# Malaria and Economic Development

*Saurabh C. Datta and Jeffrey J. Reimer\**

## Abstract

Malaria tends to have a negative correlation with national income per capita. Many existing studies emphasize how falling rates of malaria can enhance economic development due to the beneficial effect on human capital. This paper emphasizes that causality may also run in the opposite direction, in particular, that higher incomes—arising for reasons having nothing to do with human capital—may allow for increased prevention and treatment of malaria, and therefore contribute to the negative correlation. We analyze the malaria-income relationship for 100 endemic countries over a 17-year period using a simultaneous equations model that accounts for reverse causality and incidental associations. For most countries, income growth has been the most important driver of the negative correlation between malaria and income. Although reducing malaria may be its own reward, it takes much more than reductions in malaria to foster development. This holds widely for different samples of countries.

## 1. Introduction

Malaria is the world's most important parasitic infectious disease, and is a major cause of mortality and morbidity in many developing countries (Conly, 1972; McCarthy et al., 2000; Sachs, 2002). It causes over one million deaths per year in Africa alone. When malaria does not claim peoples lives, it has a detrimental effect on worker productivity, educational attainment, population growth and savings and investment (Sachs and Malaney, 2002; Barreca, 2010; Bleakley, 2010a; Percoco, 2011). Due to reasons such as these, a number of empirical studies have shown that malaria has a negative, statistically significant effect on national income per capita (e.g. McCarthy et al., 2000; Gallup and Sachs, 2001).[1]

A point little considered in the empirical literature, however, is that there is inherent endogeneity in the relationship between malaria and economic wellbeing. Since lack of income adversely affects the ability to prevent and treat a disease, the relationship between a disease and economic development probably has causality operating in both directions (Pritchett and Summers, 1996; Strauss and Thomas, 2008). In the words of Bleakley (2010b) "poor countries tend to be unhealthy, and unhealthy countries tend to be poor". In our case, not only is there a malaria-to-income causal link, there is also an income-to-malaria causal link (reverse causation). Thus if someone were to regress malaria on per capita income, we might find a negative, statistically significant effect as well, and conclude that causality runs in the opposite direction. Pritchett and Summers (1996), for example, have found such a relationship for health when it is characterized in terms of infant and child mortality.

* Datta: Internal Revenue Service, Washington, DC. Tel: 202-407-8317; Fax: 509-984-8943; E-mail: saurabh.charles.datta@gmail.com. Reimer (corresponding author): Department of Agricultural and Resource Economics, Oregon State University, 213 Ballard Hall, Corvallis, OR, 97331. Tel: 541-737-1415; E-mail: jeff.reimer@oregonstate.edu. The authors wish to thank Monica Fisher, Jeff Nugent, Steve Buccola and Bruce Weber for comments. Financial support came from the Oregon Agricultural Experiment Station and United States National Institute of Food and Agriculture.

There are a number of reasons why the income-to-malaria causal chain may be the best explanation of the inverse relationship between malaria and income. Economic growth could reduce malaria if it allows greater resources to be made available for malarial prevention (Gallup and Sachs, 2001). This is plausible because the direct costs of malaria prevention and treatment are substantial (Chima et al., 2003). In the words of Narasimhan and Attaran (2003), malaria control on a large scale "requires money—far more money" than many of the most-afflicted countries can afford. Increased income could allow households to spend more on preventative measures such as provision of bed nets, mosquito repellents, and the draining of wetlands and canals to reduce mosquito numbers. Such investments are not trivial in most endemic countries (Fisher et al., 2010). For example, in sub-Saharan Africa households spend upwards of $180 per year on malaria prevention measures alone (1999 US dollars; Chima et al., 2003).

Increased income would also allow households to spend more on treatment, including drugs, transport, doctor consultation fees and subsistence at a health facility. In sub-Saharan Africa, for example, households spend between $23 and $312 per year on malaria treatment measures alone (1999 US dollars; Chima et al., 2003). Again, these expenditures are not trivial in most endemic countries.

The income-to-malaria causal link may also operate at the national level. For example, higher incomes may enable development of public health facilities for treatment of malarial patients, and community efforts that reduce the number of mosquitoes in an area. In addition, higher income is associated with migration of workers to urban areas, which may decrease the share of the population that lives in rural malaria-prone regions. For all these reasons we might expect richer countries to have lower levels of malaria, holding constant factors such as geography and climate.

The major objective of the paper is to explain why, since the 1980s, a large number of malaria-endemic countries have been successful in raising incomes and lowering the incidence of malaria. In particular, did they do this by first controlling malaria, with a resultant rise in income? Or did the reduction in malaria come about by raising incomes first in order to pay for malaria control at the public or household level. In line with this objective, we consider a wide range of countries that have made progress in this transition, including countries in East Asia, South Asia and South America.

Our study is the first that we know of in the literature to focus on two-way causality in the relationship between malaria and economic wellbeing. We use a balanced panel of annual observations on health, economic and geographic factors for 100 countries from 1985 to 2001. We rely on World Health Organization data on malarial incidence, which corresponds to hospital admissions and deaths per million people. These data are unmatched in terms of coverage and consistency, and despite their shortcomings have been underutilized in research (World Health Organization, 1999; 2008). A majority of the 100 countries in the sample experienced income growth and falling rates of malaria over time.

To investigate the nature of this relationship, we develop a new model of malaria and economic wellbeing. We start with a household whose utility function is a function of consumption and the health status of the household, as given by malaria. Rates of malaria are affected by investment in malaria prevention and treatment as well as other exogenous factors, such as climate and medical infrastructure. Every household is a producer as well as consumer, with productivity being affected by rates of malaria as well as other factors, such as capital stock.

