The macro-economic impact of reducing malaria: an application of a dynamic general equilibrium modelling to Ghana

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Abstract

Research linking malaria and economic growth has, so far, used econometric approaches. These approaches provide results that are too broad and only partially useful for policy purposes. More detailed estimates at household and regional levels are required so that policy makers and donors can assess alternative malaria intervention strategies. To support this aim, we simulate the impact of reducing malaria morbidity and mortality on the Ghanaian economy utilising a micro-based approach.

A multi-sector, multi-agent, dynamic computable general equilibrium (DCGE) model is developed and linked with two components: (1) regional demographics; (2) labour indices for production and productivity. We leave out any additional effects (e.g., direct cost offset, tourism spending, foreign investment). The model is calibrated to Ghana, as a case study, with households disaggregated by five epidemiological malaria zones, urban-rural divide, and five income level quintiles.

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Hypothetical malaria prevention is conducted only on the under five years old, which are not yet productive. However, we find that malaria prevention clearly adds to economic growth and limits the increase in income inequality. The benefit per child covered by prevention (in terms of household income at national level) is $7, $28 and $347 (2007 US Prices) at year 1, year 15 and year 25 (respectively). Benefits also vary by epidemiological zones, due to the heterogeneity in labour resources, preferences, and malaria prevalence. These indicate which households, epidemiological zones, etc. stand to gain most from the treatment.

Our results are conservative estimates because health is only linked to labour resources, while leaving out the other possible effects. Further economic benefits would be obtained had the intervention included direct cost offset and included adults. We contribute with: (1) a public economics approach to analysing malaria impact on economic growth (2) viewing effects at national, regional, and income level dimension; (3) a method applicable to other malaria endemic countries provided a detailed SAM can be developed (4) a suitable method for other diseases, e.g. TB, HIV/AIDS, and obesity.

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Disclaimer

This is a work in progress. Improvement of the model will be made before submission to a journal.

Acknowledgements

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1 Introduction

The scale of malaria infection in Africa is widespread. In 2010 it was estimated that there were 216 million episodes of the disease, of which 81% were in the African region. Moreover, of the approximately 0.655 million deaths estimated, 91% were in Africa. Children are the most vulnerable, and approximately 86% of malaria deaths globally involve children under-five (<5) years of age (WHO, 2011).

Besides the obvious toll on human life, this has considerable economic consequences for developing countries. Research on the correlation between malaria and economic growth find that it harms efforts to stimulate growth in low-income countries. This is specifically highlighted in the seminal work of Gallup and Sachs (2001), who estimate that malaria elimination in sub-Saharan Africa could increase per capita growth by as much as 2.6% a year. Other literature using cross-country regressions generally supports these findings (McCarthy et al., 2000; Sachs, 2003).

However, the nature and extent of the link between health and economic growth remains contended. Acemoglu and Johnson (2007), for example, criticise the above-mentioned types of cross-country regressions, because they neglect the general equilibrium effects of diminishing returns to effective units of labour. Low-income countries are disadvantaged in a number of ways and these studies might be capturing omitted variables rather than health, particularly when health improvements are accompanied by population increases.

This debate, however, is neither practical, nor useful to policy makers of malaria-burdened countries and donors. They require more detailed information to assist them in assessing the optimal health provision policy and investment, and for performing distributional analysis. Consequently, Mills et al. (2008) review literature on the economic value of malaria reduction, and call for further macroeconomic modelling to inform policy makers of the efficient provision of treatment.

This research responds to this call by applying a modelling approach - a dynamic computable general equilibrium modelling (DCGE), which has gained ground recently in health...
economics in application to HIV/AIDS, anti-microbial resistance, pandemic influenza and non-communicable disease (Kambou et al., 1992; Dixon et al., 2004; Smith et al., 2005, 2009; Thurlow, 2007; Borger et al., 2008; Rutten and Reed, 2009). However, it remains a new field within health economics, and specifically in application to malaria.

The aim of this paper is to impute the economic value of malaria prevention on an endemic country. Its contribution is not only in linking health and economic growth, as is discussed mainly in the literature, but also as a useful approach for policy analysis.

There are various avenues by which malaria affects economic growth. Here, the focuses is on the link between malaria prevention and the labour resources, mainly because labour is a fundamental component to economic production and development. Other potential connections are left out in order to maintain a clearer assessment of the impact. Furthermore, the analysis centres on the effect that malaria prevention would have on children < 5 years of age, who are the most vulnerable to the disease, but do not contribute to economic production in the short-run. This provides an interesting long-term perspective into malaria prevention, because it considers the future development of a country’s labour resources.

Finally, because the preventative interventions are assumed to be administered “free of charge”, the results show the benefits of various scenarios. This is particularly useful to policy makers, who wish to compare the costs of alternative interventions with their expected benefits. Such traditional cost-benefit analysis methods, however, are not common to health policy.

As a case study, the model is calibrated to data from Ghana, an African country with endemic malaria. The following questions are addressed: (1) What are the economic benefits of malaria prevention per covered child? (2) Does prevention lead to poverty reduction? (3) Would a different allocation of limited prevention resources lead to higher benefits per capita?

This paper is structured as follows: Section 2 reviews malaria and its social and economic consequences in order to establish the context used to frame the economic model. Section 3 focuses on Ghana, as a case study, and describes the overall malaria condition, including
the epidemiological heterogeneity across the country. Section 4 describes the multi-sector multi-agent DCGE model used for the Ghanaian economy. Section 5 explains the cohort-component demographics model; Section 6 describes the labour efficiency index model; with Section 7 highlighting some limitations. Finally, Section 8 reports results, and Section 9 concludes.

2 Malaria and its social and economic consequences

Malaria is caused by a family of macroparasites, transmitted by certain species of the anopheline mosquito. When infecting humans, the parasites invade red blood cells that causes them to rupture synchronously, thus producing symptoms of fever and chills, along with headaches, vomiting, and diarrhoea. Infection may also cause long-term anaemia, liver damage, neurological damage, and even death. Malaria, therefore, significantly impacts on health, resulting in reduced economic production both in the short and long-run.

In order to reduce and eliminate malaria infection, WHO recommends a variety of preventative methods, such as insecticide treated nets (ITN), intermittent preventive treatments for infants (IPTi), children (SMC) and pregnant women (IPTp), indoor residual spraying (IRS), and reducing the breeding sites of mosquitoes. At present, there are no vaccines for malaria, but candidate vaccines are under development (Agnandji et al., 2011; Garcia-Basteiro et al., 2012).

It is generally accepted that a mentally and physically healthier population is associated with a healthier economy (Schultz, 2010). The negative effects of poor health on productivity and economic development in most sub-Saharan African countries have been widely documented (McCarthy et al., 2000; Bhargava et al., 2001; Schultz, 2010), including the specific effects of malaria (Sachs and Malaney, 2002; Bleakley, 2003, 2010). Control of malaria is therefore expected to predominantly affect the economy through improvements to the quantity and quality of human capital, which is defined as the stock of skills, education, physical
abilities, competencies and other productivity-enhancing characteristics embedded in labour (Acemoglu, 2009). In this paper, it represents the efficiency units of labour embedded in raw labour days.

There are further channels by which malaria may affect the economy, such as health care spending, revenues from tourism, foreign investment and migration (Sachs and Malaney, 2002). In order to keep a focused analysis, these are not considered here. Therefore, the economic benefits observed in the model are lower bounds, and would only be larger if these other effects were included.

The workforce is a fundamental part of a the resources of a country, and the future demographic condition has an important influence on the potential economic growth. Regional variation in labour skill-supply, and the national and international demand for various skills sets, further affect economic growth potentials.

Many studies use life expectancy as a proxy for health, and link the health status of a population with economic growth potential and the level of productivity of the country (Sachs and Malaney, 2002; Weil, 2010). A review of thirteen related studies finds that increases in life expectancy increases the long-run level of output (Bloom et al., 2004). Acemoglu and Johnson (2007) have, however, a critical opposing view to this. They find no evidence that the large increases in life expectancy raised income per capita, and explain that these econometric studies neglect general equilibrium effects such as decreasing returns, which is considered in our model.

