Title:

Impact of a malaria elimination campaign on school outcomes: Evidence from Southern Mozambique

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Abstract

We exploit an ongoing malaria elimination project implemented in Magude district (Southern Mozambique) that started in 2015 as a quasi-experiment to estimate the impact of malaria on school outcomes. We use as control a neighbouring district (Manhiça) with similar socio-economic and epidemiological characteristics. Using a difference-in-differences approach, we first show that malaria incidence significantly dropped due to the intervention in the treated district. We then examine whether this positive health shock had an impact on school achievement. Using previously unexplored school registers, we generated a dataset on school attendance and grades for 9,848 primary-school students from 9 schools (4 in the intervention district and 5 in the control district). We find that the elimination project led to a significant increase in both school attendance and grades, by 28% and 2%, respectively. Our results are robust across several specification checks. Our findings provide solid evidence on the negative impact of malaria on human capital accumulation and suggest strong economic arguments for investing in its elimination.

1) Introduction

Despite substantial improvements achieved over the past decade, malaria remains one of the leading causes of mortality and morbidity in Sub-Saharan Africa, which is estimated to host the 92% of global malaria cases (WHO, 2018). Children are at highest risk of contracting the infection and carry most of the disease burden. If not promptly diagnosed and treated, the infection can turn into severe or cerebral malaria and lead to long-term disability or death (Carneiro et al., 2010; WHO, 2018). The burden of malaria goes far beyond its impact on health. At the aggregate level, an influential work provided evidence on the association between countries' poverty (low gross domestic product per capita), low economic growth rate and malaria incidence (Gallup & Sachs, 2001).

There are several mechanisms through which the disease constrains economic development. Most of the literature examines the direct causes, such as the high medical costs and income losses due to illness (Sachs & Malaney, 2002). Since the early 2000s, increasing attention has been placed on exploring the indirect causes, such as the impact of the disease on human capital accumulation, one of the central drivers of economic growth and development across the main theoretical and empirical literature (Heckman, Lance, & Petra, 2006; Krueger & Lindah, 2001; E. Lucas, 1988; Mankiw, Romer, & Weil, 1992; Mincer, 1974; Nelson & Phelps, 1966; Romer, 1990; Temple, 1999; Topel, 1999).

Research has extensively shown the significance and magnitude of the links between early life health related events and circumstances with later health and economic outcomes such as labour market outcomes (see (Almond & Currie, 2011) for a review). Moreover, there is significant evidence on the causal effects of diseases' occurrence early in life on adulthood outcomes (see for example, Bhalotra and Venkataramani (2013) for waterborne diseases; Bhalotra and Venkataramani (2015) and Lazuka (2018) for pneumonia; or H. Bleakley (2007) for hookworm infections.

Within the context of malaria, extensive biomedical and epidemiological literature has pointed to childhood malaria as a significant contributor of long-term low cognitive performance (Holding & Snow, 2001). According to this literature, the contribution of malaria to children's poor cognitive outcomes starts before birth, during mothers' pregnancy, when malaria worsens maternal anaemia, impeding in utero nutrition and limiting the new-born's cognitive development later in life (Lozoff & Georgieff, 2006). In utero exposure to malaria can also have long-term economic consequences, by lowering educational achievement and decreasing income levels in adulthood (Barreca, 2010).

Cerebral malaria during early childhood has also been seen associated with increased cognitive deficits among childhood survivors after hospital discharge and up to 2 years later (Boivin et al., 2007; Idro et al., 2010; John et al., 2008). In a study in Kenya, cognitive impairments persist nine years after an episode of cerebral malaria (Carter et al., 2005).

Even in the absence of a severe manifestation of the disease, prolonged and repeated attacks of uncomplicated malaria can deteriorate children's cognitive performance. A series of observational studies in Sri Lanka carried out at primary schools, including a cross-sectional (Fernando, Wickremasinghe, Mendis, & Wickremasinghe, 2003), a case-control (Fernando, de Silva, & Wickremasinghe, 2003) and a historical cohort study (S. Fernando et al., 2003) find uncomplicated malaria as a significant predictor of students' cognitive performance, both in the short and long-term (6 years of follow-up). These studies use specific cognitive tests but also school outcomes such as routine end of term grades or compulsory education completion to assess students' cognitive performance.

School outcomes are widely used and recognized as valid proxies for short-term human capital accumulation within the social sciences arena (OECD, 2009). As an example, malaria has been seen associated with higher primary repetition rates in Mali in a study using self-reported school outcomes from repeated cross-sectional data (Thuilliez et al., 2010).

Most of the aforementioned research indicates a clear association between malaria and cognitive impairment during childhood, but fails to prove causality between the two factors. To address identification concerns, a few randomized controlled trials (RCT) have been carried out in Asia and Sub-Saharan Africa (SSA), providing evidence on the causal impact of childhood malaria preventive interventions on educational and cognitive outcomes, in the short-term (Clarke et al., 2017; Fernando, de Silva, Carter, Mendis, & Wickremasinghe, 2006), but also after one year (Clarke et al., 2008) and 15 years of follow-up (Jukes et al., 2006).

Alternatively, a recent body of economic literature has assessed long-term impacts of childhood malaria on economic outcomes through retrospective studies on secondary data using quasi-experimental health shocks, namely past eradication campaigns, as exogenous sources of variation in exposure. A. M. Lucas (2010) combines malaria intensity variation across regions prior to the intervention and cohort exposure over time to the malaria elimination campaign and finds that in Paraguay and Sri Lanka, malaria eradication significantly improved educational attainment. Shih and Lin (2018) also find a sharp increase in education attainment for men and married men's spouses as a result of the Taiwan's eradication campaign in the 1950s. A recent study that assesses the impact of an elimination initiative in south-western Uganda also points to a positive impact of the campaign on increasing primary school completion (Barofsky, Anekwe, & Chase, 2015).

On the other hand, no evidence from the eradication campaign in India on increased educational attainment for men and mixed evidence for women. A similar study provides significant evidence either on educational outcomes of the eradication campaigns in the United States, Brazil, Colombia and Mexico (H Bleakley, 2010; Venkataramani, 2012).

Employing a similar identification strategy, the present paper uses the first-year of a malaria elimination project in Southern Mozambique that started in August 2015, named the *Magude* project (Aide et al., 2019), as a natural experiment to explore the impact of malaria on school outcomes. Given that the malaria elimination project only takes place in Magude district, we exploit variability in key outcomes of interest across time between Magude district and a neighbouring district Manhiça (not subject to the intervention), and are able to estimate the causal effects of the elimination campaign on selected school outcomes.

Our study provides a clear contribution to the identification and measurement of the impact of malaria on school outcomes in comparison with the aforementioned studies.

Most studies that use eradication initiatives as quasi-exogenous shocks have employed campaigns that date back from 60-70 years. Available data comes mainly from national demographic and health surveys. These data often lack appropriateness as they were collected for more general purposes rather than being specific to those outlined in the studies and its collection process has been out of researchers' control. Retrospective data backing from 60-70 years not only compromises the accuracy and interpretability of the findings, but also limits its practicality in guiding countries' policymaking strategies.

Unlike these studies, we were able to directly collect and monitor all necessary data on site as well as to control for a variety of key factors when evaluating the impact of the on-going initiative. In addition, our paper employs a sample of more than 9,000 primary-school students, making our estimates generalizable to other population-wide malaria elimination efforts implemented in similar contexts.

As a first step, we assess the health impact of the first year of malaria elimination interventions by comparing changes in malaria incidence between Magude and Manhiça districts using ministry of health routine surveillance data. We conduct a difference-in-difference analysis and find that the campaign reduced malaria incidence by 2 cases per 1,000 population every week.

Next, we study whether the improved health outcomes affected students' school outcomes, namely students' attendance and performance (grades) over the same period of time. A reduction in malaria incidence could affect students' performance through two main channels: 1) by increasing the amount of time spent at school, which, mechanically, would increase the amount of knowledge accumulated; 2) by improving the health status of the student. In this case students' cognitive ability may work at its full, which would result in better school performance, irrespective of a reduction in absenteeism.

To estimate the impact of the project on our main school outcomes independently, we also provide some evidence on the presence of these two channels and the role that absenteeism might be playing on students' cognitive performance, by exploiting rich data at the student level.

Our results show that, consequent to the elimination campaign which significantly reduced malaria incidence in the region, students' absenteeism levels also experienced a marked decrease. More specifically, one year after the start of the campaign school absenteeism decreased by 28%. We also find a significant positive impact on school performance, both when using grades as a continuous variable (mean grade) as well as a discrete variable (probability of passing the exams). While the initiative has an independent and significant impact on both students' attendance and performance, we demonstrate that part of the effect on the latter results from reduced absenteeism. Our findings remain unaltered to a series of robustness checks that account for potential selection or confounding effects related to students' characteristics.

