Is malaria control profitable? Return on investment of privately-managed residential fumigations at a large sugarcane processing facility in Southern Mozambique

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Abstract

This paper provides new empirical evidence regarding the effect and return on investment of privately managed malaria control activities (indoor residual spraying with pesticides) on worker absenteeism in Mozambique. We analyze 4 years of malaria control and worker health and absenteeism data from a large sugar processing facility in Mozambique. We find that the benefits outweight the costs (ie, there is a positive return on investment) even when the consideration of benefits is limited to those directly accrued by the company. These findings suggest that the private sector may have an important role to play in malaria control in endemic areas.

Research Highlights

- This paper analyzes large, individual-level worker absenteeism data from malaria endemic zone.
- We quantify the effect of indoor residual spraying on absenteeism and clinical malaria.
- We estimate cost-effectiveness of malaria control from an investment standpoint.
- Results show ledger profitability, suggesting that the private sector could play a significant role in malaria elimination.

Keywords

Malaria; Investment; Health; Productivity; Agriculture; Absenteeism

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Introduction

Malaria accounts for a half million annual deaths worldwide (White et al., 2014) (WHO, 2016) (Ashley et al., 2018). Though rapid improvements in technology and funding have lead to important reductions in marlaria's global burden, the scale-up in activities required for eradication ("the worldwide interruption of transmission") (Lancet, 2011) will mean new partnerships and actors. One promising - albeit atypical - potential stakeholder in global malaria eradication is the private sector, given its omnipresence and potential to benefit directly from the elimination of malaria. But little evidence exists demonstrating how private sector entities can engage with malaria control and benefit at the firm level.

At the societal level, malaria has a large economic impact. By affecting saving, investment (Shretta et al., 2016), risk perception, productivity, absenteeism (Nonvignon et al., 2016), human capital accumulation (Castel-Branco, 2014), mortality, and costs of care (Sachs and Malaney, 2002), malaria likely has a negative effect on GDP and growth (McCarthy et al., 2000a) (Orem et al., 2012). Because of the relative affordability of most intereventions and the enormous societal costs of malaria, most forms of malaria control are cost-effective when a public welfare perspective is assumed, such as when a government provides the financing (White et al., 2011) (Purdy et al., 2013) (Howard et al., 2017).

From the persepctive of the private sector, however, investing in malaria control is not so clear-cut, since the benefits are often disperse, long-term, and difficult to quantify. Public health interventions targetting malaria - and their corresponding cost-effectiveness evaluations - most often focus on impacts pertaining to public welfare, such as an increase in life years adjusted for disability or quality (Goodman et al., 1999) (Shretta et al., 2016) (Lee et al., 2017) (Hanson, 2004). Though population-level health is certainly of importance to businesses, and improvements in health incidentally improve the economy at all levels (Brundtland, 1999) (Bloom and Canning, 2008) (Vecchi et al., 2013), these improvements may be too disperse or long-term to incentivize private sector involvement in health campaigns. In other words, the returns for malaria control are less for the private sector because (i) they capture only part of the benefits and (ii) they do not benefit from the externalities.

Just as the benefits of malaria control to the private sector are more limited than those to the public sector, considerations regarding costs for a firm are also distinct than those for a government. Though many firms in endemic regions engage in malaria control programs, this should not be considered, per se, evidence of its cost-effectiveness (since the extent to which corporate social responsibility plays a role is unknown).

100% of the Mozambican population are at risk of malaria, living in what the WHO classifies as a "high transmission" area (Moonasar et al., 2016). Annually, Mozambique has more than 8 million clinical malaria cases (an annual incidence of approximately 300 per 1,000 residents), with an estimated 14,000 deaths. Malaria accounts for 29% of all deaths, and 42% of deaths among those under five years of age (INE, 2011). Since 2013, Mozambique has seen a gradual increase in the incidence of malaria (Moonasar et al., 2016). 100% of the malaria in Mozambique is of the Plasmodium falciparum species, with Anopheles funestus, gambiae, and arabiensis as the primary mosquito vectors of the disease (WHO, 2015).

A significant sector of the economy in Mozambique is dominated by large-scale foreign direct investment projects (Robbins and Perkins, 2012), and the role of the private sector in health generally, and malaria specifically, is unequivocally important. Large agriculture and extractive industry firms take up wide swaths of land and employ hundreds of thousands (German et al., 2013). The Mozambican state has encouraged large-scale entreprise with the aim of general economic development (Buur et al., 2012). And where large firms exist, they often take on social roles such as housing and health care (Winkler, 2013). At times, this role is necessary from a purely practical standpoint; in other cases, it is employed under the auspices of "corporate social responsibility" (Azemar and Desbordes, 2009) (Curtis et al., 2003). Regardless of the language used, it is clear that private industry plays an important role in public health in Mozambique (Robbins and Perkins, 2012) (Castel-Branco, 2014).

To address the question of the profitability of malaria control activities from the standpoint of a private firm, we analyze data during a 4 year period from a private sugar facility in Southern Mozambique. We use absenteeism as our outcome variable, assuming that it is directly correlated with the productivity losses associated with malaria infection. We assess the effect of indoor residual spraying (IRS) on absenteeism, and demonstrate that the firm's engagement in malaria control not only improved worker health, but also generated a positive return on investment from a pure accounting perspective.

The structure of the paper is as follows. We provide an overview of the sugar company under study, and the epidemiology of malaria in the nearby area, as well as in Mozambique as a whole. We then give an overview of the data collected, and outline the theoretical and methdological assumptions and tools that underly our analysis. We assess the effect of time since IRS on worker absenteeism, controlling for malaria seasonality, and segregating models for four different worker types. In the results, we show that IRS spraying is associated with a significant reduction in worker absenteeism among permanent and fieldworkers, and has little to no effect on temporary and indoor workers. We find that, in addition to reducing absence, the IRS program has a cost savings effect. Our discussion covers potential implications from this study in terms of policy and investment, as well as the paper's limitations.

Background literature

The evidence of malaria's negative effects on both health and wealth, at both the individual (Cole and Neumayer, 2006) and collective (McCarthy et al., 2000b) levels, as well as in both the short (Asenso-Okyere and Dzator, 1997) (Ajani and Ashagidigbi, 2010) and long (Hong, 2011) (Sachs and Malaney, 2002) terms, are amply described in the public health and economics literature (Phillips, 1998). That said, very little exists in the literature examining the costs and benefits of malaria control from a private ledger perspective (ie, the point of view a business investor). Unlike a government or individual, a private firm investing in malaria control may be most interested not in its long-term macroeconomic effects, nor its short-term personal health effects, but rather on the impact on productivity (and the extent to which that producitivty's benefits accrue to the firm), absenteeism, and the opportunity costs of expenditures in malaria control. In other words, though the large magnitude of malaria control's benefits are well known, the portion of those benefits accrued by a private firm investing in malaria control is unknown.

