Does malaria control impact education? A study of the Global Fund in Africa

Maria Kuecken* Josselin Thuilliez† Marie-Anne Valfort‡

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Abstract

Relying on microeconomic data, we examine the medium term effects of the Global Fund's malaria control campaigns on the educational attainment of primary schoolchildren in 22 Sub-Saharan African countries. Combining a difference-in-differences approach with an IV analysis, we exploit exogenous variation in different measures for pre-campaign malaria risk and exposure to the timing and expenditure of the Global Fund's malaria control campaigns. In a majority of countries, we find that the disbursements lead to substantial increases in grade level and/or reductions in schooling delay. The overall positive impact of malaria control on education is confirmed when disbursements from other major actors (including the President's Malaria Initiative and World Bank Booster Program for Malaria Control in Africa) are also taken into account.

Keywords: Malaria, Sub-Saharan Africa, Education, Quasi-experimental

JEL: I15, I21, O19, O22, O55

*Paris School of Economics - Paris 1 Panthéon Sorbonne University. E-mail: maria.kuecken@univ-paris1.fr.

†Corresponding author. CNRS - Paris 1 Panthéon Sorbonne University. 106-112 Boulevard de l'Hôpital, 75013, Paris. E-mail: josselin.thuilliez@univ-paris1.fr.

‡Paris School of Economics - Paris 1 Panthéon Sorbonne University. E-mail: marie-anne.valfort@univ-paris1.fr.

1 Introduction

Malaria is a life-threatening disease. According to the World Health Organization, there were about 219 million cases of malaria in 2010 and an estimated 660,000 deaths. This disease is caused by protozoan parasites belonging to the genus *Plasmodium*. It is transmitted by several species of infected female *Anopheles* mosquitoes.[1] Differences in the distribution of mosquitoes and in the behavior of potential human hosts contribute to the variation in epidemiological patterns of malaria seen worldwide. The majority of malaria-attributed deaths occur in Sub-Saharan Africa, where children under the age of five and pregnant women are the most at-risk.

Malaria does not only kill. It is also believed to impede human capital accumulation, and hence development, by generating school absenteeism and cognitive disorders (see for instance Clarke et al. (2008), Thuilliez et al. (2010) and Nankabirwa et al. (2013)). The objective of this paper is to illuminate the impact of malaria on education. More precisely, we estimate the medium term effects of early life exposure to the Global Fund to Fight AIDS, Tuberculosis and Malaria's anti-malaria campaigns on the educational attainment of primary school students across a wide range of African countries.[2] Infants and children indeed carry the greatest burden of malaria morbidity and mortality (Arrow (2004)). By impeding their human capital accumulation, malaria may have a long term negative impact on economic growth.

Throughout the 2000s, the Global Fund served as the largest source of funding for malaria control programs in Sub-Saharan Africa (see Pigott et al. (2012)). The Global Fund is active in 47 of the 48 sub-Saharan African countries (Global Fund (2013))[3] and its campaigns, whose ultimate objective is malaria control,[4] should induce lower malaria risk even after just a few years of operation. These campaigns focus on treatment of clinical cases as well as on prevention therapies among populations who are the most at-risk through artemisinin-combination therapies (ACTs).[5] They also seek to limit the transmission of the disease

[1] Four species of these protozoan parasites account for almost all infections seen in humans: *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium ovale* and *Plasmodium malariae*. *Plasmodium falciparum* is the most aggressive of all and accounts for the majority of infections in Africa (see Greenwood et al. (2005)).

[2] Here, "medium term effects" refer to the effects of a continued exposure to anti-malaria campaigns that varies between 0 and 10 years.

[3] Seychelles is the exception.

[4] See the website of the Roll Back Malaria Partnership: http://www.rbm.who.int/.

[5] Artemisinin and its derivatives are a group of drugs that possess the most rapid action of all current

from mosquitoes to human beings with insecticide treated nets (ITNs) and indoor residual spraying (IRS).[6]

Our empirical strategy combines a difference-in-differences approach with an IV analysis. The difference-in-differences approach exploits exogenous variation in pre-campaign malaria risk and exposure to the timing and expenditure of anti-malaria campaigns based on individuals' year of birth and year surveyed. More precisely, we combine educational and demographic data from the Demographic and Health Surveys (DHS) with Global Fund disbursements and measures of sub-national malaria ecology from the Malaria Atlas Project (MAP) as proxies for pre-campaign malaria risk.

Other papers have also relied on a difference-in-differences analysis. However, we improve upon this literature in four ways. First, the scope of our analysis (22 countries) is unprecedented. One of the advantages of quasi-experimental approaches over randomized experiments is indeed that they can be performed on a larger population. Yet, the maximum number of countries covered by previous quasi-experimental studies is only four (see Bleakley (2010a)).[7] Our study is distinctive. By focusing on 22 of the 45 endemic sub-Saharan African nations, we analyze the impact of malaria control on the educational outcomes of 410,581 primary schoolchildren. Second, contrary to the bulk of previous studies, we do not focus on the malaria periphery, i.e. the set of countries characterized by species of *Plasmodium* (*P. vivax*, *P. ovale* and *P. malariae*) that are relatively less harmful to health. We concentrate instead on African countries where *P. falciparum*, the most aggressive of all species, is dominant. Third, we test the results with an exhaustive set of instruments, one of which is rather novel while the two others are more traditional. Finally, we gauge the educational externalities of anti-malaria campaigns conducted by the current primary funder in the global health arena, the Global Fund. A growing value for money agenda aims to reduce costs, increase impact per dollar spent, and focus investments on the highest impact interventions among the most affected populations.[8] Education is certainly not the primary

drugs against *Plasmodium falciparum* malaria.

[6]These approaches are sometimes combined with larval control which eliminates mosquitoes at their larval stage. However, larval control is recommended only for specific settings due to its detrimental effects on the environment and poor cost-effectiveness. It therefore remains a marginal approach.

[7]These four countries are Brazil, Colombia, Mexico and the United States.

[8]For example, the Center for Global Development's Working Group on Value for Money in Global Health recently produced the report "More Health for the Money" (2013) focused exclusively on the Global Fund. See `http://www.morehealthforthemoney.org/`.

goal of malaria control efforts, but examining educational impacts of health programs adds to this literature by exploring if there is more education for the money invested by the Global Fund.

We estimate our specifications separately for all countries in our sample in order to account for cross-country heterogeneity, especially that which stems from differences in malaria characteristics. Our results reveal a positive impact of the Global Fund's malaria disbursements on educational attainment in a majority of countries (16 of 22). The orders of magnitude for these countries are substantial. On average, a one standard deviation increase in exposure to malaria control campaigns increases grade level during the current school year by 1.5 standard deviations and decreases delay status for current grade level by 2.1 standard deviations. Put differently, if the Global Fund increases its yearly per capita disbursement over a child's lifetime by 50 cents (USD), this scale-up translates to an increase in grade level of 0.8.

Why do we observe educational improvements in 16 countries but not in the remaining 6? Further analysis of our results shows that their significance depends on the methodological adequacy of the data we use to run our quasi-experimental approach. The 16 countries in which the impact of Global Fund malaria control is positive and significant are those which are the most suitable for a difference-in-differences analysis: they are more likely to encompass individuals who are not at all exposed to the Global Fund's anti-malaria campaign. Put differently, the absence of significance of our results for 6 of the 22 countries in our sample is possibly due to a lack of suitable data, not to ineffective Global Fund anti-malaria campaigns in these countries.

Our findings are further robust to the substitution of alternative measures for pre-campaign malaria risk. Moreover, the overall positive impact of malaria control on education is confirmed when disbursements from other major actors (including the President's Malaria Initiative and World Bank Booster Program for Malaria Control in Africa) are also taken into account. Finally, our findings are robust to a falsification test. This test consists in analyzing the impact of exposure to the Global Fund's malaria disbursement on the primary educational attainment of individuals who had already left primary school when the Global Fund's campaign started. As expected, and contrary to what we observe among students who are currently enrolled in primary school, this effect is never robustly positive.

The paper proceeds as follows. In Section 2, we provide evidence on the link between malaria and education. We present our empirical strategy in Section 3. In Section 4, we describe our data. Section 5 displays and discusses our results. Section 6 provides robustness checks. Finally, Section 7 summarizes our conclusions and highlights avenues for future research.

2 Malaria and education

There are a number of ways through which malaria can impact children's educational achievement. First, malaria during pregnancy can lead to foetal growth retardation which translates into cognitive and physical impairments among children. Barreca (2010) analyzes the long-term impact of *in utero* and postnatal exposure to malaria. He finds that such exposure leads to considerably lower levels of educational attainment and higher rates of poverty later in life.

Second, during early childhood (under the age of five),[9] complicated forms of malaria may develop rapidly. The effects of severe malaria, better known as cerebral malaria, have been quantified by numerous studies (see Mung' Ala-Odera, Snow and Newton (2004) for a literature review). For instance, Ngoungou et al. (2007) provide a quantification of the burden in Mali. In this study, 101 subjects (mean age of 5.6 ± 3.6 years) who had contracted cerebral malaria were followed from 1999 to 2001. The authors find that twenty-eight children exhibited persistent neurological sequelae (26.7 %). Among them, eight children had developed these sequelae just after cerebral malaria and 20 a few months later. These included headaches, mental retardation, speech delay, bucco-facial dyspraxia, diplegia and frontal syndrome (one case each), dystonia (two cases), epilepsy (five cases) and behavioral and attention disorders (15 cases).

Third, even during late childhood (typically considered to be from 6 to 16 years of age), the protection conferred by acquired immunity is only partial. If cerebral malaria is rare at this stage, "simpler" cases of clinical malaria (called "uncomplicated malaria"), repeated illness, or chronic malaria infections are not. They can have a non-cognitive impact on educational achievement via school absenteeism, general health conditions, and investment

[9] Acquired immunity in children does not play an efficient protective role until the age of 5 to 6, even in highly endemic areas. This fact highlights why malaria is a major threat to child survival.

in curative strategies (coping strategies against the disease detrimental to educational investments). For instance in a Kenyan case study, Brooker et al. (2000) attribute 13-50 % of medically-related school absences to malaria. In Mali, malaria was the primary cause of absenteeism during a full school year (Thuilliez et al. (2010)). Moreover, asymptomatic malaria has proven to have detrimental effects on children's cognitive and therefore educational skills in three studies (Clarke et al. (2008), Thuilliez et al. (2010) and Nankabirwa et al. (2013)).

3 Empirical strategy

We aim to estimate the medium term effects of early life exposure to the Global Fund's anti-malaria campaigns on the educational attainment of primary school students across a wide range of African countries. In this section, we first describe our quasi-experimental approach theoretically and discuss its validity. We then explain how we implement this approach in practice by using malaria ecology as a proxy for pre-campaign malaria risk.

3.1 A quasi-experimental approach: theory

In the following, we introduce our baseline specification and discuss its validity.

3.1.1 Baseline specification

Our quasi-experimental framework exploits geographic variation in pre-campaign malaria risk and variation in exogenous exposure to the timing and expenditure of anti-malaria campaigns, based on individuals' years of birth and year surveyed. This approach leads to the following difference-in-differences analysis:

$$\text{educ}_{ijct} = \alpha + \beta.(\text{exposure} \times \text{malaria}_j) + \mathbf{X_{ijct}}'.\mathbf{\Gamma} + \delta_j + \delta_c + \delta_t + \epsilon_{ijct}, \quad (1)$$

where exposure $= e(\delta_c, \delta_t)$.

In Equation (1), educ_{ijct} is an educational outcome[10] of primary school student i in DHS cluster j, who belongs to cohort c (the group of individuals born in year c) and is interviewed

[10]We focus on two educational outcomes: grade level during the current school year and delay status for current grade level.

in year t; $\mathbf{X_{ijct}}$ are individual-level controls (gender, age and wealth); δ_j are DHS cluster fixed effects; δ_c are cohort fixed effects; and δ_t are survey-year fixed effects. The variable of interest is the interaction term between exposure and malaria$_j$. We define exposure as the yearly amount per capita (USD) disbursed by the Global Fund at the country level during a child's lifetime. Obviously, this variable is a function of individuals' year of birth and survey year, allowing exposure to be expressed as a function of δ_c and δ_t (exposure $= e(\delta_c, \delta_t)$). Variable malaria$_j$ is the pre-campaign malaria risk in DHS cluster j.