The paper is organized as follows: Section 2 describes the context of the malaria elimination campaign, Section 3 provides details on the sample design and evaluation, Section 4 presents the empirical strategy, Section 5 shows the results, Section 6 performs a series of robustness checks to validate the papers' findings and Section 7 concludes.

2) Malaria initiatives in Mozambique

Mozambique is among the 10 countries in the world with the highest burden of malaria, with over 10 million cases and about 15,000 malaria-related deaths in 2017. Malaria represents the main cause of death in children under the age of 5 (WHO, 2018).

Southern Mozambique has historically been targeted for malaria elimination as part of regional efforts aiming to interrupt transmission in South Africa and Eswatini (formerly Swaziland). One of the most relevant initiatives is the Lubombo Spatial Development Initiative (LSDI), which took place in the early 2000s and involved the governments of these countries. The initiative significantly reduced the burden of malaria, but the gains could not be sustained due to financial constraints, lack of leadership and poor regional coordination (Maharaj, Moonasar, Baltazar, Kunene, & Morris, 2016).

Since then, the Mozambican National Malaria Control Program (NMCP) has focused on intensifying the core malaria control interventions recommended by the WHO (2016). This has resulted in a significant reduction of malaria incidence (Ministério da Saúde, 2015), but gains have stagnated since 2014. In contrast, Mozambique's bordering countries have successfully moved towards pre-elimination stages.

Within this context and in line with regional efforts, in 2014, a new initiative was funded to design and implement a program to support the National Malaria Control Program (NMCP) to accelerate towards malaria elimination in southern Mozambique by 2020 (see Figure A1 in the appendix for a map of the provinces in Mozambique).

The program started by generating evidence through a pilot project in the district of Magude, Maputo province. The implementation package consisted in universal indoor residual spraying (IRS) (August 2015) deployed before the rainy season, followed by two monthly population-wide Mass Drug Administration (MDA) rounds with Dihydroartemisinin-Piperaquine (DHA/PPQ) (November 2015 to beginning February 2016). The same package of interventions (IRS followed by two monthly MDA rounds) was implemented one year later, along with the establishment of a reactive case detection system to rapidly detect, report and respond with focal MDA at the index cases' household level.

The impact of the *Magude* project on disease morbidity and mortality has been assessed through a before-after comparison of community-based parasite prevalence, clinical malaria incidence and inpatient admissions and mortality. An interrupted time series model has been used to estimate the number of cases averted throughout the project (Galatas, Martí-Soler, et al., 2019). This study reveals that the Magude project has led to a significant reduction in infection prevalence and disease incidence, although transmission has not been interrupted. These findings are corroborated by another study which has applied the synthetic control method and employed data from 17 neighbouring districts to construct a weighted counterfactual (Thomas, Cirera, Brew, Saúte, & Sicuri, 2019).

Within the context of this study, we estimate the extent of the project's health effect (a reduction in malaria incidence) by applying a third approach: a difference-in-difference analysis that evaluates the relative changes in malaria incidence between the treated district –Magude- and the selected control district –Manhiça- across the period of time of this study.

3) Data

We assess the health impact of the initiative by using weekly malaria incidence data from the Boletim Epidemiológico Semanal (BES), the NMCP's epidemic disease reporting system. Weekly incidence is calculated by dividing the number of cases reported through BES by the individuals identified through the Demographic Surveillance System (DSS) of Manhiça (Sacoor et al., 2013) and Magude districts (Galatas, Nhacolo, et al., 2019). The contextual variables used in the model include weekly weather data (rainfall, average temperature and minimum temperature) retrieved from the National Oceanic and Atmospheric Administration (NOAA)[1] (table 1).

Table 1. Summary statistics on malaria incidence, weather conditions and socioeconomic characteristics of primary school-age children in treated and control districts in 2015 (pre-intervention period)

Variables	**Manhiça (control)**		**Magude (treatment)**	
	mean	**SD**	**Mean**	**SD**
Malaria incidence (cases/1,000 pop)	6.1	2	3.9	3
Rainfall (mm)	0.99	1	0.93	1
Average temperature (ºC)	24.03	2	24.2	2
Minimum temperature (ºC)	17.1	3	17.1	4
Socioeconomic characteristics of all children aged 6-12				
age	9.9	2	9.7	2
number siblings household	4.3	2	4.8	3
average household size	6.4	3	7.9	4
sex (% females)	50%		50%	
head of the household with primary school studies finished(%)	19%		10%	
has electricity (%)	47%		31%	
has bike (%)	23%		30%	
has telephone (%)	87%		77%	
Number of observations (primary school-age children)	37,974		11,122	

Notes: Weather data are from the National Oceanic and Atmospheric Administration (NOAA). Socioeconomic data refers to all children between 6 and 12 years old from the latest demographic census from 2015, in Manhiça and Magude districts

In order to identify the effects of the initiative on school outcomes, we created a novel dataset containing individual level data from a sample of primary school children, aged between 6 and 12 years. Based on information provided by the Ministry of Education (table 2), we randomly selected 5 public schools from Magude and 4 for Manhiça, based on the probability

[1] NOAA data are presented at the province level. As Magude and Manhiça belong to the same province (Maputo province) there is no variation between the two districts. To solve this, we created a weighted function for each district and estimated weather variables based on districts' centroid proximity to 27 different weather stations

proportional to size sampling provided by WHO STEPS Sample Size Calculator (see figure 1). Within each school, all children enrolled during the academic years 2015 and 2016 were considered for inclusion in the study. The socioeconomic characteristics of all primary school age children in the treated and control districts are very similar (Table 1). Socio-demographic data comes from the DSS systems of Manhiça (Sacoor et al., 2013) and Magude (Galatas, Nhacolo, et al., 2019).

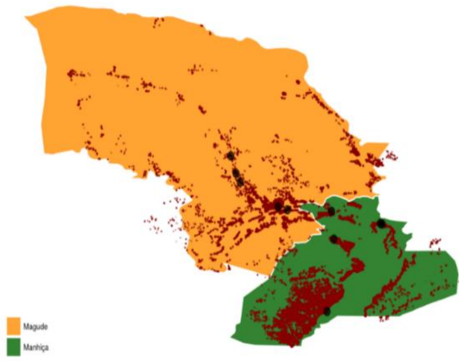
Table 2. Public Primary schools and enrolled students in control and treatment districts, 2015

Variables	**Manhiça (control)**	**Magude (treatment)**
Number of primary schools	96	63
Number of enrolled students	36,753	10,865
% female students	49%	48%
average number of students per school	383	172

Information on school outcomes is gathered from schools' paper records and consists of students' daily absenteeism as well as routine end of term examinations. Information is digitized through pictures taken page by page from the paper registries and then entered in a central database[2]. Examples of original data taken from schools' registers are included in the appendix section (figures A2 and A3).

Figure 1. Schools' location in the districts of Magude and Manhiça

[2] We used a team of 10 data entry clerks and the OpenClinica open source software for the digitalization process. Double manual entry was performed, which is still considered as the gold standard of good clinical practice for data from collected paper forms.



Notes: Map of selected schools from Magude (in orange) and Manhiça (in green) districts. The black dots represent the schools' locations within each district. The red dots are the households' geolocation identified in the 2015 demographic census.

The first package of interventions, comprising one round of IRS followed by two rounds of MDA finished earlier February 2016, so our school data covers the period from one academic year prior to the MDA implementation, from February to October 2015, to one academic year after, from February to October 2016. There is no data for November, December and January as these are school holiday months (see figure A4 in the annex).

Our final sample includes information on school outcomes for 2,761 students in the treatment area and 7,087 students in the control area. For each student, the daily absenteeism level is a binary variable, for the eligible schooldays (excluding weekends and public holidays), that takes the value 0 -if student present- or -if student absent. Grades are measured each trimester, on a scale from 0 to 20, for the following subjects: natural sciences, social sciences, maths, music, physical education, portuguese (language) and visual education. Teachers are responsible for grading each student based on individual tests, which are uniform across all schools in the country. Table 3 provides the means for the outcome variables of interest: absenteeism levels (Panel A) and mean grades for all subjects (in Panel B) for the treatment and control areas, before and after the intervention. Absenteeism was higher in the treatment area before the intervention and this difference disappears once the intervention takes place.

Similarly, average grades were lower in the treatment area before the intervention but overpass those in the control area after the intervention[3].

