality reporting. Following the public health literature on malaria and artisanal scale mining, I propose to use mining areas as the identification strategy.

Since mining areas are located where the exploitation of natural resources is feasible, it constitutes a natural random selection framework where other local characteristics between mining and non-mining areas are unlikely to vary discontinuously at the mining boundary. As a result, the exposure of health facilities to the burden of malaria is a deterministic and discontinuous function of whether a health facility belongs to a mining area. To test whether the donors are targeting the highest needs, I use a Regression Discontinuity (RD) design that evaluates the effect of mining areas on aid for malaria to health facilities.

The central idea behind the RD design is to compare the treatment outcome of units just above and below a threshold, denoted c. This threshold is based on a running variable (or score), X, which is, in this case, the distance from a health facility to its closest mine. The treatment group corresponds to health facilities located within a close distance to mines (below the mining threshold) whilst health facilities located above the mining threshold form the control group. The observed outcome is local aid for malaria that is captured by the stock value of antimalarial commodities, and the border of the mining area constitutes a threshold that generates a discontinuous probability of getting infected with malaria. I hypothesise 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. In this setting, the RD framework requires that all other factors influencing the burden of the disease are smooth across the threshold (Hahn et al., 2001). That is to say, the risk of malaria transmission and aid for malaria on either side of the threshold should only differ across health facilities in the probability of being in a mining area.

4.2 Estimation Framework

The RD design uses the distance from a health facility to its corresponding mining area threshold as the running variable. The estimation results provide an average RD treatment effect of mining areas on local aid for malaria. Specifically, the causal mining effect is estimated using the following specification

$$Y_i = \alpha + \beta_1 mine_i + g(\widetilde{X_i}) + \beta_3 z_i + \epsilon_i \tag{1}$$

where $\widetilde{X_i}$ is the centred variable X_i at the cutoff point ($\widetilde{X_i} = X_i - c$) and $mine_i$ is an indicator for mining area ($\widetilde{X_i} \leq 0$). The outcome Y_i corresponds to aid for malaria to health facility i, and $g(\widetilde{X_i})$ is the RD polynomial which controls for smooth functions of geographic distance from a mine to its closest health facility i.[23] The key parameter of interest is β_1, which captures

[23]The local Linear Regression is used in the baseline results, where $g(\widetilde{X_i}) = \delta_1 \widetilde{X_i} + \delta_2 mine_i \widetilde{X_i}$. 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 results with a cubic model that provides a more flexible form of the

the RD treatment effect. 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. The vector of covariates z_i includes geographic characteristics for facility i: elevation, slope, distance to the closest regional distribution centre of health commodities, distance to armed conflicts[24] and the number of mines in the vicinity of the facility.[25] 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 1); using chordal or relative Euclidean distances might then lead to misleading results.[26] I rather rely on a more realistic distance based on slope and surface elevation using information collected from NASA's Shuttle Radar Topography Mission.[27]

The RD approach requires that all relevant factors, besides treatment, vary smoothly across the mining threshold. The underlying assumption is that health facilities within a small bandwidth on either side of the threshold should only differ in their probability of receiving malaria cases for treatment and not in their environmental conditions or inherent capacity to treat patients. I assess the validity of this assumption in the results section 5.

For robustness checks, I also present both parametric and nonparametric estimation of the causal effect of mining area on local aid. The parametric approach assumes a functional form of the regression function. Define the conditional expectation of the outcome given the distance variable on each side of the threshold as follows

$$\mathbb{E}\left[Y_i(0) \mid X_i = c^+\right] = g(X_i) \tag{2}$$

$$\mathbb{E}\left[Y_i(1) \mid X_i = c^-\right] = \beta_1 + g(X_i) \tag{3}$$

Under the parametric approach, the functional form of $g(.)$ is assumed to be known and the estimate of the treatment effect is given by the least-square estimates of β_1. Using the full data sample for the estimation of the RD effect around the threshold is not well-suited to perform an RD analysis, as its internal validity relies on the comparability of observations around the boundary: a global polynomial may produce estimates sensitive to observations far away from the threshold (Lee and Lemieux (2010); Gelman and Imbens (2018)). Hence, I restrict the data sample to small neighbourhoods around the threshold to ensure the comparability of units on each side of the threshold.[28]

Controlling parametrically the function form of the regression function may, however, pro-

polynomial.

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

[25] The purpose of including baseline covariates is only to explore the sensitivity of the results, as they should not affect the estimated discontinuity in a RD setting (Lee and Lemieux (2010); Calonico, Cattaneo, Farrell, et al. (2018)).

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

[27] Slope was calculated from this elevation using ArcGIS 10.4.1; the distance based on slope was calculated from the *path distance* function in ArcGIS.

[28] In the results section, I show that the estimates of the RD effects are robust to various window selections.

duce biased estimates if the approximating function is insufficiently close to the true function. Thus, most RD studies employ a nonparametric estimation through local modelling that fits at any given point x_0 a parametric function fitted only to a fraction of observations in a neighbourhood of x_0 (Fan and Gijbels, 1996). The idea behind this approach is to locally approximate the unknown conditional mean function by a local polynomial function of degree p, using Taylor's expansion in the neighbourhood of interest (under the continuity assumption of the function $g(.)$).

4.2.1 Polynomial choice and bandwidth selection

The choice of the polynomial order p and the neighbourhood selection (or bandwidth h) around the cutoff are critical in determining the treatment effect. High-order polynomials have the potential to increase the accuracy of the approximated function for a given bandwidth, but it comes at the cost of high variability; they could also lead to approximations errors near the cutoff if they over-fit the data (Gelman and Imbens, 2018). Similarly, to ensure that the characteristics of the treatment and the control group are almost identical, the units should be selected as close to the threshold as possible given the data availability. Whilst smaller bandwidths reduce the misspecification bias, they also increase the variability of the estimator. The common practice is then to use a low polynomial order and control the accuracy of the approximation by the bandwidth (Gelman and Imbens, 2018). In particular, Hahn et al. (2001) recommend using the local linear regression due to its better boundary bias properties. In the following section, I report the baseline results with the local linear model and test their robustness with a cubic polynomial.

The local linear regression procedure consists of estimating two weighted least squares regressions on each side of the cutoff. To obtain the weights, I use a triangular kernel where weights decay with the distance from the cutoff point.[29] In addition, I follow Calonico, Cattaneo, and Titiunik (2014) who propose a methodology 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".

4.3 Mining threshold

As described earlier in the text, I cannot rely on the number of reported malaria cases to estimate locally the risk of malaria transmission due to donors' financing of RDTs.

Since mining areas create a conducive environment for malaria proliferation, the risk of malaria transmission in the catchment area of a health facility should be a function of the

[29] Following Imbens and Lemieux (2008), the estimation results should be less sensitive to the choice of the kernel function than to the bandwidth selection.

distance between the facility and its nearest mine. I define a mining area as the maximum distance from a mining site that miners are travelling to seek malaria treatment. This distance is crucial in my empirical strategy as it will be used to determine the mining threshold separating the control and treatment groups.

I first exploit the findings from the literature on patients' utilisation of health services in rural areas. Stock (1983) shows that in Nigeria 89% of patients in rural health centres are coming from a distance that is less than 10 km. In the malaria context, Noor et al. (2003) explore the patient's travelling distance to health facilities in Kenya and find that the median distance is 8 km for patients 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.[30]

Second, I examine the distance that separates mining sites from the living place of miners to account for the possibility that a health facility and a mining site are situated in opposite directions from the location of a miner's household. 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. More recently, Faber et al. (2017) exploit data on miners from a random sample of 150 mining areas in the DRC and show that that the average traveling distance of miners from their household is 7 km.[31] Based on these findings, I hypothesise that the maximum distance separating a mine to a health facility with a significant share of miner patients should range between 13 and 15 km.

Next, I analyse how this range of mining thresholds fits my data sample. Specifically, the threshold should indicate a discontinuity in the burden of malaria. I define malaria prevalence as the mean share of malaria cases reported by a health facility out of the total population of its catchment area. Figure 6 presents the malaria prevalence as a function of the distance from a health facility to its closest mining site. Each point plots an average value within a bin that represents a 1 km interval. Figure 7 shows the non-parametric estimations of malaria prevalence conditional on the distance to the closest mine, using a kernel-weighted local polynomial regression of order 1. In both figures, the malaria prevalence is found to fluctuate within a constant interval that ranges from approximately 12% to 18% with the first ten kilometres from the mining sites. A sharp decrease in the burden of malaria occurs at a distance lying between 14 and 15 km from mines, where the malaria prevalence falls by more than 5%. The fluctuations in the disease prevalence are not recovering from the decrease beyond this point where the 95% confidence interval ranges from about 7% to 14%, which suggests a reduced burden of malaria for all health facilities located beyond 15 km. This visual evidence is remarkably consistent with

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

[31] 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 road network in the Eastern DRC, where my data sample is, should reduce the risk of having large travelling distance among miners.

the findings from the literature.[32] I, therefore, select the midpoint distance between the two sides of the jump as the mining threshold, corresponding to 14.5 km. The selected threshold should ensure that patients are not seeking health services above or below this boundary. In the next section, I also assess the robustness of the results when varying the mining threshold.

An additional concern relates to the potential smooth geographic variations in aid for malaria. As argued above, the discontinuity in the burden of malaria at the boundary of mining areas should induce a change in donors' behaviour if they are accurately targeting the highest needs related to malaria. However, donors might also smoothly respond to the discontinuity in the risk of malaria if the density of health facilities is high at the boundary of mining areas. One explanation is that other factors besides the distance of a health facility from a mine might play a role in the decision making of malaria patients when they select a facility (such as quality of health services). To explore this possibility, I examine the geographic distribution of health facilities around the mining threshold. Figure 9 depicts the cumulative distribution function of health facilities conditional on the distance to the nearest facility. The data sample is restricted on health facilities that are located within 4 km from a mining threshold(blue dashed line) and within 10 km from the threshold (red line). The graph reveals the scattered distribution of health facilities in the Eastern DRC. The minimum distance between two health facilities is higher than 5 km for more than 70% of health facilities located within 10 km from the threshold, and almost 50% of health facilities within 4 km from the threshold have the closest facility located beyond 10 km. Only 10% of facilities are separated by less than 3 km. Under such conditions, malaria patients may have very limited possibility to select a health facility on other criteria than distance. Similarly, the probability of occurrence that two health facilities are separated by only a small distance across the mining threshold is very low. This evidence suggests that donors should simply not have the opportunity to smooth aid allocation within small distances across the threshold.

In a sharp RD design, the probability of getting malaria case in health facilities should fall abruptly from 1 to 0 at the mining threshold, an assumption that is unlikely to hold since other external factors affecting the risk of malaria transmission also exist in non-mining areas and not everyone is at risk of getting infected with the disease within mining areas (for example, some individuals may naturally acquire immunity to malaria due to long exposure to infectious mosquito bites). Yet, the disproportionate burden of malaria induced by mining areas creates a discontinuity in the share of malaria cases around the threshold, as shown previously. To be more precise, I redefine the problem as follows: let p be the share of malaria cases out the total population in the catchment area of the health facility, and p_m the minimum share of malaria cases that characterises a health facility located in an area with high burden of malaria. I further assume that the probability that a facility receives a minimum share p_m of malaria cases out of the total population that it serves is uniformly distributed within a mining area.

[32] Although this distance falls within a similar range to the findings from the literature, the concern related to the potential endogeneity issue caused by the use of RDTs remains. In the result section, I further discuss about this concern when presenting the results of the decomposition of the RD effects by commodity.

The uniform distribution can be a good approximation of the true probability distribution if the latter does not decrease significantly between a mining site and its corresponding threshold. This assumption is supported by the fact that the risk of malaria transmission by mosquito bites is significantly higher in the presence of mosquito breeding sites such as mines, leading to "hotspot" areas where the disease is endemic (Carter et al., 2000).[33] As a result, all neighbouring populations of mining sites that fall under mosquito flight range distances are intensively exposed to mosquito bites; within small geographic distances from the breeding spots, the risk of malaria transmission should be high and spatially homogeneous.

It follows that

$$Pr(p \geq p_m \mid Mine = 1) = 1$$

and

$$Pr(p \geq p_m \mid Mine = 0) = 0$$

where $Mine$ is an indicator for mining area. This setting forms a sharp RD design where only units located below the threshold (mining area) receive the treatment (malaria cases greater than p_m).

Finally, I remove hospitals from the sample selection as patients tend to travel more distance to hospitals than to smaller health centres (Stock, 1983). The risk is that they may invalidate the choice of the threshold if patients from mining sites seek treatment in non-mining areas. In addition, the National Malaria Programme indicates that malaria curative treatments in hospitals should primarily relate to severe malaria cases whereas health centres should offer treatment for simple malaria cases (MSP, 2011). This corroborates with the fact that all health facilities in the sample have stocks of antimalarial commodities to diagnose and treat simple malaria cases. As a result, I hypothesise that patients should not seek treatment in a hospital when they have symptoms related to simple malaria case.[34]

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 on the comparability of the treatment and control groups if mining areas are mostly deprived of children. Although there is imprecise information on child labour in mines, recent evidence suggests that children in the DRC may often engage in mining activities, regardless of international labour standards on child labour (Faber et al., 2017).[35]

[33] To be precise, (Carter et al., 2000) show that the distance from the breeding sites where the risk of malaria transmission is the greatest ranges from 2 to 3 km

[34] A caveat is that the existence of user fees could also play a role in the decision of patients to seek treatment to a health facility. Unfortunately, no information on setting user fees in health facilities in these regions was found; I can, thereby, only assume that user fees should not vary significantly among public health facilities within small geographic distances.

[35] The Multiple Indicator Cluster Survey (MICS) conducted in the DRC in 2010 reveals that more than 60% of children in Eastern DRC are engaged in labour activities including mining. More recently, Faber et al. (2017) use a survey from a random sample of 150 mining areas in the DRC and find that about 13% of miners were aged below 18.

5 Results

Before presenting the estimation results for the effects of mines on local malaria funding, 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.

5.1 Validity

The assumption of the RD design would be violated if health facilities can manipulate the running variable, the geographic distance from the health facility to its closest mine. However, this assignment does not leave much room for strategic behaviour as most of artisanal mining activities should be more recent than the presence of health facilities.[36] To investigate the possibility of manipulation of the running variable, McCrary (2008) suggests to examine the distribution of units on both side of the threshold: a systematic manipulating behaviour would be revealed by a peak in the distribution of units on one side of the threshold as health facilities select their preferred group. The objective of the test consists of identifying a discontinuity in the density of health facilities around the threshold that would indicate that units are altering their assignment. Figure 8 presents a visualisation of the density function of the running variable, which does not reveal obvious discontinuity around the threshold. 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.