In general, large firms operating in malaria endemic regions consider malaria to be an important enough issue to merit at least some investment (Pluess et al., 2009). Several studies examine the effect of foreign firms engaging in large-scale malaria control campaigns (Han, 2015) (Bennett et al., 2017) (Kaula et al., 2017). AngloGold-Ashanti, in partnership with local and national government in Ghana, invested in a well-rounded malaria control program in 2005, and saw worker absenteeism fall by 50% in 13 months (CCM, 2016). Lafarge's simulatenous investment in a comprehensive malaria control program in Benin was associated with an average 41% reduction in absenteeism among workers over the course of 4 years (Egedeye et al., 2011). Zambia Sugar Plc, Zambia's largest sugar processing facility, saw annual malaria cases at its company clinic fall from nearly 3,000 in 2001 to less than 500 by 2005, following investment in a malaria control program. Marathon Oil's investment of 15 million US in vector control, education, net distribution and malaria treatment on Bioko Island in Equatorial Guinea lead to an estimated 95% reduction in the number of parasite-infected mosquitoes and 50% reduction in malaria incidence among young children (Asquino, 2016) (Overgaard et al., 2012). A PATH study in Zambia found a return on investment of 28% among three companies investing in employer-based malaria control (Mouzin and al., 2011).

Still need to include stuff from http://gbchealth.org/wp-content/uploads/2014/03/IRS2

Though certainly suggestive of high returns on malaria control investments, these studies generally consider population health as the outcome measure of interest, rather than worker absenteeism or productivity. Similarly, they often neglect to differentiate between those clinical costs which are absorbed by the local health system versus those which are absorbed by the firm itself. When absenteeism itself is considered, effects of malaria control have generally been found to be high, but causation is difficult to establish, given that the previous studies rely on aggregate data.

Two studies utilize worker-level data to estimate the effect of malaria control on productivity. A World Bank analysis of Nigerian sugarcane cutters found that the simple availability of testing and treatment increased productivity by 10% in the weeks following the provision of services, the conclusion being that both the treatment and the test result were effective in increasing productivity, the latter simply increasing the information available which could influence personal labor allocation decisions (Dillon et al., 2014). A randomized controlled trial (RCT) in Zambia showed an even greater effect from investments in preventing malaria: farmers given bed nets saw fewer days lost to illness (both directly and due to caretaking responsibilities for ill family members), translating to an increase of approximately 15% in crop yield (Fink and Masiye, 2015). Though compelling, the Nigerian program only dealt with medical services (diagnostics and medication), rather than preventive interventions, and the Zambian RCT examined individual farmers, as opposed to a large firm.

In the literature, making the "investment case" for malaria control or elimination generally implies that the investor is the public sector, and takes into account those costs and benefits which are applicable from a public welfare point of view (Shretta et al., 2017). For example, an economic analysis by the Corporate Alliance on Malaria in Africa on the Bioko Island Malaria Control Program found a 4:1 cost-benefit ratio, but the perspective in this case was considered to be the "community" (Egedeye et al., 2011). Though appropriate in most cases to consider benefits accrued to the community (the government or institutions interested in public welfare primarily being the primary malaria control agents in most locations), the findings of these studies are rarely applicable to the private sector, and even less so at granular levels (such as an individual firm). In the case of a private firm not interested in "corporate social responsibility", it is not clear whether investing in malaria control would be profitable or not. This lack of clarity not only discourages investment, but also makes it difficult for governments to pinpoint the correct of amount of subsidy (if applicable) to encourage private sector scale-up in malaria control.

The literature on the effect of sugarcane cultivation on malaria risk is mixed. While some studies have found that the prevalence of malaria vectors in sugarcane areas to be similar to that of uncultivated areas (and less than in areas dedicated to other forms of more water-inensive agriculture, such as rice) (Ijumba et al., 2002), other studies have found significant increases in factors associated with malaria transmission at large-scale sugarcane facilities relative to traditional, small-scale farming and non-irrigated farming (Jaleta et al., 2013). Regardless of the effect the presence of a sugarcane farm per se on local malaria epidemiology, the time spent outdoors by sugarcane workers, the fact that many workers are migrants, and their sometimes precarious housing situations, suggest that sugarcane farmers are likely at increased risk of malaria infection (O'Laughlin, 2016). This is important, given that even among occupations with far less inherent exposure to mosquitoes (such as health professionals), malaria is one of the primary causes of work absenteeism in malaria-endemic countries (Burton et al., 1999). There is also some concern regarding the effect of large-scale insecticide use - common at essentially all Sub-Saharan African sugarcane farms - on insecticide resistance among moquitoes in the area. A study in Belize found that mosquito populations on the edge of sugarcane fields had higher tolerance to insecticide than similar populations in the core of fields or outside of the periphery (Dusfour et al., 2009). Sugarcane areas may offer the standing water necessary for mosquito breeding, but also perhaps attract mosquitoes which would otherwise be elsewhere, due to compounds in sugarcane pollen (Wondwosen et al., 2018).

This study does not endeavor to expand the current body of knowledge regarding malaria's ill effects on individuals and societies; rather, it aims to provide empirical evidence pertaining to a facet of malaria economics with very little in the literature: malaria control from a private-sector investment perspective. Our study adds to the existing literature by showing the effect of specific malaria control interventions on worker absenteeism, and translating that effect into a return on investment. Unlike previous studies on the effectiveness of malaria control interventions, our's focuses solely on one firm carrying out one intervention, takes advantage of individual-level data, and analyzes results from a ledger perspective.

Study area

Sugar has been systematically cultivated in Mozambique since the late 1800s. The Incomati Estates company, a small sugarcane processing facility started by a Scotsman on the banks of the Incomati River in 1913, was the first firm to export sugar from Mozambique. Following its purchase by international investors in the 1950s, it (along with the rest of the industry) expanded significantly, exporting to both Europe and the United States. In the late 1960s, a Portuguese family opened the Maragra Açúcar company, while a group of foreign investors started the nearby Marracuene Agrícola Açucareira mill. By the early 1970s, sugar grew to account for greater than 10% of Mozambique's national exports. Nationalized following independence in 1977, the industry's production levels fell from 320,000 annual tons to fewer than 15,000 by 1992. After the end of the civil war, foreign investment revived the sugar industry, and by 2011 production had surpassed its 1972 peak.

The mill of the Maragra Açucar SA (a subsidary of the Illovo sugar company, henceforth referred to as "Maragra") was nationalized in the 1970s (like all other Mozambican mills), went through a period of low production, and then fell completely out of use by 1984. It re-opened in private hands in 1992, and was renovated by a group of international investors in 1998. Today, Maragra accounts for roughly one quarter of Mozambique's overall sugar production (second only to the nearby Xinavane mill run by the Hulett Sugar Tongaat company) (Sutton, 2014). With a favorably close location to the port of Maputo, ample land (approximately 90 squared kilometers of plantation, and 5 squared kilometers of factory grounds), approximately 5,000 employees (of which three quarters are seasonal), and a mill with the capacity to process not only all the sugarcane grown on Maragra's land, but also the cane of the many nearby smallholders (O'Laughlin, 2016), Maragra has so far been able to weather the 2016 Mozambican crisis and concurrent collapse in global sugar prices.