Table 3. Sample design and difference in predictor means

	2015 (pre-intervention)			2016 (post-intervention)		
	Treat (i)	**Control (ii)**	**Diff.**	**Treat (iv)**	**Control (v)**	**Diff.**
Panel A. Absenteeism						
Mean absenteeism level	7.60%	6.50%	**1.10%**	6.20%	6.30%	**-0.10%**
	(2.65)	(2.45)		(2.41)	(2.43)	
Number of students	1,252	3,532		1,602	2,904	
Number of observations	143,506	361,920		196,652	294,333	
Panel B. Performance						
Mean grade (all subjects)	12.13	12.28	**-0 .2**	12.52	12.43	**0.1**
	(2.76)	(2.77)		(2.75)	(2.78)	
Number of students	1,428	3,965		1,730	4,197	
Number of observations	28,518	79,971		34,853	86,240	

Notes: The pre-intervention period is the academic year 2015 (from February until October) and the post-intervention period is the academic year 2016 (from February until October). The sample consists of all students with available data on absenteeism and performance within the 9 randomly selected schools.

Data attrition occured due to mismatches in the matching process of students over time (the match is based on students' names and surnames), to students' dropout rates or to inaccuracies in the schools' management of the registries. Therefore, our panel is unbalanced

[3] The higher absenteeism level in the pre-intervention period in the treated area might be partially driven by the fact that Magude is a much larger and less populated district, with longer distances from students' households' to school on average, and poorer roads and infrastructure. Although sharing important characteristics from any rural district in Southern Mozambique, Magude district shows lower socioeconomic levels as reflected by key indicators such as lower access to electricity, lower parents' educational level or bigger average household size. However, these characteristics of the district remain constant in our two-year sample period and are captured in our econometric specification by the treatment dummy variable.

and we treat our database as repeated cross-sections. In the annex (table A1) we provide further details regarding the sample's structure and design and in the robustness checks section we further explore issues related to sample selection.

4) Empirical models

To identify the effects of the first year of malaria interventions on clinical malaria incidence we estimate the following model:

$Y_{jt} = \alpha + \beta_1 Treatment_j + \beta_2\ After_t + \beta_3 Treatment_j * After_t + \lambda_m +$

$\delta Precipitation_{jt} + \sigma Temperature_{jt} + \varepsilon_{jt}$ **(1)**

Where Y_{jt} is malaria weekly incidence in district *j* in week *t*, $Treatment$ is a binary variable equal to 1 for Magude district (intervention district); $after$ is equal to 1 for the period after the deployment of universal IRS followed by two monthly consecutive rounds of MDA (February 2016). The coefficient of the interaction term $Treatment * After$, $\hat{\beta}3$, identifies the effects of the intervention. We include month fixed effects (FE) to control for malaria seasonality patterns (λ). We additionally include climatic variables, such as weekly minimum temperature and precipitation, given their strong influence on malaria transmission (Thomson et al., 2017). As the effects of climatological factors (rain and temperature) on malaria incidence can be delayed, we also allow for lagged effects (lags 6 and 7 of weekly mean temperature and 12 of weekly precipitation) of these variables according to recent evidence from a neighbouring area (Ferrao, Mendes, & Painho, 2017).

The impact of the interventions on school performance is assessed using a similar approach:

$Y_{ijt} = \alpha + \beta_1 Treatment_j + \beta_2 After_t + \beta_3 Treatment_j * After_t + \delta_s +$

$\Omega_p + \mu_t + \varepsilon_{ijt}$ **(2)**

where Y_{ijt} is either a continuous test score measure or a binary variable indicating whether the student has passed the course, for individual *i*, in district *j*, and trimester *t*. Treatment indicates whether the student belongs to the intervention district (Magude) and $After$ refers to the period after the implementation of the MDA (academic year 2016). The estimated coefficient of the interaction term $\hat{\beta}3$ identifies the effects of the elimination campaign on students' performance. We include school (δ), subject (Ω) and trimester (μ) fixed effects to control for school and subject specific time-invariant characteristics as well as quarterly seasonality in school grades.

To assess the impact of the initiative on students' absenteeism levels we use the following model:

$$Y_{ijt} = \alpha + \beta_1 Treatment_j + \beta_2 After_t + \beta_3 Treatment_j * After_t + \delta_s + \mu_t + \lambda_m + \varepsilon_{ijt} \quad \textbf{(3)}$$

Where Y_{ijt} is a binary variable indicating whether student *i* in district *j* was present at school on day *t*, and the coefficient $\hat{\beta}3$ represents our treatment effect. δ denotes the school fixed effects. Given the periodicity of students' absenteeism data, which is at the daily level, we estimate regressions controlling for trimester (μ) but also for calendar month (λ) fixed effects (10 months before and 10 months after the intervention).

We finally explore the potential role of absenteeism in explaining the observed changes on students' performance -due to the interventions- by estimating the following model:

$$Y_{ijt} = \alpha + \sigma Absenteeism_{ijt} + \beta_1 Treatment_j + \beta_2 After_t + \beta_3 Treatment_j * After_t + \beta_4 Att_{incr\,ij} + \beta_5 Att_{incr\,ij} * Treatment_j * After_t + \delta_s + \mu_t + \varepsilon_{ijt} \quad \textbf{(4)}$$

Where Y_{ijt} is the end of term grade, for student *i* in district *j* at trimester *t. Absenteeism* reflects students' absenteeism aggregated at the trimester level. $Treatment$ indicates whether the student belongs to the intervention district, $After$ refers to the period after the MDA distribution and Att_{incr} denotes the students who increased overall attendance from one academic year to the other. The $\hat{\beta}5$ coefficient from the interaction term identifies the potential differential effects of the campaign on performance for those students within Magude that also increased attendance levels, and thus, reflects the effect of the intervention on performance due to knowledge accumulation (increased attendance). On the other hand, the $\hat{\beta}3$ coefficient reflects the increased cognitive ability effect, regardless of absenteeism levels. We also include school and trimester fixed effects.

As the interventions were implemented at the district level, we cluster the standard errors at this level. Therefore, we consider that each within-school observation (students) is independently and identically distributed, so students are a random subset within each school, and thus, clustering should happen at the district and not necessarily at the school level. As there are only two districts, the typical cluster-robust approach suggested by (Bertrand, Duflo, & Mullainathan, 2004) could result in inappropriately small standard errors. So in addition to calculating these standard errors, we calculate and report the p-values associated with the wild cluster bootstrap-T method developed by Cameron, Gelbach, and Miller (2008).

5) Results

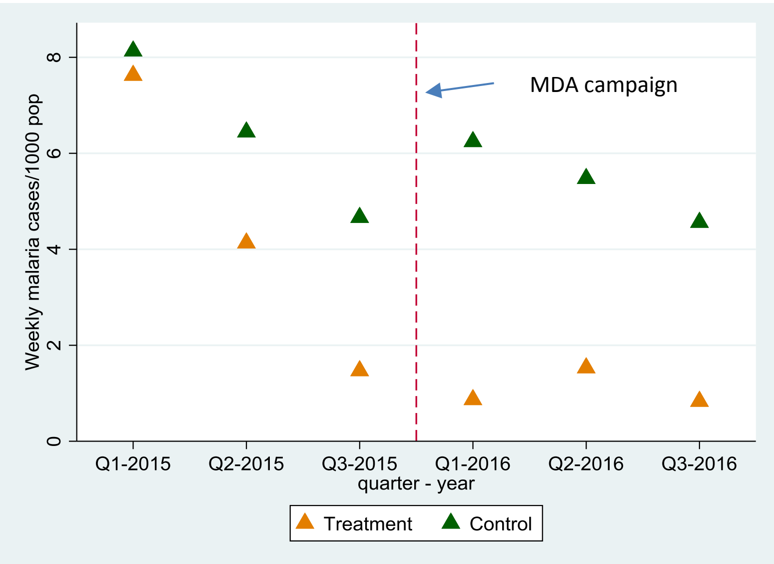
5.1) Impact on Malaria Incidence

Data on weekly malaria clinical incidence both from Magude (treatment) and Manhiça (control) districts (figure A5 in the annex), reflects the typical malaria seasonal patterns in the area, with peaks of malaria cases concentrated between January and March. Malaria incidence appears systematically higher in Manhiça, which may be attributable to environmental factors and to a potential improved reporting system due to the presence of the

Manhiça Health Research Centre that contributes to identify malaria cases through its constant research activity.

Figure 3 compiles the malaria incidence rates at the quarterly level[4], aligning the time unit measure and horizon of analysis with that of school outcomes. We observe that malaria incidence decreases over 2015, and although there is a widening gap in incidence levels in the second and third trimester of 2015 between Magude and Manhiça, probably attributable to the deployment of universal IRS in Magude (August 2015), the big shift on malaria incidence occurs after the MDA implementation (February 2016), reflecting the cumulative impact of IRS together with the mass drug administration campaign. In consequence, and aligning our study design with the primary-school academic years, we consider our post-treatment period starting after the MDA implementation (from February 2016) (see figure A4 in the annex).

Figure 3. Malaria incidence rates evolution in Magude (treatment) and Manhiça (control) districts, 2015 - 2016.



[4] Namely first quarter or Q1 (1 February-30 April), second quarter or Q2 (1 May- 31 July) and third quarter or Q3 (1 August- 30 October)

Table 4 shows the results of estimating the model specified in equation (1). Column (1) shows the results of the basic specification when controlling by months FE but excluding weather factors, while column (2) also includes climate covariates (temperature and precipitation). In Column (3) we explore the inclusion of climatological lagged variables according to evidence on fitted models from the literature (Ferrao et al., 2017). Importantly, most of climate factors are likely to be captured are likely to be captured by the months FE. Regardless of the specification, results point to a significant reduction of the weekly malaria incidence in the treated region after the start of the initiative of about 2 cases per 1,000 population.

Table 4. Estimates of the effect of the campaign on weekly malaria incidence (N malaria weekly cases / 1000 population)

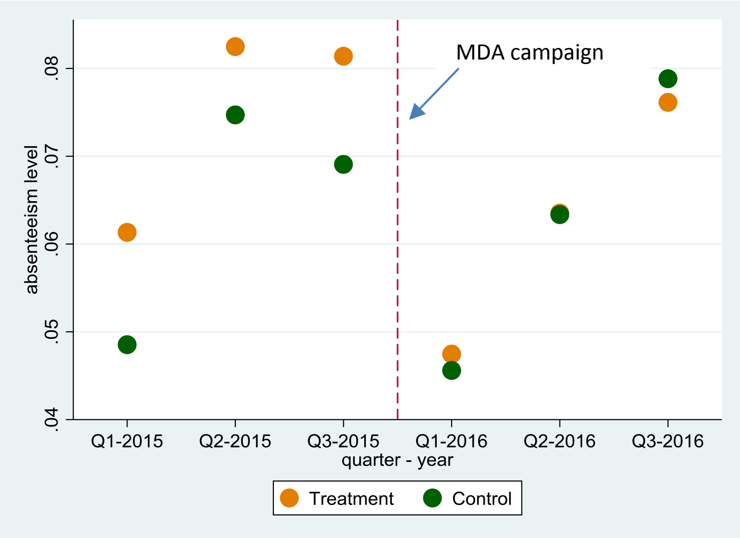
	(1)	**(2)**	**(3)**
Treatment	-2.178***	-2.123***	-2.192***
	(0.350)	(0.344)	(0.355)
After	-0.695**	-0.692**	-0.620*
	(0.351)	(0.346)	(0.358)
Treat*after	-2.256***	-2.234***	-2.152***
	(0.495)	(0.485)	(0.502)
Rain		-0.153	
		(0.102)	
Temp		-0.350***	
		(0.126)	
Temp lagged 7 weeks			-0.197*
			(0.119)
Rain lagged 12 weeks			0.066
			(0.062)
Constant	8.755***	18.657***	14.054***
	(0.479)	(3.542)	(3.335)
Month FE	x	x	x
Observations	172	172	164
R^2	0.715	0.73	0.718

Note: OLS with standard errors in parenthesis. All specifications control for months FE. Model (1) is the basic specification without climate covariates; model (2) controls for temperature and precipitation and specification (3) allows for lags in the climatological factors (precipitation and minimum temperature). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2) School outcomes

Figures 4 and 5 plot the quarterly mean absenteeism level and test score (all subjects), respectively, for primary school students in treatment and control districts over academic years 2015 and 2016[5]. Prior to the interventions (academic year 2015), the control district shows better educational outcomes with lower levels of absenteeism and higher mean grades than the intervention district. However, trends in both absenteeism levels and mean grade are similar and parallel in the two districts. After the interventions are implemented (academic year 2016), there is a more pronounced drop in absenteeism levels as well as a more pronounced increase in mean grades in the treatment vis-a-vis the control group. Consequently, in 2016, Magude catches up with Manhiça's absenteeism levels and it even overtakes the performance levels of the control group.

Figure 4. School absenteeism in Magude (treatment) and Manhiça (control) districts



Notes: The red line shows the implementation of the MDA campaign. Treatment is always defined as students attending schools located in the district were the malaria elimination

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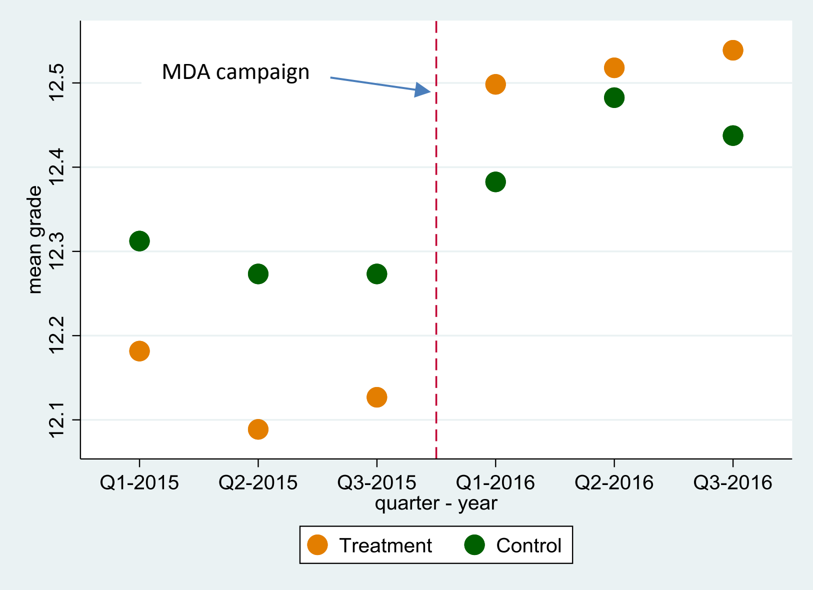
[5] For each student, daily absenteeism is a binary variable, for each eligible school day, equal to 0 if the student is present and 1 if the student is absent. Grades are measured on a scale from 0 to 20. Although daily data is analysed, absenteeism data is aggregated by trimester for facilitating comparability with performance outcomes.

campaign took place, Magude, and the pre-intervention period refers to the academic year 2015

Figure 5. School average grades in Magude (treatment) and Manhiça (control) districts



Notes: The red line shows the implementation of the MDA campaign. Treatment is always defined as students attending schools located in the district were the malaria elimination campaign took place, Magude, and the pre-intervention period refers to the academic year 2015

Table 5 reports the main results on test scores from the difference-in-difference model outlined in equation (2). We use two versions of dependent variable: a continuous test score measure (Panel A) and a binary variable (Panel B), the latter indicating whether the student has passed the course (which occurs when grades are above 10). Column (1) shows results of the model with school fixed effects, column (2) shows results of the model with school and trimester fixed effects and column (3) shows the model with the additional inclusion of subject fixed effects. The difference-in-difference estimated coefficients are positive, significant (at 1% significance levels) and stable across specifications, indicating that the interventions increased the overall grade by 0.24 percentage points. Given the pre-intervention mean grade of 12.13 in the intervention area, the policy increased average grades for treated students by 2%[6]. Analogously, the intervention increased the probability of passing exams by 2 percentage points, which corresponds to an average increase of 2.3% with respect to the pre-intervention mean[7].

There is consensus on the fact that some subjects better reflect children's cognitive performance than others, such as maths (Moeller, Klein, Kucian, & Willmes, 2014). In consequence, we also explore the impact of the intervention on maths grades only. Coefficient estimates more than double for the impact of the malaria elimination campaign on maths test scores compared to the impact on overall subjects mean grades, indicating that the intervention increased students' maths grades by 5% (table A3 in the annex).

Table 5. Impact of the malaria elimination campaign on school performance, all subjects

Dependent variable	All subjects		
	(1)	**(2)**	**(3)**
Panel A. Mean grade value			
Treatment	0.025***	0.024***	-0.002
	(0.000)	(0.000)	(0.003)
After	0.164***	0.146**	0.152**
	(0.000)	(0.004)	(0.005)
Treat*after	**0.241*** **	**0.241*** **	**0.240*** **
	(0.000)	(0.000)	(0.003)
	[0.005]	[0.005]	[0.005]
Constant	11.849***	11.877***	12.159**
	(0.000)	(0.010)	(0.848)
School FE	x	X	X
Trimester FE		X	X
Subject FE			X
Observations	229,427	229,427	229,427
R^2	0.015	0.015	0.047

[6] We get that number from: (0.24/12.13)*100

[7] Given that the mean pass rate pre-intervention in the treatment group was 87.6%, the increase due to the intervention is: (0.02/0.876*100)

Panel B. Pass value			
Treatment	0.049***	0.049***	0.043***
	(0.000)	(0.000)	(0.000)
After	0.002***	-0.002	-0.001
	(0.000)	(0.002)	(0.002)
Treat*after	**0.021*****	**0.021*****	**0.020*****
	(0.000)	(0.000)	(0.000)
	[0.005]	[0.005]	[0.005]
Constant	0.866***	0.869***	0.778*
	(0.000)	(0.002)	(0.070)
School FE	x	X	x
Trimester FE		X	x
Subject FE			x
Observations	229,427	229,427	229,427
R^2	0.004	0.004	0.128

Notes: OLS coefficients, with standard errors clustered by school in parentheses. P-values of wild bootstrap clustering procedure presented in brackets for the interaction term (based on 400 repetitions). All models controlling for school FE. Model (2) also controlling for quarterly seasonality and model (3) controlling for subject and trimester FE.
* p < 0.10, ** p < 0.05, *** p < 0.01

Results on the effect of the initiative on school absenteeism are shown in Table 6, with all models controlling for school fixed effects, and columns (2) and (3) also controlling for month and trimester fixed effects, respectively. There is robust evidence of a reduction in school absenteeism as a result of the malaria elimination campaign across the different models. More specifically, the difference-in-difference estimate shows a policy impact of a reduction in absenteeism by 2.1 percentage points. Given that Magude's pre-intervention absenteeism level was 7.63%, the decrease due to the interventions amounts to 27.72% [8].