The potential effects that malaria has on human capital are summarized in a typology of four factors (illustrated in Figure 1). First, demographic changes are a result of improved malaria control which reduces mortality rates, particularly those of children. This raises the life expectancy, and changes the population size and age structure. Second, when adult workers are healthier, they have less days off work (defined as absenteeism), which directly increases production. When workers are present at work, but less-ill (defined as presenteeism), productivity also improves. Third, when children of adult workers are healthier,
Figure 1: A typology of the effects that malaria has on economic growth

parents (carers) will loose less days off work from caring for ill children. Finally, when the adult workers were healthier as children, they benefit later in life, by having missed less school days, and having less health complications. This improves their mental and physical capacity, and allows them to generate more production and productivity as adults (Barlow, 1967; Weil, 2010).

This typology is grouped into two components: (1) a demographics component for the size of the labour force; and (2) a labour effectiveness component that accounts for the impact of the three malaria health statuses on production and productivity. The following sections review the context behind this typology, collect data, and set the stage for developing the two health models that are linked with the DCGE model.

2.1 Demographic changes and mortality (first component)

There is a wealth of evidence for the direct link between preventative interventions with malaria morbidity and mortality (e.g., D’Alessandro et al., 1995; Nevill et al., 1996; Nyarango et al., 2006; Bhattarai et al., 2007). The future potential labour resources of a country (i.e.,
working age population) is related to demographic conditions and to regional variations in malaria epidemiology. Other things being equal, an increase in the proportion of the working age population will increase the income per capita levels.

Changes to malaria prevalence affect the size, growth rate, and age structure of the population over time. In the short to medium term, a reduction in malaria may lead to an increase in the fertility rate due to pregnant women suffering fewer miscarriages, and an increased vitality of both men and women, which leads to higher levels of conception (Barlow, 1967). Additionally, the mortality rate falls overall, but proportionately more among children. This raises the population growth and shifts the age structure towards dependent children. In the long term, fertility rates are expected to fall because families do not need to compensate for the risks of high mortality with higher fertility rates. Therefore, the age structure gradually shifts towards a greater weight on the working-age adults (Weil, 2010). Section 5 discusses the population projection model that is used to estimate the link between malaria and the demography of Ghana.

2.2 Labour effectiveness (second component)

As previously mentioned, changes to malaria affect production and productivity through the absenteeism and presenteeism of adult workers. The following literature review collects the number of days lost and productivity lost, per year, due to malaria. These values are then used to develop a model for the labour effectiveness index in Section 6.

Malaria status of adult workers and their children

An example offered by Weil (2010) describes how “a person who is lying in bed suffering an acute bout of malaria is unable to supply any productive labour at all. ... People suffering disease can work fewer hours to those who are healthy, may work at a slower pace, and may be mentally less acute.” Capturing these three elements - hours of work, pace of work effort, and mental acuteness, Table 1 summarises the lost number of days from work or lower
Table 1: Adult worker lost production days and productivity due to malaria illness

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Days lost from Absenteeism (per malaria episode)</th>
<th>Days lost from Presenteeism (per malaria episode)</th>
<th>Productivity loss from Presenteeism (indexed to 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropper et al. (2000)</td>
<td>Ethiopia</td>
<td>18 (per year)#</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ettling and Shepard (1991)</td>
<td>Rwanda</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ettling et al. (1994)</td>
<td>Malawi</td>
<td>2.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Guiguemdé et al. (1997)</td>
<td>Burkina Faso</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leighton and Foster (1993)</td>
<td>Kenya</td>
<td>2-4</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Leighton and Foster (1993)</td>
<td>Nigeria</td>
<td>1-3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Sauerborn et al. (1991)</td>
<td>Burkina Faso</td>
<td>3.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sauerborn et al. (1995)</td>
<td>Burkina Faso</td>
<td>5</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Hong (2011)</td>
<td>US</td>
<td>0.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hanlon et al. (2012)</td>
<td>Ghana</td>
<td>0.75 (inc. mort)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asante et al. (2005)*</td>
<td>Ghana</td>
<td>9.35 (per year)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gollin and Zimmermann (2008)</td>
<td>Not explicit</td>
<td>0.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Murray and Lopez (1996)**</td>
<td>Not explicit</td>
<td>0.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ashraf et al. (2009)***</td>
<td>Not explicit</td>
<td>0.864</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Average: 3 days 2 days 0.9

* Males only; ** Disability weight; *** Disability weight rescaled, # 18 days per year, while other values are per malaria episode.

productivity across various countries of Africa. Generally, an adult is absent from work for one to four days per episode of malaria, and has lower output when at work equivalent to approximately two days.

Gollin and Zimmermann (2008) use an estimate for effective unit of labour of an individual with malaria as 0.9, where a malaria-free person as 1.0. Ashraf et al. (2009) develop disability weights and find that on a scale where perfect health is zero and death one, malaria episodes reduce the abilities of a person by 13.6%.\(^1\) This means that a person with malaria is only 0.864 as effective as a healthy individual.

Improvements in health treatment may reduce the amount of time that healthy adult workers need to stay out of work to take care of sick children or other family members.

\(^1\)For example, the disability weights are: blindness (0.600), severe iron deficiency anaemia (0.093), HIV (0.136), AIDS (0.505), tuberculosis seronegative for HIV (0.264), malaria episodes (0.136), and neurological sequelae of malaria (0.473) (Ashraf et al., 2009).
Table 2: Days lost due to caring for children with malaria

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Days lost to caring (per malaria episode)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aikins (1995)</td>
<td>The Gambia</td>
<td>2.16 hours per day per child for 4 days</td>
</tr>
<tr>
<td>Cropper et al. (2000)</td>
<td>Ethiopia</td>
<td>11 (per year)</td>
</tr>
<tr>
<td>Ettling and Shepard (1991)</td>
<td>Rwanda</td>
<td>1</td>
</tr>
<tr>
<td>Ettling et al. (1994)</td>
<td>Malawi</td>
<td>1.2</td>
</tr>
<tr>
<td>Guiguemé et al. (1997)</td>
<td>Burkina Faso</td>
<td>Assumed to be 1.2</td>
</tr>
<tr>
<td>Leighton and Foster (1993)</td>
<td>Kenya</td>
<td>2-4</td>
</tr>
<tr>
<td>Leighton and Foster (1993)</td>
<td>Nigeria</td>
<td>1-3</td>
</tr>
<tr>
<td>Sauerborn et al. (1991)</td>
<td>Burkina Faso</td>
<td>2.7</td>
</tr>
<tr>
<td>Sauerborn et al. (1995)</td>
<td>Burkina Faso</td>
<td>1/3 of adult illness time</td>
</tr>
<tr>
<td>Asante et al. (2005)*</td>
<td>Ghana</td>
<td>5.0 (per year)</td>
</tr>
</tbody>
</table>

*Average* 1-2 days

*Males only.*

Table 2 summarises that workers lose approximately one to two working days to care for someone with malaria.

**Malaria history of adults workers as children**

Malaria can negatively affect the development of human capital by reducing educational outcomes and achievement. This in turn lowers productivity when children reach the working age. In particular, children with repeated bouts of malaria miss more schooling days, and therefore have lower performance (Weil, 2010; Baird et al., 2011).

Studies for Sri Lanka and Kenya find that due to malaria, children miss approximately five to six school days per episode, and 20-30 days overall per year. These repeated cases lowered school performance by approximately 15%. Students that were given preventative interventions for malaria performed 26% better compared to a control group (Leighton and Foster, 1993; Fernando et al., 2003a,b, 2006).

