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Malaria and Economic Development: Panel Evidence from Fourteen Endemic Countries

Akshay Suketh Swamy
TISB

Abstract

This study examines the relationship between malaria burden and real income using a balanced panel of fourteen malaria-endemic countries observed annually from 2015 to 2024, giving 140 country-year observations. The countries are India and Cambodia in Asia and Burkina Faso, Cameroon, the Democratic Republic of the Congo, Ghana, Mali, Mozambique, Nigeria, Rwanda, Senegal, Tanzania, Uganda and Zambia in sub-Saharan Africa. The outcome variable is the natural logarithm of real GDP per capita in constant 2015 US dollars, and the main explanatory variable is the natural logarithm of malaria incidence, so its coefficient is an elasticity. The analysis uses pooled, random-effects and fixed-effects estimators, selects the fixed-effects model with a robust Mundlak test, and reports both country-clustered and Driscoll-Kraay standard errors. Two findings emerge. First, considered on its own, malaria burden has a negative and statistically significant relationship with income, with an elasticity of approximately -0.06. Second, this relationship disappears almost entirely once broad development indicators enter the model. After accounting for urbanisation and sanitation, malaria has no reliable independent negative effect on income within countries over the decade. The study therefore interprets malaria burden and income as moving together as part of a wider development process, rather than concluding that malaria has no bearing on prosperity.

Keywords: malaria, economic development, panel data, fixed effects, Driscoll-Kraay, GDP per capita, sub-Saharan Africa.

1. Introduction

Malaria remains one of the most significant infectious diseases, with a major impact on both public health and economic development. It generates direct health costs through illness, diagnosis, treatment and death, and it also has wider economic consequences through missed work, absence from school, reduced productivity, household spending on care, and strain on health systems. For these reasons malaria is not merely a health issue; it is also a development problem.

The study focuses only on malaria and does not include other mosquito-borne diseases such as dengue. This more limited scope improves data consistency, allows a single disease-burden framework, and clarifies the economic interpretation. Because malaria has already been the

*Corresponding Author Email: akshayswamy999@gmail.com
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subject of extensive research in development economics, the paper can connect its results to a broad body of evidence on disease, human capital and national income.

The study rests on the idea that healthcare quality affects malaria levels, that malaria in turn affects health and productivity, and that these effects may be reflected in GDP per capita. In its final empirical form it uses country-year data from 2015 to 2024. This span covers the years before COVID-19 and the years after the pandemic shock, which lets the paper examine whether the malaria burden and real GDP per capita changed differently across countries over the decade.

India serves as the main point of comparison in South Asia. The sample is then extended to Cambodia and twelve African countries, because a comparison based on only four countries would not be large enough for a reliable panel analysis. The final sample includes countries with very different malaria situations, ranging from settings where malaria has been nearly eliminated, such as Cambodia, to those with a very high burden, such as Nigeria, the Democratic Republic of the Congo and Burkina Faso.

2. Research Question and Hypothesis

The study attempts to fine how closely is the incidence of malaria linked to real GDP per capita in malaria-prone countries from 2015 to 2024? The main hypothesis is that a higher incidence of malaria is associated with lower real GDP per capita. The relationship is expected to be negative because malaria can reduce labour productivity, raise household and government health spending, lower school attendance, and impair long-term human capital formation. It is also expected that when wider development indicators are included as controls, particularly urbanisation and sanitation, the estimated relationship between malaria and income will weaken, because living conditions, health-system capacity and infrastructure influence both the malaria burden and economic development.

3. Literature Review

The literature on malaria and economic development falls into three broad strands. The first uses cross-country macroeconomic methods to test whether malaria is associated with lower income or slower growth. The second uses historical eradication episodes and natural experiments to estimate long-term effects on schooling, consumption and human capital. The third assesses the cost of malaria control and the returns to investment in prevention and elimination. Together they establish that malaria can plausibly affect GDP per capita through labour productivity, schooling, health spending and long-run human capital, while also showing how difficult it is to separate malaria from the broader conditions of development.

3.1 Cross-country macroeconomic studies

The macroeconomic strand provides the most direct precedent for the present study. McCarthy, Wolf and Wu (2000) apply cross-country growth regressions and find a significant negative effect of malaria morbidity on GDP growth in several specifications, though they stress the risks of omitted-variable bias and reverse causality that arise when very different economies are compared. Gallup and Sachs (2001) remain the seminal reference: controlling for geography, they show that countries with intensive malaria have markedly lower income and slower growth, and their work supplies the macroeconomic foundation for the present research

question. The causal interpretation is nonetheless debated, because geography and institutions are difficult to hold constant. Sarma et al. (2019) revisit the question with modern panel data and are the closest methodological match to this study. They confirm that malaria remains economically important, but they also find that the estimated coefficient is sensitive to the choice of controls and to the model specification, which directly motivates the control-based approach adopted here.