Table 6. Impact of the malaria elimination campaign on school absenteeism

	(1)	**(2)**	**(3)**
Treatment	0.006***	0.004***	0.004*
	(0.000)	(0.000)	(0.000)
After	-0.000***	-0.006	0.031*
	(0.000)	(0.012)	(0.003)

[8] Calculated as (0.021/0.0763)*100.

Treat*after	**-0.021*** (0.000) [0.005]**	**-0.020*** (0.000) [0.005]**	**-0.021*** (0.000) [0.005]**
Constant	0.054*** (0.000)	0.041 (0.013)	0.039** (0.002)
School FE	x	X	x
Month FE		X	x
Trimester FE			x
Observations	996,411	996,411	996,411
R^2	0.017	0.020	0.019

Notes: OLS coefficients, with standard errors clustered by school in parentheses. P-values of wild bootstrap clustering procedure presented in brackets for the interaction term (based on 400 repetitions). All models controlling for school FE. Model (2) also controlling for monthly seasonality and model (3) controlling for trimester FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, we investigate the potential role that improved attendance due to the initiative might have in boosting student's school grades. Table A3 (col 1) shows the results of the estimates of our basic equation (3) on performance outcomes for the sub-sample of students that we are able to follow up throughout the period of analysis and in both performance and absenteeism databases[9]. Controlling for students' absenteeism (col 2) or individual students' fixed effects[10] (col 3) decreases the impact of the policy on performance, but the effect remains positive and significant. Finally, (col 4) presents the results of estimating equation (4). The treatment coefficient $\hat{\beta}5$, shows a higher impact on improving the performance of those students that also increased attendance, when compared to the remaining students. These findings suggest that part of the effect of the intervention on students' performance is likely to derive directly

[9] This sub-sample includes 1,607 students

[10] In order to control for individual unobservable factors both correlated with school attendance and performance, such as students' effort and motivation, which could potentially be confounding our estimates.

from improved attendance. The remaining share of such effect, $\hat{\beta}3$, should, therefore, be a consequence of improved capacity to learn due to better health, irrespective of improved attendance.

6) Robustness checks

We test the parallel trends assumption by interacting the treatment variable with quarterly time dummies. Given that the interaction terms between pre-treatment time dummies and the treatment indicator are very close to zero (figures A6 and A7), we demonstrate that pre-intervention outcome trends are not significantly different between treatment and control districts. These results hold for both absenteeism and performance outcomes, and only after the MDA administration (November 2015- February 2016) there is a significant change in trends.

As mentioned above the follow up of students' over time is not perfect given the lack of a student unique identifier. This makes our database unbalanced. To exclude any potential bias arising from incomplete and unbalanced data, the core analysis on school attendance has been repeated on the following three subsamples (shown in table A4): including only those months with complete information (col 2); removing unrealistically long consecutive chains of presences within a class[11] (col 3) and using a balanced database[12] (col 4). While the identification strategy isolates the intervention effect from nationwide trends and district time-

[11] These are chains of 100 consecutive presences, which, given the observed baseline absenteeism levels, would occur with a probability below 0.00001

[12] We keep in our sample only students with complete information across academic months and years

invariant heterogeneity, it does not necessarily isolate it from heterogeneity across students. In consequence, in column (4) students' individual FE have been included to the balanced database. Regardless of the sub-sample or controls included, our main findings are maintained at a 5% significance level. Finally, there exists evidence on the presence of positive externalities of health interventions targeting school-age students. Failing to account for them, might result in underestimating the benefits of an intervention and, thus, drawing misleading conclusions (Miguel & Kremer, 2004). Unlike other school-based health interventions where randomization occurred at the school level (Miguel & Kremer, 2004) and variation across schools could be used to assess externalities, in our case the elimination involved the whole Magude district. However, we can explore schools' distance to the border to assess the potential presence of contamination effects among schools close to the border. In our case, there may be positive externalities from the intervention to the control area (reduced transmission of malaria in areas close to the border can benefit the adjacent control area) or negative externalities from the control to the intervention area (the control area does not reinforce malaria management, limiting the effect of the malaria elimination project in the area of the intervention district adjacent to the control district).

To test for the potential presence of externalities, we calculate each schools' distance to the shared border between Magude and Manhiça (nearest point), generate an interaction term between distance to border and the period after the MDA distribution ($Distance_{border} * After$) and include such interaction in the basic equation (3).

As table A4 (col 6) shows, we do not find any differential effect of the initiative by distance to the border (insignificant coefficient of the interaction term $Distance_{border} * After$) , Nevertheless, the initiative's effect estimates remain constant and significant pointing to either negligible contamination or to a compensation between positive and negative externalities.

7) **Discussion**

This study has explored the impact of a malaria elimination project in Southern Mozambique on both health and educational outcomes of 9,848 primary school children for the academic years 2015 and 2016, pre and post intervention, respectively. One year after the start of the project, results show that the malaria elimination interventions not only reduced the burden of malaria in the targeted district, but also significantly improved primary school students' performance and attendance relative to a neighbouring control district.

More specifically, our results show that a reduction of malaria incidence by 48% due to the elimination campaign, translates into an increase in students' mean grades by 2%, and this impact is higher on those subjects that better reflect students' cognitive performance, such as maths, with an increase by 5%. Equivalently, this represents an increase in students' score rates of 0.24 -all subjects- and 0.6 -only maths- out of a total of 20 marks, or an increase of 0.09 –all subjects- and 0.17 –only maths- standard deviations. These results align with existing findings on the short-term cognitive impact of malaria among primary school students. D. Fernando, D. de Silva, et al. (2003) find that in Sri Lanka, a child with malaria at school entry, scores 0.6 (in maths) and 0.8 (in language) marks less out of 10 than a healthy child. In another study in Tanzania, a 10 percentage-point decrease in malaria prevalence in birth year was associated with a 0.06 standard deviation increase in English literacy achievement (Klejnstrup, Buhl-Wiggers, Jones, & Rand, 2018).

The magnitude of our results can also compare to other -non-malaria- education interventions aimed at improving students' learning in developing countries, such as teacher training, volunteer teachers or students and teachers performance incentives, with a mean effect size comprised between 0.09 and 0.12 standard deviations (McEwan, 2015).

Since students' attendance has also increased over the time span analysed by 28% and given that improved attendance by itself is likely to enhance the stock of knowledge, the impact of the malaria elimination project on performance is likely to be affected by changes in attendance. Indeed, we observe that students who improved school attendance experienced an improvement in their grades, suggesting that the observed impact on performance is partially driven by attendance. Other studies also emphasize the role of school absenteeism due to malaria as a key determinant of students' poor school performance (D. Fernando, D. de Silva, et al., 2003). Improved learning abilities due to better health also played a role in enhancing school performance. In fact, even when controlling for students' absenteeism as well as for a number of other covariates, we still find a significant impact of the project in improving students' grades, suggesting that part of the effect is the result of students' improved learning abilities, regardless of their absenteeism levels.

While providing evidence over a relative short time, 1 year, our results could be representing only a starting point of the cumulative mid and long-term effects of malaria elimination on human capital accumulation. In order to be able to compare our estimates with existing findings on long-term outcomes of malaria elimination and eradication programs, we translate our main treatment effects on school attendance and performance in terms of school days prevented and grade levels gained respectively, and convert those into years of schooling. Given a baseline absenteeism level of 7.6% and an average treatment effect of the policy in reducing absenteeism by 2.1 percentage points, we find that the intervention preserved, on average, 4 days per student per year, which in turn, translates into a gain of 0.022 years of schooling per student.

Taking into consideration the students' grades distribution, we observe that the improvement in overall grades translated into an increase in the pass rate by 2.1 percentage points. Knowing that the average years of schooling in Mozambique is 3.5 (UNESCO, 2018) and assuming a constant dropout rate, the impact of the initiative on students' performance would imply an increase of 0.09 years of schooling. Aggregating the impact of the initiative on both absenteeism and performance outcomes and assuming an independent effect, this yields an increase of 0.11 years of schooling (0.022+0.09).

Finally, following Barofsky et al. (2015); H Bleakley (2010); Cutler, Fung, Kremer, Singhal, and Vogl (2010), we rescale our regression coefficients in terms of malaria incidence change, which translates into an estimated increase of 0.022 years of schooling per a 10% reduction in malaria incidence.

Compared to the educational effects found in the literature, our estimates are lower. For example, in Sri Lanka and Paraguay, A. M. Lucas (2010) found a 10% decrease in malaria incidence to be associated with a 0.1 year increase in schooling, Barofsky et al. (2015) found very similar results in Uganda (an impact of 0.09 years of schooling), while in contrast, Cutler et al. (2010) found no impact on educational outcomes. However, considering the different timeframes covered in the analysis (1 year vs 15-20 years after the intervention), our estimates could potentially achieve a similar impact in the mid and long-term.

Due to the unbalanced nature of our database, we cannot identify a potential school composition effect due to the intervention (Jones, 2016). However, we cannot exclude that the intervention may have allowed children who were very often or even totally absent due to sickness in the pre-intervention period (year 2015), to increase their presence in 2016. This may have lowered the impact of the intervention on performance.

Some *caveats* should be mentioned when interpreting our results. Malaria baseline incidence levels appear higher in the control district. This might be due to higher transmission intensity in the district of Manhiça or due to a strengthened case reporting system consequent to the presence of the Manhiça Health Research Centre. Data on malaria incidence might be also underestimating the true burden of disease, given that it only reflects passive data collected at the health facility level. Despite its limitations, routine surveillance data from the ministry of health still represents the best country-wide data source to compare malaria trends across districts.

Baseline school outcomes (attendance and performance) also appear lower in the intervention district. This might be explained by factors related to poorer roads infrastructure, higher average distances to school or the slightly lower socioeconomic status in the district of Magude. Regardless of baseline differences across districts, all children were exposed to very similar economic and environmental conditions and characteristics typical of public primary schools in rural agricultural districts. This hypothesis is confirmed graphically and analytically by confirming the "parallel trends" assumption.

Other factors unrelated to the identification strategy are also worth mentioning. First, we used *pooled* malaria incidence data –i.e. across all age groups, not only on school-age children - to assess the policy's health impact. However, given that children carry the main burden of the disease (WHO, 2018), it is reasonable to assume that the pooled incidence figures will mainly be reflecting the burden on children. Thus, our estimates only represent the lower bound of the health impact of the campaign on school age children.

Second, the use of routine school data may cast doubts on both the accuracy and the validity of our data sources (as data was not collected directly by the research team but relied on existing school records). In the existing literature, routine school grades have not only been used as proxies for student's cognitive achievement (S. Fernando et al., 2003; Thuilliez et al., 2010), but it has also been shown to lead to results highly correlated with results obtained when using specific cognitive function score tests (Thuilliez et al., 2010). Therefore, the use of school registers' data is consistent with the existing literature and sound from a methodological perspective. Furthermore, the use of administrative data allowed us to rely on a wide sample size, which would be not feasible to achieve if data would have been collected primarily.

From a public health perspective, our findings provide key estimates of the beyond-health benefits associated with malaria elimination. Within the renewed efforts towards the elimination of the disease in Southern Africa, our estimated figures do provide strong arguments for health policy makers and funders for advocating towards elimination. The existence of such benefits may justify the initially large investments needed to eliminate the disease and may also help overcoming the free-riding issue intrinsic to disease elimination as a global public good (Barrett, 2013).

Our study also provides additional further evidence on the micro-foundations of the links between health, education and economic growth within the context of a low-income country. Results from this study shed light on the channels through which health can improve schooling outcomes in the short-term, which in turn, are essential proxies for countries' economic development (Bloom, Canning, & Sevilla, 2003; Finlay, 2007). Notably, this is the first study exploring such links in Mozambique.

Because large gains on school outcomes are already evident one year after the elimination project is implemented, the potential mid and long-term benefits associated to malaria elimination policies by enhancing human capital accumulation and improving long-term economic outcomes can be substantial.

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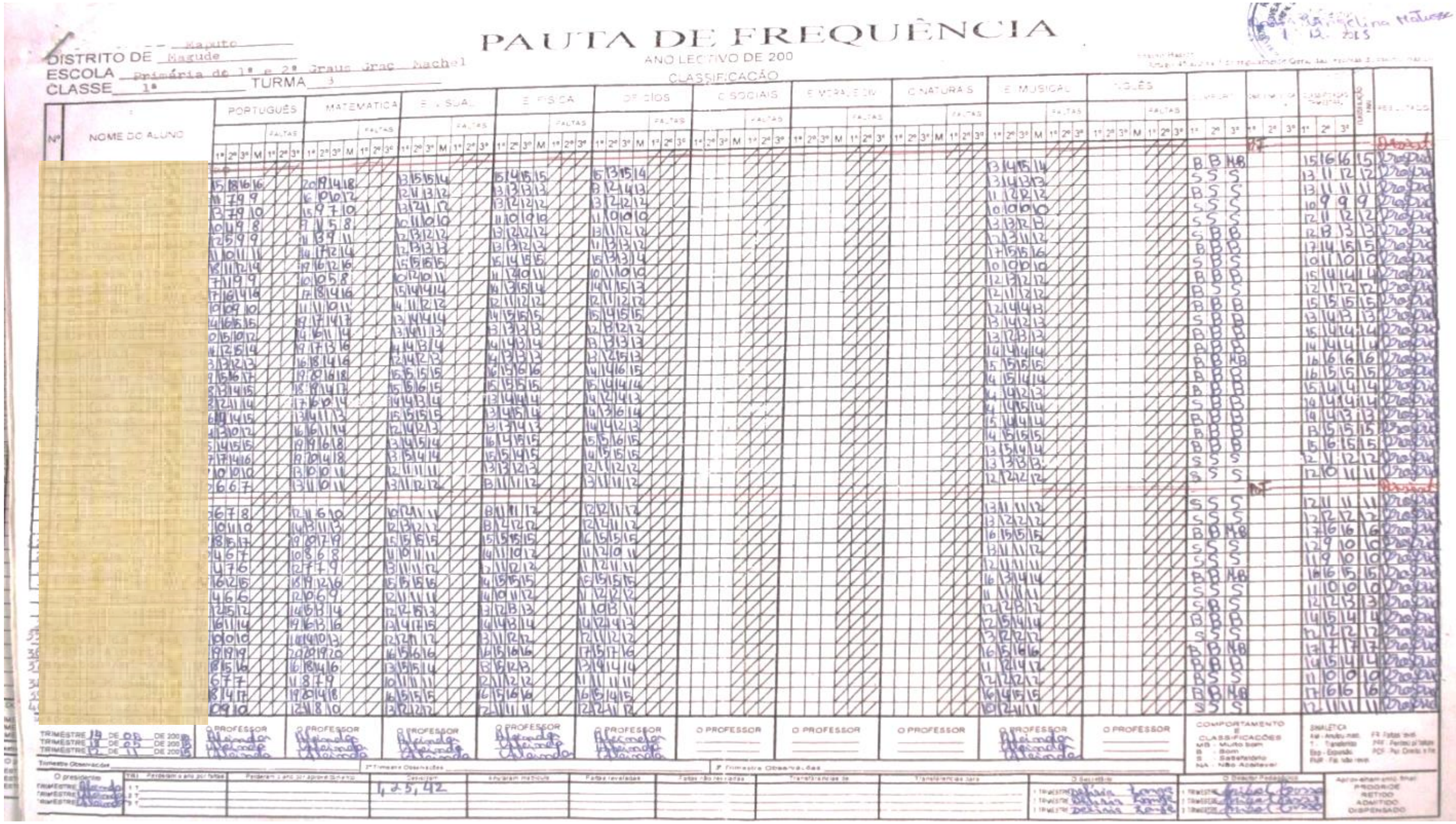
Annex

Figure A1) Provinces of Mozambique

Source: "www.mapsopensource.com"

Figure A2) School registers on quarterly grades, by subject



PAUTA DE FREQUÊNCIA

ANO LECTIVO DE 200

CLASSIFICAÇÃO

DISTRITO DE Magude

ESCOLA Primária de 1º e 2º Graus Graç Machel

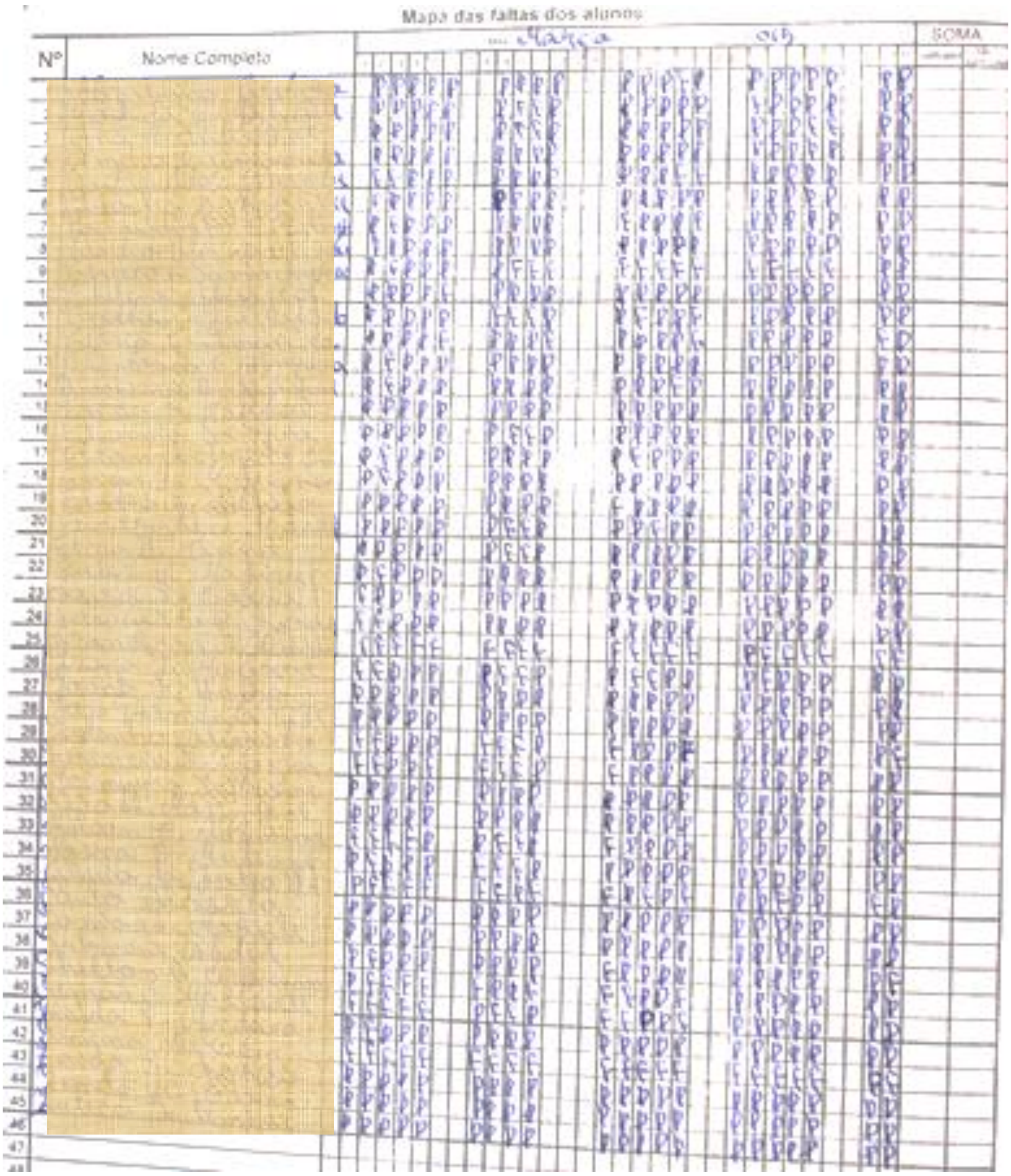
CLASSE 1ª TURMA 3

Nº | NOME DO ALUNO | PORTUGUÊS | MATEMÁTICA | E. VISUAL | E. FÍSICA | OFÍCIOS | C. SOCIAIS | E. MORAL E CÍV. | C. NATURAIS | E. MUSICAL | INGLÊS

O PROFESSOR

Notes: Students' name details have been hidden in order to protect research participants' confidentiality

Figure A3) School registers on daily absenteeism



Notes: Students' name details have been hidden in order to protect research participants' confidentiality

Figure A4) Chronogram on academic years and malaria elimination activities

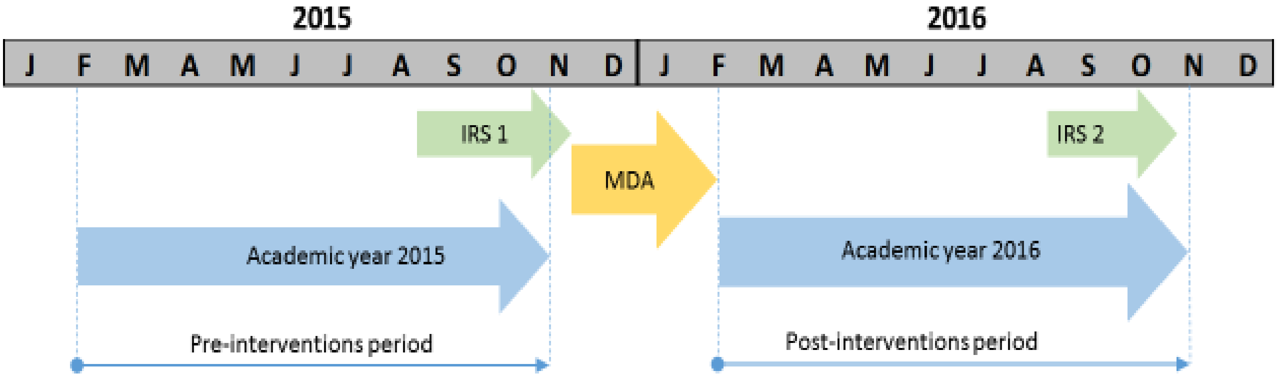
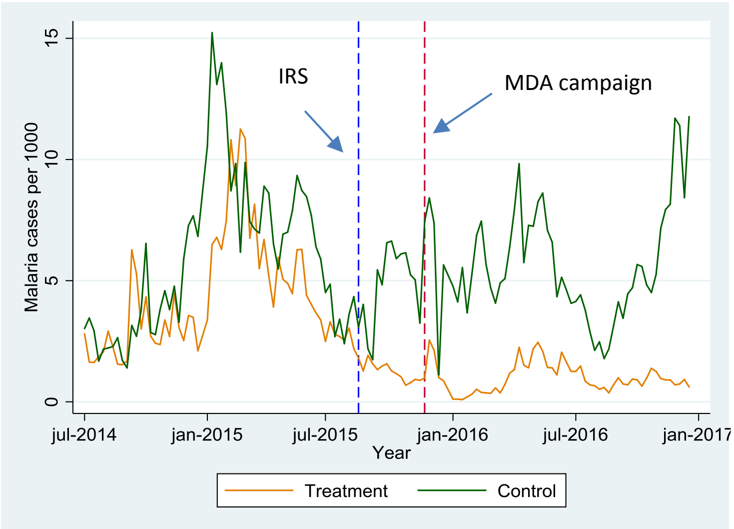
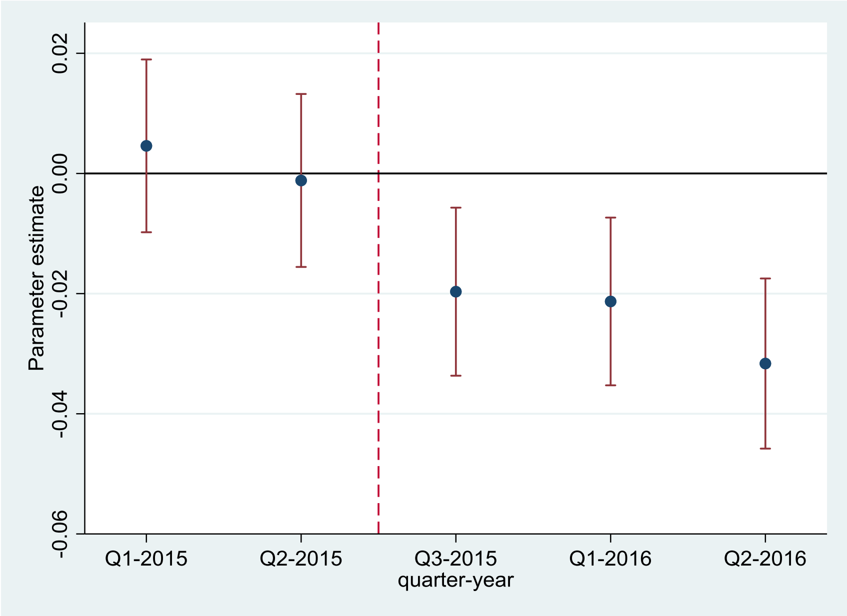