Coefficient β in Equation (1) captures the impact of the Global Fund's malaria control on educational attainment based on a difference-in-differences analysis. This analysis relies on a continuous variable, which is pre-campaign malaria risk (malaria$_j$), to define the extent to which individuals belong to the treatment group rather than to the control group. Indeed, since malaria control is the ultimate objective of the Global Fund, clusters with higher pre-campaign malaria risk should benefit relatively more from the Global Fund's anti-malaria campaigns than clusters with lower pre-campaign malaria risk for a given exposure to Global Fund's disbursements at the country level. Clusters with higher pre-campaign malaria risk therefore constitute the treatment group (the group expected to benefit relatively more from such exposure), while clusters with lower pre-campaign malaria risk constitute the control group (the group expected to benefit relatively less from such exposure). Moreover, our difference-in-differences analysis also relies on a continuous variable, exposure to the Global Fund's disbursements, to define the intensity of the treatment. For a given pre-campaign malaria risk, individuals more exposed to the Global Fund's disbursements at the country level should benefit relatively more.

Using a difference-in-differences analysis in this way is not new. Indeed, it has already been applied to analyze the effect of malaria control on various socioeconomic factors. Bleakley (2010a) focuses on the malaria control campaigns in the United States (1920) as well as in Brazil, Colombia and Mexico (1950) in order to assess the impact of childhood exposure to malaria on labor productivity. Cutler et al. (2010), Lucas (2010), Barofsky et al. (2011), and Venkataramani (2012) estimate this impact on educational and/or cognitive outcomes in India, Paraguay and Sri Lanka, Uganda and Mexico respectively. These studies establish an overall positive impact of control campaigns.

Although not original, our approach improves upon these studies in four ways. First, we

cover a much larger sample of countries (22). Second, in this sample, the most aggressive species of *Plasmodium* (*P. falciparum*) is dominant. With the exception of Barofsky et al. (2011), previous studies have focused instead on the so-called malaria periphery, the areas in which *P. vivax* is dominant. Finally, we aim to document the educational externalities of malaria-targeted disbursements from the Global Fund. As education is, understandably, not the primary goal of malaria control campaigns, we hope to illuminate the second-order consequences of these disbursements. Finally, we test the strength of our results with an exhaustive set of instrumental variables.

3.1.2 Validity of our quasi-experimental approach

In order for our quasi-experimental approach to be valid, four conditions must be satisfied. First, the Global Fund's anti-malaria campaigns should be effective, meaning that they should ultimately lead to malaria control. This claim is supported by Figure 1. Figure 1 depicts the cumulative probability of dying from malaria for children under five[11] in the 22 countries of our sample over the 1980-2010 period. The Global Fund itself was created in 2002. As reported in Table 1, most of Global Fund's anti-malaria campaigns started almost immediately after the creation of the Global Fund, in 2003 or 2004 (the two exceptions being Sierra Leone and Malawi, where the campaigns started in 2005 and 2006 respectively). Figure 1 shows an increase and then a decrease in the cumulative probability of dying from malaria for children under five in the bulk of our countries.[12] More precisely, we observe continuous decreasing trends which occur primarily after the creation of the Global Fund in 2002.[13]

[11]This cumulative probability refers to the total number of children under five out of 1,000 who are likely to die from malaria in the absence of all other causes. Figure 1 is from the Institute for Health Metrics and Evaluation (IHME) at `http://www.healthmetricsandevaluation.org/`.

[12]The first worldwide eradication programme, based on house spraying with residual insecticides, anti-malarial drug treatment, and surveillance, was launched by the WHO in 1955. However, the most malarious areas, such as tropical Africa, were excluded (Alilio et al. 2004). Newly independent states in Africa thus relied on marginal, sponsored policies (residual insecticide spraying in a few urban centers or larvacide in limited areas), national health systems and malaria control programs already operational by the 1950s, hospitals and dispensary-based antimalarial activities, mass drug administration and availability of antimalarial drugs in the open market. The extensive use of residual insecticide dichloro-diphenyl-trichloroethane (DDT) and chloroquine $(CQ)_3$ did benefit Africa as the overall trend of malaria-related deaths in Africa showed evidence of decline from the 1950s to 1980s. However, these activities may have promoted the development of both drug and insecticide resistance and hence induced the increase in the cumulative probability of dying from malaria observed in Figure 1 (Berthélemy and Thuilliez (2014)).

[13]The exceptions are Ethiopia, Kenya, Liberia, Rwanda and Tanzania where the continuous decline in the cumulative probability of dying started earlier (in 1995 for Ethiopia, in 1998 for Kenya and Liberia and in 2000 for Liberia and Tanzania). Note also that Malawi experienced a first drop in 1993. These early

This suggests that the Global Fund's anti-malaria campaigns are effective or, at the very least, cannot be associated with increases in malaria risk. Moreover, Figure 1 shows that the higher the cumulative probability at the time of decrease, the sharper the fall. The data underlying Figure 1 confirm a strongly positive (0.89) and significant (at the 0.1% confidence level) correlation between this initial cumulative probability and the absolute yearly value of the decline (results available upon request). This evidence is consistent with malaria control being the aim of the Global Fund: initially more exposed countries seem to benefit relatively more from Global Fund's anti-malaria campaigns.

Second, for our quasi-experimental approach to be justified, the start of the Global Fund's campaign should not have been expected by citizens in our sample countries. Otherwise, if expected, the start date of Global Fund disbursements would not mark the true start of the anti-malaria campaigns' effects. For instance, anticipating health improvements for their children due to the campaign and therefore smoother human capital accumulation, parents may have been more (or less) dedicated to investing in their children's education, even prior to the campaign. Yet it would be difficult for citizens to predict the creation of the Global Fund (and hence the start of the Global Fund's campaigns) which occurred after a series of discussions between donors and multilateral agencies that emerged toward the end of 1999. These discussions notably culminated with the sixth of the eight Millennium Development Goals established following the Millennium Summit of the United Nations in 2000: "To combat HIV/AIDS, malaria, and other diseases." The creation of the Global Fund was therefore not a surprise for donor and multilateral agencies and the limited community of their followers. But it is doubtful that it was anticipated by ordinary citizens, especially in developing countries where struggling to provide for one's family is the priority, not keeping up with the news on donors' initiatives. Moreover, it is only recently (2011) that the Global Fund started advertising its actions in developing countries.[14] Hence, even in countries where the Global Fund was not active until a few years after its creation (Sierra Leone and

drops can be attributed to the decision of some countries to substitute alternative antimalarial treatments for chloroquine due to resistance (see Mohammed et al. (2013)). For instance, Malawi was the first African country to replace chloroquine in 1993, followed by Kenya in 1998 and Tanzania in 2000. These early drops can also be explained by substantial increases in the GDP of these countries (Rwanda included), which may have allowed a scale-up of malaria control efforts (see Murray et al. (2012)).

[14]This promotion is based on the green leaf logo of the Affordable Medicines Facility-malaria program (AMFm). This logo is printed on antimalaria treatments provided by the Global Fund and is notably supposed to reflect price reductions through negotiations of the Global Fund with ACTs (artemisinin-combination therapies) manufacturers.

Malawi), the start of anti-malaria campaigns is unlikely to have been anticipated by potential beneficiaries.

Third, the interaction term between exposure to the Global Fund's campaign and pre-campaign malaria risk at the cluster level should be exogenous. This means that no omitted variable should be correlated with both this interaction term and educational outcomes. Yet, pre-campaign risk is likely to be negatively correlated with pre-campaign educational outcomes such that there is a correlation between (exposure $\times$ malaria$_j$) and the interaction term between exposure and pre-campaign educational outcomes. This problem arises because the latter interaction term is plausibly correlated with the dependent variable in Equation (1): the impact of malaria control campaigns may vary depending on pre-campaign educational outcomes. Initially more educated individuals are indeed more likely to adopt anti-malaria strategies (see Nganda et al. (2004), Rhee et al. (2005), Hwang et al. (2010) and Graves et al. (2011)).[15] It is therefore possible that coefficient β in Equation (1) is biased downward, which leads us to underestimate the positive impact of anti-malaria campaigns on educational attainment. Unfortunately, due to data limitations, we cannot control for the interaction term between pre-campaign educational outcomes at the cluster level and malaria$_j$. We control instead for the interaction term between region fixed effects and exposure in Equation (1).[16]

There are other reasons why the interaction term between exposure to the Global Fund's campaign and pre-campaign malaria risk at the cluster level may not be exogenous. By definition, an individual's exposure to malaria control campaigns negatively depends on his or her age (i.e. the difference between DHS survey year and the individual's date of birth). As a consequence, a correlation exists between (exposure $\times$ malaria$_j$) and the interaction term between age and pre-campaign malaria risk. But this latter interaction term may also be correlated with the dependent variable in Equation (1): the impact of pre-campaign malaria risk on educational outcomes may vary across age. To avoid this omitted variable bias, we add the interaction term between pre-campaign risk and primary school student's age in Equation (1).

[15] See also Kenkel (1991) and Dupas (2011) for the relationship between education and health behavior.

[16] We obviously cannot control for the interaction term between cluster fixed effects and exposure to malaria control campaigns since this would drop the main variable of interest in our analysis, i.e. (exposure $\times$ malaria$_j$).

Moreover, also by definition, an individual's exposure to malaria control campaigns positively depends on his or her date of birth[17], while pre-campaign malaria risk is correlated with local characteristics. Such correlations are a source of endogeneity if there are trends in educational outcomes at the local level, meaning that primary school students' born in different years and localities were initially exposed to different educational policies. To limit this endogeneity, we add an interaction term between region fixed effects and students' date of birth in Equation (1).[18]

Obviously, our controls do not allow us to treat all sources of endogeneity in Equation (1). Therefore, we combine our differences-in-differences analysis with an IV approach that consists in instrumenting pre-campaign malaria risk. We provide details about our IV approach in section 5.2.

Fourth, for our difference-in-differences analysis to estimate a treatment effect, we must ensure that the parallel trends assumption holds. This implies showing that educational outcomes, although they are likely to differ across primary school students living in clusters with different pre-campaign malaria risk, evolve similarly across these clusters during the pre-campaign period. As shown in Table 1, there are only two countries in our sample, Malawi and Uganda, in which more than one DHS survey year is available before the start of the campaign (in fact, two pre-campaign DHS survey years are available in these countries). We therefore test the parallel trends assumption by relying on pre-campaign Malawean and Ugandan data. More precisely, we estimate Equation (2):

$$\text{educ}_{ijct} = \alpha + \beta.(\text{malaria}_j \times \delta_t) + \gamma.\text{malaria}_j + \delta_t + \mathbf{X_{ijct}}'.\mathbf{\Xi} + \epsilon_{ijct}, \tag{2}$$

where educ_{ijct}, malaria_j, $\mathbf{X_{ijct}}$ and δ_t are defined as in Equation (1). Columns 1 and 2 of Table 2 present OLS estimates of Equation (2) for Malawi, while columns 3 and 4 present OLS estimates for Uganda. Coefficient β in Equation (2) never turns significant. This result indicates that educational outcomes evolve similarly across clusters showing different malaria risk during the pre-campaign period. We therefore find support for the parallel

[17]Indeed, everything else held constant, the later the date of birth, the higher the probability that the child was exposed to Global Fund's disbursements during his/her entire life.