3.2 Eradication and natural-experiment studies

A second strand exploits historical eradication campaigns as natural experiments to identify long-run effects. Bleakley (2010) studies eradication in the Americas and finds that reduced childhood exposure is associated with higher adult income, providing some of the strongest human-capital evidence in the field, even if the historical setting may not fully generalise to present-day economies. Cutler et al. (2010) examine eradication in India and link lower childhood exposure to higher adult consumption and education, which makes India a particularly meaningful comparator in the present sample. Lucas (2010) shows that eradication improved educational attainment in Paraguay and Sri Lanka, reinforcing the schooling channel even though the outcome is education rather than GDP. Barreca (2010) finds that in utero and early-life exposure has lasting effects on education and poverty, underlining that malaria can shape development across the whole life course rather than only in the year of infection. Barofsky et al. (2015) provide evidence from Uganda, a country in the present panel, that malaria reduction improves schooling and economic outcomes, although its subnational and historical design differs from a contemporary cross-country panel. Taken together, these studies suggest that malaria's largest economic effects accumulate over decades and across birth cohorts, a horizon that a ten-year panel cannot fully observe.

3.3 Conceptual frameworks and cost-of-control studies

A third strand sets out the mechanisms and the economics of control. Goodman, Coleman and Mills (1999) frame malaria control as an economic investment rather than a purely medical one, and show that its cost-effectiveness depends on intervention design, coverage and health-system capacity. Sachs and Malaney (2002) provide the conceptual backbone for the hypothesis of this paper, describing how malaria and poverty reinforce one another through labour productivity, fertility, schooling and investment. Malaney, Spielman and Sachs (2004) explain why economic-burden estimates vary so widely, since studies measure different things, from direct costs to long-run human-capital losses, and therefore call for caution in interpretation. Gollin and Zimmermann (2007) model disease and prevention behaviour dynamically and show how malaria can shape saving, investment and income over the long run, a persistence that short panels may miss. On the policy side, Shretta, Avancena and Hatefi (2016) review the economics of control and elimination and conclude that investment can generate benefits beyond the health sector, while Andrade et al. (2022) show in a systematic review that cost estimates remain difficult to compare across settings because methods differ. Patouillard et al. (2023) model the macroeconomic returns to higher control investment in high-burden countries and project gains in productivity and output, subject to the assumptions of their model.

Across all three strands, two themes recur that shape the present study. Malaria is repeatedly found to be negatively associated with income, which supports the paper's central hypothesis. At the same time, its effect is consistently entangled with broader development conditions and tends to operate over horizons longer than a single decade. This is why the present study estimates the relationship within a panel that controls for urbanisation, sanitation and other development indicators, and why it interprets its results as associations rather than causal effects.

4. Methodology

4.1 Data and sample

The study uses a balanced panel of fourteen malaria-endemic countries with annual observations from 2015 to 2024, giving 140 country-year observations. The countries are India and Cambodia in Asia and, in sub-Saharan Africa, Burkina Faso, Cameroon, the Democratic Republic of the Congo, Ghana, Mali, Mozambique, Nigeria, Rwanda, Senegal, Tanzania, Uganda and Zambia. They represent the full spectrum of malaria burden, from settings where the disease is nearly eliminated to some of the highest-transmission countries in the world. Several countries recorded large decreases in burden over the decade, which matters because the fixed-effects estimator relies on within-country changes over time.

The malaria figures cover estimated cases, deaths and population at risk, and are taken from Annex 4H of the World Health Organization's World Malaria Report 2025. Incidence is expressed as cases per 1,000 population at risk and mortality as deaths per 100,000 population at risk. The economic and control data come from the World Bank's World Development Indicators. Table 1 lists the countries in the final panel and the reason each is included.

Table 1. Countries in the final panel and selection rationale

Country	Selection rationale
India	Asian comparator and central country for the study.
Cambodia	Asian comparator with a dramatic decline in malaria burden.
Nigeria	Largest estimated malaria case burden in the sample.
Democratic Republic of the Congo	Very high case burden, incidence and mortality.
Uganda	High-burden East African comparator.
Mozambique	High-burden African comparator with strong malaria relevance.
Ghana	Good economic and health data coverage.
Tanzania	Large population and substantial malaria burden.
Rwanda	Sharp burden reduction over the decade.
Zambia	Southern African comparator with continuing transmission.
Senegal	Lower-burden comparator with substantial reduction.

Burkina Faso	High-transmission Sahelian setting.
Mali	High-transmission Sahelian setting.
Cameroon	Central African comparator with solid data coverage.

4.2 Variables

The dependent variable is the natural logarithm of real GDP per capita in constant 2015 US dollars. Real, constant-price GDP is used so that the findings reflect changes in output per person rather than movements in exchange rates or inflation. The main explanatory variable is the natural logarithm of malaria incidence. Because both the dependent variable and the main explanatory variable are logged, the malaria coefficient can be read as an elasticity, that is, the percentage change in real income associated with a one-percent change in malaria incidence.

