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Behavioral Response to an Anti Malaria Spraying Campaign, with Evidence from Eritrea*

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Abstract

It is sometimes argued that introducing Indoor Residual Spray (IRS) in areas with high coverage of mosquito bed nets may discourage net ownership and use, which would hinder Malaria eradication rather than promote it. We analyze new data from a Randomized Control Trial conducted in Eritrea in 2009, and we show that this does not happen in practice. IRS actually induced households to acquire more nets and even led to increased net use among certain demographic groups. IRS was further not associated to any perverse behavioral response. We explore two arguments that can explain this. The IRS campaign may have conveyed information about the importance of preventing Malaria and about how to do so, and people adjusted their behavior accordingly. Alternatively, people may perceive bed nets and spray as complements, even though they are substitutes. Further research is needed to disentangle these two effects.

JEL codes: D12, D83, H42, I12.

Keywords: Malaria, Bednets, Spray, Information, Beliefs, Behavior.

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1 Introduction

Malaria is a disease which poses a threat in 109 countries, putting half of the world's population at risk. The disease affects about 250 million people, killing more than 800 thousand annually. 90 percent of fatalities occur in Africa and 85 percent of the victims are among children under the age of five. Over the past decade, national Governments and International Organizations have worked together in a concerted effort to fight Malaria. Good results have been achieved in some countries including Eritrea and Rwanda, where the number of cases and deaths has declined by more than half[1].

The ultimate objective of all anti Malaria programs is complete eradication. Once the Malaria burden has been reduced by appropriate policies, this goal may be achieved by scaling up the current anti Malaria policies and by complementing them with newly introduced tools. In particular, Malaria control has relied in recent years on mass distribution of Insecticide Treated mosquito bed Nets (ITNs), and policy makers have recently started contemplating the possibility of additionally introducing regular Indoor Residual Spray (IRS) campaigns, which consist in spraying the inside walls of dwellings with insecticide to repel and kill the Malaria vector, ie mosquitoes.

The introduction of IRS on top of ITNs may be conducive to Malaria eradication if this combination offers more protection from infectious bites than ITNs alone afford (more on this in Section 3), and if the introduction of the new tool does not crowd out people's investment in the pre-existing one. This paper focuses on the latter part of this argument, ie we study the behavioral response to the introduction of a spraying campaign, in areas where other anti Malaria technologies including ITNs have long been available.

Concerns about a "perverse" reaction to the introduction of IRS have been raised eg at a recent meeting[2] of the Roll Back Malaria Partnership (RBM), based on the idea that, when two technologies are available, few people will use both if the good effects of one tool reduce the perceived benefits from using the other one. At this meeting, more specifically, Lengeler (2011) expressed concerns that introducing IRS in areas where ITNs are widely available may have a negative impact on the *acceptability* of bed-nets, possibly inducing people to reduce use of this technology.

The Malaria Action Plan further discusses the risk of "Malaria fatigue", by which it is meant that a policy-induced reduction of the Malaria burden may lead people to lose interest in Malaria. This would in turn induce them to invest less in preventive and remedial health-care. With this concerns in mind, the Global Malaria Action Plan of RBM (2008) underlines the importance of implementing strong education and communication programs, and of investing in research on behavior change to improve intervention uptake and usage and to promote compliance, as new strategies are introduced and programs are scaled up.

In the specific case at hand, if people believe that IRS is effective in reducing the size of the mosquito population and hence the Malaria burden, then we would expect them to *reduce* their involvement in the existing campaigns, including particularly ITN take-up and use, because IRS would lower their expected benefits from participation[3]. Such behavioral response is clearly undesirable and strong,

[1] Source: Roll Back Malaria website.

[2] 3rd Meeting of Optimal Choice of Vector Control Work Stream. Minutes are available on the RBM website.

[3] That would not be a problem if one single IRS campaign were enough to kill Malaria completely. In reality, instead,

credible information campaigns could help mitigate this problem. However, no such campaign was conducted in our study area to promote consistent behavior in the introductory phase of IRS.

In rural villages, people are not perfectly informed about the local Malaria prevalence, but they can draw inference from their observations and they may adjust their behavior accordingly. When IRS is introduced, people see that the Government is investing real money in a new campaign against the disease. They also know that the Government has been committed to reducing Malaria for many years and that its policies have successfully managed to reduce the disease burden. If they believe that the Government has precise information about the actual prevalence and that it spends its money efficiently, then their observation may induce them to revise upward their beliefs about the current risk of infection and to use the available technologies *more*.

This paper aims to shed some light on the question of which of these two countervailing forces prevails, ie whether people use the pre-existing anti Malaria technologies consistently when IRS is introduced, or whether they choose to shirk. This may ultimately help answer the question whether it is worth it to invest in the introduction of IRS in areas with already high ITN coverage.

The remainder of the paper is organized as follows. In Section 2 we briefly describe the study area and the status quo in Malaria eradication. The relevant literature is reviewed in Section 3. In Section 4 we describe our dataset, and we introduce our model in Section 5. We bring it to the data, and we present our estimates in Section 6. Section 7 concludes and outlines the main policy implications we envisage.

2 Study Area and Malaria Eradication

Eritrea has an estimated population of 3.6 million and is divided into 6 administrative zones. Malaria dramatically declined in Eritrea over the past decade, from a national peak of 110,000 cases diagnosed in 1998 to just under 18,000 cases in 2009. More than half of all diagnosed Malaria cases and over 60% of all related deaths in the country come from Gash Barka Zone (2007, 2008), where this study was conducted[4].

Malaria is transmitted during the night, from person to person, by female *Anopheles* mosquitoes. Three main technologies are currently available to reduce transmission, namely mosquito bed-nets[5], Larval Habitat Management (LHM) and IRS. Nets must be hung over the bed during the night to protect sleeping people from infectious mosquito bites and prevent transmission; LHM includes eg draining stagnant water to destroy the habitat of mosquitoes; and IRS was defined in Section 1.

The potential of IRS to kill mosquitoes and reduce Malaria prevalence *without* requiring any cost or effort from beneficiaries is a feature that makes it peculiar with respect to the other interventions. All

several rounds are necessary and it is therefore crucial that people remain consistently involved in the existing policies when IRS is introduced.

[4]Please refer to the Appendix for a map of the area under investigation.

[5]Three types of mosquito bed-nets exist: traditional untreated nets, ITNs, and Long-Lasting Insecticide Treated Nets (LLINs). ITNs require periodical re-treatment whereas the insecticide on LLINs is effective for a period of 3–5 years. Recent distribution programs operated in Eritrea by the Government and International Organizations have supplied only ITNs and LLINs. We will henceforth refer to both types of treated nets as ITNs.

costs of IRS are borne by the Government, who is in charge of conducting the spraying campaigns[6]. In contrast, bed nets must be first of all acquired by the people, then set up every day above the bed and people may additionally incur disutility from sleeping under a net when it is warm; LHM campaigns are carried out by the Government with the active involvement of local populations; finally, effort is also required for the other behaviors promoted by information campaigns to reduce the risk of Malaria infection, eg burning animal dung and keeping cattle far from the dwellings.

Eritrea has been successful in greatly reducing[7] Malaria infection prevalence. However, eradication has not yet been achieved. RBM (2008) explains that, in such a policy-induced low transmission setting, young generations are no longer highly exposed to Malaria and so they do not acquire partial immunity. Should Malaria make a comeback, severe epidemics may ensue, putting at risk the entire population, and especially young children and pregnant women. Complete Malaria eradication is therefore a top priority there. Accordingly, the National Malaria Control Program (NMCP) is currently developing strategies to continue its efforts to reduce the infection rate to zero.

The NMCP has historically controlled Malaria with a combination of mass ITN distribution, LHM and information campaigns, offering prompt treatment of diagnosed cases and limiting use of IRS to respond to epidemics. In fact, after being used extensively in the mid twentieth century in large anti-Malaria campaigns worldwide[8], IRS lost momentum. However, Zhou et al. (2010) stress that there has recently been renewed interest in the deployment of spraying campaigns for Malaria prevention and control. In line with this trend, the NMCP has lately been contemplating the introduction of regular IRS campaigns on top of the existing package of integrated interventions.

Positive externalities arise from widespread bed-net usage and LHM, and extensive IRS campaigns: however, achieving a sufficiently high coverage makes such interventions particularly expensive, which is especially true for the Governments of low-income countries, eg Eritrea. As a cost-effective solution to reduce and interrupt the Malaria transmission cycle, the World Health Organization (WHO) recommends an appropriate combination of these actions, in order to exploit their synergies, maximizing their efficacy and keeping costs to a minimum[9]. The optimal design of such a package of integrated interventions requires that the individual and joint effectiveness of these policies be assessed.

3 Literature Review

The protective efficacy of ITNs has been quantified in a large number of studies; an extensive review by Lengeler (2004) finds that ITNs are very effective in reducing Malaria morbidity and mortality, especially among children. Several recent studies have also shown IRS to be an effective strategy for preventing Malaria; a recent review is presented in Pluess et al. (2010). They highlight the need for Randomized Control Trials (RCT) aimed to evaluate the additive protective efficacy that IRS can offer in combination with ITNs, which had not been quantified in the previous literature. Using our same

[6]IRS is conducted by Governments using the insecticide DDT (Dichloro Diphenyl Trichloroethane), which is effective for 6 months. DDT is not available to individual households. They can still purchase from local markets other types of sprays to repel and kill mosquitoes, but those sprays are less powerful and their effect is not long lasting.

[7]See Figure 4 in the Appendix

[8]Bleakley (2010) reviews some of these IRS campaigns.

[9]Source: WHO website, http://www.who.int/malaria/vector_control/ivm/en/index.html.

dataset, Keating et al. (2011) make a first attempt[10] to quantify the combined effect of IRS and ITNs, but they cannot find evidence that the introduction of IRS reduces the probability of Malaria infection in the short run, in the low transmission setting under investigation.

Malaria infections bear both short and long term consequences for the health of affected people and hence for their economic outcomes[11]. However, it was not until the recent work of Bleakley (2010), Lucas (2010) and Cutler et al. (2010) that the long-term economic consequences of Malaria were estimated[12]. Altogether, these papers lend support to the argument that Malaria reduction and eradication can improve people's economic long-term well-being.

Mosquito bed-nets are the main tool available to hh's to prevent infection. Therefore, several studies have investigated ways to promote ITN acquisition and usage in malarious villages, and attention has been focused on the comparison between free-distribution and cost-sharing programs. The most influential work on this topic is the paper by Cohen and Dupas (2010), who provide evidence in support of free distribution. Not only does free distribution not lead to wastage of resources, but also take-up declines dramatically when even a small positive price is charged. As a result, free-distribution programs are likely to save many more lives than cost-sharing programs, and to be the most cost-effective solution, thanks to the positive externalities that ensue from widespread ITN use.

In addition to lowering the price of a technology, providing information about high returns from its use can be a good way to promote take-up and actual use. Dupas (2011b) highlights that hh's decision to invest in preventive health technologies depends on their beliefs about the risk of receiving a negative health shock and about the perceived protection that the technology would afford them. Her paper reviews studies (Rhee et al. (2005); Madajewicz et al. (2007); Jalan and Somanathan (2008); Dupas (2011a)) that show how provision of information can effectively influence people's health-seeking behavior, when they are not already fully informed about the health situation they face, when the source of information is credible, and when they are able to process this new information.

The breadth of the literature reviewed in Dupas (2011b) suggests that similar issues may be of relevance in studies of Malaria, HIV and other diseases[13]. In a study on HIV in Malawi, De Paula et al. (2011) highlight that policies may affect people's behavior if they are able to change their beliefs,

[10] Kleinschmidt et al. (2009) make a first attempt to quantify the impact of IRS on top of ITNs, but they do not use a RCT. They compare instead previous studies, where either or both technologies were implemented, and they find that the protective efficacy of either technology is not altered by the introduction of the new one.

[11] The main symptoms include fever, headache and weakness, and they last for about a week, during which students and workers stay home from school and work. Absence from school may hinder human capital accumulation and absence from work reduces the income available to the household (hh). Malaria infections also carry important long term health consequences eg anemia, possibly compounding a pre-existing condition caused by malnutrition and parasitic worms.

[12] Bleakley (2010) uses data from past Malaria eradication campaigns conducted in the US, Brazil, Colombia and Mexico, to estimate the impact of early exposure on future labor productivity, and finds that cohorts born after eradication are more literate and earn 12–25% more than cohorts exposed to the disease. Lucas (2010) uses data from two country-wide IRS campaigns conducted in Paraguay and Sri Lanka, to show that Malaria has a negative and significant effect on years of completed education and literacy. Finally, using data from India, Cutler et al. (2010) find that Malaria eradication can increase consumption, especially among men, while they find mixed evidence on its impact on educational attainment.

[13] HIV and Malaria can be regarded as similar diseases. Both are transmitted from person to person, and technologies are available and widely advertised, that are capable of reducing transmission with a high probability. The key difference between HIV and Malaria is that Malaria can be cured, while a cure for HIV has not yet been developed.

and if this induces in turn a behavioral response. The first link is not always observed: along the lines of Delavande and Kohler (2009), they do not find evidence that HIV testing can *consistently* affect people's beliefs about their own HIV+ status. This may have possibly stemmed from lack of credibility of test results. Considering then the second link, they find that that downward revisions in beliefs about own HIV status increase risky behavior, while the opposite occurs with upward revisions. Using a simulation, they conclude that HIV testing leads to an overall reduction in transmission rate.

Borrowing from the literature in marketing and psychology, Dupas (2009) analyzes changes in take-up and use of mosquito bed-nets, depending on the framing of the benefits from using the device, stressing the financial gains from a reduction in missed work or highlighting the health gains from avoiding Malaria. Using data from a RCT from Kenya, Dupas finds that neither take-up nor usage are affected by how benefits are framed in a marketing campaign. As a possible explanation, she proposes that the stakes are so high, that liquidity constraints are probably the main barrier to investments in Malaria prevention.

This aspect is further investigated in Tarozzi et al. (2010), who conduct a RCT in India, to estimate the effectiveness of micro-loans in promoting bed-net take-up and use, and hence in reducing Malaria prevalence. Subjects were selected among clients of a micro-finance institution, and in one intervention arm they were offered a chance to borrow money to purchase mosquito nets. In principle, such opportunity was available to everybody, even before the intervention. So we can interpret this treatment as a marketing campaign promoting an existing financial product. Their intervention was effective in promoting net ownership and use.

Interestingly, Tarozzi et al. (2010) rule out that the intervention caused any "perverse" behavioral responses, ie a reduction in any pre-existing anti-Malaria behavior. If anything, such behaviors actually *increased* in treated groups. The authors, however, do not explain how this may have happened and our model fills this gap, providing a useful framework to think about how people react to the information conveyed by a newly-identified channel, ie the intervention itself. A clear understanding of people's behavioral response is crucial to ensure the long run success of these policies, and we aim to shed some light on this issue with this paper.

Nikolov (2011) asks a question which is very similar to ours, ie whether the provision of antiretroviral (ARV) can distort incentives for consistent HIV preventive behavior. He notices that – if ARV provision reduces the future cost of getting HIV and improves the lives of the sick – it also increases the proportion of healthier HIV+ people in the "market for risky exposures". Using data from South Africa, Nikolov finds evidence that widespread ARV provision distorts incentives for good behavior, leading to both a reduction in condom use and to an increase in the number of sexual partners. We notice that, among the possible margins of behavior changes, he does not consider the possibility that the introduction of ARV may provide information on the importance of HIV prevention, which would in turn promote good behavior. This facet represents the focus of our paper.

4 Data

The NMCP compiled a list of the most malarious villages in GB. We used STATA 10.1 to randomly select 116 of these villages and to randomize them between treatment and control groups. The NMCP verified the distance between treatment and control villages, and replacements were made where distance was not at least 5 km[14]. All villages benefitted from existing NMCP vector control interventions (ie ITNs and LHM) while IRS was conducted only in the treatment arm. Spraying was done during the months of June–July 2009, just before the rainy season[15]. Large villages were segmented into roughly equal segments with 200 hh's, and one segment was randomly chosen. Hh's were enumerated and simple random sampling was used to select 15 hh's to interview[16]. Random hh assignment for interview was performed using tables that we had previously prepared using Microsoft Excel 2007. At all stages, we performed random assignment privately in office.

Data was collected only after the intervention, between 6–15 October 2009, just after the peak of the Malaria transmission season. Collection of baseline data was initially scheduled for the summer of 2008, but it could not be conducted. Ethical approval was received from Tulane University. Medical students from the Orotta School of Medicine and Dentistry (OSMD) in Asmara served as data collectors, under the supervision of NMCP and OSMD staff. Comprehensive training was provided before the data collection. Hh members were eligible to answer the questionnaire if they were 18 years of age and above, and preference was given to the head of the hh head or his/her partner[17].

Enumerators informed respondents that participation in the survey was voluntary and they explained the main objectives of the project. Only one person per hh was interviewed, and all present and consenting hh members were tested for Malaria using Carestart® Rapid Diagnostic Tests (RDT). Response rate was very high at 94.23%, which leaves us with a total sample size of 7,895 observations from 1,617 hh's, of which 809 lived in treatment villages and 808 resided in control villages. At the time of the interview, 15.40% of hh members were away, mainly unemployed[18] men (26%), working men (22%) and school age youths (18%). 8.95% of present hh members refused RDT testing; refusal was most common among children under 5 (16%) and school age youths (9%). This leaves us with data about the Malaria status of about three quarters of the sample.

In the absence of data on the exact location and altitude of each village, we complement our dataset with subzone[19] level panel data on a vegetation index called Normalized Difference Vegetation Index (NDVI). This index has been shown to be very highly correlated with the species of Malaria called *Plasmodium falciparum*, which accounts for more than 80% of Malaria inflections in Eritrea (Shililu et al. (2004)), and it has been used extensively in the literature to model Malaria transmission and to

[14]Mosquitoes cannot fly so far away.

[15]At least 80% of the hh's were sprayed in each control village, as per WHO recommendations.

[16]Some villages had less than 15 hh's, and so all available hh's were interviewed there.

[17]If no one lived there, the hh was not replaced. If no one was present or no eligible hh member could be found, then up to two more visits were paid to the same hh. Three visits could not be paid in one single day, but they had to be spread at least over two days to allow time for the hh to come back. At the third and last visit, any hh member aged 15 and above was deemed eligible to answer the questionnaire. The respondent was most often the hh head (61.71%) or the spouse (33.83%).

[18]The definition of "unemployed" encompasses enrollment in national service, as discussed in the Data Appendix.

[19]Each Zone of Eritrea is composed of several subzones, or provinces.

forecast epidemics. We use NDVI time series to assign to each subzone a value $ndvi \in \{0, 1, 2\}$, where 0 hints to "very limited vegetation", 1 stands for "some vegetation" and 2 means "with significant vegetation". The Data Appendix describes in detail how we constructed this variable. The resulting classification of subzones is presented in Table 1.

Table 1: Classification of the subzones of Gash Barka by vegetation level

Vegetation	Subzones	ndvi
Arid	Akurdet, Dighe, Forto, Mensura	0
With some vegetation	Barentu, Gogne, Haykota, Mogolo, Tesseney	1
With much vegetation	Goluj, Laelay-Gash, Mulki, Shambko	2

Summary statistics are presented in Table 2. This table also presents, for each characteristic Y, the p-value of the test $\beta = 0$ where β was estimated as follows: $Y_i = \beta \cdot T_i + \varepsilon_i$, where T_i is an indicator variable, which is equal to 1 if hh i resides in a treatment village, and 0 otherwise. All p-values but one are greater than 0.10, which suggests that randomization was effective. The Tigre tribe seems however to be over represented in the treatment group ($p = 0.05$) and we take this into account in our analysis, including in all regressions a dummy variable equal to 1 if hh i belongs to the Tigre tribe, and 0 otherwise. We further tested whether three sets of controls – available for all, for respondents only and at hh level – jointly determine treatment, and we reject this hypothesis in all cases. This provides additional evidence that randomization was effective.

The list we initially used to randomly assign villages to treatment or control included 116 villages. Some names were changed at the time of the intervention or when the data collection was conducted. We paid a great deal of attention to understand what happened, because we lack baseline data and we wanted to make sure that randomization had not been compromised. We discussed this issue at length with the NMCP and we conducted a very detailed analysis along with robustness checks, presented in the Appendix. Our analysis makes us confident that randomization was indeed effective.

The data show that 6% of hh's living in control villages reported having their dwelling sprayed in the 5 months to the survey[20]; most likely they used simple insecticide sprays purchased from local shops, whose effectiveness is not comparable to IRS. Also, 25% of hh's in treatment villages reported not receiving IRS; this may have occurred eg if hh's were absent at the time of the intervention or if residents denied permission to spray inside their house[21]. Having identified a problem of partial compliance, we cannot recover unbiased estimates of the Average Treatment Effect (ATE), but we can estimate the Intention to Treat (ITT) parameter, which represents a difference in means between the outcomes of the individuals randomized into treatment and those originally left out.

[20]This is roughly the period of time between treatment and the interviews, allowing for some recall error.
[21]Participation was voluntary. Data tells us that 2.5% of respondents would not allow IRS in their homes.