[18]We focus on region rather than cluster fixed effects because educational policies are more likely to be determined at the region rather than cluster level in case they are (at least partly) decentralized. Regardless, an interaction term between cluster fixed effects and students' date of birth would drop the main variable of interest in our analysis, i.e. (exposure $\times$ malaria_j).

trends assumption in the two countries for which this assumption is testable.[19]

A final concern may remain. Variable malaria$_j$ in Equation (1) captures pre-campaign malaria risk in the DHS cluster where the respondent currently lives. There is no guarantee that this place of residence coincides with the respondent's place of birth (this information is absent from the DHS surveys, as is the respondent's migrant status). Yet, is it unlikely that migration of primary schoolchildren from non-malarious to malarious regions drives our results. First, we are working with a youth population which limits the time window available for migration. Second, our results are consistent across countries that show different internal migration rates. For instance, we find a positive impact of the Global Fund's anti-malaria campaigns on educational attainment in Ghana, Kenya, Mali, Rwanda, Senegal, Uganda and Zimbabwe, although lifetime crude internal migration intensity[20] varies substantially across these countries, from 10.4% in Rwanda to 28.9% in Zimbabwe (see United Nations (2013)). Third, evidence suggests that individuals prefer migrating to non-malarious rather than to malarious regions (see Sachs and Malaney (2002) and Hong (2011)). Notably, Sawyer (1993) shows that malarious regions in Brazil deter permanent migration. If anything, they attract male temporary workers who do not migrate with their family. Note that one might still worry about a selection bias whereby individuals (parents) with higher levels of education will likely choose to live in areas that are the least conducive to malaria risk – and parents' education is strongly correlated to their children's education. Controlling for the household's wealth in Equation (1) helps us to proxy for parental education and mitigate concerns about this selection bias.

3.2 A quasi-experimental approach: practice

Theoretically, our difference-in-differences analysis exploits geographic variation in pre-campaign malaria risk and variation in exogenous exposure to the timing and expenditure of anti-malaria campaigns, based on individuals' years of birth and year surveyed. In practice, we combine educational and demographic data from the Demographic and Health Surveys (DHS) with Global Fund disbursements and measures of sub-national malaria ecology from the Malaria Atlas Project (MAP). Without information on pre-campaign malaria risk, we

[19]These results hold when we instrument $malaria_j$ by the set of instruments provided in section 5.2.

[20]Crude internal migration is the proportion of internal migrants across regions in a country's population.

use malaria ecology directly as a proxy for risk. Below, we explain why malaria ecology is an acceptable measure for pre-campaign malaria risk.

In our data, malaria ecology stands for the average, at the DHS cluster level, of the probability of occurrence of *Anopheles* species that constitute dominant and secondary vectors of malaria in a given country in 2010. Our study is not the first quasi-experimental study to rely on malaria ecology as a proxy for pre-campaign malaria risk. Previous quasi-experimental approaches rely on a malaria ecology index provided by Kiszewski et al. (2004) (see Bleakley (2010a), Lucas (2010) and Venkataramani (2012)). This index is based on monthly temperature and precipitation and computed for the late 1990s. However, we prefer MAP over Kiszewski et al. (2004)'s malaria ecology for two reasons. First, vector occurrence provided by MAP is estimated at a much more disaggregated level (see Malaria Atlas Project (2011)). It uses grids of 5 km $\times$ 5 km resolution while Kiszewski et al. (2004) rely on 55 km x 55 km grids (see Sinka et al. (2010) and Sinka et al. (2012)). As a result, our malaria ecology index offers higher precision but also greater cross-cluster variation. Second, contrary to Kiszewski et al. (2004), MAP does not only rely on geographic and climatic variables (such as elevation, precipitation or temperature)[21] to estimate vector occurrence. It also uses vector-specific population dynamics models that predict how environmental and climatic factors impact the ecology and bionomics of each vector species. Moreover, MAP exploits survey-based information about control methods (such as the use of insecticide treated nets (ITNs) and indoor residual spraying (IRS)) in order to model their potential impact on vector distribution. Our malaria ecology index therefore accounts for a multitude of factors shaping vector distribution.

We rely on malaria ecology as a proxy for malaria risk since these two variables have proven to be strongly correlated (see Gallup and Sachs (2001), Bhattacharyya (2009) and Carstensen and Gundlach (2006)). However, the fact that malaria ecology is estimated in 2010 may raise skepticism about its ability to capture *pre-campaign* malaria risk. The more intensive use of insecticide-treated nets (ITNs) and indoor residual spraying (IRS) after the creation of the Global Fund may indeed lead to malaria ecology data in 2010 that are lower than if these data had been computed before Global Fund's campaigns.[22] This bias should

[21] These variables are known to be strong determinants of vector distribution (see Bhattacharyya (2009)).

[22] However, one has to bear in mind that the Global Fund's anti-malaria campaigns do not target vector elimination which has proven to be globally difficult. Moreover, new techniques, such as the genetic modifi-

be stronger in regions showing higher pre-campaign malaria risk given that these regions are supposed to have received the bulk of the Global Fund's attention. Put differently, one expects malaria ecology as computed in 2010 to underestimate pre-campaign malaria risk, particularly in regions with higher initial malaria risk. This bias runs against us finding a significant (positive) impact of coefficient β in Equation (1). As a result, our estimates should be considered as a lower bound of the impact of the Global Fund's anti-malaria campaigns on education.

This downward bias should, however, be of low magnitude. ITNs and IRS have indeed been found to have a modest impact on vector occurrence (see Zhou et al. (2010)). Two reasons may account for this finding. First, despite tremendous progress, the coverage of ITNs and IRS is far from universal in Africa. For instance, the proportion of the population protected by IRS has increased substantially starting from 2006. However, this figure remains low: in 2011, 11% of the at-risk population in Africa was estimated to be protected (World Health Organization (2012)). Second, it is well known that mosquitoes have developed resistance to pyrethroids as well as other types of insecticides (see Santolamazza et al. (2008)).[23] Though drug resistance has long been acknowledged, countermeasures are recent. In 2011, the World Health Assembly and the Board of the Roll Back Malaria Partnership requested the WHO to draft a global strategy to provide a basis for coordinated action to maintain the effectiveness of vector control interventions. However, the Global Plan for Insecticide Resistance Management in malaria vectors was launched in May 2012, which is after the year for which MAP provides malaria ecology.

To further support our claim that our malaria ecology index is an acceptable measure for pre-campaign malaria risk, we test the robustness of our results when we replace malaria ecology by proxies for malaria risk that are unambiguously *pre-campaign* (see Section 6). The first proxy is the Kiszewski et al. (2004) index computed for the late 1990s. The second proxy stems from Mapping Malaria Risk in Africa/Atlas du Risque de la Malaria en Afrique (MARA/ARMA) data. It represents the percentage of population living in either holo-endemic or hyper-endemic[24] areas the year prior to the start of the Global Fund's campaigns

cation or sterilization of vectors that could have the potential to achieve this goal are still experimental.

[23]WHO-recommended ITNs use pyrethroids. Insecticides used for IRS come from four classes: pyrethroids (the most common), organochlorines (of which DDT is the only compound in use), organophosphates, and carbamates.

[24]In holo-endemic areas, malaria prevalence is greater than 75% while it is between 50% and 75% in

in the regions of a subsample (9) of our 22 countries. Our results are robust to both checks.

Although our malaria ecology index is an acceptable proxy for pre-campaign malaria risk, we are careful to note that it may induce an endogeneity bias. First, reverse causality could be at work since education positively influences the adoption of preventive strategies such as ITNs or IRS (see Nganda et al. (2004), Rhee et al. (2005), Hwang et al. (2010) and Graves et al. (2011)) which translates to reductions in malaria ecology. DHS collection of primary school students' educational attainment, as shown in Table 1, mainly took place before 2010. It could then be possible that higher individual educational attainment in a given cluster leads to lower malaria ecology in this cluster in 2010. This negative causal effect would be particularly strong if exposure of students to the Global Fund's disbursements is high. To attempt to rule out reverse causality, we include cluster fixed effects in Equation (1) which absorb the average level of individual educational achievement and individual exposure at the cluster level. Yet, heterogeneity at the individual level remains untreated.

Additionally, bias might also derive from an omitted variables problem. There are characteristics at the individual level (like a household's readiness to adopt preventative strategies) which might be correlated with both malaria ecology and education levels. Finally, there might be an attenuation bias induced by measurement error of malaria ecology if this error is classical (uncorrelated with the true value of malaria ecology). To ensure the exogeneity of the interaction term (exposure $\times$ malaria$_j$), we combine our differences-in-differences analysis with an IV approach that instruments pre-campaign malaria risk with three different sets of instruments (see Section 5.2 for further details).

4 Data

In this section, we first present the two dependent variables that allow us to capture primary school students' educational attainment. We then present our malaria ecology index and the way we compute exposure to the Global Fund's anti-malaria campaign. Finally, we comment on the descriptive statistics related to each of these variables.

hyper-endemic areas.

4.1 Educational attainment

We use household member information from the Demographic and Health Surveys (DHS) to develop our measures of educational attainment. Specifically, we focus on those individuals currently enrolled in primary school. If we were to focus on all students of primary school age, we would face a selection bias due to the effect of malaria control on enrollment/dropout decisions. Given that malaria risk impedes enrollment, we expect that including all of-age children would overestimate the impact of the Global Fund's malaria control campaigns on educational attainment and, therefore, discount the value of our results.

Among enrolled children, we study two types of respondent-reported educational outcomes: grade level during the current school year[25] and delay status for current grade level. A student is considered delayed if her grade is below the average grade of students of the same age at the national level. We rely on the procedure by Moock and Leslie (1986) to capture delay status. In doing so, we first regress the logarithm of grade on the logarithm of age in each country of our sample. We then estimate the predicted grade level for each individual in each of these countries. Finally, we create a dummy variable that is equal to one if a student's observed grade level is lower than its predicted value.

In addition to educational measures, we also draw controls on the gender, age, and wealth of primary school students from the DHS. Wealth is an asset-based index ranging from one (poorest) to five (richest).[26]

4.2 Malaria ecology

As described in Section 3.2, malaria ecology stands for the average, at the DHS cluster level, of the probability of occurrence of *Anopheles* species that constitute dominant and secondary vectors of malaria in a given country. This approach for computing the ecology measure implies that different species must be taken into account for each country: *funestus*, *nili*, *gambiae*, *arabiensis* for Burkina Faso, Malawi, Mali and Namibia; *funestus*, *nili*, *gambiae*, *arabiensis*, *moucheti* for Burundi, Rwanda, Uganda and Zambia; *funestus*, *nili*, *gambiae*, *arabiensis*, *melas*, *moucheti* for Cameroon, DRC and Nigeria; *funestus*, *nili*, *arabiensis* for

[25] It is important to emphasize that our results hold when we substitute total years of schooling completed for grade as the dependent variable.

[26] More precisely, 1 stands for "poorest", 2 for "poorer", 3 for "middle", 4 for "richer", and 5 for "richest".

Ethiopia; *funestus*, *nili*, *gambiae*, *arabiensis*, *melas* for Ghana, Guinea, Liberia, Senegal and Sierra Leone; *funestus*, *nili*, *gambiae*, *arabiensis*, *moucheti*, *merus* for Kenya and Tanzania; *funestus*, *gambiae*, *arabiensis*, *merus* for Madagascar; *funestus*, *nili*, *gambiae*, *arabiensis*, *merus* for Mozambique and Zimbabwe.

4.3 Exposure to Global Fund's anti-malaria campaigns

We define exposure as the yearly amount per capita[27] (USD) disbursed by the Global Fund at the country level during a child's lifetime. A child's lifetime is defined as the difference between the DHS survey year and this child's year of birth, from which we subtract one year (since individuals' exposure starts during the year of their birth, not the year after they are born).[28]

To illustrate the construction of this variable, we take the example of Ethiopia. As reported in Table 1, the Global Fund's anti-malaria campaigns started in 2003 in Ethiopia. Moreover, three DHS surveys years are available (in 2000, 2005 and 2010). Let's consider a child born in 1999. If this child is surveyed in 2000, she experiences no exposure since the Global Fund's disbursements were to begin only in 2003. If she is surveyed instead in 2005, she experiences three years of exposure to Global Fund's disbursements. Her exposure variable will therefore be equal to the sum of the Global Fund's disbursements per capita during these three years, divided by her lifetime, hence 2005-(1999-1)=7 years. Similarly, if this child is surveyed in 2010, she experiences eight years of exposure to Global Fund's disbursements. Her exposure variable will therefore be equal to the sum of Global Fund's disbursements per capita during these eight years, divided by her lifetime, hence 2010-(1999-1)=12 years.