Malaria may also affect the quality of education that students receive, as teachers miss school days due to acquiring malaria or to care for family members, who have acquired malaria. Leighton and Foster (1993) find that primary teachers in Nigeria miss on average six days per year because of malaria, which reduces the number of days that students receive
### Table 3: Impact of malaria as a child for labour productivity later in life

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Efficiency units due to illness as a child, using wages as proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bleakley (2003)</td>
<td>US</td>
<td>0.85</td>
</tr>
<tr>
<td>Cutler et al. (2010)</td>
<td>India</td>
<td>0.83-0.97</td>
</tr>
<tr>
<td>Bleakley (2010)</td>
<td>US, Brazil, Colombia, Mexico</td>
<td>0.5</td>
</tr>
<tr>
<td><strong>On Average</strong></td>
<td></td>
<td><strong>0.75</strong></td>
</tr>
</tbody>
</table>

When children are carers, the amount of education they earn is reduced. The education of girls may be inordinately affected by malaria because when parents cannot stay home to care for sick children, they often turn to their daughters to care for their siblings. The girls therefore may miss more school days than boys, while tending to sick siblings (Fernando et al., 2006).

Malaria can also cause cognitive declines through negative effects on health, such as anaemia, malnutrition, or neurological injury, leading to learning disabilities or psychological difficulties (Holding and Snow, 2001; Chima et al., 2003). In Kenya, school children who are hospitalised with cerebral malaria are 4.5 times more likely to develop learning difficulties (Holding et al., 1999). Malaria during pregnancy raises the risk of low birth weight babies, which in turn raises the risk of neurosensory, cognitive and behavioural development problems in children. Low birth weight babies are found to be two to four times more likely to fail grades in school (Taylor, 1984; McCormick et al., 1992; Sachs and Malaney, 2002).

Bleakley (2003, 2010) demonstrates that individuals with malaria as children earn 15 to 50% less in adulthood than those who were malaria-free. Cutler et al. (2010) also confirms this for India, but with less severity. These wage deviations partly indicate the differences in worker productivity, which were caused by malaria. On this aspect, however, no data from Africa is available.

In summary, malaria has both direct and indirect effects on education, and on the potential of children to engage actively and productively in the labour force later in life. As
Table 4: Key statistics on malaria in Ghana, 2009

<table>
<thead>
<tr>
<th>All Ages</th>
<th>3.1-3.8 million</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual number of cases of clinical malaria</td>
<td>3.1-3.8 million</td>
</tr>
<tr>
<td>reported 2002-2009</td>
<td>3.1-3.8 million</td>
</tr>
<tr>
<td>Malaria as cause of admission (of total admissions)</td>
<td>32.9%</td>
</tr>
<tr>
<td>Malaria as case of death (of total deaths)</td>
<td>13.4%</td>
</tr>
<tr>
<td>&lt; 5 years of age</td>
<td></td>
</tr>
<tr>
<td>Malaria as cause of admission (of total admissions)</td>
<td>58.1%</td>
</tr>
<tr>
<td>Malaria as cause of death (of total deaths)</td>
<td>20.2%</td>
</tr>
</tbody>
</table>

Source: Ghana Health Service (GHS, 2009; GSS, 2009).

reported in Table 3, the average reduction in productivity caused by malaria is estimated at 20-30%.

3 Ghana case study

Ghana is a sub-Saharan African country with a population of 24 million. The country has recently experienced economic growth and development towards becoming a middle-income country. However, life expectancy of Ghanaian women and men was 59 and 58, respectively (Agyeman-Duah et al., 2006), compared to 81 and 75 in the EU, in 2005 (Eurostat, 2012).

Furthermore, malaria in Ghana is still endemic, and is a major public health concern. Malaria is the single largest cause of morbidity and a significant cause of mortality. 20% of deaths in < 5 year old Ghanaian children are attributed to malaria. Whilst there are public health programmes to deliver malaria prevention and manage cases, malaria prevalence has changed little since the early 2000s.

A number of attempts have been made to address the malaria problem in the country. For example, household ownership of an insecticide treated net (ITN) has risen from 3% in 2003 to 33% in 2008 (GSS, 2009). However, as reported by Ghana Demographic and Health Survey (see Table 4), more than three million cases of clinical malaria are reported to public

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2Endemic areas are defined as areas with significant annual transmission, be it seasonal or perennial (Snow et al., 1999).

3Prevalence is defined as the number of malaria cases per population. This could be stratified by age group, region, etc.
health facilities each year. In 2009, it was the top single cause of hospital admission for children aged < 5 (58.1%), and their main cause of death (20.2%). This suggests that there is a great deal of room for improvement in terms of malaria prevention and case management - particularly for children.

The entire Ghanaian population is at risk of malaria, but there are variations across the zones by prevalence, annual duration of transmission, and the type of malaria parasite. (See Figure 2 for prevalence by zone.) To consider the geographical epidemiological variation within the economy, and to link between health and the labour force, we divide Ghana into five malaria epidemiological zones: (1) the tropical rainforest; (2) Accra; (3) the coastal savannah and mangrove swamps; (4) the northern savannah and (5) the southern savannah. These zones reflect four different ecological zones in Ghana and one metropolitan Accra.

Broadly speaking, Ghana has ten administrative regions, which were mapped onto the five epidemiological zones as summarized in Figure 3. The Coastal zone covers the Eastern and Volta regions; the Forest zone includes the Ashanti, Western, and Central regions; the Southern Savannah includes Brong Afaso and part of Volta; and the Northern Savannah includes the Upper West, Upper East, and Northern regions.

The reasons for this demarcation are the following: First, the zones are used to capture some of the heterogeneity in malaria endemicity (see Figure 2). Data on malaria prevalence across regions and age groups of Ghana (2002) is available from the Mapping Malaria in Africa/Atlas du Risque de la Malaria en Afrique (MARA/ARMA). High malaria parasite prevalence rates are concentrated in the Northern district (North Savannah) and in Ashanti (Forest), where malaria parasite prevalence ranges from 23 to 63% for < 1 years old across the zones, as reported in Table 5. For the > 15 population, prevalence ranges from 23.5 to 54%.

Second, the Social Accounting Matrix (SAM) used in this paper is based on previous studies by the International Food Policy Research Institute (IFPRI) (Breisinger et al., 2009, 2011). Their focus has been to capture economic activity variation at the sub-national level
due to agricultural production patterns and technologies. IFPRI had referred to zones as (agri-) ecological zones, while we overlay them on (malaria) epidemiological zones.

Social accounting matrix

Our economic dataset is based on a highly disaggregated social accounting matrix (SAM) for Ghana, which contains the revenues and expenditures for commodities and agents. The SAM is developed by Breisinger et al. (2009, 2011) and represents the Ghanaian economy in 2007.\(^4\) It is constructed from a wide range of data: Using 2005/2006 Ghana Living Standards Survey (GSS, 2008), the SAM includes 90 households that are differentiated by

\(^4\)The SAM was generously provided by the International Food Policy Research Institute (IFPRI).
Figure 3: Mapping administrative districts to ecological zones

<table>
<thead>
<tr>
<th>Administrative District</th>
<th>Ecological Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western Central Ashanti</td>
<td>Forest</td>
</tr>
<tr>
<td>Greater Accra</td>
<td>Accra</td>
</tr>
<tr>
<td>Volta (50% of pop.)</td>
<td>Coastal</td>
</tr>
<tr>
<td>Eastern</td>
<td></td>
</tr>
<tr>
<td>Northern</td>
<td>North Savannah</td>
</tr>
<tr>
<td>Upper East</td>
<td>Savannah</td>
</tr>
<tr>
<td>Upper West</td>
<td></td>
</tr>
<tr>
<td>Volta (50% of pop.)</td>
<td>South Savannah</td>
</tr>
<tr>
<td>Brong Afaso</td>
<td></td>
</tr>
</tbody>
</table>

Note: Social Accounting Matrix from Breisinger et al. (2009, 2011).