To formally assess the validity of the continuity assumption, I also perform several density continuity tests of the running variable based on a data-driven procedure proposed by Cattaneo et al. (2017) to explore the possibility of self-selection of units around the threshold. Table 4 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 the choice of the bandwidth (in metres) on each side of the threshold, columns (3) and (4) indicate the number of observations used and the last column gives the p-value of the test. I perform the test using two different MSE optimal bandwidth on each side of the threshold (Cattaneo et al., 2017) 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 results fail to reject the null hypothesis of the continuity assumption.

The falsification (or placebo) test provides further evidence about the plausibility of the identification strategy. Placebo covariates are the pre-intervention (or predetermined) covariates that should not be affected by the mining area under a valid RD design. For each of these covariates, I perform a local polynomial regression where the predetermined covariate is the outcome variable, in order to test the existence of an RD treatment effect. Figure 11 provides a

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

visual effect of the mining area on the predetermined covariates, where the running variable is the distance to mines centred around the threshold (mining and non-mining areas corresponds respectively to the right and left hand side of the threshold). Importantly, these graphs do not present visual evidence of a discontinuity between mining and non-mining areas for each of the predetermined covariates.

5.2 Mining effect on local malaria funding

Table 5 reports the parametric estimates of the effect of mining on the outcome of interest and the placebo outcomes from equation (1). Columns (1) and (2) report the OLS estimates of the RD treatment effect on local aid for malaria using a linear model in distance. The corresponding window selection restricts health facilities to be located within 3 km from the mining threshold. Columns (3) and (4) present the OLS estimates when health facilities fall within 8 km from the threshold, and I use a cubic polynomial model to give more flexibility in the approximation of the regression function as the latter spans more observations. For each window selection, I explore the sensitivity of the results to the inclusion of baseline covariates.

As expected in a valid RD design, the coefficient estimates are not affected by the covariates whilst the precision slightly improves. The RD estimates on local aid for malaria indicate a significant positive effect of mining areas that is stable across the window selections. Specifically, the presence of mines induces an increase in local aid per capita between \$0.06 and \$0.07 at the health facility level either when facilities are restricted to be near the threshold (less than 3 km) or further away (within 8 km); these effects are statistically significant, even with the largest window. With an average local population of 10,000 in their catchment areas, health facilities within mining areas receive an additional aid for malaria that ranges between \$600 and \$700 per month.

The bottom part of the table provides the results of placebo tests which investigate the presence of a mining effect on the outcomes of four pre-determined covariates: total expenditures, total revenue, number of health workers and number of births per health facility. Selecting these covariates enables to test the existence of significant discontinuity across the mining threshold in some of the leading features of health facilities' performance that could relate to local aid absorption capacity. Expenditures and revenue capture the financial dynamic of health facilities whilst the number of births and the number of health workers can capture the ability of health facilities to attract and treat patients respectively. Importantly, these indicators could be causal factors for local aid targeting if donors are able to identify health facilities' characteristics. A systematic difference in these placebo covariates between mining and non-mining areas would then invalidate the RD design. However, the reported p-values indicate that mining areas have statistically insignificant effects on these placebo outcomes.

Table 6 documents the non-parametric estimates. The RD treatment effect corresponds to the difference of the estimates of two locally weighted regressions on each side of the cutoff using a triangular kernel function. Following Calonico, Cattaneo, and Titiunik (2014), the reported

results are based on robust confidence intervals and MSE-optimal bandwidth.[37] Column (1) estimates the baseline regression on the sample defined by the MSE-optimal bandwidth and using a local linear polynomial in distance to the threshold. Column (2) adds baseline covariates corresponding to geographic characteristics (elevation and slope) and the number of mines in the surrounding area of the health facility. Columns (3) and (4) replicate the first two columns using a local polynomial of order 3.

The estimates of the contribution of mines on local aid for malaria are all statistically significant and consistent with the parametric results, ranging from \$0.06 to \$0.07 per capita. Once again, the bottom part of the table documents the results of the placebo tests on the predetermined covariates and provide evidence of the validity of the RD design.

5.3 Sensitivity analysis

Choice of neighbourhood. Although the estimates of mining areas on local aid for malaria are consistent across both parametric and non-parametric approaches, they might be sensitive to the choice of neighbourhood. In particular, choosing smaller bandwidths has the advantage of reducing the misspecification error related to the approximation of the true function around the threshold, but it comes at the price of greater variability of the RD estimate. The first two graphs in figure 12 present the sensitivity of the coefficient of aid for malaria to the bandwidth selection and the polynomial order in the non-parametric approach.[38] The bandwidth selection following Calonico, Cattaneo, and Titiunik (2014) is referred as "CCT" on the x-axis of the first graph, and is also used to obtain the RD estimates for varying polynomial orders in the second graph. These graphs reveal that the estimates are remarkably constant across varying neighbourhoods around the threshold and specification models.

Mining threshold. The third graph in figure 12 presents the sensitivity of the RD estimate to the choice of the threshold. This exercise allows to test the validity of the 14.5 km mining threshold described in section 4 and enables to estimate an upper bound on the discontinuity effect on antimalarial stock value by varying the threshold distance between mining and non-mining area. As expected, the RD coefficient estimate is sensitive to the location of the threshold as the latter is a critical element of the RD design. The variations of the coefficient estimate provide suggestive evidence for the validity of the 14.5 km threshold selection. The RD estimates are alternately positive and negative but centred around zero when the threshold is below 14.5 km, that is, supposedly located within the mining area. This finding is consistent with the assumption that the mining border is at least located at a 14.5 km distance from the mine: given the uniform distribution of the burden of malaria within

[37] The MSE-optimal bandwidth selection and point estimators are specifically chosen to include covariates (see Calonico, Cattaneo, Farrell, et al. (2016) who propose efficient driven methods to incorporate covariates in the RD design).

[38] The sensitivity analysis leads to similar results with the parametric approach.

the "true" mining area, there should be little variations in aid for malaria between the health facilities of these areas. Thus, the average difference of aid for malaria between the treatment and the control group conditional on the distance from the mine should not be systematically positive or negative when the threshold of the RD design is located within the "true" mining area. Similarly, for every threshold located beyond the "true" threshold of the mining area, the burden of malaria should decay gradually with distance as the mining effects shade off. The RD estimates should once again be centred around zero, assuming no other external factors would cause a systematic difference in aid for malaria between the treatment and control group. The point estimator of interest is then located at the "true" mining area threshold, for which the RD estimate should reach its maximum value: if the treatment and the control group are correctly identified, the RD strategy based on the "true" threshold is cleared from any unit that would incorrectly be assigned to the treatment or control group, causing a downward bias estimation of the RD effect. The bottom graph in figure 12 indicates that the upper bound of the RD estimate is obtained with the 14.5 km threshold which has the highest point estimator and is the only estimate whose 95% confidence interval is entirely positive.

Aid targeting within mining areas. Donors could also perfectly observe the distribution of the needs within a mining area and decide to restrict the allocation of malaria resources to the closest health facilities from mining sites.[39] This donor's strategic decision could have detrimental implication on the availability of care in health facilities away from the mining site, but it could arguably ease the targeting approach if mining sites have better road access within mining areas or if donors choose to strictly targeting miners. Importantly, this assumption would explain the relative small difference that is observed in aid for malaria between health facilities around the mining threshold. I explore this hypothesis in figure 13 by analysing how aid for malaria at the facility level relates to the distance to its closest mine. The figure shows the non-parametric estimations of local aid conditional on the distance from a health facility, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The y-axis represents local aid for malaria per capita at the health facility level and the x-axis corresponds to the distance from the health facility to its closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients. The plot shows a relative constant share of aid for malaria in health facilities located within mining areas, independent of the distance from the mine. This graph, therefore, suggests that there is no evidence that donors choose to target the closest health facilities around mining sites.

[39] As discussed above, the burden of malaria should be equally distributed within a mining area so this donor's approach would entail inequalities in treatment access among patients within the area.

5.4 Decomposition by commodity and additional tests

I now turn to the decomposition of the mining effects by aid allocated to each antimalarial commodity. The baseline results, presented above, focus on all commodities to locally capture the amount of aid for malaria. However, each commodity has a specific role in tackling the disease burden, which can be decomposed in three sub-categories: prevention, identification and curative treatment. The aid decomposition enables to examine how the burden of malaria affects the allocation of aid resource to each of these sub-categories.

Figure 10 provides a visual discontinuity on the stock value of ACT and SP against the distance to the mining threshold in panel A and B respectively. Both plots fit a local cubic polynomial in distance; the jump in outcome at the threshold appears much larger for the stock value of SP than ACT, although in both cases, the effects fade away with distance.

Table 7 reproduces the table with the parametric regressions presented for the effects on local aid for malaria. Column(1) corresponds to the OLS estimates of the mining area effects on each antimalarial commodity using a 3 km window around the threshold and a linear model in distance. The second column reports the OLS estimates for observations falling in a 8 km window from the threshold and using a cubic model in distance. The mining effect is statistically significant for the stock value of all antimalarial commodities for both window selection except for ITN. The highest mining effects are found to be on aid for SP and ACT for which the stock value increase by \$0.04 and \$0.02 per capita respectively, whilst the effect on the stock value of RDT is marginal (less than \$0.01 per capita).

Table 8 shows the results with the non-parametric approach, where column (1) and (2) estimate respectively a local linear polynomial and a local cubic polynomial in distance. Compared to the parametric approach, the estimate of aid for ACT and SP are lowered by approximately \$0.005 per capita when using a local linear model; the estimate for RDT remains unchanged. When the specification involves a local cubic model in distance, only the stock value of SP and RDT are statistically significant, and aid to SP reaches almost \$0.05 per capita.

Together, the outcomes from parametric and non-parametric estimations illustrate important findings. First, the effects of mining areas on aid allocated to each antimalarial commodity are relatively constant with respect to the distance from the mining threshold, which attests to the robustness of the results. Second, the mining effect on aid for malaria is largely driven by the effect on aid for SP which accounts for 65% ($0.046/0.072 = 0.64$) of the overall mining effect on local aid for malaria. The remaining part of additional aid in mining areas is mostly devoted to ACTs (about 22 %) and RDTs (11 %).

Disentangling the mining effects on antimalarial commodities. A potential concern with the increase in aid for SP commodity relative to ACT is that health facilities within mining areas might be subject to systematically more frequent disruptions in the provision of a specific commodity for reasons inherent to the presence of mines. To assess this eventuality, table 9 documents the mining effects on the monthly number of stock-out days, consumption and the

share of consumption in the stock level for each antimalarial commodity. Column (1) reports the estimates for SP and columns (2)-(5) decompose the mining effects for each age category of ACT treatment that corresponds to age-specific dosage. 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, indicating that mining areas do not disrupt the provision of a specific commodity. Monthly consumption is statistically significant for all commodities except for ACT to children between 6 and 13 and RDT. This result confirms the predominance of the burden of malaria within mining areas through increased demand in antimalarial medicines, in particular among children between 1 and 5 for whom the ACT consumption rose by 4%. The bottom part of the table reveals that the share of consumption in the stock level of each commodity has a negative coefficient estimate which is explained by the higher stock level of antimalarial in mining areas. The estimates are only statistically significant and negative for SP and RDT, indicating that the increase in demand (monthly consumption) within mining areas for these two commodities is lower than their increase in supply. This last result corroborates with the previous finding of SP receiving the highest share of aid for malaria.

As a final test, I explore the existence of systematic differences between mining and non-mining areas in the sub-populations targeted by donors. As previously described, ACT treatments are characterised by specific dosages which relate to four different age categories (below 1, between 1 and 5, between 6 and 13 and above 13) whilst SP is a preventive treatment specific to pregnancy. Unfortunately, data limitation prevents from exploring the distribution of age population between mining and non-mining areas. I can therefore only assume that this distribution is similar in the two areas and I rely on the additional burden of malaria caused by the mines as the unique driver for the provision of ACT drugs.[40] Regarding SP preventive treatment, the commodity is given to pregnant women during routine antenatal care (ANC) visits (WHO, 2018). I examine the presence of a discontinuity in the population of pregnant women by using the reported number of ANC visits.[41] Table 10 documents the effect of mining areas on the share of ANC visits per capita and malaria prevalence using non-parametric estimations. Columns (1) and (2) denote respectively the local linear and cubic models. Malaria prevalence is defined as the share of malaria cases received in health facility per local population. The RD estimate for the share of ANC visits is statistically insignificant which could reasonably be interpreted as an equal distribution of pregnant women between mining and non-mining areas. This last result, combined with the findings on the similarities in the number of stock-out days for all commodities between the two areas, provides suggestive evidence that malaria prevalence should be the primary causal factor for the determination of

[40] One concern with this assumption is that mining areas could be characterised with lower rate of children due to the health and safety hazards of mines. However, as described in section 4, recent studies on child labour suggests that the presence of children should not be significantly lower within mining areas.

[41] For the validity of the test, I hypothesise that antenatal care attendance among pregnant women do not systematically differ in mining areas, an assumption that is not directly testable. Although pregnant women are banned from mining activities, mining work is also more lucrative for them than any other activities surrounding mining areas (Buss et al., 2017). Hence, I suspect that pregnant women in mining areas should have little incentives to move home during their pregnancy and attend a different health facility for antenatal care.

local aid for malaria.

Equity of local aid. Whilst local aid for malaria increases by \$0.06 per capita in mining areas, the decomposition of the mining effects reveals an unequal distribution of resources allocated to antimalarial commodities. I further document how the distribution of local aid for malaria is matching the needs by examining the variations in the stock of commodities with respect to the change in burden of malaria between mining and non-mining areas. The bottom part of table 10 corresponds to the RD estimation of mining effects on malaria prevalence using a local linear polynomial. In mining areas, the number of malaria cases increases between 7 and 8 percent when the nonparametric estimation employs a local linear and a cubic model respectively; both results are statistically significant.[42] In baseline results presented earlier, mining areas were found to have a small but significant effect on aid for malaria. The rise in local aid could underestimate the coefficient of the mining effect on malaria prevalence if aid for malaria contributes (through preventive treatment) to reduce the burden of the disease. The obtained result on malaria prevalence should therefore represents a lower bound estimate.

