Do Firms Benefit from Public Health Interventions?

Evidence from Malaria Control in Sub-Saharan Africa

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October 16, 2026

Abstract

This paper studies whether, and by how much, firms benefit from large-scale public health interventions. We study donor-financed malaria interventions in sub-Saharan Africa, exploiting year-to-year variation in global funding interacted with regions' pre-program malaria burden. We find that these interventions substantially reduced the disease burden: a ten-percentage point increase in insecticide-treated-net coverage lowers the *Plasmodium falciparum* parasite rate (PfPR) by approximately nine percentage points. We also find that firms benefit from these interventions. A ten percentage point reduction in malaria prevalence increases maize and commercial scale mining production by approximately thirty percent. Our findings push toward a public–private financing architecture rather than a purely public (or donor) one: we propose a mechanism in which firms contribute in proportion to the benefits they extract from these interventions, freeing scarce donor resources for the diffuse-benefit settings, such as smallholder agriculture and child health, where no single actor captures enough return to finance provision privately.

1 Introduction

Public health interventions are conventionally justified by a public-health accounting: lives saved, illness avoided, and out-of-pocket medical costs averted. A large literature on cost-effectiveness analysis values malaria control, deworming, and vaccination based on the cost per disability-adjusted life-year (DALY) gained or death averted, consistently concluding that these programs rank among the highest-return uses of development finance. This framework, however, captures only the direct health benefits of disease control. An intervention that makes a population healthier does more than improve health. By reducing morbidity, it raises workers' physical capacity, attendance, and effort, allowing firms and farms to produce more with the same workforce. These productivity gains accrue not to the health system that financed the intervention, and not solely

to the households whose health improved. They accrue to the producers who employ healthier workers and to public finance systems that tax that production. In this sense, public health generates productive spillovers that extend beyond its immediate beneficiaries. These spillovers create opportunities for novel financial regimes.

Whether these spillovers are quantitatively important is a first-order question. If the economic returns to disease control are largely captured by firms, then conventional cost-effectiveness analyses understate the social value of public health investments by omitting an important class of production benefits. Public health is an investment in productive capacity, not just a humanitarian good. Understanding the magnitude of public health returns and the extent that they accrue to private firms is essential for evaluating how public health interventions could be valued and financed. This paper measures productive spillovers by estimating the effect of donor-financed malaria control on firm productivity across sub-Saharan Africa.

Malaria control in sub-Saharan Africa remains one of the largest sustained public-health programs, and has been for the past 25 years. Malaria remains overwhelmingly an African disease. Of the estimated 282 million malaria cases and 610,000 malaria deaths worldwide in 2024, about 95 percent were recorded in Africa (WHO, 2025). Just four African countries, Nigeria (68.5 million cases), the Democratic Republic of the Congo (35.2 million), Uganda (13.2 million), and Ethiopia (12.4 million), account for approximately 46% of all malaria cases estimated worldwide (WHO, 2025). This concentration also highlights the disproportionate role of a small number of African countries in the global malaria burden. The international response, built around insecticide-treated bed nets (ITNs), indoor residual spraying (IRS), and artemisinin-based combination therapy (ACT), has scaled from roughly $250 million per year in 2000 to a peak of about $4 billion in the early 2020s, measured in constant 2024 US dollars (WHO, 2025). Most of the funding comes from the Global Fund to Fight AIDS, Tuberculosis and Malaria (hereafter, the Global Fund) and the U.S. President's Malaria Initiative (PMI).[1] If reducing malaria raises labor productivity, then donor-funded malaria control is not only a welfare-improving public service but also an investment in productive capacity. The gains accrue to households and firms through higher earnings and output, and to governments through a larger tax base and potentially lower public treatment costs, creating a fiscal return alongside the private return despite public and donor financing.

A small number of documented cases suggest that the private returns to malaria control can be sufficiently large to motivate firm-level investment. AngloGold Ashanti's Obuasi gold mine in southern Ghana offers the clearest documented case. [2] In 2005, AngloGold identified malaria as the leading health threat facing the operation. The mine hospital reported between 6,000 and 7,000

[1]Funding figures are from the *World Malaria Report 2025* (WHO), Figures 4.2 (source shares, 2010–2024) and 4.4 (funding by channel, 2000–2024), in constant 2024 US$. See https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2025.

[2]Other documented examples of private-sector engagement in malaria control include Illovo Sugar in Malawi and Zambia Sugar in Zambia (agriculture); Mineração Novo Astro S/A in Brazil, Société d'Exploitation des Mines d'Or de Sadiola in Mali, Konkola Copper Mines, Mopani Copper Mines, and the Roan Antelope, Mufulira, Nkana-Kitwe, and Nchanga mines in Zambia (mining); and ExxonMobil, Petronas, and Chevron in Chad and Cameroon, Marathon Oil in Equatorial Guinea, and Shell in the Philippines (oil and gas) (Jones et al., 2020).

new malaria cases each month, with employees accounting for approximately 27% of cases, while their dependents and surrounding community members accounted for 40% and 33%, respectively (AngloGold Ashanti, 2004). Among mine employees, malaria generated substantial productivity losses: workers lost an average of three days per malaria episode, resulting in nearly 7,500 man-shifts lost each month, while monthly malaria treatment costs averaged US$55,500 (AfDB, 2016; AngloGold Ashanti, 2004). AngloGold launched a self-financed workplace-and-community vector-control program (indoor spraying, net distribution, larviciding, and improved case management) covering the Obuasi Municipal Assembly, with about 40,000 households. Confirmed malaria cases at the mine hospital fell by 70–74 percent by 2007–2008. Average worker-days lost to malaria fell from 6,983 per month in 2005 to 282 in 2009, a 96 percent reduction. Monthly malaria medication costs fell from about US$55,000 to US$9,800 over the same period, an 82 percent reduction (AngloGold Ashanti, 2009; AfDB, 2016; Mouzin et al., 2011). The case is notable for two reasons. First, the program was undertaken by a single firm rather than the public sector. Second, it was justified by higher labor productivity rather than by population-health objectives in their own right. It is direct evidence that, for at least one large operation, the private return can be substantial to motivate firm's investment in malaria control.

Do comparable private returns exist systematically across sub-Saharan Africa, beyond the well-publicized operations that chose to act? And if firms capture meaningful private returns from malaria control, why is the intervention financed almost exclusively by governments and international donors rather than jointly by the public and private sectors? One possibility is that, even when returns are sizable in aggregate, they are difficult for any single firm to internalize because the benefits are diffuse, mobile, and shaped by transmission externalities. This paper addresses the first question and, in doing so, sheds light on the second

In order to answer the first question, an analyst must address the fact that interventions are not randomly assigned. Donors and national programs deliberately target high-burden, high-poverty regions. The U.S. President's Malaria Initiative (PMI), for example, explicitly allocates resources based on malaria burden and implementation capacity, and national programs largely follow the same strategy. As a result, a simple comparison of regions with high and low intervention intensity confounds the effects of malaria control with the underlying characteristics that made those regions intervention targets. To address these challenges, we employ a shift-share (Bartik) instrument that interacts each region's pre-program malaria burden (measured by the *Plasmodium falciparum* parasite rate (PfPR) in 2000) with year-to-year fluctuations in global donor funding for malaria control.

International malaria control is financed primarily by a small set of external donors, and this concentration means that funding levels are often driven by donor-country budget politics rather than by contemporaneous conditions in recipient regions. About a third of malaria funding is financed domestically by the governments of malaria-endemic countries. The remaining two-thirds comes from external donors and is highly concentrated. The United States alone supplies 37 percent of all malaria funding, making it the single largest source, followed by the United Kingdom at 8

percent, with the remander coming from other bilateral and multilateral donors (WHO, 2025). Two channels dominate external financing: the Global Fund and U.S. bilateral assistance delivered largely through the President's Malaria Initiative (PMI). Because the United States is also the largest single contributor to the Global Fund, much of international malaria financing ultimately reflects U.S. funding decisions, with funding levels shaped by donor-country budget politics rather than by contemporaneous conditions in recipient regions.

We therefore exploit plausibly exogenous time variation in donor contributions to malaria-control programs, primarily driven by donor budget cycles and policy priorities. Our baseline measure focuses on contributions to the Global Fund, while we show robustness using variation from PMI and global insecticide-treated bed net (ITN) distribution programs. Second, we exploit cross-sectional variation in each region's pre-program malaria burden, measured by the *Plasmodium falciparum* parasite rate (PfPR) in 2000 [3]. Using these two sources of variation, we construct our shift-share (Bartik) instrument that interacts each region's pre-program malaria burden with year-to-year fluctuations in donor funding for malaria control. The intuition is that regions with higher baseline malaria exposure were mechanically more exposed to increases in global malaria-control funding, while the timing of these funding shocks was determined by donor-country budget cycles and international policy priorities rather than by contemporaneous conditions within recipient regions. This approach isolates variation in malaria-control intensity that is plausibly unrelated to local economic activity, allowing us to estimate the causal effects of malaria reduction on regional productivity outcomes.

Our sample is an annual panel of 469 regions (second subnational administrative units) [4] across 33 sub-Saharan countries over 2000–2024. Malaria outcomes and intervention coverages come from the Malaria Atlas Project's raster surfaces aggregated to the region-year level; agricultural production (including quantity in tonnes, area harvested, and yield) comes from HarvestStat Africa (Lee et al., 2025); and mining production comes from S&P Global's mine-level database. Our main outcomes of interest are agricultural and mining production variables. The agricultural production data cover 90 crops across sub-Saharan Africa. We focus on maize because it has broad and relatively consistent regional coverage in the data, spanning 388 regions. Maize is also one of the major staple crops in sub-Saharan Africa and is cultivated across diverse agro-ecological zones, making it a particularly relevant crop for studying agricultural production and productivity in the region (Lee et al., 2025). For mining outcomes, we focus on output from large-scale commercial gold mines. We classify a mine as large-scale commercial if its median annual production, computed over all years in which the mine is observed producing, is at least 50,000 ounces. This classification is assigned at the mine level and held fixed over time: once a mine enters the sample, all of its

[3] Our unit of analysis is the administrative region (ADM1), nested within countries. We use pre-program malaria prevalence measured at the regional level.

[4] The first subnational administrative units are districts. Districts are nested within regions, while regions are nested within countries. Our main specification is at the region-year level because the agricultural production data is widely populated at the region level. We also consider the district-year level in the appendix for testing the effect of interventions on malaria outcomes.

producing-year observations are retained (and conversely, excluded mines are dropped in all years). This avoids endogenous sample selection driven by transitory year-to-year output movements, such as ramp-up, maintenance shutdowns, or the malaria-related shocks we study, that could otherwise cause mines to enter and exit the sample.

We find that malaria interventions substantially reduce malaria burden and increase productivity. Our 2SLS estimate implies that a ten-percentage-point increase in insecticide-treated bed net coverage causally reduces malaria prevalence (PfPR) by 9.4 percentage points. Second, the returns to intervention are large. There is evidence that firms and farms benefit from these malaria interventions. The OLS estimates show that malaria interventions increase maize production, but this effect is statistically insignificant. In contrast, the 2SLS estimate shows a large and statistically significant effect of malaria interventions on maize production. A 10-percentage-point reduction in prevalence raises maize production by about 36 percent [5], of which 79 percent comes from the expansion of cultivated area (the extensive margin) and 21 percent from yield. We find similar results for mining production. A 10 percentage-point reduction in prevalence raises commercial gold mining production by about 33 percent [6]. These estimates are robust to specifications and sources of identifying variation.