The controls are the development indicators with complete coverage over the study period: urban population share, annual population growth, basic sanitation coverage and basic drinking-water coverage. Health expenditure per capita is described but not included in the main regression because it is available only to 2023. Secondary-school enrolment and physician density are too sparse to include reliably, so they are treated as limitations rather than regression controls. Table 2 lists the variables and their sources.

Table 2. Variables and data sources

Variable	Source	Unit	Purpose
ln(real GDP per capita)	World Bank WDI	Log of GDP per capita, constant 2015 US$	Dependent variable; real output per person.
ln(malaria incidence)	Calculated from WHO Annex 4H	Log of cases per 1,000 at risk	Main explanatory variable; burden elasticity.
Malaria mortality	Calculated from WHO Annex 4H	Deaths per 100,000 at risk	Descriptive severity measure.
Urban population share	World Bank WDI	% of total population	Controls for urbanisation and structural development.
Population growth	World Bank WDI	Annual %	Controls for demographic pressure on GDP per capita.
Basic sanitation	World Bank WDI / JMP	% of population	Controls for environmental and infrastructure development.
Basic drinking water	World Bank WDI / JMP	% of population	Controls for basic-services access.

Health expenditure per capita	World Bank WDI / WHO GHED	Current US$	Descriptive health-system variable; incomplete for 2024.

Source: Author's compilation

4.3 Empirical specification

$$\ln(GDPpc)_{it} = \beta_0 + \beta_1 \ln(Incidence)_{it} + \beta_2 X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

Here i indices countries and t indexes years. X is the vector of control variables, α_i denotes the country fixed effects, λ_t denotes the year fixed effects, and ε_{it} is the error term. The country fixed effects remove the influence of time-invariant country characteristics such as geography, established institutions and baseline climate. The year fixed effects account for shocks that affect all countries in a given year, such as the COVID-19 pandemic and general macroeconomic conditions.

4.4 Estimation and diagnostic tests

The model is estimated by pooled OLS, random effects and fixed effects. The choice between random and fixed effects is assessed using a Hausman-type approach. Because heteroskedasticity and cross-sectional dependence can make the classical Hausman test unstable, the study uses the Mundlak auxiliary-regression version of the test for the full model. This approach adds the country means of the time-varying regressors to the random-effects model and tests whether they are jointly significant.

The study then examines the key classical assumptions. The Breusch-Pagan test is used to check for heteroskedasticity, the Wooldridge test to detect first-order serial correlation, variance inflation factors to assess multicollinearity, and the Pesaran CD test to assess cross-sectional dependence. Because the panel involves common shocks across countries, the paper also reports Driscoll-Kraay standard errors alongside country-clustered standard errors. Driscoll-Kraay standard errors are robust to heteroskedasticity, to serial correlation within countries, and to correlation across countries in the same year.

5. Results

5.1 Descriptive statistics

Table 3 summarises the 140 country-year observations. Malaria burden varies widely across the sample. Incidence ranges from near zero in Cambodia and India to more than 700 cases per 1,000 at risk in the highest-transmission year, while real GDP per capita ranges from about US$471 to US$2,586 in constant 2015 US dollars.

Table 3. Descriptive statistics for the pooled sample (n = 140)

Variable	N	Mean	SD	Min	Median	Max
Malaria incidence /1,000	140	223.1	134.5	0.03	259.8	711.4
Malaria mortality /100,000	140	45.0	28.8	0.00	41.9	114.4
Real GDP per capita (2015 US$)	140	1,270.0	572.2	470.9	1,169.4	2,585.7

ln(real GDP per capita)	140	7.04	0.47	6.15	7.06	7.86
Urban population (%)	140	39.5	11.5	18.2	35.6	63.0
Population growth (%)	140	2.53	0.68	0.79	2.77	3.66
Basic sanitation (%)	140	42.3	18.8	16.1	37.4	83.4
Basic drinking water (%)	140	67.7	15.6	35.1	68.5	95.7
Health expenditure pc (US$)	126	55.6	22.8	17.3	55.9	137.4

Source: authors' calculations from WHO World Malaria Report 2025 (Annex 4H) and World Bank World Development Indicators.

The decisive feature of this panel is that malaria burden changed within countries over the decade. Incidence fell by about 99.9 per cent in Cambodia, 77.0 per cent in India, 75.0 per cent in Rwanda and 46.9 per cent in Senegal, while it rose slightly in Nigeria, the Democratic Republic of the Congo and Zambia. This within-country variation is what allows the fixed-effects model to identify a relationship over time rather than relying only on cross-country differences.