Table 2: Randomization checks

Variables (Y)	Observations	Mean	St. Dev.	p-value (T)
ALL				
1- Female	7,826	0.52	0.5	0.722
2- Usually lives here	7,740	0.98	0.15	0.206
3- Stayed there last night	7,709	0.96	0.2	0.113
4- Age	7,880	22.17	19.35	0.484
5- Currently enrolled in school	2,715	0.34	0.47	0.458
6- Current grade in school	932	4.33	2.58	0.426
	P-value [variables 1-4]			0.25
RESPONDENTS ONLY				
7- Age	1,616	41.74	15.13	0.492
8- Ever attended school	1,615	0.19	0.39	0.832
9- Only primary school	296	0.76	0.43	0.481
10- Literate	1,615	0.19	0.39	0.639
11- Muslim religion	1,610	0.81	0.39	0.377
12- Tigre tribe	1,615	0.48	0.5	0.05*
13- Married	1,609	0.93	0.25	0.348
	P-value [variables 7-8,10-13]			0.16
BY HOUSEHOLD				
14- Hh size	1,617	4.89	2.29	0.239
15- # members under 5	1,616	0.83	0.92	0.705
16- # members under 18	1,616	2.64	1.97	0.471
17- Main source of drinking water:				
17.a- Public tap	1,615	0.43	0.49	0.893
17.b- Unprotected well	1,615	0.24	0.43	0.721
17.c- Unprotected spring	1,615	0.13	0.34	0.696
18- Has any toilet	1,615	0.06	0.24	0.629
19- Has radio	1,615	0.25	0.43	0.797
20- Firewood is main fuel	1,601	0.95	0.23	0.248
21- Has no window	1,556	0.32	0.47	0.939
22- # separate rooms	1,615	1.84	1.19	0.831
23- # sleeping rooms	1,615	1.38	0.77	0.969
24- # sleeping spaces	1,615	4.53	2.4	0.39
	P-value [variables 14-24]			0.925
	P-value [variables 7-8,10-24]			0.276

Note: The table presents, for each characteristic Y, the p-value of the test $\beta = 0$, where β was estimated as follows: $Y_i = \beta T_i + \varepsilon_i$. In addition, we use an F-test to check whether groups of controls (with comparable sample size) jointly predict treatment and we report the p-values. Observations clustered at village level. *** p<0.01, ** p<0.05, * p<0.1.

5 Theoretical framework

To guide our empirical analysis we introduce here a very simple model of behavioral response to the introduction of IRS under perfect and imperfect information about the probability of Malaria infection. The structure and the assumptions of our model aim to reflect the key feature of the economic environment under investigation, and in particular that: labor demand is concentrated during the malaria season, because the rainy season brings about both malaria and irrigation allowing for agricultural work; there is only one worker in the median hh; during this period every worker wants to work as much possible; and wages for agricultural laborers are fixed. All derivations and proofs are presented in the Appendix.

There are N identical workers, indexed by $i = 1, 2, \ldots, N$. Each worker has the same time endowment $time_i = T, \forall i$. There is only one firm, with infinite labor demand at wage w, so labor demand is perfectly elastic. Labor supply is perfectly inelastic: workers want to spend their entire time endowment at work. Malaria may affect workers' time endowment: Malaria reduces available time from T to $T - t, t > 0$.[22] If a mosquito finds a worker, it will bite and infect him. The probability that a mosquito finds a worker is $\pi \geq 0$.

Two technologies, namely ITNs and IRS, exist to protect workers from Malaria. In the following, we refer to ITNs and IRS as Φ and Ψ respectively. Technology Φ, ITNs, is freely available to every worker i, and it can protect them from infected mosquitoes with probability $p^{\Phi} \in (0, 1)$,[23] preventing a reduction in time endowment. Use of Φ causes workers disutility[24] $d_i > 0$ so that some workers may decide not to use it. Technology Ψ, IRS, may be also made freely available to every worker i, and it can protect them from infectious bites with probability $p^{\Psi} \in (0, 1)$, preventing a reduction in time endowment. Use of Ψ does not entail any disutility for users. Therefore, all workers will choose to use it when it is made available to them.

Technology Φ is already in place and it cannot be removed. Technology Ψ may be introduced on top of Φ in an attempt to grant workers additional protection from Malaria and allow them to work as much as possible. We assume[25] that using two technologies jointly offers more protection than using either alone:

Assumption 1. $\max(p^{\Phi}, p^{\Psi}) < p^{\Phi \cup \Psi}$, *where* $p^{\Phi \cup \Psi}$ *is the probability that at least one technology works, when both are in place.*

Worker are risk neutral, with utility function $U_i = Y_i - \phi_i d_i$,[26] where ϕ_i is a dummy variable equal

[22] This simplifying assumption means that workers can catch Malaria just once a year and all Malaria cases entail an identical loss of working time, equal to t.

[23] We let $p^{\Phi} < 1$ because a mosquito may still bite a net user eg before they go to sleep or in the early morning.

[24] Disutility may arise from a variety of factors that negatively impact mosquito-net users, including: the need to hang the net over the bed every night; sleeping closer to other hh members to fit more people inside a net; a reduction in ventilation during the hours of sleep; possible allergic reaction from contact with the insecticide on the net.

[25] Assumption 1 draws from the evidence presented in Kleinschmidt et al. (2009), that combined use of IRS and ITNs reduces the probability of malaria infection more than use of either technology alone. They show that the protective efficacy of either technology is unaffected by the use of the other.

[26] Notice that, once the disutility d is allowed to vary from person to person, there is no need to specify the utility function as $U_i = u_i(Y_i) - \phi_i d_i$ or as $U_i = u(Y_i) - \phi_i d_i$. We just need to avoid the case in which all workers choose

to 1 if worker i chooses to use Φ and 0 otherwise, and d_i represents an idiosyncratic disutility incurred using technology Φ. Each worker chooses whether to use Φ, to maximize his[27] own expected utility:

$$\phi_i^* \in \arg \max_{\phi_i \in \{0,1\}} E(U_i|\Psi) \tag{1}$$

In this simple model, we have not accounted for any externalities which may arise from others' use of ITNs, ie we do not model $\Pr(\phi_i)$ as function of $\Pr(\phi_{-i})$, where $-i$ includes all agents but i. We discuss in the Appendix several arguments that could guide the agents' decisions, and it is unclear which have the largest influence in reality. In the absence of more information, we prefer to abstain from including externalities in our model.

5.1 Perfect information

With exogenous wage w, workers are actually maximizing their expected time endowment $E(time_i)$. Under perfect information, all workers know that the probability of infectious bites is $\pi > 0$ and

$$\begin{aligned} E(time_i) &= (1-\pi)T + \pi \left\{(1-\phi_i)(T-t) + \phi_i[(p^\Phi T + (1-p^\Phi)(T-t)]\right\} \\ &= T - \pi t \left(1 - \phi_i p^\Phi\right) \end{aligned} \tag{2}$$

where ϕ_i is an individual dummy for net use. If no mosquitoes find and infect[28] worker i, he will have full time endowment T irrespective of his use of Φ. If instead a mosquito finds him, if he does not sleep under a mosquito net, he will lose time endowment t and will be left with $T - t$. Net use would grant him protection with probability p^Φ, preventing him from losing t.

Worker i will use technology Φ if and only if its use can increase his expected utility, which happens if the expected gains can compensate for the disutility incurred from its use:

$$\begin{aligned} \phi_i^* = 1 \quad &\Leftrightarrow \quad E(U_i|\phi_i = 1) > E(U_i|\phi_i = 0) \\ &\Leftrightarrow \quad wE(time_i|\phi_i = 1) - d_i > wE(time_i|\phi_i = 0) \\ &\Leftrightarrow \quad w\left(T - \pi t + \pi p^\Phi t\right) - d_i > w\left(T - \pi t\right) \\ &\Leftrightarrow \quad w\pi p^\Phi t > d_i \end{aligned} \tag{3}$$

Expressions (4) and (5) are analogous to (2) and (3) for the case in which Ψ is available:

$$E(time_i|\Psi = 1) \quad = \quad T - \pi t[1 - (p^\Psi)^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}] \tag{4}$$

$$\phi_i^* = 1|\Psi = 1 \quad \Leftrightarrow \quad w\pi(p^{\Phi\cup\Psi} - p^\Psi)t > d_i \tag{5}$$

the same ϕ_i in the utility maximization problem, which would occur if the utility function were $U_i = Y_i - \phi_i d$. Our specification accomplishes this goal in the simplest way.

[27] We refer to workers using the male pronoun as they constitute 70% of the sample.

[28] We have assumed that it will infect him with certainty.

Equation (4) shows that the probability of infection now depends also on Ψ. Condition (5) means that, once spraying campaigns have been rolled out, workers will choose to sleep under a net if and only if the *additional* expected gains from its use can compensate for the associated disutility.

We are interested in understanding how average net use changes after the introduction of IRS. Call $\theta^{\Phi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*)$ the average use of Φ before the introduction of Ψ, and let $\theta^{\Psi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*|\Psi = 1)$ represent the same measure after the introduction of Ψ. The direction in which average net use may change depends on the relationship between conditions (3) and (5). This comparison requires an assumption on the degree of complementarity between Φ and Ψ. We find it reasonable to assume that Φ and Ψ are imperfect substitutes and we formalize this in Assumption 2:

Assumption 2. $p^{\Phi\cup\Psi} \leq p^{\Phi} + p^{\Psi}$.

Assumption 2 says that the additional protection offered by Φ when Ψ is also available cannot exceed that granted by Φ alone. Therefore, when agents are perfectly informed that $\pi > 0$, average use of Φ cannot increase following the introduction of Ψ, ie $\Pr(\theta^{\Psi} > \theta^{\Phi}) = 0$.[29]

5.2 Imperfect information

In a more realistic setting, workers do not know the probability of infection. In particular, they do not know whether it is $\pi > 0$ or $\pi = 0$.[30] Each worker i is endowed with a prior $P_i(\pi > 0)$ drawn from a $Uniform(0, 1)$. Workers know that the provider of Ψ, ie the Government, has perfect knowledge about π. Assume further that it is common knowledge that the probability of spraying when the true risk of infection is 0 cannot exceed the probability of doing so when Malaria poses a threat:

Assumption 3. $\Pr(\Psi = 1|\pi > 0) \geq \Pr(\Psi = 1|\pi = 0)$.

When workers observe $\Psi = 1$, they update their beliefs using Bayes' rule[31]. For the expected time endowment we can compute expressions (6) and (7) analogous to (2) and (4).

$$
\begin{aligned}
E(time_i) &= T - P_i(\pi > 0)\pi t(1 - \phi_i p^{\Phi}) && (6)\\
E(time_i|\Psi = 1) &= T - P_i(\pi > 0|\Psi = 1)\pi t[1 - (p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}] && (7)
\end{aligned}
$$

Expressions (6) is identical to (2), but for the fact that the prior probability of infection now weights expected time savings; this weight is replaced in equation (7) by the posterior probability $P_i(\pi > 0|\Psi = 1)$. We can use these two equations to obtain conditions (8) and (9) for net use, depending on the availability of Ψ.

[29] All those who do not use Φ in the absence of Ψ will make the same choice once Ψ is introduced. And some workers initially using Φ may decide to shirk following the introduction of Ψ, as the new technology decreases the expected returns from using Φ. As a result, average Φ use may either remain unchanged or decline, but it cannot increase.

[30] This formulation simplifies considerably the structure of the problem, still capturing its essence.

[31] Workers can never observe $\Psi = 0$. In the absence of IRS, they ignore its existence. If IRS is rolled out in other regions, we assume that there is no communication between populations that received Ψ and those who did not.

$$\phi_i^* = 1 \quad \Leftrightarrow \quad P_i(\pi > 0) w\pi t \; p^{\Phi} > d_i \tag{8}$$
$$\phi_i^* = 1 | \Psi = 1 \quad \Leftrightarrow \quad P_i(\pi > 0 | \Psi = 1) w\pi t (p^{\Phi\cup\Psi} - p^{\Psi}) > d_i \tag{9}$$

Assumption 3 implies that the posterior probability of infection cannot be smaller than the prior $\forall i$. The relationship between $(p^{\Phi\cup\Psi} - p^{\Psi})$ and p^{Φ} is governed by Assumption 2. As a result, under imperfect information, θ^{Ψ} may be either larger or smaller than θ^{Φ}. We notice in particular that $P(\theta^{\Psi} > \theta^{\Phi}) > 0$, which is in contrast with the analogous result for the perfect information case, for which we showed that $P(\theta^{\Psi} > \theta^{\Phi}) = 0$.

We appreciate that the results of our model are entirely driven by Assumption 2, which we deem the most sensible in the setting under investigation. It is possible, however, that agents perceive Φ and Ψ as imperfect complements rather than substitutes, and we formalize this in Assumption 4:

Assumption 4. $p^{\Phi\cup\Psi} \geq p^{\Phi} + p^{\Psi}$.

It is easy to show that, under Assumption 4, under both perfect and imperfect information, average Φ use may either remain unchanged or increase after the introduction of Ψ, but it cannot decline, ie $\Pr(\theta^{\Psi} < \theta^{\Phi}) = 0$. Table 3 summarizes the predictions of the model, under either Assumption.

Table 3: Summary of the theoretical predictions

	Imperfect substitutes	Imperfect complements
Perfect Information	$\theta^{\Psi} \leq \theta^{\Phi}$	$\theta^{\Psi} \geq \theta^{\Phi}$
Imperfect Information	$\theta^{\Psi} \leq \theta^{\Phi}$ or $\theta^{\Psi} \geq \theta^{\Phi}$	$\theta^{\Psi} \geq \theta^{\Phi}$

Average use of Φ depending on the complementarity between Φ and Ψ and on the availability of information about Malaria prevalence.
Note: $\theta^{\Phi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*)$ and $\theta^{\Psi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^* | \Psi = 1)$.

6 Data analysis

In this section we analyze the impact of the IRS campaign on a set of behavioral and socio-economic outcomes. In particular, we look at the effect of spraying (1) on the level of information and awareness of Malaria among the people of GB, (2) on the ownership and use of mosquito bed-nets as well as on their intra-hh allocation, and (3) on a set of other Malaria prevention behaviors. Summary statistics are presented in the first two columns of Tables 4–7. For each variable we report its mean and standard deviation, separately for villages in the treatment and control groups. We do not include here an analysis of the impact of the IRS campaign on Malaria prevalence because we do not have enough power to estimate this effect[32]. Further to this, we do not present an analysis of a possible

[32]This RCT was conducted in an extremely low transmission setting. Out of a total of 5,502 people tested with RDT, only 30 individuals tested positive. Such low prevalence is in line with the figures on the population of GB (N=670,000)

treatment effect on education and employment. For completeness, we report summary statics also for these outcomes in Table 8.

Table 4 shows that, in spite of the fairly low levels of parasite prevalence in the region, Malaria is still perceived as a problem in the community by a large majority of the population, both in treatment and control villages. There is also widespread knowledge that mosquitoes are an important transmission vector. Even though almost everyone agrees that children are especially at risk from Malaria, only about a third of respondents believe pregnant women suffer greatly from having Malaria. Finally, about half the respondents were aware of information campaigns during the 6 months preview to the interview, concerning ITNs, health seeking behavior, and environmental management.

Table 5 reports information on net ownership and use. On average, there are about 1.58 nets and 1.26 ITNs per hh in the control group villages, although very few of these nets were recently acquired. Furthermore, an average of 1.16 nets per hh were used the previous night. These figures are slightly higher in the treatment villages. Among households without any net, willingness to pay for a bed net is below the minimum market price of 30 Nakfa. We do not focus on households' participation in net re-impregnated activities, because since 2006 the NMCP has distributed Long Lasting Insecticide Nets (LLINs) rather than ITNs: LLINs are effective for up to 5 years and need not be re-impregnated, while re-impregnation would be needed for ITNs.

We also have information on respondent's reasons for using a net: the main are to stop biting, mentioned by 77% of respondents, fear of Malaria (38%) and to stop buzzing (18%). In a a regression of net use on dummies for reasons mentioned by respondents, none of the coefficients is significant[33] in the unrestricted sample, whereas net use is significantly explained by fear of Malaria (0.06*, se = 0.03) among adult respondents, who are more likely to choose their own sleeping arrangements.

In addition to use mosquito nets, people can engage in other preventive behaviors to reduce the risk of Malaria infection. Eg they can keep any cattle away from home, cover any stored water and participate in environmental management campaigns, among others. Tables 6 shows that participation in LHM is fairly low, as pointed out in Keating et al. (2011). However, we can see from Table 7 that hh's seem to engage in a variety of Malaria-preventive behaviors.

6.1 Homogeneous treatment effects

Tables 4–7 allow us to do some comparisons between treatment and control villages across a wide set of variables. Simple differences are shown in column 3 of these tables. However, to accurately determine the impact of the program it is important to include in the regression some basic controls, which are likely to reduce both the bias and the variance of the estimate of the program impact, or treatment

and on the number of Malaria cases diagnosed there in 2008 (M=20,320). Malaria prevalence in the region was therefore equal to $M/N = 3$. RDT can capture current Malaria infections and those occurred in the month to the test. Data from 2002–2007 shows that the percentage of Malaria cases that occur in September, is about 15%. Back of the envelope computations suggest then that we can expect to find at most $3\% \times 5,502 \times 15 = 25$ Malaria cases with a single round of RDT at the beginning of October. A detailed epidemiological analysis is presented in the companion paper by Keating et al. (2011), whose main finding is that there was little or no impact of the IRS campaign on parasite prevalence in the short run, at least at the current levels of parasite prevalence in GB.

[33] We also checked whether the *share of net users in hh* is determined by reasons mentioned by head or the head's wife/husband, especially the *share of U5s using nets*. Neither measure is explained by mentioned reasons for using nets.

effect. Therefore, for each variable Y, we estimate the program impact (1) using an OLS regression of Y on a treatment indicator and several indicators when Y is a continuous variable, or (2) using a probit model when Y is binary. Our basic controls are a dummy indicating whether an individual belongs to the Tigre tribe[34], a dummy indicating Muslim religion and dummies for subzone of residence.

Formally, we estimate the following models for cases (1) and (2) above:

$$Y = \alpha + \beta\ Treatment + \gamma_1\ TigreTribe + \gamma_2\ Muslim + \gamma'\ Subzones + \epsilon \tag{10}$$

$$Y = \Phi(\alpha + \beta\ Treatment + \gamma_1\ TigreTribe + \gamma_2\ Muslim + \gamma'\ Subzones) \tag{11}$$

where Φ is the cumulative density function of the standard normal.

Column 4 of Tables 4–7 reports estimates of β for our main continuous outcomes, and estimates of $\partial\Phi(.)/\partial Treatment$ (ie marginal effects) when the outcome variables are discrete. Standard errors are clustered at village level. To check the robustness of our estimates, column 5 shows in the same tables the estimated treatment effect when all[35] exogenous variables used for the randomization checks are included in the set of controls. Estimates are almost identical in columns 4 and 5.

Table 4 presents the estimated effect of the IRS campaign on information and knowledge about Malaria. Our estimates suggest that treatment increased knowledge that mosquitoes are a vector by about 3%, and awareness that children are especially at risk from Malaria by almost 7%. On average, respondents did not become more aware that Malaria was a problem in their community, nor that women are particularly vulnerable to Malaria. As a final remark, it appears that respondents in treatment villages did not receive any additional information on ITNs, early seeking behavior and environmental management over the previous 6 months, compared to those in the control group, which points to the fact that any changes in information and knowledge stemmed directly from IRS.

These outcomes play a key role in the analysis of the treatment effect on people's behavior, for the following reason. If the IRS campaign carries no information with it, if people understand that spraying kills mosquitoes reducing the risk of Malaria infection, and if IRS and nets are substitutes, then we would expect our intervention to induce a reduction in net use. The same reasoning could be applied to the other risk-mitigating behaviors eg LHM. This behavior would take place as long as net use and preventive behaviors are costly, while IRS is not, either in terms of money or of effort. However, if the spraying intervention, as we have just seen, changes perceptions about the risk posed by Malaria[36], then net use and participation in environmental management may possibly increase. These are two possible countervailing forces affecting people's behavior and we want to estimate the direction and the size of the total effect on people's behaviors conducive to Malaria prevention.

An interesting question is now whether hh can acquire new nets if they want to do so, or whether supply is determined solely by free distribution campaigns that provide the same number of nets to all hh. To shed some light on this point, we use the asset index described in the Appendix to compare statistics on net ownership by wealth quintile. Focusing on the control group, ie in the absence of

[34] This is the main tribe in GB and it is over-represented in treatment villages.

[35] School enrolment is excluded because it is recorded only for children in school age.