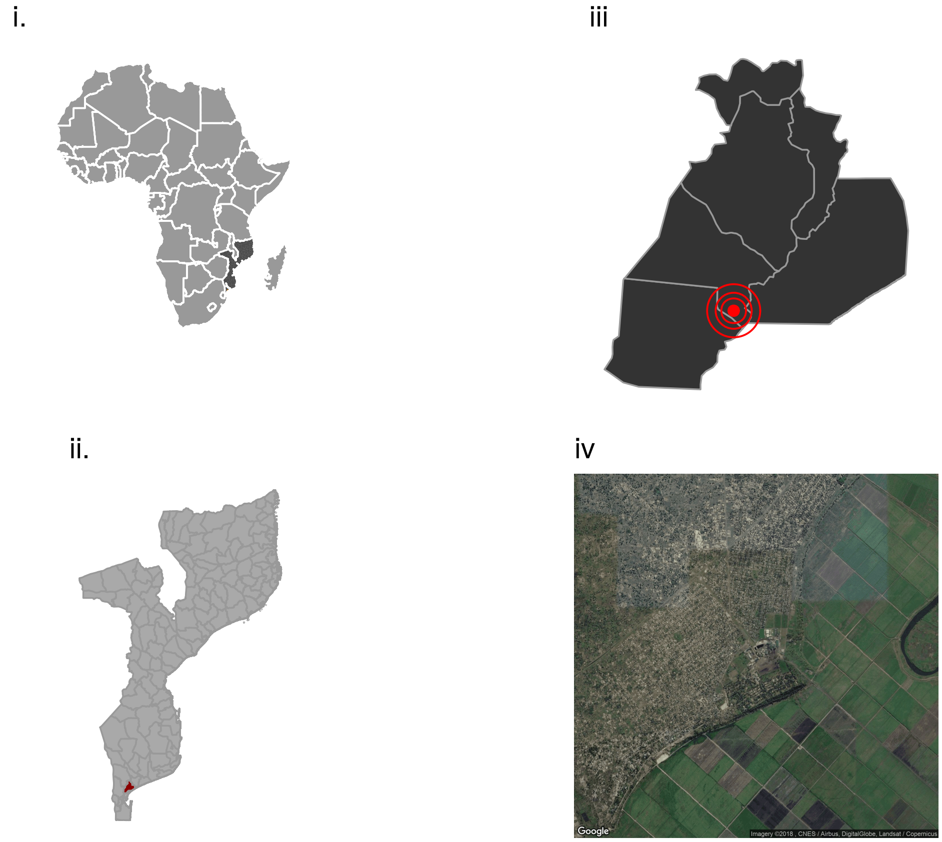

Figure 1: (i) Mozambique in Africa, (ii) Districts of Mozambique with Manhiça highlighted in red, (iii) District of Manhiça with Maragra highlighted in red, (iv) Maragra SA with surrounding fields and village

Maragra (figure 1, panel iii) is located in the district of Manhiça (figure 1, panel ii), a semi-rural area in the south of Mozambique (figure 1, panel i). 80 kilometers north of the Mozambican capital of Maputo, the district is low-lying, consisting largely of savannah and wetlands along the Incomati River. Most of the areas 160,000 residents (Sacoor et al., 2013) work as subsistence farmers. Migration from the area to South Africa for the purpose of employment in the profitable construction industry is common, especially among men (Nhacolo et al., 2006), as is migration to the area (from other parts of Mozambique) for seasonal work on the sugarcane plantations at Maragra and the slightly larger facility in Xinavane (at the district's border with Magude) (O'Laughlin, 2016).

Poverty is rife in southern Mozambique, and its associated illnesses take their toll on the population. The community prevalence of HIV/AIDS is as high as 40% (González et al., 2012); even in a more recent study suggesting a much lower prevalence of 22%, the risk of infection is still twice that of nearby areas (Mocumbi et al., 2017). Recent years have seen a three-fold increase in tuberculosis (García-Basteiro et al., 2017). Malaria, which has the greatest mortality burden due to the fact that the young are especially vulnerable to its effects, is perennial, though worse during the rainy season (December - March) (Saúte et al., 2003). Adult malaria is essentially universal, albeit much of it asymptomatic (Mayor et al., 2007). In regards to worker health, malaria is Maragra's primary concern, being so important as to justify the existence of both an on-site testing laboratory and clinic, as well as a malaria control department.

Maragra workers are mostly seasonal, working for the firm approximately half of the year during harvest time, and cultivating crops, working in construction, or going unemployed (or working elsewhere) during the other half. Though many workers live "on-site" (ie, within the delineated property of the firm itself), a sizeable minority resides in the environs (figure 1, panel iv). Maragra provides indoor residual spraying (IRS) using ACT (alpha-cypermethrin) and DDT (Dichlorodiphenyltrichloroethane) depending on stocks (a preference apparently exists for the former, but it is not always available). IRS activities, managed by Maragra's Malaria Control program, are ongoing throughout the year (Figure 1, panel i). Nearly all on-site houses are sprayed, though the time between fumigations is irregular (Figure 2, panel ii). Off-site houses may also receive IRS (managed and carried out by the National Malaria Control Program), but the status and timing of these fumigations is not known at the individual level.

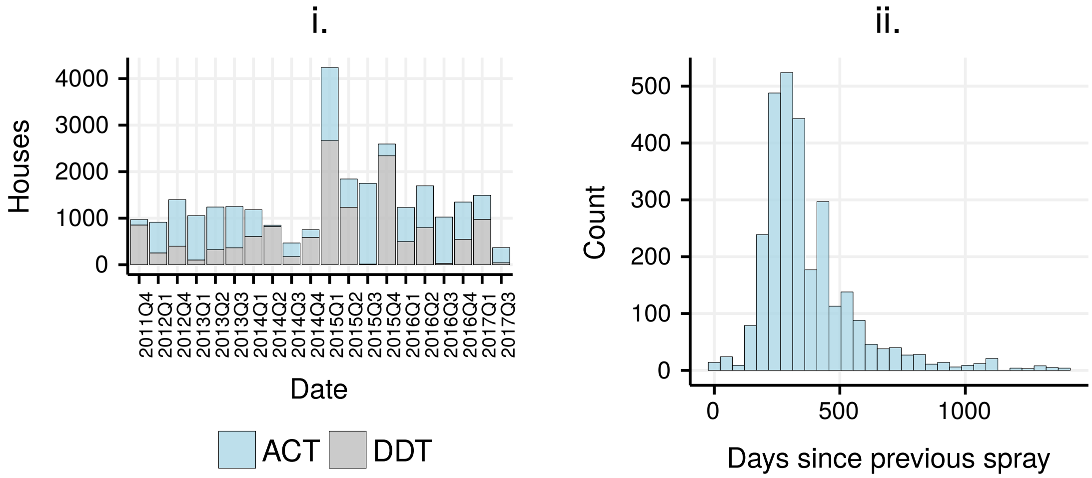

Figure 2: i. Fumigation activities carried out by Maragra Malaria Control during study period, ii. Distribution of average time between sprayings of households

Methods

Data

In collaboration with the sugar processing facility, we collected data for the period from January 2010 through December 2016. Data came from four sources: (i) the Human Resources' roster of worker details and absences, (ii) the facility's on-site clinic's medical and laboratory records, (iii) the facility's on-site malaria control program's records pertaining to the dates, chemicals, and location of IRS activities, and (iv) interviews with company employees pertaining to costs, data limitations, etc. Digitization and collection of data took place during the period from March 2016 through May 2017. Supplementary data pertaining to worker characteristics was obtained from through the Centro de Investigação em Saude de Manhiça's (CISM) demographic census, which covered workers from the district, but not those who migrated from other parts of the country (Nhacolo et al., 2006).

Data pertaining to district-wide malaria incidence was obtained from Mozambique's Boletim Epidemiológico Semanal (BES), which is the system by which the National Malaria Control Program monitors incidence at the district level throghout the entire country, and reports the number of confirmed weekly malaria cases at government health facilities. Using these case numbers, combined with population estimates from the National Statistical Institute (INE), we estimate each day's annualized weekly malaria incidence rate (cases per 1000 population at risk), interpolated from the weekly figures. We retrieved weather data for all Mozambican stations from NOAA. We estimated the meteorological conditions at the centroid of Manhiça using a simple interpolation method whereby the district's weather conditions were estimated to be a function of all Mozambican weather stations' reported conditions, inversely weighted by kilometers from district centroid.

Maragra regularly employs IRS at on-site worker households in order to reduce those workers' (and their families') risk of malaria infection. IRS works by killing the malaria vector (mosquito), thereby preventing infection of the household occupants. When administered correctly, IRS is a low-risk intervention to its recipients, and is assumed not to affect absenteeism in the short-term (to the extent that it may cause negative side-effects, these are generally long-term). It is preventive only, and does not cure current malaria infection, nor does it affect the parasite load of mosquitoes. Workers living off-site (our control group) also may have received IRS at some point during the study period (from government programs). Even though we do not have reliable person-level data on IRS carried out by the government, off-site workers are a suitable control in the sense that they represent "business as usual" (ie, what would happen if the company carried out no IRS and relied solely on public interventions). Using company HR and clinical records, we were able to identify absences and episodes of clinical malaria among all workers, as well as identify the time since the most recent IRS episode before the onsent of absence or illness.

Worker characteristics, illness and absenteeism data, along with IRS activity data, were systematically stored, collected, and used at the individual level by Maragra, and therefore of generally high quality. Because cost data was less systematically collected by Maragra, and because many costs could not be precisely quantified due to the abundance of in-kind and cross-departmental expenditures, we had to rely on rough estimations based on a mix of interviews, reciepts, and interpolations. Since our program cost data is not as reliable as our worker characteristic and outcome data, we were conservative in our estimates, and generally tried to err on the side of program activities and materials costing more than what was reported, when doubt was aired. Cost data consisted of three types: (i) wages of malaria control employees, (ii) transporation and vehicle costs for IRS teams, and (iii) acquisition costs of purchasing IRS chemicals for fumigation (ACT and DDT), the latter two being combined into malaria control "programme" costs.

Conceptual framework and identification strategy

We sought to understand the effect of IRS on individual workers' likelihood of absence from work as well as their likelihood of clinical malaria. To estimate this effect, we estimated separate models for absence and illness. We employed linear mixed effects models (Minalu et al., 2011) (Liu et al., 2010) (with individual worker fixed effects, and random effects for other covariates) in lieu of interrupted time series (Lopez Bernal et al., 2016) so as to explicitly adjust for confounders (Bell and Jones, 2014). We divide into 4 different models for different worker types, so as to account for the potential time-varying effects of worker type on risk of malaria. Our model specification is as follows

$$\hat{Y_{it}} = \hat{\beta}_0 + \hat{\beta}_1 \text{Season}_t * (\hat{\beta}_2 IRS_{it} * \hat{\beta}_3 IRStime_{it}) + \alpha_i + \delta_t + \upsilon_{it}$$

$\hat{Y}_{it}$ is the rate of absence. β_1 is the binary "season" variable, imputed from overall district clinical incidence. Our intervention is whether the residence of the worker in question was treated in the last year, and, if so, the time since treatment, represented, respectively, by β_2 and β_3. α_i reprsents the time invariant worker fixed effects, and δ_i represents the fixed effect of the particular malaria season. υ is the error term.

We define the malaria season as any time during which the clinical incidence of malaria in the district of Manhiça was at or greater than the median clinical incidence of malaria for the entire study period. These weeks are flagged as red in Figure 1, Panel A. By using clinical incidence of the area of residence of the workers (as opposed to more typical proxies for malaria risk, such as only rainy vs. non rainy season), our seasonality estimate is a closer approximation of true malaria risk, incorporating lagged effects such as the incubation period of the parasite, as well as any inherent non-linear effects of weather. In addition, we adjust for daily precipitation; though its lagged effect on malaria incidence is likely captured by the seasonality term, we include rainfall since it's immediate effect (through its impact on transportation and working conditions) may also affect absenteeism.

Details will go here about externalities (neighborhood effects, positive spillover to district, negative spillover from district, how large firm may mean that most positive externalities are absorbed by the firm, and not many negative externalities, but maybe with a smaller firm it wouldn't work as well) NOT DONE YET.

Estimating return on investment

Our formula for return on investment can be described in a straightforward fashion…

$$R = \frac{P_w - S_{wa} - S_{wc}}{P_w}$$

…where R is the return on investment, P is the malaria control program's total operating cost, w refers to costs at the per-worker level, a refers to savings through avoided absences, and $ c $ refers to savings through avoided clinical encounters. We define the malaria control program as "profitable" from an investment standpoint if ROI is greater than 100%, ie if the savings associated with the estimated effect of IRS is greater than the costs of the program's administration.

Reproducibility and ethical approval

All data processing and analysis were carried out in R (R Core Team, 2017) and all analysis code is freely available online (Brew, 2017). Ethical approval for this project was obtained from the Institutional Ethics Review Board for Health at the CISM (CIBS-CISM) prior to data collection.

Results

Descriptive statistics

We collected absenteeism and demographic data data on 3362 workers from 2012 through 2016. Workers were approximately 60% male, and more than 80% fieldworkers (predominantly cane-cutters). Most were in their 20s and 30s and employed on temporary contracts. Table 1 shows overall worker details divided by "Treatment" versus "Control" status. "Treatment" is considered the time beginning at IRS administration and ending one year later; "Control" is considered time observed either prior to IRS administration (and greater than 1 year after previous IRS administration) or among workers who never received IRS. Because of the temporal nature of these categories, many workers belong to both treatment and control groups, albeit at different times.

Variable		Treatment workers	Treatment days	Control workers	Control days
Department	Administrative	35	12523	157	173151
	Factory	71	20533	453	280416
	Field	410	91302	2691	1181175
Sex	F	228	47907	1274	489484
	M	288	76451	2027	1145258
Status	Permanent	127	47075	500	655311
	Temporary	389	77283	2801	979431
Age	20	140	29463	960	347758
	30	176	39119	1225	550783
	40	123	30186	652	366936
	50	58	18881	344	268877
	60	17	5893	116	96555
	70	2	816	4	3833

Table 1: Overall worker characteristics

Temporary workers tended to be younger and male; female temporary workers being on average 5-10 years older than their male counterparts. Permanent workers had a bi-modal age distribution, the older peak explained by the greater density of males in administrative roles. Females accounted for 43% of temporary workers but only 16% of permanent workers (figure x).

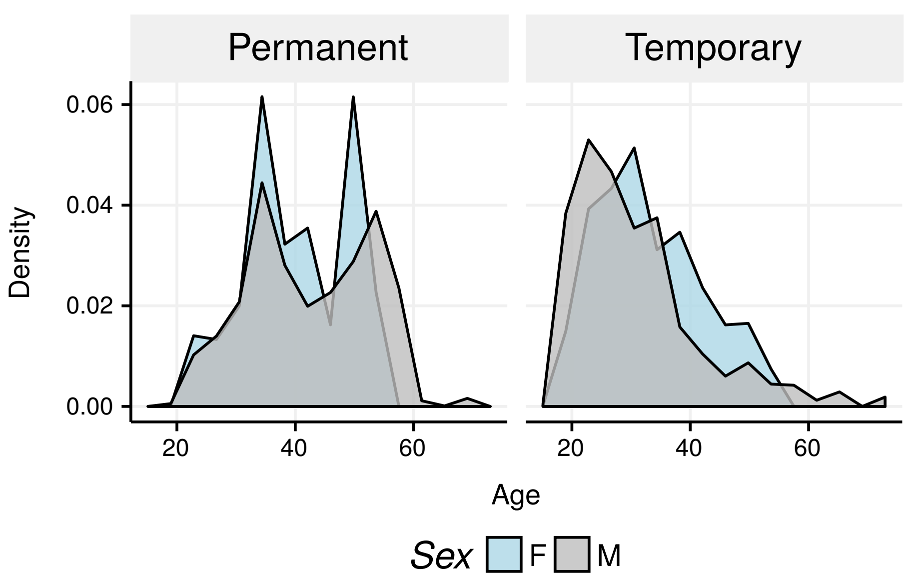

Figure 3: Age distribution by sex and worker status

During the study period, weather followed typical seasonal trends for the area, albeit slightly drier than previous periods.