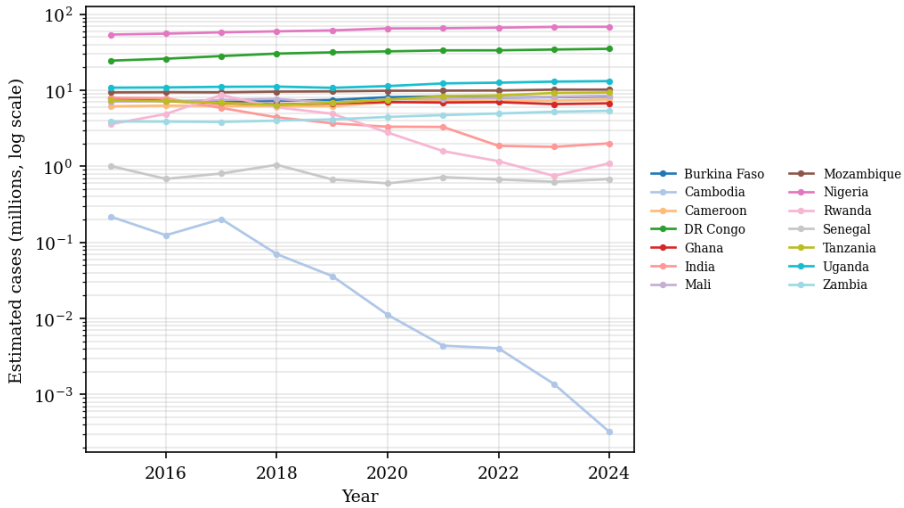

Figure 1. Estimated annual malaria cases by country, 2015 to 2024 (millions, log scale).

As shown in Figure 1, the raw case burden is highly concentrated. Nigeria averaged about 62.3 million estimated cases each year, followed by the Democratic Republic of the Congo at about 31.0 million. India averaged around 4.2 million cases per year, far below the largest African high-burden countries but still significant as the main South Asian comparator. Table 4 reports country-level averages.

Table 4. Country-level averages, 2015 to 2024

Country	Cases (m)	Incidence	Mortality	Real GDPpc	Urban %	Sanit. %	Water %
Nigeria	62.25	293.8	86.6	2,367	59.4	43.8	75.4
DR Congo	31.00	326.7	74.3	500	43.1	16.6	35.7

Uganda	11.74	268.9	37.7	914	28.2	22.2	55.5
Mozambique	9.77	322.4	66.4	608	33.9	32.8	57.4
Burkina Faso	7.78	368.0	82.9	707	26.6	27.2	50.6
Tanzania	7.78	129.1	40.6	1,037	33.6	30.5	57.6
Mali	7.63	357.0	74.2	881	28.7	41.9	80.0
Ghana	6.94	220.9	37.1	1,955	56.0	26.0	85.3
Cameroon	6.76	261.1	47.4	1,451	54.1	45.1	69.0
Zambia	4.45	235.9	44.5	1,300	43.7	34.3	68.6
India	4.21	3.3	0.6	1,935	34.0	70.5	92.8
Rwanda	3.54	284.1	24.8	858	23.9	75.0	58.8
Senegal	0.75	46.1	11.8	1,371	50.7	57.7	82.9
Cambodia	0.07	5.9	0.9	1,897	37.7	68.8	78.0

Source: authors' calculations using WHO and World Bank data.

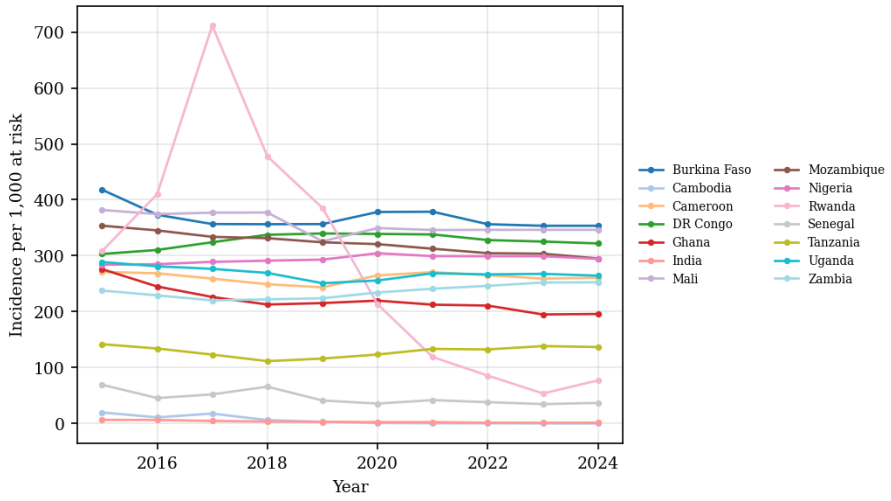

Figure 2. Annual malaria incidence per 1,000 population at risk by country, 2015 to 2024.