The model highlights the conflict that arises from provision of costly malaria prevention and treatment. This takes away from direct consumption of other goods, but

enhances utility through better health and leads to an increase in household productivity. The model yields two equations that can independently generate an inverse relationship between malaria and economic wellbeing, which is what we find in simple plots of data.

When we econometrically estimate these equations, we use identifying restrictions to distinguish the effect that malaria has on income separately from the effect that income has on malaria. We carry out a battery of specification tests and find that our results are robust across a range of specifications and estimation techniques. While our results verify those of previous studies showing that reductions in malaria have a beneficial impact on income, we find that rising national income per capita—owing to a wide range of factors not necessarily associated with health and human capital—has an even stronger effect on malaria incidence. In particular, a 1% rise in the number of malaria cases per million decreases per capita income by less than 0.01%, which is similar to magnitudes obtained by Gallup and Sachs (2001) and McCarthy et al. (2000). However, a 1% rise in income per capita decreases the number of malaria cases per million by more than 1%. This result is robust to estimation technique and examination of different subsets of countries, including an analysis of sub-Saharan African countries alone and East Asian countries alone. We conclude that the inverse relationship between income and malaria witnessed for many countries over time and space has been driven more by the enhanced prevention and treatment afforded from higher incomes (arising from a broad array of factors) as opposed to the beneficial effect that lower malarial incidence itself has on income. For countries seeking to move away from a high-malaria/low-income equilibrium trap, this result suggests that economic development policy needs to consider much more than just malaria prevention and control.

## 2. Conceptual Framework

We start with a household whose utility function $u$ is a function of consumption ($c$) and the health status of the household, in this case represented by incidence of malaria ($m$):

$$u = u(c, m). \tag{1}$$

This relationship has the following derivatives: $u_c > 0$, $u_m < 0$, $u_{cc} < 0$ and $u_{mm} > 0$, which implies that utility rises when there are increases in consumption, but at a diminishing rate. In turn, utility declines from a rise in malaria, but at a diminishing rate. The household budget constraint is:

$$c + pi = y, \tag{2}$$

where $i$ is private investment in malaria treatment and prevention, $p$ is the ratio of the price of $i$ to a price index of other goods ($c$), and $y$ is the amount available to spend.

We assume that households own factors of production directly. These factors can be transformed into final goods according to a production technology. Household output is denoted $y$, and is a function of a fixed stock of capital per household ($k$), fixed labor ($l$), malaria incidence ($m$), and exogenous factors that influence output ($X$). We express this as:

$$y = f(k, l, m, X), \tag{3}$$

where $f_k$, $f_l > 0$, $f_{kk}$, $f_u < 0$, $f_m < 0$ and $f_{mm} > 0$. This implies that the arguments have diminishing marginal effects on output.

Malaria appears to directly influence output in (3), but in reality its effect will arise through interactions with other factors. Malaria may potentially affect: the productivity of labor (through its effect on human capital), the availability of labor (since it incapacitates part of the labor force), the volume and productivity of capital (since malaria depresses savings and since investment may avoid certain malaria-infested areas), and total factor productivity (e.g. since malaria may prevent specialization patterns from being pursued). In short, (3) is meant to be general enough to allow for malaria to have a variety of potential effects on output.[2]

The incidence of malaria is affected by investment in malaria prevention and treatment, which we denote as $i$. Malaria is also determined by other exogenous geographic, climatic, and demographic factors ($Z$):

$$m = m(i, Z), \tag{4}$$

Malaria declines from an increase in investment ($m_i < 0$), but at a diminishing rate ($m_{ii} > 0$). The budget equation can be re-written by re-arranging (2), and then substituting into (4):

$$c = f(k, l, m(i, Z), X) - pi. \tag{5}$$

We can substitute (4) and (5) into (1) to form the household's utility maximization problem. It is cast as a decision about the optimal level of $i$ to select:

$$\operatorname*{Max}_i u(f(k, l, m(i, Z), X) - pi, m(i, Z)). \tag{6}$$

The first-order conditions are such that:

$$\frac{\partial u}{\partial c}\left[\frac{\partial f}{\partial m}\frac{\partial m}{\partial i} - p\right] + \frac{\partial u}{\partial m}\left[\frac{\partial m}{\partial i}\right] = 0. \tag{7}$$

We can re-arrange this to show that:

$$\frac{\partial f}{\partial m}\frac{\partial m}{\partial i} + \frac{\partial u}{\partial m} \bigg/ \frac{\partial u}{\partial c}\left[\frac{\partial m}{\partial i}\right] = p, \quad \text{with } \frac{\partial f}{\partial m}, \frac{\partial m}{\partial i}, \frac{\partial u}{\partial m} < 0 \text{ and } \frac{\partial u}{\partial c} > 0. \tag{8}$$

Equation (8) equates total marginal gain from private malaria investment to marginal cost ($p$). The first term on the left hand side is positive and indicates how much output per capita can be gained from increased investment. The second term on the left-hand side is also positive, and indicates how much utility is gained from investing in malaria prevention and treatment.

Each country has a large number of households with identical preferences, identical endowments of labor and capital, and identical constant-returns to scale technologies. In this way we can work with a representative household for each country, and use per capita, macroeconomic versions of these equations (Reimer and Hertel, 2010).

Recall that there tends to be an inverse relationship between malaria ($m$) and income ($y$) over time. We now show how the model can capture these stylized facts. Starting with equation (3), rising malaria can decrease output:

$$\frac{\partial y}{\partial m} = \frac{\partial f(k, l, m, X)}{\partial m} < 0. \tag{9}$$

On the other hand, from (2) we have that: $i = (y - c)/p$. Using this along with (5), we see that:

$$\frac{\partial m}{\partial y} = \frac{\partial m(i, Z)}{\partial i} \frac{\partial i}{\partial y} < 0. \tag{10}$$

The negative relationship between malaria and income arises from (9), (10) or from some kind of incidental association (from $X$ or $Z$). To get at this, we estimate structural equations (3) and (4) in a simultaneous equations framework.