4.4 Summary statistics

Summary statistics are reported in Table 3. The number of primary school students within our sample varies greatly by country. The sample size ranges from as low as 5,384 students in Liberia to as many as 53,088 in Malawi.

[27] Yearly population data come from the World Development Indicators.

[28] Note that changing individuals' exposure start year to the year after they are born does not alter our results.

Mean exposure to Global Fund's disbursements, which captures the yearly amount per capita (USD) disbursed by the Global Fund at the country level during a child's lifetime, also varies substantially across countries, from 0.01 USD in Mali to 0.71 USD in Rwanda.[29] The same pattern is observed for the within-country variation of exposure to the Global Fund's disbursements. Standard deviation in exposure ranges from 0.01 in DRC, Guinea and Mali to 0.58 in Rwanda. Half of our 22 countries comprise fully untreated individuals (their exposure to the Global Fund's disbursements is equal to 0).

As expected, mean malaria ecology, i.e. the probability of occurrence of *Anopheles* species that constitute dominant and secondary vectors of malaria in a given country, is high. It is equal to 0.69 on average, ranging from 0.31 in Namibia to 0.89 in Burkina Faso. However, it varies significantly across DHS clusters within each country. In a majority (16 of 22), the minimum value for malaria ecology is 0% while the maximum value is above 90%.

Let us conclude by commenting on basic socioeconomic characteristics of the respondents. Given that DHS survey teams rely on a stratified (notably by gender) recruitment procedure, the proportion of male and female respondents is well-balanced. As for mean ages, they correspond to those expected from primary school students. They span from 9.37 years old in Madagascar to 12.85 in Liberia. Finally, given that wealth is an asset-based index that captures quintiles, it is not surprising to observe a mean value roughly equal to 3, which stands for the "middle" category.

5 Results

In this section, we present OLS and then 2-SLS estimates for Equation (1).

5.1 OLS estimates

Columns 1 and 5 of Table 4 present OLS estimates of coefficient β in Equation (1) where the dependent variable is grade level during the current school year and delay status for current grade level respectively. Put differently, we rely on a linear probability model when we analyze delay status (since this dependent variable is binary). Our objective is indeed to

[29]The situation in Mali might be explained by the fact that, as reported by their official website in 2010, the Global Fund suspended funding of two malaria grants with immediate effect and terminated a third grant for tuberculosis (TB) after it found evidence of misappropriation and unjustified expenditure.

measure the average marginal impact of exposure to the Global Fund anti-malaria campaigns, that is the impact of exposure to the Global Fund when explanatory variables in Equation (1) are set at their average. In this case, an OLS approach provides similar marginal effects as would a probit or a logit analysis (see Angrist (2001) and Wooldridge (2009)).

Table 4 then displays OLS estimates after adding into Equation (1) the interaction term between regional fixed effects and exposure (columns 2 and 6), the interaction term between pre-campaign malaria risk and student's age (columns 3 and 7), and the interaction term between regional fixed effects and student's date of birth (columns 4 and 8).

Our results reveal that, in a majority of countries (14 of 22), malaria control leads to statistically significant increases in grade and/or statistically significant reductions in schooling delay, while they are not significant in the remaining countries. Finding an overall positive impact was not a given. Section 2 emphasized the channels through which malaria control has a positive impact on children's human capital accumulation: better general health conditions, reduced absenteeism and means for investing in curative strategies, as well as better cognitive skills. However, this positive impact may never emerge in poor countries. Indeed, by reducing the mortality of children under the age of five, anti-malaria campaigns can impose considerable strain on educational resources. If these resources remain limited (a plausible situation in our sample), the impact of malaria control on schoolchildren's educational attainment may not be positive overall. Moreover, anti-malaria campaigns potentially lead to a higher diversity among children enrolled, instead of enrollment being restricted only to those who survive to the disease. Again, in the absence of sufficient educational resources, the weakest students who are enrolled thanks to the campaign will likely fall behind. Finally, as emphasized by Bleakley (2010b), the effect of childhood health on years of schooling and therefore grade level is ambiguous. Childhood health increases the marginal benefit of schooling. But it also increases the marginal (opportunity) cost of going to school: a healthier child can earn more on the labor market. This opportunity cost may be particularly high in poor countries.

We do, however, take these results with caution. A basic OLS strategy is unable to address the sources of endogeneity previously mentioned. We therefore turn to an instrumental variables approach in the following section.

5.2 IV estimates

We rely on three different sets of instruments for malaria ecology (Set I, Set II, and Set III hereafter). These instruments must be such that they impact educational outcomes only through their impact on malaria ecology. They should have no direct impact on educational outcomes, nor be correlated with any characteristics at the individual level, such as the household's willingness to adopt preventive strategies, that might be correlated with educational outcomes. The latter two sets (Sets II and III) have already been tested and validated by previous studies. Set I is more novel. As a result, we are hesitant to settle on a first-best strategy and instead present results for all three sets of instruments.

5.2.1 Set I

Set I of instruments relies on geographic variables that have been strongly linked to malaria, that is, on the latitude, longitude and altitude at the cluster level (Craig et al. (1999)). (See for instance Burlando (2013) for the use of altitude as an instrumental variable where higher altitudes are less malarious). Latitude and longitude are provided by DHS surveys. Altitude captures average elevation above sea level and is made available by the Shuttle Radar Topography Mission (SRTM).[30] Geographic variables combined together are expected to be uncorrelated with educational achievements as well as with any characteristics at the individual level that could influence such outcomes.

5.2.2 Sets II and III

Sets II and III of instruments are similar to those used by Bleakley (2010a) and Cutler et al. (2010) respectively. These instruments combine geographic and climatic variables. Bleakley (2010a) instruments average malaria risk with average temperature and average altitude as well as the interaction of the two. We rely on the same instruments. Average temperature is the annual mean temperature provided by WorldClim[31] while average altitude is defined as in Set I. Cutler et al. (2010) use average temperature, average altitude, average humidity, average precipitation, and squared terms of all four variables as instruments. We rely on similar instruments and their squared terms: average temperature (annual mean

[30]This database is available at `http://www2.jpl.nasa.gov/srtm/`.
[31]This database is available at `http://www.worldclim.org/`.

temperature, maximum temperature of warmest month, minimum temperature of coldest month) as well as annual precipitation from WorldClim and average altitude from SRTM.

5.2.3 Results

For a specific set of instruments, the first-stage of the 2SLS consists of regressing the interaction term between exposure to Global Fund disbursements and malaria ecology on interaction terms composed of exposure and each of the instruments that belong to this set. Naturally, we include in this first-stage the other explanatory variables displayed in Equation (1) as well as the following controls: the interaction term between regional fixed effects and exposure, the interaction term between pre-campaign malaria risk and student's age, and the interaction term between regional fixed effects and student's date of birth. We provide results of an OLS estimation which regresses malaria ecology on the various sets of instrumental variables in Section S1 of the supplemental appendix.[32] Tables S1-1 to S1-22 reveal highly significant correlations between malaria ecology and all three sets of instruments. Moreover, Section S1 displays F-statistics that are, with rare exceptions, greater than 10.

Results from the second stage of the 2-SLS approach, which relies on Equation (1), are reported in Table 5. The following controls are included: an interaction term between regional fixed effects and exposure, an interaction term between malaria ecology and primary student's age, and an interaction term between regional fixed effects and student's date of birth are added. We report the Durbin-Wu-Hausman (DWH) χ^2 test for each country in Table 5. For the majority of cases, this test rejects the null hypothesis according to which OLS and IV estimates are not significantly different from each other.

Figure 2 helps us to visualize the findings. For each country, we report information on the IV results if the DWH test is rejected in all of the three IV sets; we report information on the OLS results otherwise. For each dependent variable and country, cases where the impact of the Global Fund's anti-malaria campaign is statistically significant are highlighted in grey, while cases where the impact of the Global Fund's anti-malaria campaign is not statistically significant are reported in white. Plus and minus signs indicate the sign of coefficient β in Equation (1). In a majority of countries (16 of 22), we find that the program leads to

[32]This supplemental appendix is available at `https://mariakuecken.files.wordpress.com/2012/05/supplementalappendixgf300514.pdf`.

significant increases in grade level and/or reductions in schooling delay. In the remaining countries, the impact of the Global Fund's anti-malaria campaigns is insignificant (Guinea, Liberia, Madagascar, Sierra Leone, Tanzania and Zambia).

In the group of countries where the impact of the Global Fund's anti-malaria campaigns is positive and significant, the orders of magnitude are substantial. On average, a one standard deviation increase in exposure to malaria control campaigns increases grade level during the current school year by 1.5 standard deviations and decreases delay status for current grade level by 2.1 standard deviations. Put differently, if the Global Fund increases its yearly per capita disbursement over a child's lifetime by 50 cents (USD), this scale-up translates through an increase in grade by 0.8 level.

It is worth emphasizing that the orders of magnitude are greater with an IV than with an OLS approach. This means that our OLS estimates are subject to an underestimation bias which is consistent with the various sources of endogeneity previously highlighted: (i) a reverse causality problem whereby more education leads to lower malaria ecology; (ii) an omitted variables problem whereby individual characteristics such as a household's adoption of preventative strategies is negatively correlated with malaria ecology but positively correlated with educational achievements; and (iii) a measurement error problem that leads to an attenuation bias.

5.3 Discussion

Why do we find a positive and significant impact of the Global Fund's anti-malaria campaigns in some countries but not in others? The significance of our findings may depend on the methodological adequacy of the country data that we use to run our difference-in-differences analysis. As already emphasized, malaria ecology shows high variation in each country, meaning that the control and treatment groups are strongly distinguished in our sample: pre-campaign malaria risk is unambiguously low in some clusters and unambiguously high in others. However, summary statistics show that half of our 22 countries do not comprise fully untreated individuals (their minimum exposure to Global Fund's disbursement is not equal to 0), which may compromise our ability to measure a significant treatment effect. We confirm this statistically.

The 16 countries where the impact of the Global Fund's malaria control campaign is

positive and significant are those which are the most suitable for a difference-in-differences analysis: they are more likely to encompass both pre- and post-campaign DHS rounds, and hence individuals who are not exposed at all to the campaign. Notably, we observe that the 6 countries in which we find an insignificant impact of the Global Fund's campaign encompass only *post*-campaign DHS rounds. Yet, we wish to further test our conjecture that the absence of significance of our results for 6 of the 22 countries in our sample is due to an absence of pre-campaign DHS rounds. We do so by keeping, for countries which are initially endowed with both pre- and post-campaign DHS rounds, only those which are post-campaign. More precisely, we estimate Equation (1) on the final post-campaign DHS round among these countries. Focusing on this last round indeed constitutes a harder test for our conjecture. To be sure, there are no untreated individuals in this round. But the intensity of the treatment for the treatment group (i.e. the clusters which show higher pre-campaign malaria risk) is maximal. So if this test leads the coefficient of the interaction term (exposure $\times$ malaria$_j$) to be insignificant, this will increase our confidence that this loss of significance is due to the absence of pre-campaign DHS rounds and hence to the absence of a proper counterfactual. The result of the test is reported in Section S2 of the supplemental appendix. Among the 11 countries which are initially endowed with both pre- and post-campaign DHS rounds and which (therefore) display a significant and positive impact of the Global Fund's malaria control campaign in the baseline estimation, only two (Kenya and Uganda) show a significant impact[33] for at least one of the two dependent variables when we rely on OLS (see Table S2-1). IV results provided by Tables S2-2a and S2-2b show a similar pattern. For grade, only three countries are characterized by a significant impact of the Global Fund's malaria control campaign for at least one of the three IV sets,[34] while none shows a significant impact for delay.