Our findings contribute to several strands of the literature. First, we contribute to the literature on malaria, health, and economic productivity. A large body of research has established that malaria can have persistent effects on human capital and economic outcomes. Bleakley (2010), for example, exploits malaria eradication campaigns in the United States and Latin America to show that childhood exposure to malaria reduced subsequent labor productivity and adult income. Cutler et al. (2010) similarly find that malaria eradication in India increased income among prime-age men, with the effects consistent with improvements in labor-market productivity. Lucas (2010) shows that malaria eradication in Paraguay and Sri Lanka increased educational attainment, highlighting the longer-run human-capital channel through which disease affects economic development. More recent evidence documents immediate productivity effects: Dillon et al. (2021) find in a randomized intervention among Nigerian sugarcane workers that workplace malaria testing and treatment increased worker earnings by approximately 10 percent.

Our paper complements this literature in two ways. First, much of the existing causal evidence examines the long-run effects of historical eradication campaigns or the productivity of individual workers. In contrast we provide evidence on the effects of contemporary, large-scale malaria interventions on aggregate productive activity. Second, we move beyond individual workers and firms to examine whether reductions in malaria burden translate into higher production at the economy-wide regional level. Using subnational variation in malaria interventions across 33 sub-Saharan African countries, we provide evidence that malaria control increases agricultural and commercial mining production. In this sense, our estimates connect the established microeconomic evidence on health and worker productivity to aggregate production responses. Our agricultural results are also

[5] $\left(e^{0.3038} - 1\right) \times 100 \approx 35.5\%$
[6] $\left(e^{0.2816} - 1\right) \times 100 \approx -32.5\%$

related to Malpede (2023), who shows that malaria eradication increased agricultural development in the United States through greater agricultural land use and higher productivity. We show that a similar process can play out in contemporary sub-Saharan Africa and in an environment where malaria remains endemic, with interventions actively deployed at scale.

Second, our findings contribute to the literature on the role of the private sector in local development and the economic returns to public investment. A growing literature emphasizes that private firms can generate benefits beyond their own production when they invest in local public goods and amenities. Méndez and Van Patten (2022), for example, show that the United Fruit Company made substantial investments in local education and health infrastructure to attract and retain workers, generating positive and persistent effects on living standards in surrounding communities. Our findings highlight a related but distinct channel: public health investments can generate substantial returns for private firms even when firms themselves are not the primary providers of the intervention. This channel is particularly relevant in malaria-endemic regions, where firms depend on local labor markets and where industrial activity can interact with the environmental conditions that shape vector-borne disease transmission. The large response of commercial gold production to reductions in malaria prevalence suggests that the benefits of public malaria control extend beyond households and workers to the productive capacity of firms and local economies.

Third, our paper contributes to the broader literature on the economic returns to investments in health. A central insight from this literature is that health investments can affect economic development through human-capital accumulation and labor-market outcomes. Baird et al. (2016), for example, show that a childhood health investment in the form of school-based deworming generated long-run increases in labor supply and changes in occupational specialization. Similarly, the literature on disease eradication has documented effects on education, income, and adult productivity (Bleakley, 2010; Cutler et al., 2010; Lucas, 2010). We complement this literature by identifying an immediate production channel: reductions in malaria burden increase the quantity of agricultural and industrial output. This distinction is important because malaria can constrain production through contemporaneous worker absenteeism, morbidity, and reduced labor productivity in addition to long-run effects on human capital. Our results suggest that the returns to public-health investment may be substantially broader than their effects on health outcomes alone, extending to the productive capacity of farms, firms, and local economies. Furthermore, those effects may be capitalizable through firms in minning and agriculture.

The paper is organized as follows. Section II provides the overview of the malaria campaign program in Africa, the donors, and the data. Section III presents the estimation strategy. Section IV discusses the main results. The final section concludes.

2 Context and Data

A. Malaria Program in Africa and how it is controlled

Malaria in sub-Saharan Africa is caused mainly by *Plasmodium falciparum*, the deadliest malaria parasite, and is spread by *Anopheles* mosquitoes. Malaria directly affects people's ability to work. Typical symptoms are fever, chills, headache, and fatigue, which keep people away from work for several days. Severe cases can cause seizures, coma, and death (WHO, 2005).

Malaria control relies on three main tools. Insecticide-treated nets (ITNs) and indoor residual spraying (IRS) prevent infection by blocking mosquitoes or killing them, respectively. In addition, Artemisinin-based combination therapies (ACTs) treat infection once it occurs. Since 2000, spending on these tools has grown from approximately US$250 million to about US$4 billion a year (constant 2024 dollars; (WHO, 2025)), and coverage has grown with it. In our sample, the average share of the population sleeping under a net rose from 4.5 percent in 2000 to about 50 percent in 2024 (Appendix Figure F1). Malaria decreased sharply in the 2000s and early 2010s, but progress has stagnated since 2015 due to drug and insecticide resistance, operational problems, population growth, climate, and conflict (WHO, 2025). As mentioned in the introduction, it remains a widely spread disease in Africa, with close to 300 million cases estimated as recently as 2024.

B. Funding of malaria interventions

The late 1990s and 2000s marked a major expansion of the global funding architecture for malaria, including the establishment of the Roll Back Malaria Partnership in 1998, the Bill & Melinda Gates Foundation in 2000, the Global Fund in 2002, the World Bank's Malaria Booster Program and the U.S. President's Malaria Initiative in 2005, and Unitaid in 2006. About one-third of malaria financing comes from domestic governments in endemic countries, while most of the remainder is provided by external donors, led by the United States, with the majority of funding allocated to the WHO African Region (WHO, 2025).

Two main donors dominate external financing: the Global Fund to Fight AIDS, Tuberculosis and Malaria (the *Global Fund*) and U.S. bilateral assistance delivered largely through the President's Malaria Initiative (*PMI*). The Global Fund was established in January 2002, following an initiative conceived by Kofi Annan (then Secretary-General of the United Nations), as a multilateral financing institution designed to mobilize and channel resources toward HIV/AIDS, tuberculosis, and malaria. Unlike bilateral aid programs, the Global Fund pools resources from governments, foundations/philanthropies, and private-sector donors and allocates them to eligible countries through a standardized allocation framework. Its financing base is overwhelmingly public: as of 2026, 93.9% of the contributions it receives come from governments, and only 6.1% from private-sector and other nongovernmental sources. The United States is the largest government contributor, accounting for 36.8% of all public-sector contributions, followed by France (11.1%), the United Kingdom

(10.1%), Germany (8.7%), and Japan (6.8%).[7] Collectively, G7 countries account for 81.3% of all public-sector contributions. They are also major shareholders in the World Bank and IMF, and major non-regional shareholders of the African Development Bank. Since these multilateral lenders are important creditors to many African governments and hold significant sovereign claims, G7 countries are indirectly financially exposed to sovereign repayment capacity and thus have a financial interest in factors that affect productivity and growth.[8]

Since its inception, the Global Fund has become the largest international funder of malaria programs. As of June 2025, it had spent more than US$20.3 billion in malaria programs, accounting for approximately 59% of all international financing for malaria (Global Fund, 2025). The scale of these expenditures is particularly important for sub-Saharan Africa, where the overwhelming majority of the global malaria burden is concentrated. The Global Fund resources fund a broad portfolio of interventions, with substantial resources directed toward insecticide-treated mosquito nets and indoor residual spraying, alongside seasonal malaria chemoprevention, intermittent preventive treatment during pregnancy, diagnostic testing, antimalarial medicines, surveillance, and health-system strengthening.

The U.S. President's Malaria Initiative (PMI) is the second major pillar of the external malaria financing architecture. PMI was launched by President George W. Bush in June 2005 as a five-year, US$1.2 billion initiative targeting a 50% reduction in malaria-related mortality across 15 high-burden countries in sub-Saharan Africa. Unlike the Global Fund's multilateral model, PMI operated primarily through bilateral country programs, implemented by USAID[9] in collaboration with the U.S. Centers for Disease Control and Prevention and national malaria programs.

PMI has been the second major source of external malaria funding in Africa. The program was extended beyond its initial five-year mandate, spending approximately US$10.117 billion by 2023.[10] Annual funding increased from US$30 million in 2006 to US$778 million in 2023, while the number of African countries receiving PMI financing increased from three (3) in 2006 to twenty-nine (29) in 2023, with the program expanding into new countries as funding increased (US PMI 2024). These resources support many of the same core interventions financed by the Global Fund, including the

[7] Estimated from the Global Fund's 2026 pledges and contributions report. The Debt2Health and government-funded components of the Affordable Medicines Facility are counted as public-sector contributions.

[8] At end-2024, African sovereign borrowers owed about $75bn to G7 governments, export credit agencies, and G7-domiciled commercial banks, about 10% of the continent's public external debt (see the World Bank *International Debt Statistics* (IDS)). There is also indirect exposure through multilateral lenders. For example, the World Bank (IDA and IBRD) held $150.9bn of Africa's public external debt at end-2024, and multilateral creditors in total accounted for more than $200bn. In addition, $193bn was held by bondholders; IDS does not record creditor nationality for bond investors.

[9] The United States was the world's largest provider of official development assistance (ODA) in 2024 (OECD, 2025), with USAID accounting for 61.9% of ODA disbursed by U.S. government entities in 2020 (OECD, 2022). In 2025, the Trump administration substantially restructured U.S. foreign assistance, including a temporary pause and review of foreign aid and the termination of most USAID programs, with remaining functions transferred to the State Department. See KFF's timeline for the sequence of U.S. foreign-aid policy changes : https://www.kff.org/global-health-policy/u-s-foreign-aid-freeze-dissolution-of-usaid-timeline-of-events/. OECD 2025 preliminary data show that U.S. ODA fell by 55.6% in real terms in 2025, from approximately $65.3 billion in 2024 to $28.3 billion in 2025 (constant 2024 prices).

[10] Calculated from the U.S. President's Malaria Initiative, 18th Annual Report to Congress.

distribution of insecticide-treated nets, indoor residual spraying, and artemisinin-based combination therapies. By 2023, PMI estimated that its programs had contributed to 11.7 million lives saved and 2.1 billion malaria cases prevented since its establishment (US PMI 2024).

In this paper, we exploit variation in the funding from these two large funders of interventions to build a Bartik instrument for anti-malaria interventions.

C. Data

In this paper we perform a large-scale study of malaria intervention on economic outcomes that covers the entirety of the African continent, at a substantially disaggregated scale (regions, and in some cases districts, all of which are subunits of countries) and over time. We therefore need to combine a number of different datasets covering malaria prevalence, interventions, funding sources, and measures of economic productivity (specifically: agricultural and mining) at those disaggregated levels. We now describe each of these datasets in detail.

I. Malaria Burden and Intervention Data

We obtain malaria burden and intervention data from the Malaria Atlas Project (MAP) database for the period 2000–2024. The MAP database is one of the largest open-access repositories of global malaria datasets with a well-populated spatial dimension, and is widely used in malaria epidemiological research. It provides raster data on model-based estimates of malaria burden, including infection prevalence, incidence, and mortality rates for *Plasmodium falciparum* and *Plasmodium vivax*. We focus on *Plasmodium falciparum*, which is the predominant malaria parasite in sub-Saharan Africa. We use raster data on *P. falciparum* infection prevalence and incidence rates. The MAP database defines *P. falciparum* infection prevalence as the proportion of children aged 2–10 years with detectable *P. falciparum* parasites in a given year, and *P. falciparum* incidence as the number of newly diagnosed *P. falciparum* cases per 1,000 people in a given year. Both *P. falciparum* infection prevalence and incidence rates are modeled as per person rates (between 0 and 1) in the raster data.