[36] In particular some people may have learnt that the disease still poses a serious health threat, despite the sharp decline in Malaria prevalence witnessed in GB over the past decade, and that mosquitoes are indeed the main transmission vector.

the intervention, we see that net ownership increases with wealth, so that hh in the top quintile own a number of nets (2.17) which is about double that of hh in the lowest quintile (1.24).[37] This is suggestive that net ownership is not exogenously determined by free distribution campaigns. To the contrary, wealthier hh can and do obtain a larger number of nets. They may do so eg purchasing nets from a local market[38] or from poorer[39] hh's, or they may possibly exploit their bargaining power to obtain more free nets during distribution campaigns. It is unclear which is the main channel.

In Table 5 we present the estimated program effects on net ownership and use. Hh's living in treated villages own 0.214 more nets and 0.169 more ITNs than hh's from control villages. However, our estimates also suggest that the number of nets acquired after treatment[40] does not differ between the two groups; this is hard to reconcile with the higher number of nets observed in treated villages, but it may be explained by the presence of large recall error. The reported willingness to pay for a net, among those who have none, remained constant at about 24 Nakfa. This figure is lower than the price of nets on the market, ie 30 or 50 Nakfa. Finally, the number of nets used the night before the survey was 0.186 higher in treated hh's, although average net use was not significantly affected by treatment.

An important indicator of net coverage is the share of hh's with "adequate" access to mosquito nets, defined as ≥ 1 net per 2 hh members. While in the two lowest wealth quintiles this figure is about 25.6%, it increases over the higher quintiles to 32%, 39% and up to 46%. As a consequence of the increase in net ownership induced by treatment, this figure increased on average from 34% to 39%, even though the significance of this difference is not robust to the choice of controls. This remains however an interesting result for the area under investigation, because only a minority of surveyed hh's had adequate access to a bed net prior to IRS. However, the share of hh's with "full" net coverage, defined as ≥ 1 net per 1.5 hh members, did not increase significantly after treatment (p=0.105) from its 16% pre-treatment level.

Tables 6 and 7 report estimates of the impact of spraying on risk-mitigating behaviors other than net use. The former focuses on participation in LHM campaigns. The latter includes behaviors eg keeping any cattle away from home and covering any stored water, along with the full range of mentioned ways how respondents try to prevent mosquito bites. We do not find evidence of any "perverse behavioral response", ie of a negative impact of the intervention on any preventive behavior. If anything, the IRS campaign had a positive effect, especially on the proportion of hh's who keep their livestock away from their dwelling, which increased by as much as 6.76%.

[37] The same holds for ITNs: ownership increases progressively over wealth quintiles, from 0.99ITNs/hh to 1.59ITNs/hh.

[38] Most of the bed nets owned by hh's in GB come from free distribution campaigns conducted by the government. Just a small share of the stock of nets was probably purchased from the market, as mosquito nets are not widely available. They can more easily be found in larger villages and cities. Not only untreated nets are available, but also ITNs can be purchased. The price of a net in GB is approximately 50 Nakfa.

[39] Notice that our wealth index is based on characteristics of the dwelling, so that migrants may live in a more fragile structure and demand less nets because they need to be carried from place to place. Alternatively, migrants may not have been reached by the distribution campaigns.

[40] Number of nets acquired in the previous 4 or 6 months is used as a proxy.

6.2 Heterogeneous treatment effects

So far, we have looked at the average effect of the intervention, assuming that IRS affected all individuals and hh's in the same way. It is possible, however, that the impact of IRS varied across groups of individuals or hh's. Eg hh's residing in more arid areas may have reacted differently from those living in villages with more vegetation, either because the direct impact of spraying is different across areas, or because the role of information and perceptions varies. Similarly workers may have been impacted in a different way from the unemployed, because they have more to lose more from a Malaria infection.

First of all, we analyzed this possibility for the case of the information outcomes, ie Malaria awareness and knowledge that mosquitoes are the vectors. Tables 9–10 report the estimates from Probit regressions (12) and (13), that allow the impact of IRS to vary depending on the local vegetation level and on the employment status of the respondent:

$$Y = \Phi(\alpha + \beta_0 T + \beta_1 T \times (ndvi = 1) + \beta_2 T \times (ndvi = 2) + \gamma X) \tag{12}$$

$$Y = \Phi(\alpha + \beta_0 T + \beta_1 work + \beta_2 T \times work + \gamma X) \tag{13}$$

where T is short for $Treatment$, and $X = (female, Tigre\ tribe, Muslim, subzone\ dummies)$.

Our estimates in Table 9 suggest that Malaria awareness did not change on average in any vegetation area, but we do find a significant 10% increase among workers. Table 10 shows that knowledge about the vector increased on average by 3%, and that the increase was concentrated among respondents living in subzones with more vegetation (8.41%). Knowledge increased especially among the unemployed (4.68%), and particularly among men (11.1%). Overall, these results suggest that while the unemployed learned that mosquitoes are the vector, it is workers who became more worried about Malaria.

Secondly, keeping in mind the determinants of demand for nets identified in Section **??**, we looked for heterogenous treatment effects on net ownership. Table 11 shows that hh's with literate heads[41], or whose head ever went to school, acquired significantly more nets than those with an illiterate head, or whose head never went to school. We estimate an increase in net ownership of 0.35–0.49 nets for the former group vs only 0.16–0.20 for the latter. Only hh's with an employed head increased their stock of nets (+0.31, se=0.11), as the others could probably not afford to. We expected some difference across tribes and religions, due eg to different traditions and sleeping patterns: the largest treatment effect (+0.37, se=0.18) is observed in the Tigrigna tribe, which is the only non-Muslim tribe in the area, while increases were at best modest among Muslim tribes eg the Tigre.

From Table 12 we can see that the treatment effect was only slightly larger in male-headed hh's than in female-headed ones (+0.24 vs +0.21). Households without children under five, who have significantly less nets in the absence of treatment, acquire 0.28 (0.10) new nets on average, while a smaller increase is observed among hh's with young children. Finally, we checked whether treatment effects varied depending on hh's socio-economic status (SES). The poorest hh's did not (or could not) increase their stock of nets, while an increase of about 0.40 units is generally observed among wealthier hh's.

[41] We use respondents as a proxy for hh heads. We replicated these regressions including and excluding respondents who are not the head or the spouse. Their inclusion does not affect the estimates, so we use the unrestricted sample.

Finally, we checked whether spraying affected net use among some demographic groups and how this changed the intra-hh allocation of nets. To do so, we divided the population into six mutually exclusive categories (U5s, children in school age, adult employed men and women, and adult unemployed men and women) and we analyzed how the intervention affected net use in each of them.

In the absence of spraying, net usage varies greatly by age and employment status: U5s are the most likely to sleep under a bed net (50%), followed by school age youths (36%), unemployed and employed women in working age (44 and 40%) and finally by employed and unemployed adult men (27 and 24%). No significant gender difference can be observed among U5s (p=0.39) or among young people (p=0.11). Among employed adults, women are much more likely to sleep under a bed-net (+13%, p<0.01) and the same is true among the unemployed (+20%, p<0.01). To estimate the treatment effect on net use and intra-hh allocation, we run probit regression (14),

$$\begin{aligned} NetUse &= \Phi(\alpha + \beta_0 T + \beta_{11}[0-4yo] + \beta_{21} SchoolAge + \beta_{31} WorkF \\ &\quad + \beta_{41} UnemplM + \beta_{51} UnemplF + \beta_{12} T \times [0-4yo] \\ &\quad + \beta_{22} T \times SchoolAge + \beta_{32} T \times WorkF \\ &\quad + \beta_{42} T \times UnemplM + \beta_{52} T \times UnemplF + \gamma X) \end{aligned} \tag{14}$$

where T is short for $Treatment$, and $X = (female, Tigre\ tribe, Muslim, subzone\ dummies)$.

Estimates are shown in Table 13. Treatment increased net use among male workers by 7.72% and approximately by the same percentage among female workers, when we additionally control for hh size. These results, showing increased net use among workers, are consistent with the previous finding that Malaria awareness increased among them and with the idea that hh's became more sensitive to the importance of protecting their breadwinners, and adapted intra-hh allocation of nets accordingly. Importantly, this did not have any negative consequences for net use among the most vulnerable groups, ie U5s and pregnant women[42]. Increased net use among workers may have stemmed from the observed increase in net ownership or from a change in sleeping arrangements, with workers sharing more often sleeping space with their wives and young children. In Table 14 we repeat our analysis of net use, restricting the sample in turn to each of our six demographic groups: estimates confirm the robustness of an increase in net use among men and the lack of a negative impact on vulnerable groups, but we cannot confirm the effect on net use among working women.

7 Conclusions

Several countries in Sub-Saharan Africa, including Eritrea, have successfully reduced the Malaria burden in their territory in recent years, using a combination of free ITN distribution, LHM, case management and information campaigns. These Governments are now contemplating strategies to eradicate the disease once and for all, and in particular they are now considering the introduction of regular IRS campaigns to achieve their goal, whereas spraying has been used so far chiefly for emergency response.

[42] We do not have data about pregnancy, so we look at adult women as a proxy for pregnant women.

IRS is peculiar in that - unlike ITNs, LHM and other risk-mitigating behaviors - it is capable of killing mosquitoes and of reducing Malaria prevalence without requiring beneficiaries to incur any cost or to put any effort. Therefore it is possible that implementing IRS campaigns may induce a reduction in people's willingness to incur the costs necessary for the existing risk mitigating technologies, which may possibly lead to a resurgence of the disease, rather than to a sharp decrease and its eventual eradication.

A single IRS intervention is not sufficient to eradicate Malaria completely in a policy-induced low-transmission setting, where the disease prevalence has been drastically reduced with a combination of free ITN distribution, LHM and information campaigns. It is therefore of paramount importance that people consistently make use of the preventive technologies available to them, to ensure that Malaria eradication can be achieved in the medium run, with the help of several IRS campaigns.

Our main result is that IRS did not lead to any perverse behavioral response, ie it did not have any negative effect on the risk mitigating behaviors in which villagers are engaged, at least in the short run. As a result, any positive effect of the spraying campaign will not be counteracted by reduced effort in the other preventive activities. If spraying had any impact on people's behavior, this was actually in the sense of *promoting* preventive behaviors. Crucially, we show that IRS increased average ownership of mosquito bed nets, and that it promoted net use among workers.

We explain this with a simple behavioral model in a setting with imperfect information, in which we allow people to update their beliefs about the prevalence of a disease when they observe the introduction of a new intervention. This model proposes that additional policies act as marketing campaigns, capable to promote take-up of the existing preventive technologies, and as an information campaign, that fosters active use of the available risk mitigating tools.

We observe in our data very high pre-intervention awareness about Malaria, the mode of transmission and who is at increased risk – which is a very important precursor to developing strategies for elimination – and we crucially show that IRS promoted Malaria awareness even further, especially among some population groups ie workers, who increased net use accordingly.

Mosquito net ownership increased after treatment, both overall and focusing on ITNs alone. Such increase in the stock of nets can explain how net use increased among workers, but this may also have stemmed from a change in sleeping arrangements, with workers sharing more often sleeping space with their wives and young children. An alternative explanation could be that hh's became more sensitive to the importance of protecting their breadwinners, and adapted intra-hh allocation of nets accordingly. Crucially, we show that net use among the most vulnerable categories, ie U5s and pregnant women, was not negatively affected by the rise in use among workers.

This paper has also briefly investigated the possibility that people perceive IRS and bed nets as complements rather than substitutes, as a way to explain the observed increase in net use after the spraying campaign. However it is hard to argue that these technologies can be regarded as complements, so our preferred explanation relies on the role of IRS as an information channel.

The evidence presented in this paper may be of help to policy makers, concerned about the possibility that introducing IRS could be in fact counterproductive. We do not find any evidence supporting this fear.

Table 4: Information and knowledge about Malaria

	(1)	(2)	(3)	(4)	(5)
Variables	Treatment	Control	Difference	β	β_{all}
1. Mosquitoes mentioned among Malaria vectors	0.908	0.854	0.0541**	0.0305*	0.0341**
	(0.289)	(0.353)	(0.0213)	(0.016)	(0.0164)
2. Malaria is a problem in community	0.726	0.670	0.0564	0.035	0.0477
	(0.446)	(0.471)	(0.0442)	(0.035)	(0.0359)
3. Children mentioned among most affected by Malaria	0.863	0.788	0.0744***	0.0679***	0.0634***
	(0.344)	(0.409)	(0.0248)	(0.019)	(0.0177)
4. Pregnant women mentioned among most affected	0.367	0.365	0.002	-0.0143	-0.00703
	(0.482)	(0.482)	(0.0403)	(0.024)	(0.0258)
5. Heard/saw messages about ITNs in past 6 months	0.484	0.469	0.0152	-0.00050	0.00608
	(0.500)	(0.499)	(0.0421)	(0.038)	(0.0356)
6. Heard/saw messages on early seeking behavior in past 6 months	0.537	0.501	0.0365	0.019	0.0197
	(0.499)	(0.500)	(0.0420)	(0.040)	(0.0360)
7. Heard/saw messages on environmental management in past 6 months	0.450	0.387	0.0638	0.029	0.0235
	(0.498)	(0.487)	(0.0430)	(0.036)	(0.0352)
Joint tests on variables:	2,3,4	p-values =	0.0037	0.0009	0.0028
	5,6,7		0.4462	0.7562	0.8026

Notes: Columns 1 and 2 report means for treatment and control groups, with standard deviations in parentheses. Column 3 reports the difference between treatment and control groups; observations are clustered at village level and robust standard errors are reported in parentheses. β in column 4 represents the treatment effect, estimated using probit regression (11) for which marginal effects are reported. Additional controls: Tigre tribe, Muslim and subzone dummies. Column 5 is presented to check the robustness of our results: all controls used in the randomization checks are included. We also run a probit regression of treatment on sets of variables in the table plus the controls listed above and we test if these sets of coefficients are jointly significant. We report p-values at the bottom of the table.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Ownership and use of mosquito bed nets

	(1)	(2)	(3)	(4)	(5)
Variables	Treatment	Control	Difference	β	β_{all}
1. Number of nets owned by household	1.774	1.575	0.200*	0.214**	0.199**
	(1.279)	(1.207)	(0.110)	(0.0996)	(0.0833)
2. Number of ITNs owned by household	1.444	1.278	0.166*	0.176*	0.168**
	(1.206)	(1.126)	(0.0963)	(0.0926)	(0.0799)
3. Number of nets acquired in past 4 months	0.232	0.217	0.0142	0.0288	0.0213
	(0.641)	(0.593)	(0.0451)	(0.0388)	(0.0370)
4. Number of nets acquired in past 6 months	0.290	0.284	0.00551	0.0211	0.0135
	(0.676)	(0.646)	(0.0489)	(0.0432)	(0.0403)
5. How much is willing to pay for a net, having none	24.346	23.296	1.051	1.564	1.682
	(22.390)	(23.823)	(3.247)	(3.126)	(3.317)
6. Reported net use (of each household member)	0.429	0.380	0.049	0.034	0.051
	(0.495)	(0.486)	(0.035)	(0.033)	(0.038)
7. Number of observed nets used the night before	1.384	1.164	0.220**	0.186**	0.156*
	(1.214)	(1.054)	(0.0990)	(0.0877)	(0.0803)
8. Number of observed nets left unused the night before	0.676	0.736	-0.0600	0.0152	0.0106
	(0.993)	(1.001)	(0.0763)	(0.0626)	(0.0633)
9. Number of owned nets left unused the night before	0.756	0.818	-0.0627	0.0118	0.00817
	(1.038)	(1.057)	(0.0807)	(0.0689)	(0.0694)
Joint tests on variables:	1,6,7,8	p-values =	0.1489	0.0936	0.0702

Notes: Columns 1 and 2 report means for treatment and control groups, with standard deviations in parentheses. Column 3 reports the difference between treatment and control groups; observations are clustered at village level and robust standard errors are reported in parentheses. β in column 4 represents the treatment effect, estimated using LS regression (10). Additional controls: Tigre tribe, Muslim and subzone dummies.
Column 5 is presented to check the robustness of our results: all controls used in the randomization checks are included. We also run a probit regression of treatment on sets of variables in the table plus the controls listed above and we test if these sets of coefficients are jointly significant. We report p-values at the bottom of the table.
*** p<0.01, ** p<0.05, * p<0.1.

Table 6: Participation in Larval Habitat Management (LHM)

	(1)	(2)	(3)	(4)	(5)
Variables	Treatment	Control	Difference	β	β_{all}
1. Respondent participated in LHM[1]	0.322	0.282	0.040	0.012	0.017
	(0.468)	(0.450)	(0.044)	(0.038)	(0.037)
2. Days spent by household in LHM[2]	0.632	0.618	0.013	0.025	0.059
	(2.774)	(1.978)	(0.181)	(0.161)	(0.173)
3. Household members who participated in LHM[2]	0.456	0.39	0.066	0.051	0.066
	(1.007)	(0.898)	(0.077)	(0.071)	(0.066)
4. Male household members >15 years old who participated in LHM[2]	0.167	0.125	0.042	0.025	0.034
	(0.462)	(0.399)	(0.031)	(0.027)	(0.026)
5. Female household members >15 years old who participated in LHM[2]	0.215	0.219	-0.004	-0.001	-0.005
	(0.47)	(0.483)	(0.038)	(0.034)	(0.033)
6. Household members <15 years old who participated in LHM[2]	0.075	0.046	0.029	0.027	0.038
	(0.467)	(0.372)	(0.025)	(0.026)	(0.024)
Joint tests on variables:	1-2,4-6	p-values =	0.3683	0.5752	0.3940

Notes: Columns 1 and 2 report means for treatment and control groups, with standard deviations in parentheses.
Column 3 reports the difference between treatment and control groups; observations are clustered at village level and robust standard errors are reported in parentheses. β in column 4 represents the treatment effect, estimated using LS regression (10). Additional controls: Tigre tribe, Muslim and subzone dummies.
Column 5 is presented to check the robustness of our results: all controls used in the randomization checks are included. We also run a probit regression of treatment on sets of variables in the table plus the controls listed above and we test if these sets of coefficients are jointly significant. We report p-values at the bottom of the table.
*** p<0.01, ** p<0.05, * p<0.1.
[1] over the previous 6 months. [2] over the previous month.

Table 7: Behaviors conducive to Malaria eradication, other than LHM

	(1)	(2)	(3)	(4)	(5)
Variables	Treatment	Control	Difference	β	β_{all}
1. Household keeps livestock >100m from home	0.807	0.776	0.031	0.068**	0.074**
	(0.395)	(0.417)	(0.032)	(0.031)	(0.030)
2. Household covers stored water	0.942	0.953	-0.011	-0.027	-0.020
	(0.234)	(0.212)	(0.020)	(0.018)	(0.015)
3. Respondent does anything to prevent mosquito bites	0.834	0.804	0.030	-0.006	-0.000
	(0.372)	(0.397)	(0.031)	(0.025)	(0.026)
4. Respondent mentions using net	0.680	0.649	0.029	0.011	0.019
	(0.467)	(0.478)	(0.039)	(0.029)	(0.029)
5. Respondent mentions burning coils	0.225	0.211	0.015	0.003	0.004
	(0.418)	(0.409)	(0.035)	(0.022)	(0.022)
6. Respondent mentions using spray	0.025	0.021	0.004	0.010	0.010
	(0.156)	(0.143)	(0.009)	(0.008)	(0.007)
7. Respondent mentions burning animal dung	0.058	0.046	0.012	0.005	0.006
	(0.234)	(0.209)	(0.014)	(0.012)	(0.011)
8. Respondent mentions burning herbs	0.048	0.054	-0.006	-0.017	-0.013
	(0.215)	(0.226)	(0.018)	(0.014)	(0.012)
9. Respondent mentions draining stagnant water	0.106	0.120	-0.014	-0.022	-0.018
	(0.309)	(0.325)	(0.021)	(0.018)	(0.016)
Joint tests on variables:	3-8	p-values =	0.8851	0.5764	0.4071

Notes: Columns 1 and 2 report means for treatment and control groups, with standard deviations in parentheses. Column 3 reports the difference between treatment and control groups; observations are clustered at village level and robust standard errors are reported in parentheses. β in column 4 represents the treatment effect, estimated using LS regression (10). Additional controls: Tigre tribe, Muslim and subzone dummies.

Column 5 is presented to check the robustness of our results: all controls used in the randomization checks are included. We also run a probit regression of treatment on sets of variables in the table plus the controls listed above and we test if these sets of coefficients are jointly significant. We report p-values at the bottom of the table.

*** p<0.01, ** p<0.05, * p<0.1.

Table 8: Education and labor supply

	(1)	(2)	(3)	(4)
Variables	Treatment	Control	Difference	β
1. Current school enrolment status	0.310	0.347	-0.0366	0.00275
	(0.463)	(0.476)	(0.0499)	(0.0387)
2. Current grade in school	4.440	4.233	0.206	0.310
	(2.490)	(2.653)	(0.258)	(0.225)
3. Has missed school during the last 2 weeks	0.036	0.022	0.0143	0.0184
	(0.187)	(-0.147)	(0.0125)	(0.0114)
4. Number of school days missed in last 2 weeks, 0 if none	0.099	0.061	0.0386	0.0626
	(0.867)	(0.488)	(0.0544)	(0.0518)
5. Is unemployed	0.557	0.551	0.00572	0.000017
	(0.497)	(0.498)	(0.0274)	(0.0183)
6. Has missed work during the last 2 weeks	0.068	0.066	0.00116	0.00401
	(0.251)	(0.249)	(0.0171)	(0.00787)
7. Number of working days missed in last 2 weeks, 0 if none	0.282	0.444	-0.162	-0.134
	(1.449)	(2.081)	(0.118)	(0.12)
Joint tests on variables:	1-4	p-values =	0.8641	0.3131
	5-7	p-values =	0.0642	0.0901

Notes: Columns 1 and 2 report means for treatment and control groups, with standard deviations in parentheses. Column 3 reports the difference between treatment and control groups; observations are clustered at village level and robust standard errors are reported in parentheses. β in column 4 represents the treatment effect, estimated using LS regression (10). Additional controls: Tigre tribe, Muslim and subzone dummies.
Column 5 is not reported for this table because regressions cannot be computed for these outcomes with all controls. We also run a probit regression of treatment on sets of variables in the table plus the controls listed above and we test if these sets of coefficients are jointly significant. We report p-values at the bottom of the table.
*** p<0.01, ** p<0.05, * p<0.1.

Table 9: Estimated treatment effect on Malaria awareness

	Y=1(Malaria is a problem)				
	(1)	(2)	(3)	(4)	(5)
Subsample:	All	All	Working age	Working age men	Working age women
Treatment	0.035	0.052	-0.026	-0.018	-0.037
	(0.035)	(0.072)	(0.043)	(0.081)	(0.047)
T x *ndvi*=1		-0.027			
		(0.085)			
		[0.5251]			
T x *ndvi*=2		-0.028			
		(0.113)			
		[0.7514]			
Work			-0.034	-0.003	-0.032
			(0.045)	(0.078)	(0.060)
T x work			0.126***	0.100	0.131**
			(0.049)	(0.095)	(0.062)
			[0.0178]	[0.1655]	[0.1385]
Female	-0.0709***	-0.0707***	-0.0564**		
	(0.024)	(0.024)	(0.027)		
N	1,567	1,567	1,479	549	918

Note:
1: Probit regression (11), reporting marginal effects.
2: Probit regression (12), reporting marginal effects.
3-5: Probit regression (13), reporting marginal effects. Selected sub-samples.
Additional controls include: Tigre tribe dummy, Muslim dummy, subzone dummies.
Main effects for *ndvi* omitted from model 2, to avoid collinearity with subzone dummies.
Observations clustered at village level. Robust standard errors in parentheses.
P-value for the F-test interaction+treatment=0 in square brackets.
*** p<0.01, ** p<0.05, * p<0.1.

Table 10: Estimated heterogeneous treatment effects on knowledge that mosquitoes are the Malaria vector

	Y=1(Mosquitoes are a Malaria vector)				
	(1)	(2)	(3)	(4)	(5)
Subsample:	All	All	Working age	Working age men	Working age women
Treatment	0.0302*	0.020	0.0468**	0.111*	0.036
	(0.016)	(0.025)	(0.023)	(0.058)	(0.025)
T x *ndvi*=1		-0.035			
		(0.043)			
		[0.6704]			
T x *ndvi*=2		0.0641***			
		(0.024)			
		[0.0005]			
Work			0.034	0.041	0.039
			(0.024)	(0.040)	(0.031)
T x work			-0.061	-0.154**	0.001
			(0.045)	(0.077)	(0.054)
			[0.7791]	[0.4006]	[0.4213]
Female	-0.025	-0.027	-0.023		
	(0.018)	(0.017)	(0.019)		
N	1,597	1,597	1,504	515	937

Note:
1: Probit regression (11), reporting marginal effects.
2: Probit regression (12), reporting marginal effects.
3-5: Probit regression (13), reporting marginal effects. Selected sub-samples.
Additional controls include: Tigre tribe dummy, Muslim dummy, subzone dummies.
Main effects for *ndvi* omitted from model 2, to avoid collinearity with subzone dummies.
Observations clustered at village level. Robust standard errors in parentheses.
P-value for the F-test interaction+treatment=0 in square brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Estimated heterogeneous treatment effects on net ownership (Part A)

	(1)	(2)	(3)	(4)	(5)
Treatment	0.1674*	0.3112***	0.2012**	0.3708**	0.3986**
	(0.0890)	(0.1062)	(0.0884)	(0.1783)	(0.1779)
Literate	-0.0455				
	(0.1563)				
Treatment x literate	0.3221**				
	(0.1548)				
	[0.0017]				
Unemployed		0.0281			
		(0.0924)			
Treatment x unemployed		-0.1410			
		(0.1311)			
		[0.1117]			
Ever attended school			-0.0504		
			(0.1639)		
Treatment x ever attended school			0.1524		
			(0.1745)		
			[0.0403]		
Muslim				-0.1361	
				(0.2590)	
Treatment x Muslim				-0.1807	
				(0.1944)	
				[0.0433]	
Treatment x Tigre tribe					-0.1976
					(0.2049)
					[0.1111]
Treatment x Hedarib tribe					-0.0921
					(0.2646)
					[0.1432]
Treatment x Nara tribe					-0.1268
					(0.2522)
					[0.1290]
N	1,441	1,441	1,441	1,441	1,441

Controls in all regressions include dummies for: tribes, Muslim, subzones, literacy, employment status, any schooling, gender of household head, household size tertiles, presence of any children under 5, radio ownership, wealth quintiles.
Observations clustered at village level. Robust standard errors in parentheses
P-value for the F-test interaction+treatment=0 in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Estimated heterogeneous treatment effects on net ownership (Part B)

	(1)	(2)	(3)	(4)
Treatment	0.2075**	0.1933**	0.2780***	-0.0773
	(0.0881)	(0.0869)	(0.0995)	(0.1350)
Male household head	0.2215***			
	(0.0820)			
Treatment x male head	0.0336			
	(0.1197)			
	[0.0268]			
Treatment x 2nd household size tertile		-0.0539		
		(0.1339)		
		[0.2504]		
Treatment x 3rd household size tertile		0.2124		
		(0.1658)		
		[0.0190]		
Household has any kids <5 years old			0.2713***	
			(0.0907)	
Treatment x any kids <5			-0.0857	
			(0.1163)	
			[0.0638]	
Treatment x 2nd wealth quintile				0.4557**
				(0.1853)
				[0.0040]
Treatment x 3rd wealth quintile				0.4027**
				(0.1905)
				[0.0198]
Treatment x 4th wealth quintile				0.2891
				(0.2349)
				[0.2937]
Treatment x 5th wealth quintile				0.4051*
				(0.2223)
				[0.0541]
N	1,441	1,441	1,441	1,441

Controls in all regressions include dummies for: tribes, Muslim, subzones, literacy, employment status, any schooling, gender of household head, household size tertiles, presence of any children under 5, radio ownership, wealth quintiles.
Observations clustered at village level. Robust standard errors in parentheses
P-value for the F-test interaction+treatment=0 in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Estimated heterogeneous treatment effects on intra-household net allocation

	Y=1(Net use)			
	(1)	(2)	(3)	(4)
Treatment	0.095**	0.089**	0.077	0.073
	(0.045)	(0.045)	(0.047)	(0.047)
0-4 years old	0.231***	0.234***	0.236***	0.241***
	(0.028)	(0.028)	(0.030)	(0.030)
School age	0.092***	0.100***	0.100***	0.111***
	(0.024)	(0.024)	(0.025)	(0.025)
Working female	0.130***	0.127***	0.152***	0.147***
	(0.036)	(0.036)	(0.036)	(0.036)
Unemployed male	-0.050	-0.058	-0.046	-0.054
	(0.036)	(0.037)	(0.036)	(0.037)
Unemployed female	0.177***	0.170***	0.181***	0.174***
	(0.029)	(0.029)	(0.030)	(0.030)
Treatment x (0-4 years old)	-0.057	-0.053	-0.056	-0.052
	(0.044)	(0.045)	(0.047)	(0.047)
	[0.4119]	[0.3996]	[0.6141]	[0.5983]
Treatment x (school age)	-0.041	-0.039	-0.045	-0.045
	(0.037)	(0.038)	(0.038)	(0.038)
	[0.1578]	[0.1462]	[0.4071]	[0.3775]
Treatment x (working female)	0.008	0.015	0.006	0.013
	(0.060)	(0.059)	(0.060)	(0.059)
	[0.0527]	[0.0419]	[0.1228]	[0.0977]
Treatment x (unemployed male)	-0.015	-0.005	-0.013	-0.006
	(0.062)	(0.063)	(0.063)	(0.064)
	[0.1908]	[0.1809]	[0.3374]	[0.3247]
Treatment x (unemployed female)	-0.055	-0.048	-0.055	-0.048
	(0.039)	(0.040)	(0.041)	(0.042)
	[0.3483]	[0.3372]	[0.5893]	[0.5662]
Household size dummies	no	yes	no	yes
Subzone dummies	no	no	yes	yes
Observations	7,726	7,726	7,726	7,726

Note: Probit regressions (14), reporting marginal effects.
Omitted category: working men. School age 7-20 years old, approximated to 5-20 years old. Working age defined as >20 years old.
Additional controls: indicator for Tigre tribe and indicator for Muslim religion.
Robust standard errors in parentheses. Observations clustered at village level.
P-value for the F-test interaction+treatment=0 in square brackets.
*** p<0.01, ** p<0.05, * p<0.1.

Table 14: Estimated treatment effects on net use, by gender and age group

	(1)	(2)	(3)	(4)	(5)	(6)
Subsample:	Children under 5	Youth aged 5-20	Adult male workers	Adult female workers	Adult male unemployed	Adult female unemployed
Treatment	0.017	0.033	0.084**	0.070	0.058	0.014
	(0.039)	(0.038)	(0.042)	(0.057)	(0.056)	(0.040)
Observations	1,343	3,385	972	417	432	1,182

Note: Marginal effects estimated after probit regressions of dummy for net use.
Additional controls include: Tigre tribe dummy, Muslim dummy, subzone dummies.
Samples restricted as shown above. Observations clustered at village level.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix to “Behavioral Response to an Anti Malaria Spraying Campaign, with Evidence from Eritrea” by P. Carneiro et al.

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Contents

1 Data

This section provides greater detail on the data sources and the construction of the variables used in the paper. Section 1.1 refers to the data collected in Gash Barka, Eritrea, in 2009, as part of the Randomized Control Trial that represents the focus of the paper. The structure of this section reflects the order followed in the paper. Section 1.2 contains details on the vegetation data which was retrieved from other sources.

1.1 Data from the RCT

1.1.1 Information and knowledge about Malaria

1. *Mosquitoes mentioned among Malaria vectors* =1 if respondent mentioned mosquitoes answering the question "How does one get malaria?", and =0 otherwise. Mentioning mosquitoes does not rule out that respondents may have mentioned also other incorrect options. Correct answer is: mosquitoes.

2. *Malaria is a problem in community* =1 if respondent answered yes to the question "Is Malaria a problem in this community?", and =0 otherwise. *Don't know* was recoded to missing.

3. *Children mentioned among most affected by Malaria* =1 if respondent mentioned children answering the question " Who is most affected by malaria?", and =0 otherwise. Mentioning children does not rule out that respondents may have mentioned also other incorrect options. Correct answer is: children under 5 and pregnant women.

4. *Pregnant women mentioned among most affected* =1 if respondent mentioned pregnant women answering the question " Who is most affected by malaria?", and =0 otherwise. Mentioning pregnant women does not rule out that respondents may have mentioned also other incorrect options. Correct answer is: children under 5 and pregnant women.

5. *Heard/saw messages about ITNs in past 6 months* =1 if respondent answered yes to the question "During the last six months have you heard or seen any messages about insecticide treated mosquito nets?", and =0 otherwise.

6. *Heard/saw messages on early seeking behavior in past 6 months* =1 if respondent answered yes to the question "During the last six months, have you heard or seen any messages about early seeking behavior for malaria treatment?", and =0 otherwise.

7. *Heard/saw messages on environmental management in past 6 months* =1 if respondent answered yes to the question "During the last six months, have you heard or seen any messages about environmental management to control mosquitoes?", and =0 otherwise.

1.1.2 Ownership and use of mosquito bed nets

The definition of ITN that we use for variable "2. Number of ITNs owned by household" is the following.

Definition 1. *An ITN is any net that was treated at least once in last 11 months (including 11 months), or is a permanently treated net (LLIN), ie Olyset or Permanet. In addition, as most nets handed out over the past several years are indeed ITN/LLIN, if the hh reports obtaining a net in the last 3 years it is most likely an ITN/LLIN, so we include also these nets in the definition of ITNs.*

1. *Number of nets owned by household* = number of mosquito nets reportedly owned by hh, including 0 if respondent reported having none.

2. *Number of ITNs owned by household* = number of ITNs owned by household, as defined in Definition 1.
3. *Number of nets acquired in past 4 months* = number of observed nets reportedly acquired at most 4 months before the survey. This variables is probably affected by significant recall error.
4. *Number of nets acquired in past 6 months* = number of observed nets reportedly acquired at most 6 months before the survey. This variables is probably affected by significant recall error.
5. *How much is willing to pay for a net, having none* = reported maximum willingness to pay for a net, among respondents who do not have any net. Answer recoded to 0 if respondent is not willing to pay for a net.
6. *Reported net use (of each household member)* =1 if person reportedly slept under a bed net the night before the survey, and =0 otherwise.
7. *Number of observed nets used the night before* = count of the bednets observed during survey, and reportedly used the night before the survey by at least one hh member.
8. *Number of observed nets left unused the night before* = difference between the total number of nets observed during the survey and the number of observed nets used the night before.
9. *Number of owned nets left unused the night before* = difference between the total number of nets owned by household and the number of observed nets used the night before.

1.1.3 Participation in Larval Habitat Management (LHM)

Remark 1. *For all variables, "don't know" was recoded to missing, in order to have dummy variables, =1 if yes and =0 if no.*

Remark 2. *Due to an incorrect skip instruction, no further information on LHM was recorded if the respondent reported not participating in LHM during the previous 6 months.*

1. *Respondent participated in LHM* =1 if respondent answered yes to the question "In the past six months, have you participated in environmental management in the village?", and =0 otherwise.
2. *Days spent by household in LHM* =1 if respondent answered yes to the question "For how many days did your household participate during the last month?", and =0 otherwise.
3. *Household members who participated in LHM* = total number of hh members who participated in LHM during the last month.
4. *Male household members >15 years old who participated in LHM* = number of male hh members older than 15 who participated in LHM during the last month.
5. *Female household members >15 years old who participated in LHM* = number of female hh members older than 15 who participated in LHM during the last month.
6. *Household members <15 years old who participated in LHM* = = number of hh members younger than 15 who participated in LHM during the last month.

1.1.4 Behaviors conducive to Malaria eradication, other than LHM

1. *Household keeps livestock >100m from home* = 1 if respondent answered yes to the question "Are these animals kept 100 metres or less from your house?", and =0 otherwise. "Don't know" was recoded to missing, in order to have dummy variables. This question was asked only if respondent reported having any livestock ("Do you have livestock such as goats, sheep or camels etc?").

2. *Household covers stored water* = 1 if respondent answered yes to the question "Is the stored water covered?", and =0 otherwise. "Don't know" was recoded to missing, in order to have dummy variables. This question was asked only if respondent reported storing water ("Does this household usually store water for domestic use?").

3. *Respondent does anything to prevent mosquito bites* =1 if respondent answered yes to the question "Do you do things to stop mosquitoes from biting you?", and =0 otherwise.

4. The remaining variables are =1 if they were mentioned among the possible answers to the question "What do you do to stop mosquitoes from biting you?", and =0 if not mentioned or if respondent answered no to the question "Do you do things to stop mosquitoes from biting you?".

1.1.5 Education and labor supply

Remark 3. *The school system in Eritrea provides education only to people who are 7–20 years old. Accordingly, few answers about school enrolment provided by children younger than 7 or people older than 20, or provided on their behalf, were recoded to missing. This was done before the data was received for analysis. However, it is reassuring that there were very few such instances. Answers relating to the working status of people under the age of 20 were also recoded to missing. This was done before the data was received for analysis. However, it is reassuring that there were very few such instances. Accordingly, variables 1–4 have missing values for all people younger than 7 and older than 20, and variables 5–7 have missing values for all people younger than 20.*

Remark 4. *National Service and Unemployment in Eritrea. During the training sessions that preceded data collection there was a discussion regarding the employment question "Is (NAME) currently working?". Allowed answers included "1. Unemployed", "2. Self-employed", and "3. Employed". Trainees and supervisors suggested that national service, not being allowed as an answer, should have been regarded as unemployment, and it was agreed to do so in the field. So, our definition of unemployed includes also national service. A problem arises here in that the size of national service is very large in Eritrea. It is compulsory for some years for all young people of the country, both men and women, and it continues for many well into their thirties or forties. The salary provided to people in national service is very low, and therefore it was deemed to be a form of unemployment.*

1. *Current school enrolment status* =1 if hh member is currently enrolled in school, and =0 otherwise. Missing if older than 20 years old.

2. *Current grade in school* = current grade in school. Missing if older than 20 years old.

3. *Has missed school during the last 2 weeks* =1 if student missed school any time during the 2 weeks to the survey, and =0 otherwise. Missing if older than 20 years old.

4. *Number of school days missed in last 2 weeks, 0 if none* = number of school days missed during the 2 weeks to the survey. Replaced =0 if did not miss any school day in this period. Missing if older than 20 years old.

5. *Is unemployed* =1 if hh member is currently unemployed, and =0 if employed or self employed. Missing if younger than 20 years old.

6. *Has missed work during the last 2 weeks* =1 if worker missed work any time during the 2 weeks to the survey, and =0 otherwise. Missing if younger than 20 years old.

7. *Number of working days missed in last 2 weeks, 0 if none* = number of work days missed during the 2 weeks to the survey. Replaced =0 if did not miss any work day in this period. Missing if younger than 20 years old.

1.2 Other data

1.2.1 Vegetation

Vegetation data was retrieved from the website of the International Research Institute for Climate and Society (IRI) of Columbia University, which provides free Interactive maps of the Normalized Difference Vegetation Index (NDVI) for Africa, available at the following short URL: http://goo.gl/0u2T0.

Selecting East Africa and zooming on Eritrea, it is possible to display the districts, ie zones and subzones. For zone Gash Barka only, we downloaded the available time series for each of its subzone, over the entire available period. The website reports that its data source is the United States Geological Survey, Land Processes Distributed Active Archive Center, Moderate Resolution Imaging Spectroradiometer (USGS LandDAAC MODIS).

We focused on data the period 2000 - 2009 and we kept in mind the main finding of Gaudart et al (2009)[1], who find an NDVI threshold of 0.361, above which *P. Falciparum* malaria is more likely to develop. Accordingly, for each subzone we counted the number of 2–week periods in which NDVI exceeded 0.361. We also tried a lower threshold of 0.3 to allow for a possibly lower threshold in the context of Eritrea. Figures are reported in the Tables A and B in Figure 1.

Tables A and B are colored from red to green (or blue), from the lowest to the highest value; numbers represent the number of 2-week periods with NDVI above the threshold shown in the table header. Red means arid, while green (or blue) means with more vegetation.

Based on these two similar tables, we classified subzones as having low, medium or high NDVI vegetation and we assigned to each of them a value $ndvi = 0, 1, 2$ respectively, as shown in Table 1. In this way we defined the variable $ndvi$ that we use in our regressions.

Table 1: Values of *ndvi* attributed to the subzones of Gash Barka

Color	RED	ORANGE	GREEN/BLUE
$ndvi$	0	1	2
Vegetation	Low/none	Medium	More
Subzones of Zone Gash Barka	Akurdet, Dighe, Forto, Mensura.	Barentu, Gogne, Haykota, Mogolo, Tesseney.	Goluj, Laelay-Gash, Mulki, Shambko.

[1] Gaudart Jean, Ousmane Touré, Nadine Dessay, A lassane Dicko, Stéphane Ranque, Loic Forest , Jacques Demongeot and Ogobara K Doumbo , "Modelling malaria incidence with environmental dependency in a locality of Sudanese savannah area, Mali", Malaria Journal 2009, 8:61.

Table A. Number of 2-week periods with NDVI > 0.361

	LAELAY-GASH	GOLUJ	MULKI	SHAMBKO	TESSENEY	GOGNE	BARENTU	HAYKOTA	MOGOLO	MENSURA	AKURDET	DIGHE	FORTO
2000	6	5	3	3	2	2	2	0	0	0	0	0	0
2001	7	6	5	4	5	4	2	3	1	2	0	0	0
2002	5	5	4	4	2	4	1	1	0	0	0	0	0
2003	6	5	5	5	4	4	4	3	2	1	0	0	0
2004	7	5	2	3	0	2	1	0	0	0	0	0	0
2005	7	6	4	4	3	4	0	0	1	0	0	0	0
2006	7	4	5	5	4	3	3	3	3	0	0	0	0
2007	7	7	7	7	5	6	6	5	5	3	0	2	0
2008	5	5	3	2	3	2	1	0	0	0	0	0	0
2009	4	5	4	3	1	3	3	0	0	0	0	0	0
10y avg	6.1	5.3	4.2	4.0	2.9	3.4	2.3	1.5	1.2	0.6	0.0	0.2	0.0
rank	1	2	3	4	6	5	7	8	9	10	12	11	12
5y avg	6.0	5.4	4.6	4.2	3.2	3.6	2.6	1.6	1.8	0.6	0.0	0.4	0.0
rank	1	2	3	4	6	5	7	9	8	10	12	11	12
3y avg	5.3	5.7	4.7	4.0	3.0	3.7	3.3	1.7	1.7	1.0	0.0	0.7	0.0
rank	2	1	3	4	7	5	6	8	8	10	12	11	12

high NDVI medium NDVI low NDVI

Table B. Number of 2-week periods with NDVI > 0.3

	LAELAY-GASH	GOLUJ	MULKI	SHAMBKO	TESSENEY	GOGNE	BARENTU	HAYKOTA	MOGOLO	MENSURA	AKURDET	DIGHE	FORTO
2000	9	8	7	6	5	4	4	2	0	0	0	0	0
2001	9	8	8	5	5	5	4	4	2	3	2	1	0
2002	8	6	5	5	4	4	4	4	3	1	0	0	0
2003	8	7	7	6	5	5	4	4	4	3	1	1	0
2004	7	8	6	6	2	5	4	2	1	0	0	0	0
2005	8	8	7	6	5	4	3	1	3	0	0	0	0
2006	8	8	8	7	4	4	4	4	4	3	0	0	0
2007	9	8	9	8	5	7	6	5	5	5	2	4	0
2008	8	8	7	5	3	4	4	2	1	0	0	0	0
2009	6	6	4	5	4	4	3	1	3	1	0	0	0
10y avg	8.0	7.5	6.8	5.9	4.2	4.6	4.0	2.9	2.6	1.6	0.5	0.6	0.0
rank	1	2	3	4	6	5	7	8	9	10	12	11	13
5y avg	7.8	7.6	7.0	6.2	4.2	4.6	4.0	2.6	3.2	1.8	0.4	0.8	0.0
rank	1	2	3	4	6	5	7	9	8	10	12	11	13
3y avg	7.7	7.3	6.7	6.0	4.0	5.0	4.3	2.7	3.0	2.0	0.7	1.3	0.0
rank	1	2	3	4	7	5	6	9	8	10	12	11	13

high NDVI medium NDVI low NDVI

Figure 1: Classification of subzones of Gash Barka by vegetation level

2 Theoretical Framework

This Section complements the paper, providing detailed derivations and proofs of the results presented in the Section titled "Theoretical framework". The assumptions are reported in the following, as presented in the paper. So it is possible to start reading this Appendix starting from Section 2.1. Section 2.4 discusses why we do not account for externalities in our model.

To guide our empirical analysis we introduce here a very simple model of behavioral response under perfect and imperfect information about the probability of Malaria infection. The structure and the assumptions of our model aim to reflect the key feature of the economic environment under investigation, which are described elsewhere in this paper. The derivation and proofs of all results are presented in detail in Appendix D.

There are N identical workers, indexed by $i = 1, 2, \ldots, N$. Each worker has the same time endowment $time_i \equiv T$. There is only one firm, with infinite labor demand at wage w, so labor demand is perfectly elastic. Labor supply is perfectly inelastic: workers want to spend their entire time endowment at work. Malaria may affect workers' time endowment: Malaria reduces available time $time_i$ from T to $T - t, t > 0$[2]. If a mosquito finds a worker, it will bite and infect him. The probability that a mosquito finds a worker is $\pi > 0$.

Two technologies, namely ITNs and IRS, are available to protect workers from Malaria. In the following, I refer to ITNs and IRS as Φ and Ψ respectively. Technology Φ, ITNs, is freely available to every worker i, and it can protect workers from infected mosquitoes with probability $0 < p^{\Phi} < 1$, preventing a reduction in time endowment. Use of technology Φ causes workers disutility[3] $d_i > 0$ so that some workers may decide not to use it. Notice that

[2]This simplifying assumption means that workers can catch malaria just once a year and all malaria cases entail an identical loss of working time, equal to t.

[3]Disutility may arise from a variety of factors that negatively impact mosquito-net users, including: the need to hang the net over the bed every night; sleeping closer to other household members to fit more people inside a net; a reduction in ventilation during the

I let $p^\Phi < 1$ because it is still possible for a person sleeping under a net to be bitten by a mosquito before or after sleeping, or through the net if the body touches it, or by any mosquitoes found inside the net.

Technology Ψ, IRS, is also freely available to every worker i, and it can protect them from infected bites with probability $0 < p^\Psi < 1$, preventing a reduction in time endowment. Use of technology Ψ does not entail any disutility for users, and so all workers will decide to use Ψ when it is made available to them.

Technology Φ is already in place and it cannot be removed. Technology Ψ may be introduced on top of Φ in an attempt to grant workers additional protection from Malaria and allow them to work as much as possible. We make the following assumption:

Assumption 1. $\max(p^\Phi, p^\Psi) < p^{\Phi\cup\Psi}$, *where* $p^{\Phi\cup\Psi}$ *is the probability that at least one technology works, when both are in place.*

Assumption 1 says that using two technologies jointly cannot offer less protection than using either alone. It draws from the evidence, presented in Kleinschmidt et al. (2009), that…

Every worker i is risk neutral, with utility function $U_i = Y_i - \phi_i d_i$, where ϕ_i is an indicator variable equal to 1 if worker i chooses to use Ψ and 0 otherwise, and d_i represents an idiosyncratic disutility incurred by user i of technology Ψ. Notice that, once the disutility d is allowed to vary from person to person, there is no need to specify the utility function as $U_i = u_i(Y_i) - \phi_i d_i$ or as $U_i = u(Y_i) - \phi_i d_i$. We just need to avoid the case in which all workers choose the same ϕ_i in the utility maximization problem, which would occur if the utility function were $U_i = Y_i - \phi_i d$. Our specification accomplishes this goal in the simplest way.

Each worker chooses whether to use Φ, to maximize his own expected utility:

$$\phi_i^* \in \arg\max_{\phi_i \in \{0,1\}} E(U_i|\Psi) \tag{1}$$

2.1 Perfect information

In our setting with exogenous wage w, workers are actually maximizing their expected time endowment $E(time_i)$. Under perfect information, all workers know that the probability of infectious bites is $\pi > 0$. In this case, the expected time endowment $E(time_i)$ of worker i will be:

$$\begin{aligned}
E(time_i) &= (1-\pi)T + \pi\left\{(1-\phi_i)(T-t) + \phi_i[(p^\Phi T + (1-p^\Phi)(T-t)]\right\} \\
&= (1-\pi)T + \pi\left[(T-t) + \phi_i p^\Phi t\right] \\
&= T - \pi t\left(1 - \phi_i p^\Phi\right)
\end{aligned} \tag{2}$$

where $\phi_i = 1$ if worker i uses a net and $\phi_i = 0$ otherwise, as described in condition 1.

Irrespective of his[4] use of Φ, worker i will have full time endowment T if no mosquitoes find and infect[5] him. If the worker does not sleep under a mosquito net, if a mosquito finds him, he will lose time endowment t and he will be left with $T - t$. Net use would grant him protection with probability p^Φ, preventing him from losing time endowment t.

Worker i will use technology Φ if and only if its use can increase his expected utility, ie if the following condition holds:

hours of sleep; possible allergic reaction from contact with the insecticide used to treat the net. Disutility thus defined may vary from person to person, as each individual may be more or less susceptible to different facets of the problem.

[4]We refer to workers using the male pronoun as they constitute 70 percent of the sample.

[5]We have assumed that it will infect him with certainty.

$$
\begin{aligned}
\phi_i^* = 1 \quad & \Leftrightarrow \quad E(U_i|\phi_i = 1) > E(U_i|\phi_i = 0) \\
& \Leftrightarrow \quad wE(time_i|\phi_i = 1) - d_i > wE(time_i|\phi_i = 0) \\
& \Leftrightarrow \quad w\left(T - \pi t + \pi p^{\Phi} t\right) - d_i > w\left(T - \pi t\right) \\
& \Leftrightarrow \quad w\pi p^{\Phi} t - d_i > 0 \\
& \Leftrightarrow \quad w\pi p^{\Phi} t > d_i
\end{aligned} \tag{3}
$$

This means that workers will choose to sleep under a net if the expected gains from its use, in terms of expected income, can compensate for the disutility incurred to use the technology.

Now we want to find the analogous condition for the case when Ψ is introduced, ie $\Psi = 1$:

$$
\begin{aligned}
E(time_i|\Psi = 1) \quad & = \quad (1-\pi)T + \pi \left\{ \begin{array}{l} (1-\phi_i)[(p^{\Psi}T + (1-p^{\Psi})(T-t)]+ \\ \phi_i[(p^{\Phi\cup\Psi}T + (1-p^{\Phi\cup\Psi})(T-t)] \end{array} \right\} \\
& = \quad (1-\pi)T + \pi \left\{ \begin{array}{l} (T-t) + [p^{\Psi}T - p^{\Psi}(T-t)]^{1-\phi_i} \times \\ [p^{\Phi\cup\Psi}T - p^{\Phi\cup\Psi}(T-t)]^{\phi_i} \end{array} \right\} \\
& = \quad T - \pi t[1 - (p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}]
\end{aligned} \tag{4}
$$

As before, worker i will use technology Φ if and only if its use can increase his expected utility:

$$
\begin{aligned}
\phi_i^* = 1|\Psi = 1 \quad & \Leftrightarrow \quad E(U_i|\Psi = 1, \phi_i = 1) > E(U_i|\Psi = 1, \phi_i = 0) \\
& \Leftrightarrow \quad wE(time_i|\Psi = 1, \phi_i = 1) - d_i > wE(time_i|\Psi = 1, \phi_i = 0) \\
& \Leftrightarrow \quad w(T - \pi t + \pi p^{\Phi\cup\Psi} t) - d_i > w(T - \pi t + \pi p^{\Psi} t) \\
& \Leftrightarrow \quad w\pi p^{\Phi\cup\Psi} t - w\pi p^{\Psi} t - d_i > 0 \\
& \Leftrightarrow \quad w\pi(p^{\Phi\cup\Psi} - p^{\Psi})t > d_i
\end{aligned} \tag{5}
$$

This means that, once spraying campaigns have been rolled out, workers will choose to sleep under a net if and only if the *additional* expected gains from its use $(p^{\Phi\cup\Psi} - p^{\Psi})$ can compensate for the disutility incurred from use of the technology.

To assess the relationship between conditions (3) and (5) and thus find conditions for use of Φ, we need to make an additional assumption about the relationship between p^{Φ}, ie the protection offered by Φ alone, and $(p^{\Phi\cup\Psi} - p^{\Psi})$, ie the additional protection Φ offers when Ψ is also available. We explore two alternative assumptions.

2.1.1 Technologies Φ and Ψ are imperfect substitutes

The assumption that seems most sensible to us is that the additional protection offered by Φ when Ψ is also available should be no larger than that granted when Ψ is not offered. This assumption means that Φ and Ψ are imperfect substitutes and can be formalized as follows:

Assumption 2. $p^{\Phi\cup\Psi} \leq p^{\Phi} + p^{\Psi}$.

The following proposition follows:

Proposition 1. *When workers are perfectly informed that the probability of infection is $\pi > 0$ and technologies Φ and Ψ are imperfect substitutes, average use of technology Φ cannot increase following the introduction of a new technology Ψ, ie* $\Pr(\theta^{\Psi} > \theta^{\Phi}) = 0$*, where* $\theta^{\Psi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*|\Psi = 1)$ *and* $\theta^{\Phi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*|\Psi = 0)$.

Proof. We have shown that, before the introduction of Ψ, $\phi_i^* = 1 \Leftrightarrow w\pi p^{\Phi} t > d_i$ and that, after its deployment, $\phi_i^* = 1|\Psi = 1 \Leftrightarrow w\pi(p^{\Phi\cup\Psi} - p^{\Psi})t > d_i$. Assumption 2 implies that $p^{\Phi\cup\Psi} - p^{\Psi} \leq p^{\Phi}$. Notice now that condition (5) is stricter than (3), ie (5)$\Rightarrow$(3) but (3)$\not\Rightarrow$(5). Therefore, if a worker uses Φ when Ψ is available, then he must have certainly used it also when Ψ was not available. Then it is impossible that average use of Φ increases after the introduction of Φ, ie $\Pr(\theta^{\Psi} > \theta^{\Phi}) = 0$ and hence $\theta^{\Psi} \leq \theta^{\Phi}$ almost surely. $\square$

This means that all those who choose not to use a mosquito net in the absence of spraying, will make the same choice once spraying is introduced. To the contrary, some workers who initially slept under a net may decide to interrupt this behavior following the introduction of the new technology, because the latter decreases the returns from using the former. As a result, average net use θ^{Φ} may either remain unchanged or decline, but it cannot increase.

2.1.2 Technologies Φ and Ψ are imperfect complements

Now we come to consider the possibility that technologies Φ and Ψ are actually imperfect complements, ie demand for one technology increases with ownership of the other. Assumption 2 is then replaced by the following:

Assumption 3. $p^{\Phi\cup\Psi} \geq p^{\Phi} + p^{\Psi}$.

As before, under a perfect information scenario, workers will decide to use Φ when Ψ is unavailable depending on condition (3); in the presence of Ψ, the relevant condition will be (5). Notice now that our new assumption implies that $p^{\Phi\cup\Psi} - p^{\Psi} \geq p^{\Phi}$. As a result, (3)$\Rightarrow$(5) but (5)$\not\Rightarrow$(3). This implies that the share of people using Φ in the presence of Ψ cannot be lower than when Ψ was unavailable, ie $\theta^{\Phi} \leq \theta^{\Psi}$ almost surely.

2.2 Imperfect information

Finally, we consider the case of imperfect information, in which workers do not know the probability of infection. In particular, they do not know whether it is $\pi > 0$ or $\pi = 0$[6]. Each worker i is endowed with a prior $P_i(\pi > 0)$ which is drawn from a $Uniform(0,1)$. Notice that $P_i(\pi = 0)$ is just the complement of $P_i(\pi > 0)$ ie $P_i(\pi = 0) = 1 - P_i(\pi > 0)$.

Workers know that the provider of Ψ, ie the Government, has perfect knowledge about π. We further assume that the probability of spraying when the true risk of infection is 0 cannot be greater than the probability of introducing IRS when Malaria represents a possible threat, and we formalize this as follows:

Assumption 4. $P(\Psi = 1|\pi > 0) \geq P(\Psi = 1|\pi = 0)$.

When workers observe $\Psi = 1$, they update their beliefs using Bayes' rule. Notice that workers can never observe $\Psi = 0$. In fact, in the absence of IRS, people ignore its existence and if it is rolled out in other areas of the country, we assume that there is no communication between populations that received Ψ and those who did not.

We can compute conditions analogous to (3) and (5) for the case of imperfect information. Now the expected time available to worker i will be:

$$
\begin{aligned}
E(time_i) &= (1-p_i)T + p_i\left[(1-\pi)T + \pi\left\{\begin{array}{l}(1-\phi_i)(T-t)+\\ \phi_i[(p^{\Phi}T + (1-p^{\Phi})(T-t)]\end{array}\right\}\right] \\
&= [1-p_i]T + p_i[T - \pi t + \pi\phi_i p^{\Phi} t] \\
&= T - p_i T + p_i[T - \pi t + \pi\phi_i p^{\Phi} t] \\
&= T - p_i \pi t[1 - \phi_i p^{\Phi}] \qquad (6)
\end{aligned}
$$

[6]This formulation simplifies the structure of the problem.

where $p_i \equiv P_i(\pi > 0)$.

Notice that condition (6) is analogous to (2), but for the presence of the extra weight p_i, which represents the prior that $\pi > 0$ in the absence of spraying. As before, worker i will use technology Φ if and only if its use increases his expected utility.

$$\begin{aligned}
\phi_i^* = 1 \quad &\Leftrightarrow \quad E(U_i|\phi_i = 1) > E(U_i|\phi_i = 0) \\
&\Leftrightarrow \quad wE(time_i|\phi_i = 1) - d_i > wE(time_i|\phi_i = 0) \\
&\Leftrightarrow \quad Tw - P_i(\pi > 0)w\pi t(1 - p^{\Phi}) - d_i > Tw - P_i(\pi > 0)w\pi t \\
&\Leftrightarrow \quad P_i(\pi > 0)w\pi t(1 - p^{\Phi}) - P_i(\pi > 0)w\pi t > d_i \\
&\Leftrightarrow \quad P_i(\pi > 0)w\pi t\ p^{\Phi} > d_i
\end{aligned} \tag{7}$$

Condition (7) says that worker i will now choose to sleep under a mosquito net if and only if the expected protection granted from its use can more than compensate from the disutility incurred. Compare (7) to (3) and notice that the new condition depends on the prior probability of Malaria infection. Lemma 1 describes how workers update their beliefs using Bayes' Rule.

Lemma 1. $P_i(\pi > 0|\Psi = 1) \geq P_i(\pi > 0)$, *ie following the introduction of* Ψ, *the posterior probability of Malaria infection* $P_i(\pi > 0|\Psi = 1)$ *cannot be smaller than the prior probability of Malaria infection* $P_i(\pi > 0)$.

Proof. Recall that, when workers observe Ψ, they update their beliefs using Bayes' rule:

$$\begin{aligned}
P_i(\pi > 0|\Psi = 1) \quad &= \quad \frac{P(\Psi = 1|\pi > 0)P_i(\pi > 0)}{P(\Psi = 1)} \\
&= \quad \frac{P(\Psi = 1|\pi > 0)P_i(\pi > 0)}{P(\Psi = 1|\pi > 0)P(\pi > 0) + P(\Psi = 1|\pi = 0)P(\pi = 0)}
\end{aligned}$$

By Assumption 4, workers also know that $P(\Psi = 1|\pi > 0) \geq P(\Psi = 1|\pi = 0)$.

Assume by contradiction that $P_i(\pi > 0|\Psi = 1) < P_i(\pi > 0)$.

$$\begin{aligned}
P_i(\pi \quad > \quad &0|\Psi = 1) < P_i(\pi > 0) \\
\Leftrightarrow \quad &\frac{P(\Psi = 1|\pi > 0)P_i(\pi > 0)}{P(\Psi = 1|\pi > 0)P(\pi > 0) + P(\Psi = 1|\pi = 0)P(\pi = 0)} < P_i(\pi > 0) \\
\Leftrightarrow \quad &P(\Psi = 1|\pi > 0) < P(\Psi = 1|\pi > 0)P(\pi > 0) + P(\Psi = 1|\pi = 0)P(\pi = 0) \\
\Leftrightarrow \quad &P(\Psi = 1|\pi > 0)[1 - P(\pi > 0)] < P(\Psi = 1|\pi = 0)P(\pi = 0) \\
\Leftrightarrow \quad &P(\Psi = 1|\pi > 0)P(\pi = 0) < P(\Psi = 1|\pi = 0)P(\pi = 0) \\
\Leftrightarrow \quad &P(\Psi = 1|\pi > 0) < P(\Psi = 1|\pi = 0)
\end{aligned}$$

Contradiction! □

Following the introduction of Ψ, and given that worker specific disutility d_i is left unchanged, workers may revise their beliefs that $\pi > 0$ only upward: more workers will then choose to use Φ.

The expected time available to worker i is now as follows:

$$
\begin{aligned}
E(time_i|\Psi=1) &= \\
&= (1-p_i)T + p_i\left[(1-\pi)T + \pi\left\{\begin{array}{l}(1-\phi_i)[(p^{\Psi}T+(1-p^{\Psi})(T-t)]+\\ \phi_i[(p^{\Phi\cup\Psi}T+(1-p^{\Phi\cup\Psi})(T-t)]\end{array}\right\}\right] \\
&= (1-p_i)T + p_i\left\{\begin{array}{l}(1-\pi)T+\pi(p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}T\\ +[1-(p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}](T-t)\end{array}\right\} \\
&= [1-p_i]T + p_i[T-\pi t+\pi(p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i}t] \\
&= Tw - p_i w\pi t[1-(p^{\Psi})^{1-\phi_i}(p^{\Phi\cup\Psi})^{\phi_i})] \qquad (8)
\end{aligned}
$$

After the introduction of Ψ, and having updated their beliefs, workers will use Φ if its use can increase their own expected utility:

$$
\begin{aligned}
\phi_i^* = 1|\Psi=1 &\Leftrightarrow E(U_i|\Psi=1,\phi_i=1) > E(U_i|\Psi=1,\phi_i=0) \\
&\Leftrightarrow wE(time_i|\Psi=1,\phi_i=1) - d_i > wE(time_i|\Psi=1,\phi_i=0) \\
&\Leftrightarrow Tw - p_i w\pi t(1-p^{\Phi\cup\Psi}) - d_i > Tw - p_i w\pi t(1-p^{\Psi}) \\
&\Leftrightarrow p_i w\pi t(p^{\Phi\cup\Psi} - p^{\Psi}) > d_i \\
&\Leftrightarrow P_i(\pi>0|\Psi=1)w\pi t(p^{\Phi\cup\Psi} - p^{\Psi}) > d_i \qquad (9)
\end{aligned}
$$

So we have found conditions (7) and (9), which are analogous to (3) and (5). From Lemma 1 we know that $P_i(\pi > 0|\Psi = 1) \geq P_i(\pi > 0)$ and the relationship between $(p^{\Phi\cup\Psi} - p^{\Psi})$ and p^{Φ} depends on whether we make Assumption 2 or 3.