One may further expect orders of magnitude among the countries showing positive and significant results to be strongly correlated with pre-campaign malaria risk. Indeed, countries showing higher pre-campaign malaria risk should benefit relatively more from Global Fund's anti-malaria campaigns. Our results confirm this intuition. Notably, the correlation between

[33]Note however that the sign of the coefficient of the interaction term (exposure $\times$ malaria$_j$) is reversed compared to the one found in the baseline estimation.

[34]Again, the sign of the coefficient of the interaction term (exposure $\times$ malaria$_j$) is reversed compared to the one found in the baseline estimation.

orders of magnitude for delay and malaria ecology amounts to 0.48 (significant at the 10% confidence level) in these countries: the higher the pre-campaign malaria risk, the higher the reduction in schooling delay due to the Global Fund's anti-malaria campaigns.

6 Robustness checks

In this section, we first test the robustness of our IV results when we replace our malaria ecology index by other proxies for malaria risk that belong unambiguously to the pre-campaign period. We also ensure that our results hold when we rely on other (non-pre-campaign) proxies. We then analyze whether our IV results hold when we no longer restrict our attention to the Global Fund but estimate instead the impact of exposure to all of the four main anti-malaria campaigns (including the President's Malaria Initiative and World Bank Booster Program for Malaria Control in Africa). Finally, we run a falsification test.

6.1 Alternative malaria ecology variables

We use two alternative measures for malaria ecology that are unambiguously pre-campaign. The first is the malaria ecology index computed by Kiszewski et al. (2004) for the late 1990s. The second derives from the Mapping Malaria Risk in Africa/Atlas du Risque de la Malaria en Afrique (MARA/ARMA) data. It represents the percentage of the population living in holo- and hyper-endemic areas during the year prior to the start of the Global Fund's disbursements in the regions of a subsample (9) of our 22 countries.

Sections S3.1 and S4.1 in the supplemental appendix present OLS estimates of coefficient β in Equation (1) when our malaria ecology index is replaced by Kiszewski et al.'s (2004) index and by MARA/ARMA data respectively. The following controls are included: an interaction term between regional fixed effects and exposure (except for MARA/ARMA data which are measured at the regional level), an interaction term between the alternative malaria ecology and primary student's age, and an interaction term between regional fixed effects and student's date of birth are added. Sections S3.2 and S4.2 of the supplemental appendix present IV estimates of coefficient β in Equation (1) (when the aforementioned controls are included) by distinguishing each of the three sets of instrumental variables.

Our findings are robust to these checks. In the baseline specification, when we rely on

our malaria ecology index, malaria control leads to statistically significant increases in grade and/or statistically significant reductions in schooling delay in 16 of the 22 countries in our sample (see Figure 2). After substituting Kiszewski et al.'s (2004) index, we still find a positive and significant impact of the Global Fund's malaria control campaigns in 15 of the 22 countries, whether we rely on OLS or IV results.

Over the nine countries for which MARA/ARMA data are available, our baseline results show a positive and significant impact of the Global Fund's malaria disbursement on educational outcomes for six of them (see Figure 2). With MARA/ARMA data substituted, this number rises to seven if we rely on OLS estimates. If we rely on IV estimates instead, a positive and significant impact of the Global Fund's malaria control campaigns is observed for at least one of the IV sets in eight countries, whether we focus on grade or delay

We also ensure that our results hold when we rely on two additional proxies for malaria risk. As with our malaria ecology measure, these proxies were computed over periods that are not exclusively pre-campaign. The first of these two proxies is the *P. falciparum* basic reproductive number under control (PfRc) as computed by MAP for the 1985-2010 period. The PfRc measures the potential for malaria to spread at the cluster level, in case the population in this cluster is naive (i.e. not yet affected by malaria) and endowed with its current level of malaria control (see Smith et al. (2007) and Gething et al. (2011)). The PfRc is a function of the human feeding rate, infectivity of mosquitoes to humans (and vice versa), death rate of mosquitoes, number of mosquitoes per human, number of days required for mosquito to complete sporogony, and expected waiting time to naturally clear a simple infection (Smith et al. (2007)). The MAP protocol modify this formula to account for heterogeneous biting behavior and existing control efforts. Therefore, by construction, PfRc correlates well to our malaria ecology index. Section S5 in the supplemental appendix presents our results when our malaria ecology index is replaced by PfRc. We still find a positive impact of the Global Fund's malaria control campaign in a majority of countries: 18 if we rely on OLS and 16 if we rely on our IV approach.

The second additional proxy that we use for malaria risk is an inherited blood disorder called "G6PD deficiency". The use of G6PD deficiency is motivated by the fact that several human innate factors influence malaria infection. For example, individuals who carry the sickle cell trait (heterozygotes for the abnormal hemoglobin gene HbS) will be relatively

protected against severe disease and death caused by *P. falciparum* malaria. The frequency of hemoglobin-related disorders and other blood cell dyscrasias, such as Hemoglobin C, the thalassemias and G6PD deficiency, have also been shown to provide protection from malaria. Due to natural selection, these inherited blood disorders are more frequent in areas showing historically higher malaria risk.

Two inherited blood disorder variables are available in the MAP database: the frequency of G6PD deficiency and the frequency of the sickle cell trait that are computed for the 1959-2010 period. To our knowledge, because it is asymptomatic for most carriers, G6PD deficiency has not been associated with poor educational or cognitive outcomes (Olson et al. (2009)) whereas the sickle cell trait has been associated with central nervous system complications (Armstrong et al. (1996)). We therefore rely on the frequency of G6PD deficiency at the cluster level as a proxy for pre-campaign malaria risk since this variable has no known direct impact on individuals' cognitive skills nor on any variables other than malaria risk that could influence educational outcomes (Cappellini and Fiorelli (2008)). Moreover, it has not been associated with resistance to any other diseases. Put differently, while the frequency of G6PD deficiency indicates the historic burden of malaria within a given area (higher G6PD frequency meaning the area is more malarious), its effect on educational outcomes passes only through malaria risk. We therefore consider it to be a good proxy for this risk.

Section S6 in the supplemental appendix presents our results when our malaria ecology index is replaced by G6PD deficiency. Again, we still find a positive impact of the Global Fund's malaria control campaign in a majority of countries: 16 if we rely on OLS and 15 if we rely on our IV approach.

6.2 Exposure to four main anti-malaria expenditures

According to Pigott et al. (2012), the second, third and fourth largest funders of anti-malaria campaigns to date are the governments of African countries themselves, as well as the President's Malaria Initiative and World Bank Booster Program for Malaria Control in Africa. With respect to our sample, the PMI began disbursing funds to Tanzania and Uganda in 2006. Additional countries were added in 2007 (Malawi, Mozambique, Rwanda, Senegal), 2008 (Ethiopia, Ghana, Kenya, Liberia, Madagascar, Mali, Zambia), and 2011 (DRC, Guinea, Nigeria, Zimbabwe). The World Bank's Booster Program also began in 2006

for Burkina Faso, DRC, Ethiopia, Ghana, Guinea, Kenya, Malawi, Mali, Nigeria, Senegal, Tanzania, and Zambia. It is therefore important to test if our results hold when disbursements from these other major actors (inclusive of governmental expenditures) are also taken into account. These disbursements, kindly provided by David Pigott, allow us to construct a new exposure variable that captures the yearly amount per capita (USD) disbursed by all of the four largest funders of anti-malaria campaigns.

Section S7 in the supplemental appendix presents OLS estimates and IV estimates of coefficient β in Equation (1) respectively, when our original exposure variable is replaced by the global disbursement index. Again, our results barely change.

6.3 Falsification test

We conclude these robustness checks with a falsification test. This test analyzes the impact of exposure to the Global Fund's malaria disbursement on primary education levels of individuals who had already left primary school when the Global Fund's campaign began. More precisely, we define these individuals as those whose age is above the maximum age among our primary school students when the campaign started (this maximum age varies between 24 and 25).

Section S8 in the supplemental appendix presents OLS estimates and IV estimates for this falsification test. As expected, and contrary to what we observe among students who are currently enrolled in primary school, this impact is never robustly positive. Though 12 countries exhibit a significantly positive relationship between (exposure $\times$ malaria$_j$) and the years of education completed when we rely on OLS, this relationship disappears when instrumented.

7 Conclusion

Malaria impacts not just mortality - it also produces nuanced outcomes related to health and education. The early 21st century has seen renewed efforts toward fighting this disease. Various funders have undertaken malaria control efforts in Sub-Saharan Africa, with the Global Fund emerging as a leader in terms of both duration and disbursements. While control efforts have seen substantial decreases in malaria risk, the effects on secondary outcomes such

as education are less clear. With this paper, we seek a better understanding of the impact of malaria control efforts on educational outcomes among primary school students.

Combining a difference-in-differences approach with an IV analysis, we exploit exogenous variation in pre-campaign malaria risk (malaria ecology) and exposure to the timing and expenditure of the Global Fund's malaria control campaigns (based on students' birth and survey years). In a majority of countries (16 of 22), we find that the program leads to substantial increases in grade level and/or reductions in schooling delay. More precisely, we observe that a one standard deviation increase in exposure to malaria control campaigns increases grade level during the current school year by 1.5 standard deviations and decreases delay status for current grade level by 2.1 standard deviations. Put differently, if the Global Fund increases its yearly per capita disbursement over a child's lifetime by 50 cents (USD), this scale-up translates through an increase in grade by 0.8 level. Our findings are robust to the substitution of alternative measures for pre-campaign malaria risk. Moreover, the overall positive impact of malaria control on education is confirmed when disbursements from other major actors (including the President's Malaria Initiative and World Bank Booster Program for Malaria Control in Africa) are also taken into account. Our results are further robust to a falsification test.

Closer analysis of our results shows that their significance depends on the methodological adequacy of the data we use to run our quasi-experimental approach. More precisely, the 16 countries where the impact of Global Fund malaria control is positive and significant are those which are the most suitable for a difference-in-differences analysis: they are more likely to encompass individuals who are not treated at all (i.e. not exposed to the Global Fund's anti-malaria campaign). Put differently, the absence of significance of our results for 6 of the 22 countries of our sample is possibly due to a lack of suitable data, not to ineffective Global Fund anti-malaria campaigns in these countries.

With colossal amounts of funding on the table, researchers have begun to push the Global Fund for "more health for the money."[35] We strive to place our results in this context. To be sure, our estimates of the medium term effects of malaria control campaigns do not get at whether these effects accumulate over time. Therefore, continuing efforts to measure the

[35]In particular, the Center for Global Development's Value for Money Working Group has recently shed a spotlight on such issues.

long term economic effects of massive health investments constitute important avenues for future research.