Figure A5). Weekly malaria incidence in treatment (Magude) and control (Manhiça) districts



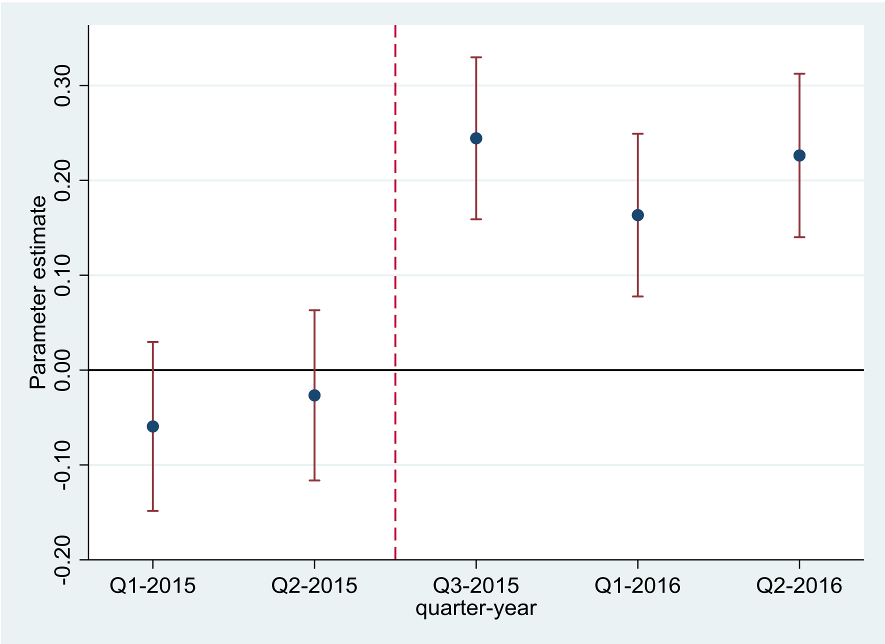
Notes: The blue line shows the deployment of universal IRS (August 2015) and the red line shows the start of the population-wide MDA (November 2015).
Source: Boletim Epidemiológico Semanal, Mozambican Ministry of Health

Figure A6) Event study on students' absenteeism between treatment and control districts



Note: The red line shows the implementation of the population-wide MDA (November-January 2015)

Figure A7) Event study on students' performance between treatment and control districts



Note: The red line shows the implementation of the population-wide MDA (Dec-Jan 2015)

Table A1) Data sample design and structure

	Treatment						Control					
	2015			**2016**			**2015**			**2016**		
	Q1	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**
Panel A. Absenteeism												
Number of students in absenteeism sample frame	1,246	1,180	1,207	1,577	1,549	1,451	3,510	3,462	3,193	2,757	2,881	2,739
Number of observations (daily)	39,360	53,751	50,395	61,941	74,557	60,154	108,598	142,067	111,255	82,148	124,174	88,011
Follow up across months [a]	8 (1.3)			8.4 (1.5)			7.8 (1.4)			7.6 (1.5)		
Follow up of students across years [b]	745 (35%)						1,511 (31%)					
Panel B. Performance												
Number of students in performance sample frame	1,428	1,398	1,356	1,730	1,697	1,667	3,964	3,837	3,752	4,191	4,116	4,011
Number of observations (quarterly)	9,750	9,535	9,233	11,841	11,611	11,401	27,406	26,545	25,955	29,314	28,791	28,045
Follow up across trimesters [c]	2.97 (0.22)			2.98 (0.19)			2.96 (0.24)			2.98 (0.21)		
Follow up of students across years [d]	1,670 (53%)						4,374 (54%)					
Panel C. Across datasets												
Number of students in both datasets [e]	1,671 (61%)						3,813 (54%)					

Notes: The sample consists of all students with available data on absenteeism and performance within the 9 randomly selected schools.
[a] Average number of months for which we have information on absenteeism for a student, per year . Standard deviation in brackets.
[b] Number and percentage of students within our absenteeism sample frame that we can observe across years
[c] Average number of trimesters for which we have information on performance for a student, per year. Standard deviation in brackets.
[d] Number and percentage of students within our performance sample frame that we can observe across years.
[e] Number and percentage of students, per year, that we can identify in both absenteeism and performance datasets

Table A2) Impact of the malaria elimination campaign on maths grades

	(1)	**(2)**
Panel A. Mean grade value		
Treatment	-0.417***	-0.421***
	(0.000)	(0.000)
After	0.109***	-0.459**
	(0.000)	(0.029)
Treat*after	**0.586*** **	**0.586*** **
	(0.000)	(0.000)
	[0.005]	[0.005]
Constant	11.869***	12.206***
	(0.000)	(0.086)
School FE	x	X
Trimester FE		X
Observations	33,113	33,113
R^2	0.009	0.013
Panel B. Pass value		
Treatment	0.026***	0.026***
	(0.000)	(0.000)
After	0.003***	-0.030***
	(0.000)	(0.000)
Treat*after	**0.056*** **	**0.056*** **
	(0.000)	(0.000)
	[0.005]	[0.005]
Constant	0.777***	0.798***
	(0.000)	(0.006)
School FE	x	X
Trimester FE		X
Observations	33,113	33,113
R^2	0.005	0.006

Notes: OLS coefficients, with standard errors clustered by school in parentheses. P-values of wild bootstrap clustering procedure presented in brackets for the interaction term (based on 400 repetitions). All models controlling for school FE. Model (2) also controlling for quarterly seasonality. * p < 0.10, ** p < 0.05, *** p < 0.01

Table A3) Heterogeneous impact on performance by attendance growth rate

	(1)	**(2)**	**(3)**	**(4)**
Treatment	-0.131**	-0.110**	0.000	0.000
	(0.004)	(0.004)	(.)	(.)
After	-0.147**	-0.035	-0.138*	-0.140*
	(0.012)	(0.014)	(0.016)	(0.019)
Treat*after	**0.650*** **	**0.584*** **	**0.575*** **	**0.427** **
	(0.000)	(0.004)	(0.005)	(0.015)
	[0.005]	[0.005]	[0.005]	[0.005]
Absenteeism		-2.722**	-0.977	-0.899
		(0.187)	(0.203)	(0.326)
Treat*after*decr_abs				0.275*
				(0.042)
Constant	11.947***	12.024***	12.572***	12.568***
	(0.039)	(0.019)	(0.022)	(0.015)
School FE	x	x		
Trimester FE	x	x	x	x
Individual FE			x	x
Observations	9,252	9,252	9,252	9,252
R^2	0.043	0.062	0.028	0.030

Notes: OLS coefficients, with standard errors clustered by school in parentheses. P-values of wild bootstrap clustering procedure presented in brackets for the interaction terms (based on 400 repetitions). Models (1) and (2) control for school and trimester FE. Models (3) and (4) also control for individual FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4) Impact of the elimination campaign on absenteeism for selected sub-samples

	(1)		(2)		(3)		(4)		(5)		(6)	
Treatment	0.004***	(0.000)	0.002	(0.000)	0.023**	(0.001)	0.010*	(0.001)	-	-	-0.63**	(0.013)
After	-0.006	(0.012)	0.034	(0.006)	-0.006	(0.012)	-0.050	(0.001)	0.032	(0.036)	-0.0056	(0.012)
Treat*after	**-0.020*** **	**(0.000)**	**-0.019*** **	**(0.000)**	**-0.023*** **	**(0.000)**	**-0.034** **	**(0.001)**	**-0.014** **	**(0.001)**	**-0.015*** **	**(0.001)**
	[0.005]		[0.005]		[0.005]		[0.005]		[0.005]		[0.005]	
Distance_border											0.42**	(0.001)
After*distance_border											0.00	(0.001)
Constant	0.041	(0.013)	0.034**	(0.002)	0.057*	(0.006)	0.008	(0.006)	0.021	(0.017)	-0.13*	(0.016)
School FE	x		x		x		x		x		x	
Month FE	x		x		x		x		x		x	
Individual FE									x			
Observations	996,411		949,026		732,944		389,175		389,175		996,411	
R^2	0.020		0.020		0.014		0.015		0.020		0.020	

Notes: OLS coefficients, with standard errors clustered by intervention in parentheses. P-values of wild bootstrap clustering procedure presented in brackets for the interaction term (based on 400 repetitions). All models control for school and months FE. Model (1) is the raw data. Model (2) excludes months with few observations , models (3) drops consecutive chains of presences, model (4) includes a balanced dataset and model (5) includes individual FE in the balanced dataset. Finally, model (6) accounts for differential effects for schools' distance to border.

* p < 0.10, ** p < 0.05, *** p < 0.01