2.2.1 Technologies Φ and Ψ are imperfect substitutes

In the imperfect information setting, if workers are Bayesian updaters and we assume that $p^{\Phi\cup\Psi} \leq p^{\Phi} + p^{\Psi}$, the share θ^{Ψ}, of workers who choose to use Φ once Ψ is available, may be larger or smaller than θ^{Φ}, the share of workers using Φ when Ψ is not available.

Proof. $P_i(\pi > 0|\Psi = 1) \geq P_i(\pi > 0)$ and $p^{\Phi\cup\Psi} \leq p^{\Phi} + p^{\Psi}$ imply that (7) $\nRightarrow$ (9) and (7) $\nLeftarrow$ (9). So it is possible that $\theta^{\Psi} < \theta^{\Phi}$, or $\theta^{\Psi} = \theta^{\Phi}$, or finally $\theta^{\Psi} > \theta^{\Phi}$. $\square$

Notice in particular that $P(\theta^{\Psi} > \theta^{\Phi}) > 0$. This is contrast with the analogous result for the perfect information case, for which we showed that $P(\theta^{\Psi} > \theta^{\Phi}) = 0$.

2.2.2 Technologies Φ and Ψ are imperfect complements

In the imperfect information setting, if workers are Bayesian updaters and we assume that $p^{\Phi\cup\Psi} \geq p^{\Phi} + p^{\Psi}$, then θ^{Ψ} cannot be smaller than θ^{Φ}.

Proof. $P_i(\pi > 0|\Psi = 1) \geq P_i(\pi > 0)$ and $p^{\Phi\cup\Psi} \geq p^{\Phi} + p^{\Psi}$ imply that (7) $\Rightarrow$ (9) and (7) $\nLeftarrow$ (9). So $P(\theta^{\Psi} > \theta^{\Phi}) > 0$. $\square$

In this case we obtain the same prediction as in the analogous result we found in the perfect information case, for which we also showed that $P(\theta^{\Psi} > \theta^{\Phi}) > 0$.

2.3 Summary of the predictions

Table 2 summarizes the predictions of this model.

Table 2: Summary of the theoretical predictions

	Imperfect substitutes	Imperfect complements
Perfect Information	$\theta^{\Psi} \leq \theta^{\Phi}$	$\theta^{\Psi} \geq \theta^{\Phi}$
Imperfect Information	$\theta^{\Psi} \leq \theta^{\Phi}$ or $\theta^{\Psi} \geq \theta^{\Phi}$	$\theta^{\Psi} \geq \theta^{\Phi}$

Average use of Φ depending on the complementarity between Φ and Ψ and on the availability of information about Malaria prevalence.
Note: $\theta^{\Phi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*)$ and $\theta^{\Psi} \equiv \frac{1}{N}\Sigma_{i=1}^{N}(\phi_i^*|\Psi = 1)$.

2.4 Externalities

In this simple model, we have not accounted for any externalities which may arise from others' use of ITNs, ie we do not model $\Pr(\phi_i)$ as function of $\Pr(\phi_{-i})$, where $-i$ includes all agents but i. We do so because it is unclear, in reality, which of the following arguments are most relevant to agents in their decision to adopt technology Φ and to sustain its use, and whether they keep any of such considerations into account at all. First of all, the more people use nets, the less likely it is that mosquitoes will carry the disease, because mosquitoes do not *have* Malaria but can only *transfer* Malaria from person to person. Secondly, because ITNs are treated with insecticide, the more ITNs are used[7], the smaller the size of the mosquito population. Third, it is possible that network effects are in place, so that the larger the group of adopters within a certain network, the more people are likely to follow their example.

The first two channels may put downward pressure on agents net use, as it becomes more common in their community. In the extreme case in which everyone else sleeps under a mosquito net, a person cannot benefit from doing so: in fact, mosquito bites can at worst be annoying but certainly not infectious, as the vector cannot bite anyone else who has Malaria[8]. If instead no one sleeps under a mosquito net, then a person benefits the most from doing so, because there are many mosquitoes and they are very likely to carry the disease. Finally, in an intermediate situation, benefits from ITN use decline with the share of net users in the village.

The information campaigns conducted in Eritrea explain to the people that they should use ITNs to protect themselves from mosquitoes and that the insecticide on them can kill mosquitoes. This is a simple message that illiterate people can easily understand. As a result of this information strategy, we believe that the people living in the study area are not aware that mosquitoes are solely a vector rather than the source of the disease. This consideration allows us to rule out the first channel. On the one hand, the second channel may be well understood by people, though we have no data on this. If people understand that the more ITNs are used, the smaller the size of the mosquito population, incentives for net use will be small in villages with high usage rates. Finally, in the presence of network effects, agents would be more willing to use technology Φ when its use is common in their community.

Having no data on the importance and on the relative size of these two channels, and hence on the overall effect of average net use in the community on own net use, we prefer to exclude this consideration from our model. Richer data may help shed some light on this point, which future research shall try to address.

[7]What matters for this effect is that they are not inside a container, but that they are hung in the house. This effect does not require people to actually sleep under a net.

[8]Except outside the sleeping hours, in the evening and in the early morning.

3 Study Area

3.1 Area under investigation: Gash Barka, Eritrea

The survey was conducted in Eritrea in Zone Gash Barka (GB). The location of the zone is shows in Figure 2. GB was chosen because it is the most malarious zone in Eritrea. GB is a mostly rural/agricultural area, inhabited by one fifth of the country's population. Altitudes range between 500–1,500 meters and temperatures are generally associated with hot and dry climatic conditions. Significant variation can be observed across the region in terms of precipitations, leading to marked differences in vegetation and Malaria prevalence. The rainy season is concentrated between July–September and precipitations are scarce during the rest of the year.

GB is composed of 14 subzones, as shown in Figure 3. We surveyed only 13 of those subzones because one (Logo Anseba) was deemed to have a very low Malaria prevalence. Logo Anseba is the black area in Figure 3.

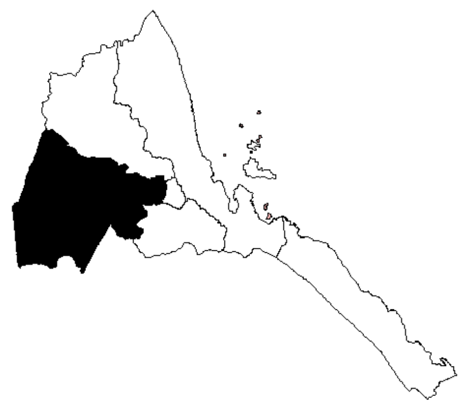

Figure 2: Location of Zone Gash Barka in Eritrea

Figure 3: Subzones of Zone Gash Barka

3.2 Malaria in Gash Barka

Malaria transmission is seasonal and it extends from July until November/December. A peak is reached between September–November, following the rainy season. Our survey was conducted in the first half of October. This period corresponds to the Malaria peak and it is highlighted in black in Figure 4. The average number of Malaria cases[9] in GB, over the period 2002-2007, is shown in Figure 4.

[9]Figures include both IPD (in-patient department)and OPD (out-patient department) Malaria cases.

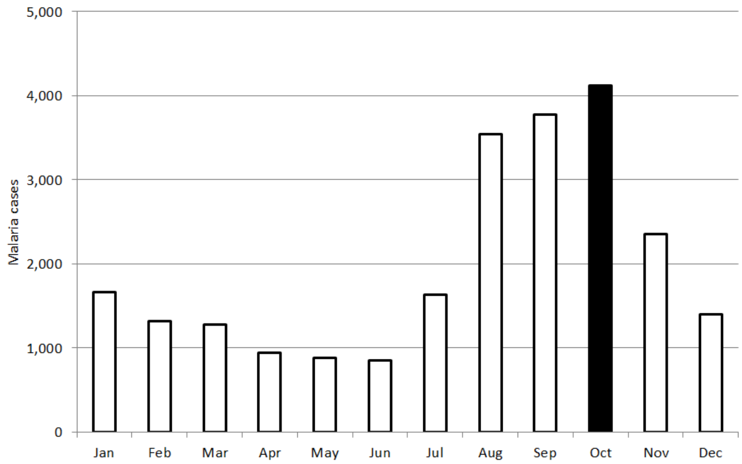

Figure 4: Monthly Malaria cases in Gash Barka (2002-2007)

Figure 5 shows that Malaria[10] has declined sharply in Eritrea over the past decade. Most cases are concentrated in GB, and this zone has witnessed a similar trend over the same time period. Climate change may have caused such a sharp decline in Malaria prevalence, if the area under investigation has progressively desertified. To the contrary, we show in Section 3.3 that vegetation has remained roughly constant over the same time period. This evidence suggests that the policies implemented by the NMCP of Eritrea have been crucial to reduce the burden of the disease.

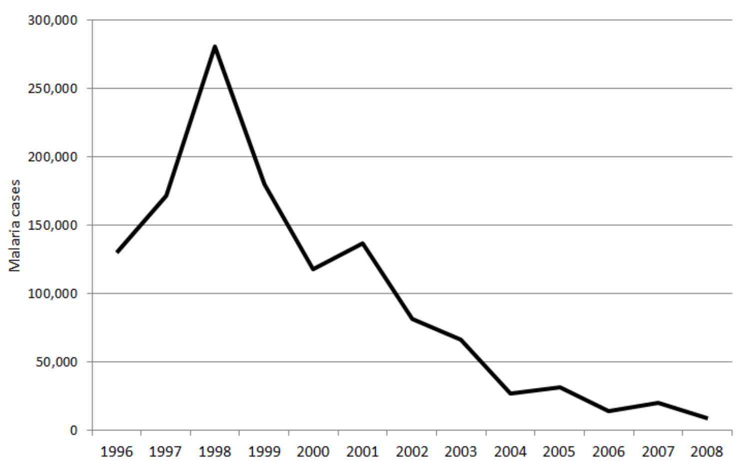

Figure 5: Malaria cases in Eritrea (1996-2008)

3.3 Vegetation in Gash Barka

The Normalized Difference Vegetation Index (NDVI) is an index of the vegetation level of region, which is obtained from the analysis of the color spectrum of satellite imagery. The NDVI ranges from between -1 and 1. In the absence of water surfaces or snow, it ranges between 0 and 1, where 1 means most vegetation and 0 stands for least vegetation.

[10]These figures refer to OPD Malaria cases only. IPD are a minority of cases.

Gaudart et al. (2009) underline that the relationship between NDVI and Malaria incidence has been demonstrated in previous work and that NDVI can therefore be used a proxy of climatic and environmental factors. They use the index from July 1981 – December 2006 to assess the statistical relationship between NDVI and the incidence of *P. falciparum* in Sudan and they find that the seasonal pattern of *P. falciparum* incidence is significantly explained by NDVI; they also identify a threshold NDVI value of 0.361, above which an increase in the incidence of parasitemia is predicted. Nihei et al. (2002) study 1997 NDVI data from the Indochina Peninsula and find that *P. falciparum* Malaria is most prevalent in regions with an NDVI higher than 0.4 for at least 6 consecutive months[11].

NDVI data for GB was made available from NMCP and can be downloaded from the website of the International Research Institute for Climate and Society[12], part of the Earth Institute at Columbia University. Over the period July 1981 – December 2009, NDVI in GB ranged from a minimum of 0.073 to a maximum of 0.714. NDVI varies widely across subzones: some are arid throughout the year (eg Akurdet) while others have a lot more vegetation (eg Laelay-Gash). Accordingly we divided the subzones of GB into three groups, depending on their vegetation level over the ten years to the survey (2000-2009), and we assigned to each of them a value $ndvi \in \{0, 1, 2\}$, as shown in Table 3.

Table 3: Classification of the subzones of Gash Barka by vegetation level

Vegetation	Subzones	ndvi
Arid	Akurdet, Dighe, Forto, Mensura	0
With some vegetation	Barentu, Gogne, Haykota, Mogolo, Tesseney	1
With much vegetation	Goluj, Laelay-Gash, Mulki, Shambko	2

The average value of NDVI in the 13 surveyed[13] subzones of GB is represented in Figure 6. Figure 6 shows that vegetation starts increasing in July, following the inception of the rainy season. The NDVI peaks in September and declines sharply by the end of October. A slow decline in vegetation is observed between then and June. The dashed vertical lines in Figure 6 show the period when the survey was conducted, ie the second week of October.

Figure 7 shows that – Despite a general sense that vegetation has declined in GB in the recent past – a moderate increase in NDVI can actually be observed over the three decades covered by our dataset. Vegetation has been moderately increasing overall in the Zone, where the number of months with an NDVI >0.35 gradually increased over the past three decades. This would be normally associated with an increase in Malaria morbidity and mortality, contrary to the available data that point to a strong decrease in the number of Malaria cases in GB and in Eritrea overall. This suggests that policies of the NMCP have been crucial to fight Malaria, and that efforts to fight the disease must be sustained because the environment remains hospitable for the vector.

3.4 Small vs. large towns

Large cities may be unbalanced between treatment and control group. If life in large cities is more expensive than in small towns, then this could explain why expenditure is higher in the treatment group, and such difference would not stem from treatment. However, in the case of Eritrea, even though the towns with larger population and with more modern technologies and infrastructure could be more expensive than smaller villages, life in large towns like Omhajer and Tesseney is probably much cheaper than elsewhere in the region, or in the whole country. In fact, because of their proximity to the border with Sudan and Ethiopia, they have larger supplies of basic consumer and

[11] Over the whole time period covered by our data, in no subzone was an NDVI over 0.35 observed for more than 5 consecutive months, so the results of Nihei et al. (2002) cannot be applied in our setting.

[12] Website: http://iridl.ldeo.columbia.edu/maproom/.Health/.Regional/.Africa/.Malaria/.NDVI/.EAF/

[13] Logo Anseba not included.

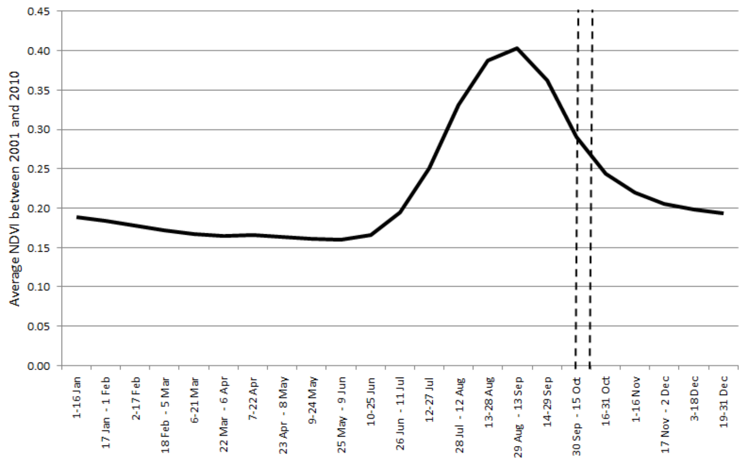

Figure 6: NDVI in Gash Barka (2001-2010)

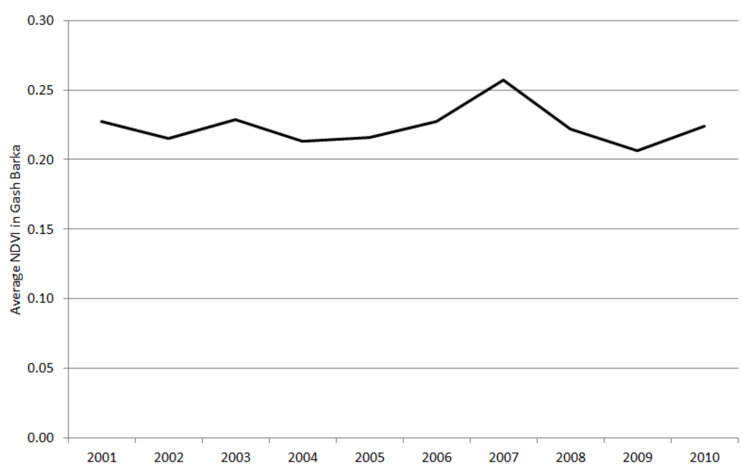

Figure 7: Yearly mean NDVI in Gash Barka (2001-2010)

durable commodities, at considerably lower prices.

Data on population size is not available for the villages in our survey. One possible data source is the village list used by spraying teams during field operations, which reports the number of sprayed houses, reported in Table 5. However this list contains only information on the treated villages, while nothing is reported for the controls. To have a more comprehensive, though possibly more inaccurate, picture, we asked local people to identify, for each subzone, the capital (if listed[14]) and any other large city. Notice that some of the village in our lists are actually one neighborhood of a town. For example, the village name Zoba Meskerm is one neighborhood of Tesseney. Being in the capital, we regard this area as a large town.

Table 4: Difference between small and large towns

	(1)	(2)	(3)	(4)	(5)
Large village	-0.06	0.68**	0.66***	839.32*	720.66*
	(0.13)	(0.27)	(0.20)	(446.57)	(399.20)
Subzone dummies	no	no	yes	no	yes
Observations	115	1,543	1,543	1,614	1,614

LS regressions of outcome on *Large village* Outcome is *treatment* in column 1, *monthly household expenditure* in columns 2 and 3, and *wealth* in columns 4 and 5. *Large village* is a dummy =1 for large villages. One observation per village is used in column 1. One observation per household in used in columns 2-5; observations are clustered at village level. Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows evidence that this is not a problem in our data. We can see from columns 3 and 5 that it is actually the case that large cities are wealthier (0.66, se=0.20) and that life is more expensive there (+720 Nakfa, se=399), compared to smaller towns. In columns 3 and 5 we include subzone dummies to control for proximity to the border. The key figure for us is shown in column 1, which reassures us that large villages are equally distributed between treatment and control group; the coefficient estimate is insignificant, close to 0 and actually even negative.

[14]Capitals are often not included in our survey. This is why we look at any large town as a proxy.

Table 5: Number of houses sprayed in each treatment village

subzone		total houses	houses sprayed	houses not sprayed	other sprayed	populations houses
Akurdet	mean	180	162	18	29	563
	sd	252	227	26	32	788
Barentu	mean	478	475	3	49	2262
	sd	120	122	3	2	578
Dighe	mean	96	74	22	8	403
	sd	55	46	12	8	309
Forto	mean	416	391	25	123	1157
	sd	285	267	21	74	820
Gogne	mean	582	545	37	90	899
	sd	452	440	18	64	793
Goluj	mean	1888	1760	128	90	6387
	sd	227	177	50	18	829
Haykota	mean	319	307	12	0	338
	sd	306	300	10	0	306
Laelay-Gash	mean	447	454	51	59	1419
	sd	824	677	120	79	2120
Mensura	mean	159	158	1	0	703
	sd	50	49	2	0	559
Mogolo	mean	481	412	69	88	1030
	sd	53	53	5	23	289
Mulki	mean	709	688	21	9	1886
	sd	80	81	1	5	5
Shambko	mean	489	481	14	13	1987
	sd	107	112	12	11	1393
Tesseney	mean	394	351	43	72	1257
	sd	497	428	69	112	1478
Total	mean	417	394	30	45	1125
	sd	490	442	53	62	1472
	N	59	59	59	59	59

4 Wealth Index

As is standard in Demographic and Health Surveys (DHS)[15], we construct an asset index using factor analysis, exploiting the information available in our dataset. In particular, we use data on hh's main water source, toilet type, fuel used for cooking, wall and roof material, presence and type of any windows, access to electricity, ownership of electronics and any vehicles, size of the dwelling[16] and ownership of any livestock. We obtain an index, to which we refer also as a *wealth* index, which seems to describe well the differences between poorer and richer hh's, despite the fact it explains just about 5% of the total variance of the variables used to construct it.

In particular, conducting a comparison by wealth quintile, as hh's become wealthier: they source their water from a tap rather than from an unprotected well; they use a latrine rather than going to the bushes; they cook not only with firewood, but also with more expensive charcoal; their walls are made far less often in cane and wood, but rather in stone and cement; roofs are more solidly made in stone and cement, rather than in leafs; dwellings have windows, often with shutters, unlike their poorer versions which have none; they have access to electricity and a the majority has a radio; and some even have some vehicles, and especially a bike (10%) or a cart (10%).

We have data on hh expenditure, which we do not use for this paper. Comparing hh expenditure by wealth quintile we find that it progressively increases from 625 to 750 Nakfa[17] if we look at overall food expenditure, and from 725 to 1000Na considering total per-capita expenditure. As expected, per-capita expenditure for basic food is roughly constant over the whole distribution, at about 500Na per month, and the expenditure share spent on food decreases from 84% to 70%. This provides further evidence that our wealth index provide a suitable proxy for the actual unobservable hh wealth.

