Effectiveness of private sector malaria control: The case of sugarcane workers in Mozambique

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Introduction

Context

- Malaria has a nearly unquantifiably large economic impact.
- Many channels: fertility, fecundity, saving, investment (Shretta, Avanceña, and Hatefi 2016), risk perception, productivity, absenteeism, human capital accumulation (Castel-Branco 2014), mortality, costs of care (Sachs and Malaney 2002).
- Cost-benefit studies often only consider the costs of an intervention and associated costs of care, without quantifying the societal cost of non-intervention.
- In elimination context, scaling-up private sector involvement is very appealing.

What we already know

- Malaria is associated with absenteeism in workers (Nonvignon et al. 2016).
- Malaria has a negative effect on GDP (Orem et al. 2012) and growth (McCarthy, Wolf, and Wu 2000).
- Malaria control is cost-effective from the societal/public perspective (Purdy et al. 2013).
- Indoor residual spraying (IRS) is cost-effective (Howard et al. 2017), (White et al. 2011) *from a public perspective*.

What we want to know

What is the investment case *from the investor's perspective*?

- Is malaria control just good "corporate social responsibility"? Or is it also good business?
- From a purely financial/investment point-of-view, what benefits does a private company experience in engaging in malaria control?
- What is the short-term **benefits** of IRS for large companies in malaria-endemic regions?
- What are the **costs** of of carrying out IRS for large companies?

Research questions

We can't answer all the previous questions (yet). So we focus on one:

What is the short-term effect of IRS on worker absenteeism and clinical illness among sugarcane workers?

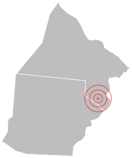
Research site

Africa

Mozambique

Manhiça district

Manhiça and Maluana posts



Research Site II

Methods

Identification strategy

- 1 intervention (IRS, time to/from)
- 2 outcomes (absence and illness, probabilistic / binomial)
- Many confounders (age, worker type, seasonality, etc.).

$$\text{Pr}(\text{Outcome} = 1 \mid \text{X}) = \beta_0 + \beta_1 \text{Location} + \beta_2 \text{Season} + (\beta_3 IRS * \beta_4 IRS_t + ...) \tag{1}$$

Modeling

We employ two approaches:

1. **Propensity score matching** of workers who *ever* received IRS with workers who *never* received IRS. **Advantage**: No need to adjust for confounders with a matched sample, thereby avoiding reduction in degrees of freedom
2. **Regresion-discontinuity** of only those workers who *ever* received IRS (ie, ignoring those who never received IRS). **Advantage**: Those who *never* received IRS may be qualitatively different, and therefore not an appropriate comparison group.

Propensity score matching I

- We generate a matched sample of similar workers by first estimating the likelihood of having ever received the intervention, given a worker's age, sex, department and temporary vs. permanent status.
- This is necessary due to below, significant differences:

Table 1: Comparison of unmatched samples

	IRS	No IRS	p
n	1506	692	
STATUS = Temporary (%)	1386 (92.0)	548 (79.2)	<0.001
DEPARTMENT (%)			<0.001
Administrative	38 (2.5)	53 (7.7)	
Factory	155 (10.3)	137 (19.8)	
Field	1313 (87.2)	502 (72.5)	
AGE (mean (sd))	35.41 (9.86)	36.23 (11.15)	0.084
SEX = M (%)	827 (54.9)	460 (66.5)	<0.001
RECEIVED = No IRS (%)	0 (0.0)	692 (100.0)	<0.001

Propensity score matching II

We match, employing the nearest neighbor method for identifying those workers from our control group who most resemble those workers in the treatment group. (Ho et al. 2007).

- Our match is a 1-to-1 cut, meaning those control workers who do not resemble those in the treatment group are left out of primary analysis. The below table shows the match results.