Table 5: Malaria parasite prevalence (%) by region and age groups of Ghana, 2002

<table>
<thead>
<tr>
<th>Agro-ecological zones</th>
<th>Administrative region</th>
<th>Age groups</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Forest</td>
<td>Ashanti region</td>
<td>63.12</td>
</tr>
<tr>
<td></td>
<td>Western region</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>Central region</td>
<td>n/a</td>
</tr>
<tr>
<td>Southern Savannah</td>
<td>Brong Ahafo</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>Volta region*</td>
<td>34.99</td>
</tr>
<tr>
<td>Coastal</td>
<td>Eastern region</td>
<td>46.76</td>
</tr>
<tr>
<td>Northern Savannah</td>
<td>Upper East region</td>
<td>56.28</td>
</tr>
<tr>
<td></td>
<td>Upper West region</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>Northern region</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>Greater Accra</td>
<td>23.25</td>
</tr>
</tbody>
</table>

Note: Prevalence is defined as the total number of cases in the population at a given moment as a percentage of the total population. * Half of Volta is in the Coastal region. n/a is not available.
Source: MARALite.
the ten Ghanaian administrative regions, urban-rural characteristics, income and consumption. With data from the Ministry of Food and Agriculture (MOFA) and Industrial Census (GSS), 142 activities and 70 commodities were estimated. It also includes accounts for the government, investment and savings, and the rest of the world.

For our particular study, the SAM was re-aggregated and stratified by the five malaria epidemiological zones, urban-rural location, and five income level quintiles. The exception is Greater Accra which is assumed to be fully urban. Therefore, the re-aggregated SAM, and the DCGE model, characterise nine epidemiological urban-rural regions, which have overall 45 heterogeneous representative households.

Finally, production sectors are not the main focus of this research, and will not directly affect economic growth. Therefore, the large number of activities and commodities in the original SAM were aggregated into four main ecological agricultural sectors, an industry sector, and a services sector.

4 A dynamic general equilibrium model for Ghana

To explore the effects of malaria on the labour force, we developed a dynamic, multi-sector, multi-agent, computable general equilibrium (DCGE) model, which integrates two components: (1) a demographics model; and (2) a model for the labour effectiveness index.

The DCGE model does not attempt to make precise predictions about the future development of the Ghanaian economy. Its purpose, however, is to measure how additional malaria health prevention would affect the economy-wide growth and poverty reduction, compared to a baseline scenario of no additional intervention. The model is also different from traditional DCGE models, which usually focus on the national level. Here, the focus is on the regional heterogeneity in health between many households.

\[5\text{We follow the original SAM, and therefore Greater Accra is fully urban.}\]
\[6\text{To be completely explicit, there are four epidemiological zones with an urban rural divide, and therefore, eight regions. Greater Accra is fully urban. This leads to nine regions, each having five income level quintiles, and therefore, to 45 separate households.}\]
Table 6: Coverage of the preventative malaria intervention in the baseline and three alternative scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Coverage is 0%</td>
</tr>
<tr>
<td>Scenario 1:</td>
<td>Coverage rises to 65% nationally in year 1 onwards for under-fives (basic intervention)</td>
</tr>
<tr>
<td>Scenario 2:</td>
<td>Scenario 1 coverage from year 1 until year 10, then increases to 85% nationally (comprehensive)</td>
</tr>
<tr>
<td>Scenario 3:</td>
<td>Scenario 1 coverage from year 1 until year 10, then increase to 100% for two high malaria prevalence zones (comprehensive)</td>
</tr>
</tbody>
</table>

In the baseline scenario, the model projects economic growth for a case where there is no additional malaria intervention above the current situation. In the three counterfactual scenarios, we simulate cases where additional malaria interventions are given “free of charge,” e.g., by administering additional insecticide treated nets or other prophylaxis. Each scenario assumes that the efficacy of the intervention is 50%, but they differ by the level of coverage and targeting of zones. Furthermore, the intervention is given only to children < 5, and then taken away as their cohort moves to ages > 5. No indirect effect such as transmission reduction is considered for the population >5. Finally, the model begins at year 0, and malaria intervention at year 1, which thereafter continues throughout the simulated period.

As summarised in Table 6, Scenario 1, which provides “basic coverage”, assumes that a malaria intervention is rolled-out nationally, covering 65% of the < 5 population. This scenario is considered feasible in the short-run. In Scenarios 2 and 3, which provide more “comprehensive coverage”, we assume that the hard-to-reach population can gain access to the intervention, in the medium to long-run. Therefore, in Scenario 2, coverage increases after 10 years to 85% nationally. In Scenario 3, coverage rises to 100%, for the two high prevalence zones, while remains at 65% for the rest of the zones. Figure 4 reports the number of children covered for each of the simulated scenarios.

The next section gives a summary of the DCGE model that is developed for this research. A technical appendix is available upon request, and provides a full analytical description of
4.1 A description of the model

We follow Mathiesen (1985) and Rutherford (1995, 1999) and set up an Arrow–Debreu equilibrium as a mixed complementarity problem (MCP). Three types of weak inequality conditions are satisfied simultaneously: (1) zero profit, (2) market clearance, and (3) income balance, each associated with a non-negative variable.

We design a multi-sector, multi-agent, recursive dynamic CGE model, and use the social accounting matrix (SAM) by Breisinger et al. (2009, 2011) to calibrate the model for Ghana. As mentioned previously, the SAM is re-aggregated so that it characterises five epidemiological malaria zones, two urban-location (urban, rural), and five income levels. This leads to 45 representative households, $h \in H$.

Each household is endowed with capital, land, and three occupational categories of labour.

---

7Coded in GAMS using Rutherford (1995, 1999)'s MPSGE. This allows handling of CGE models in a consistent and compact format with mixed complementarity.
We define the set of labour skill-types by

\[
\{\text{self-employed, skilled, unskilled}\} \in l
\]

Households accumulate capital (depreciated capital plus investment), transfer (receive) funds from the government and the rest of the world, and also pay tax to the government, thus forming the disposable income of households.

Households are assumed to be rational, with a locally non-satiated preference relation, and a continuous, multi-level, extended linear expenditure system (ELES) utility function (Howe, 1975). In the first-level, a representative household maximizes a utility function comprising of a consumption bundle and private savings, in fixed shares, subject to the disposable income. In the second-level, the household maximizes a Stone-Geary utility function that accounts for the minimum subsistence requirements, and allows income elasticities to be different than one. The maximization problem is constrained by the residual disposable income.

The government receives income from collecting taxes and tariffs, and also receives (transfers) funds from domestic households and the rest of the world. It provides a public service by purchasing commodities, and saves a fixed proportion of income.

Firms produce a single good using a multi-level, differentiable, constant return to scale (CRS) production function that combines the factor inputs with intermediate goods. Similar to Rutherford et al. (2002) and Hosoe et al. (2010), a constant elasticity of transformation function is used to split production into export and domestic consumption. Then, domestic consumption and imports are aggregated to form the Armington final good, which is finally demanded by private and public consumption, investment, and/or as an intermediate good (Armington, 1969).

Ghana is assumed to be a small open economy (SOE), which cannot affect world prices.

---

8 For any bundle of goods there is always another bundle of goods arbitrarily close that is preferred.

9 Armington composite goods are used to account for cross hauling (two-way trading) in the same good, i.e., goods are both imported and exported.
Export and import prices quoted in foreign currency are exogenously given. It has unrestricted borrowing (lending), and international capital can freely flow between the domestic and foreign economies.

Being a SOE, the domestic rental rate of capital is therefore fixed to world prices through the level of the foreign exchange rate. This is characterised by introducing two mutually exclusive functions that convert units of capital in (out) of the domestic economy to the ROW. For example, whenever the rental rate of capital is higher (lower) compared to that in the ROW, reflecting higher (lower) demand for capital compared to other non-transferable domestic inputs \( i.e., \) labour and land, capital will flow in (out) through the capital account. This, therefore, imposes capital price equalization. Furthermore, it affects the level of demand for investment, \( e.g., \) too much capital will dampen the demand for investment.