Next, I quantify the results on local aid for malaria by estimating 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 14), the total monthly estimated cost for providing malaria treatment and prevention per capita is \$1.25.[43] This result corroborates with the finding from WHO (2015a) who estimates that the cost of curative treatment is approximately \$1 in Sub-Saharan African countries. The total cost is decomposed as follows: ACT \$0.7, SP \$0.09, RDT \$0.25 and ITN \$0.21.

The amount of aid required for financing diagnosis, prevention and treatment of malaria relates to the disease burden within a given area. Figure 15 plots the evolution of malaria-related costs with the additional risk of malaria transmission. The horizontal red dashed line shows the additional aid for malaria that is received in high burden areas according to the nonparametric RD estimation (table 6) of the mining effect. The graph indicates that local aid can potentially cover the costs associated to the burden of malaria when the additional risk of malaria transmission does not exceed 4.4%. Beyond this point, health facilities within mining areas do not get their share of aid.

What is the actual risk of malaria transmission? As discussed above, I find that malaria prevalence increases by at least 7 percent in mining areas. At this rate, local aid should increase

[42] Malaria cases are usually detected at the facility level by RDTs, the latter being provided mostly by donors. This could pose a threat of endogeneity bias but table 9 reports insignificant effects on the number of stock-out days of RDTs between mining and non-mining areas. This means that the number of detected cases should not be more constrained by the availability of RDT in health facilities located in non-mining area.

[43] To calculate the overall monthly financial costs per capita, I rely on the decomposition of the Congolese population that was taken from the United Nations World Population Prospects: 57 percent of adults (above 14), 25% of children between 6 and 14 and 16% that are less than 5. The share of pregnant women and children who are receiving SP medicines is assumed to be 25% following the estimations in the National Health Accounts in the DRC (MSP, 2017).

by a minimum of $0.09 per capita to fully meet the needs related to malaria. On the other hand, the results of both parametric and nonparametric RD estimations of the mining effects on local aid indicate that the increase in aid for malaria ranges between $0.05 and $0.06. Presumably, this result implies that at least more than one third of the additional malaria needs in areas with high burden of the disease is not financed by aid.

Altogether, these results suggest two main conclusions on the patterns of aid targeting. First, the additional risk of malaria transmission is not followed by a proportional increase in local funding for malaria curative treatments. Given the cost of malaria prevention and treatment approximately equals to $1.25 per patient, a minimum 7 % increase in malaria prevalence would require an additional $0.09 of aid per capita whilst health facilities are found to receive less than $0.06 per capita.

Second, aid for preventive commodities for pregnant women (SP) are more responsive to the change in the risk of malaria transmission, although this disproportionate response raises concerns about the effectiveness of aid for this commodity. Whilst the estimated cost of SP represents approximately 7% of the overall costs of providing antimalarial commodities, SP accounts for more than 65% of the additional aid allocated to high risk areas. On the other hand, the share of ACT is 56% in the overall antimalarial cost whilst only 22% of aid is targeting it. There is no evidence that external funding for insecticide-treated bed nets (ITN) rises among mining areas.

6 Discussion and Conclusion

Targeting of health needs is central in low-income countries with high disease burden and limited resources (Dupas and Miguel, 2017). Important health gains could be achieved through more precise allocation of resources to areas with the greatest health risk.[44] In this study, I exploit the variations in the burden of malaria between mining and non-mining areas to estimate the response of donors to local needs. Using a novel data source to track aid for malaria at the health facility level, I find no evidence to support the assumption that donors are accurately targeting areas with the greatest burden of malaria. Although I document a significant effect of local variations in the burden of malaria on local aid for the disease, the evidence also suggests that local populations with the highest burden of malaria do not receive the highest share of aid for malaria comparatively to those living in neighbouring areas with reduced exposure to malaria infection.

First, the small increase in local aid for malarial does not match the costs incurred for the extra burden of malaria in mining areas. In particular, my findings suggest that local aid is covering at maximum 60 percent of the additional costs induced by the additional risk of malaria transmission. Second, the decomposition of aid by targeted population reveals that

[44] As a recent example in the DRC, Dolan et al. (2019) show that national insecticide-treated bed net campaigns against malaria between 2009 and 2013 achieve significant mortality reduction among children under 5 only in areas with the highest risk of malaria transmission.

resources are unequally distributed with respect to local health needs; this inequality is in turn exacerbated by the overall mistargeting of aid for malaria.

These results pinpoint some limitations in the actual aid allocation and suggests that aid could be more closely tailored to local health needs. Better allocation of aid could generate health efficiency gains and reduce inequities in treatment access for patients across areas with different burdens of malaria (difference in allocated aid) and within areas (across sub-group populations). In cases where health information is fragmented and difficult to collect, donors could seek the engagement of local community leaders in aid targeting decisions (Alatas et al., 2012).

My findings resonate with the literature on geographical targeting of aid at subnational levels. Öhler et al. (2017) find no evidence that funding from World Bank to anti-poverty projects is allocated to the poorest areas within countries in Sub-Saharan Africa. Briggs (2018) shows that aid from World Bank and African Development Bank targets comparatively richer geographic areas across African countries. In the health sector, Kotsadam et al. (2018) show that external funding is allocated to subnational areas of Nigeria with lower infant mortality.

More broadly, my findings question the effectiveness of aid in settings with limited information about local needs, and challenge the view that donors possess sufficient knowledge to make optimal decisions of resource allocations (Easterly, 2006). The results best support the assumption that aid mistargeting reflects donors' inaccurate information about local population needs. The fact that the distribution of local funding per commodity does not equally match the needs of each targeted population could be explained by two factors: the incomplete information of donors about local health needs or ineffective supply chains of health products leading to poor availability of medicines in health facilities (Yadav, 2015). However, the evidence does not support the latter: the number of stock-out days for each antimalarial commodity does not systematically differ among areas with varying risk of malaria transmission. This finding partially rules out the role of the supply chain of health products to explain the difference in the stock of antimalarial commodities between local areas with different burden of malaria.[45] Hence, the results suggest that mistargeting is primarily caused by the decisions of donors.

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 in this paper underscore important research questions. First, I have 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/AIDS) could help to uncover the root causes of targeting deficiencies. Second, the fact that funding for some health commodities (ACT, SP) is more sensitive to local variations in the burden of malaria than others (RDT, ITN) suggests that donors have imprecise information about the local variations of

[45] I cannot completely exclude the possibility that the supply chain of medicines locally affect their provision level to health facilities located in areas with high disease burden without causing systematic stock-outs. However, this eventuality is highly improbable: the quantity of health commodities provided to the facility could hardly remain systematically low without experiencing more frequent stock-outs.

the disease burden. An alternative explanation is that health workers might be more successful in signalling the need for being provided some specific health commodities than for other health commodities. The signalling efforts of health workers would then induce a partial adjustment in donors' targeting decisions, improving thereby the aid allocation for the specific commodities. Future research on these questions is important to improve health aid targeting.

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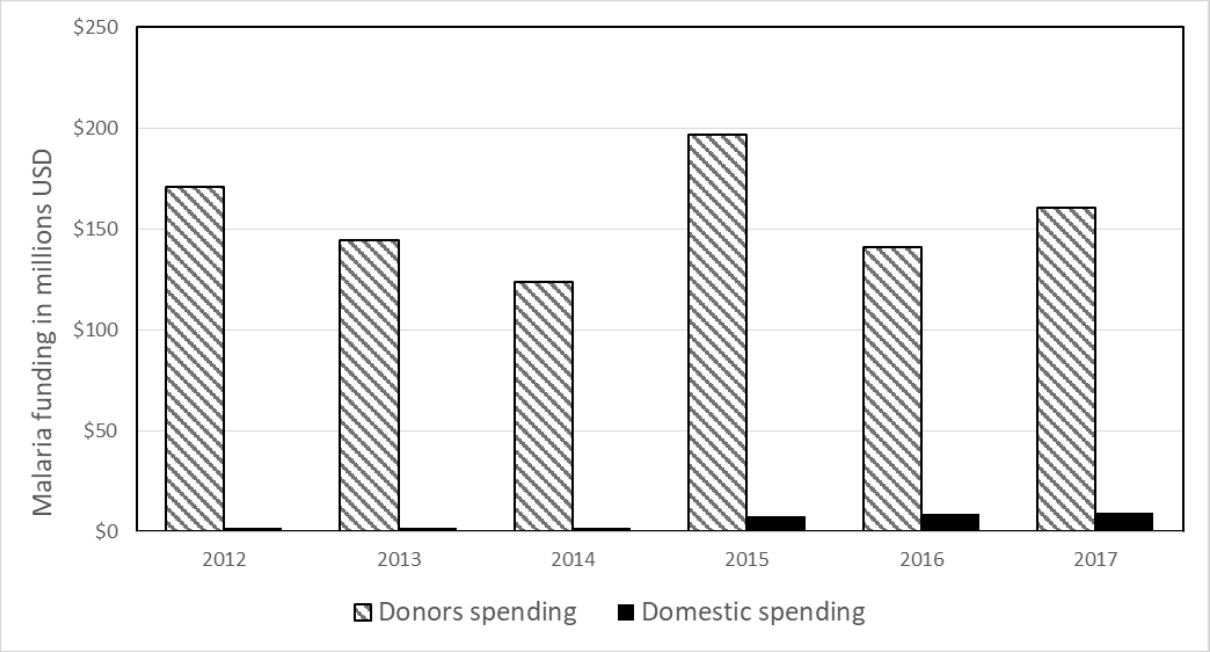
Figure 1: Share of donors and domestic spending in total malaria investment



Notes: The above figure documents the evolution of the contributions of external aid and government spending to the national malaria programme, which highlights the strong dependence of the health system of the country on donors. This information was extracted from the National Health Accounts of the DRC, MSP (2017). External aid and government spending amount respectively to $160 million and $9 million in 2017.

Table 1: Summary statistics and difference-in-means, full sample

	Outside mining area			Within mining area			Difference-in-means		
	Obs.	Sample mean	s.d.	Obs.	Sample mean	s.d.	Diff-in-means	s. e.	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Geographic characteristics									
Elevation (in metres)	489	1,251.23	24.84	738	1,218.87	19.27	-32.36	31.44	0.30
Slope	489	5.03	0.30	738	6.34	0.31	1.31	0.43	0.00
Distance from closest facility (km)	489	5.56	0.28	738	4.63	0.19	-0.93	0.34	0.01
Distance from closest hospital (km)	436	20.78	0.96	700	20.22	0.68	-0.56	1.18	0.63
Facilities characteristics*									
Antimalarial stock value	446	0.08	0.00	652	0.10	0.00	0.02	0.01	0.00
Total other drugs stock value	474	0.11	0.01	724	0.13	0.01	0.02	0.01	0.01
Revenue	477	0.90	0.07	709	0.88	0.07	-0.02	0.10	0.85
Investment	316	0.07	0.01	520	0.06	0.00	-0.01	0.01	0.21
Payroll tax	394	0.03	0.00	595	0.02	0.00	-0.01	0.00	0.03
Government bonus	335	0.04	0.00	557	0.05	0.00	0.01	0.01	0.00
No. nurses	469	0.00	0.00	705	0.00	0.00	0.00	0.00	0.00
No. births	451	0.02	0.00	686	0.02	0.00	0.00	0.00	0.46
Local Population**	489	14.43	0.82	738	12.20	0.37	-2.24	0.90	0.01
No. days antimalarial stock outs									
Insecticide-Treated bed Nets	423	6.47	0.31	583	5.87	0.24	-0.60	0.40	0.13
Rapid Diagnostic Tests	391	2.83	0.51	524	2.09	0.16	-0.74	0.53	0.16
Sulfadoxine-Pyrimethamine	396	3.73	0.44	532	4.26	0.57	0.52	0.72	0.47
ACT (ages +14)	400	3.41	0.23	529	3.53	0.46	0.12	0.52	0.81
ACT (ages 6-13)	403	3.02	0.20	512	3.39	0.53	0.37	0.57	0.52
ACT (ages 1-5)	407	3.08	0.24	537	3.82	0.24	0.74	0.33	0.03
ACT (ages -1)	409	3.30	0.25	560	4.44	0.26	1.14	0.36	0.00

Notes: Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars. All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the p-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

** Mean and standard deviation of local population are expressed in thousands.

Table 2: Summary statistics and difference-in-means, 8km window around the border

	Outside mining area			Within mining area			Difference-in-means		
	Obs.	Sample mean	s.d.	Obs.	Sample mean	s.d.	Diff-in-means	s. e.	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Geographic characteristics									
Elevation (in metres)	161	1,319.01	44.37	232	1,217.65	34.40	-101.36	56.14	0.07
Slope	161	5.88	0.47	232	5.91	0.48	0.03	0.67	0.97
Distance from closest facility (km)	161	5.72	0.47	232	5.42	0.37	-0.30	0.60	0.61
Distance from closest hospital (km)	142	21.08	1.50	214	20.89	1.15	-0.19	1.89	0.92
Facilities characteristics*									
Antimalarial stock value	145	0.08	0.01	201	0.10	0.01	0.01	0.01	0.12
Total other drugs stock value	157	0.12	0.01	226	0.12	0.01	0.01	0.01	0.55
Revenue	157	0.73	0.06	217	0.73	0.05	-0.00	0.08	0.98
Investment	116	0.05	0.01	157	0.06	0.01	0.01	0.01	0.52
Payroll tax	128	0.02	0.00	178	0.01	0.00	-0.01	0.00	0.07
Government bonus	114	0.03	0.00	158	0.05	0.01	0.01	0.01	0.04
No. nurses	155	0.00	0.00	219	0.00	0.00	0.00	0.00	0.51
No. births	146	0.02	0.00	216	0.02	0.00	0.00	0.00	0.82
Local Population**	161	12.36	0.57	232	11.44	0.50	-0.93	0.76	0.22
No. days antimalarial stock outs									
Insecticide-Treated bed Nets	132	6.19	0.53	179	5.96	0.45	-0.22	0.70	0.75
Rapid Diagnostic Tests	117	2.38	0.31	159	1.80	0.30	-0.58	0.43	0.18
Sulfadoxine-Pyrimethamine	119	3.83	0.56	165	2.88	0.35	-0.94	0.66	0.16
ACT (ages +14)	115	3.57	0.38	165	4.49	1.41	0.92	1.46	0.53
ACT (ages 6-13)	116	3.19	0.35	156	4.56	1.69	1.37	1.72	0.43
ACT (ages 1-5)	127	3.36	0.42	170	3.40	0.40	0.04	0.58	0.95
ACT (ages -1)	124	3.86	0.51	175	4.12	0.48	0.26	0.70	0.71