The MAP database also provides data on three major malaria interventions: (1) insecticide-treated nets (ITNs), (2) indoor residual spraying (IRS), and (3) antimalarial effective treatment. We use raster data on ITN use and IRS coverage. MAP defines ITN use as the proportion of the population that sleeps under an ITN during a given year, and IRS coverage as the proportion of households covered by indoor residual spraying during a given year. We spatially aggregate these malaria burden and intervention rasters to the geographic units used in our analysis, as described below.

II. Production Data

We obtain two types of production data: agricultural production data and mining production data. We obtain agricultural production data from HarvestStat Africa (Lee et al., 2024), covering the period from 1980 to 2022. HarvestStat Africa provides a freely available, harmonized subnational database of crop statistics covering 90 crop categories across 33 countries in sub-Saharan Africa. The database is constructed from agricultural data compiled by the U.S. Famine Early Warning Systems Network (FEWS NET) from national ministries of agriculture and other sources. It contains information on crop production, harvested area, and yields. The data are standardized and calibrated across changing administrative boundaries to construct consistent subnational time series over time.

The agricultural data are organized according to FEWS NET's unique geographic unit identifier (FNID). The first-level administrative unit (admin 1) is the region, while the second-level administrative unit (admin 2) is the district. For 18 of the 33 countries, agricultural production data are available at the region level. For the remaining countries data are available at the district level. To construct a consistent unit of analysis across countries, we aggregate district-level observations to the region level where necessary. We focus primarily on maize production because maize is one of the most widely cultivated crops in the region and has relatively extensive spatial and temporal coverage in the HarvestStat Africa data.

We obtain mine-level production data from S&P Global's mine-level database. S&P Global is a leading commercial provider of global mining and metals data, with detailed information on mining operations worldwide, including mine location, ownership, commodity, and operational status. We use gold production data because gold mines have the most extensive coverage in our sample. In addition to production, we obtain information on mine operational status and the longitude and latitude of each mining site. We spatially match these coordinates to the administrative boundaries described below and assign each mine to its corresponding geographic unit.

III. Geographical Boundary and Units

We use the U.S. Famine Early Warning Systems Network (FEWS NET) geographical boundaries to define the administrative units in our analysis. This choice ensures consistency with the geographic identifiers used in the HarvestStat Africa agricultural production data. The first-level administrative unit (admin 1) corresponds to a region, while the second-level administrative unit (admin 2) corresponds to a district. Each administrative unit is linked to a country and identified using FEWS NET's unique geographic identifier (FNID).

We map the malaria burden and intervention raster data to the FEWS NET administrative boundaries and aggregate the raster data to the district level. Similarly, we assign each mining site to an administrative unit based on its geographic coordinates. Finally, we aggregate the district-level data to the region level to construct a consistent regional panel for our analysis. Our

primary unit of analysis is the region-year, with malaria burden, malaria interventions, agricultural production, and mining activity measured at the same geographic level.

IV. Malaria Funding Data

We obtain malaria financing data from the two major international funding sources. First, we obtain the Global Fund contributions from the Global Fund Data Explorer. Second, we obtain funding data for the U.S. President's Malaria Initiative (PMI) from the 2024 U.S. President's Malaria Initiative: 18th Annual Report to Congress (p. 28).

3 Empirical Strategy

The main challenges in estimating the effects of malaria interventions and malaria burden on productivity are the endogenous targeting of malaria funding and potential for reverse causality. Malaria interventions are not randomly allocated across regions. The U.S. President's Malaria Initiative (PMI), for example, explicitly allocates resources based on malaria burden and implementation capacity, and national programs generally follow a similar strategy. As a result, comparing regions with high and low intervention intensity would confound the effects of malaria control with the underlying characteristics that lead to the selection of those regions as intervention targets.

Conceptually, for malaria interventions to improve economic performance (and produce private benefits for firms as well as for governments through fiscal channels) in malaria-endemic countries, three links must hold: changes in external malaria financing must translate into changes in intervention intensity (e.g., ITN coverage); greater intervention intensity must reduce malaria burden (PfPR); and lower malaria burden must raise worker productivity. Therefore, we examine each of these links independently, and we also assess them jointly as part of a connected system.

The endogeneity concern does not only apply to the (non-random) assignment of interventions. One step down this chain, malaria burden's effect on productivity is also potentially endogenous. For example, they could both correlate with other unobserved variables, and there could be reverse causality: it is possible that malaria burden affects productivity, but is also possible that productivity affects malaria burden. We hypothesize that malaria can reduce productivity through absenteeism, lost workdays, and reduced worker health. However, higher-income regions may have greater private resources to invest in malaria prevention and treatment, thereby reducing malaria burden.

To address these identification challenges, we employ a shift-share (Bartik) instrument that interacts each region's pre-program malaria burden – measured by the *Plasmodium falciparum* prevalence rate (PfPR) in 2000 – with year-to-year fluctuations in global donor funding for malaria control. The instrument exploits differences in regions' predetermined exposure to malaria and common changes in the availability of external malaria financing over time, providing plausibly

exogenous variation in the intensity of malaria interventions.

The shift-share (Bartik) instrument is:

$$Z_{rt}^{j} \;=\; \bar{q}_r \times G_t^{j}, \qquad j \in \{\text{GF}, \text{PMI}, \text{Ship}\},$$

where $\bar{q}_r$ is region r's 2000 PfPR (the "share" in the shift-share construction) and G_t^j is the annual time series for the funding (the "shift"): total contributions to the Global Fund in U.S. dollars (in billions), total U.S. President's Malaria Initiative appropriations (in billions), or total global ITN net shipments (in millions of nets). The Global Fund Bartik serves as our headline instrument. The PMI and ITN-shipment Bartiks are used in the robustness exercises.

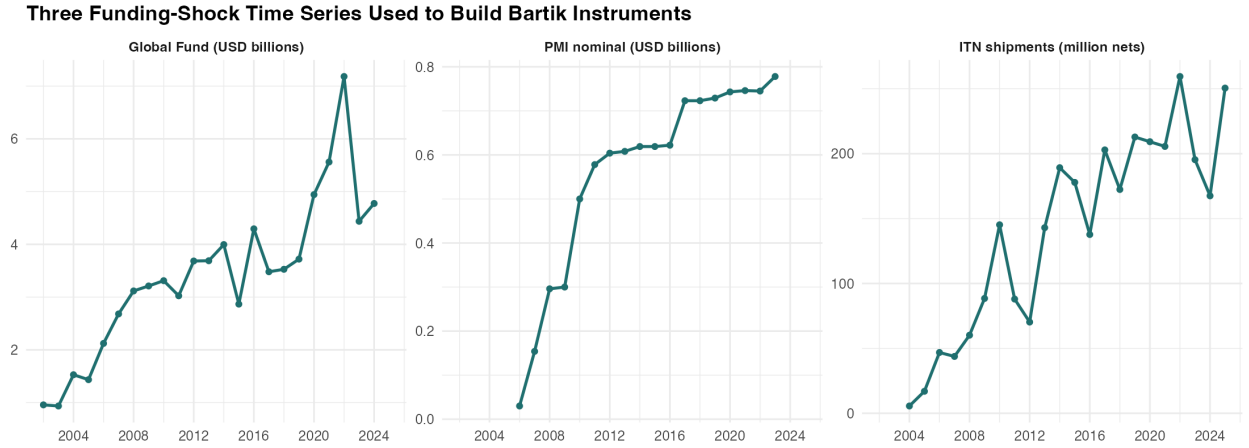


Figure 1: The three global funding-shock series used to build the shift-share instruments.

Notes. Annual Global Fund contributions (USD billions), U.S. PMI nominal appropriations (USD billions), and global insecticide-treated-net shipments (millions of nets). The instrument $Z_{rt} = \bar{q}_r \times G_t$ interacts each series with a region's year-2000 prevalence.

The institutional structure of malaria financing is what enables the shift-share empirical design, because the institutional setup cleanly separates the two ingredients that the shift-share instrument requires. The *shift* (the annual level of global malaria funding) is a common shock determined largely outside recipient regions, through U.S. Congressional appropriations and the Global Fund's replenishment cycle. Funding therefore fluctuates with donor-country fiscal conditions and international pledging decisions rather than with contemporaneous harvests, commodity prices, economic conditions, or health-system performance in individual recipient regions. The *share* (a region's exposure to the common shock) is its pre-program malaria burden, $\bar{q}_r$, measured by the *Plasmodium falciparum* parasite rate (PfPR) in 2000. Because this exposure is determined by pre-existing climatic, ecological, and epidemiological conditions, it is predetermined with respect to subsequent economic shocks. Thus, when global funding increases, high-burden regions receive a larger increase in malaria-control resources than low-burden regions; when funding contracts, their exposure falls correspondingly. The interaction $\bar{q}_r \times G_t$ therefore generates differential exposure to common changes in global malaria financing, analogous to a difference-in-differences

design: it compares changes in outcomes between high- and low-burden regions as global malaria funding rises and falls. The identifying assumption is that, controlling for region and year fixed effects, global funding shocks affect regional productivity only through their differential exposure to malaria-control interventions, with no other contemporaneous channels correlated with pre-program malaria burden.

3.1 Estimating Equations

First, we estimate the effect of malaria interventions on malaria burden. This is the first step in the conceptual chain described above. The first stage uses plausibly exogenous shifts in global malaria financing (captured by our Bartik instrument) to isolate variation in intervention intensity (ITN or IRS coverage), which establishes the malaria spending-to-intervention link. The second stage then uses this instrumented intervention intensity to identify the marginal effect of interventions on malaria outcomes (PfPR or PfIR). We implement this approach in a two-stage least squares (2SLS) framework, with the following first- and second-stage equations:

$$I_{rt} = \pi\, Z_{rt} + \delta_r^I + \phi_t^I + \nu_{rt}, \tag{1a}$$

$$M_{rt} = \beta\, \hat{I}_{rt} + \delta_r^M + \phi_t^M + \varepsilon_{rt}, \tag{1b}$$

Equation 1b represents the second stage of our 2SLS framework, while Equation 1a represents the corresponding first stage. The index r denotes regions[11] and t denotes years. The dependent variable, M_{rt}, measures the malaria burden in region r in year t, proxied by either the *Plasmodium falciparum* prevalence rate (PfPR) or the *Plasmodium falciparum* incidence rate (PfIR). The PfPR is defined as the proportion of children aged 2–10 years with detectable *P. falciparum* parasites in a given year, while the PfIR measures the number of newly diagnosed *P. falciparum* cases per 1,000 people in a given year. The prevalence rate is bounded between 0 and 1, while the incidence rate is measured per 1,000 people. I_{rt} denotes the endogenous malaria intervention variable, measured as either insecticide-treated net (ITN) coverage or indoor residual spraying (IRS) coverage in region r and year t. Both intervention measures are expressed as proportions ranging from 0 to 1. Z_{rt} denotes the instrument, constructed as the interaction between pre-program malaria burden (measured by the *P. falciparum* prevalence rate in 2000) and year-to-year fluctuations in global donor funding for malaria control. Finally, δ_r and ϕ_t denote region and year fixed effects, respectively. Standard errors are two-way clustered by region and year. The coefficient of interest is β, which captures the effect of malaria intervention coverage on malaria burden under the identifying assumptions described above. A negative estimate of $\hat{\beta}$ indicates that greater ITN or IRS coverage reduces malaria prevalence or incidence, holding other factors constant.