Using incidence per 1,000 at risk gives a more reasonable comparison than absolute cases, because it accounts for the size of the population at risk. Burkina Faso, Mali, the Democratic Republic of the Congo and Mozambique have the highest average incidence, while Cambodia and India have much lower rates.

5.2 Comparison of the periods before and after COVID-19

The years 2015 to 2019 are treated as the pre-COVID period and 2020 to 2024 as the post-COVID period. This comparison is descriptive and does not imply that COVID-19 caused the observed changes. In several high-burden countries the average number of cases rose after 2020, mainly because the population at risk kept increasing. Once the denominator is taken into account, however, incidence fell in many countries. Figure 3 and Table 5 present the comparison.

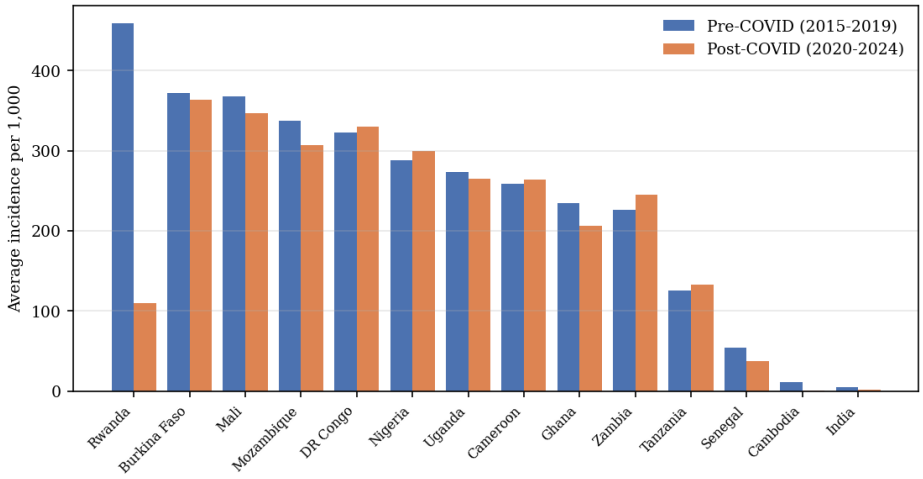

Figure 3. Average malaria incidence before COVID (2015-2019) and after COVID (2020-2024).

Table 5. Malaria incidence and real GDP per capita: change before versus after COVID-19

Country	Pre incidence	Post incidence	Incidence change (%)	Real GDPpc change (%)
Nigeria	288.3	299.2	3.8	-8.7
DR Congo	322.9	330.4	2.3	5.2
Uganda	273.3	264.5	-3.2	6.5
Mozambique	337.6	307.2	-9.0	-3.1
Burkina Faso	372.1	364.0	-2.2	10.4
Tanzania	125.3	132.8	6.0	7.9
Mali	367.2	346.8	-5.6	1.0
Ghana	235.0	206.7	-12.0	12.1
Cameroon	258.2	264.0	2.2	0.8
Zambia	226.6	245.2	8.2	-0.9
India	4.7	1.9	-60.8	17.8
Rwanda	458.5	109.6	-76.1	19.2
Senegal	54.8	37.4	-31.7	10.2
Cambodia	11.5	0.4	-96.9	14.6

Source: authors' calculations.

5.3 Change from 2015 to 2024

Between 2015 and 2024 the largest proportional decreases in malaria cases occurred in Cambodia, India, Rwanda and Senegal. Cambodia moved towards elimination, while in India cases fell by about 77.0 per cent and mortality by about 78.5 per cent. Nigeria, the Democratic

Republic of the Congo and Zambia saw an increase in cases over the period, even where mortality rates were falling. Figure 4 and Table 6 show the endpoint changes in burden and real income.

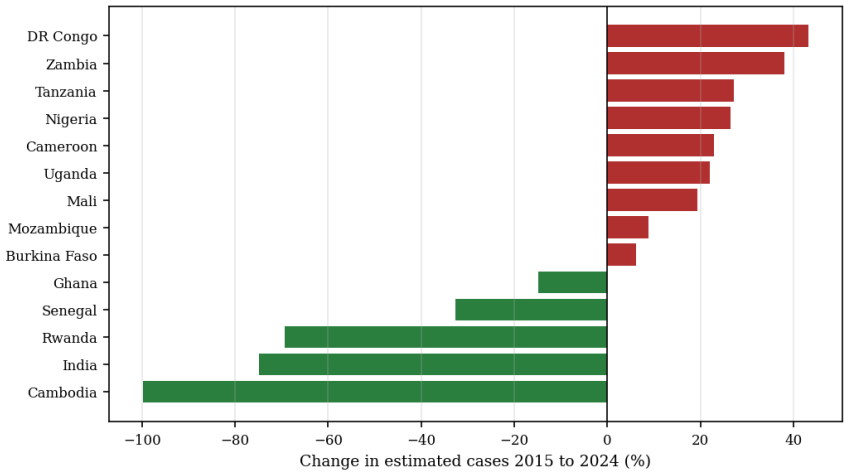

Figure 4. Percentage change in estimated malaria cases from 2015 to 2024.