Table 2: Sample sizes

	Control	Treated
All	692	1506
Matched	692	692
Unmatched	0	814
Discarded	0	0

Propensity score matching III

The distributions of our numeric variables are now extremely similar:

Table 3: Summary of balance for matched data

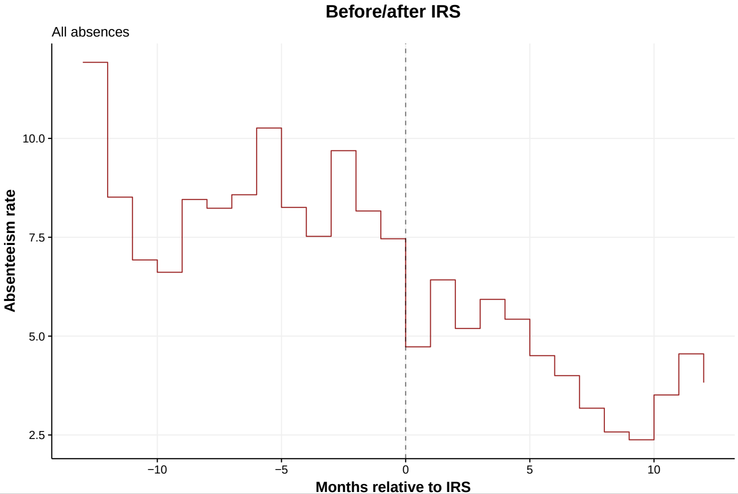
	Means Treated	Means Control	SD Control	Mean Diff
distance	0.76	0.65	0.13	0.11
age	34.62	36.23	11.15	-1.60
sexF	0.92	0.34	0.47	0.59
sexM	0.08	0.66	0.47	-0.59
permanent_or_temporaryTemporary	1.00	0.79	0.41	0.21
departmentFactory	0.00	0.20	0.40	-0.20
departmentField	1.00	0.73	0.45	0.27

Regression discontinuity analysis

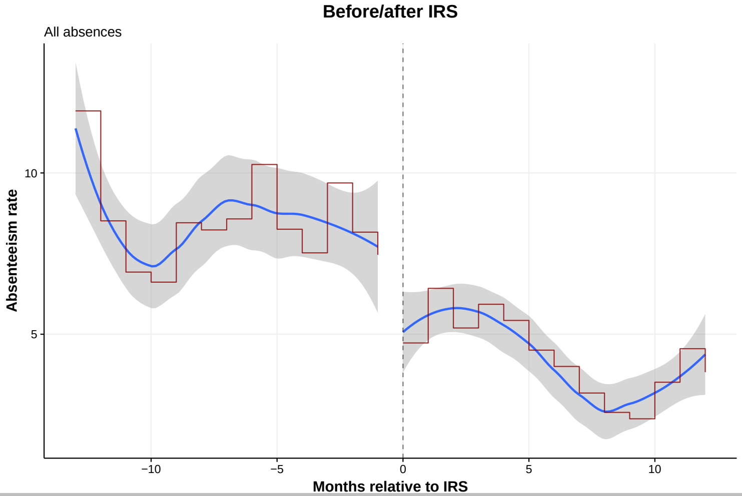
- We simply only consider those workers who *ever* got IRS.
- We take into account one full year prior to IRS and one full year after IRS.
- Our dataset constitutes one observation per worker-day.
- We incidentally achieve a sort of “matching” through the fact that workers are their own controls.

Results

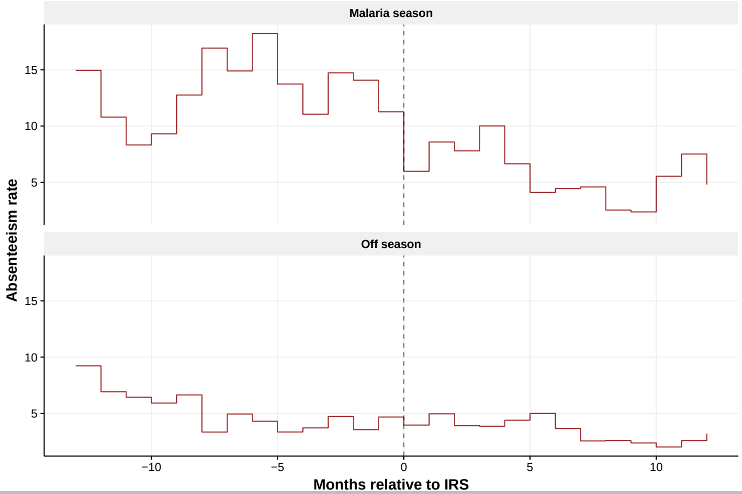
Descriptive: absenteeism by time from/to intervention



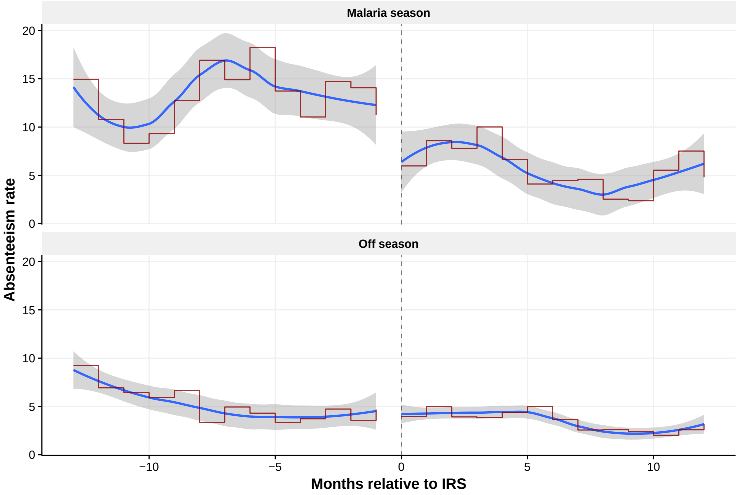
Descriptive: absenteeism by time from/to intervention (with local regression lines)



Descriptive: absenteeism by time from/to intervention (by time period)



Same chart with local regression lines



Modeling after matching I

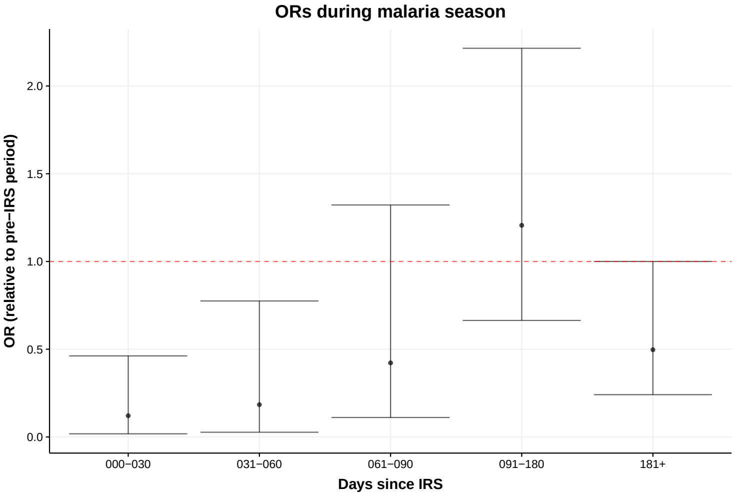
- Matched sample of 1384 workers, of which 50% received IRS and 50% did not.
- Model only takes into account seasonality, since matching theoretically handles other differences.
- For the purposes of this first pass, we "bin" IRS exposure and estimate a logit model to calculate odds ratios.

Modeling after matching II

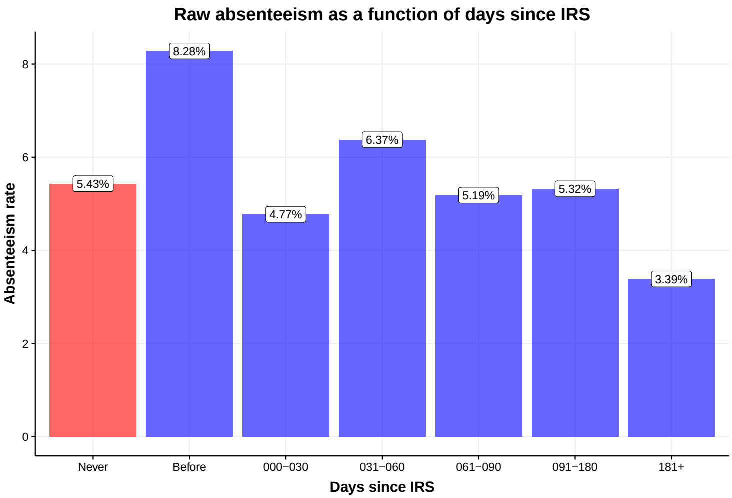
All absence:

Variable	OR	Lower	Upper
(Intercept)	0.014	0.010	0.019
days_since000-030	0.912	0.507	1.564
days_since031-060	0.538	0.246	1.050
days_since061-090	0.771	0.399	1.390
days_since091-180	1.040	0.674	1.597
days_since181+	0.599	0.403	0.893
time_periodMalaria season	1.383	0.875	2.164
days_since000-030:time_periodMalaria season	0.121	0.018	0.462
days_since031-060:time_periodMalaria season	0.184	0.027	0.775
days_since061-090:time_periodMalaria season	0.422	0.111	1.322
days_since091-180:time_periodMalaria season	1.206	0.664	2.215
days_since181+:time_periodMalaria season	0.497	0.241	1.000

Modeling after matching III



Ever IRS'ers compared with never-IRS'ers

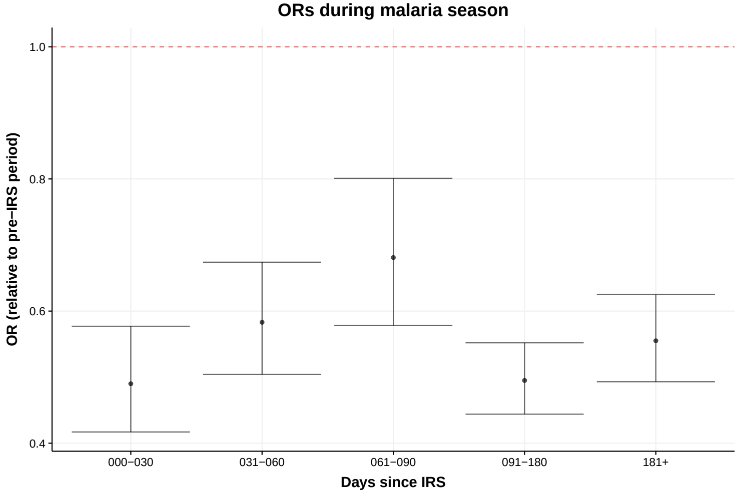


Regression discontinuity analysis I

All absenteeism:

Variable	OR	Lower	Upper
(Intercept)	0.049	0.047	0.052
days_since000-030	0.847	0.754	0.949
days_since031-060	1.046	0.938	1.163
days_since061-090	0.817	0.727	0.917
days_since091-180	0.919	0.845	0.998
days_since181+	0.557	0.510	0.607
time_periodMalaria season	3.120	2.940	3.313
days_since000-030:time_periodMalaria season	0.490	0.417	0.577
days_since031-060:time_periodMalaria season	0.583	0.504	0.674
days_since061-090:time_periodMalaria season	0.681	0.578	0.801
days_since091-180:time_periodMalaria season	0.495	0.444	0.552
days_since181+:time_periodMalaria season	0.555	0.493	0.625

Regression discontinuity analysis II



BACK OF THE ENVELOPE CALCULATIONS

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)

Discussion

General

- 30-50% reduction in absenteeism in the 6 months after IRS during malaria season.
- Depending on detailed cost data (pending), IRS may be effective even from a purely financial point of view (ie, beyond just "corporate social responsibility").
- Next steps are incorporation of (a) productivity data (via cane cut), (b) better clinical data (via local health facilities), and (c) full cost data.
- Will also be comparing with a sugarcane facility in a zone where an elimination campaign is taking place.

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.

Thank you

Your "pre-publication peer review" comments are appreciated:

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Presentation: economicsofmalaria.com/ihmt.pdf

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