After estimating the effect of interventions on malaria outcomes, we estimate the effect of

[11] Regions are nested within countries.

malaria burden on productivity. This step corresponds to the final link in our conceptual chain: once malaria burden is shifted by plausibly exogenous variation in malaria financing (via differential exposure driven by baseline PfPR and common funding shocks), we can identify the marginal effect of malaria burden on economic output. We implement this approach in a two-stage least squares (2SLS) framework with the following first- and second-stage equations:

$$M_{rt} = \omega\, Z_{rt} + \delta_r^Z + \phi_t^Z + \eta_{rt}, \tag{2a}$$

$$Y_{rt} = \psi\, \hat{M}_{rt} + \delta_r^Y + \phi_t^Y + \mu_{rt}, \tag{2b}$$

Equation 2b represents the second stage of our 2SLS framework, while Equation 2a represents the corresponding first stage. The dependent variable, Y_{rt}, measures productivity in region r and year t, proxied by maize production or gold mining production. M_{rt} is the endogenous malaria-burden variable, measured by either *Plasmodium falciparum* prevalence or incidence rate, and is instrumented using Z_{rt} (note that the first stage of this step is effectively the reduced-form of the previous step in the chain, reported above). The coefficient of interest is ψ, which captures the effect of malaria burden on regional productivity under the identifying assumptions described above. δ_r and ϕ_t denote region and year fixed effects, respectively. Standard errors are two-way clustered by region and year.

4 Results

4.1 Descriptive Statistics

The analysis sample comprises 469 first-level subnational administrative units ("regions") in 33 sub-Saharan African countries observed annually over 2000–2024. Coverage is limited for productivity outcomes: the maize panel includes 379 regions in 28 countries, and the commercial gold panel covers 118 mines in 14 countries over 2002–2024. Table 1 reports summary statistics for the main variables.

Table 1 Panel A shows that malaria burden in our sample is both substantial and highly heterogeneous across regions, providing meaningful scope for interventions to matter and for baseline differences to generate differential exposure in our shift-share design. PfPR is the share of children ages 2–10 with detectable *P. falciparum* parasitemia in a given year (bounded between 0 and 1). PfIR is the number of newly diagnosed *P. falciparum* cases per 1,000 population-year; in the data it is reported in per-capita terms (0–1), so a value of 0.242 corresponds to 242 cases per 1,000 population. Mean PfPR is 0.228 (SD 0.205; IQR 0.044–0.369) and mean PfIR is 0.242 (SD 0.169; IQR 0.084–0.382), indicating wide dispersion in epidemiological conditions rather than small fluctuations around a common level. Baseline PfPR (year 2000), which supplies the cross-sectional exposure term in the shift-share instrument (Panel C), averages 0.326 (SD 0.231) and is similarly dispersed,

implying that common year-to-year funding shocks generate materially different predicted changes in intervention intensity across regions.

Table 1 Panel B reports intervention measures. Average ITN use is 0.300 at the region-year level. This pooled mean masks a pronounced scale-up: mean ITN use rises from 0.045 in 2000 to 0.497 in 2024, an elevenfold increase. Indoor residual spraying (IRS) is coded as an indicator equal to one if any spraying is recorded in a region-year; accordingly, its mean (0.367) is the share of region-years with a program, not a coverage or intensity measure. IRS adoption is non-monotonic, increasing from 0.141 in 2000 to 0.610 in 2010 and declining to 0.348 by 2024.[12]

Table 1 Panels D and E summarize productivity outcomes. Agricultural production variables are strongly right-skewed; we therefore use logs in the main specifications. Mean maize production is 175,000 tonnes (median 63,000), and the standard deviation (428,000 tonnes) exceeds the mean. The average maize area harvested is 97,000 hectares (median 49,000). We drop four region-years in the Democratic Republic of the Congo with implausibly large reported maize area ($>$ 10 million hectares). Panel E reports mine-level gold production. We classify a mine as commercial if its median annual gold output (computed over the years in which it is observed producing) is at least 50,000 ounces.[13] This classification is time-invariant: mines enter the commercial sample based on their median output, and remain included for all observed years. Average production among commercial mines is 226,500 ounces per mine-year.

[12]IRS is measured at the region level; it is available at finer geographic resolution (districts) in some settings. Districts are nested within regions, and regions within countries.

[13]We also report robustness to alternative cutoffs.

Table 1
Descriptive Statistics

Variable	N	Mean	SD	p25	Median	p75
Panel A. Malaria Outcomes						
P. falciparum prevalence rate (PfPR)	11,725	0.228	0.205	0.044	0.179	0.369
P. falciparum incidence rate (PfIR)	11,725	0.242	0.169	0.084	0.234	0.382
Panel B. Malaria Interventions						
ITN use (share)	11,725	0.300	0.250	0.054	0.250	0.519
IRS (any) $\mathbf{1}[\cdot > 0]$	11,725	0.367	0.482	0.000	0.000	1.000
Panel C. Baseline exposure and instrument						
Baseline PfPR (year 2000)	11,725	0.326	0.231	0.105	0.313	0.500
GF contributions ($B)	10,787	3.412	1.443	2.681	3.480	4.294
GF Bartik (baseline × GF)	10,787	1.112	0.977	0.317	0.862	1.707
Panel D. Agricultural Outcomes						
Maize production (1,000 tonnes)	5,990	175.2	427.6	10.4	63.2	179.1
Maize area harvested (1,000 hectares)	5,990	96.8	142.3	12.6	49.2	126.6
Maize yield (t/ha)	5,990	1.549	2.097	0.750	1.229	1.910
ln(Maize production)	5,990	10.558	2.199	9.254	11.054	12.096
ln(Maize area)	5,990	10.410	1.860	9.438	10.804	11.749
ln(Maize yield)	5,990	0.148	0.757	−0.288	0.206	0.647
Panel E. Commercial Gold Mines (mine-year)						
Gold production (1,000 oz)	1,254	226.5	197.0	97.7	164.3	280.2
ln(gold oz), mine-year	1,254	11.984	0.891	11.489	12.009	12.543

Sample. The sample comprises 469 regions (first-level subnational administrative units) across 33 sub-Saharan African countries over 2000–2024. Coverage is narrower for the productivity outcomes: the maize panel includes 379 regions across 28 countries, while the commercial gold panel covers 116 mines across 14 countries over 2002–2024.

Notes. Malaria Outcomes and Intervention (Panels A–B) are obtained from the Malaria Atlas Project (MAP). IRS is an indicator for any recorded spraying in a region-year; its mean therefore represents the share of region-years with an IRS program rather than a coverage rate. First-level subnational administrative boundaries are defined using the U.S. Famine Early Warning Systems Network (FEWS NET). Baseline malaria exposure and funding (Panel C) are used to construct the shift-share (Bartik) instrument. Agricultural production data are obtained from HarvestStat Africa (Lee et al., 2024). Gold mining production data (Panel E) are obtained from S&P Global.

4.2 First-stage estimates

Table 2 reports the first-stage regression results, for malaria interventions and malaria burden, exploring the relevance of the Global Fund shift-share instrument (*GF Bartik*) instrument. All specifications include region and year fixed effects, with standard errors two-way clustered by region and year.

Specifically, columns (1)–(2) estimate equation 1a, instrumenting intervention coverage with the Global Fund shift-share (Bartik) instrument. Column (1) shows a strong positive first stage for ITN use: positive Global Fund shocks, interacted with baseline malaria burden, predict higher regional ITN coverage. The Kleibergen–Paap F-statistic is 34.5, indicating that weak-instrument concerns are unlikely to be quantitatively important. By contrast, the first stage for IRS is weak at the region level. Although the point estimate in column (2) is positive, it is imprecise and the Kleibergen–Paap F-statistic is 1.5. Appendix Table A1 shows that the IRS first stage strengthens when IRS is measured at the district level.[14] Accordingly, in estimating the effect of interventions on malaria burden, we focus on ITN use.

Columns (3)–(4) estimate equation 2a, instrumenting malaria burden (prevalence and incidence) with the same Global Fund Bartik instrument. The first-stage coefficients are negative: positive Global Fund shocks (scaled by baseline malaria burden) predict lower malaria prevalence and incidence. The Kleibergen–Paap F-statistics are 42.6 for prevalence and 59.3 for incidence, supporting a strong first stage. We use the specifications in columns (3)–(4) in the second stage to estimate the effects of malaria burden on agricultural and mining output.

The results are robust to alternative fixed effects structures (Table 3) . Column (1) reports the baseline region and year fixed effects specification. Column (2) replaces year fixed effects with baseline-malaria (year 2000) quartile-by-year fixed effects. Column (3) uses country-by-year fixed effects, and column (4) uses geographic-zone-by-year fixed effects (West, East, Central, and Southern Africa). Across specifications, the estimated relationship remains negative: larger Global Fund shocks, interacted with baseline burden, are associated with declines in malaria prevalence. The instrument is weaker in the more demanding specifications; especially columns (2) and (3) with Kleibergen–Paap F-statistics of 14.5 and 15.9, respectively.

[14] Districts are nested within regions.

Table 2
First Stage: Effect of the GF Bartik on Each Endogenous Regressor

	Intervention coverage		Malaria burden	
	(1) ITN use	(2) IRS (any)	(3) Prevalence	(4) Incidence
GF Bartik	0.115***	0.043	−0.108***	−0.060***
	(0.020)	(0.035)	(0.017)	(0.008)
Kleibergen–Paap F	34.5	1.5	42.6	59.3
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,787	10,787	10,787	10,787

Notes. Each column is a separate first-stage regression of the indicated endogenous regressor on the GF Bartik instrument, with Region + Year FE and standard errors two-way clustered by Region and year. The paper uses two instrumenting strategies and this table reports the first stage for both: columns (1)–(2) correspond to specifications that instrument *intervention coverage*, used for the effect of coverage on the malaria burden; columns (3)–(4) to specifications that instrument the *malaria burden* directly, used for the agricultural and mining results. Signs are as the design predicts. The IRS first stage is weak ($F = 1.5$) but better at district level, as shown in the appendix table A1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
First Stage: Effect of the GF Bartik on Prevalence, by Fixed-Effect Specification

	(1) Baseline	(2) Quartile×Yr	(3) Country×Yr	(4) Zone×Yr
GF Bartik	−0.108***	−0.122***	−0.112***	−0.111***
	(0.017)	(0.032)	(0.028)	(0.020)
Kleibergen–Paap F	42.6	14.5	15.9	30.1
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes			
Quartile × Year		Yes		
Country × Year			Yes	
Zone × Year				Yes
N	10,787	10,787	10,787	10,787

Notes. First stage of prevalence on the GF Bartik across fixed-effect specifications. Column (1) includes Region and Year fixed effects. Column (2) includes Region fixed effects and malaria-baseline (year 2000) quartile-by-Year fixed effects. Column (3) includes Region fixed effects and Country-by-Year fixed effects. Column (4) includes Region fixed effects and geographic-zone-by-Year fixed effects. The four geographic zones are West, East, Central, and South. SE two-way clustered by Region and Year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Identification Validity

We now estimate a more extensive lead-lag specification for the Bartik shift-share instrument, that allows us to both understand the timing of the relation between the shock to the Bartik instrument and the endogenous variables, and test for pre-trends.