Notes: Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars. All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the p-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

** Mean and standard deviation of local population are expressed in thousands.

Table 3: Summary statistics and difference-in-means, 3km window around the border

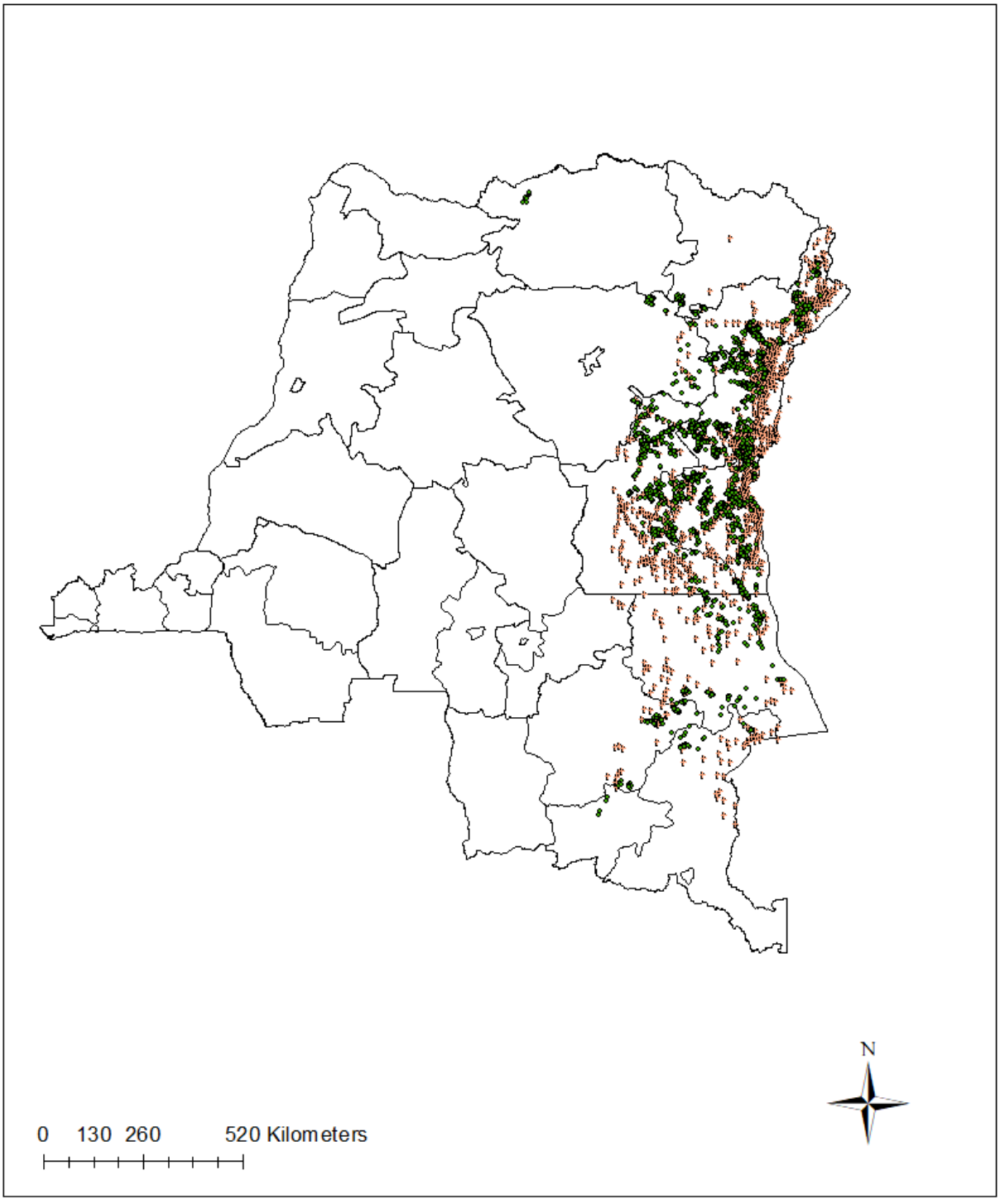
	Outside mining area			Within mining area			Difference-in-means		
	Obs.	Sample mean	s.d.	Obs.	Sample mean	s.d.	Diff-in-means	s. e.	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Geographic characteristics									
Elevation (in metres)	68	1,302.82	71.69	81	1,278.82	61.83	-24.01	94.67	0.80
Slope	68	6.81	0.79	81	6.61	1.18	-0.20	1.42	0.89
Distance from closest facility (km)	68	6.10	0.80	81	5.60	0.60	-0.50	1.00	0.62
Distance from closest hospital (km)	58	20.98	2.35	74	22.28	1.91	1.29	3.03	0.67
Facilities characteristics*									
Antimalarial stock value	59	0.08	0.01	71	0.09	0.01	0.01	0.01	0.29
Total other drugs stock value	67	0.11	0.01	78	0.14	0.02	0.04	0.02	0.12
Revenue	66	0.76	0.10	76	0.68	0.09	-0.08	0.13	0.56
Investment	51	0.06	0.01	51	0.06	0.01	0.00	0.02	0.87
Payroll tax	56	0.01	0.00	59	0.01	0.00	0.00	0.01	0.50
Government bonus	47	0.04	0.01	52	0.05	0.01	0.01	0.01	0.22
No. nurses	66	0.00	0.00	79	0.00	0.00	0.00	0.00	0.68
No. births	57	0.02	0.00	80	0.02	0.00	-0.00	0.00	0.63
Local Population**	68	12.72	0.94	81	11.47	0.91	-1.25	1.31	0.34
No. days antimalarial stock outs									
Insecticide-Treated bed Nets	59	7.02	0.86	65	6.32	0.81	-0.70	1.18	0.56
Rapid Diagnostic Tests	50	2.18	0.37	59	1.46	0.33	-0.73	0.50	0.15
Sulfadoxine-Pyrimethamine	52	5.03	1.10	59	2.71	0.59	-2.31	1.24	0.07
ACT (ages +14)	51	2.90	0.44	61	3.20	0.57	0.30	0.71	0.67
ACT (ages 6-13)	50	3.11	0.54	60	7.13	4.34	4.02	4.38	0.36
ACT (ages 1-5)	55	3.66	0.81	65	3.17	0.68	-0.48	1.05	0.65
ACT (ages -1)	56	4.49	0.82	64	4.22	0.79	-0.27	1.14	0.81

Notes: Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars per capita (sing local population catchment area of the facility). All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the p-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

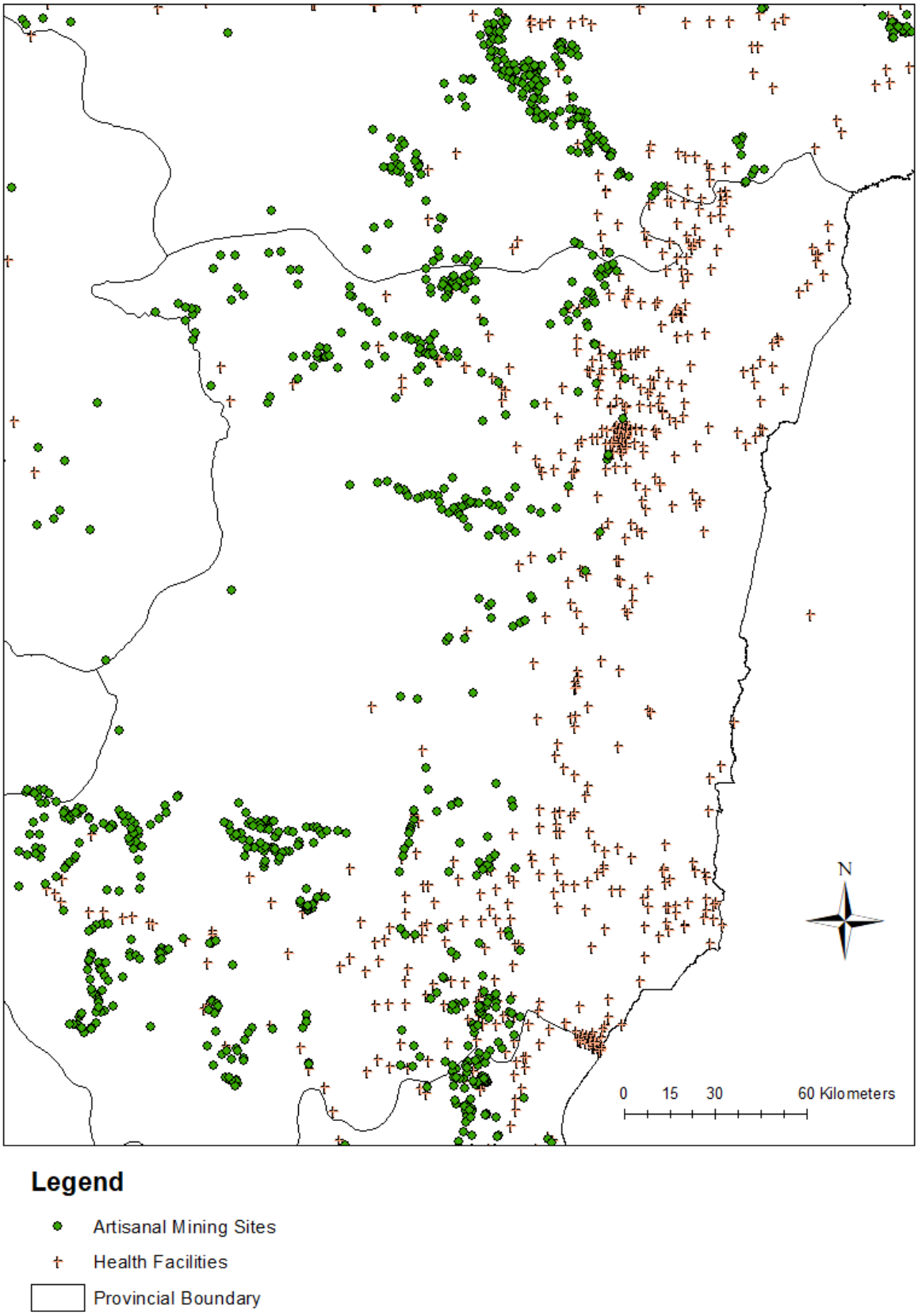
** Mean and standard deviation of local population are expressed in thousands.

Figure 2: Mapping of the full sample of health facilities and mines in the DRC



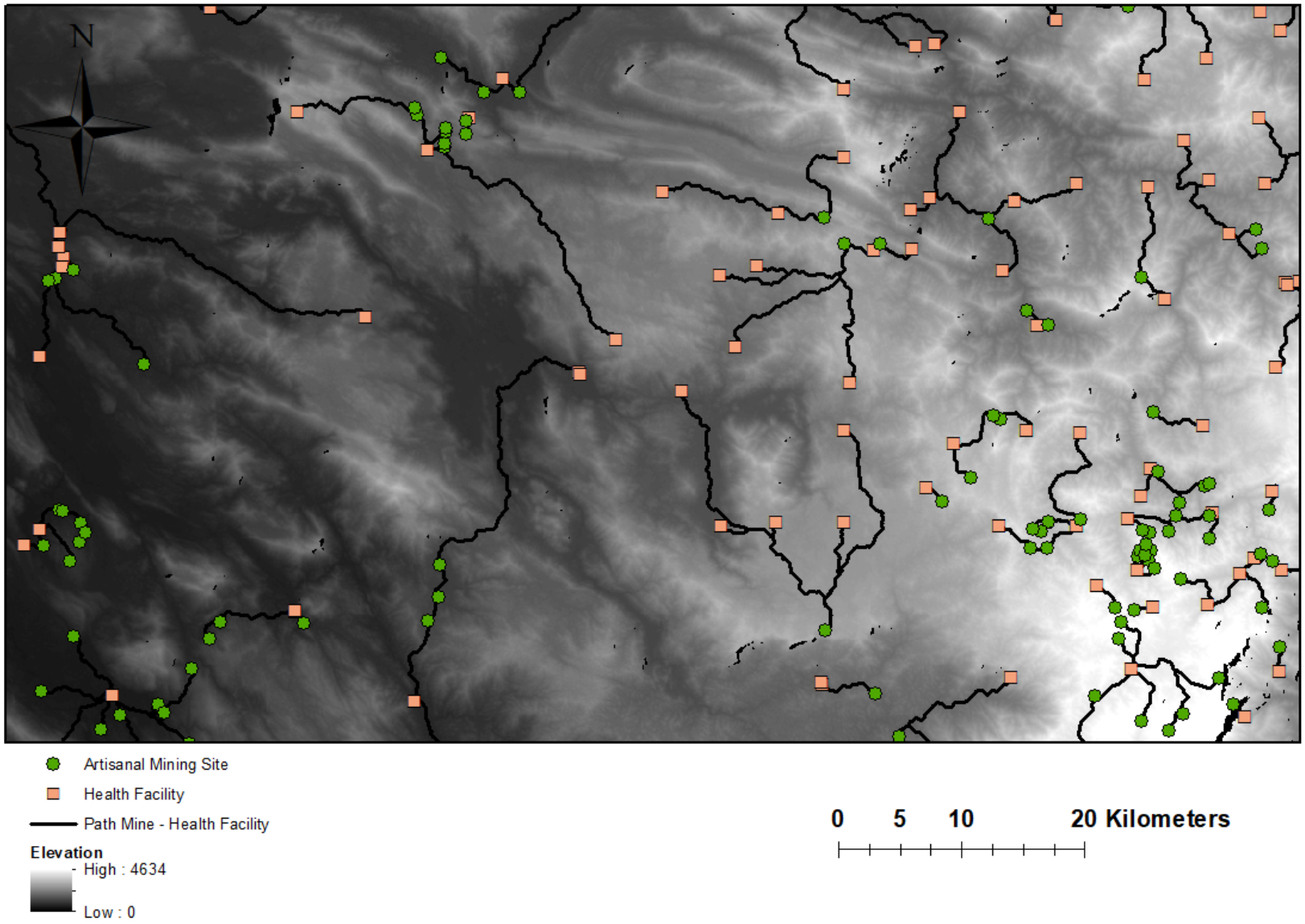
Notes: The map shows the geo-location of the mines and the health facilities in the Estern DRC along with provincial level boundaries. The mines and health facilities are located in North and South Kivu, Ituri, Maniema, Tshopo and Tanganyika.

Figure 3: Mapping of health facilities and mines in North Kivu



Notes: The map shows the exact geo-location of the mines and the health facilities in North Kivu, one of the provinces which contains the most observations in the sample.