The rest of the world (ROW) is modelled as a simple agent that demands foreign savings (in the domestic economy). Its budget is equal to ownership of domestic capital (if any), net remittances, and demand for net imports.\(^{10}\)

Finally, a virtual investment firm builds new capital stock for the next period. Its budget is comprised of the private, public and foreign savings, and it demands (Armington) final consumption goods in fixed proportion, as inputs for investment.

### 4.2 Recursive dynamics

The model uses a recursive dynamics approach, where agents are assumed to be myopic rather than forward-looking. This means that they do not change saving-consumption behaviour in the present, due to knowledge of future expectations. The model is solved sequentially for 30 years, where stock variables are updated exogenously, at each period, based on the health models, and other assumptions that are described in detail in the technical appendix of this paper. The exception is capital accumulation, which occurs through endogenous linkages with previous-period investment.

\(^{10}\)A net export, from the perspective of the domestic economy.
There are four reasons for using a recursive model (rather than a forward-looking): First, the main purpose of our simulation is to link the role of health on the labour resource, and thus on the economy. Having households increase consumption today, due to their forward-looking expectations that they will have a healthier labour resource in the future, seems questionable.

Second, there is doubt whether developing countries, such as Ghana, can be characterised as forward-looking. Empirical observations suggest that low income agents are most often myopic, mainly because they are credit constrained (Deaton, 1991, 1992; Foster, 1995; Morduch, 1995). Therefore, they are unable to allocate resources optimally across time, which negates the, theoretically elegant, permanent income hypothesis.

Third, Babiker et al. (2009) compare the recursive versus forward-looking models and conclude that the recursive produces similar behaviour, but also provides greater flexibility in the details of the system that can be represented compared to a forward-looking approach.

Finally, given the complexity of the model in terms of the large numbers of production sectors and households, a fully forward looking dynamic model cannot be solved computationally. Breisinger et al. (2009, 2011) report the same problem.

We therefore set up a capital accumulation assumption that resemble those modelled by Springer (2002), Klepper et al. (2003) and Thurlow (2007), whereby a virtual investment firm, as described previously, characterizes a competitive capital market. This assumption means that the purchasing price of one unit of new capital equals the rental earnings of that unit, plus the value of the remaining capital sold in the subsequent period, i.e., zero profit condition. An agent decides between consumption and investment, and the model resembles a Solow-type model, with savings proportional to household income. However, it also differs because the small open economy (SOE) assumption fixes the rental rate of capital

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11 A forward looking model was initially implemented, but became unfeasible when presented with more than three households.

12 Kinnunen (2007); Breisinger et al. (2009, 2011); Diao (2009) use a different approach, whereby newly invested capital is influenced by each sector’s initial share of gross surplus, and the final allocation depends on depreciation and sector specific profit-rate differentials.
to world prices, as described previously.

Figure 5 illustrates the general structure of the economic model, and the way in which Malaria impacts the economy through the factor markets. This is further discussed in the next section.

4.3 Integrating health into the DCGE model

The stock of labour, $\bar{L}_{h,t,t}$, is assumed to be fully employed, and mobile across sectors with flexible real wages. It is disaggregated across 45 households, and three occupational categories, i.e., self-employed, skilled, low skilled. The DCGE model integrates the effects that malaria has on labour by (1) projecting the stock of labour forward; and (2) estimating the labour effectiveness index, for each epidemiological zone.

Production is labour-augmenting, whereby total labour supply is the stock of household labour $\bar{L}_{hlt}$ multiplied by its effectiveness level, $E_{hlt}$. The labour augmenting supply, $L_{hlt}$, is
therefore

\[ L_{hl} = \bar{L}_{hl} \cdot E_{hl} \]  

(1)

and updated yearly by

\[ L_{hl,t+1} = \bar{L}_{hl0} \cdot (1 + g_{hl}) \cdot E_{hl0} \cdot (1 + e_{hl}) \]

(2)

with \( \bar{L}_{hl0} \) defined as the stock of labour in the base year, and labour effectiveness in the base year as \( E_{hl0} = 1 \). Inputs into the DCGE model are (1) the household-specific labour growth \( g_{hl} \), which comes from the demographic model; (2) changes to labour effectiveness \( e_{hl} \), which come from the labour efficiency model. The next two sections explain the health models in further detail.

5 Population projection model

The main purpose of the population projections component is to estimate the size of the workforce in Ghana, and the changes that would follow from malaria prevention. Because the core of the research is the link between health, labour efficiency, and economic outcomes, we require a simplified, yet realistic and uncontroversial approach to estimating the mortality impact of malaria prevention. We have, therefore, deliberately selected a widely used platform for linking maternal and child survival interventions with health interventions and demographic projections.

This platform, called Spectrum, which includes various modules (Stover et al., 2010). DemProj, being the core module, projects the population using a cohort-component method that is a commonly used approach to project population size, composition, and structure (Stover and Kirmeyer, 2008). A second module, Lives Saved Tool (LiST), is used when malaria interventions are introduced in the counterfactual scenarios (Winfrey et al., 2011). DemProj and LiST interact simultaneously to estimate the number of < 5 deaths that can
be averted by interventions of eleven different diseases, with malaria being one of them.

Spectrum contains a database that provides instant access to population estimates and projections for Ghana at country level, as well as for 192 other countries and regions from the United Nations Population Division. In this Ghana case study, we ‘borrow’ the basic structure of Spectrum, but introduce the regional specific information that correspond to the previously mentioned epidemiological zones. The following sections describe the main methodology and the assumptions.

5.1 Baseline projections using a cohort-component method

The cohort-component model requires assumptions for life expectancy at birth, total fertility rates, age distribution of fertility, sex ratio at birth, and the number and distribution by age and sex of international migrants. DemProj uses a Coal-Demeny North model life table with age and sex specific patterns of mortality. Using the base year age structure, age cohorts incrementally move forward in time, and amend according to a set of age-specific fertility rates, age-specific survival rates, and migration rates, by rural urban location (Pearl and Reed, 1920; Bowley, 1924; Dorn, 1950).

The population for each age cohort $i \in N$, region $r \in R$, for time $t \in T$ is expressed by

$$Pop_{i, r, t} = Pop_{i, r, t-1} + B_{i, r, t-1} - D_{i, r, t-1} + M_{i, r, t-1}$$

with $Pop_{i, r, t-1}$ being the stock of population in the previous year, which will rise (fall) by the flows of $B_{i, r, t-1}$, $D_{i, r, t-1}$, $M_{i, r, t-1}$, which are the births, deaths, and net migration, respectively. The total regional population is, therefore, $pop_{r, t} = \sum_i pop_{i, r, t}$.

For each region, we use the national average migration values for Ghana, which are given in the DemProj database. Fertility, mortality, and urbanization are estimated separately, for each epidemiological zone, and are applied to Equation (3) with the following assumptions:

---

Table 7: Total fertility rates for epidemiological zones for selected year

<table>
<thead>
<tr>
<th></th>
<th>Coastal</th>
<th>Forest</th>
<th>Southern Savannah</th>
<th>Northern Savannah</th>
<th>Accra</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>7.0</td>
<td>7.2</td>
<td>7.6</td>
<td>5.9</td>
<td>5.9</td>
</tr>
<tr>
<td>1979/80</td>
<td>6.6</td>
<td>6.5</td>
<td>6.7</td>
<td>N/A</td>
<td>5.1</td>
</tr>
<tr>
<td>1988</td>
<td>6.3</td>
<td>6.3</td>
<td>7.5</td>
<td>6.9</td>
<td>4.7</td>
</tr>
<tr>
<td>1993</td>
<td>5.1</td>
<td>5.3</td>
<td>4.9</td>
<td>6.0</td>
<td>3.4</td>
</tr>
<tr>
<td>1998</td>
<td>4.4</td>
<td>4.7</td>
<td>4.9</td>
<td>5.9</td>
<td>2.7</td>
</tr>
<tr>
<td>2003</td>
<td>4.3</td>
<td>4.3</td>
<td>4.7</td>
<td>6.1</td>
<td>2.9</td>
</tr>
<tr>
<td>2008</td>
<td>3.7</td>
<td>4.0</td>
<td>4.0</td>
<td>5.8</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Note: Total fertility rates in the administrative regions from the Ghana Demographic and Health Surveys (GDHS). N/A = not available.