We estimate

$$I_{rt} = \sum_{k=-3}^{3} \pi_k \, Z_{r,t+k} + \delta_r^I + \phi_t^I + \nu_{rt}, \tag{3}$$

$$M_{rt} = \sum_{k=-3}^{3} \omega_k \, Z_{r,t+k} + \delta_r^M + \phi_t^M + \eta_{rt}, \tag{4}$$

where I_{rt} denotes the intervention (ITN use or IRS) and M_{rt} denotes malaria burden measure (prevalence or incidence) in region r and year t. The regressor $Z_{r,t+k}$ is the Global Fund Bartik instrument evaluated k years relative to t. Thus, π_1, π_2, and π_3 (and analogously ω_1, ω_2, and ω_3) are the lead coefficients; π_0 and ω_0 are contemporaneous; and $\pi_{-1}, \pi_{-2}, \pi_{-3}$ (and $\omega_{-1}, \omega_{-2}, \omega_{-3}$) are lags. All specifications include region and year fixed effects, and standard errors are two-way clustered by region and year.

Table 4 shows that in all cases, the effect of the Bartik shock on the endogenous variable is stronger after a lag. It also shows that the lead coefficients are broadly insigificant and smaller in magnitude compared to the lags, providing evidence against differential pre-trends correlated with baseline malaria exposure.

Table 4

Validity Test: Intervention and Malaria Burden on Leads and Lags of the GF Bartik Instrument

	(1) ITN use	(2) IRS (any)	(3) Prevalence	(4) Incidence
Panel A. Leads				
GF Bartik$(t+3)$	-0.033^{**}	0.078	-0.010	-0.011
	(0.014)	(0.063)	(0.011)	(0.008)
GF Bartik$(t+2)$	-0.005	0.053	-0.008	-0.009^{*}
	(0.010)	(0.047)	(0.005)	(0.005)
GF Bartik$(t+1)$	0.025	-0.113	-0.003	-0.007
	(0.025)	(0.066)	(0.014)	(0.009)
Panel B. Contemporaneous				
GF Bartik(t)	-0.009	-0.022	-0.018	-0.012
	(0.035)	(0.120)	(0.021)	(0.015)
Panel C. Lags				
GF Bartik$(t-1)$	-0.005	0.091	-0.022	-0.010
	(0.025)	(0.112)	(0.020)	(0.016)
GF Bartik$(t-2)$	0.086^{***}	0.240^{***}	-0.038^{*}	-0.011
	(0.016)	(0.051)	(0.019)	(0.014)
GF Bartik$(t-3)$	0.111^{***}	-0.189^{*}	-0.051^{**}	-0.024
	(0.017)	(0.091)	(0.019)	(0.014)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7,973	7,973	7,973	7,973

Notes. Each column reports a distributed lead–lag regression of the indicated outcome on the GF shift-share (Bartik) instrument at seven horizons ($k = -3, \ldots, 3$), all entered jointly. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year. Under the identifying assumption, these leads should not predict current outcomes; we therefore interpret statistically indistinguishable lead coefficients as evidence against differential pre-trends correlated with baseline exposure. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Second Stage: Effect of Intervention on Malaria Burden

Using the Bartik instrument, we can then study the first step of the conceptual chain: how interventions affect malaria burden. As mentioned above, we focus on ITN here as its first stage is strong (as opposed to IRS for which the instrument is weak). Instrumenting ITN use with the GF Bartik, we find large and precisely estimated effects of nets on malaria burden: a 10 percentage point increase in ITN use reduces malaria prevalence by 9.43 percentage points and lowers incidence by 52.3 newly diagnosed cases per 1,000 people (Table 5, Panel B). These IV effects are substantially larger than the corresponding OLS associations, indicating that OLS substantially understates intervention effectiveness.

Panel A of Table 5 reports OLS estimates of the second stage equation 1b. All specifications include region and year fixed effects, and we report standard errors two-way clustered by region and year. Columns (1)–(2) show a strong negative association between ITN use and malaria burden. The coefficient for prevalence is -0.193 (statistically significant), implying that a 10 percentage point increase in ITN use is associated with a 1.93 percentage point decline in malaria prevalence. The coefficient for incidence is -0.127 (statistically significant), corresponding to 12.7 fewer newly diagnosed cases per 1,000 population for a 10 percentage point increase in ITN use. Columns (3)–(4) show that the OLS association between IRS and malaria burden is close to zero and statistically insignificant for both malaria prevalence and incidence.

Panel B of Table 5 reports the corresponding IV estimates of equation 1b, instrumenting intervention coverage with the GF Bartik instrument. Columns (1)–(2) identify the effect of ITN use on malaria prevalence and incidence. The prevalence estimate is -0.943 and statistically significant, and the incidence estimate is -0.523 and statistically significant. The IV estimates for IRS are negative but imprecise and statistically insignificant, consistent with the weak first stage for IRS at the region level (Kleibergen–Paap F-statistic of 1.5). Appendix Table B1 shows that the ITN results are robust across alternative fixed-effect specifications.

Table 5
Effect of Malaria Interventions on Prevalence and Incidence

	Endogenous: ITN use		Endogenous: IRS (any)	
	(1) Prevalence	(2) Incidence	(3) Prevalence	(4) Incidence
Panel A. OLS				
Endogenous	-0.193^{***}	-0.127^{***}	-0.006	-0.003
	(0.027)	(0.018)	(0.007)	(0.005)
Panel B. 2SLS (GF Bartik instrument)				
Endogenous (inst.)	-0.943^{***}	-0.523^{***}	-2.504	-1.389
	(0.090)	(0.051)	(1.819)	(1.057)
Kleibergen–Paap F	34.5	34.5	1.5	1.5
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,787	10,787	10,787	10,787

Notes. Panel B reports two-stage least squares estimates of equation 1b, instrumenting endogenous regressor with the Global Fund shift-share (Bartik) instrument; Panel A reports the corresponding OLS estimates. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year. Columns (1)–(2) use ITN use as the treatment and report effects on malaria prevalence (PfPR) and incidence (PfIR), respectively. Columns (3)–(4) analogously use IRS (any) as the treatment. The 2SLS estimates for ITN are approximately five times larger in magnitude than the corresponding OLS estimates. The first stage for IRS is weak at the region level (Kleibergen–Paap $F = 1.5$), so the IRS 2SLS point estimates are imprecise and we do not interpret them. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Malaria Burden and Production Outcomes

Next, we estimate the effect of malaria burden (measured by prevalence and incidence) on production outcomes – again, using the Bartik instrument. We focus on agricultural production, proxied by maize, and on mining production, proxied by gold. Agricultural and mining are important industries in Africa, and productivity in these sectors could have economy-wide implications.

4.5.1 Effect on Agricultural Production

Malaria reduces agricultural productivity, as proxied by maize productivity (Table 6). Maize is a good proxy for general agricultural productivity because maize has broad coverage across the malaria-endemic sample region and data on maize are widely available. OLS estimates are imprecise and underestimate the malaria's reduction on productivity relative to the 2SLS results. We decompose maize production into area harvested, the extensive margin, and yield per area, the intensive margin.

Panel A presents OLS estimates of equation 2b. The OLS associations between malaria burden (prevalence and incidence) and maize outcomes are negative but statistically insignificant.

Panel B reports 2SLS estimates of equation 2b, instrumenting malaria burden with the GF Bartik instrument. The results indicate that reductions in malaria burden increase maize production. The coefficient of malaria prevalence on ln(maize production) is -3.038 (statistically significant). Interpreting the magnitude, a 10 percentage point decline in prevalence ($\Delta\text{PfPR} = -0.10$) implies

$$\Delta \ln(Y) \approx (-3.038) \times (-0.10) = 0.3038,$$

which corresponds to an approximately $100 \times (\exp(0.3038) - 1) = 35.5\%$ increase in maize production. Likewise, the coefficient of malaria incidence on ln(maize production) is -5.496 (statistically significant). A reduction of 10 newly diagnosed cases per 1,000 population implies an increase in maize production of about $100 \times (\exp(0.05496) - 1) = 5.65\%$.[15]

The production effect can be decomposed into extensive and intensive margins (Panels C and D), and approximately 80 percent of the productivity effect comes from changes in the extensive margin. Panel C reports 2SLS estimates for ln(area harvested). The prevalence coefficient is -2.386 (statistically significant), implying that a 10 percentage point decline in prevalence increases area harvested by about $100 \times (\exp(0.2386) - 1) = 26.9\%$. The incidence coefficient is -4.316, implying that a reduction of 10 cases per 1,000 increases area harvested by about $100 \times (\exp(0.04316) - 1) = 4.41\%$.

Panel D reports 2SLS estimates for ln(yield). The point estimates suggest that reductions in malaria burden increase yield as well, but the effects are not statistically significant. Taken together, the decomposition indicates that the increase in maize production is driven primarily by

[15] These semi-elasticity conversions use $100 \times (\exp(\Delta \ln Y) - 1)$.

the extensive margin: area harvested accounts for about 79% of the production response, versus 21% for yield. Results under alternative fixed-effect specifications in appendix table B2 remain negative, though statistical significance is attenuated.

Table 6
Effect of Malaria Burden on Agricultural Production (Maize)

	(1) Prevalence (inst.)	(2) Incidence (inst.)	Decomp. share
Panel A. OLS, ln(*production*)			
Endogenous	−0.324	−0.275	
	(0.311)	(0.423)	
Panel B. ln(**Maize production**)			
Endog. (inst.)	−3.038***	−5.496***	100%
	(0.785)	(1.235)	
Panel C. ln(**Maize area**) – **extensive**			
Endog. (inst.)	−2.386***	−4.316***	**79%**
	(0.547)	(0.863)	
Panel D. ln(**Maize yield**) – **intensive**			
Endog. (inst.)	−0.652	−1.180	**21%**
	(0.430)	(0.752)	
Kleibergen–Paap F	92.7	135.5	
Region FE	Yes	Yes	
Year FE	Yes	Yes	
N	5,412	5,412	

Notes. Panel A reports OLS estimates. Panels B–D report two-stage least squares estimates of equation 2b, instrumenting the endogenous regressor (malaria burden) with the Global Fund shift-share (Bartik) instrument. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year. Column (1) uses malaria prevalence as the endogenous regressor and reports effects on maize outcomes; column (2) uses malaria incidence as the endogenous regressor and reports effects on maize outcomes. Column (3) reports the decomposition share. The main outcome is ln(maize production). We decompose production into the extensive and intensive margins using

$$\ln(\text{production}) = \ln(\text{area harvested}) + \ln(\text{yield}).$$

Accordingly, Panel C reports estimates for ln(area harvested) (extensive margin) and Panel D reports estimates for ln(yield) (intensive margin). The decomposition share in column (3) summarizes the relative contribution of each margin to the total production effect.
Significance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2 Effect on Mining Production

Mining is also an important industry in Africa, in areas where malaria is endemic. Therefore, we examine the effect of malaria burden (prevalence and incidence) on commercial gold production. Table 7 reports estimates at two levels of aggregation. Columns (1)–(2) present region-year regressions, while columns (3)–(4) present mine-year regressions; in all cases, standard errors are two-way clustered by region and year. Panel A reports OLS estimates. The associations between malaria burden and gold production are negative but imprecise in both the region-year and mine-year specifications.