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9 Figures & tables

Figure 1: Cumulative probability of dying from malaria for children under five (IHME)

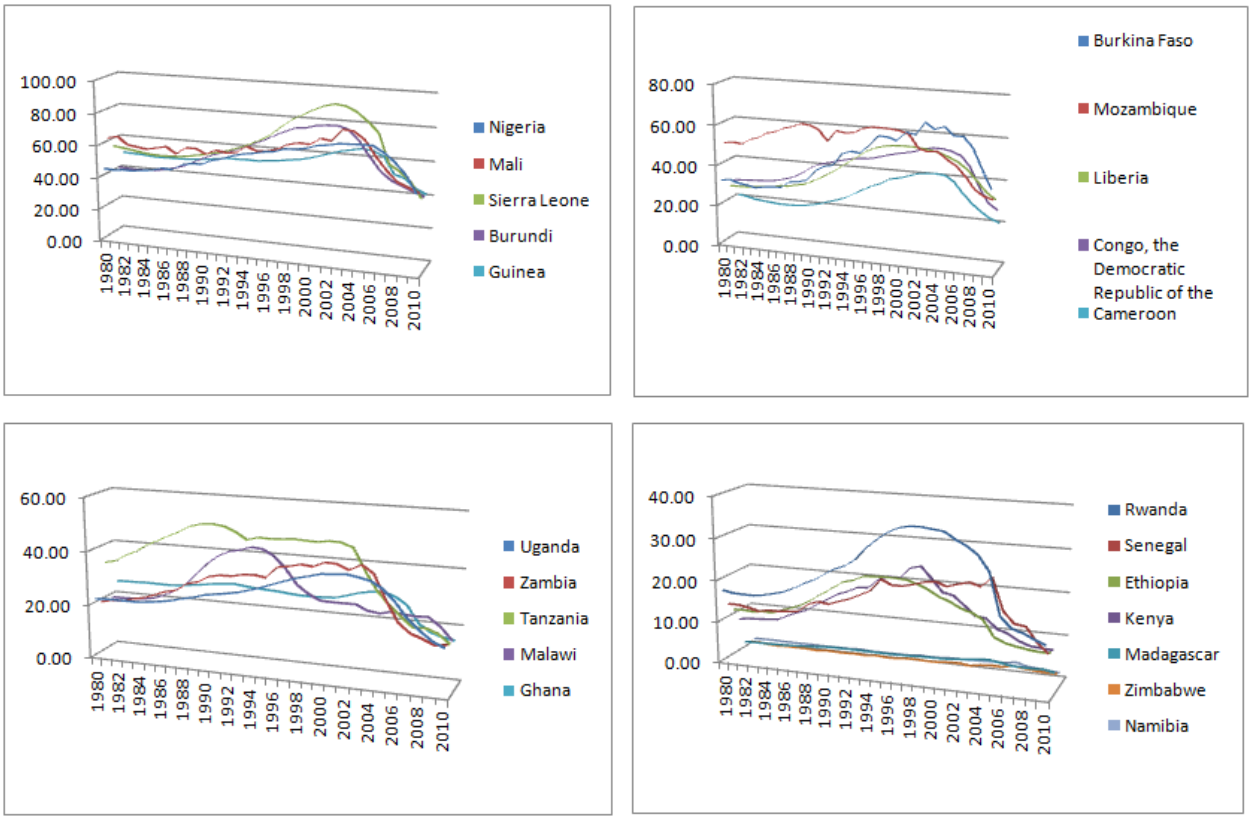

Figure 2: Summary of impact of Global Fund exposure on educational outcomes

Country	OLS		IV	
	Grade	Delay	Grade	Delay
Burkina Faso			+	-
Burundi			+	-
Cameroon			+	-
DRC		+	+	
Ethiopia			+	-
Ghana			+	-
Guinea	-	+		
Kenya			+	-
Liberia	-	-		
Madagascar	+	+		
Malawi	+			-
Mali			+	-
Mozambique	+	-		
Namibia			+	-
Nigeria			+	-
Rwanda			+	-
Senegal			+	-
Sierra Leone	-	+		
Tanzania	+	+		
Uganda	-			-
Zambia	-	+		
Zimbabwe			+	-

Notes: This figure summarizes the results reported in Table 4 (columns 4 and 8) when OLS results are displayed and in Table 5 when IV results are presented. Information on IV results is presented when the Durbin-Wu-Hausman test rejects the null hypothesis for all three of the IV sets, while information on OLS results is presented in the remaining cases. For each dependent variable and country, cases where the impact of the Global Fund's anti-malaria campaign is statistically significant are highlighted in grey, while cases where the impact of the Global Fund's anti-malaria campaign is not statistically significant are reported in white. Plus and minus indicate the sign of coefficient β in Equation (1).

Table 1: Global Fund's anti-malaria campaign start date and DHS survey years available, per country.

	Global Fund's start date	DHS survey years
	(1)	(2)
Burkina Faso	2003	2003; 2010
Burundi	2003	2010; 2011
Cameroon	2004	2004; 2011
DRC	2004	2007
Ethiopia	2003	2000; 2005; 2010
Ghana	2003	2003; 2008
Guinea	2003	2005
Kenya	2003	2003; 2008; 2009
Liberia	2004	2006; 2007
Madagascar	2003	2008; 2009
Malawi	2006	2004; 2005; 2010
Mali	2003	2001; 2006
Mozambique	2004	2011
Namibia	2004	2000; 2006; 2007
Nigeria	2004	2003; 2008
Rwanda	2004	2005; 2010; 2011
Senegal	2003	2005; 2010; 2011
Sierra Leone	2005	2008
Tanzania	2003	2011; 2012
Uganda	2004	2000; 2001; 2006; 2011
Zambia	2003	2007
Zimbabwe	2003	1999; 2005; 2006; 2010; 2011

Notes: DHS survey years refer to the years of available DHS surveys.

Table 2: Testing the parallel trends assumption based on pre-campaign data: OLS estimates for Malawi and Uganda.

	Malawi		Uganda	
	Grade	Delay	Grade	Delay
	(1)	(2)	(3)	(4)
Malaria ecology × DHS survey year dummy	-0.417	0.017	0.118	-0.009
	(0.448)	(0.086)	(0.158)	(0.040)
Malaria ecology	0.077	-0.011	0.085	-0.013
	(0.180)	(0.036)	(0.116)	(0.031)
DHS survey year dummy	0.732ˆ	-0.091	-0.254*	0.042
	(0.395)	(0.075)	(0.115)	(0.029)
Male	-0.150***	0.039***	-0.115***	0.031***
	(0.021)	(0.006)	(0.026)	(0.007)
Age	0.488***	-0.099***	0.460***	-0.102***
	(0.004)	(0.001)	(0.006)	(0.001)
Wealth	0.306***	-0.059***	0.242***	-0.050***
	(0.012)	(0.003)	(0.015)	(0.004)
R^2	0.637	0.471	0.634	0.464
Observations	16,535	16,535	10,190	10,190

Notes: The table reports OLS estimates. The unit of observation is the primary school student. The dependent variable "Grade" stands for grade level during the year when the interview is conducted. The dependent variable "Delay" stands for delay status for grade level. Standard errors (in parentheses) are clustered at the DHS cluster level. ˆ, *, ** and *** indicate significance at the 10, 5, 1 and 0.1% levels.

Table 3: Descriptive statistics

		Mean	SD	Observations	Min	Max
		(1)	(2)	(3)	(4)	(5)
Burkina Faso	Grade	3.31	1.69	16,178	0	6
	Delay	0.37	0.48	16,178	0	1
	Exposure to Global Fund's disbursements	0.29	0.21	16,180	0.00	0.73
	Malaria ecology	0.89	0.19	939	0.00	0.99
	Male	0.54	0.50	16,179	0	1
	Age	10.20	2.61	16,180	5	24
	Wealth	3.45	1.36	16,180	1	5
Burundi	Grade	3.11	1.67	9,110	1	6
	Delay	0.42	0.49	9,110	0	1
	Exposure to Global Fund's disbursements	0.53	0.14	9,113	0.25	0.89
	Malaria ecology	0.68	0.10	381	0.20	0.93
	Male	0.49	0.50	9,113	0	1
	Age	11.87	3.23	9,113	5	24
	Wealth	3.25	1.42	9,113	1	5
Cameroon	Grade	3.27	1.75	26,682	0	7
	Delay	0.39	0.49	26,682	0	1
	Exposure to Global Fund's disbursements	0.32	0.30	26,685	0.00	1.05
	Malaria ecology	0.70	0.12	1,036	0.00	0.95
	Male	0.53	0.50	26,677	0	1
	Age	9.54	3.12	26,685	3	24
	Wealth	2.92	1.31	26,685	1	5
DRC	Grade	3.13	1.66	8,849	0	6
	Delay	0.41	0.49	8,849	0	1
	Exposure to Global Fund's disbursements	0.05	0.01	8,849	0.02	0.09
	Malaria ecology	0.60	0.14	299	0.00	0.82
	Male	0.55	0.50	8,847	0	1
	Age	10.75	3.20	8,849	5	24
	Wealth	3.17	1.39	8,849	1	5
Ethiopia	Grade	3.28	2.00	33,546	0	8
	Delay	0.43	0.50	33,546	0	1
	Exposure to Global Fund's disbursements	0.21	0.17	33,553	0.00	0.62
	Malaria ecology	0.74	0.22	1,615	0.00	1.00
	Male	0.53	0.50	33,553	0	1
	Age	11.98	3.72	33,553	5	24
	Wealth	3.30	1.50	33,553	1	5
Ghana	Grade	3.27	1.67	13,043	0	10
	Delay	0.39	0.49	13,043	0	1
	Exposure to Global Fund's disbursements	0.14	0.11	13,044	0.00	0.50
	Malaria ecology	0.79	0.18	814	0.00	0.99
	Male	0.52	0.50	13,044	0	1
	Age	10.21	2.87	13,044	3	24
	Wealth	2.70	1.39	13,044	1	5

Guinea	Grade	3.20	1.68	5,667	0	6
	Delay	0.41	0.49	5,667	0	1
	Exposure to Global Fund's disbursements	0.05	0.01	5,667	0.02	0.09
	Malaria ecology	0.72	0.16	290	0.00	0.99
	Male	0.55	0.50	5,667	0	1
	Age	10.67	2.93	5,667	5	24
	Wealth	3.45	1.35	5,667	1	5
Kenya	Grade	4.13	2.29	18,671	0	11
	Delay	0.30	0.46	18,671	0	1
	Exposure to Global Fund's disbursements	0.12	0.12	18,672	0.00	0.54
	Malaria ecology	0.49	0.18	793	0.00	0.83
	Male	0.52	0.50	18,672	0	1
	Age	11.41	3.39	18,672	4	24
	Wealth	2.86	1.38	18,672	1	5
Liberia	Grade	3.07	1.71	5,379	1	6
	Delay	0.44	0.50	5,379	0	1
	Exposure to Global Fund's disbursements	0.29	0.09	5,384	0.15	0.94
	Malaria ecology	0.76	0.11	186	0.41	0.96
	Male	0.54	0.50	5,384	0	1
	Age	12.85	3.67	5,384	3	24
	Wealth	3.29	1.39	5,384	1	5
Madagascar	Grade	2.63	1.36	17,273	0	5
	Delay	0.51	0.50	17,273	0	1
	Exposure to Global Fund's disbursements	0.40	0.11	17,275	0.16	0.67
	Malaria ecology	0.72	0.17	594	0.00	1.00
	Male	0.52	0.50	17,275	0	1
	Age	9.37	2.65	17,275	5	24
	Wealth	2.96	1.40	17,275	1	5
Malawi	Grade	3.43	2.15	53,087	0	8
	Delay	0.42	0.49	53,087	0	1
	Exposure to Global Fund's disbursements	0.19	0.15	53,088	0.00	0.50
	Malaria ecology	0.85	0.16	1,382	0.00	1.00
	Male	0.51	0.50	53,088	0	1
	Age	10.72	3.45	53,088	5	24
	Wealth	2.99	1.39	53,088	1	5
Mali	Grade	3.24	1.67	14,726	0	6
	Delay	0.38	0.49	14,726	0	1
	Exposure to Global Fund's disbursements	0.01	0.01	14,729	0.00	0.03
	Malaria ecology	0.79	0.28	741	0.00	0.99
	Male	0.55	0.50	14,727	0	1
	Age	10.16	2.77	14,729	5	24
	Wealth	3.39	1.42	14,729	1	5
Mozambique	Grade	3.50	1.98	14,099	0	7
	Delay	0.39	0.49	14,099	0	1
	Exposure to Global Fund's disbursements	0.28	0.07	14,101	0.12	0.45
	Malaria ecology	0.77	0.14	609	0.00	0.99

	Male	0.50	0.50	14,101	0	1
	Age	10.35	3.15	14,101	5	24
	Wealth	3.41	1.37	14,101	1	5
Namibia	Grade	3.90	1.98	14,992	0	8
	Delay	0.30	0.46	14,992	0	1
	Exposure to Global Fund's disbursements	0.21	0.23	14,995	0.00	0.81
	Malaria ecology	0.31	0.22	731	0.00	0.89
	Male	0.50	0.50	14,993	0	1
	Age	10.58	2.93	14,995	3	24
	Wealth	2.85	1.39	14,995	1	5
Nigeria	Grade	3.22	1.66	28,895	0	6
	Delay	0.40	0.49	28,895	0	1
	Exposure to Global Fund's disbursements	0.04	0.02	28,898	0.00	0.08
	Malaria ecology	0.70	0.14	1,201	0.00	0.99
	Male	0.54	0.50	28,895	0	1
	Age	9.66	2.96	28,898	5	24
	Wealth	3.04	1.31	28,898	1	5
Rwanda	Grade	2.78	1.62	24,921	0	8
	Delay	0.50	0.50	24,921	0	1
	Exposure to Global Fund's disbursements	0.71	0.58	24,922	0.05	2.38
	Malaria ecology	0.59	0.13	967	0.00	0.92
	Male	0.50	0.50	24,922	0	1
	Age	11.17	3.16	24,922	3	24
	Wealth	3.05	1.41	24,922	1	5
Senegal	Grade	3.24	1.71	20,983	0	6
	Delay	0.40	0.49	20,983	0	1
	Exposure to Global Fund's disbursements	0.25	0.16	20,992	0.04	0.63
	Malaria ecology	0.74	0.22	757	0.00	0.99
	Male	0.50	0.50	20,992	0	1
	Age	10.17	2.91	20,992	5	24
	Wealth	2.73	1.29	20,992	1	5
Sierra Leone	Grade	3.25	1.68	8,205	0	6
	Delay	0.39	0.49	8,205	0	1
	Exposure to Global Fund's disbursements	0.05	0.02	8,206	0.02	0.14
	Malaria ecology	0.71	0.16	351	0.00	0.99
	Male	0.51	0.50	8,206	0	1
	Age	9.88	3.16	8,206	3	24
	Wealth	3.31	1.36	8,206	1	5
Tanzania	Grade	3.83	2.04	10,898	1	10
	Delay	0.33	0.47	10,898	0	1
	Exposure to Global Fund's disbursements	0.58	0.13	10,898	0.26	0.97
	Malaria ecology	0.51	0.18	1,080	0.00	0.83
	Male	0.49	0.50	21,126	0	1
	Age	10.99	2.77	21,127	5	24
	Wealth	3.09	1.34	21,127	1	5
Uganda	Grade	3.28	1.90	35,241	0	7
	Delay	0.41	0.49	35,241	0	1

	Exposure to Global Fund's disbursements	0.24	0.21	35,257	0.00	0.70
	Malaria ecology	0.69	0.24	1,070	0.00	0.96
	Male	0.51	0.50	35,257	0	1
	Age	10.78	3.24	35,257	3	52
	Wealth	3.06	1.42	35,257	1	5
Zambia	Grade	3.70	1.95	8,083	0	7
	Delay	0.34	0.47	8,083	0	1
	Exposure to Global Fund's disbursements	0.36	0.09	8,083	0.17	0.67
	Malaria ecology	0.72	0.11	319	0.00	0.91
	Male	0.51	0.50	8,083	0	1
	Age	10.91	2.95	8,083	5	23
	Wealth	3.04	1.37	8,083	1	5
Zimbabwe	Grade	3.82	2.00	24,223	0	7
	Delay	0.32	0.47	24,223	0	1
	Exposure to Global Fund's disbursements	0.18	0.22	24,225	0.00	0.75
	Malaria ecology	0.71	0.19	1,042	0.00	0.98
	Male	0.51	0.50	24,225	0	1
	Age	9.91	2.51	24,225	3	24
	Wealth	2.67	1.37	24,225	1	5

Table 4: Impact of Global Fund's anti-malaria campaign on primary students' educational outcomes: OLS estimates

	Grade				Delay			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Burkina Faso	5.388***	5.184***	17.253***	18.241***	-1.511***	-1.416***	-4.754***	-5.213***
	(1.074)	(1.104)	(3.078)	(4.259)	(0.271)	(0.257)	(0.725)	(1.065)
R^2	0.674	0.676	0.682	0.685	0.561	0.564	0.570	0.573
Observations	16,177	16,177	16,177	16,177	16,177	16,177	16,177	16,177
Burundi	-0.042	0.660	-2.102	-0.083	-0.051	-0.143	1.552	0.654
	(0.930)	(1.095)	(4.011)	(4.248)	(0.283)	(0.344)	(1.513)	(1.718)
R^2	0.704	0.704	0.704	0.707	0.566	0.566	0.566	0.570
Observations	9,110	9,110	9,110	9,110	9,110	9,110	9,110	9,110
Cameroon	5.842***	7.990***	9.206***	8.232***	-2.759***	-3.221***	-3.695***	-3.896***
	(0.959)	(1.144)	(1.036)	(1.062)	(0.252)	(0.300)	(0.269)	(0.324)
R^2	0.662	0.667	0.667	0.669	0.549	0.552	0.553	0.555
Observations	26,674	26,674	26,674	26,674	26,674	26,674	26,674	26,674
DRC	4.190	-6.179	8.881	-21.180	1.572	2.707	-6.342	10.154
	(8.607)	(6.470)	(24.749)	(22.432)	(1.886)	(1.721)	(7.830)	(7.095)
R^2	0.595	0.600	0.600	0.602	0.491	0.491	0.492	0.497
Observations	8,847	8,847	8,847	8,847	8,847	8,847	8,847	8,847
Ethiopia	1.289	6.749***	13.241***	14.658***	-0.487*	-2.034***	-4.486***	-5.448***
	(0.926)	(1.239)	(1.504)	(2.117)	(0.178)	(0.354)	(0.435)	(0.827)
R^2	0.547	0.555	0.557	0.559	0.394	0.400	0.405	0.408
Observations	33,546	33,546	33,546	33,546	33,546	33,546	33,546	33,546
Ghana	8.560***	7.217***	16.043***	14.512***	-4.219***	-3.765***	-6.677***	-5.901***
	(2.071)	(2.028)	(2.094)	(2.085)	(0.786)	(0.765)	(0.776)	(0.774)
R^2	0.593	0.600	0.602	0.605	0.476	0.481	0.484	0.487
Observations	13,043	13,043	13,043	13,043	13,043	13,043	13,043	13,043
Guinea	9.060	3.515	19.646	-11.700	-0.721	-0.709	-7.585	1.185
	(8.443)	(8.963)	(25.647)	(24.082)	(2.116)	(2.048)	(8.823)	(8.267)
R^2	0.626	0.626	0.626	0.629	0.502	0.502	0.502	0.505
Observations	5,667	5,667	5,667	5,667	5,667	5,667	5,667	5,667

Kenya	3.494*	0.867	3.174	5.518*	-4.817***	-3.886***	-6.209***	-6.571***
	(1.636)	(1.874)	(2.196)	(2.394)	(0.512)	(0.772)	(0.794)	(0.883)
R^2	0.724	0.729	0.730	0.731	0.509	0.530	0.533	0.539
Observations	18,671	18,671	18,671	18,671	18,671	18,671	18,671	18,671
Liberia	3.202	3.161	2.815	-0.806	-0.150	-0.632	-1.086	-0.813
	(2.800)	(3.574)	(5.155)	(5.951)	(0.801)	(1.056)	(1.548)	(1.964)
R^2	0.444	0.447	0.447	0.452	0.355	0.357	0.357	0.361
Observations	3,227	3,227	3,227	3,227	3,227	3,227	3,227	3,227
Madagascar	0.515	-0.453	0.094	0.089	-0.215	0.026	0.038	0.348
	(0.554)	(0.620)	(1.571)	(1.589)	(0.175)	(0.188)	(0.649)	(0.638)
R^2	0.623	0.631	0.631	0.632	0.513	0.518	0.518	0.522
Observations	17,273	17,273	17,273	17,273	17,273	17,273	17,273	17,273
Malawi	1.896***	0.530	0.951	1.627*	-3.421***	-3.313***	-5.998***	-5.324***
	(0.537)	(0.514)	(0.697)	(0.752)	(0.333)	(0.371)	(0.275)	(0.327)
R^2	0.701	0.702	0.702	0.702	0.548	0.548	0.558	0.559
Observations	53,087	53,087	53,087	53,087	53,087	53,087	53,087	53,087
Mali	77.587***	246.300***	270.571***	327.517***	-41.628***	-109.811***	-119.710***	-150.649***
	(14.572)	(33.560)	(27.815)	(25.542)	(5.701)	(16.794)	(13.339)	(8.532)
R^2	0.655	0.664	0.664	0.667	0.525	0.544	0.545	0.552
Observations	14,724	14,724	14,724	14,724	14,724	14,724	14,724	14,724
Mozambique	-0.282	1.362	7.961	7.834^	-0.268	-0.227	-1.215	-1.171
	(1.572)	(1.319)	(5.222)	(4.325)	(0.286)	(0.311)	(1.191)	(1.055)
R^2	0.694	0.701	0.701	0.705	0.546	0.546	0.546	0.551
Observations	14,099	14,099	14,099	14,099	14,099	14,099	14,099	14,099
Namibia	5.469***	3.983***	1.140	4.903***	-1.916***	-3.194***	-3.058***	-3.855***
	(0.764)	(1.105)	(1.168)	(1.190)	(0.177)	(0.349)	(0.343)	(0.331)
R^2	0.721	0.724	0.725	0.728	0.568	0.579	0.579	0.584
Observations	14,990	14,990	14,990	14,990	14,990	14,990	14,990	14,990
Nigeria	37.648***	84.952***	121.405***	125.223***	-21.829***	-35.559***	-46.203***	-51.340***
	(5.534)	(7.838)	(7.207)	(8.654)	(1.694)	(2.484)	(2.057)	(2.706)
R^2	0.534	0.541	0.545	0.546	0.423	0.430	0.434	0.436

Observations	28,892	28,892	28,892	28,892	28,892	28,892	28,892	28,892
Rwanda	0.392ˆ	0.636*	0.963*	1.382***	-0.886***	-0.841***	-1.186***	-1.308***
	(0.227)	(0.240)	(0.298)	(0.309)	(0.088)	(0.089)	(0.092)	(0.100)
R^2	0.670	0.671	0.671	0.674	0.545	0.549	0.550	0.555
Observations	24,921	24,921	24,921	24,921	24,921	24,921	24,921	24,921
Senegal	3.758*	2.518	3.112ˆ	4.375*	-1.290***	-1.047*	-2.094***	-2.347***
	(1.238)	(1.557)	(1.851)	(1.988)	(0.347)	(0.440)	(0.563)	(0.639)
R^2	0.622	0.623	0.623	0.625	0.516	0.517	0.518	0.519
Observations	20,983	20,983	20,983	20,983	20,983	20,983	20,983	20,983
Sierra Leone	11.954*	7.888	9.375	-5.345	-2.650	-2.125	-3.690	2.227
	(5.234)	(5.565)	(14.966)	(16.046)	(1.773)	(1.964)	(5.557)	(5.802)
R^2	0.602	0.603	0.603	0.604	0.496	0.496	0.496	0.497
Observations	8,205	8,205	8,205	8,205	8,205	8,205	8,205	8,205
Tanzania	-1.293*	-1.087ˆ	-5.648*	3.589	-0.168	0.277	1.866***	0.356
	(0.509)	(0.603)	(2.225)	(3.391)	(0.153)	(0.174)	(0.531)	(0.731)
R^2	0.761	0.763	0.763	0.766	0.578	0.582	0.582	0.586
Observations	10,898	10,898	10,898	10,898	10,898	10,898	10,898	10,898
Uganda	-1.286*	-0.541	-0.552	-0.467	-0.757***	-1.051***	-1.355***	-1.336***
	(0.559)	(0.515)	(0.656)	(0.638)	(0.175)	(0.209)	(0.263)	(0.267)
R^2	0.701	0.702	0.702	0.703	0.530	0.532	0.532	0.532
Observations	35,241	35,241	35,241	35,241	35,241	35,241	35,241	35,241
Zambia	-0.303	0.209	-8.719ˆ	-4.659	-0.343	-0.225	1.866	0.823
	(1.589)	(1.727)	(4.888)	(4.712)	(0.441)	(0.451)	(2.082)	(1.645)
R^2	0.699	0.701	0.701	0.702	0.538	0.538	0.539	0.542
Observations	8,083	8,083	8,083	8,083	8,083	8,083	8,083	8,083
Zimbabwe	2.502*	3.944***	3.901***	4.787***	-2.050***	-2.599***	-3.348***	-3.859***
	(0.941)	(1.027)	(1.121)	(1.222)	(0.316)	(0.423)	(0.389)	(0.400)
R^2	0.761	0.762	0.762	0.763	0.588	0.591	0.592	0.594
Observations	24,223	24,223	24,223	24,223	24,223	24,223	24,223	24,223
Individual controls	yes	yes	yes	yes	yes	yes	yes	yes
Year of birth fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
DHS cluster fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

DHS survey year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
exposure x regional fixed effects	no	yes	yes	yes	no	yes	yes	yes
age x malaria ecology	no	no	yes	yes	no	no	yes	yes
year of birth x regional fixed effects	no	no	no	yes	no	no	no	yes

Notes: The table reports OLS estimates. The unit of observation is the primary school student. The dependent variable "Grade" stands for grade level during the year when the interview is conducted. The dependent variable "Delay" stands for delay status for grade level. Columns 1 and 5 include controls for gender, age and wealth, as well as fixed effects for year of birth, DHS cluster, and DHS survey year. Columns 2 and 6 add an interaction term between regional fixed effects and exposure. Columns 3 and 7 add an interaction term between malaria ecology and primary student's age. Columns 4 and 8 add an interaction term between regional fixed effects and student's date of birth. Standard errors (in parentheses) are clustered at the DHS cluster level. ^, *, ** and *** indicate significance at the 10, 5, 1 and 0.1% levels.