However, dwellings do not become bigger relative to hh size, leaving the ratio of persons per room to about 4:1; finally, livestock ownership seems to be most common in the 3rd and 4th quintile, possibly because the richest quintile is not engaged in farming but in more productive activities. Details on the construction of the wealth index are presented in Section 4.1.

4.1 Construction of the Wealth Index

We constructed our wealth index following the method suggested by Filmer and Pritchett (2001), which has become the standard in Demographic and Health Surveys (DHS). To do so, we exploited the data we have on: main water source and fuel for cooking; presence and type of any toilet facility and of any windows; main material of the walls and of the roof; access to electricity and ownership of any consumer electronics, eg radio and TV; ownership of any vehicles; livestock ownership; and number of household members per room.

Ownership variables are dichotomous. Following the Filmer-Pritchett (FP) procedure, we split all categorical variables into sets of dummy variables, and we use Principal Components Analysis (PCA)[18] to assign the indicator weights. Finally, we use only the first factors produced by PCA to represent our wealth index, as suggested in McKenzie (2005)[19].

In Sections 4.2 and 4.3 we discuss some problems related to the use of PCA for the construction of the wealth index, and to the use of the FP procedure in particular. In Section 4.4 we discuss alternative methods to conduct PCA. Section 4.5 reports some checks we have conducted on the internal coherence of the weights used for our wealth index. Overall, our analysis suggests that this may be a good proxy for household's wealth, so in Section 4.6 we conclude explaining why we prefer the FP method over the other possibilities we have explored.

[15] See Rutstein et al. (2004) for details.

[16] Number of persons per room is used as a proxy.

[17] 1 USD = 15 Nakfa.

[18] We use the *factor* command in STATA 10.1 for PCA.

[19] McKenzie (2005) considered using more than one PC to characterize socio-economic status (SES) and he concluded that the first PC was enough as a wealth measure.

4.2 Issues with PCA

McKenzie (2005) highlights the importance of using a wide-enough range of asset variables for the construction of a wealth index with PCA. A narrow range may result in two problems called *clumping* and *truncation*. Clumping (or clustering) occurs when the wealth index groups households into a limited number of groups. Truncation arises from limited variation in asset ownership, which may makes it hard to distinguish groups with small wealth differences. This could be an important problem if we were interested in distinguishing several degrees of poverty. Notice finally that the difficulty in distinguishingly household by SES may arise from the fact they are actually homogenous along the wealth margin.

These two problems could arise in the Eritrean setting we are considering. In GB, in fact, asset ownership is very limited and the range of owned asset is quite narrow. Most dwelling are similar and most households do not have toilets. Also, almost no one has electricity. This situation may make it hard to group our households by wealth level.

Our situation is akin to that faced by Vyas and Kumaranayake (2006), who analyze villages in rural Ethiopia and raise analogous issues. As a possible solution, they stress the importance of including additional variables that can capture intra-household inequality, if available. Our wealth index relies on all available assets information contained in our dataset.

4.3 Issues with the Filmer-Pritchett procedure

Several issues can arise using the FP procedure for PCA. First of all, Kolenikov and Angeles (2009) discuss why the FP procedure should not be used for the analysis of discrete data. Distributional assumptions are violated because the procedure assumes that variables are continuously distributed.

Problems relating to high skewness and kurtosis are also likely to arise in the analysis of discrete data with little or no variation. This happens also in our case, and Figure 8 shows that the wealth distribution is indeed skewed to the right. Vyas and Kumaranayake (2006) have a similar problem in Ethiopia, and they suggest that this shape highlights the extent of clumping and truncation, so that it may be hard to distinguish socio-economic groups.

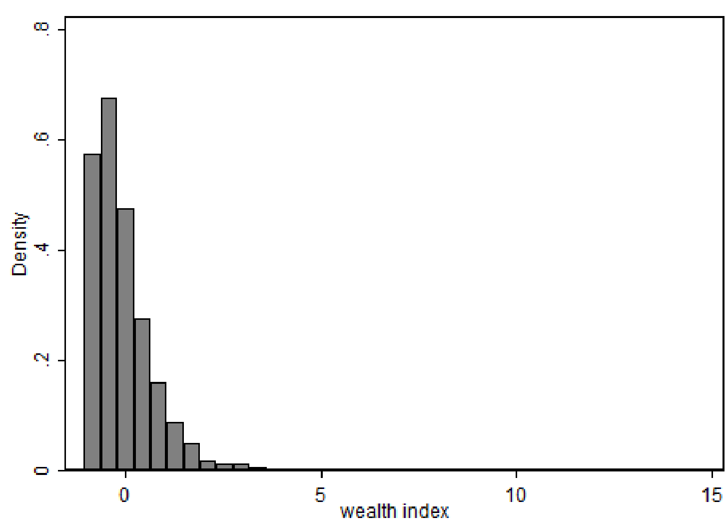

Figure 8: Distribution of wealth in Gash Barka

Further, wealth indexes obtained from FP PCA often explain only a small percentage of the variance in asset ownership, 5% in our case. We also try to collapse asset categories that include a very small number of households into broader categories, and even so the percentage of explained variance raises to just about 7%. These figures are quite low, also compared to the studies surveyed in Vyas and Kumaranayake (2006), where the first PC accounted for 12–27% of the total variation.

4.4 Alternative PCA methods

Kolenikov and Angeles (2009) use montecarlo simulations and a DHS dataset from Bangladesh to compare three methods to conduct PCA:

1. The mainstream PCA methodology that follows Filmer and Pritchett (2001) in splitting categorical variables into dummies, eg dwelling materials and water source;

2. The use of ordinal variables, depending on quality of eg dwelling materials and water source;

3. The use of polychoric correlations for PCA.

They conclude that the polychoric method 3 should not be used, unless we want to estimate precisely the proportion of explained variance for important reporting or decision making purposes. This is the only gain it offers compared to method 2. Between 1 and 2, wherever possible they recommend using the latter, ie ordinal variables, exploiting the information available from the ordering. They argue that this improves the goodness of fit and limits the extent to which we under-estimate the explained variance.

4.5 Internal coherence

We checked whether the wealth index we obtained from FP CPA was sensible. To do so, with divided households by wealth quintile and we checked whether ownership of assets and quality of dwelling materials increased with SES. From Tables 6–8 we can *generally* see that, as wealth increases: water sources improve; households have better toilets and use bushes less often; they use not only firewood to cook, but also electricity and fuels; they have more solid walls (not made in wood or cane but more often in cement, bricks or stone) and roofs (made in cement or stone rather than leafs); own electronics, especially a radio, and hence have better access to information; they also have some vehicles, mainly bikes and carts. Finally, the number of persons per room does not change much.

There are however some instances in which we expect ownership to increase over SES, while the opposite is observed. In other cases, ownership initially increases and then decreases as households become wealthier, while monotonicity is expected. The main explanation lies in that the FP procedure works with dichotomous variables only and does not exploit the ordinal information available in the data; as a result, it only pays attention to the number of individuals that own an asset or not, irrespective of its quality and worth.

In particular, the scores assigned by the FP procedure to different materials and assets owned should increase in their quality and worth. Eg car ownership should receive a higher score than bike ownership, and cement walls a higher score than weaker bamboo walls. This property held in the analysis of Filmer and Pritchett (2001), but it is possible that it fails.

For example, a negative weight is assigned to bike ownership in McKenzie (2005) and wall types of better quality are sometimes given smaller weights in Kolenikov and Angeles (2009). McKenzie concluded that this problem was not severe in his case, because the weight with the wrong sign was actually small and thus unlikely to affect the results. An important problem of internal incoherence is found instead by Vyas and Kumaranayake (2006) in data from rural Ethiopia.

We can use the last column of Tables 6–8 to check whether the weights given by PCA have the sign we expect and are monotonically increasing in assets quality. Table 8 shows that ownership of any electronics is associated with a

Table 6: Asset ownership, by wealth quintile

	1	2	3	4	5	Factor loadings
Water source						
piped into dwelling	0.000	0.000	0.000	0.003	0.006	0.040
piped into yard	0.003	0.006	0.003	0.003	0.003	-0.008
public tap	0.000	0.359	0.497	0.583	0.675	0.333
tube well	0.071	0.097	0.058	0.078	0.068	-0.026
protected well	0.136	0.094	0.049	0.026	0.026	-0.121
unprotected well	0.453	0.223	0.208	0.197	0.107	-0.187
protected spring	0.032	0.013	0.010	0.006	0.032	0.019
unprotected spring	0.243	0.133	0.143	0.081	0.062	-0.124
other	0.061	0.074	0.032	0.023	0.019	-0.049
Toilet type						
flush to PSS	0.000	0.000	0.000	0.000	0.006	0.044
flush to septic tank	0.000	0.000	0.000	0.000	0.006	0.045
to other byte	0.000	0.000	0.000	0.000	0.010	0.042
vip latrine	0.000	0.000	0.000	0.006	0.032	0.118
pit latrine slab	0.000	0.000	0.000	0.003	0.049	0.166
pit latrine open	0.000	0.000	0.000	0.013	0.153	0.339
composting	0.000	0.000	0.000	0.003	0.000	-0.001
bucket	0.000	0.000	0.000	0.000	0.003	0.046
hanging	0.000	0.000	0.000	0.000	0.010	0.037
bush	1.000	1.000	1.000	0.971	0.724	-0.406
other	0.000	0.000	0.000	0.003	0.006	0.034
Main cooking fuel						
electricity	0.000	0.000	0.000	0.003	0.003	0.012
kerosene	0.000	0.000	0.000	0.000	0.023	0.181
coal	0.000	0.000	0.000	0.000	0.019	0.143
charcoal	0.000	0.000	0.000	0.065	0.198	0.312
firewood	1.000	1.000	0.994	0.922	0.747	-0.399
dung	0.000	0.000	0.006	0.010	0.000	-0.002
other	0.000	0.000	0.000	0.000	0.010	0.205
Observations	309	309	308	309	308	

Table 7: Asset ownership, by wealth quintile (continued)

	1	2	3	4	5	Factor loadings
Main wall material						
None	0.010	0.071	0.026	0.016	0.019	0.005
Cane	0.498	0.366	0.224	0.094	0.117	-0.235
Bamboo	0.000	0.087	0.169	0.188	0.127	0.050
Stone wood	0.000	0.071	0.175	0.320	0.299	0.185
Uncovered adobe	0.000	0.000	0.000	0.006	0.006	0.058
Plywood	0.000	0.000	0.006	0.000	0.000	-0.009
Carton	0.006	0.016	0.010	0.010	0.000	-0.028
Cement	0.000	0.000	0.003	0.013	0.023	0.096
Stone cement	0.000	0.000	0.006	0.036	0.097	0.173
Bricks	0.000	0.000	0.036	0.087	0.068	0.083
Cement blocks	0.000	0.000	0.000	0.003	0.110	0.408
Covered adobe	0.000	0.000	0.016	0.013	0.006	0.017
Wood planks	0.424	0.236	0.120	0.074	0.029	-0.235
Other	0.061	0.152	0.208	0.139	0.097	-0.026
Main roof material						
Leaf	0.702	0.680	0.510	0.456	0.386	-0.193
Cane	0.000	0.000	0.003	0.003	0.000	-0.004
Bamboo	0.006	0.000	0.006	0.003	0.003	-0.012
Stone mud	0.100	0.104	0.162	0.139	0.136	0.004
Uncovered adobe	0.084	0.061	0.156	0.178	0.133	0.033
Cement	0.000	0.000	0.000	0.000	0.198	0.396
Stone cement	0.058	0.052	0.091	0.104	0.068	-0.009
Cement blocks	0.000	0.000	0.000	0.000	0.003	0.062
Coverer adobe	0.000	0.000	0.000	0.000	0.010	0.348
Other	0.049	0.104	0.071	0.117	0.062	-0.025
Window type						
any	0.000	0.078	0.341	0.570	0.513	0.269
shutters	0.000	0.000	0.029	0.227	0.305	0.360
glass	0.000	0.000	0.000	0.006	0.006	0.081
screens	0.000	0.000	0.000	0.000	0.003	0.073
none	0.570	0.518	0.334	0.084	0.097	-0.297
other	0.430	0.405	0.295	0.113	0.075	-0.237
Observations	309	309	308	309	308	

Table 8: Asset ownership, by wealth quintile (continued)

	1	2	3	4	5	Factor loadings
Electronics						
electricity	0.000	0.000	0.000	0.000	0.049	0.506
radio	0.000	0.155	0.244	0.317	0.539	0.362
TV	0.000	0.000	0.000	0.000	0.023	0.486
phone	0.000	0.000	0.000	0.000	0.023	0.393
fridge	0.000	0.000	0.000	0.000	0.010	0.481
Dwelling						
persons per room	3.935	3.972	3.973	4.055	3.794	-0.003
Vehicles						
bike	0.000	0.000	0.000	0.006	0.097	0.342
moto	0.000	0.000	0.000	0.000	0.006	0.198
car	0.000	0.000	0.000	0.000	0.010	0.165
cart	0.000	0.000	0.000	0.003	0.097	0.425
Other						
livestock	0.550	0.553	0.588	0.602	0.539	-0.011
Observations	309	309	308	309	308	

large positive weight: only radios are owned by a non-trivial population share, and this increases monotonically over wealth quintiles. Vehicles ownership also receives positive weights, and their ownership increases with SES. However more expensive electronics and vehicles do not receive a higher weight, probably as a result of the extremely low ownership rates in the data. The number of rooms and livestock ownership receive almost no weight.

Tables 6 and 7 show that our wealth index can account for: better access to water, especially comparing public tap to wells and springs as sources; better toilet facilities, keeping in mind that bushes are the most common option in all wealth quintiles, on a decreasing trend with SES; more expensive cooking fuels, whereas poor people use firewood; stronger wall and roof types, made of stone, cement and adobe rather than canes, wood planks and leafs; and finally for the presence of any windows and their quality.

4.6 Discussion

The evidence presented in Section 4.5 tells us that the simple wealth index obtained from PCA following Filmer and Pritchett (2001) does a pretty good job in terms of explaining variation in SES among our households, in spite of all criticism moved to this approach presented in Section 4.3.

It is true that we do not explicitly exploit any ordinal information on our asset variables. Assigning appropriate weights is a daunting task and we find arbitrary the suggestion from Kolenikov and Angeles (2009) to recode categorical answers as 1,2,3..., so we prefer to follow the FP procedure.

Our index seems to explain only 5% of total variation. Kolenikov and Angeles (2009) show that the explained variance is severely underestimated using the FP method, and more so the more categories are contained in the original variables. Ours is probably a large under-estimate, given how well it can qualitatively describe variation in asset ownership.

Indeed, we may have too many categories in our variables, and we may collapse those with few households. We tried this exercise, which we also found arbitrary in the definition of the larger categories, and we did not gain in terms of internal coherence or explained variance, always below 7%.

For all these reasons, we chose to construct our wealth index using principal component analysis á la Filmer and Pritchett.

5 Checks on Village Lists

Four village lists were used in the RCT under investigation. Comparison reveals some differences across the lists, and we attempt to identify precisely how these lists differ. About 70% of the villages have the same name in the first and last list, and another 10% can be matched using supplementary information. Two villages were arbitrarily replaced. The remaining 20% of village names do not match between the first and last list. Robustness checks suggest that the identified name changes did not alter our estimates of the treatment effects.

Treatment allocations were altered in 5 instances, and we explain possible reasons underlying these changes. Villages included in the RCT, despite not being in the initial list, do not differ significantly from villages initially listed. We find evidence suggesting that some Tigre villages received preferential treatment, which underlines the importance of controlling for this ethnic group in all our regressions.

5.1 Village lists

Four village lists were used for the RCT conducted in Eritrea, and we have a copy of each. Several differences exist between these tables. This section aims to keep track of what happened, to allow us to account for any problems in our analysis. The following are the village lists under investigation:

1. Initial village list, provided by the NMCP of Eritrea to J. Keating, to conduct the initial random allocation to treatment (2008);

2. Village list provided by the NMCP to the spraying teams that actually conducted the IRS campaign in Gash Barka (GB) in June–July 2009. This list includes only the names of treatment villages, because spraying teams need not visit the other villages. Names of control villages were added by hand[20]; this was probably done by NMCP staff in GB;

3. Village list provided by the NMCP to data collectors (October 2009), including both treatment and control villages;

4. Final village list, provided by the NMCP to The World Bank, at the end of all field operations (November 2009).

5.2 Initially identified issues

Difference between village lists may have arisen from a variety of situation-specific problems. Those issues were discussed at length with NMCP and analyzed with the help of local staff. The following are the main issues that we identified for each village list:

1. The initial list was outdated, possibly from the census of 2002 or 2003: eg a subzone had changed name since then, from Omhajer to Goluj, and village sizes do not correspond to the current situation; eg Omhajer had only 70 household at the time, while some 1,200 households live there at present. Some villages moved from a subzone to another, eg Hawashait moved from subzone Dighe to subzone Laelay Gash. Some may even have moved abroad to Sudan or Ethiopia, making it impossible to reach them.

   Existence and location of treatment and control villages were not checked prior to randomization and to the different stages of the intervention. Notice however that, even if this had been properly done, it would still be possible to miss some migrant villages, so this problem could be expected in a setting like ours. Tracking or following those villages may at times be hard or even impossible, eg if they have moved abroad.

[20] They are often very hard to read.

Due to a sustained process of villagization, several villages may have merged into a new one. Villages may also have changed name. Villages recorded under similar names are deemed to be the same, because transliteration problems may occur when a different alphabet is used in the study area. Villages may even have several names, so that the same village could be recorded in two lists under very different names; we were able to reconcile some of these cases.

Two major issues, reported by NMCP, are worth pointing out here:

(a) The minimum distance[21] between villages had to be 3-5km. After randomization some villages were found to be adjacent, so they were replaced to ensure the minimum distance would be kept. In fact, this issue should have been identified before the random treatment allocation. We do not know which instances were affected by this problem.

(b) Some treatment and control villages are located in the highlands, where there is no malaria[22]. Two such instances in subzone Mulki were reported, whereby one treatment and one control village were replaced with two new villages, located nearby, moving down to the lowlands. The new villages were chosen by NMCP staff in GB. In Section 5.2.1 we compare the new villages to the other two which were left unchanged.

2. When spraying teams tried to reach the treatment villages in List 2, sometimes they could not find some of the *treatment* villages or they had moved abroad and were out of reach. Migrant villages were followed whenever possible. Missing treatment villages were replaced with the closest available village.

3. Once the existence of treatment villages had been ascertained by spraying teams, the table was updated accordingly. The number of villages in List 1 was 116, but this was reduced to 115 from List 3 onward. The reason for this change is unclear. A possible reason could be found in the process of villagization, if two listed villages merged into one. We cannot conclusively answer this question.

   New problems arose when enumerators went to the field to conduct the survey. Issues occurred when data collectors could not find some of the *control* villages, some of which had moved abroad and could not be reached. Missing control villages were replaced with the nearest available village. How many such cases occurred? To answer, we compare this list to List 4. This problem concerns: 3 controls in subzone Goluj (villages 4, 5, 7); 1 control in subzone Tesseney (52), and 2 controls in subzone Shambko (93, 95).

   We analyze the determinants of such changes in Table 9. We do not find evidence of differential treatment for Tigre-populated villages. The negative coefficients estimated in models (5)–(9) suggest that replacement control villages are poorer (ie less wealthy and spending less) than the rest of the subzone where they are located. However, we are comparing them to all treatment and control villages in the same region, and treatment villages may have become richer following the malaria-reducing intervention. We do not compare the new controls to the pre-existing controls only because we would have too few observations for this analysis.

4. The final list was drafted by NMCP after all field operations, and it accounts for all problems discussed above.

5.2.1 Arbitrary village choice in subzone Mulki

Two villages were replaced in subzone Mulki: as discussed in Section 5.2, one was chosen as a new treatment, and one as a new control. We check if preference was given to the Tigre tribe, which is over-represented in the treatment

[21] A minimum distance was set to make sure that mosquitoes cannot fly from village to village and thus avoid treatment to spill over to control villages.

[22] There is no malaria >1,000 meters of altitude.

group. We have no data on the omitted villages. The new treatment village is number 43 and the new control is number 46. No Tigre households resides in either village; in our data there is only one Tigre household in this subzone. This suggests that no active effort was put to offer treatment to Tigre villages. We further notice that village 43, Mulki, is the capital of the homonymous subzone, and the data tells that it is richer than the other villages in the same subzone. Our estimates are very unlikely to be affected by two villages only.

5.3 Newly identified problems

5.3.1 Change in number of villages surveyed in each subzone

Not only the total number of listed villages was reduced from 116 to 115, but also the number of villages in each subzone was changed from List 1 to List 4, as shown in Table 18.

The number of treatment villages was finalized when List 2 was drafted for the spraying teams. The total was reduced from 58 to 57. As we can see from column (5) of Table 18, the largest disparities with respect to List 1 appear in subzone Haykota, where 3 extra villages were treated, and in subzone Mensura, where 3 less villages were treated. In the other subzones, the number of treated villages differs from the original figure by at most 1. Only in 6 subzones out of 13 was the number of treatments left unchanged. The number of treatments, both in total and by subzone, was not changed in the subsequent lists.