Table 6. Change in malaria burden and real GDP per capita, 2015 to 2024

Country	Cases 2015 (m)	Cases 2024 (m)	Inc. 2015	Inc. 2024	Inc. change (%)	GDPpc change (%)
Nigeria	54.12	68.47	283.8	294.3	3.7	-10.1
DR Congo	24.56	35.18	303.0	321.9	6.2	11.8
Uganda	10.84	13.22	288.7	264.2	-8.5	14.3
Mozambique	9.39	10.22	353.7	295.1	-16.6	-0.8
Burkina Faso	7.85	8.32	418.0	353.5	-15.4	21.3
Tanzania	7.38	9.37	141.8	136.7	-3.6	19.3
Mali	7.10	8.47	381.7	346.2	-9.3	8.6
Ghana	7.92	6.74	276.0	195.8	-29.1	26.1
Cameroon	6.17	7.59	271.1	260.5	-3.9	4.6
Zambia	3.90	5.38	237.8	252.4	6.2	3.7
India	7.99	2.01	6.4	1.5	-77.0	49.4
Rwanda	3.59	1.10	308.0	77.1	-75.0	43.7
Senegal	1.01	0.68	69.3	36.8	-46.9	24.6
Cambodia	0.22	0.00	19.7	0.0	-99.9	41.1

Source: authors' calculations.

5.4 Model selection: fixed versus random effects

The study must decide whether fixed or random effects are more appropriate. Fixed effects

control for all time-invariant differences between countries, so estimates rest on changes within each country over time. Random effects treat these differences as random and uncorrelated with the regressors, which allows both within- and between-country variation to be used and gives more efficient estimates when the assumption holds; if the country effects are correlated with the regressors, however, random-effects estimates are biased. A Hausman-type test is used to decide which model is more appropriate.

For the baseline model the classical Hausman test gives chi-square(1) = 1.44 with p = 0.23, so it does not reject the random-effects estimator, and the fixed- and random-effects slopes are almost identical at -0.061 and -0.062. For the full model with controls the classical Hausman test is not well behaved, because the difference between the two variance matrices is not positive definite. This is a known problem when the errors are heteroskedastic and cross-sectionally dependent, both of which hold here. The study therefore applies the Mundlak auxiliary-regression form of the test, which rejects the null strongly, with chi-square(5) = 71.0 and $p < 0.001$. Fixed effects are therefore preferred. This is also the more conservative choice, because it removes all time-invariant country differences and identifies the malaria coefficient only from within-country variation over time.

5.5 Regression results

Table 7 reports the fixed-effects estimates. Each specification is shown with country-clustered standard errors and with Driscoll-Kraay standard errors. The coefficients are identical across the two; only the standard errors differ.

Table 7. Dependent variable: log real GDP per capita

Variable	(1) FE base	(2) FE base D-K	(3) FE controls	(4) FE controls D-K	(5) Two-way FE D-K
log malaria incidence	-0.061***	-0.061***	0.012	0.012***	0.007**
	(0.020)	(0.010)	(0.011)	(0.004)	(0.003)
Urban population %	—	—	0.018***	0.018***	0.015***
			(0.003)	(0.002)	(0.002)
Population growth %	—	—	-0.044	-0.044***	-0.028
			(0.033)	(0.015)	(0.019)
Basic sanitation %	—	—	0.012***	0.012***	0.011***
			(0.003)	(0.001)	(0.001)
Basic water %	—	—	-0.013***	-0.013***	-0.013***
			(0.004)	(0.000)	(0.001)

Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	Yes
Observations	140	140	140	140	140
Within R-squared	0.356	0.356	0.729	0.729	0.690

*Source: authors' calculations using WHO and World Bank data. Standard errors in parentheses. D-K denotes Driscoll-Kraay standard errors. *** p<0.01, ** p<0.05, * p<0.10. The coefficient on log incidence is an elasticity.*

The findings show a two-part pattern. On its own, malaria burden has a negative and significant elasticity of -0.061 in columns 1 and 2, so a 10 per cent lower incidence is associated with real GDP per capita about 0.6 per cent higher. This relationship is significant under both country-clustered and Driscoll-Kraay standard errors.

Once the development controls enter, the malaria coefficient falls to near zero. Under the conservative clustered standard errors, it is not significant. Under Driscoll-Kraay standard errors it becomes small and positive in columns 4 and 5, but this sign is counter-theoretical and economically negligible, and its significance reflects the very small standard errors that method produces here. The most sensible reading is that, once development conditions are held constant, malaria has no robust independent negative effect on income within countries over this single decade.