Panel B reports 2SLS estimates of equation 2b, instrumenting malaria burden with the GF Bartik instrument. The 2SLS estimates are similar across region-year and mine-year specifications, and they are negative and precisely different from zero. At the region-year level, the coefficient of prevalence on ln(gold production) (measured in thousands of ounces) is -2.816, implying that a 10 percentage point decline in malaria prevalence is associated with an increase in commercial gold production of approximately $100 \times (\exp(0.2816) - 1) = 32.5\%$. The coefficient on incidence is -4.513, implying that a reduction of 10 newly diagnosed *P. falciparum* cases per 1,000 population is associated with an increase in gold production of approximately $100 \times (\exp(0.04513) - 1) = 4.62\%$. The mine-year estimates are of comparable magnitude and statistical significance.

Appendix estimates using alternative fixed-effect specifications (Appendix Table B2) are still negative, though less precisely estimated. This loss of precision coincides with a weaker first stage in these more demanding specifications: the Kleibergen–Paap F-statistic is 4.0 for quartile-by-year fixed effects, 7.2 for country-by-year fixed effects, and 7.1 for geographic-zone-by-year fixed effects.

Commercial gold mines are defined as mines with median annual output of at least 50,000 ounces over observed producing years. We also conduct sensitivity analyses varying this median-output cutoff. At the mine-year level, coefficient estimates remain negative and statistically significant across all cutoffs, though precision declines at lower thresholds. At the region-year level, estimates remain negative for all cutoffs but are less precisely estimated and become statistically insignificant at lower thresholds. Overall, the sensitivity analysis supports the conclusion that reductions in malaria burden increase commercial gold production (Appendix Table C1).

Table 7
Effect of Malaria Burden on Commerical Gold Production

	Region level		Mine level	
	(1) Prevalence	(2) Incidence	(3) Prevalence	(4) Incidence
Panel A. OLS, ln(*gold oz*)				
Endogenous	−0.927	−1.107	−0.821	−0.956
	(0.593)	(0.882)	(0.486)	(0.710)
Panel B. 2SLS, ln(*gold oz*)				
Endog. (inst.)	−2.816**	−4.513**	−2.326***	−3.664***
	(1.021)	(1.597)	(0.682)	(1.104)
Kleibergen–Paap F	29.1	35.3	33.1	46.7
Region FE	Yes	Yes		
Mine FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	549	549	1,254	1,254

Notes. Panel A reports OLS estimates of the association between malaria burden and commercial gold production. Panel B reports two-stage least squares estimates of equation 2b, instrumenting the endogenous regressor (malaria burden) with the Global Fund shift-share (Bartik) instrument. The sample is restricted to commercial gold mines, defined as mines with median annual output of at least 50,000 ounces over observed producing years. Columns (1)–(2) aggregate mine output to the region-year level; columns (3)–(4) use mine-year observations. All specifications include region and year fixed effects. Standard errors are two-way clustered by region and year. *Significance.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusion

This paper documents positive spillovers of large-scale public health interventions for firms. Malaria control is primarily financed by endemic-country governments and international donors. If a meaningful share of the economic returns to disease control is captured by firms, then public health spending should be understood not only as an investment in human welfare, but also as an investment in productive capacity.

We ask whether, and by how much, firms benefit from large-scale malaria interventions in sub-Saharan Africa by estimating the causal effect of malaria burden on production. Credible identification is complicated by the endogenous targeting of malaria funding and by reverse causality between economic activity and disease. To address these concerns, we develop a shift-share (Bartik) instrument that combines cross-sectional variation in baseline malaria exposure with plausibly exogenous time variation in global malaria funding.

We first estimate the effect of interventions on malaria burden. Using the Global Fund Bartik

instrument, we find that increases in intervention coverage reduce malaria burden. A 10 percentage point increase in ITN use reduces malaria prevalence by 9.43 percentage points and reduces incidence by 52.3 newly diagnosed cases per 1,000 population.

We then show that reductions in malaria burden increase both agricultural and mining production. A 10 percentage point decline in malaria prevalence raises maize production by approximately 35.5% and commercial gold production by approximately 32.5%. Likewise, a reduction of 10 newly diagnosed cases per 1,000 population increases maize production by about 5.65% and gold production by about 4.62%.

These findings have implications for the financing of public health interventions. If firms capture substantial economic returns from disease control, then financing should not be viewed solely through the lens of public provision. Instead, our results motivate a role for mixed public–private financing, with firms contributing in proportion to the benefits they receive from these interventions.

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Appendix

Appendix A: District-Level Results

This appendix presents district-level 2SLS estimates of equations 1a and 1b. The district-level first stage for IRS is substantially stronger than at the region level: the Kleibergen–Paap F-statistic rises from 1.5 (region level) to 11.2 (district level). Consistent with the main results, increases in malaria intervention coverage reduce malaria prevalence and incidence. In addition, at the district level we also find evidence that IRS reduces prevalence and incidence, with effects that are statistically significant, in contrast to the imprecise region-level estimates.

Table A1
District-Level Effect of Malaria Intervention on Prevalence and Incidence

	Treatment: ITN use		Treatment: IRS (any)	
	(1) Prevalence	(2) Incidence	(3) Prevalence	(4) Incidence
Panel A. OLS				
Treatment	−0.176***	−0.116***	−0.010	−0.003
	(0.022)	(0.015)	(0.008)	(0.006)
Panel B. 2SLS (GF Bartik instrument)				
Treatment (instr.)	−1.188***	−0.589***	−1.159***	−0.575***
	(0.106)	(0.044)	(0.212)	(0.126)
Panel C. First Stage (treatment on GF Bartik)				
GF Bartik	0.097***	0.097***	0.099***	0.099***
	(0.016)	(0.016)	(0.030)	(0.030)
Kleibergen–Paap F	34.5	34.5	11.2	11.2
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	92,526	92,526	92,526	92,526

Notes. This table reports district-level estimates of the effect of malaria interventions on malaria prevalence (PfPR) and incidence (PfIR). Panel A reports OLS estimates. Panel B reports two-stage least squares estimates of equation 1b, instrumenting the endogenous regressor (intervention coverage) with the Global Fund shift-share (Bartik) instrument. Panel C reports first-stage estimates from equation 1a, regressing intervention coverage on the Bartik instrument. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year. Columns (1)–(2) use ITN use as the endogenous regressor and report effects on PfPR and PfIR, respectively. Columns (3)–(4) analogously use IRS (any) as the endogenous regressor. *Significance.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Fixed Effect specifications

Table B1
Effect of ITN Use on Prevalence: Fixed-Effect Specifications

	(1) Baseline	(2) Quartile×Yr	(3) Country×Yr	(4) Zone×Yr
Panel A. OLS				
Endogenous	-0.193^{***}	-0.096^{***}	-0.109^{***}	-0.187^{***}
	(0.027)	(0.022)	(0.028)	(0.026)
Panel B. 2SLS (GF Bartik instrument)				
Endog. (inst.)	-0.943^{***}	-1.020^{***}	-2.265^{***}	-1.041^{***}
	(0.090)	(0.256)	(0.486)	(0.118)
Kleibergen–Paap F	34.5	19.5	14.1	32.5
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes			
Quartile × Year		Yes		
Country × Year			Yes	
Zone × Year				Yes
N	10,787	10,787	10,787	10,787

Notes. Effect of ITN use on prevalence across fixed-effect specifications. Column (1) includes Region and Year fixed effects. Column (2) includes Region fixed effects and malaria-baseline (year 2000) quartile-by-Year fixed effects. Column (3) includes Region fixed effects and Country-by-Year fixed effects. Column (4) includes Region fixed effects and geographic-zone-by-Year fixed effects. The four geographic zones are West, East, Central, and South. SE two-way clustered by Region and Year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2
Effect of Malaria Prevalence on Maize Production: Fixed-Effect Specifications

	(1) Baseline	(2) Quartile×Yr	(3) Country×Yr	(4) Zone×Yr
Panel A. OLS				
Endogenous	−0.324	0.447*	0.214	0.137
	(0.311)	(0.250)	(0.258)	(0.248)
Panel B. 2SLS (GF Bartik instrument)				
Endog. (inst.)	−3.038***	−1.545	−0.461	−0.798
	(0.785)	(1.659)	(0.740)	(0.717)
Kleibergen–Paap F	92.7	27.3	19.8	37.0
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes			
Quartile × Year		Yes		
Country × Year			Yes	
Zone × Year				Yes
N	5,412	5,412	5,406	5,412

Notes. Effect of malaria prevalence on maize production across fixed-effect specifications. Column (1) includes Region and Year fixed effects. Column (2) includes Region fixed effects and malaria-baseline (year 2000) quartile-by-Year fixed effects. Column (3) includes Region fixed effects and Country-by-Year fixed effects. Column (4) includes Region fixed effects and geographic-zone-by-Year fixed effects. The four geographic zones are West, East, Central, and South. SE two-way clustered by Region and Year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C: Sensitivity of Gold Production to Cutoff

Table C1
Sensitivity of the Gold Production Result to the Commercial-Mine Cutoff

Cutoff		Region level				Mine level			
(median oz/yr)	Countries	Prevalence	Incidence	Regions	N	Prevalence	Incidence	Mines	N
None	17	−1.515	−2.451	53	705	−1.487*	−2.338*	173	1,927
		(1.055)	(1.672)			(0.744)	(1.172)		
10,000	15	−1.180	−1.880	48	676	−1.836**	−2.916**	130	1,576
		(1.127)	(1.776)			(0.769)	(1.191)		
25,000	15	−1.632	−2.594	42	605	−1.856**	−2.911**	108	1,394
		(1.148)	(1.817)			(0.759)	(1.190)		
50,000	**14**	−2.816**	−4.513**	**38**	**549**	−2.326***	−3.664***	**94**	**1,254**
		(1.021)	(1.597)			(0.682)	(1.104)		
75,000	14	−3.132***	−5.021***	36	513	−2.101***	−3.324***	88	1,181
		(1.041)	(1.621)			(0.598)	(0.989)		
100,000	12	−3.321**	−5.313***	31	469	−2.728***	−4.379***	72	995
		(1.184)	(1.854)			(0.704)	(1.162)		
150,000	10	−2.663*	−4.004*	24	383	−2.772***	−4.274***	44	681
		(1.449)	(2.154)			(0.898)	(1.386)		

Notes. Each row re-estimates the 2SLS specification of Table 7 on the sample of gold mines whose median annual output over their observed producing years is at least the stated cutoff. The classification is at the mine level and time-invariant, so a qualifying mine remains in the sample in every year it reports. Region and year fixed effects at the Region level, mine and year fixed effects at the mine level; standard errors two-way clustered by Region and year throughout. The bolded row is the definition used in the paper. Kleibergen–Paap F is essentially flat across the ladder at the Region level (25–29), so the pattern below is not driven by instrument strength. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D: Interventions and Production Outcomes

Table D1
Intervention and Productivity: Effect of ITN Use on Maize Production

	(1) Baseline	(2) Quartile×Yr	(3) Country×Yr	(4) Zone×Yr
Panel A. OLS				
Endogenous	0.506**	0.124	0.547*	0.262
	(0.227)	(0.195)	(0.301)	(0.205)
Panel B. 2SLS (GF Bartik instrument)				
Endog. (inst.)	2.250***	1.300	1.032	0.733
	(0.651)	(1.330)	(1.552)	(0.634)
Kleibergen–Paap F	45.6	16.3	14.7	42.3
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes			
Quartile × Year		Yes		
Country × Year			Yes	
Zone × Year				Yes
N	5,412	5,412	5,406	5,412

Notes. Panel A reports OLS estimates. Panels B report two-stage least squares estimates, instrumenting the endogenous regressor (ITN use) with the Global Fund shift-share (Bartik) instrument. Column (1) includes Region and Year fixed effects. Column (2) includes Region fixed effects and malaria-baseline (year 2000) quartile-by-Year fixed effects. Column (3) includes Region fixed effects and Country-by-Year fixed effects. Column (4) includes Region fixed effects and geographic-zone-by-Year fixed effects. The four geographic zones are West, East, Central, and South. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year.
Significance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D2
Intervention and Productivity: Effect of ITN Use on Gold Production

	(1) Baseline	(2) Quartile×Yr	(3) Country×Yr	(4) Zone×Yr
Panel A. OLS				
Endogenous	1.003**	0.302	0.751	0.493
	(0.364)	(0.334)	(0.670)	(0.403)
Panel B. 2SLS (GF Bartik instrument)				
Endog. (inst.)	1.660***	2.493	2.246	1.614
	(0.475)	(1.799)	(12.601)	(2.463)
Kleibergen–Paap F	23.1	10.1	2.0	12.8
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes			
Quartile × Year		Yes		
Country × Year			Yes	
Zone × Year				Yes
N	549	549	449	547

Notes. Panel A reports OLS estimates. Panels B report two-stage least squares estimates, instrumenting the endogenous regressor (ITN use) with the Global Fund shift-share (Bartik) instrument. Column (1) includes Region and Year fixed effects. Column (2) includes Region fixed effects and malaria-baseline (year 2000) quartile-by-Year fixed effects. Column (3) includes Region fixed effects and Country-by-Year fixed effects. Column (4) includes Region fixed effects and geographic-zone-by-Year fixed effects. The four geographic zones are West, East, Central, and South. All specifications include region and year fixed effects; standard errors are two-way clustered by region and year.
Significance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E: Mining and Agriculture Share of Government Revenue

Table E1

Extractive and Mining Revenue as a Share of Total Government Revenue, EITI-Reporting African Countries

	Report years EITI reports		Share of total government revenue mean over report years		Mining share of extractive revenue	Mining share of total government revenue EITI reports (our compilation)		
		With				Mean	Latest	
Country	Covered	data	Extractives	Oil and gas	Mean		Value	Year
DR Congo†	2015–2021	5	45.3	3.4	93.5	**41.9**	39.7	2021
Zambia†	2017–2022	5	37.6	0.0	100.0	**37.6**	44.1	2022
Guinea†	2014–2022	9	22.9	0.0	99.8	**22.8**	30.8	2022
Mali†	2012–2023	11	21.6	0.3	97.9	**21.2**	27.8	2023
Mauritania†	2015–2022	8	17.1	2.5	81.2	**14.6**	28.2	2022
Burkina Faso†	2014–2020	6	12.6	0.1	99.6	**12.6**	14.3	2020
Liberia†	2015–2019	3	14.6	6.9	52.7	**7.7**	9.7	2019
Senegal†	2015–2024	10	6.5	1.1	80.3	**5.5**	10.8	2024
Tanzania†	2013–2022	6	9.3	4.2	59.1	**5.1**	4.1	2022
Ghana†	2015–2020	6	10.1	5.1	49.2	**4.9**	7.7	2020
Sierra Leone	2012–2016	4	5.6	1.2	67.8	**4.4**	4.0	2016
Madagascar	2012–2021	10	5.3	2.1	52.5	**3.2**	0.4	2021
Gabon	2021–2022	2	57.2	54.0	6.0	**3.2**	2.6	2022
Mozambique	2017–2022	6	9.7	6.7	32.1	**3.0**	6.1	2022
Malawi	2016–2022	2	2.4	0.0	99.0	**2.4**	3.9	2022
Togo	2015–2021	7	2.4	0.2	92.0	**2.2**	2.5	2021
Niger	2019–2020	2	6.8	4.7	30.5	**2.1**	2.2	2020
Congo	2014–2017	4	48.7	47.5	1.9	**1.2**	0.0	2017
Côte d'Ivoire†	2016–2018	3	2.9	1.8	37.9	**1.2**	0.9	2018
Ethiopia†	2014–2019	6	0.9	0.0	99.0	**0.9**	0.4	2019
Uganda	2020–2021	2	0.8	0.2	66.2	**0.6**	0.2	2021
Angola	2021–2022	2	42.5	42.2	0.8	**0.3**	0.4	2022
Chad	2014–2019	6	56.7	56.5	0.4	**0.3**	0.1	2019
Nigeria†	2012–2016	3	79.4	79.2	0.3	**0.2**	0.0	2016
Cameroon	2009–2017	8	25.7	25.7	0.3	**0.1**	0.2	2017
Seychelles	2015–2016	2	0.3	0.3	0.0	**0.0**	0.0	2016

Source. Extractive Industries Transparency Initiative (EITI) open database (https://eiti-database.eiti.org). The table compiles 138 country-years for 26 African EITI-reporting countries (2009–2024). All entries are percentages. † denotes a country with at least one commercial gold mine in the S&P sample used in Table 7.

Columns. "Covered" gives the first and last EITI report year included. "With data" is the number of report years within that range for which the ratios in columns (4)–(6) can be constructed (i.e., the number of annual observations underlying the reported means); missing years typically reflect absent information or a currency/units mismatch across tables within a report. "Extractives" is total extractive-industry revenue as a share of total government revenue. "Oil and gas" is the petroleum component of the extractive share. "Mining share of extractive revenue" is the fraction of extractive-company payments attributable to mining companies. The final three columns report the implied mining share of total government revenue: the mean over available report years, and the latest available value with its year.

Construction. Mining share of total government revenue is computed as

$$\text{Mining share} = \left(\frac{\text{extractive revenue}}{\text{total government revenue}}\right) \times \left(\frac{\text{mining revenue}}{\text{total extractive revenue}}\right).$$

The first term is taken from the report's economic-contribution table; the second from sector-tagged revenue streams (or, for pre-2017 reports, from company payments by sector). The oil-and-gas share equals the residual of the extractive share after subtracting the implied mining share. Country-years with a currency or units mismatch between the two inputs are excluded. Table E2 compares these figures to narrower IMF and World Bank measures.

Caveats. EITI reporting covers companies above a materiality threshold; artisanal and small-scale mining is therefore largely excluded, so the mining shares may understate the sector's full fiscal footprint. Two country-years in which reported extractive revenue exceeds total government revenue (Cameroon 2018; Guinea 2011) are treated as missing. Non-EITI-reporting countries (including South Africa, Zimbabwe, Kenya, Rwanda, Sudan, South Sudan, and Namibia) do not appear.

Table E2
Mining's Economic Weight Across Three Data Sources

	Mining revenue, % of government revenue			Mining revenue, % of GDP			Mining value added, % of GDP			Mining exports, % of total exports		
Country	EITI	IMF	WB	EITI	IMF	WB	EITI	IMF	WB	EITI	IMF	WB
Period	2009–24	2010–16	2017/18	2009–24	2010–16	2017	2009–24	2014–19	2017	2009–24	2014–19	2016/17
DR Congo†	41.9	3.9	–	4.0	1.4	–	14	14	–	98	95	–
Zambia†	37.6	15.8	12.1	12.3	2.9	–	10	15	15	80	72	80
Guinea†	22.8	17.3	–	3.5	2.5	–	17	15	–	86	86	–
Mali†	21.2	12.7	–	3.9	2.1	–	9	7	–	65	54	–
Burkina Faso†	12.6	5.8	–	2.3	1.3	–	11	4	–	72	58	–
Liberia†	7.7	4.7	–	1.7	1.4	–	–	6	–	89	46	–
Tanzania†	5.1	3.6	–	0.6	0.5	–	9	4	–	34	16	–
Ghana†	4.9	2.9	–	1.1	0.3	–	9	11	–	68	43	–
Sierra Leone	4.4	8.6	–	0.7	1.2	–	–	4	–	82	60	–
Niger	2.1	6.7	–	0.3	1.4	–	8	11	–	44	36	–
South Africa†	–	2.3	1.3	–	0.6	1.3	–	3	7	–	5	28
Botswana	–	36.5	34.2	–	12.8	–	–	19	19	–	83	92
Namibia†	–	9.7	6.8	–	3.0	2.0	–	13	13	–	36	51
Zimbabwe†	–	13.2	3.7	–	2.5	–	–	6	7	–	55	50

Sources. All entries are percentages. EITI: this paper's compilation from the EITI open database—mining revenue shares are the "Mean" column in Table E1, and mining value added and exports are taken from the same reports' economic-contribution tables—averaged over each country's available report years. IMF: Albertin et al. (2021), Figure 5 (revenue measures; averages 2010–2016) and Figure 3 (value added and exports; averages 2014–2019), values digitized from the published charts. WB: World Bank (2019), Tables 2.3–2.4 (revenue shares for 2017/18, using IMF and National Treasury estimates) and the country overviews in Chapter 1 (value added and exports). Countries shown are those covered by more than one source. † denotes a country with at least one commercial gold mine in the S&P sample used in Table 7.

What each column measures (and why sources differ). The three sources do not define "mining" identically; the discussion below highlights where this matters.

- *Revenue (first two blocks).* The IMF and World Bank report only mining-specific fiscal instruments (royalties, mining corporate income tax, and dividends from state participation). EITI records all payments made by mining companies to government, which typically includes general taxes and fees (e.g., VAT, customs duties, payroll withholding, and license fees). As a result, EITI revenue shares are mechanically larger and exceed the IMF/WB shares for every country; the gap is largest where general taxes are a substantial part of mining-company payments (e.g., DR Congo).
- *Value added (third block).* EITI reports the national-accounts aggregate "mining and quarrying, including oil and gas" (SNA 2008, section C). Thus, in petroleum-producing countries it primarily reflects oil and gas rather than mining (e.g., Chad, Congo, Gabon, Cameroon, Nigeria). The IMF's "resource GDP" applies to its non-oil, resource-intensive sample and is therefore mining; the World Bank series is "mining and quarrying." Where these sector concepts coincide, the series draw on the same national accounts and are broadly comparable.
- *Exports (fourth block).* EITI reports exports of the extractive industries as a whole (mining plus petroleum). The IMF reports resource exports for its non-oil sample, and the World Bank reports mining exports. As with value added, EITI export shares correspond to mining exports only in countries without petroleum; all series ultimately rely on the same underlying trade statistics.