Note that in (3), $m$ has a simultaneous effect on $y$. In (4), the relationship between $m$ and $i$ is more likely to be recursive in nature, since there is more likely to be a lag between investments and health outcomes ($m$).

## 3. Empirical Specification

The data are a balanced panel of 17 annual observations on 100 countries from 1985 to 2001. Countries are classified into six regional groupings that we use in later empirical work. The large sample provides a rich source of variation for efficient estimation of model parameters. The Appendix has specific information about the sources of data and construction of certain variables.

Summary statistics for key variables are reported in Table 1. A few details stand out. For example, average malaria cases per million population is 39,882, ranging from as few as one to as many 395,550 in a given year. National income (measured as gross domestic product) per capita also ranges substantially, from 175 to 18,682 (1990–91 US dollars). The climate variable shows that 70% of the countries are sub-tropical or tropical, with the remainder temperate or desert.

Malaria and income averages for the six regional groupings are reported in Table 2. Comparison of averages across the first and last years of the sample suggests that neither malaria incidence or income has been stable over time.

Equations (3) and (4) are too general for empirical purposes. It is necessary to form more explicit functions for these relationships. We first motivate our specification of (3). We proxy for household output ($y$) in (3) using the level of income per capita at purchasing power parity ($GDP_{it}$). The subscripts $i$ and $t$ index country and time, respectively. This is the same dependent variable as in Gallup and Sachs (2001), and is consistent with our idea that production occurs at the household level, which may be appropriate in a developing country context. We capture malaria on the right-hand side of (3) with World Health Organization data on reported malaria cases per million population ($MAL_{it}$).

Equation (3) also depends on per capita capital stock ($k$), labor ($l$), and other exogenous factors ($X$), which are an important part of our identification strategy. The latter may include human capital, trade openness (Sachs and Warner, 1995; Dollar and Kraay, 2004), demographic characteristics (McCarthy et al., 2000; Gallup and Sachs, 2001), and quality of institutions. These relationships may hold not only at the household level but also at the country level. For $k$ and $l$ we have capital investment as a percentage of national income ($CAP_{it}$) and labor's share of the population ($LAB_{it}$). A quality of institutions index ($INS_{it}$) is included for the potential impact of this on per

*Table 1.  Data Overview*

| Variables | Description | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| $MAL_{it}$ | Malaria cases per million population | 39,882 | 75,807 | 1 | 395,550 |
| $GDP_{it}$ | Gross domestic product per capita at purchasing power parity | 3,478 | 3,256 | 175 | 18,682 |
| $COAST_{it}$ | % of population within 100 km of the coast | 5.0 | 4.0 | 0.1 | 16.9 |
| $INS_{it}$ | Quality of institutions index (–2 to +2) | –0.58 | 0.55 | –2.00 | 1.15 |
| $LAB_{it}$ | Laborers per 100 population | 40.00 | 11.00 | 22.42 | 64.83 |
| $CAP_{it}$ | Investment as a % of gross domestic product | 10.90 | 7.33 | 1.12 | 14.06 |
| $OPN_{it}$ | Sachs–Warner index of openness | 0.32 | 0.47 | 0 | 1 |
| $TAR_{it}$ | Average applied tariff rate | 20.82 | 12.78 | 0 | 100 |
| $CLIM_i$ | Climate binary variable: one for sub-tropical/tropical and zero for temperate/desert | 0.70 | 0.46 | 0 | 1.00 |
| $CHLD_{it}$ | Population below 15 years of age per 100 population | 40.9 | 6.0 | 19.9 | 57.5 |
| $IMUNE_{it}$ | Population that is immunized per 100 population | 67.0 | 24.0 | 2.0 | 100.0 |
| $PHY_{it}$ | Physicians per thousand population | 6.63 | 15.74 | 1.00 | 179.78 |
| $LAT_i$ | Central latitude of the country (in degrees and minutes) | 10.3 | 17.5 | –35.4 | 42.2 |
| $ELEV_i$ | Average elevation of the country (meters) | 666.1 | 592.9 | 0 | 3,185.9 |
| $TEMP_{it}$ | Mean deviation of temperature (Celsius) | 0.11 | 0.27 | –0.21 | 1.00 |

*Note*:  There are observations for 100 countries (*i*) and 17 years (*t*). The Appendix has more information on the data.

*Table 2.  Aggregate Changes in Malaria and Income over Time*

| Region (number of countries) | Year | Average malaria cases (weighted by population) | Average gross domestic product per capita, measured at 1990–91 purchasing power parity |
|---|---|---|---|
| Sub-Saharan Africa (42) | 1985 | 29,204 | 1,510 |
| | 2001 | 42,641 | 1,541 |
| East Asia (13) | 1985 | 3,206 | 2,109 |
| | 2001 | 1,859 | 3,189 |
| South Asia (6) | 1985 | 2,354 | 1,716 |
| | 2001 | 1,414 | 1,792 |
| Central/South America (20) | 1985 | 1,766 | 4,589 |
| | 2001 | 1,114 | 5,094 |
| North Africa (5) | 1985 | 140 | 1,959 |
| | 2001 | 111 | 2,405 |
| Central/West Asia (14) | 1985 | 49 | 3,874 |
| | 2001 | 58 | 4,138 |

capita national income. It ranges from –2 (low quality) to +2 (high quality). The percentage of population within 100 km of the coast ($COAST_{it}$) is included, based on the approach in Gallup and Sachs (2001). We use two measures that proxy for a country's general "openness" to trade: the Sachs–Warner Index of openness ($OPN_{it}$), and the average applied tariff rate ($TAR_{it}$).[3]

In some of our specifications we consider regional fixed effects ($D_j$). Note that $D_j$ is equal to one when $j = i$, otherwise zero. A trend variable ($TRND_t$) is also included in some regressions as a parsimonious way to capture time effects.