Among the controls, urbanisation and sanitation enter with positive and significant coefficients. A one-percentage-point rise in the urban share is associated with about 1.8 per cent higher real income in the one-way fixed-effects model, and a one-point rise in basic sanitation with about 1.2 per cent higher real income. The coefficient on basic drinking water is negative, which is counterintuitive. It is not interpreted causally, because water coverage is highly correlated with sanitation and general development and within-country changes over ten years are small.

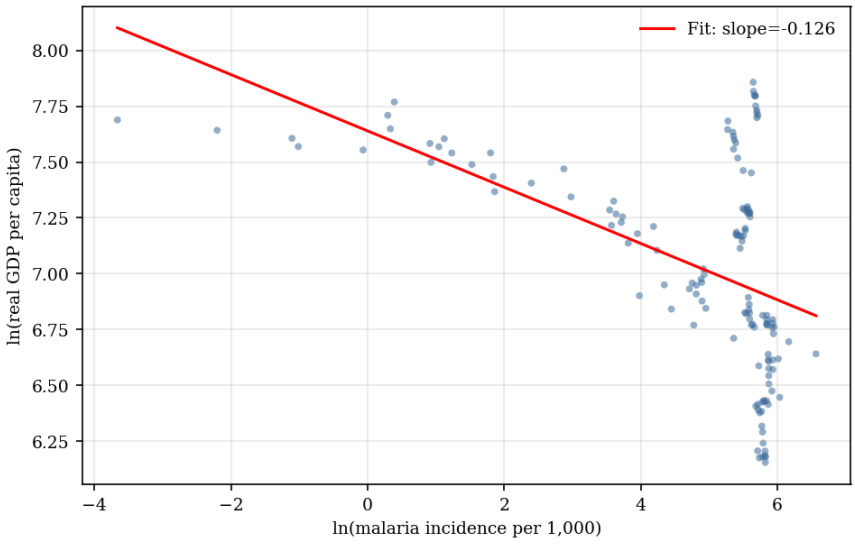

Figure 5. Pooled relationship between log malaria incidence and log real GDP per capita.

5.6 Diagnostic tests and standard errors

Table 8. Diagnostic and specification tests

Test	What it checks	Statistic	p-value	Result
Mundlak (robust Hausman)	Fixed vs random effects	chi-square (5) = 71.0	<0.001	Fixed effects preferred
Breusch-Pagan	Heteroskedasticity	LM = 27.30	<0.001	Heteroskedastic
Wooldridge	Serial correlation	F = 71.85	<0.001	Autocorrelated
Variance inflation (VIF)	Multicollinearity	max = 3.15	—	No major problem
Pesaran CD	Cross-sectional dependence	CD = 7.57	<0.001	Dependence present

Source: authors' calculations. The baseline classical Hausman test gives chi-square (1) = 1.44 (p = 0.23); the Mundlak test is used for the full model because the classical version is ill-defined under heteroskedasticity and cross-sectional dependence.

Table 8 shows the results for the diagnostic tests. The diagnostic tests confirm that the panel structure matters. The Breusch-Pagan test rejects constant error variance, the Wooldridge test rejects the absence of first-order serial correlation, and the Pesaran CD test rejects cross-sectional independence. These results mean that ordinary standard errors would be unreliable. Country-clustered standard errors address heteroskedasticity and serial correlation within countries, but they do not fully address correlation across countries in the same year. Driscoll-Kraay standard errors are therefore reported, because they are robust to heteroskedasticity, serial correlation and cross-sectional dependence. Table 9 shows the pooled correlations of each variable with log real GDP per capita.

Table 9. Pooled correlations with log real GDP per capita

Variable	Correlation with ln(real GDPpc)
Malaria cases	0.105
Incidence per 1,000 at risk	-0.559
Mortality per 100,000 at risk	-0.442
Health expenditure per capita	0.789
Urban population %	0.589
Population growth %	-0.671
Basic sanitation %	0.462
Basic drinking water %	0.807

Source: authors' calculations.

5.7 Summary of key results

Across the fourteen countries, higher malaria incidence is associated with lower real GDP per capita when malaria is considered on its own. The baseline elasticity is approximately -0.06, so a 10 per cent reduction in incidence is associated with about a 0.6 per cent increase in real GDP per capita. Once urbanisation, population growth, sanitation and water access are added, the independent malaria coefficient is no longer robustly negative. The central empirical result is therefore not that malaria is unimportant, but that malaria burden and income are closely embedded in the wider development process.

6. Discussion

The first finding supports the hypothesis directly, because countries and years with higher malaria incidence tend to have lower real GDP per capita. This aligns with the direction of the earlier malaria-and-growth literature, in particular Gallup and Sachs (2001), McCarthy et al. (2000) and Sarma et al. (2019). It also fits the theoretical mechanisms described by Sachs and Malaney (2002), namely that malaria can reduce labour productivity, disrupt education, raise health spending and weaken long-term human capital.