From List 1 to List 4, the total number of control villages was left unchanged, at 58. However, column (10) of Table 18 shows that the allocation of control villages across subzones changed significantly: in the case of subzone Akurdet, it was increased by 3, while it was decreased by 3 in subzone Haykota[23]. The problem is less severe in the other subzones, in 5 of which the number of controls was left untouched.

5.3.2 Reallocation of treatment status

The treatment allocation of five villages was altered:

1. We compare List 2 to List 1 to see which control villages were reallocated to the treatment group. Here we report the ascertained cases. In subzone Haykota, this happened for 2 villages, ie Biet Hama (56) and Akyeb (59). In subzone Laelay Gash, this possibly[24] happened for one village, ie Amir/Uguma (19). We cannot identify any other instance in which this problem occurred.

2. We compare List 3 to List 1 to see which treatment villages were reallocated to the control group. Here we report the ascertained cases. In subzone Dighe, one village was re-allocated to serve as control, ie Aflanda (72). In subzone Forto, the same happened to one village, ie Grgr (16). In fact, no household was reportedly sprayed in Grgr, and only 1 was in Aflanda. Notice further that those villages are very small, the former with 11 households and the latter with 9 households.

5.3.3 Unchanged villages

To conclude this section, we want to answer two questions: How many villages from List 1 are still present in List 4? How many of them have the same treatment status?

1. Out of 116 villages, 82 have the same name (or a similar one) in both List 1 and List 4. Another 10 villages have names that can be matched in the two lists; possibly they have multiple names and this information is available. The former group includes 70% of the villages and the latter represents 9.5% of the total. Two

[23]Notice that in subzone Haykota the problem is severe for both treatment villages (+3) and control villages (-3).
[24]Names do not match perfectly.

villages were replaced in subzone Mulki. So we are left with 22 cases of mismatch that we can't explain, which represents 19% of the total.

2. We check to which of these categories the villages reallocated to treatment or to control belong. Villages 56 and 59 (reallocated to treatment) and 72 and 16 (reallocated to control) have matching names in Lists 1 and 4. Village 19 (reallocated to treatment) may be matched using the province (*kebabi*) where it is located. Therefore, to answer our question, 78 of the 82 villages with identical names have unaltered treatment status, and so do 87 of the 92 with matching names. This is roughly a 95% share.

5.4 Analysis

We want to understand whether changed villages differ from those that were not changed and, if so, along which dimensions. For this purpose, we conduct the same randomization checks used to compare treatment and control, this time applied to the old and new groups of villages. In addition, we include wealth and household expenditure[25]. A possibility is that preference for treatment may have given to those villages with better infrastructure, eg access to electricity, as a way to make operations smoother in a hostile natural environment like ours. In some cases, it may be hardly possible to reach some villages, and operators confronted with this problem may have chosen the easiest available alternative.

Notice that we compare villages with altered name or treatment allocation, to all other villages in GB, rather than to those in the respective subzone. We do so because we have documented evidence of changes in the number of villages per subzone, which hints to a possibility to choose replacement villages across the entire region.

5.4.1 Altered village names

In Tables 10 and 11 we investigate the presence of any systematic differences between villages whose name was not changed during the operations of the RCT, and those villages which instead were changed. Column 1 is analogous to the randomization checks presented in the paper, and we include it as a benchmark. In addition to the p-values shown in the paper from LS regressions of individual variables on treatment, we report here also the coefficient estimates, to understand the sign and magnitude of any differences between comparison groups. In column 2 we focus on villages with the same name in Lists 1 and 4. In column 3 we broaden the definition of unchanged villages to include also those villages whose name we were able to re-conduct to the original list, with the help of additional information (eg on multiple village names).

We find no evidence of systematic differences between changed and unchanged villages. Column 2 suggests that replaced villages are slightly less educated, while the opposite appears from column 3. We find no evidence of any discrimination on grounds of ethnicity or wealth. Lastly, we find a significant age difference between unchanged and replaced villages, but we do not interpret this as a sign of age-based discrimination.

In Tables 14–17 we replicate the analysis of homogeneous treatment effects conducted in the main body of the paper, adding a dummy =1 if the name of the villages was left unchanged across village lists, and =0 otherwise. Estimates do not change appreciably, either in terms of magnitude or in terms of statistical significance.

5.4.2 Altered treatment allocations

Comparing the village lists used in the field, we noticed that two villages, originally randomized in the treatment, were used as controls, while three villages initially randomized out, were actually treated. In Tables 12 and 13 we investigate the presence of any systematic differences between these villages and those whose treatment allocation

[25]Expenditure may serve as a proxy for village size, if we assume that more urban cities are more expensive, which seems reasonable.

was left unchanged. In column 4 we compare villages whose treatment allocation was changed to all others. In columns 5 and 6 we restrict the sample to the treatment group and the control group respectively[26]. In this way, we can look in turn at the case of the new treatments and of the new controls.

We are particularly interested in checking whether we find opposite signs in columns 5 and 6, as this would suggest that some variables were used as grounds for preferential treatment allocation. We find evidence suggesting that Tigre villages were reallocated into treatment and away from the control group, which could possibly explain the imbalance in Tigre presence across treatment groups. The differences estimated along other dimensions are quite similar in columns 5–6, suggesting that treatment status was not altered based on those characteristics. We control for the Tigre tribe in all of our regressions.

Table 9: Choice of replacement control villages

		Tigre			Expenditure			Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
village 4	-0.17			-3990.16			-2.45**		
	(0.15)			(2833.59)			(0.78)		
village 5	-0.17			-3720.21			-2.23**		
	(0.15)			(2833.59)			(0.78)		
village 7	-0.17			-2852.65			-1.71*		
	(0.15)			(2833.59)			(0.78)		
village 52		0.38			-885.85***			-0.59	
		(0.20)			(121.59)			(0.41)	
village 93			-			627.40			0.25
						(494.73)			(0.13)
village 95			-			-1390.75**			-0.68***
						(494.73)			(0.13)
Constant	0.24	0.62**		6129.12*	3476.73***	4762.95***	2.22**	0.38	0.09
	(0.15)	(0.20)		(2833.59)	(121.59)	(494.73)	(0.78)	(0.41)	(0.13)
Obs.	73	88	90	74	88	90	72	87	90

(1)-(3) LS regressions of a Tigre dummy on village dummies. No Tigre households in subzone Shambko.
(4)-(6) LS regressions of overall household expenditure on village dummies.
(7)-(9) LS regressions of household wealth on village dummies.
Villages 4,5,7 are in subzone Goluj; village 52 is in subzone Tesseney; villages 93,95 are in subzone Shambko.
All samples restricted to subzone where villages are located. Observations clustered at village level.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[26]Altered villages in column 5 were moved from the control to the treatment group. Altered villages in column 6 were moved from the treatment to the control group.

Table 10: Which villages were replaced?

Variables (Y)	(1) Treatment status	(2) Same name	(3) Matched name
ALL			
1. Female	-0.00	-0.01	-0.01
	[0.722]	[0.549]	[0.655]
2. Usually lives here	0.01	-0.00	-0.00
	[0.206]	[0.795]	[0.704]
3. Stayed there last night	0.01	-0.01	-0.00
	[0.113]	[0.304]	[0.689]
4. Age	0.35	1.41***	1.33**
	[0.484]	[0.004]	[0.019]
5. Currently enrolled in school	-0.04	0.02	-0.08
	[0.458]	[0.711]	[0.178]
6. Current grade in school	0.21	0.45*	0.30
	[0.426]	[0.077]	[0.251]
FOR RESPONDENTS ONLY			
7. Age	0.62	1.83*	1.52
	[0.492]	[0.065]	[0.186]
8. Ever attended school	0.01	-0.02	-0.08*
	[0.832]	[0.522]	[0.071]
9. Only primary school	-0.04	0.05	0.06
	[0.481]	[0.353]	[0.324]
10. Literate	-0.02	-0.03	-0.09**
	[0.639]	[0.440]	[0.034]
11. Muslim religion	0.06	0.06	0.14
	[0.377]	[0.415]	[0.136]
12. Tigre tribe	0.17*	0.04	0.14
	[0.050]	[0.684]	[0.184]
13. Married	-0.01	-0.01	-0.01
	[0.348]	[0.293]	[0.723]

For each variable Y, we report the coefficient β_1 estimated from LS regression $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$. Column (1) is analogous to the randomization checks.
In column (1) X_i is a dummy =1 if village i is in treatment group.
In column (2) X_i=1 if village i has same name in Village Lists 1 to 4.
In column (3) X_i=1 if name of village i was changed but can be matched.
P-values in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Which villages were replaced? (continued)

Variables (Y)	(1) Treatment status	(2) Same name	(3) Matched name
BY HOUSEHOLD			
14. Hh size	0.18	-0.16	-0.14
	[0.239]	[0.314]	[0.429]
15. Members under 5	0.02	-0.07	0.00
	[0.705]	[0.232]	[0.940]
16. Members under 18	0.09	-0.18	-0.18
	[0.471]	[0.156]	[0.196]
17. Main source of drinking water:			
17.1.Public tap	-0.01	-0.05	-0.15
	[0.893]	[0.556]	[0.155]
17.2.Unprotected well	0.02	0.00	0.04
	[0.721]	[0.946]	[0.486]
17.3.Unprotected spring	-0.02	0.04	0.06
	[0.696]	[0.358]	[0.129]
18. Has any toilet	-0.01	-0.01	0.01
	[0.629]	[0.758]	[0.749]
19. Has radio	0.01	-0.01	-0.01
	[0.797]	[0.828]	[0.871]
20. Firewood, main fuel for cooking	-0.02	-0.02	-0.03*
	[0.248]	[0.325]	[0.076]
21. Has no window	0.01	-0.04	-0.06
	[0.939]	[0.610]	[0.420]
22. Separate rooms	0.02	-0.14	-0.14
	[0.831]	[0.202]	[0.255]
23. Sleeping rooms	0.00	-0.02	-0.03
	[0.969]	[0.652]	[0.619]
24. Sleeping spaces	-0.16	-0.06	-0.28
	[0.390]	[0.777]	[0.201]
25.Wealth index		-0.06	-0.15
		[0.697]	[0.408]
26.Monthly hh expenditure		-399.25	-389.83
		[0.114]	[0.155]
27.Monthly per-capita expenditure		-51.88	-48.36
		[0.417]	[0.490]

For each variable Y, we report the coefficient β_1 estimated from LS regression $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$. Column (1) is analogous to the randomization checks.
In column (1) X_i is a dummy =1 if village i is in treatment group.
In column (2) X_i=1 if village i has same name in Village Lists 1 to 4.
In column (3) X_i=1 if name of village i was changed but can be matched.
P-values in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Which villages were reallocated across treatments?

Variables (Y)	(4) All villages	(5) Treatment group	(6) Control group
ALL			
1. Female	0.02	0.02	0.01
	[0.689]	[0.729]	[0.776]
2. Usually lives here	0.01***	0.01	0.03***
	[0.002]	[0.186]	[0.000]
3. Stayed there last night	0.01	0.02***	-0.01
	[0.477]	[0.000]	[0.194]
4. Age	4.14***	3.37***	5.38***
	[0.000]	[0.000]	[0.000]
5. Currently enrolled in school	-0.24***	-0.23***	-0.24***
	[0.000]	[0.000]	[0.000]
6. Current grade in school	-1.35***	-1.46***	-1.24*
	[0.000]	[0.000]	[0.097]
FOR RESPONDENTS ONLY			
7. Age	0.17	2.55	-3.41
	[0.950]	[0.176]	[0.494]
8. Ever attended school	-0.14***	-0.13***	-0.16***
	[0.000]	[0.003]	[0.000]
9. Only primary school	0.24***	0.26***	0.22***
	[0.000]	[0.000]	[0.000]
10. Literate	-0.12***	-0.14***	-0.09
	[0.006]	[0.003]	[0.255]
11. Muslim religion	0.20***	0.17***	0.23***
	[0.000]	[0.001]	[0.000]
12. Tigre tribe	0.04	0.30**	-0.38***
	[0.844]	[0.024]	[0.000]
13. Married	-0.08***	-0.05**	-0.12***
	[0.000]	[0.016]	[0.000]

For each variable Y, we report the coefficient β_1 estimated from LS regression $Y_i = \beta_0 + \beta_1 \Delta_i + \epsilon_i$, where Δ_i is a dummy =1 if treatment status of village i was changed. Sample restricted to treatment group in (5) and to control group in (6). P-values in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Which villages were reallocated across treatments? (continued)

Variables (Y)	(4) All villages	(5) Treatment group	(6) Control group
BY HOUSEHOLD			
14. Hh size	-0.83***	-0.59**	-1.23***
	[0.005]	[0.012]	[0.008]
15. Members under 5	-0.15	-0.04	-0.30**
	[0.131]	[0.618]	[0.030]
16. Members under 18	-0.81***	-0.57***	-1.17***
	[0.000]	[0.000]	[0.000]
Main source of drinking water:			
17.1.Public tap	0.19	0.12	0.29**
	[0.214]	[0.610]	[0.015]
17.2.Unprotected well	-0.20***	-0.18**	-0.24***
	[0.000]	[0.011]	[0.000]
17.3.Unprotected spring	-0.03	0.05	-0.15***
	[0.631]	[0.605]	[0.000]
18. Has any toilet	-0.03	-0.01	-0.07***
	[0.252]	[0.884]	[0.001]
19. Has radio	-0.11*	-0.01	-0.25***
	[0.078]	[0.835]	[0.000]
20. Firewood, main fuel for cooking	0.01	-0.01	0.05***
	[0.799]	[0.876]	[0.000]
21. Has no window	0.43***	0.31	0.59***
	[0.001]	[0.103]	[0.000]
22. Separate rooms	-0.52***	-0.57***	-0.46***
	[0.000]	[0.000]	[0.004]
23. Sleeping rooms	-0.28***	-0.30***	-0.25***
	[0.000]	[0.000]	[0.000]
24. Sleeping spaces	-1.14***	-0.90	-1.44***
	[0.006]	[0.177]	[0.000]
25.Wealth index	-0.35***	-0.30**	-0.43***
	[0.001]	[0.048]	[0.000]
26.Monthly hh expenditure	-23.16	241.48	-520.60**
	[0.966]	[0.763]	[0.021]
27.Monthly per-capita expenditure	220.37	246.80	166.83
	[0.135]	[0.275]	[0.246]

For each variable Y, we report the coefficient β_1 estimated from LS regression $Y_i = \beta_0 + \beta_1 \Delta_i + \epsilon_i$, where Δ_i is a dummy =1 if treatment status of village i was changed. Sample restricted to treatment group in (5) and to control group in (6). P-values in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Information and knowledge about Malaria

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treatment	0.035	0.031*	0.068***	-0.014	-0.001	0.019	0.029
	(0.035)	(0.016)	(0.019)	(0.024)	(0.038)	(0.040)	(0.036)
treatment	0.026	0.027*	0.069***	-0.015	0.005	0.025	0.033
	(0.035)	(0.016)	(0.019)	(0.024)	(0.039)	(0.040)	(0.036)
same name	-0.083**	-0.027*	0.010	-0.004	0.047	0.059	0.038
	(0.032)	(0.015)	(0.020)	(0.027)	(0.037)	(0.041)	(0.042)
Observations	1575	1605	1610	1610	1599	1600	1602

Additional controls: dummies for Tigre tribe, Muslim religion, subzone of residence.
The upper part of the table reports estimated homogeneous treatment effect.
In the bottom part, we report the same estimate when ”same name” is added as a control.
”same name” is a dummy =1 if name of village was not changed from list 1 to list 4.
Standard errors in parentheses. Observations clustered at village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Ownership and use of mosquito bed nets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treatment	0.214**	0.176*	0.029	0.021	1.564	0.033	0.186**	0.015	0.012
	(0.100)	(0.093)	(0.039)	(0.043)	(3.126)	(0.032)	(0.088)	(0.063)	(0.069)
treatment	0.216**	0.180*	0.021	0.011	1.397	0.028	0.187**	0.025	0.022
	(0.099)	(0.091)	(0.037)	(0.041)	(3.178)	(0.030)	(0.086)	(0.061)	(0.067)
same name	0.019	0.035	-0.092*	-0.119**	-1.424	-0.042	0.001	0.099	0.111
	(0.114)	(0.107)	(0.048)	(0.052)	(4.068)	(0.033)	(0.097)	(0.062)	(0.068)
Observations	1603	1587	1281	1281	288	7867	1267	1267	1263

Additional controls: dummies for Tigre tribe, Muslim religion, subzone of residence.
The upper part of the table reports estimated homogeneous treatment effect.
In the bottom part, we report the same estimate when ”same name” is added as a control.
”same name” is a dummy =1 if name of village was not changed from list 1 to list 4.
Standard errors in parentheses. Observations clustered at village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Participation in Larval Habitat Management (LHM)

	(1)	(2)	(3)	(4)	(5)
treatment group	0.025	0.051	0.025	-0.001	0.027
	(0.161)	(0.071)	(0.027)	(0.034)	(0.026)
treatment	0.033	0.035	0.021	-0.004	0.018
	(0.165)	(0.068)	(0.027)	(0.034)	(0.023)
same name	0.067	-0.154	-0.041	-0.023	-0.090***
	(0.175)	(0.096)	(0.037)	(0.044)	(0.031)
Observations	1587	1610	1610	1610	1603

Additional controls: dummies for Tigre tribe, Muslim religion, subzone of residence.
The upper part of the table reports estimated homogeneous treatment effect.
In the bottom part, we report the same estimate when ”same name” is added as a control.
”same name” is a dummy =1 if name of village was not changed from list 1 to list 4.
Standard errors in parentheses. Observations clustered at village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Behaviors conducive to Malaria eradication, other than LHM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treatment group	0.068**	-0.027	-0.006	0.011	0.003	0.010	0.005	-0.017	-0.022
	(0.031)	(0.018)	(0.025)	(0.029)	(0.022)	(0.008)	(0.012)	(0.014)	(0.018)
treatment group	0.066**	-0.020	-0.011	0.005	0.004	0.011	0.005	-0.018	-0.022
	(0.031)	(0.016)	(0.025)	(0.028)	(0.021)	(0.008)	(0.012)	(0.014)	(0.017)
same name	-0.013	0.039*	-0.043	-0.057*	0.018	0.008	-0.002	-0.009	-0.011
	(0.029)	(0.025)	(0.026)	(0.030)	(0.026)	(0.008)	(0.013)	(0.016)	(0.022)
Observations	914	818	1451	1443	1443	1208	1280	1388	1443

Additional controls: dummies for Tigre tribe, Muslim religion, subzone of residence.
The upper part of the table reports estimated homogeneous treatment effect.
In the bottom part, we report the same estimate when ”same name” is added as a control.
”same name” is a dummy =1 if name of village was not changed from list 1 to list 4.
Standard errors in parentheses. Observations clustered at village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Number of villages in Lists 1, 2 and 4

Subzone	List 1			List 2		List 4						
	(1) total	(2) treatment	(3) control	(4) treatment	(5) delta1	(6) total	(7) delta1	(8) treated	(9) delta1	(10) delta2	(11) control	(12) delta1
Akurdet	6	3	3	4	1	10	4	4	1	0	6	3
Barentu	2	2	0	2	0	3	1	2	0	0	1	1
Dighe	12	6	6	5	-1	11	-1	5	-1	0	6	0
Forto	9	6	3	5	-1	9	0	5	-1	0	4	1
Gogne	11	5	6	5	0	10	-1	5	0	0	5	-1
Goluj (Omhajer)	7	2	5	2	0	5	-2	2	0	0	3	-2
Haykota	16	9	7	12	3	16	0	12	3	0	4	-3
Laelay-Gash	15	7	8	8	1	15	0	8	1	0	7	-1
Mensura	15	6	9	3	-3	12	-3	3	-3	0	9	0
Mogolo	7	4	3	3	-1	8	1	3	-1	0	5	2
Mulki	4	2	2	2	0	4	0	2	0	0	2	0
Shambko	6	2	4	2	0	6	0	2	0	0	4	0
Tesseney	6	4	2	4	0	6	0	4	0	0	2	0
Total	116	58	58	57	-1	115	-1	57	-1	0	58	0

For List 1, this table reports in columns 1–3 the number of villages for each subzone, divided by treatment allocation.
Column 4 reports the number of treatment villages that NMCP included in List 2, to be used by the spraying teams.
Column 5 marked as "delta1" reports the difference between the previous column and the corresponding column for List 1: (5) = (4) - (2).
Columns 6–12 refer to List 4. Column 6 shows the total number of villages for each subzone according to the final list.
Column 7 marked as "delta1" reports the difference between the previous column and the corresponding column for List 1: (7) = (6) - (2).
Column 8 reports the number of treated villages. The following columns 9-10 report the difference between that and the figure for Lists 1 and 2.
Column 11 reports the number of control villages by subzone: (11) = (6) - (8).
Column 12 marked as "delta1" reports the difference between the previous column and the corresponding column for List 1: (12) = (11) - (3).

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