Taking all of the above into consideration, the most general version of (3) that we estimate is the following, which we denote (3′):

$$GDP_{it} = \alpha_0 + \alpha_1 MAL_{it} + \alpha_2 LAB_{it} * MAL_{it} + \alpha_3 CAP_{i,t-1} * MAL_{it} + \alpha_4 LAB_{it} + \alpha_5 CAP_{i,t-1}$$

$$+ \alpha_6 INS_{it} + \alpha_7 COAST_{it} + \alpha_8 OPN_{it} + \alpha_9 TAR_{it} + \sum_{j=1}^{6} \gamma_j D_j + \alpha_{10} TRND_t + \varepsilon_{it}, \quad (3')$$

where $\varepsilon_{it}$ is an error term with classical properties except as discussed below. All variables are logged except $INS_{it}$, $OPN_{it}$, $D_j$ and $TRND_t$. Capital enters as a lagged term ($CAP_{i,t-1}$) to allow for a time gap between provision of capital and the effect on the economy. This also reduces potential problems with endogeneity associated with having capital on the right-hand side of the equation. Malaria is also allowed to enter as a multiplicative factor to both $CAP_{i,t-1}$ and $LAB_{it}$ to get at the idea that malaria may have additional effects on output. There may be an overall effect on total factor productivity, an effect just on labor, or an effect just on capital.

We now turn to our specification of (4), which draws from insights in Pritchett and Summers (1996), Erdil and Yetkiner (2004), and Bloom et al. (2004). We are unable to observe expenditure on malaria prevention and treatment ($i$) over time for a large number of countries, whether this is at the private household level or whether these are public health expenditures. An important proxy for investment ($i$) at the household level may be per capita national income, which corresponds to the partial derivative, $\partial i / \partial y$, in the model. This strategy has been used productively in Grossman (1972).

Other proxies for $i$ include the share of population that is immunized against major diseases such as cholera and diphtheria ($IMUNE_{it}$), and physicians per thousand population ($PHY_{it}$). While these factors may not by themselves be expected to reduce malaria incidence, they may be correlated with general health investments in a country over time.

Malaria incidence over time and space also depends on geographic variables, which are an important part of our identification strategy. Exogenous factors ($Z$) used to estimate (4) include a climate dummy variable ($CLIM_i$) that is one if a country is primarily tropical or sub-tropical, and zero if it is primarily temperate or desert (Gallup and Sachs, 2001). We also consider the central latitude of the country ($LAT_i$), average elevation ($ELEV_i$), and the mean deviation of temperature ($TEMP_{it}$). These types of factors have been used in studies such as McCarthy et al. (2000), Gallup and Sachs (2001) and Filmer (2005). Since younger populations tend to be somewhat more prone to malaria, we include the percentage of the population that is below fifteen years of age ($CHLD_{it}$). We also include the percentage of the population that is within hundred kilometers of coast ($COAST_{it}$). Coastal areas are somewhat more likely to have problems with malaria. Finally, as with (3), on the right-hand side of (4) we include the quality of institutions index ($INS_{it}$). Higher values of $INS_{it}$ are expected to dampen the incidence of malaria.

The most general version of (4) that we estimate is:

$$MAL_{it} = \beta_0 + \beta_1 GDP_{i,t-1} + \beta_2 GDP_{i,t-1} * CLIM_i + \beta_3 CLIM_i + \beta_4 LAT_i$$
$$+ \beta_5 ELEV + \beta_6 COAST_{it} + \beta_7 TEMP_{it} + \beta_8 CHLD_{it} + \beta_9 PHY_{it}$$
$$+ \beta_{10} IMUNE_{it} + \beta_{11} INS_{it} + \sum_{j=1}^{6} \gamma_j D_i + \beta_{12} TRND_t + \delta_{it} \qquad (4')$$

where $\delta_{it}$ is an error term with classical properties except as discussed below. Note that all variables are logged except for $CLIM_i$, $INS_{it}$, $LAT_i$, $ELEV_i$, $TEMP_{it}$, $D_i$ and $TRND_t$. In (4') there is a recursive relationship between *MAL* and *GDP* such that it takes one year for income to have an effect on malaria incidence rather than having an instantaneous effect (Filmer, 2005).[4] The remaining variables in (4') have been introduced already, and should be largely self-evident. Note that we also include the interaction of lagged income per capita with the climatic characteristics when explaining $MAL_{it}$.

In thinking about how to estimate (3') and (4') we first check rank and order conditions. Both equations are over-identified. We then carry out Hausman (1978) specification tests. The first two tests compare ordinary least squares (OLS) to two-stage least squares (2SLS), and OLS to three-stage least squares (3SLS). In both cases a null hypothesis of no endogeneity is rejected, and OLS is found to be an inconsistent estimator. A third test rejects a hypothesis of no simultaneity, and concludes that 3SLS is consistent and efficient, while 2SLS is consistent and inefficient (the chi-square statistic is 5.44). For these reasons we rely mainly on 3SLS in the subsequent analysis.

Under 3SLS, the instrumental variable for $MAL_{it}$ in (3') is its predicted value based upon all the exogenous variables of the system. When we regress $MAL_{it}$ on the exogenous variables in the first stage of our 3SLS procedure, we get an $R$-square of 0.64. This suggests it is a good instrumental variable. The instrumental variable for $GDP_{i,t-1}$ in (4') is its predicted value based upon all the exogenous variables of the system. When we regress $GDP_{i,t-1}$ on all the exogenous variables of the system in the first stage of our 3SLS procedure, we get an $R$-square of 0.61 which suggests it is a good instrumental variable.