The second point is more conservative. The negative relationship between malaria and income disappears once broad development factors are taken into account, but this does not mean malaria has no economic cost. It means that malaria's effects are difficult to distinguish from the wider development context in a ten-year, country-level panel. When malaria falls, improvements in sanitation, expansions of basic services, urbanisation and greater health-system capacity usually occur at the same time. Because these changes happen together, a single regression cannot isolate a pure effect attributable to malaria alone.

This reading is consistent with the long-run eradication literature. Studies by Bleakley (2010), Cutler et al. (2010), Lucas (2010) and Barreca (2010) show that malaria exposure affects outcomes in childhood, in education and in adult life, through channels that can span many years or pass across generations. A panel covering 2015 to 2024 can detect short-run associations within countries, but it is unlikely to capture the full effect of malaria reduction on human capital.

Progress has been uneven. Cambodia, India, Rwanda and Senegal all achieved substantial reductions in malaria cases, while Nigeria, the Democratic Republic of the Congo and Zambia did not show similar reductions. This difference indicates that malaria reduction is achievable, but that continued progress depends on context, the strength of programmes, surveillance systems, infrastructure and general development conditions.

7. Conclusion

This study examined the relationship between malaria burden and real GDP per capita using a balanced panel of fourteen malaria-endemic countries from 2015 to 2024. It found that malaria incidence and income are negatively related when malaria is considered on its own. The baseline elasticity is about -0.06, so a 10 per cent decrease in incidence corresponds to real GDP per capita about 0.6 per cent higher.

When the model includes wider development indicators, however, the negative relationship disappears. Urbanisation and sanitation account for a large share of the within-country variation in income, and the malaria coefficient becomes small and no longer robustly negative. The conclusion is therefore cautious. Although malaria burden is associated with lower income, over this decade its effect cannot be clearly separated from the broader process of development. Malaria control still has economic importance, but it should be seen as part of an integrated development strategy that includes health systems, sanitation, infrastructure and human capital.

7.1 Policy implications

The results favour a broad approach to malaria policy. Malaria control should not be treated as a stand-alone disease programme; it is more likely to yield economic benefits when it is embedded in a wider development strategy that also improves sanitation, living conditions, access to health services and human capital. In this study, urbanisation and sanitation are the factors most closely associated with real income, and they are also the kinds of developmental conditions under which malaria transmission can more easily be reduced.

In countries where the burden remains high, the policy implication is that funding for malaria control should be sustained and integrated into broader efforts. Bed nets, testing, treatment and surveillance still play a central role, but their effect can be greater when basic services and health-system readiness also improve. For lower-burden countries such as India and Cambodia, the challenge is to protect the progress already made and prevent resurgence, especially in areas where transmission remains geographically focused.

7.2 Limitations and scope for future research

Several limitations should be kept in mind. First, the time frame is short; ten years is a limited span for a relationship that may operate through childhood health, education and adult productivity. Second, the estimates are associations rather than causal effects, because poorer countries may find it harder to finance malaria control, so income can affect malaria levels at the same time that malaria levels affect income.

Third, not all theoretically important controls can be included in the regression. Health expenditure per capita is available for 126 rather than all 140 observations, and there are wider gaps for secondary-school enrolment and physician density. Omitting these variables preserves observations, but it leaves part of the development and health-system pathway unmeasured. Fourth, the malaria figures are WHO estimates, which are revised over time. Finally, although Driscoll-Kraay standard errors are appropriate under cross-sectional dependence, they can be optimistic when the number of years is small, which is why the paper also reports country-clustered standard errors.

Future work could extend the time span to twenty or thirty years, incorporate the lagged effects of malaria on income, and use causal-identification methods such as natural experiments or instrumental variables. It could also examine the health-system channel more directly using facility-readiness data from WHO SARA, WHO HHFA or the DHS Service Provision Assessment, and use subnational malaria data from the Malaria Atlas Project to study variation within countries.

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Appendix: Data Preparation Notes

Malaria incidence was calculated by dividing the estimated number of malaria cases by the population at risk and multiplying by 1,000. Malaria mortality was calculated by dividing the estimated number of malaria deaths by the population at risk and multiplying by 100,000. The case fatality ratio was calculated by dividing the estimated number of malaria deaths by the estimated number of malaria cases and multiplying by 1,000.

The pre-COVID averages are based on 2015 to 2019 and the post-COVID averages on 2020 to 2024. This classification is used only for descriptive comparison and is not a causal estimate of the effects of COVID-19. The dependent variable is the natural logarithm of World Bank real GDP per capita in constant 2015 US dollars, and the main explanatory variable is the natural logarithm of malaria incidence; because both are in log form, the primary coefficient is interpreted as an elasticity.