Figure 4: Paths from health facilities to mines with elevation feature

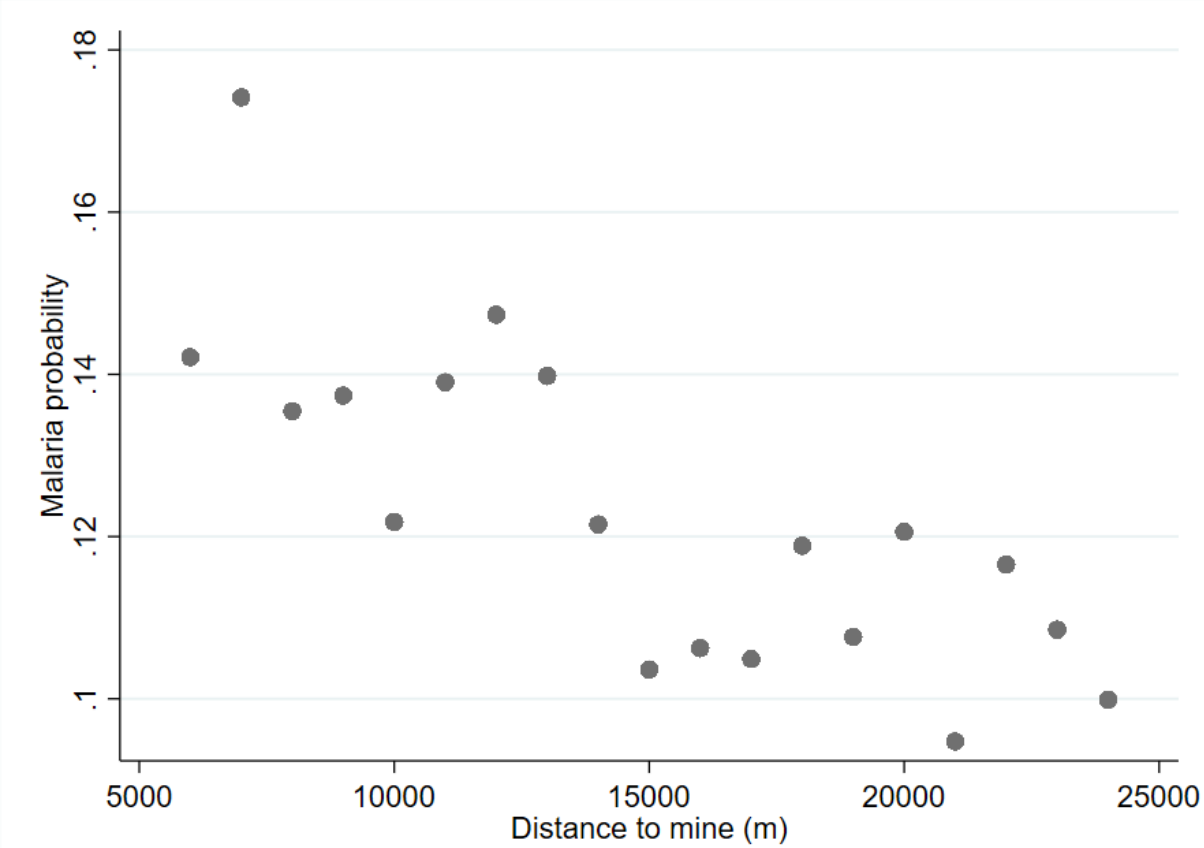


Notes: This map plots health facilities and mines along with the algorithm-derived shortest paths based on elevation. The cost path function was used in ArcGIS 10 to estimate the least cost path from each health facility to the closest mine.

Figure 5: Administrative map of the DRC and the selected provinces

Notes: The map shows the provincial boundaries of the DRC and the selection of provinces that contains the location of health facilities and mines from the data sample: North and South Kivu, Ituri, Maniema, Tshopo and Tanganyika.

Figure 6: Malaria prevalence as a function of the distance to mines



Notes: Each point plots an average value within a bin that represents a 1 km interval. The y-axis indicates the malaria probability which is defined as the total number of malaria cases divided by the total population in the catchment area of each health facility.

Table 4: Manipulation Density tests

Density tests	(1) h_{mining}	(2) $h_{non-mining}$	(3) N_{mining}	(4) $N_{non-mining}$	(5) p-value
Separate MSE Optimal bandwidth	3,647	5,348	84	105	0.84
Restricted C.D.F	6,723	6,723	175	129	0.89

Notes: The table shows the results of the manipulation test based on the local polynomial density estimation technique (Cattaneo et al., 2017) 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, columns (3) and (4) indicate the number of observations used and the last column gives the p-value of the test. I perform the test using two different MSE optimal bandwidth 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.

Table 5: Parametric estimation of the effect of mining areas

	Linear model (p=1)		*Cubic model (p=3)*	
Window selection	3 km		8 km	
Control variables*	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Aid for malaria per capita				
RD Mining effect	0.058	0.058	0.072	0.070
s.e.	0.024	0.022	0.027	0.026
Standard p-value	0.017	0.011	0.008	0.007
Obs.	130	130	346	346
Placebo outcomes, standard p-values				
Expenditures	0.414		0.614	
Revenue	0.693		0.767	
No. of health workers	0.768		0.633	
No. of births	0.826		0.716	

Notes: The table reports the results of the weighted least squares estimations based on specification (1). In the upper part of the table, the dependent variable is the antimalarial stock value and the bottom part of the table reports the standard p-value of the β_1 estimates for a list of pre-determined covariates. Each of these covariates is used as the dependent variable in order to test the validity of the RD design, and I report robust standard errors. Columns (1) to (4) report the results obtained using a local linear regression and columns (5) to (8) present results using a local cubic model that provides more flexibility as the $g(.)$ function covers a larger support (7 to 10 km).

* Control variables are the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table 6: Non-parametric estimation of the effect of mining areas

	Linear model (p=1)		*Cubic model (p=3)*	
Control variables*	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Bandwidth h (in metres)**	3,997	3,945	8,093	7,755
Aid for malaria per capita				
RD Mining effect	0.053	0.054	0.072	0.073
Robust s.e.	0.024	0.022	0.029	0.026
Robust p-value	0.011	0.006	0.009	0.004
Obs.	170	165	348	339
Placebo outcomes, robust p-values				
Expenditures	0.539		0.608	
Revenue	0.857		0.937	
No. of health workers	0.472		0.466	
No. of births	0.845		0.795	

Notes: The table reports the results from nonparametric estimations of specification (1) using a local linear and cubic model. In the upper part of the table, the dependent variable is the antimalarial stock value whilst the bottom part of the table presents the robust p-values of the estimates of the mining effects on several pre-determined covariates following the procedure described by Calonico, Cattaneo, and Titiunik (2014).

* Control variables are elevation and slope.

** The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors p-values. The smoothed distribution function used is the triangular kernel.

Table 7: Parametric estimation of the effect of mining areas by antimalarial commodity

	Linear model (p=1) (1)	*Cubic model (p=3)* (2)
Window selection (km)	3	8
ACT - Treatment		
RD Mining effect	0.016	0.019
s.e.	0.009	0.010
p-value	0.068	0.049
Obs.	147	388
Sulfadoxine-Pyrimethamine (SP) - Prevention		
RD Mining effect	0.039	0.046
s.e.	0.011	0.013
p-value	0.001	0.001
Obs.	134	357
Rapid Diagnostic Test (RDT)		
RD Mining effect	0.006	0.005
s.e.	0.002	0.003
p-value	0.022	0.077
Obs.	145	380
Insecticide-Treated bed Net (ITN)		
RD Mining effect	0.002	0.003
s.e.	0.006	0.009
p-value	0.771	0.700
Obs.	134	347

Notes: The table reports the results of the weighted least squares estimations based on specification (1) for each antimalarial commodity, with robust standard errors. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the government bonus and geographic characteristics (distance to the closest health facility, elevation and slope) and the number of mines surrounding a health facility.

Table 8: Non-parametric estimation of the effect of mining areas by antimalarial commodity

	Linear model (p=1) (1)	*Cubic model (p=3)* (2)
ACT - Treatment		
RD Mining effect	0.013	0.014
s.e.	0.008	0.010
Robust p-value	0.061	0.180
Bandwidth (metres)	4,178	6,516
Obs.	201	329
Sulfadoxine-pyrimethamine (SP) - Prevention		
RD Mining effect	0.036	0.046
s.e.	0.012	0.014
Robust p-value	0.001	0.001
Bandwidth (metres)	3,131	7,680
Obs.	136	345
Rapid Diagnostic Test (RDT)		
RD Mining effect	0.005	0.008
s.e.	0.003	0.003
Robust p-value	0.049	0.002
Bandwidth (metres)	4,928	8,063
Obs.	224	268
Insecticide-Treated bed Net (ITN)		
RD Mining effect	0.006	-0.002
s.e.	0.008	0.011
Robust p-value	0.332	0.742
Bandwidth (metres)	4,324	5,656
Obs.	186	252

Notes: The table reports the results from nonparametric estimations of specification (1) using a local linear and cubic model for each antimalarial commodity. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors p-values. The smoothed distribution function used is the triangular kernel. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table 9: Effect of mining areas on stock-outs, consumption and stock

	SP (1)	ACT < 1 (2)	ACT 1-5 (3)	ACT 6-13 (4)	ACT < 14 (5)	ITN (6)	RDT (7)
No. of stock-out days per month							
RD Mining effect	-0.461	-1.144	-1.038	7.869	0.495	1.992	-0.775
s.e.	1.656	1.895	1.686	9.326	1.121	1.731	0.792
Robust p-value	0.977	0.545	0.498	0.317	0.746	0.143	0.290
Obs.	134	221	226	182	122	202	145
Monthly consumption							
RD Mining effect	0.006	0.019	0.038	0.005	0.021	0.006	0.059
s.e.	0.003	0.012	0.016	0.005	0.011	0.004	0.040
Robust p-value	0.026	0.071	0.013	0.385	0.032	0.106	0.122
Obs.	180	202	187	168	221	273	214
Monthly stock							
RD Mining effect	0.101	0.007	0.007	0.003	0.006	0.021	0.169
s.e.	0.036	0.005	0.005	0.003	0.005	0.037	0.108
Robust p-value	0.002	0.142	0.124	0.189	0.144	0.520	0.090
Obs.	130	180	163	202	264	220	294
Monthly share of consumption per stock							
RD Mining effect	-0.165	-1.083	-0.418	-1.396	-0.359	-0.171	-0.839
s.e.	0.088	1.022	1.522	1.120	1.005	0.170	0.448
Robust p-value	0.029	0.208	0.667	0.154	0.741	0.205	0.029
Obs.	164	183	171	178	175	161	193

Notes: The table reports the results from nonparametric estimations of specification (1) using local linear regressions for each outcome. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors p-values. The smoothed distribution function used is the triangular kernel. ACT drugs are decomposed by age category in columns (2) to (5) and correspond to below 1 year old, between 1 and 5, between 6 and 13 and above 14 years old respectively. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

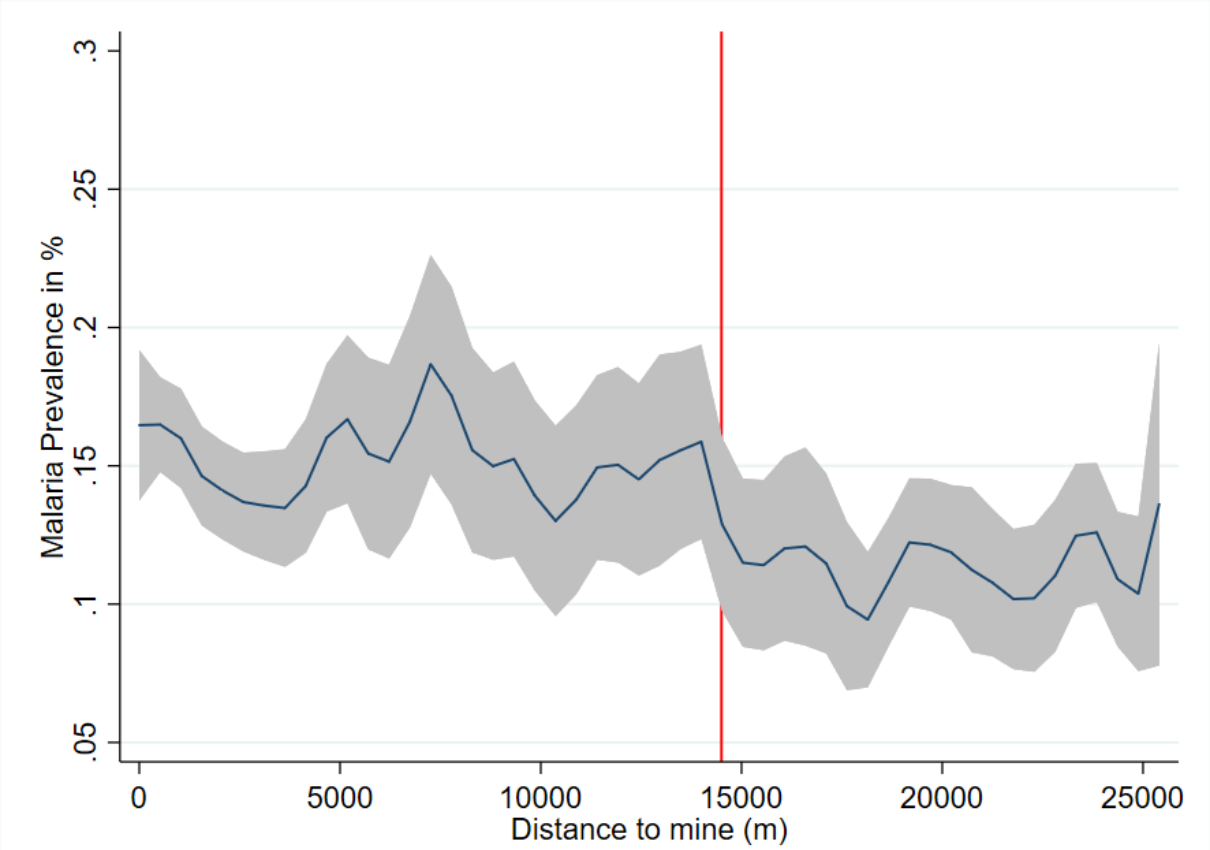
Table 10: Effect of mining areas on ANC and malaria prevalence