## 4. Results

We report the results of six variations of the model in Table 3.

*Model 1*

We start our discussion with Model 1, in which (3') and (4') are estimated jointly using 3SLS. Model 1 includes all countries and all possible variables. The model appears to fit the data well, with a system-wide $R^2$ of 0.58. The expected sign for each coefficient is almost always consistent with what we find using 3SLS.

The Model 1 coefficient on *MAL* for (3') is –0.0002. As an elasticity, this implies that a 1% increase in the number of malaria cases per million (holding constant its effect in the interaction terms) is associated with a 0.0002% decrease in income per capita. This is the expected sign, and the coefficient is statistically different than zero at the 1% level. While in this case malaria is affecting total factor productivity, we also allow for additional, individual effects on labor and capital productivity. We capture these through the interaction terms between malaria and labor, and malaria and capital. The corresponding coefficients are –0.007 and –0.004, respectively, with statistical significance in both cases.

Looking further down this column we see that, by themselves, increases in labor and capital usage in a country have a positive, statistically significant effect on income

*Table 3. Results*

| Variable | Model 1 3SLS $n = 1{,}600$ | Model 2 3SLS $n = 1{,}600$ | Model 3 3SLS $n = 656$ | Model 4 3SLS $n = 208$ | Model 5 OLS $n = 1{,}600$ | Model 6 OLS $n = 1{,}600$ |
|---|---|---|---|---|---|---|
| Equation (3′), dependent variable: $GDP_{it}$ | | | | | | |
| $MAL_{it}$ | –0.0002** | –0.0003** | –0.0043** | –0.0027** | –0.013** | — |
| $LAB_{i,t-1}*MAL_{it}$ | –0.007** | — | — | — | –0.009** | — |
| $CAP_{i,t-1}*MAL_{it}$ | –0.004** | — | — | — | –0.005** | — |
| $LAB_{i,t}$ | 0.012* | — | — | — | 0.017* | — |
| $CAP_{i,t-1}$ | 0.476** | — | — | — | 0.484** | — |
| $INS_{it}$ | 0.440** | 0.593* | 0.419** | 1.094** | 0.419** | — |
| $COAST_{it}$ | 0.146** | 0.199** | 0.114* | 0.180** | 0.127** | — |
| $OPN_{it}$ | 0.071* | 0.110** | 0.060* | 0.230* | 0.059* | — |
| $TAR_{it}$ | –0.007** | — | — | — | –0.004** | — |
| Sub-Saharan Africa | –1.006** | — | — | — | –0.896** | — |
| South Asia | –0.569** | — | — | — | –0.377** | — |
| East Asia | –0.712** | — | — | — | –0.321** | — |
| C./S. America | –0.279** | — | — | — | –0.166** | — |
| North Africa | –0.791** | — | — | — | 0.439** | — |
| $TRND_t$ ($t = 1, 2, 3, \ldots$) | 0.004 | — | — | — | 0.005 | — |
| Intercept | 6.591 | 8.083** | 12.735** | 7.858** | 8.347** | — |
| Equation (4′), dependent variable: $MAL_{it}$ | | | | | | |
| $GDP_{i,t-1}$ | –0.897** | –1.126* | –1.853** | –0.907* | — | –0.776* |
| $GDP_{i,t-1}*CLIM_i$ | 0.648** | — | — | — | — | 0.741** |
| $CLIM_i$ | 3.247** | 1.994* | 0.783** | 0.683* | — | 3.941** |
| $LAT_i$ | –0.035** | –0.053** | –0.016* | –0.078** | — | –0.036** |
| $ELEV_i$ | –0.0002* | –0.0001* | –0.0002* | –0.0001* | — | –0.0001* |
| $COAST_{it}$ | 0.220** | 0.227* | 0.172* | 0.161* | — | 0.274** |
| $TEMP_{it}$ | 0.340* | 0.389* | 0.581** | 0.177* | — | 0.397* |
| $CHLD_{it}$ | 0.136** | 0.171* | 0.186** | 0.143** | — | 0.139* |
| $PHY_{it}$ | –0.394** | — | — | — | — | –0.408** |
| $IMUNE_{it}$ | –0.010** | — | — | — | — | –0.011** |
| $INS_{it}$ | –0.168* | –0.187* | –0.644* | –1.172** | — | –0.246* |
| Sub-Saharan Africa | 1.293** | — | — | — | — | 1.338** |
| South Asia | 0.807** | — | — | — | — | 0.846** |
| East Asia | 0.674** | — | — | — | — | 0.682** |
| C./S. America | 0.279* | — | — | — | — | 0.289* |
| North Africa | 0.091* | — | — | — | — | 0.052* |
| $TRND_t$ ($t = 1, 2, 3, \ldots$) | 0.047** | — | — | — | — | 0.044* |
| Intercept | 8.731** | 8.750* | 16.459** | 4.669 | — | 10.001** |
| $R^2$ | 0.58 | 0.46 | 0.56 | 0.63 | 0.64 | 0.66 |
| Durbin–Watson | 2.11 | 1.88 | 1.91 | 1.88 | 1.80 | 2.09 |
| Breusch–Pagan | 18.90 | 13.99 | 13.62 | 14.81 | 7.05 | 6.96 |
| Shapiro–Wilk | 0.044 | 0.042 | 0.047 | 0.032 | 0.048 | 0.041 |

*Notes*: Standard errors are not reported due to space restrictions, but are available from the authors upon request. Abbreviation *n* stands for number of observations. Model 3 is estimated for sub-Saharan African countries only. Model 4 is estimated for East Asian countries only. A single asterisk (*) implies significance at 0.05 level in a two-tailed test. A double asterisk (**) implies significance at 0.01 level in a two tailed test. *R*-squared is system weighted in 3SLS models.

per capita. The coefficients are 0.012 and 0.476, respectively. Quality of institutions (*INS*) also has a positive, statistically significant impact on income per capita (the coefficient is 0.440). Closeness of population to the coast (*COAST*) has a positive effect on income per capita (the coefficient is 0.146, and is statistically significant). Greater openness (*OPN*) and higher average tariffs (*TAR*) increase and decrease income per capita, respectively (the coefficients are 0.071 and –0.007). Model 1 also includes regional fixed effects for (3′), with Central/West Asia taken as a reference category. All of these effects are negative and statistically different than zero. Finally, we include a trend variable for equation (3′). It is statistically zero and therefore we do not interpret it.

We now turn to the second equation estimated as part of Model 1, (4′), which quantifies the effect of income on malaria. The coefficient on lagged *GDP* in Table 3 is –0.897 and is statistically different than zero at the 1% level. As above, this coefficient can be interpreted as an elasticity. Therefore, a 1% increase in income per capita (holding constant its effect elsewhere) is associated with a 0.897% decrease in the number of malaria cases per million. Just below this coefficient is an interaction term between *GDP* and climate. The coefficient is positive and statistically significant (0.648), which suggests that the ability of higher income to overcome malaria is weakened if a country is sub-tropical or tropical. This implies that tropical/sub-tropical countries would require a larger increase in income per capita to achieve a given reduction in malaria. Below this result is the coefficient on climate alone. It is positive (3.247) and statistically significant, which—as expected—suggests that malaria is more likely in tropical/sub-tropical climates.

Geographical factors such as greater distance from the equator (*LAT*) and elevation from the sea level (*ELEV*) have negative, statistically significant impacts on malaria incidence (the coefficients are –0.035 and –0.0002, and are statistically significant). Meanwhile, the higher the share of the population that lives near the coast (*COAST*), and the higher a country's temperature variation (*TEMP*), the greater the incidence of malaria (the coefficients are 0.220 and 0.340, and statistically significant). Countries with high percentages of population below age 15 years (*CHLD*) have higher rates of malaria (the coefficient is 0.136, and is statistically significant).

In addition to income per capita, a number of other variables are included to proxy for a nation's ability and willingness to invest in health infrastructure that might lessen the incidence of malaria. These results are reported in the lower section of the column corresponding to Model 1. We find that malaria incidence is reduced by availability of physicians (*PHY*), greater rates of immunization (*IMUNE*), and the quality of institutions (*INS*). The corresponding coefficients are –0.394, –0.010, and –0.168, and are all statistically non-zero.

We also include regional fixed effects for (4′) in the case of Model 1. These are all positive and statistically significant, which mainly suggests that malaria is more prevalent in these regions than in Central/West Asia (the base category). Finally, a trend variable for (4′) is included. We find this coefficient (0.047) to be positive and statistically significant. Note that all of the signs of the coefficients in Model 1 are as expected. We believe this adds a great deal of credibility to our results.

## Model 2

A potential problem with Model 1 is that some of the right hand side variables may be correlated with the error term. For example, Hausman tests (not reported) suggest that this might be the case for labor and capital usage in the *GDP* equation (3′). One

way to investigate the extent to which this affects the results is to estimate a pared down version of Model 1 in which these variables are eliminated. We can also use this opportunity to gauge the sensitivity of Model 1's results to the presence of other variables, such as the regional and time effects. This new approach is called Model 2, and the results are reported once again in Table 3. Despite the many changes in specification, we see that the Model 2 coefficient on *MAL* is almost exactly the same as that in Model 1 (–0.0003). The coefficient on lagged *GDP* in (4′) is somewhat greater in magnitude in Model 2 than it was in Model 1 (–1.126 versus –0.897). However, this greater magnitude appears only to be the result of having eliminated other variables with a negative correlation with *MAL*, such as the number of physicians (*PHY*) and immunizations (*IMUNE*). The system-wide $R^2$ falls to 0.46 in Model 2 from 0.58 in Model 1. All other aspects of the results are highly consistent with those of Model 1. We conclude that our basic results are robust.

*Models 3 and 4*

In the next two approaches we consider what happens if our sample is restricted to sub-Saharan Africa (Model 3) and East Asia (Model 4), respectively. Malaria is prevalent in these two regions yet there may be important differences in the historical experience of these regions. East Asia has in general had greater economic growth over the past few decades, and a sharper fall in malaria incidence, than in most sub-Saharan African countries. We examine whether the results hold when we look at these two very different regions on an independent basis.

For both Models 3 and 4, we retain the same specification as Model 2. In both cases the results differ only slightly. The signs and significance of all coefficients remain as in Model 2. The most notable result is that the coefficient on malaria in the *GDP* equation (3′) and the coefficient on *GDP* in the malaria equation (4′) are slightly larger in magnitude for sub-Saharan Africa than for either East Asia (Model 4) or all countries combined (Model 2). This may reflect greater uniformity of the experience of countries in sub-Saharan Africa, perhaps due to geographic, cultural or institutional factors that are not picked up by the other control variables. We conclude that our results are robust to different sub-samples of the data.