Table E3

What Individual Mining Companies Pay to Government: Largest and Smallest Payers

Company	Commodities	Years	n	Payments to government		Share of payments, %		
				Mean per year	Latest year	Royalty	Profit tax	Import duties
All African EITI countries (mining, 1999–2024): ten largest payers (USD million)								
Kansanshi Mining PLC	Ag, Au, Co, Cu, Fe, S,...	2008–2022	15	390.6	610.8 (2022)	24	48	16
Mutanda Mining	Cu, Co	2011–2019	8	270.3	524.2 (2019)	13	45	18
Tenke Fungurume Mining SA	Cu, Co	2011–2019	8	241.6	383.4 (2019)	15	29	20
Kamoto Copper Company	Cu, Co	2011–2019	8	199.3	289.5 (2019)	19	8	41
Compagnie Des Bauxites De Guinee (Cbg)	Bauxite	2006–2018	13	196.5	109.8 (2018)	12	45	5
FEKOLA	Au	2016–2023	8	193.8	361.2 (2023)	10	42	10
SNIM	Fe	2010–2022	12	184.4	482.3 (2022)	28	3	7
Chambishi Copper Smelter Limited	Cu	2008–2022	15	159.2	393.9 (2022)	22	20	26
SOMILO	Au	2006–2023	18	145.5	373.7 (2023)	14	40	15
Kalumbila Minerals Limited	Ag, Au, Co, Cu, Fe, Ni...	2011–2022	12	140.5	408.2 (2022)	46	21	31
All African EITI countries (mining, 1999–2024): ten smallest payers among companies reporting in three or more years (USD thousand)								
Eta Star Mocambique SA	Coal	2009–2016	7	10.2	3.4 (2016)	0	92	0
Elegant One Company Limited	Granite	2009–2013	5	10.1	12.5 (2013)	90	0	0
Curve Capital Venture	Au	2010–2017	3	9.7	0.0 (2017)	50	0	0
Nativite Investe	Sands, Latierite	2018–2020	3	9.4	1.0 (2020)	4	7	0
Cilcon LTD	Rock aggregrate	2015–2020	6	9.1	0.0 (2020)	61	1	18
Equishare Nig. LTD	Granite	2012–2014	3	8.5	1.0 (2014)	88	0	0
Pomar Togo SA	Marble	2015–2017	3	6.2	1.0 (2017)	0	63	16
Picollo Bruneli Engineering LTD		2007–2011	5	5.7	4.0 (2011)	83	0	0
G.S. Cimentos SARL	Limestone	2012–2016	5	4.1	3.1 (2016)	0	80	0
Nyala Mines LTD	Corundum	2015–2020	5	3.3	0.0 (2020)	70	0	4
Totals (USD million)								
Ten largest payers, combined		2006–2023		2,122	3,937	20	33	18
All reporting mining companies (1,712)		2009–2022	368	4,114	4,576 (2022)	22	31	16

Source. EITI bulk export of company-level payments (https://eiti.org/sites/default/files/bulk-export/; files `companies_revenue_streams-<ISO2>.csv`). The sample covers the 24 African EITI-reporting countries whose reports list mining companies, comprising 1,712 mining companies. In each reconciled EITI report, payment streams are reported for all companies above the materiality threshold and expressed in USD using the report's exchange rate. For each company-year, we sum all payment streams. Company identities are linked across reports using the EITI entity identifier and a normalized company name.

Construction. "Mean per year" is the company's average annual payments over the years in which it appears, and n is the number of such years. The "smallest payers" panel reports amounts in USD thousands and is restricted to companies that appear in at least three years with positive payments, excluding one-off license holders. In the totals block, the "all reporting companies" row reports: (i) the average annual sum of payments over years in which at least ten countries report; (ii) the average number of reporting companies in such a year (reported as n); and (iii) the sum in the latest year meeting this criterion. Reported payment shares are based on cumulative payments by all mining companies. "Profit tax" denotes corporate income tax and minimum-tax substitutes; remaining categories (e.g., payroll and withholding taxes, dividends and bonuses, fees, and other levies) are not separately shown. Sector is assigned using the report's sector and commodity fields; petroleum and gas companies are excluded.

Table E4

Agriculture's Weight in the Economy: Value Added and Exports

	Agricultural value added, % of GDP World Bank			Agricultural exports, % of merchandise exports World Bank (UN Comtrade data)					
	Mean	Latest		Mean	Latest		Of which, mean 2000–24		Years
Country	2000–24	Value	Year	2000–24	Value	Year	Food	Raw mat.	with data
Liberia	49.1	33.8	2024	61.7	88.2	2023	11.8	49.8	7
Ethiopia†	39.0	34.8	2024	82.1	90.1	2023	73.6	8.5	24
Niger†	37.9	48.0	2024	25.9	4.3	2024	23.9	2.0	25
Burundi†	37.5	35.1	2024	54.6	46.6	2023	52.9	1.7	24
Sierra Leone	35.8	29.2	2024	60.9	55.1	2018	57.1	3.9	7
Chad†	34.0	37.2	2024	–	–	–	–	–	0
Central African Republic†	33.1	27.9	2024	31.3	6.1	2024	1.5	29.9	25
Sudan	30.7	22.2	2024	19.8	58.3	2018	16.4	3.4	19
Mali†	28.3	32.6	2024	22.4	14.6	2023	6.7	15.7	20
Madagascar†	27.1	21.9	2024	38.3	32.0	2024	35.5	2.8	25
Benin†	26.3	24.2	2024	87.1	92.5	2024	32.3	54.7	25
Malawi†	25.9	31.8	2024	87.5	91.1	2024	84.5	3.0	25
Rwanda†	25.7	20.8	2024	46.8	28.0	2022	43.6	3.3	22
Ghana†	25.7	20.6	2024	32.1	19.2	2023	28.9	3.2	22
Tanzania†	25.5	23.3	2024	39.4	39.9	2024	33.9	5.5	25
Nigeria†	25.2	25.9	2024	3.5	6.4	2024	2.4	1.1	23
Uganda†	25.2	24.6	2024	64.0	40.7	2024	57.2	6.8	25
Mozambique†	24.5	25.2	2024	20.9	12.7	2024	17.6	3.2	25
Burkina Faso†	22.8	20.9	2024	42.1	13.1	2024	13.4	28.8	24
Kenya†	21.6	22.4	2024	58.8	62.2	2024	46.6	12.2	22
Mauritania†	20.1	19.3	2024	27.4	25.8	2024	27.3	0.0	24
Guinea	19.5	31.0	2024	5.8	6.1	2016	4.0	1.9	12
Togo†	18.8	21.3	2024	30.5	38.1	2024	20.9	9.6	24
DR Congo†	17.6	10.1	2024	1.2	0.9	2023	0.7	0.5	9
Cameroon†	17.0	18.5	2024	40.8	37.7	2023	22.6	18.1	24
Côte d'Ivoire	16.8	15.9	2024	58.4	60.8	2024	48.5	10.0	25
Senegal†	14.9	15.6	2024	33.8	22.4	2024	31.8	2.0	25
Zimbabwe†	13.6	8.7	2024	34.7	22.5	2024	26.4	8.3	25
Angola†	12.5	21.6	2024	0.3	0.4	2024	0.3	0.1	16
Zambia†	8.8	2.8	2024	11.3	9.2	2024	8.9	2.4	25
Namibia	8.5	7.2	2024	29.1	29.8	2024	28.0	1.1	25
South Sudan	6.6	10.4	2015	–	–	–	–	–	0
Lesotho†	5.5	6.6	2024	15.8	28.5	2024	11.7	4.1	23
South Africa†	2.4	2.8	2024	12.2	14.3	2024	9.8	2.4	25
Botswana	2.1	1.8	2024	2.7	1.9	2023	2.5	0.2	24

Sources and definitions. Value added. World Bank World Development Indicators (WDI), series NV.AGR.TOTL.ZS: value added of agriculture, forestry, and fishing (ISIC divisions 1–3) as a share of GDP, compiled from national accounts. (The corresponding FAOSTAT series for the same aggregate is typically within 1–2 percentage points, since both rely on UN national-accounts estimates.) *Exports.* Export shares are from the World Bank WDI, constructed from UN Comtrade records, and expressed as shares of *merchandise* exports (goods only; services are excluded from the denominator). "Food" is series TX.VAL.FOOD.ZS.UN, covering SITC sections 0 (food and live animals), 1 (beverages and tobacco), 4 (animal and vegetable oils and fats), and division 22 (oil seeds and nuts); for the countries in the table, this category includes major exports such as cocoa, coffee, tea, tobacco, sugar, fish, cashew, and livestock. "Raw materials" is series TX.VAL.AGRI.ZS.UN, covering SITC section 2 (crude materials) excluding division 22 and excluding divisions 27 (crude fertilizers and minerals) and 28 (metalliferous ores); this captures unprocessed non-food agricultural products, chiefly cotton, rubber, timber, hides and skins, and wool. "Agricultural exports" is the sum of "Food" and "Raw materials," so ores, phosphates, and petroleum are excluded by construction. "Mean" is the average over 2000–2024 across years with available data. "Latest" is the most recent available value and its year. "Years with data" counts the number of years between 2000 and 2024 for which an export share is available (i.e., the number of annual observations underlying the export means). A value of 25 indicates a complete series; Liberia and Sierra Leone (7 years each) and DR Congo (9 years) have incomplete Comtrade coverage, so their export means are based on relatively few observations; Chad and South Sudan have no export-share data, hence dashes. This count applies to the export columns only. The value-added series is complete for all countries except South Sudan (8 years) and the Central African Republic (16 years). Countries include the 33 in the Region panel plus the four additional countries in Tables E1 and E2. † denotes a country contributing region-years to the maize estimation sample in Table 6 (28 countries).

Reading the table. Among countries contributing to the maize estimates, agriculture typically accounts for roughly one-fifth to one-half of GDP; exceptions are the four southern economies (South Africa, Botswana, Lesotho, and Zambia) and Angola, where it is below 13%. Compared to the mining shares in Table E2, agriculture exceeds mining as a share of output everywhere except Botswana, South Africa, Namibia, and Zambia. Agriculture's share of exports is generally largest where mining and petroleum exports are smallest.

Appendix F: Malaria interventions coverage over time

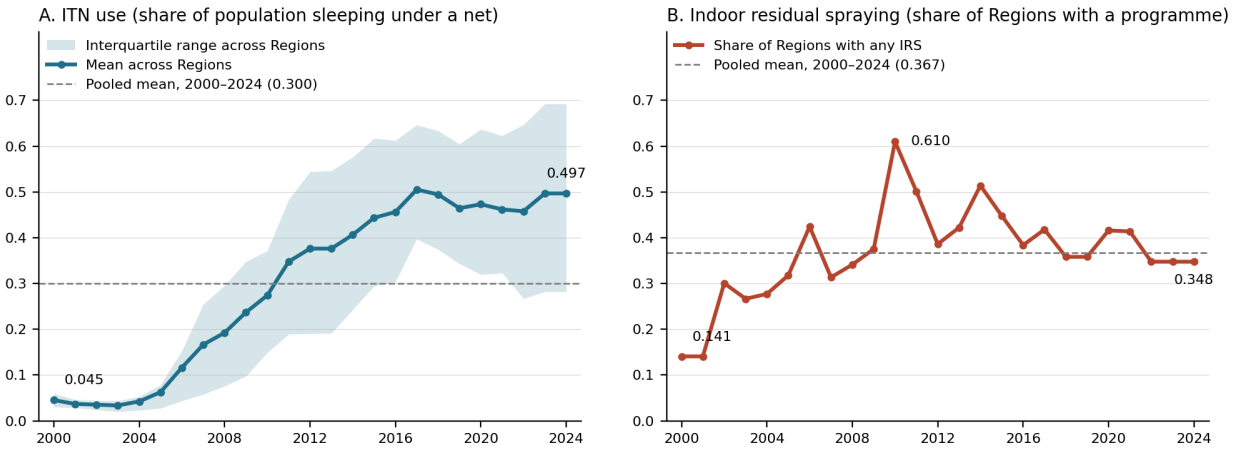


Figure F1: Malaria intervention coverage over the sample period, 2000–2024.

Notes. Panel A plots the mean across Regions of ITN use, the share of the population sleeping under an insecticide-treated net; the shaded band is the interquartile range across Regions in each year. Panel B plots the share of Regions with any indoor residual spraying recorded in the year; IRS is an indicator rather than a coverage rate. Dashed lines mark the pooled Region-year means reported in Table 1, Panel B (0.300 for ITN use, 0.367 for IRS). Annotated points are the values cited in the text: ITN use of 0.045 in 2000 and 0.497 in 2024; the IRS share of 0.141 in 2000, its peak of 0.610 in 2010, and 0.348 in 2024.