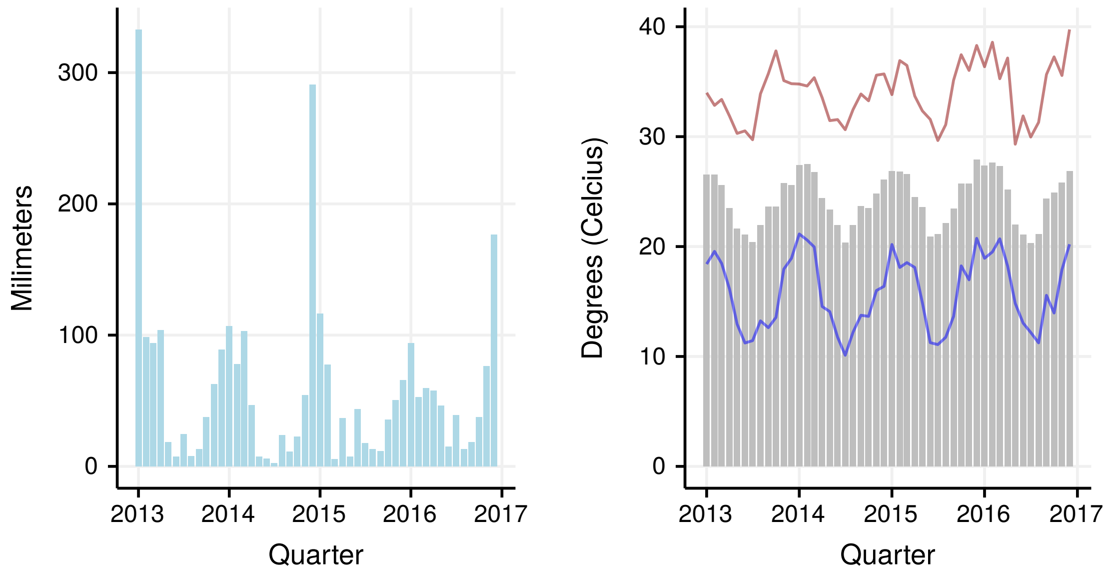

Figure 4: i. Monthly total precipitation in the Maniça district; ii. Average monthly temperature (bars) during the study period, as well as monthly maximum (red) and minimum (blue) temperatures

In Southern Mozambique, malaria peaks during the summer months (December through March) most years (Figure 5, panel A), and worker absenteeism at Maragra rates track malaria incidence closely, following the same seasonal patterns (figure 4, panel B). Both all-cause absenteeism and sick absenteeism have declined in recent years at Maragra (figure 5, panel C), with the latter declining at a faster rate than the former. The fact that the rate of confirmed cases at the company clinic is largely non-seasonal (figure 5, panels E and F) suggests that a significant portion of workers either seek care for malaria elsewhere (for example, government health posts, of which several are nearby and in some many cases closer to workers' residence than the company clinic) or do not seek care during malaria infection. Accordingly, we focus our analysis on all-cause absenteeism rather than sickness absenteeism or malaria diagnostics, with the assumption that much of illness is captured by absenteeism but not by the clinical data.

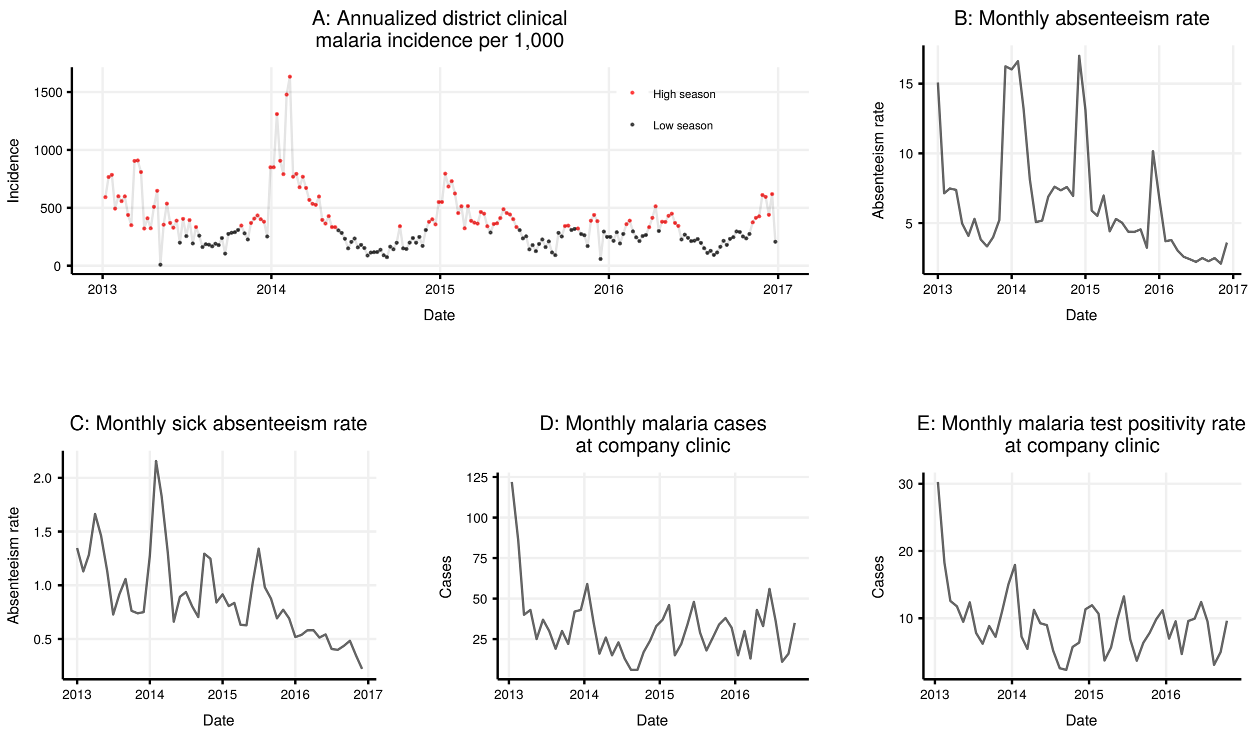

Figure 5: Clinical malaria (district of Manhiça), all-cause absenteeism among Maragra workers, sick absenteeism among Maragra workers, positive cases at company clinic, and test positivity rate at company clinic

Fumigations: During the period from January 1st, 2013 through December 31st, 2016, the Maragra Malaria Control Unit carried out 11,007 episodes of fumigation of residential "agregados" (household combinations), for a total of 13,260 building-fumigation combinations. The total number of unique agregados sprayed during this period was 3,998. Among the 3,362 workers for whom we have reliable absenteeism and residential data, 692 had their homes fumigated at least once (the majority of workers live off of the facility).

Absences: We observed 1,759,100 unique worker-days among the 3,362 workers. The all-period average absenteeism rate was 5.56%, though this rate varied widely as a function of worker department, sex, residence, and season (table 1).

Variable		2013	2014	2015	2016
Malaria season	Low	5.2%	7%	5.4%	3.3%
	High	8.2%	12.8%	6.3%	2.7%
Worker type	Field worker	4.4%	7.6%	3.9%	1.7%
	Not field worker	10.7%	12.4%	11.5%	9.6%
Contract	Permanent	12.1%	12.6%	12%	10.2%
	Temporary	0.1%	5%	2.3%	0.5%
Sex	F	4%	8.1%	4.4%	1.9%
	M	8.1%	10%	6.5%	3.7%
Residence	Off site	6.4%	9.6%	5.9%	3%
	On site	9.4%	9.7%	6.1%	3.1%
Precipitation	Dry	5.4%	7.7%	4.8%	2.4%
	Rainy	7.9%	10.6%	7%	3.3%

Table 2: Absenteeism rate by year and worker characteristics

Precipitation: Of the 1454 days observed, 940 had no rainfall at all (ie, approximately two-thirds). On days for which there was any rainfall at all, the average amount was approximately 2.99 centimeters. Rain was most common in

December and January (average of 5-5.5 cm daily) and least common in August and September (average of 0.5 cm daily). Days with any rainfall saw more absenteeism than days with no rainfall (Figure 6, panel A) and among days with any rainfall, more precipitation was associated with greater absenteeism (Figure 6, panel B) (correlation coefficient of 0.25).

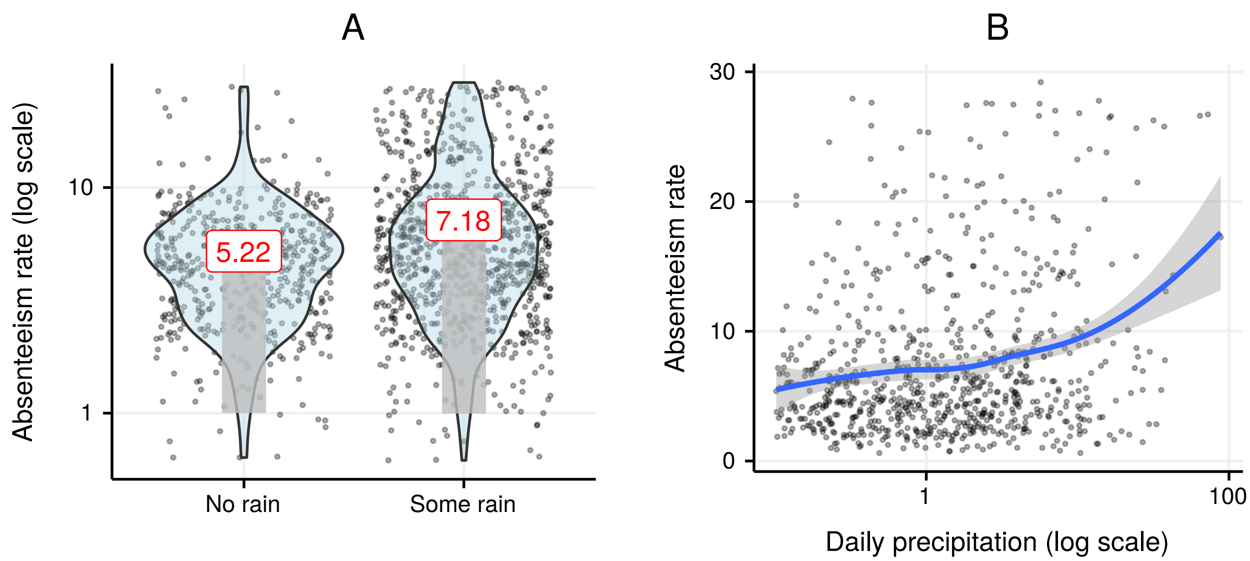

Figure 6: Rainfall and absenteeism: association of any rainfall with absenteeism rate (left) and association of rainfall amount and absenteeism (right)

The extent to which rainfall's effect on absenteeism is confounded by its effect on malaria is discussed in the model results section.

Effect of IRS on clinical malaria: The number of malaria cases registered at the company clinic during that time was 1873, for an approximate annualized clinical incidence of 110 cases per 1,000.

Not done yet. In fact, not even sure if I should do this section at all, since it's basically just a distraction.

Costs of program: The malaria control program at Maragra has an annual operating budget of approximately $112,000, which includes the purchase of insecticide, the wages of IRS sprayers and drivers, transportation, record-keeping, and general administrative costs. Assuming linearity in costs, the program spends approximately $19 per building sprayed. With each agregado containing an average of 2.2 workers. Much of the benefit of IRS goes to non-worker residents of sprayed agregados (who constitute a majority), but this benefit is purposefully ignored for this analysis.

Cost of malaria: Given the likelihood that clinical data does not fully capture all malaria cases (and most likely captures only a small fraction of actual infections, given the high rates of acumulated adult immunity [Mayor2007]), we do not quantify the costs of malaria infection to the company. Rather, we first estimate the reduction in absenteeism attributible to IRS, and then quantify the savings associated with prevented absences. Additionally, we calculate the clinical savings of IRS by first estimating the share of absences which are associated with an episode of clinical malaria, and then applying the clinical cost per case to the equivalent share of prevented absences. We intentionally ignore the savings accrued by the public health system, as well as the likely utility gains in secondary realms such as school absenteeism, producitivity, etc.

Analysis

Effect of IRS on absenteeism

Immediately following IRS, a worker's likelihood of absence drops significantly (appendix figure, panel A). As one would expect if the mechanism by which IRS reduces absence is through reduced malaria infection, the effect of IRS during the low transmission season is significant, but far less substantial in effect size (appendix figure, panel B).

In order to assess the effect of IRS on absenteeism, we created 4 worker fixed effects models for the 4 principal worker types (permanent field worker, temporary field worker, permanent non-field worker, temporary non-field worker) for both outcoms (all cause absenteeism vs. sickness absenteeism). The reason for segregating models rather than incorporating worker type as a fixed effect was that it seemed plausible that the effect of the treatment (IRS) on the outcome would be different (and vary differently over time) depending on these worker types. For instance, it is reasonable to assume that IRS' effect would be differential for a temporary worker (who likely lives in the fumigated house less than 100% of the year) than for a permanent worker.

Given that IRS is carried out on a continuous rolling basis, we used relative worker time (as opposed to calendar) as the time component of our model - that is, each workers' days until and since IRS were standardized so that day 0 (date of fumigation) was the interruption point. This has the advantage of incorporating into the model a variety of potential time-varying confounders in a quasi-randomized fashion, thereby making it unecessary to adjust for them specifically. Our model took into account workers' residential location (on or off site) - even though off site workers by definition could not be administered IRS by Maragra - so as to capture other seasonal effects from those workers.

This is not very eloquent yet and needs to be improved.

The model results for all cause absenteeism (table 4) suggest a significant decrease in absenteeism following the administration of IRS. The effect is ambivalent among temporary workers, whereas among permanent workers the administration of IRS decreases absenteeism betwen 2.5 and 8.4 percentage points in the 2-9 month following administration. These effects are consistent with IRS decreasing absence through the medium of malaria, since (a) the effect is not as strong in the first month (potentially during the parasite incubation phase), the effect is stronger on field workers (who are more socioeconomically the demographic at greater risk of malaria than their administrative counterparts), and the effect is ambivalent among temporary workers (since the protective effect of IRS is only a function of the amount of time that the worker spends in the fumigated house).