	Linear model (p=1) (1)	*Cubic model (p=3)* (2)
No. of prenatal visits per capita		
RD Mining effect	0.002	0.005
Robust s.e.	0.004	0.006
Robust p-value	0.456	0.353
Bandwidth h (in metres)*	4,943	8,049
Obs.	224	378
Malaria prevalence		
RD Mining effect	0.065	0.079
Robust s.e.	0.028	0.038
Robust p-value	0.011	0.038
Bandwidth h (in metres)*	4,212	7,273
Obs.	202	352

Notes: The table reports the results from nonparametric estimations of specification (1) using local linear regressions for each outcome. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors *p*-values. The smoothed distribution function used is the triangular kernel. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

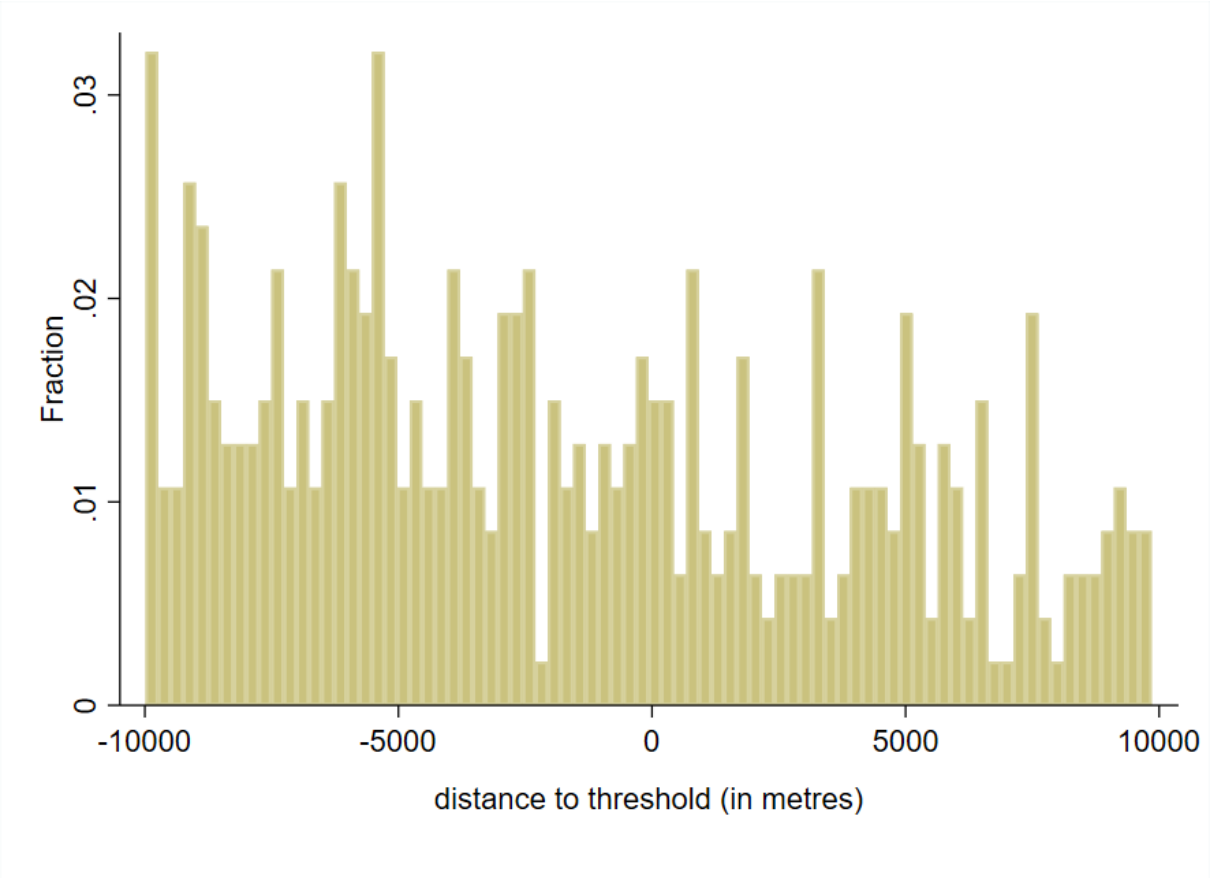
* The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors *p*-values. The smoothed distribution function used is the triangular kernel.

Figure 7: Local polynomial estimations of malaria prevalence as a function of the distance to mines



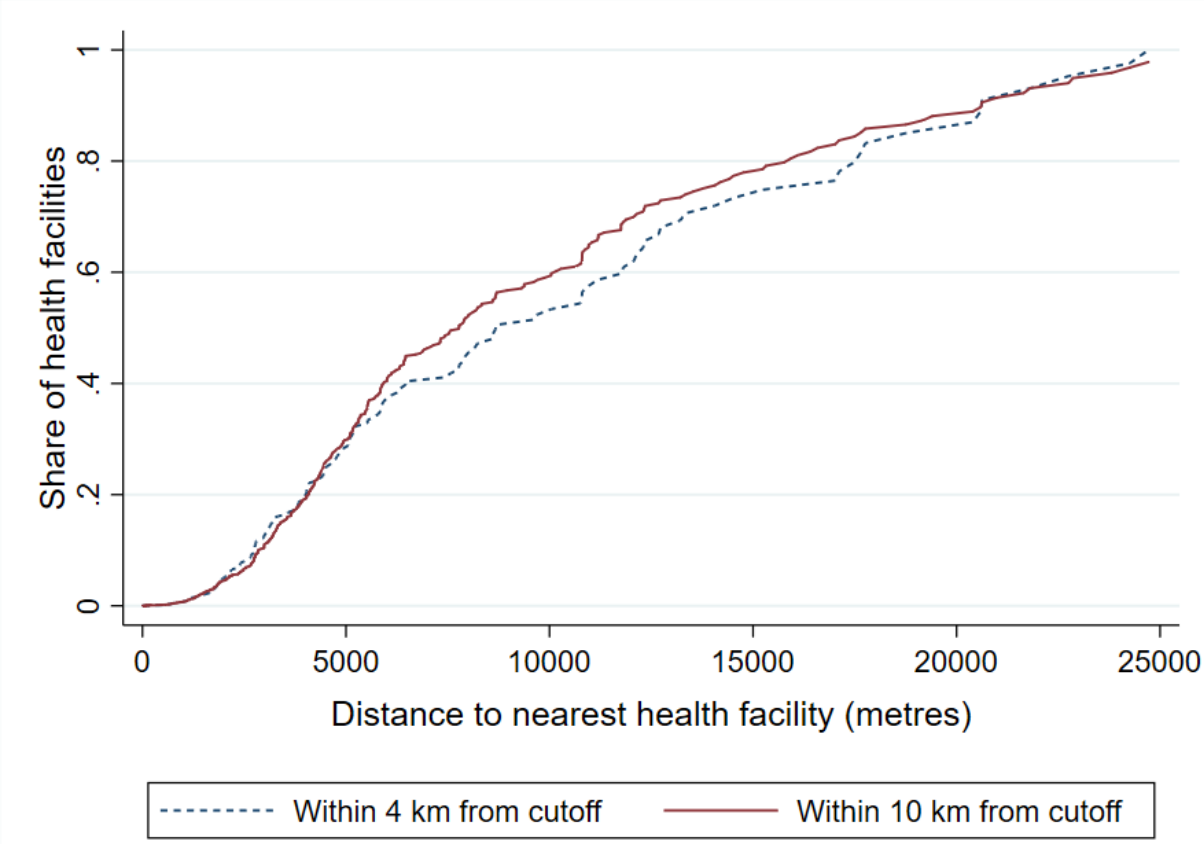
Notes: This figure shows the non-parametric estimations of malaria prevalence conditional on the distance from a health facility to its the closest mine, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The y-axis represents the malaria prevalence defined as the share of malaria cases in the population catchment area of the health facility and the x-axis corresponds to the distance from health facility to the closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients.

Figure 8: Density of the running variable



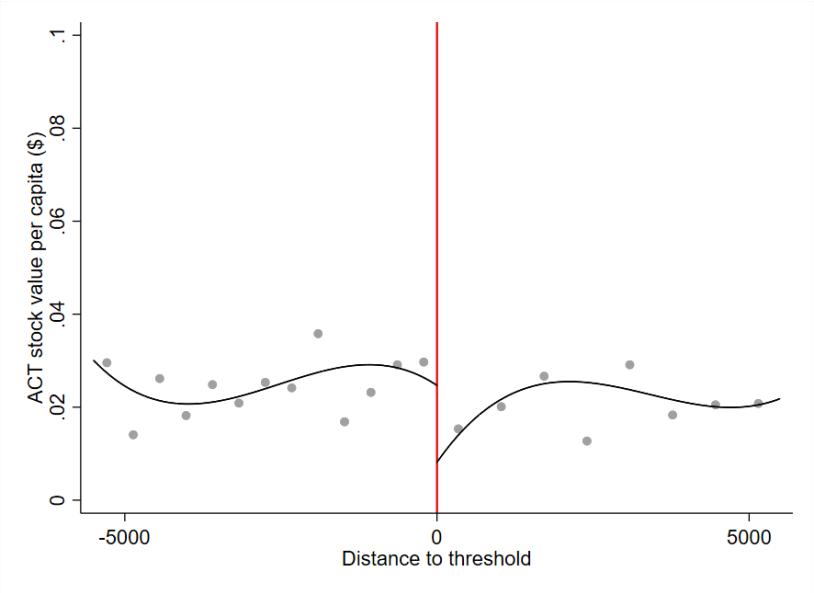
Notes: The above figure shows the distribution of the running variable for health facilities in the sample. The running variable is the distance from the health facility to the mining threshold, which is located 14.5 km from a mine. The running variable is centred around the threshold, so distances are 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 metre-interval.

Figure 9: Cumulative Distribution Function

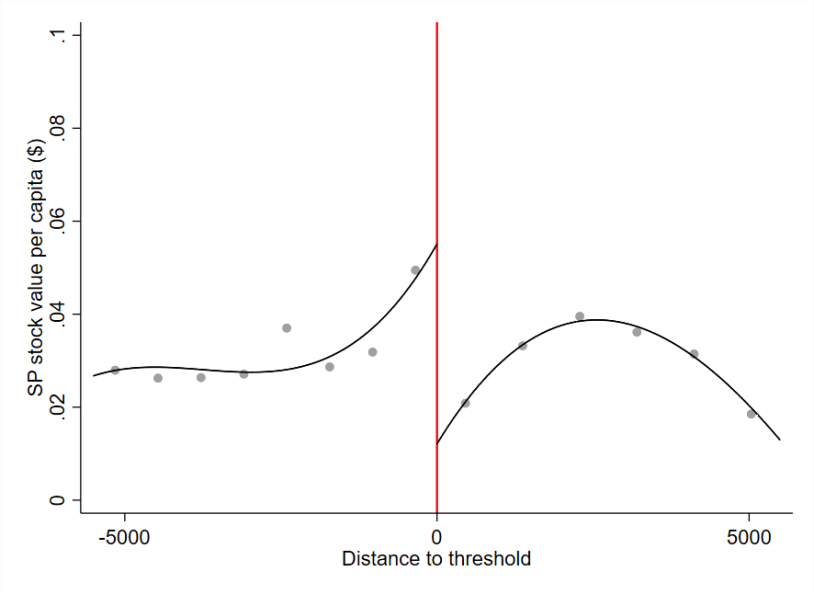


Notes: The above figure shows the cumulative distribution function of health facilities conditional on the distance to the nearest health facility. The data sample is restricted on health facilities located within 10 km (red line) and 4 km (blue dashed line) from the threshold. Distances are reported in metres on the x-axis. The sample is also restricted to health facilities whose maximum distance to another closest facility is 30 kilometres.

FIGURE 10: RD EFFECT ON THE STOCK VALUE OF ACT AND SP COMMODITIES



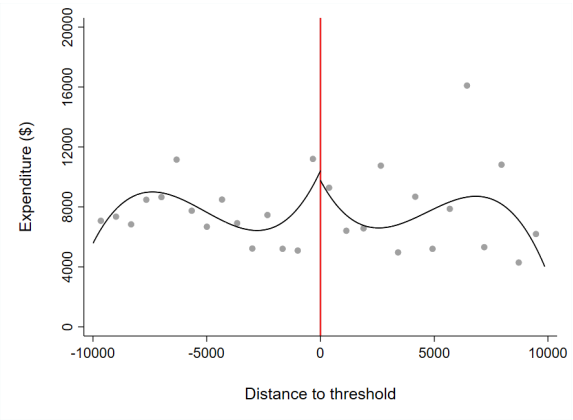
(A) Stock value of ACT



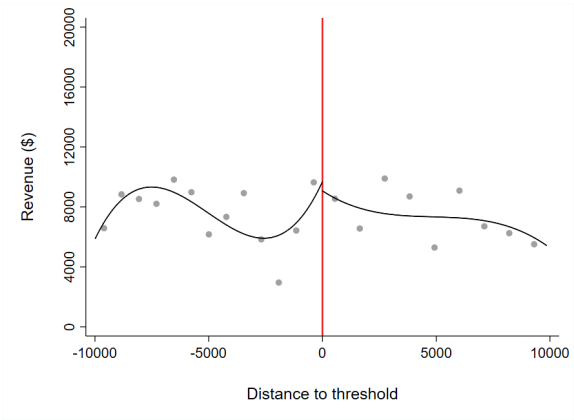
(B) Stock value of SP

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 line plots a local cubic regression.