*Models 5 and 6*

To round out our robustness checks we examine what would happen if the *GDP* equation and the malaria equation (4′) are no longer estimated as part of a system of equations. The alternative, of course, is to simply estimate (3′) and (4′) with single-equation OLS methods. We call these Model 5 and Model 6, respectively. Model 6 is a regression of income on a health measure and is representative of several studies that have explored this issue in the past. A major point of this study is that the OLS estimator is potentially biased in this case due to the endogeneity of gross domestic product per capita on the right-hand side. We allow for the full set of right-hand side variables in Models 5 and 6. Despite the large differences in specification and estimation technique relative to Models 1–4, the coefficient estimates are once again very similar across them. It appears that any bias arising from endogenous right-hand side variables is mild. Due to the similarity of coefficient estimates, we skip a detailed discussion of the results.

*Diagnostic Tests*

A number of diagnostic tests are reported at the bottom of Table 3. Goodness of fit ($R^2$) varies from a low of 0.46 to 0.66. The simple OLS regression of malaria on income (Model 6) has the highest $R^2$. The Durbin–Watson statistic ranges from 1.80 to 2.11, suggesting that autocorrelation is not a serious problem. Breush–Pagan tests fail to reject a null hypothesis of no heteroskedasticity in each of the specifications. Finally, Shapiro–Wilk tests fail to reject a null hypothesis of normality in regression residuals for all of our models.

*Comparison to Other Studies*

It is useful to consider our results in the context of earlier studies, which rely on other sources of information about malaria. For example, Gallup and Sachs (2001) use a malaria exposure index, which corresponds to the product of the fraction of area that was exposed to malaria in 1994 and the fraction of falciparum cases in total cases in 1990. Kiszewski et al. (2004) use an index corresponding to the anopheles vector, with a focus on the ease with which mosquito-borne disease is spread from person to person. In contrast to these approaches, we use reported malaria cases per million, and account for individuals who contract and survive malaria, as well as die from malaria, regardless of whether this is caused by the falciparum or anopheles vector.

Another difference with previous studies is that they are generally not based on panel data, which allows identification and estimation of effects that are not detectable in pure cross sections or time series. One exception is McCarthy et al. (2000), who have 187 observations at three points in time, compared to our 100 observations at 16 points in time.

In spite of these differences, our estimate of the effect of malaria on income is similar to that of McCarthy et al. (2000), who find that growth in malaria morbidity reduces annual per capita growth by 0.25% per year, and that of Gallup and Sachs (2001), who find that a 1% reduction in their malaria index is associated with 0.03% higher economic growth. We believe the overall similarity of results lends a great deal of credence to our data and methods.

It is important to emphasize that we differ from such studies, however, in that we adopt a simultaneous equations approach in our econometric analysis. Our exploration of the income-to-malaria causal link has few parallels in the previous literature. The closest such study may be Pritchett and Summers (1996), who calculate that in 1990 alone, more than half a million child deaths in the developing world could be attributed to poor economic performance in the 1980s. This is a very different dimension of health, however, and the authors do not employ the simultaneous equations approach that we propose in this study.

## 5. Conclusions

As in several previous studies, we show that declines in rates of malaria morbidity and mortality have beneficial effects on national income per capita. As important as this effect is, however, it cannot explain the inverse relationship between malaria incidence and income that we uncover across time and space for 100 endemic countries. This relationship is driven mainly by the ability of higher incomes—arising from factors not necessarily related to health and human capital—to decrease

malaria. Accounting for simultaneity and incidental associations, we find that a 1% increase in income per capita decreases the number of malaria cases by approximately 1.1%.

This result also holds when we restrict the analysis to sub-Saharan Africa alone, or East Asia alone. It means that if income were just 1% higher among the 100 countries of our sample, 603,189 cases of malaria could be averted on an annual basis. Our results are consistent with prior evidence that it is expensive to prevent and treat malaria—whether at the household level or government level. It appears that economic growth is a precursor to, or at least coincident with, sustained reductions in malaria, and that economic development programs centered exclusively around the reduction of malaria are unlikely to be productive.

The methods and results of this study are relevant for a wider variety of diseases and health conditions. Our economic model could be applied at the household level using survey data, for example. This might make it possible to directly estimate some of the structural relations that we have posited. For example, we would ideally estimate the extent that new income goes toward malaria prevention and treatment, the effectiveness of investments in reducing malaria, and the effect of malaria on productivity and output. While some aspects of these relationships may be observable, it may be very hard to quantify them in a general way. In this study we have estimated their joint effect, which corresponds to the product of these partial derivatives. This has allowed us to draw from the historical experience of 100 endemic countries in investigating why malaria tends to have a negative correlation with income over time and over space.

# Appendix

*Malaria cases per million* ($MAL_{it}$) From World Health Organization (1999; 2005; 2008).

*Gross domestic product per capita at purchasing power parity* ($GDP_{it}$) From Penn World Tables.

*Population within 100 km of coast* ($COAST_{it}$) From United Nations Environmental Program.

*Quality of institutions index* ($INS_{it}$) From World Bank's Learning Program.

*Percentage of labor in population* ($LAB_{it}$) From Penn World Tables.

*Investment as % of national income* ($CAP_{it}$) Total business spending on fixed assets that provide the basis for future production. From Penn World Tables.

*Sachs and Warner index of openness* ($OPN_{it}$) Described in Sachs and Warner (1995).

*Applied average tariff rate* ($TAR_{it}$) From World Bank's Trade Statistics.

*Climatic dummy* ($CLIM_i$) Authors' own calculation.

*Percentage of children below 15* ($CHLD_{it}$) From World Development Indicators, 2007.

*Percentage of population immunized* ($IMUNE_{it}$) From World Bank's World Development Indicators, 2007, for 1985, 1990, 1995 and 2000. A linear interpolation fills in yearly data gaps.

*Physicians per thousand population* ($PHY_{it}$) From World Bank World Development Indicators.

*Central latitude of the country* ($LAT_i$) From Center for International Development, Harvard.