Regional fertility

For regional fertility, we use a statistical software package in the R statistical language that is based on a Bayesian hierarchical model (Raftery et al., 2009; Alkema et al., 2011; Sevcikova et al., 2011).

Empirical data from the Ghana Demographic and Health Surveys (GDHS), going back to 1970, is used to estimate the total fertility rates (TFR). Table 7 presents the TFRs for the epidemiological zones for specific years. Further details on the method and its application are explained by Raftery et al. (2009).

Due to the lack of better data, we assume that each epidemiological zone in Ghana uses the national age distribution of fertility, and that the sex ratio was held constant at 105 males per 100 females. These data were taken from the UN Population Prospects (UN, 2010).

Regional mortality

Mortality requires assumptions for male and female life expectancy over the course of the modelling period. We use life expectancy for districts from the Ghana Statistical Service (Agyeman-Duah et al., 2006) and the projection of life expectancy for Ghana as a whole until 2035 from the UN World Population Prospects (United Nations, 2010). We then assume that
the relative annual increase in life expectancy for each region is equivalent to the percentage increase of national life expectancy. This is a simple assumption, but given the lack of regional projections, as well as the lack of sufficient historical time series, it is infeasible to project region-specific life expectancy trends.

**Regional urban and rural population**

Using the DemProj module, we also project urban and rural populations for each of the epidemiological zones (Coastal, Forest, Northern Savannah and Southern Savannah), with the exception of Accra, which is assumed to be entirely urban.

With $U_{r,t}$ defined as the urban population of a region, $R_{r,t}$ the rural population, $Pop_{r,t}$ the total regional population, and $\Delta\lambda$ as the difference in the urban and rural growth rates, the urban population is projected by

$$U_{r,t} = U_{r,t-1} \cdot \frac{(Pop_{r,t} + \Delta\lambda \cdot R_{r,t-1})}{Pop_{r,t-1}}$$

For a further detailed description, see the DemProj Manual (Stover and Kirmeyer, 2008).

The data for the base-year population per district were taken from Ghana Statistical Service (GSS, 2010) and the age distribution per region for the rural and urban population by sex from the Ghana Demographic and Health Survey (GSS, 2009). The product of these provides estimates for the rural and urban population by age and sex per district. Furthermore, lacking better data, the rate of urbanization, $\Delta\lambda$, is assumed to be the same across all epidemiological zones, and follows the national trend.

### 5.2 Malaria prevention scenarios for children under 5 years

We use the LiST module that interacts with the cohort-component model, DemProj, to estimate the impact of a malaria intervention on children under 5 years old.

At the beginning of each projection year, DemProj provides LiST with the number of
deaths for children aged 0, 1, 2, 3 and 4 years. LiST disaggregates those deaths into age bands: 0-1, 1-5, 6-11, 12-23 and 24-59 months by fitting a double log function to the neonatal, infant, and < 5 mortality rates. The equation has the following form:

$$\ln (u) = a + b \ln (age) + c \cdot age \ln (age)$$

(5)

where $u$ is the cumulative mortality at the corresponding age (Stover et al., 2010).

A hypothetical intervention of malaria prevention is introduced through changes to the efficacy of the intervention in reducing mortality, adjusted for the impact of coverage. The following sets are defined: prevention scenario $sc \in SC$, region $r \in R$, age bands by months for $< 5$ year old $a \in [0-1, 1-5, 6-11, 12-23, 24-59$ months], and time $t \in T$.

Following Winfrey et al. (2011) the proportional reduction $PR_{sc,r,a,t}$ in malaria mortality is a function of the efficacy of the intervention $E_{sc,a}$, the increase in the coverage of intervention $(C_{sc,r,a,t} - C_{sc,r,a,0})$ and the affected fraction $AF_{sc,a}$,\footnote{Affected fraction is the percent of death directly caused by malaria.} adjusted for the unrealized potential impact $(1 - E_{sc,a,0} \cdot C_{sc,r,a,0})$ and is defined as

$$PR_{sc,r,a,t} = \frac{E_{sc,a} \cdot (C_{sc,r,a,t} - C_{sc,r,a,0}) \cdot AF_{sc,a}}{1 - E_{sc,a,0} \cdot C_{sc,r,a,0}}$$

(6)

Based on the cohort-component method, the DemProj module calculates the number of births each year from the number of women 15-49 years old, the total fertility rate, and the age distribution of fertility. New births are subject to the estimated mortality rates as they age each year. Simultaneously, the LiST module estimates the impact that the malaria prevention has on the mortality rates of children, which is used by the cohort-component module. Together, LiST and DemProj estimate the number of children saved by the intervention at each year.

As previously described in Section 4, we assume that the efficacy of the hypothetical malaria prevention is 50%, and that the coverage for each counterfactual intervention scenario varies over time, as summarized in Table 6. Projections are made for each zone, separately,
under the different scenario conditions.

**Malaria mortality assumptions**

LiST furthermore requires a distribution of $< 5$ mortality by cause, where malaria is one of eleven possible causes. To do so, we multiply the $< 5$ average case fatality rate of 2.6%, *(i.e., the probability of dying from an episode of malaria,)*\(^{15}\) with the regional average of $< 5$ yearly incidence rate (GSS, 2004; GHS, 2007), to estimate the $< 5$ yearly probability of dying from malaria per epidemiological zone. This is then divided by the total $< 5$ mortality rate for that zone, to estimate the percentage of deaths caused by malaria per zone. The remaining percentage is then distributed among the other causes of death by keeping their original respective ratios constant. Figure 6 depicts the resulting proportions of death causes for $< 5$ mortality, which were used for the base year in LiST.

Using a fixed malaria case fatality rate, 2.6%, for Ghana as a whole, does not consider any regional variability. However, given the lack of reliable empirical data on the number of malaria incidences and deaths by region, this provides the best available assumption.

### 6 Labour efficiency model

Based on the discussion in Section 2 (illustrated in Figure 1), we review three potential effects that contribute to workforce efficiency: (a) malaria status of an adult worker, (b) malaria status of the child of an adult worker, and (c) malaria history of an adult worker as a child. Each of these contributes to the loss of production, *i.e.*, the amount of output lost from days *off* work (absenteeism), and loss to productivity, *i.e.*, the amount of output lost per day *at* work (presenteeism).

We refer to status as the number of malaria incidences per year, $x \in [0, 9]$, for three agents $[a,c,a25] \in i$, *i.e.*, adult, child, and adult’s status 25 years previous, respectively. For each

\(^{15}\)Ghana Health Survey (GHS, 2007) reports malaria case fatality was 2.8%, 2.7%, and 2.4% for the years 2005, 2006 and 2007, respectively.
Figure 6: Proportion of death by cause by zone

Note: Authors’ calculations using Ghana Demographic and Health Survey (2003)

rural-urban location \( ru \in RU \), at time \( t \in T \), the labour efficiency loss \( l_{i,ru,t}(x) \) is a function of \( x \) incidents of malaria that have a Poisson distribution \( P(x, \mu_{i,ru}) \) with mean incidents \( \mu_{i,ru} \).\(^\text{16}\) Presenteeism and absenteeism is differentiated by \( j \in \text{[presenteeism, absenteeism]} \).