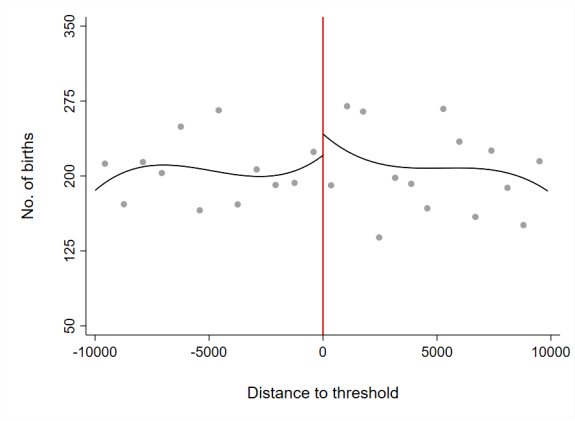
FIGURE 11: EVIDENCE ON CONTINUITY CONDITION



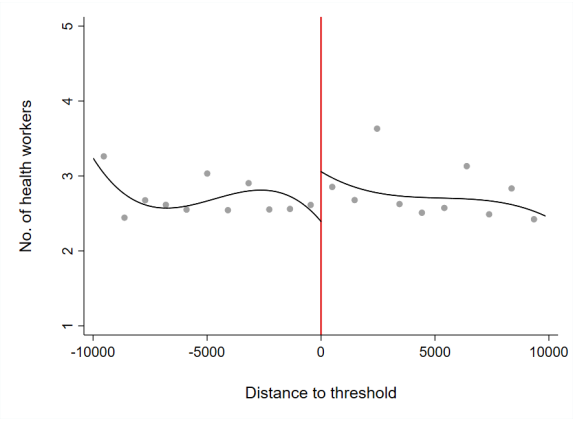
(A) Expenditure



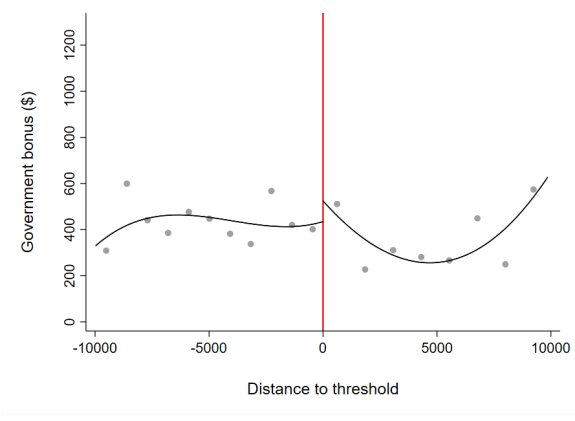
(B) Revenue



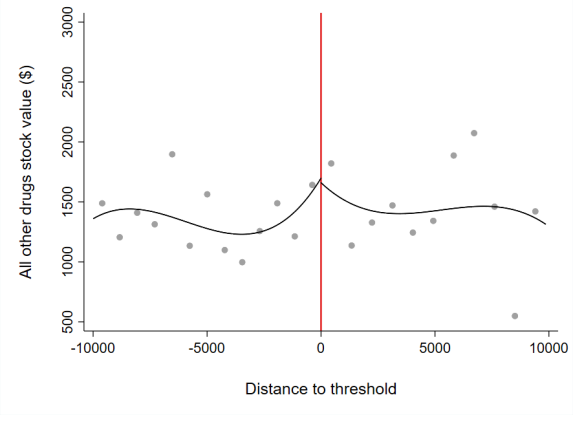
(C) Number of births



(D) Number of health workers



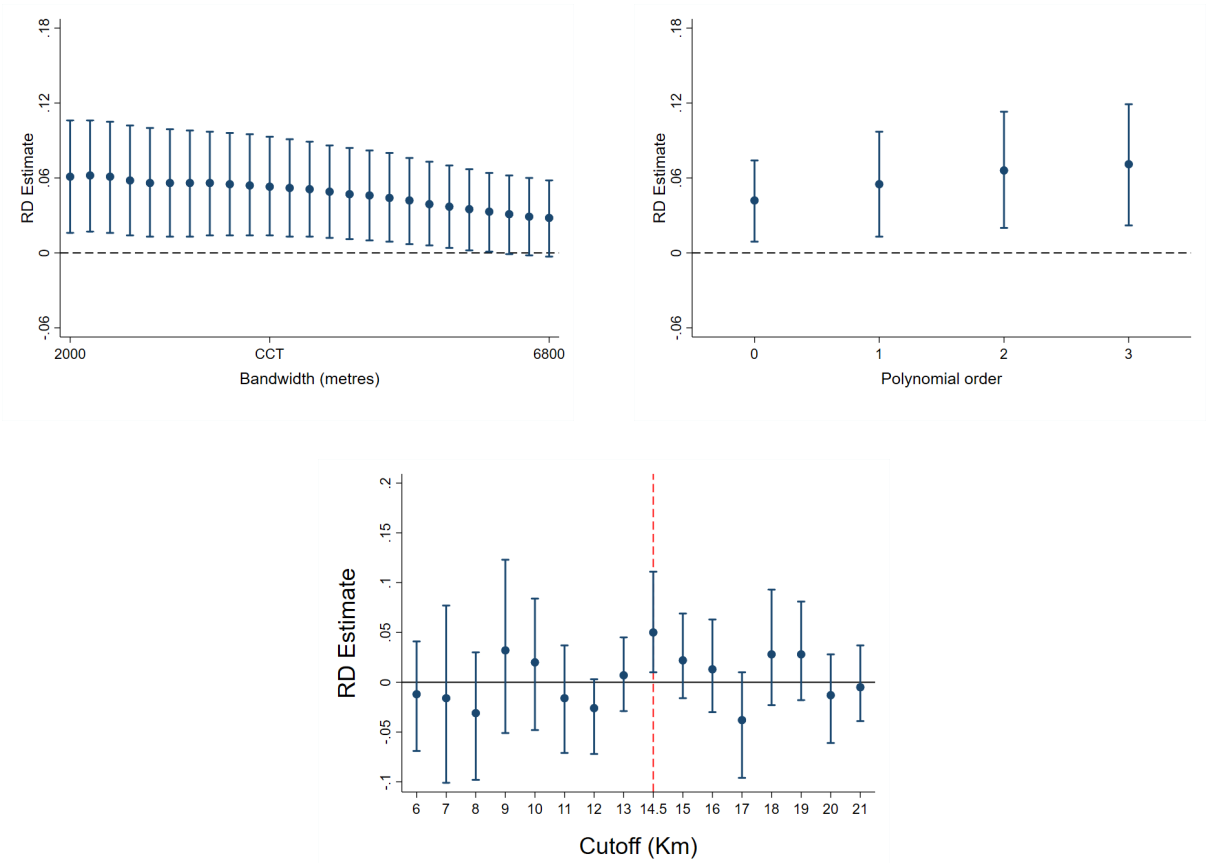
(E) Government bonus



(F) Stock value of total other drugs

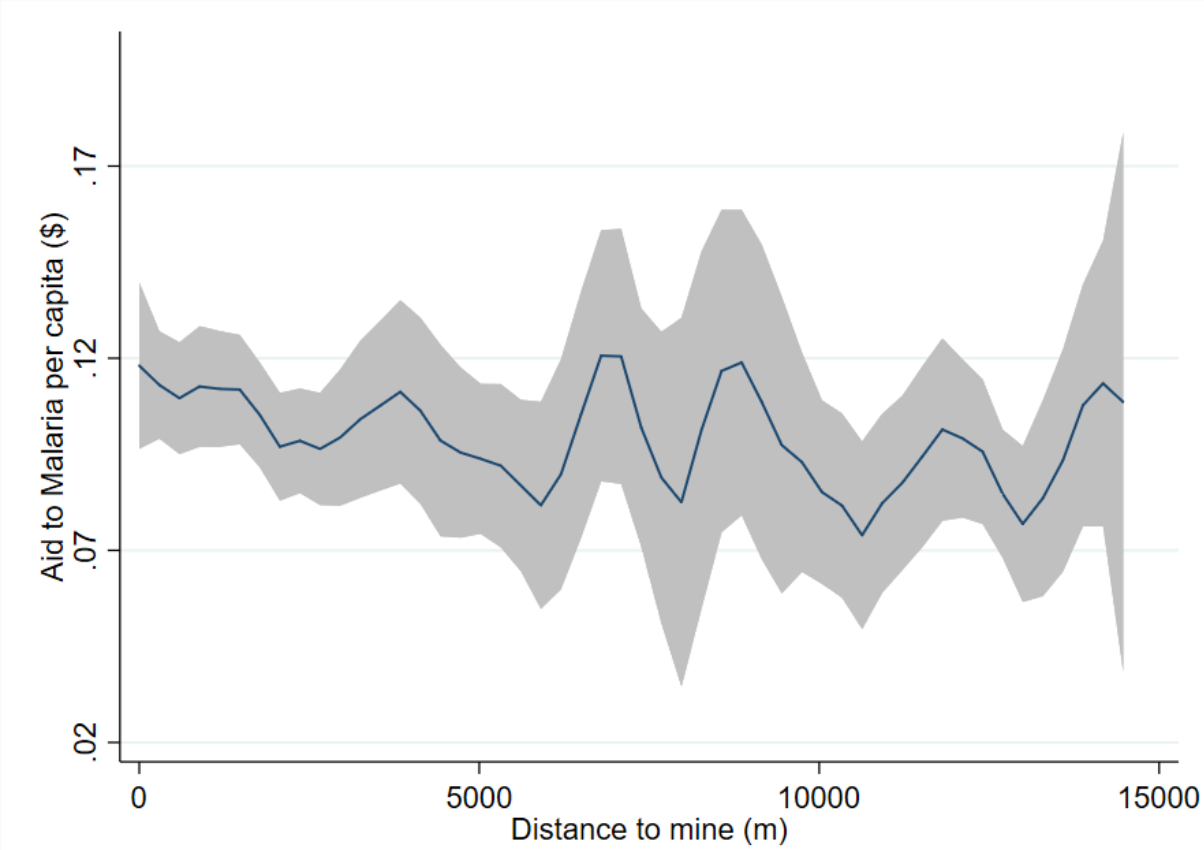
Notes: Each point plots an average value within a bin conditional on the distance to the mining threshold. The distance is in metres and the solid line plots a local cubic regression.

FIGURE 12: ROBUSTNESS CHECKS



Notes: The figures plot estimates from separate RD regressions of the outcome on mining area. The regressions include pre-determined covariates for geographic characteristics and use robust standard-errors. Each graph shows the point estimates and 95% confidence intervals. The bandwidth selection follows the data-driven procedures suggested by Calonico, Cattaneo, and Titiunik (2014) for figures (B) and (C) and is referred to "CCT" in figure (A). The vertical red line in figure (C) plots the 14.5 km cutoff that is used in all baseline results.

Figure 13: Local polynomial estimations of aid for malaria as a function of the distance to mines within mining areas



Notes: This figure shows the non-parametric estimations of aid for malaria conditional on the distance from a health facility to its the closest mine within mining areas, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The y-axis represents the malaria prevalence defined as the share of malaria cases in the population catchment area of the health facility and the x-axis corresponds to the distance from health facility to the closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients.

Figure 14: Prices of antimalarial commodoties

The Global Fund

21-Sep-18

Pooled Procurement Mechanism Reference Pricing: Antimalarial medicines (version: quarter 3 2018)

The Global Fund has established Framework Agreements with manufacturers of antimalarial medicines artemisinin-based combination therapy and other antimalarials medicines with the aim to achieve lower prices sustainable and reliable on-time supply of the full range of the needed antimalarial medicines.

Reference prices for Artemether/Lumefantrine 20/120mg, 6x1 and 6x2 are equal for dispersible and non-dispersible. We encourage to procure the dispersible form as better formulations for children.

The Pooled Procurement Mechanism (PPM) aims to deliver the orders for the following antimalarial medicines at or below reference pricing below. These prices should be used for budgeting purposes and will be us Quotes.

Actual prices achieved for a grant will depend on how early the orders (> 5 months) are placed by Principal Recipients - and additionally the achievement of certain volume thresholds through the pooled volumes to negotiated prices through the mechanism. Actual prices achieved will be charged to the grant.

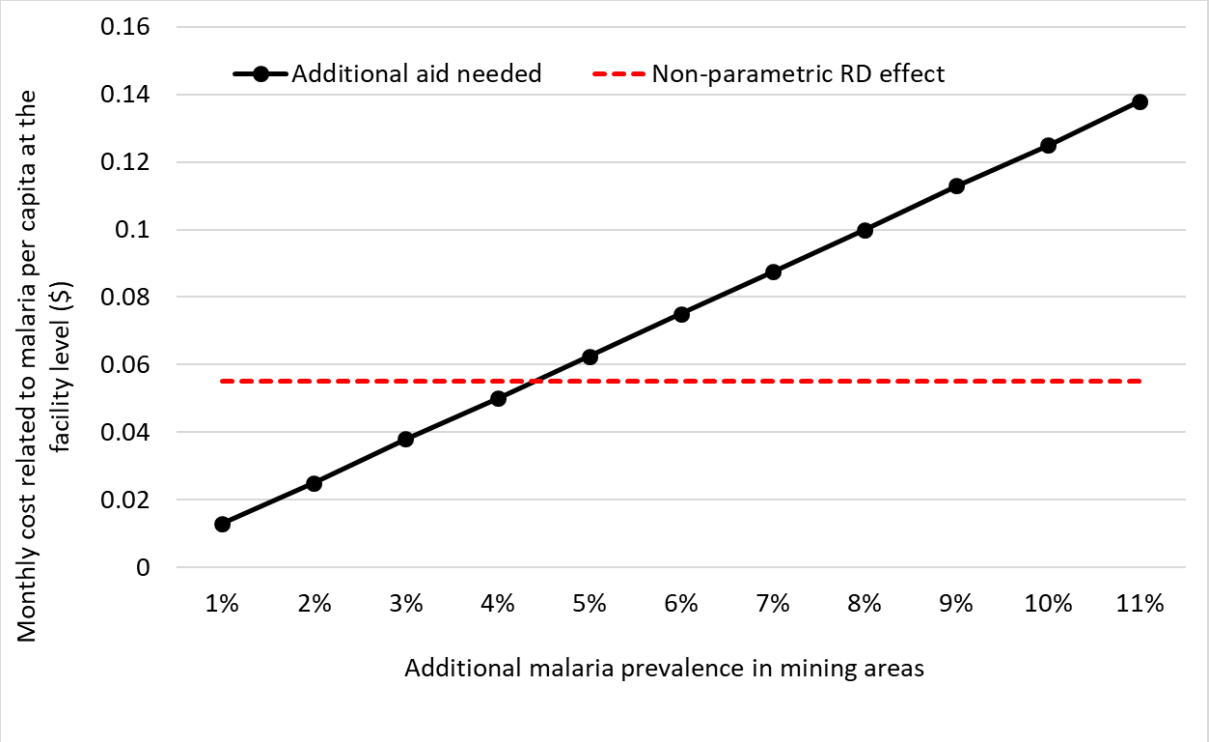
Note that pricing for some items may not be available for some countries due to patent or licensing restrictions.

Some non-optimal products/formulations/pack-sizes have been removed from this version of the reference price list: pricing can be provided on request should the product still be commercially available.

Product Description	Pack Size	Reference price US$ Per Pack for planned procurement (>5 months)	Maximum price US$ Per Pack for late orders or country registration constraints	Reference price US$ Per Treatment for planned procurement (>5 months)
Antimalarial medicines				
Artemether/Lumefantrine 20/120mg, 6x1, dispersible tablets	30 blisters	$ 9.00	$ 11.70	$ 0.30
Artemether/Lumefantrine 20/120mg, 6x2, dispersible tablets	30 blisters	$ 14.40	$ 20.70	$ 0.48
Artemether/Lumefantrine 20/120mg, 6x1, non dispersible tablets	30 blisters	$ 9.00	$ 11.70	$ 0.30
Artemether/Lumefantrine 20/120mg, 6x2, non dispersible tablets	30 blisters	$ 14.40	$ 20.70	$ 0.48
Artemether/Lumefantrine 20/120mg, 6x3, non dispersible tablets	30 blisters	$ 16.50	$ 16.50	$ 0.55
Artemether/Lumefantrine 20/120mg, 6x4, non dispersible tablets	30 blisters	$ 20.40	$ 21.00	$ 0.68
Artemether/Lumefantrine 40/240mg 6 tablet	30 blisters	$ 9.90	-	$ 0.33
Artemether/Lumefantrine 40/240mg 12 tablet	30 blisters	$ 19.50	-	$ 0.65
Artemether/Lumefantrine 60/360mg 6 tablet	30 blisters	$ 15.00	-	$ 0.50
Artemether/Lumefantrine 80/480mg 6 tablet	30 blisters	$ 18.00	-	$ 0.60
Artemether/Lumefantrine 40/240mg 6 tablet	1 blister	$ 0.45	-	$ 0.45
Artemether/Lumefantrine 60/360mg 6 tablet	1 blister	$ 0.55	-	$ 0.55
Artemether/Lumefantrine 80/480mg 6 tablet	1 blister	$ 0.65	$ 1.25	$ 0.65
Artesunate / Amodiaquine 25/67.5mg, 3x1	25 blisters	$ 5.00	-	$ 0.20
Artesunate / Amodiaquine 50/135mg, 3x1	25 blisters	$ 7.25	-	$ 0.29
Artesunate / Amodiaquine 100/270mg, 3x1	25 blisters	$ 11.29	-	$ 0.45
Artesunate / Amodiaquine 100/270mg, 3x2	25 blisters	$ 19.44	-	$ 0.78
Artesunate 30mg powder for solution for injection	1 vial	$ 1.45	-	-
Artesunate 60mg powder for solution for injection	1 vial	$ 1.45	-	-
Artesunate 120mg powder for solution for injection	1 vial	$ 2.60	-	-
Artesunate suppository 100mg	2's	$ 0.63	-	$ 0.63
Amodiaquine (as hydrochloride)+Sulfadoxine/Pyrimethamine 153mg+500/25mg 3+1 tablet dispersible co-blistered	50 blisters	$ 14.75	-	$ 0.30
Amodiaquine (as hydrochloride)+Sulfadoxine/Pyrimethamine 76.5mg+250/12.5mg 3+1 tablet dispersible co-blistered	50 blisters	$ 13.25	-	$ 0.27
Artesunate+Sulfadoxine/Pyrimethamine 100mg+500/25mg 6+3 tablet co-blistered	25 blisters	$ 40.00	-	$ 1.60
Artesunate+Sulfadoxine/Pyrimethamine 50mg+500/25mg 6+2 tablet co-blistered	25 blisters	$ 23.75	-	$ 0.95
Artesunate/Pyronaridine 60/180mg tablet 9	10 blisters	$ 20.44	-	$ 2.04
Artesunate/Pyronaridine 20/60mg granule	90 sachets	$ 12.22	-	$ 0.14
Artesunate/Mefloquine 25/50mg 3 tablet	30 blisters	$ 36.60	-	$ 1.22
Artesunate/Mefloquine 25/50mg 6 tablet	30 blisters	$ 43.50	-	$ 1.45
Artesunate/Mefloquine 100/200mg 3 tablet	30 blisters	$ 57.00	-	$ 1.90
Artesunate/Mefloquine 100/200mg 6 tablet	30 blisters	$ 90.00	-	$ 3.00
Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) tablet 100	bulk	$ 3.80	-	-
Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) tablet 1000	bulk	$ 34.00	-	-
Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) 10 tablet 10 blister	10 blisters	$ 3.70	-	$ 0.37
Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) 100 tablet 10 blister	10 blisters	$ 39.00	-	$ 3.90
Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) tablet 1000	bulk	$ 30.20	-	-
Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) 10 tablet 10 blister	10 blisters	$ 3.80	-	$ 0.38
Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) 10 tablet 100 blister	100 blisters	$ 48.00	-	$ 0.48
Sulfadoxine/Pyrimethamine 500/25mg 3 tablet	10 blisters	$ 3.50	-	$ 0.35
Sulfadoxine/Pyrimethamine 500/25mg 3 tablet	100 blisters	$ 33.50	-	$ 0.34
Sulfadoxine/Pyrimethamine 500/25mg 3 tablet	10 blisters 5 boxes	$ 14.85	-	-
Sulfadoxine/Pyrimethamine 500/25mg tablet 100	bulk	$ 11.15	-	-
Sulfadoxine/Pyrimethamine 500/25mg tablet 1000	bulk	$ 95.90	-	-

Notes: The above document presents the reference pricing of antimalarial medicines negotiated by the Global Fund through the Pooled Procurement mechanism (reference prices for Rapid Diagnostic Tests (RDT) and Insecticide-Treated bed Nets (ITNs) were also extracted from the Global Fund's documents (The Global Fund, 2018) . The Global Fund's objectives are to stabilise prices and ensure market sustainability of health commodities by pooling demand of countries that participate to the programme (The Global Fund, 2018).

FIGURE 15: EVOLUTION OF AID NEEDED WITH THE ADDITIONAL RISK OF MALARIA TRANSMISSION



Notes: The figure plots the evolution of malaria-related costs that are required to cope with the additional risk of malaria transmission. The horizontal red dashed line shows the additional aid for malaria that is received in high burden areas according to the nonparametric RD estimation (table 6) of the mining effect. The total cost of malaria diagnosis, prevention and treatment is calculated from the price list of antimalarial commodities of the Global Fund (figure 14).

Data Appendix

I detail in this section the variables that are used in the analysis.

Geographic Characteristics

Elevation: Elevation measured in metres above the sea level. Data on elevation and terrain features were obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images. Elevation information is provided at a high spatial resolution (3 arc-second resolution or approximately 90 metres). Information is then processed in ArcGIS to obtain elevation data.

Slope: Slope is measured in degrees and is obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images and processed in ArcGIS.

Distance from closest facility: corresponds to the geographic distance from a health facility to the closest facility. Distances are calculated with ArcGIS based on the latitude and longitude of each health facility in the data sample.

Distance from closest hospital: corresponds to the geographic distance from a health facility to the closest hospital. Distances are calculated with ArcGIS based on the elevation and surface features, and using the latitude and longitude of each health facility in the data sample. The function *costpath* is used in ArcGIS to calculate the optimal path based on the geographic features; distance information on the estimated path is then extracted for each health facility.

Facilities Characteristics

Antimalarial stock value: Antimalarial commodity corresponds to any commodity that is used as mean of prevention, identification or treatment of malaria. It comprises Insecticide-Treated mosquito Nets (ITNs) and Sulfadoxine-Pyrimethamine (SP), (chemoprevention administered to pregnant women and children less than five) for prevention ; 2) Rapid Diagnostic Test (RDT) for identification and Artemisinin-based Combination Therapy (ACT) for treatment of malaria. Data on the monthly stock of each antimalarial commodity is obtained from the DHIS2. The estimated value is U.S. Dollars and is based on the reference pricing of antimalarial medicines negotiated by the Global Fund through the Pooled Procurement mechanism for 2017.

Total other drugs stock value: corresponds to the medicines listed as Essential Medicines from the WHO Model list (https://www.who.int/medicines/publications/essentialmedicines/en/). Data on the monthly stock of these medicines are obtained from the DHIS2, and the stock value is expressed in U.S. Dollars.

Revenue: is the monthly revenue reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

Investment: is the monthly investment reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

Payroll tax: is the monthly payroll tax reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

Number of nurses: is the monthly number of nurses who are working in the health facility as reported in the DHIS2. The number includes nurses with two different qualification levels, A1 and A2.

Number of births: is the monthly number of birth in the health facility as reported in the DHIS2.

Stock outs days antimalarial

Insecticide-Treated mosquito Net: corresponds to the average monthly number of days the health facility ran out of ITNs in 2017.

Rapid Diagnostic Test: corresponds to the average monthly number of days the health facility ran out of RDTs in 2017.

Sulfadoxine-Pyrimethamine: corresponds to the average monthly number of days the health facility ran out of SPs in 2017.

ACT (ages +14): corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients above 14 in 2017.

ACT (ages 6-13): corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients between 6 and 13 in 2017.

ACT (ages 1-5): corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients between 1 and 5 in 2017.

ACT (ages -1): corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients below 1 in 2017.

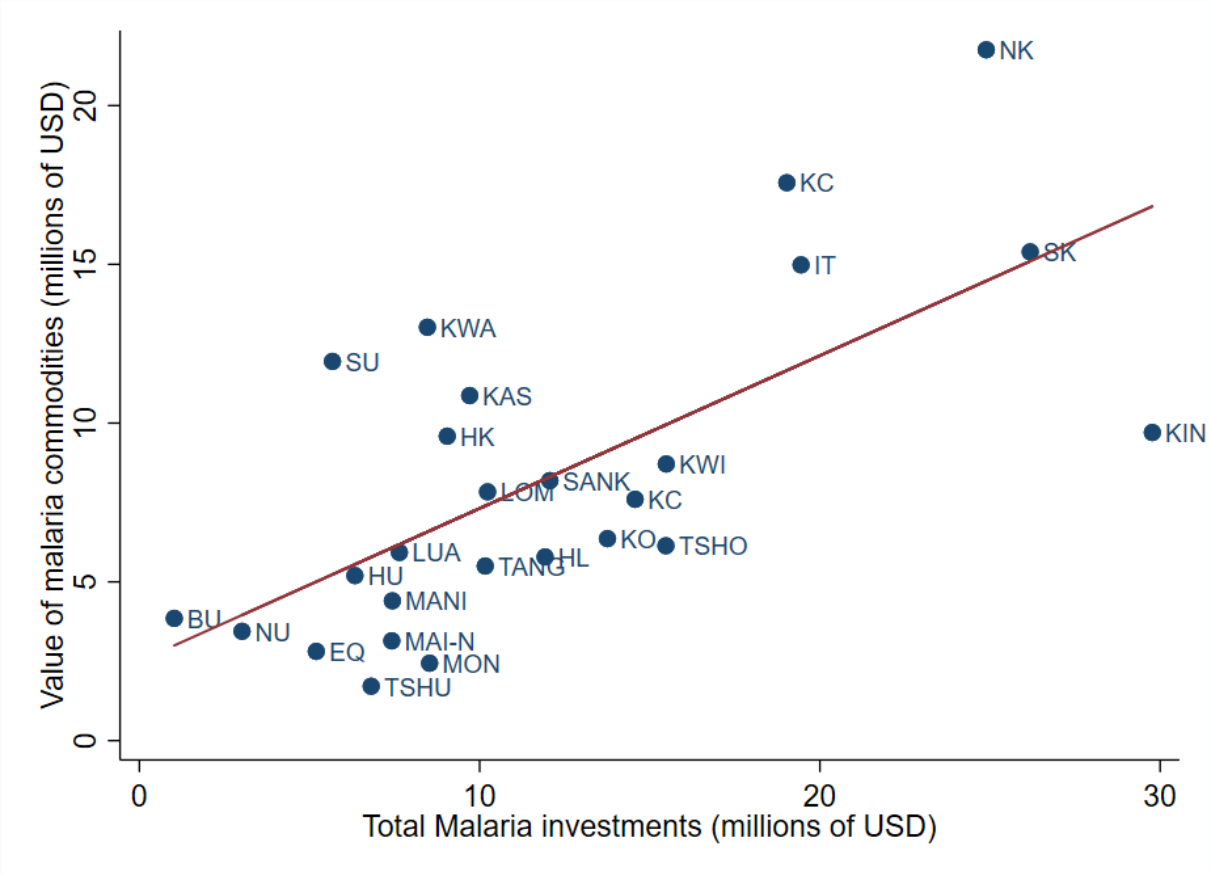
Evidence of Data quality in the DHIS2

DHIS2 is notoriously known to exhibit varying data quality performance across African countries where it is implemented. Even within the DRC, there is considerable heterogeneity in the completeness of reported data depending on the type of indicators. In particular, indicators (number of patients, stock and consumption of commodities, number of stock-out days, estimated number of affected population) pertaining to diseases heavily funded by donors (HIV, malaria) exhibits a significant higher quality performance than those related to disease mostly funded by government funding (such as non-communicable diseases). Moreover, two provinces which contain most of health facilities analysed in this study (North and South Kivu) have the highest state of data completeness across provinces in the country. To ensure the validity of the data, I also cross validated the epidemiological and financial data with two external sources. For data on malaria prevalence, I compare the obtained numbers from DHIS2 with the most recent Demographic Health Surveys in the DRC that was conducted in 2013/2014

and I do not find significant variations. Furthermore, I estimated the stock value of antimalarial commodities from the reported stock at health facility level and the cost of procurement of each commodity (obtained from the Pooled Procurement Mechanism Reference Pricing of the Global Fund, see figure 14). I then calculated for each province of the DRC the sum of the estimated stock value of antimalarial commodities of each health facilities. Furthermore, information on total malaria's funding at the provincial level was obtained from the three most important donors for malaria in the DRC (namely the Global Fund, U.S. Government (USAID) and U.K. Government (DFID)), representing approximately 97% of total donors' funding for malaria in the country (MSP, 2017). Figure 1 graphs the scatter plot of the estimated stock value of antimalarial commodities at the provincial level on the donors' malaria funding. The estimated coefficient indicates that the stock value of antimalarial commodities represents 48% of total malaria investment (see figure 16). This information is consistent with the findings from a recent audit report of the Global Fund in the DRC (The Global Fund, 2016) which estimates that 53% of total the Global Fund's investment is dedicated to the procurement of antimalarial commodities[46].

[46]This estimate was obtained from the financial information of the Global Fund's local partners and the estimated annual budget of the malaria control programme.

Figure 16: Stock value of antimalarial commodities and total malaria investment



Notes: Scatter plot of stock value of antimalarial commodities in 2017 for each of the 23 provinces of the Democratic Republic of Congo with fitted line versus total malaria investments in each province.