The model results for sickness only absenteeism (table 5) suggest that IRS has a significant effect on permanent field workers. The effect is directionally similar among temporary fieldworkers (but does not reach the level of significance). Among non-fieldworkers, the effect of IRS is mixed.

I'll probably remove this from the final version, since we're saying that the data aren't that good...

Externalities

One potential shortcoming of our analysis thus far is that a "control" worker (ie, one whose house has never been sprayed or was sprayed greater than one year ago) may actually be conferred some protection against malaria by the fumigations at his/her neighbors' houses. This positive spillover effect would theoretically go through two channels: (i) via a reduction of mosquitoes in the vicinity and (ii) via a reduction of the malaria parasite in the blood of humans in the vicinity (ie, the parasite "reservoir").

By the same token, just as being surrounded by IRS-treated homes may indirectly protect someone living in a home not treated by IRS, one might surmise that living on the periphery of the company grounds might lead to more malaria risk relative to living in the core, since homes near the periphery but outside of Maragra are less likely to be fumigated. In other words, to the extent that both positive and spillover effects are significant enough to warrant inclusion in our model, we would expect that (i) the prevalence of IRS in a worker's neighborhood should be associated with a reduction in absenteeism of the worker and (b) workers living further from the periphery of the company grounds should have lower absenteeism than workers living at the periphery. We test both of these hypotheses.

Neighborhood protective effect

Working on this now

Core-periphery difference

Working on this now

Table 3: All cause absenteeism: model results

Term	Estimate
Permanent field worker	
Malaria season	2.533 (P<0.001)
Months since IRS: 01	5.382 (P<0.001)
Months since IRS: 02-04	4.747 (P<0.001)
Months since IRS: 05-09	-2.669 (P<0.001)
Precipitation (mm)	0.206 (P<0.001)
Malaria season:Months since IRS: 01	-6.262 (P<0.001)
Malaria season:Months since IRS: 02-04	-8.388 (P<0.001)
Malaria season:Months since IRS: 05-09	-3.71 (P<0.001)
Permanent not field worker	
Malaria season	0.957 (P<0.001)
Months since IRS: 01	-0.987 (P=0.071)
Months since IRS: 02-04	4.375 (P<0.001)
Months since IRS: 05-09	-0.55 (P=0.254)
Precipitation (mm)	0.548 (P<0.001)
Malaria season:Months since IRS: 01	1.787 (P=0.016)
Malaria season:Months since IRS: 02-04	-5.208 (P<0.001)
Malaria season:Months since IRS: 05-09	-2.04 (P=0.003)
Temporary field worker	
Malaria season	-0.368 (P<0.001)
Months since IRS: 01	-0.075 (P=0.526)
Months since IRS: 02-04	-0.193 (P=0.072)
Months since IRS: 05-09	-0.036 (P=0.738)
Precipitation (mm)	0.02 (P<0.001)
Malaria season:Months since IRS: 01	-0.154 (P=0.406)
Malaria season:Months since IRS: 02-04	0.297 (P=0.05)
Malaria season:Months since IRS: 05-09	0.041 (P=0.769)
Temporary not field worker	
Malaria season	2.025 (P<0.001)
Months since IRS: 01	-2.536 (P=0.134)
Months since IRS: 02-04	-1.177 (P=0.282)
Months since IRS: 05-09	-1.821 (P=0.084)
Precipitation (mm)	0.078 (P<0.001)
Malaria season:Months since IRS: 01	6.121 (P=0.002)
Malaria season:Months since IRS: 02-04	1.333 (P=0.343)
Malaria season:Months since IRS: 05-09	-4.639 (P<0.001)

Table 4: Sick absenteeism only: model results

Term	Estimate
Permanent field worker	
Malaria season	-0.073 (P=0.089)
Months since IRS: 01	0.891 (P<0.001)
Months since IRS: 02-04	1.223 (P<0.001)
Months since IRS: 05-09	-0.236 (P=0.249)
Precipitation (mm)	0 (P=0.984)
Malaria season:Months since IRS: 01	-1.501 (P<0.001)
Malaria season:Months since IRS: 02-04	-0.597 (P=0.031)
Malaria season:Months since IRS: 05-09	-0.484 (P=0.097)
Permanent not field worker	
Malaria season	-0.056 (P=0.204)
Months since IRS: 01	-0.667 (P=0.003)
Months since IRS: 02-04	0.904 (P<0.001)
Months since IRS: 05-09	0.127 (P=0.526)
Precipitation (mm)	-0.002 (P=0.565)
Malaria season:Months since IRS: 01	1.121 (P<0.001)
Malaria season:Months since IRS: 02-04	-0.122 (P=0.652)
Malaria season:Months since IRS: 05-09	1.198 (P<0.001)
Temporary field worker	
Malaria season	-0.106 (P<0.001)
Months since IRS: 01	0.029 (P=0.545)
Months since IRS: 02-04	0.04 (P=0.35)
Months since IRS: 05-09	-0.046 (P=0.291)
Precipitation (mm)	0 (P=0.966)
Malaria season:Months since IRS: 01	-0.108 (P=0.148)
Malaria season:Months since IRS: 02-04	-0.032 (P=0.595)
Malaria season:Months since IRS: 05-09	-0.052 (P=0.36)
Temporary not field worker	
Malaria season	-0.135 (P=0.236)
Months since IRS: 01	1.427 (P=0.092)
Months since IRS: 02-04	-0.569 (P=0.299)
Months since IRS: 05-09	-1.42 (P=0.007)
Precipitation (mm)	-0.005 (P=0.613)
Malaria season:Months since IRS: 01	-1.796 (P=0.069)
Malaria season:Months since IRS: 02-04	2.479 (P<0.001)
Malaria season:Months since IRS: 05-09	0.18 (P=0.794)

Translating absences to costs

xxx

Not done yet. This will be relatively straightforward arithmetic, but I want to first make sure that the models are rock solid (since all of the "translation" hinges on them).

Return on investment

Not done yet. In conversation with Eduardo from MC about getting more accurate costs

Savings

- In percentage point terms, reduction from 13% to 8%.
- 5 annually prevented absences per worker.
- 8,000 workers: 40,000 prevented absences, wage of 3 USD
- TOTAL: 120,000 USD in productivity-only savings.

Costs

- 8 IRS workers, 1500 USD yearly = 12,000 USD
- ACT + DDT: 50,000 USD
- Facilities, vehicles, gas: 50,000 USD
- TOTAL: 112,000 USD in IRS-only costs

7% ROI (ignoring clinical costs)

Robustness and generalizability

Two principal concerns call into question the results of our analysis. First, the application of IRS to a workers house may be endogenous.It is reasonable to suspect that the application of IRS to households is not random, but rather that IRS was applied more frequently to houses which had already seen a malaria case. In this case, our estimated effect of IRS on absenteeism would likely be underestimated, with the post-IRS absenteeism rates actually having declined from a greater pre-IRS absenteeism rate than otherwise suggested.

Is this the right term here? We're not dealing with an "unobserved" factor per se, rather we're dealing with a situation in which the cause might influence the effect, and the effect might influence the cause, ie a feedback loop.

To check for this, we estimate the odds of absenteeism as a function of receiving IRS during the 10 day period prior to receiving IRS. If IRS application is indeed endogenous, we would expect absenteeism to be elevated during this period (since the increase in absenteeism would be theoretically responsible for the application of IRS), a situation which would require further statistical adjustment. If, on the other hand, there is no endogeneity, we would expect absenteeism in the 10 day period prior to IRS administration to be similar to other pre-IRS absenteeism (adjusting for seasonality).