*Average elevation of the country from sea level in meters* ($ELEV_i$) From Center for International Development, Harvard University.

*Deviation of temperature* (*TEMP$_{it}$*) From National Weather Services Climate Prediction Center.

## References

Acemoglu, D. and S. Johnson, "Disease and Development: The Effect of Life Expectancy on Economic Growth," *Journal of Political Economy* 115 (2007):925–85.

Akaike, H., "Maximum Likelihood Identification of Gaussian Autoregressive Moving Average Models," *Biometrika* 60 (1973):255–65.

Barreca, A., "The Long-term Economic Impact of In Utero and Postnatal Exposure to Malaria," *Journal of Human Resources* 45 (2010):865–892.

Bleakley, H., "Malaria in the Americas: A Retrospective Analysis of Childhood Exposure," *American Economic Journal: Applied* 2 (2010a):1–45.

———, "Health, Human Capital, and Development," *Annual Reviews of Economics* 2 (2010b):283–310.

Bloom, D., D. Canning, and D. Jamison, "Health, Wealth and Welfare," *Finance and Development* (2004):10–15.

Chima, R., C. Goodman, and A. Mills, "The Economic Impact of Malaria in Africa: A Critical Review of the Evidence," *Health Policy* 63 (2003):17–36.

Conly, G., "The Impact of Malaria on Economic Development—A Case Study," *American Journal of Tropical Medicine and Hygiene* 21 (1972):668–74.

Dollar, D. and A. Kraay, "Trade Growth and Poverty," *Economic Journal* 114 (2004):22–49.

Erdil, E. and I.H. Yetkiner, "A Panel Data Approach for Income-Health Causality," in J. Yfantopoulos (ed.), *The Economics of Health Reforms*. Athens, Greece: Athens Institute for Education and Research (2004):701–24.

Fielding, D. and S. Torres, "Health, Wealth, Fertility, Education and Inequality," *Review of Development Economics* 13 (2009):39–55.

Filmer, D., "Fever and its Treatment Among the More and Less Poor in Sub-Saharan Africa," *Health Policy and Planning* 20 (2005):337–46.

Fisher, M.G., J.J. Reimer, and E.R. Carr, "Who Should be Interviewed in Surveys of Household Income?" *World Development* 38 (2010):966–73.

Gallup, J. and J. Sachs, "The Economic Burden of Malaria," *American Journal of Tropical Medicine and Hygiene* 64 (2001):85–96.

Grossman, M., "On the Concept of Health Capital and the Demand for Health," *Journal of Political Economy* 80 (1972):223–55.

Hausman, J.A., "Specification Tests in Econometrics," *Econometrica* 46 (1978):1251–71.

Kiszewski, A., A. Mellinger, A. Spielman, P. Malaney, S. Ehrlich, and J. Sachs, "A Global Index Representing the Stability of Malaria Transmission," *American Journal of Tropical Medicine and Hygiene* 70 (2004):486–98.

McCarthy, F.D., H. Wolf, and Y. Wu, "Malaria and Growth," Policy Research Working Paper 2303, The World Bank, Washington, DC (2000).

Narasimhan, V. and A. Attaran, "Roll Back, Malaria? The Scarcity of International Aid for Malaria Control?" *The Malaria Journal* 2 (2003):8.

Percoco, M., "The Fight against Geography: Malaria and Economic Development in Italian Regions," Fondazione Eni Enrico Mattei Global Challenges Papers, Working Paper 558, Milan, Italy (2011).

Pritchett, L. and L. Summers, "Wealthier is Healthier," *Journal of Human Resources* 31 (1996):841–68.

Reimer, J.J. and T.W. Hertel, "Non-homothetic Preferences and International Trade," *Review of International Economics* 18 (2010):408–25.

Sachs, J. and A. Warner, "Economic Reform and the Process of Global Integration," *Brookings Papers on Economic Activity* 1 (1995):1–118.

Sachs, J. "A New Global Effort to Control Malaria," *Science* 298 (2002):122–24.

Sachs, J. and P. Malaney "The Economic and Social Burden of Malaria," *Nature* 415 (2002):680–85.

Self, S. and R. Grabowski, "Female Autonomy and Health Care in Developing Countries," *Review of Development Economics* 16 (2012):185–98.

Strauss, J., and D. Thomas, "Health Over the Life Course," in T. Paul Schultz and John Strauss Editors, *Handbook of Development Economics Vol. 4*, Amsterdam: North Holland Press (2008).

World Health Organization, "Malaria, 1982–1997," *Weekly Epidemiological Record*, 74 (1999):265–72.

———, *World Malaria Report 2005*, WHO, Geneva (2005).

———, *World Malaria Report 2008*, WHO, Geneva (2008).

## Notes

1. One study with a contrasting result is Acemoglu and Johnson (2007), but they focus on the 1940s epidemiological transition, which may not have direct relevance to the case of malaria in the modern era. Other studies that consider health and development include Self and Grabowski (2012) and Fielding and Torres (2009).

2. Ideally we might quantify these individual linkages. For example, malaria's effect on labor productivity could possibly be quantified as wages. However, wages are likely to be different from labor productivity in many developing countries due to market distortions (we thank an anonymous reviewer for this point.) In any case, it would be exceedingly difficult to quantify every potential linkage for each of the 100 countries.

3. Additional right-hand side variables considered for (3), but not ultimately reported due in part to concerns about the potential for multicollinearity and/or endogeneity, include life expectancy at birth and secondary school enrolment ratio. Inclusion of these variables did not change any result in a substantive way.

4. The length of this lag is verified by use of an Akaike (1973) Information Criteria procedure. This result is consistent with the findings of Erdil and Yetkiner (2004), who show that national income impacts health status with a lag varying from one to three years.