Suppressing the rural-urban location index (for simplicity), the labour efficiency index is defined as:

\[
E_t = \left( 1 - \sum_j \sum_x p_u(x_u) l_{j,t}(x_u) \right) \left( 1 - \sum_j \sum_x p_c(x_c) \cdot l_{j,t}(x_c) \right) \left( 1 - \sum_x p_{ac25}(x_{ac25}) \cdot l_t(x_{ac25}) \right)
\]

Each internal component represents the weighted average loss, normalized to labour output per year. Furthermore, the efficiency loss from the malaria history of an adult worker as a child, 25 years previous, is only affected by having two or more incidents per year as a child.\(^{16}\)

\(^{16}\)As an example, if \( x = 0 \) then \( l = 0 \).
child. Therefore,

\[
l_{ac25}(x_{ac25}) = \begin{cases} 
    l_{ac25} = 0 \text{ if } 0 \leq x \leq 1 \\
    l_{ac25} > 0 \text{ if } 2 \leq x \leq 9 
\end{cases}
\]

The components within Equation 7 are assumed to be independent, i.e., an intervention in children would affect the probability to acquire malaria in children independently to that in adults. Given that only the < 5 will receive the malaria intervention, this simplified assumption seems reasonable for the following reasons: the parasite reservoir relies on the adult population, rather than the children. A model simulation by the Swiss Tropical & Public Health Institute finds that administering a pre-erythrocytic vaccine to < 5 will have limited impact on adults when delivered through the expanded programme on immunisation (EPI) (Amek et al., 2011). Another study finds that the impact of insecticide treated net (ITN) distribution to the < 5, also has a limited, or no impact on transmission to adults (Unpublished computation based on Killeen and Smith (2007)). Most studies on eradication recommend targeting the whole population to clear parasites at regular intervals, including vaccination (Griffin et al., 2010; Maire et al., 2011). Targeting adults, rather than children, would probably have the largest impact on transmission.

Table 8 summarises the key parameters previously identified that are used to derive the efficiency index: (1) production days lost by adults that have taken off work due to being ill with malaria, or for caring for a child with malaria, i.e., absenteeism. (2) The productivity lost from being ill, but working, i.e., presenteeism, and (3) the change in labour efficiency for adults that have had malaria as children, 25 years previous.

7 Limitations and discussion

As with every modelling approach, the method used here has a number of limitations, and is only a simplified version of reality. There are, therefore, aspects regarding malaria and its effect on production and economic growth, which have not been included in the analysis.
Table 8: Key assumptions and parameter values of the labour effectiveness index

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of working days</td>
<td>235</td>
</tr>
<tr>
<td>Range of number of malaria episodes per person-year with a Poisson distribution</td>
<td>0-9</td>
</tr>
<tr>
<td>Lost days per malaria episode</td>
<td></td>
</tr>
<tr>
<td>For Absenteeism</td>
<td></td>
</tr>
<tr>
<td>Adult is ill</td>
<td>3</td>
</tr>
<tr>
<td>Child is ill, and adult absent from work to take care of child</td>
<td>2</td>
</tr>
<tr>
<td>For Presenteeism</td>
<td></td>
</tr>
<tr>
<td>Adult is at work but ill</td>
<td>2</td>
</tr>
<tr>
<td>Productivity factor (as proportion of output compared to malaria-free)</td>
<td></td>
</tr>
<tr>
<td>Adult at work, but ill</td>
<td>90%</td>
</tr>
<tr>
<td>An adult that had 2 malaria episodes per year as a child</td>
<td>90%</td>
</tr>
<tr>
<td>An adult that had 3 or more malaria episodes per year as a child</td>
<td>75%</td>
</tr>
<tr>
<td>Malaria case fatality for &lt; 5 (probability of death given having a malaria episode)</td>
<td>2.6%</td>
</tr>
<tr>
<td>Full benefits of malaria prevention as a child are obtained after 25 years</td>
<td>25</td>
</tr>
</tbody>
</table>

First, the main limitation is that this model does not account for direct cost offset, which means the benefits per are underestimates of the true benefits.

Second, the model does not incorporate indirect effects contagion because the medical literature has an ambiguous consensus about the epidemiological consequences of malaria prevention. After careful deliberation, we decided not to enter the medical debate.

Third, both malaria seasonality and transmission vary across geographical zones, and agricultural production varies by type of sector, season, and geography. As discussed by Weil (2010), the effect of malaria and malaria prevention on production, therefore, depends on whether the height of agricultural production is pro-cyclical (or counter-cyclical) with the height of the malaria season.

Fourth, agricultural production tends to be a communal activity, in which extended families may reside together and pool resources. If any one worker needs to stay home with an illness, another person in the home may replace him or her. This reduces the effect that improving malaria prevalence has on the overall household production.

Fifth, childcare is often shared among extended family in Ghana; therefore, when children get malaria, they may stay home with someone who is already taking care of younger
children and/or other ill children. This similarly reduces the impact that improving malaria prevalence may have on agricultural production.

Finally, the informal economies tend to constitute a relatively large proportion of the overall economy in developing countries. In this research, the SAM considers the informal economy, but is probably incomplete due to lack of reliable data. Therefore, the results of the model are likely to underestimate the economic benefits of malaria intervention in areas that exhibit a high proportion of the informal sector, especially in rural areas.

**Scenarios revisited**

Many possible preventative strategies could be assessed to evaluate the impact of malaria reduction on the labour force. In this paper, we simulate cases where children < 5 years receive a malaria preventative intervention. This leads to two issues that need clarification.

First, because adults are not included in the intervention, the immediate economic benefit that could have been gained from healthier adults is not measured, i.e., the first component in Equation (7), “Malaria status of an adult worker,” is omitted. Therefore, economic benefits are only gained through the reduced days in caring for children, and through changes to the units of effective labour when treated children become adults later in life.

Second, because prevention is “taken away” when children reach an age > 5, the hypothetical preventative scenarios are short-lasting prophylaxis, similar to insecticide treated nets or anti-malarial preventative drugs, rather than a long-lasting vaccine. The scenarios alter the probability of the < 5 deaths from malaria, but do not change malaria endemicity overall. A hypothetical vaccine providing long-lasting protection to children, for example, would have had a compounding effect on the economy because the prevention would continue even after the children are > 5. This would resemble some of the effects if adults were added into the intervention. However, a hypothetical vaccine was not tested mainly because it is not yet known how long the new candidate-vaccine protects against malaria.
### Table 9: Additional value compared to baseline, year 1-30

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Additional annual GDP growth rate</td>
<td>0.067%</td>
<td>0.070%</td>
<td>0.070%</td>
</tr>
<tr>
<td>Additional income (cumulative, million 2007 US$)</td>
<td>8,382</td>
<td>8,926</td>
<td>8,874</td>
</tr>
<tr>
<td>Annual additional income (average, million 2007 US$)</td>
<td>279</td>
<td>298</td>
<td>296</td>
</tr>
</tbody>
</table>

Source: Authors’ own calculations

### 8 Results

The results overall show that even under a limited intervention to only < 5 years old, there is economic growth and that the rise in income inequality slows in Ghana. Furthermore, malaria prevention is best viewed as a long-run investment strategy. As Table 9 reports for the hypothetical scenarios of this research, annual GDP growth rate would rise by approximately 0.07% (above baseline). This is an additional cumulative income to the Ghanaian households of approximately $8.3 to $9.9 billion (2007 US$) over a 30 year period. Equivalently, this is an additional yearly average income of US$ 279 to 298 million.

In the first 10 years of the intervention, however, the dependency ratio rises and income per capita falls. This process is halted when the first cohort of healthier children reaches the working age population, approximately at age > 15. As they reach their prime working age, of approximately > 25 years, the economy gains the full benefit of the prevention, which raises income per capita (as illustrated in Figure 7). Therefore, 25 years later, the economy reaches a new long-run path of income per capita above baseline.

In the baseline scenario (with no intervention), the model projects a rise in income inequality for the top 20% richest to the lowest 20% poorest households. In the counterfactual simulations, this rise in income inequality slows down, as illustrated in Figure 8, which compares the income inequality ratio relative to that in the baseline. Similar to income per capita, the first 10 years of the intervention actually leads to a minimal rise in income inequality due to the increase in dependency ratio. But as the healthier children reach working

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17 A cohort includes children ages 0-5. We have assumed that the full effective units of labour is reached at the age of 25. Therefore, a proportion of the < 5 will reach this age 20 years after the intervention first began.
age, they enter the work force with more valuable, productive, labour resources. Therefore, even with a limited malaria preventative strategy to the < 5, the rise in income inequality ratio slows down by approximately 1.3% after 30 years.