Should add model specification formula here.

The below shows our robustness check for all cause absenteeism.

Variable	Estimate	Lower	Upper	P value	Significant
(Intercept)	0.0661899	0.0614958	0.0711710	0.0000000	xxx
10 days prior to IRS	0.9229176	0.7300243	1.1503819	0.4886243	
Malaria season	3.1173457	2.9319429	3.3156586	0.0000000	xxx
departmentFactory	1.0944261	1.0118141	1.1841680	0.0245210	x
departmentField	0.5426841	0.5036184	0.5850353	0.0000000	xxx
10 days prior to IRS:Malaria season	0.8172244	0.6161822	1.0908542	0.1653822	

The below shows our robustness check for sick only absenteeism. Unlike with all cause absenteeism, during malaria season, being in the period 10 days prior to IRS is associated with statistically greater likelihood of being absent for illness. In other words, it appears that there is somewhat of a feedback loop: when a worker misses work due to illness, his/her likelihood of getting IRS doubles in the next 10 days.

What to do about this???

Variable	Estimate	Lower	Upper	P value	Significant
(Intercept)	0.0098162	0.0079914	0.0119339	0.0000000	xxx
10 days prior to IRS	0.6780540	0.3484288	1.1791509	0.2069281	
Malaria season	1.1637020	0.9827900	1.3767569	0.0777162	
departmentFactory	1.3068546	1.0428447	1.6460818	0.0214002	x
departmentField	0.6713828	0.5396839	0.8403182	0.0004142	xxx
10 days prior to IRS:Malaria season	2.2225088	1.0747201	4.8587934	0.0360020	x

The second concern is that our quantification of return on investment is distorted by the fact that we treat IRS operations as essentially linear in nature, when in reality economies of scale, in-kind purchases and other factors likely make the true cost-per-spraying convex. We address this by creating three scenarios: (1) a "start-up" scenario in which we take into account all costs incurred by starting a program from scratch, (2) a "normal" scenario in which we match the assumptions with those used in this paper (ie, account for "wear-and-tear" depreciation but not vehicle purchase, etc.) and a (3) "absorbed costs" scenario which ignores all costs which are not directly incurred by the program.... xxx...

Will address this with some sensitivity analysis

Discussion

This entire section will not be done until methods/results are finalized.

- Overview of findings
- How this contributes to the literature
- Implications for policy and for businesses
- Spillover effects !
- How absenteeism might be underestimating true effect, since at the margin a sick worker might go to work (ie, not be absent), but be less productive

Limitations

- No analysis yet of different worker types (agricultural vs. industrial).
- Have not yet ventured at all into side-analyses (effect on employment, tonnage, etc.).
- Sick absenteeism seems to track absenteeism poorly: lack of clarity regarding pathways.
- Large sample size, but all from same place: questionable generalizability.

Appendix

Unadjusted absenteeism by time since IRS

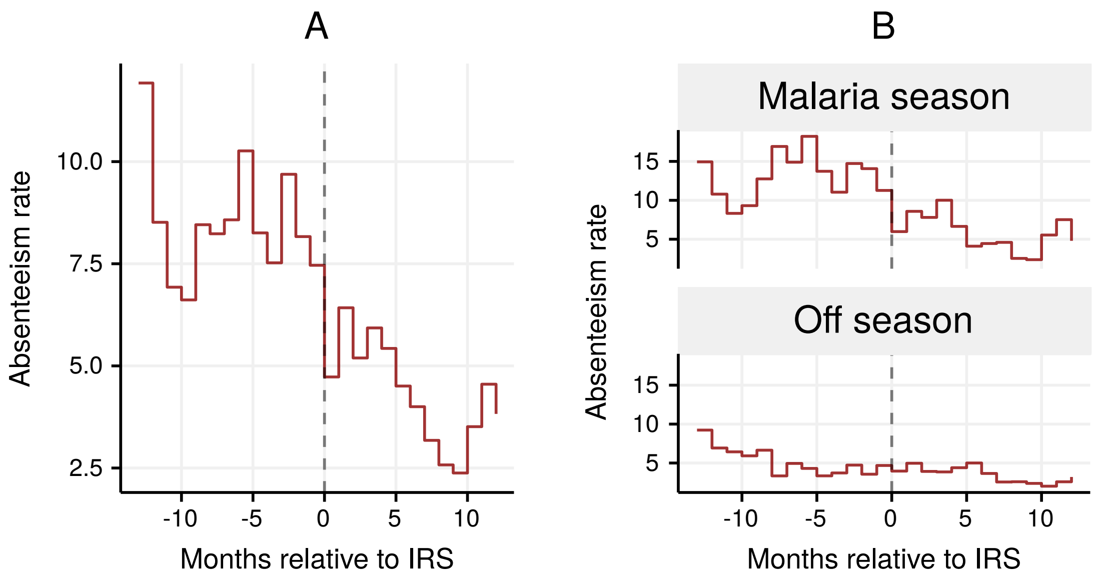

Figure 7: i. Absenteeism before and after IRS administration for all workers who ever received IRS; ii. The same, but segregated by malaria and non-malaria seasons

Unadjusted sick absenteeism by time since IRS

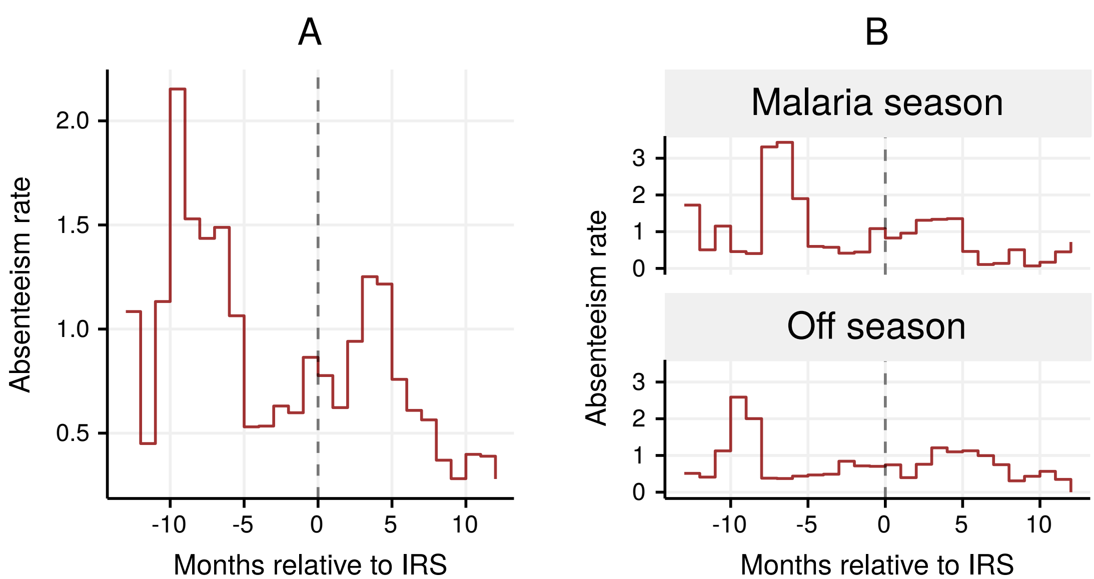

Figure 8: i. Sick absenteeism before and after IRS administration for all workers who ever received IRS; ii. The same, but segregated by malaria and non-malaria seasons

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