Table 5: Impact of Global Fund's anti-malaria campaign on primary students' educational outcomes: IV estimates

	Grade			Delay		
	Set I	Set II	Set III	Set I	Set II	Set III
	(1)	(2)	(3)	(4)	(5)	(6)
Burkina Faso	45.376***	36.922***	33.211***	-12.525***	-10.171***	-9.238***
	(2.698)	(1.960)	(1.974)	(0.633)	(0.375)	(0.397)
R^2	0.650	0.654	0.654	0.527	0.530	0.531
Observations	15,448	15,448	15,448	15,448	15,448	15,448
Durbin-Wu-Hausman χ^2	173.863***	198.503***	65.944***	117.766***	129.455***	52.291***
Burundi	42.448***	40.797***	37.601***	-7.704*	-7.301*	-5.834*
	(10.124)	(11.493)	(8.278)	(2.835)	(3.518)	(2.302)
R^2	0.671	0.672	0.673	0.531	0.531	0.532
Observations	9,110	9,110	9,110	9,110	9,110	9,110
Durbin-Wu-Hausman χ^2	29.221***	14.051***	34.612***	11.112***	5.299**	10.644***
Cameroon	23.648***	22.652***	15.723***	-6.574***	-7.444***	-6.102***
	(1.663)	(1.249)	(0.991)	(0.410)	(0.315)	(0.243)
R^2	0.626	0.628	0.635	0.516	0.513	0.518
Observations	26,591	26,591	26,591	26,591	26,591	26,591
Durbin-Wu-Hausman χ^2	240.458***	578.542***	296.371***	82.839***	392.402***	320.010***
DRC	1486.784*	1681.956	1137.694*	-148.584	-208.789	-146.127
	(693.051)	(1408.199)	(489.516)	(101.511)	(213.697)	(78.562)
R^2	0.419	0.373	0.486	0.450	0.434	0.451
Observations	8,642	8,642	8,642	8,642	8,642	86,42
Durbin-Wu-Hausman χ^2	23.190***	12.725***	44.836***	1.620	1.834	6.262**
Ethiopia	45.775***	44.844***	20.640***	-22.010***	-19.341***	-7.615***
	(6.933)	(3.032)	(1.995)	(2.570)	(0.919)	(0.495)
R^2	0.430	0.432	0.461	0.178	0.215	0.307
Observations	32,802	32,802	32,802	32,802	32,802	32,802
Durbin-Wu-Hausman χ^2	126.860***	457.592***	213.396***	403.318***	1109.530***	317.895***
Ghana	78.195***	38.561***	33.867***	-23.488***	-15.844***	-14.521***
	(6.984)	(2.591)	(2.451)	(1.931)	(0.682)	(0.639)

R^2	0.515	0.558	0.560	0.406	0.434	0.437
Observations	12,797	12,797	12,797	12,797	12,797	12,797
Durbin-Wu-Hausman χ^2	188.339***	165.469***	99.171***	112.704***	268.558***	213.246***
Guinea	8.661	772.856	-28.386	168.514	-35.325	34.553
	(767.613)	(599.320)	(248.371)	(277.766)	(133.238)	(67.151)
R^2	0.580	0.525	0.579	0.402	0.442	0.440
Observations	5,464	5,464	5,464	5,464	5,464	5,464
Durbin-Wu-Hausman χ^2	0.003	2.128	0.459	0.730	0.026	1.245
Kenya	21.240***	33.247***	18.564***	-19.205***	-22.005***	-14.870***
	(3.007)	(2.918)	(2.534)	(0.820)	(0.696)	(0.667)
R^2	0.701	0.697	0.702	0.463	0.446	0.481
Observations	18,503	18,503	18,503	18,503	18,503	18,503
Durbin-Wu-Hausman χ^2	57.951***	238.477***	63.790***	854.176***	1160***	567.238***
Liberia	-19.641^	-12.705	-14.393^	7.453*	4.926^	5.460*
	(10.146)	(8.616)	(8.236)	(3.281)	(2.677)	(2.687)
R^2	0.400	0.401	0.401	0.303	0.305	0.305
Observations	3,227	3,227	3,227	3,227	3,227	3,227
Durbin-Wu-Hausman χ^2	-4.330	8.692***	-14.621	-10200	14.648***	26.636***
Madagascar	-22.491*	-16.919^	-19.248*	6.405*	2.588	5.805*
	(7.010)	(9.356)	(5.964)	(2.447)	(2.945)	(2.114)
R^2	0.588	0.590	0.589	0.474	0.477	0.475
Observations	16,901	16,901	16,901	16,901	16,901	16,901
Durbin-Wu-Hausman χ^2 -1780	114.113***	-1620	-130	22.228***	-205	
Malawi	3.517***	2.967***	3.064***	-8.199***	-8.514***	-8.165***
	(0.845)	(0.853)	(0.832)	(0.172)	(0.189)	(0.172)
R^2	0.678	0.678	0.678	0.532	0.531	0.532
Observations	52,187	52,187	52,187	52,187	52,187	52,187
Durbin-Wu-Hausman χ^2	9.877***	0,387	1,419	454.235***	552.975***	477.814***
Mali	316.679***	313.686***	310.173***	-158.094***	-156.876***	-154.524***
	(22.265)	(21.899)	(21.730)	(5.519)	(5.347)	(5.290)
R^2	0.620	0.620	0.620	0.496	0.496	0.496
Observations	14,678	14,678	14,678	14,678	14,678	14,678

Durbin-Wu-Hausman χ^2	9.720***	11.376***	8.453***	46.536***	77.523***	62.4278***
Mozambique	-642.933^	-253.536	-124.365*	32.258	30.006	12.171
	(365.397)	(196.594)	(50.121)	(30.540)	(31.155)	(8.363)
R^2	0.059	0.569	0.642	0.485	0.488	0.506
Observations	14,052	14,052	14,052	14,052	14,052	14,052
Durbin-Wu-Hausman χ^2	-209	-713	7590***	-1270	28.524***	18400***
Namibia	6.031***	6.874***	5.644***	-4.535***	-4.940***	-4.424***
	(1.340)	(1.386)	(1.327) (0.348)	(0.359)	(0.349)	
R^2	0.708	0.708	0.708	0.557	0.557	0.557
Observations	14,733	14,733	14,733	14,733	14,733	14,733
Durbin-Wu-Hausman χ^2	7.680**	16.890***	4.840**	20.843***	46.062***	19.598***
Nigeria	207.595***	181.821***	168.542***	-79.108***	-72.578***	-69.243***
	(13.861)	(9.839)	(8.905)	(3.952)	(2.696)	(2.451)
R^2	0.511	0.513	0.514	0.397	0.399	0.400
Observations	28,837	28,837	28,837	28,837	28,837	28,837
Durbin-Wu-Hausman χ^2	133.269***	215.670***	161.704***	137.482***	278.665***	257.881***
Rwanda	2.066***	2.056***	1.982***	-2.441***	-2.462***	-2.357***
	(0.402)	(0.401)	(0.388)	(0.126)	(0.126)	(0.122)
R^2	0.645	0.645	0.645	0.517	0.517	0.517
Observations	24,801	24,801	24,801	24,801	24,801	24,801
Durbin-Wu-Hausman χ^2	37.922***	38.928***	38.096***	252.904***	275.463***	251.383***
Senegal	29.950***	40.501***	17.880***	-13.380***	-13.440***	-7.606***
	(8.170)	(9.616)	(3.330)	(2.871)	(2.989)	(1.187)
R^2	0.592	0.584	0.598	0.471	0.471	0.484
Observations	20,442	20,442	20,442	20,442	20,442	20,442
Durbin-Wu-Hausman χ^2	21.725***	64.708***	35.611***	42.228***	56.378***	58.423***
Sierra Leone	-150.939	-248.241	110.495	54.074	46.735	-25.493
	(188.966)	(316.604)	(68.038)	(57.395)	(89.742)	(20.472)
R^2	0.563	0.552	0.568	0.449	0.452	0.459
Observations	8,123	8,123	8,123	8,123	8,123	8,123
Durbin-Wu-Hausman χ^2	1.205	0.087	-4.389	1.397	1.735	0.605
Tanzania	5.350	5.046	3.923	8.117***	6.617*	7.072***

	(7.376)	(8.561)	(6.844)	(2.141)	(2.576)	(1.949)
R^2	0.748	0.748	0.748	0.555	0.556	0.555
Observations	10,564	10,564	10,564	10,564	10,564	10,564
Durbin-Wu-Hausman χ^2	-42.828	-41.894	-42.688	-31.463	-33.966	-31.185
Uganda	8.296***	8.734***	0.865	-7.252***	-7.139***	-3.890***
	(1.575)	(1.568)	(1.192)	(0.504)	(0.508)	(0.421)
R^2	0.679	0.679	0.681	0.494	0.494	0.503
Observations	32,747	32,747	32,747	32,747	32,747	32,747
Durbin-Wu-Hausman χ^2	82.561***	95.944***	1.648	326.309***	326.894***	105.383***
Zambia	-30.106	-30.002	-21.619	-3.043	-2.012	-3.264
	(39.137)	(69.840)	(30.845)	(9.334)	(17.535)	(8.135)
R^2	0.680	0.680	0.680	0.516	0.516	0.516
Observations	8,083	8,083	8,083	8,083	8,083	8,083
Durbin-Wu-Hausman χ^2	-5,078	124,886	-16,467	-0.538	889.775***	-56.825
Zimbabwe	7.320***	9.220***	6.588***	-7.421***	-8.229***	-5.613***
	(1.817)	(1.971)	(1.610)	(0.421)	(0.404)	(0.451)
R^2	0.750	0.749	0.750	0.568	0.564	0.572
Observations	23,759	23,759	23,759	23,759	23,759	23,759
Durbin-Wu-Hausman χ^2	33.1346***	70.902***	43.680***	363.103***	496.124***	177.999***
Individual controls	yes	yes	yes	yes	yes	yes
Year of birth fixed effects	yes	yes	yes	yes	yes	yes
DHS cluster fixed effects	yes	yes	yes	yes	yes	yes
DHS survey year fixed effects	yes	yes	yes	yes	yes	yes
exposure x regional fixed effects	yes	yes	yes	yes	yes	yes
age x malaria ecology	yes	yes	yes	yes	yes	yes
year of birth x regional fixed effects	yes	yes	yes	yes	yes	yes

Notes: The table reports IV estimates. The unit of observation is the primary school student. The dependent variable "Grade" stands for grade level during the year when the interview is conducted. The dependent variable "Delay" stands for delay status for grade level. Sets I, II, and III of instrumental variables are reported for each dependent variable. Standard errors (in parentheses) are clustered at the DHS cluster level. ˆ, *, ** and *** indicate significance at the 10, 5, 1 and 0.1% levels.