Using a DCGE model, rather than econometric approaches, enables us to incorporate diminishing returns. For example, given a stock of land and capital, improvement in labour size and labour efficiency will initially raise welfare. But, as “more lives are saved,” competition within the labour market reduces their marginal labour productivity, and hence, erodes the marginal rise in income. The interaction of these opposing forces gives a truer picture of the economic value of an intervention. This is illustrated in Figure 7, in which income per capita is lower for the “comprehensive” intervention scenarios (i.e., the scenarios which provide greater intervention coverage), compared to the “basic” intervention.

Furthermore, and related to the above, not all zones benefit in the same way from malaria intervention. Forest, which is a high prevalence zone, receives the largest economic benefits from malaria intervention (illustrated in Figure 9). The labourers in Forest have the same
potential to produce and earn income as other zones, but malaria disadvantages them. The intervention, therefore, raises the value of the labour resource, which improves their income per capita, and even more so for the “comprehensive” scenario 3.

This rather intuitive result is, however, not necessarily true for all regions. For example, North Savannah, which is also a high prevalence zone, gains less from the comprehensive scenario 3, compared to the basic scenario 1 (see Figure 9). The key driver of welfare variation between households, in this model, is the heterogeneity in labour skill-type endowments and their overlap with the epidemiological zones. From a purely economic point of view, when households reside in high malaria prevalence zones, which coincides with having a high proportion of skill-types that are less in demand as inputs of production, they are expected to suffer from malaria intervention. The reason is that lives saved by malaria intervention might not be matched with the increase in demand for their labour resource. Poverty is exacerbated if the dependency ratio rises, while income rises less than sufficiently.

This situation also occurs in the rural households in Ghana, who benefit economically
Figure 9: Annual average income per capita relative to baseline (% change)

Source: Authors’ own calculations

Figure 10: Income per capita relative to baseline, by zone and urbanity (average over 30 years)

Source: Authors’ own calculations
less from malaria intervention (as shown in Figure 10), especially with the higher coverage scenarios. However, as discussed in the model limitations (Section 7), the value of the informal sector is higher in rural areas in developing countries, and the benefits of malaria intervention in those regions are most likely an underestimate. Furthermore, we do not consider the social value of malaria prevention in this model.

### 8.1 The benefit of prevention per individual covered

The economic benefit of a prevention given to individual children is reported in Figure 11, which is in terms of income gain per < 5 covered. The main results are that the benefit of a prevention rises from US$ 7 (2007 prices) to approximately US$ 16 per child covered, in the first 10 years. These welfare gains (per child) are mainly a result of the reduction of lost working days that parents have to make for taking care of sick children.

In later years, the benefits per covered child rises considerably higher, as the children mature and enter the work force as healthier and more productive, individuals. In other
words, because they were given malaria prevention as children, they will directly benefit as adults. The 30 year annual cumulative average benefit per covered child is between US$ 98 to US$ 124 (depending on the scenario).

Furthermore, as reported in Figure 11, the benefit per covered child is highest for the “basic coverage” Scenario 1, which again is precisely the result of diminishing returns to effective units of labour.

## 8.2 Variation in benefit by epidemiological zone

Table 10 reports the 30 year annual average regional benefits per covered child, and indicates which zones stand to gain most from the prevention. It shows, for example, that individuals in the Forest zone benefit the most; while individuals in North Savannah gain the least.

From a purely economic point of view, an optimal provision would be to increase coverage
to those children in zones that benefit the most from prevention, while reduce coverage to the areas below average. Health provision is maximized when all children have the same benefits across all zones.

However, this is of course an unacceptably narrow approach because it only provides a partial view of the optimal provision, as it does not consider aspects that have intrinsic non-economic value, e.g., moral, social, and equity implications. A better method to rank policy would be to include a social agenda within the provision, and evaluate it within this predefined framework; for example, assessing an optimal provision strategy within a pro-poor health subsidization policy.

8.3 Sensitivity analysis

To test the sensitivity of results, many robustness checks were conducted on the key parameters of the economic model. We applied low and high values of the income elasticities and Frisch parameters, which may influence results of the scenarios compared to the baseline. These are described in Table 11, and are well above/below the accepted values within the literature.

Overall, the results are very close to the main results, and suggest that the model is well behaved. For example, the values presented in Figure 11 for the income-benefit per covered individual vary by approximately US$ 2, for the low sensitivity values, but are nearly the same for the high values. The percentage difference of GDP above baseline (compared to the main model result) is approximately 0.01 percentage points until year 25, when it increases to a 0.05 percentage point difference. The results for high values are even more similar to the main results, and would alter our results from 25 years onwards by less than 0.015 percentage points. These provide some confidence that changing the deep parameters of the DCGE model do not alter the overall conclusions.

The model is, however, sensitive to some of the labour unit efficiency parameters that were summarised in Table 8. For example, increasing the loss to adult productivity from
Table 11: Sensitivity analysis

<table>
<thead>
<tr>
<th>Parameters used in model</th>
<th>Low</th>
<th>Urban</th>
<th>Rural</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income elasticity of demand</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.3</td>
<td>0.66</td>
<td>0.68</td>
<td>1</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.45</td>
<td>0.91</td>
<td>0.86</td>
<td>1</td>
</tr>
<tr>
<td>Services</td>
<td>1</td>
<td>1.52</td>
<td>1.30</td>
<td>2</td>
</tr>
<tr>
<td>Frisch Parameter</td>
<td>-2</td>
<td>-3</td>
<td>-5</td>
<td>(respectively) -5,-6</td>
</tr>
</tbody>
</table>

90% to 75%, which had two bouts of malaria as a child, would raise the benefits per child covered in the final year by approximately US$ 150 (but not in the first 25 years). This raises the average benefit per covered child. Our results are, therefore, the conservative estimates.

Finally, sensitivity analysis was performed on the demographic model and its interaction with the DCGE model. However, the overall effect that malaria has on the general demographic trends is relatively small. Therefore, the major economic effects are a result of the labour efficiency index, and not the demographic model.

9 Conclusion

The analysis of malaria and its link with economic growth using econometric approaches has, so far, been too broad and partially useful for policy analysis. To fill the gap, we developed a recursively dynamic computable general equilibrium (DCGE), and used Ghana as a case study. We find that malaria prevention clearly adds to economic growth and slows down the rise in income inequality, even under a limited intervention where only the under-five years old are treated. Our results are conservative estimates because health is only linked to labour resources, while leaving out the other possible effects. Furthermore, immediate economic benefits would be obtained had the intervention included adults.

Public, private, and third-sector organisations require a more detailed picture of how malaria influences various households and production sectors over time. The scenarios developed here were hypothetical, but in the “real world,” policy makers decide on the most appropriate
health provision within a framework of a limited budget and social goals. Our approach is useful for policy makers to assess the expected benefits, and target towards a certain desired level of return on (health) investment, because framing the results as a cost-benefit analysis is rather straight forward. All that is needed is to compare the results with the cost of the various provisions. Moreover, designing complex health provision policies, e.g., pro-poor health subsidies, require assessing the treatment benefits per individual covered, which is a natural outcome of our approach.

This methodology is a step forward in the \textit{a priori} impact assessments of alternative malaria interventions. Malaria intervention has a key role in the economic development of endemic countries. However, it is a long-term investment, and governments and donors must view it as such.
References


Fernando, D., D. de Silva, and R. Wickremasinghe: 2003a, ‘Short-term impact of an acute attack of malaria on the cognitive performance of schoolchildren living in a malaria-endemic


of Sciences of the United States of America 6(6), 275–288. PMID: 16576496 PMCID: PMC1084522.


Sauerborn, R., D. S. Shepard, M. B. Ettling, U. Brinkmann, A. Nougta, and H. J. Diesfeld:


