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.

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).

What we want to know

What is the investment case *from the private perspective*?

- Is malaria control just good "corporate social responsibility"? Or is it also good business?
- From a purely financial 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 on absenteeism and clinical illness of IRS at the homes of sugarcane workers?

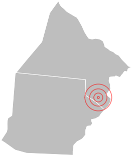
Research site

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.).

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

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. **ARIMA / time-from-intervention / 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	3395	10796	
STATUS = Temporary (%)	3134 (92.3)	10142 (93.9)	0.001
DEPARTMENT (%)			0.001
Administrative	112 (3.3)	294 (2.7)	
Factory	336 (9.9)	886 (8.2)	
Field	2947 (86.8)	9616 (89.1)	
AGE (mean (sd))	35.34 (10.10)	36.12 (10.23)	<0.001
SEX = M (%)	1947 (57.3)	6478 (60.0)	0.006
RECEIVED = No IRS (%)	0 (0.0)	10796 (100.0)	<0.001

Propensity score matching II

-We carry out the matching, 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	10796	3395
Matched	3395	3395
Unmatched	7401	0
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

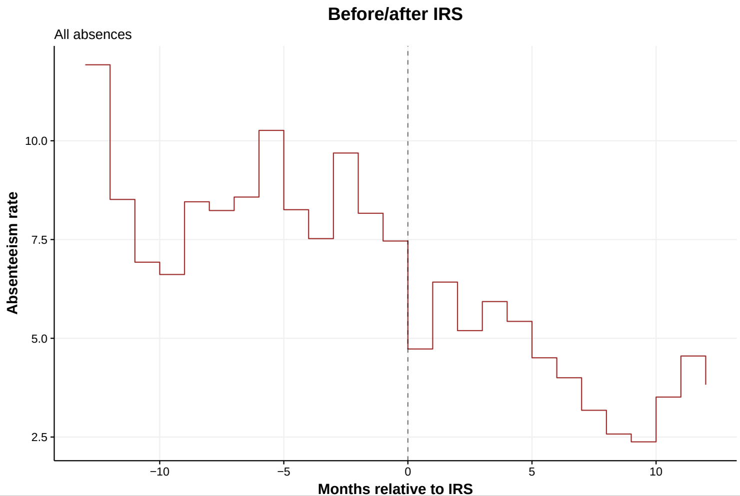
	Means Treated	Means Control	SD Control	Mean Diff
distance	0.24	0.24	0.03	0.00
age	35.34	35.23	10.07	0.11
sexF	0.43	0.40	0.49	0.02
sexM	0.57	0.60	0.49	-0.02
permanent_or_temporaryTemporary	0.92	0.92	0.28	0.01
departmentFactory	0.10	0.10	0.30	0.00
departmentField	0.87	0.86	0.35	0.01

ARIMA / Discontunity analysis

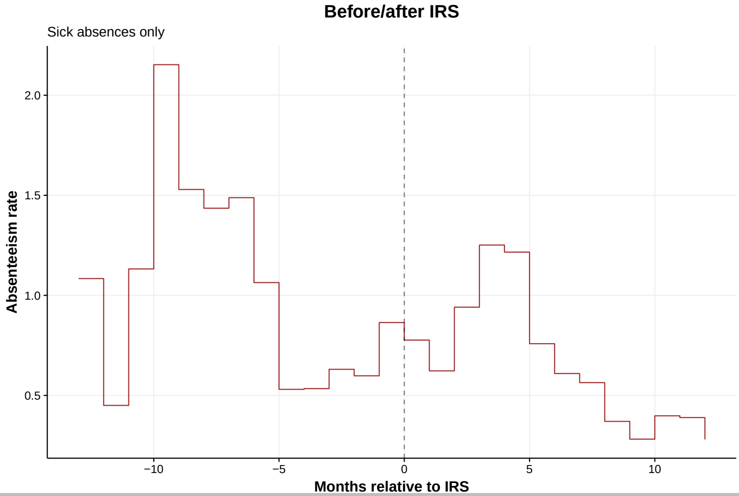
- We simply only consider those workers who *ever* got IRS.
- We take into account one full year prior to IRS and one full year after IRS.
- Our dataset constitutes one observation per worker-day.
- We incidentally achieve a sort of "matching" through the fact that workers are their own controls.

Results

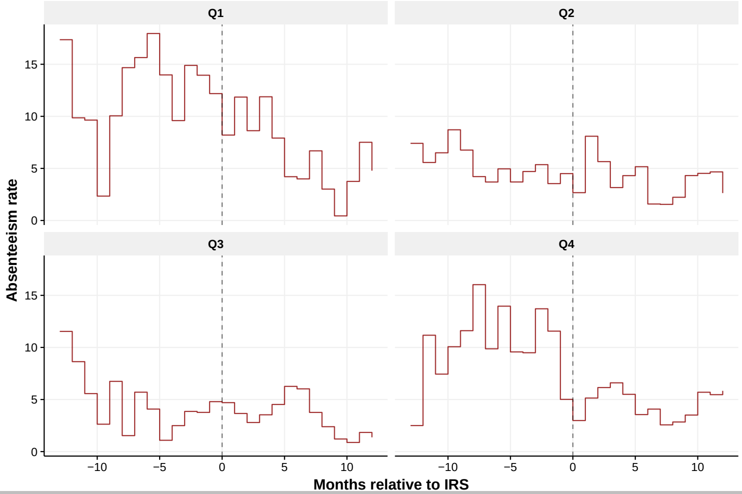
Descriptive: absenteeism by time from/to intervention



Descriptive: sick absenteeism by time from/to intervention



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



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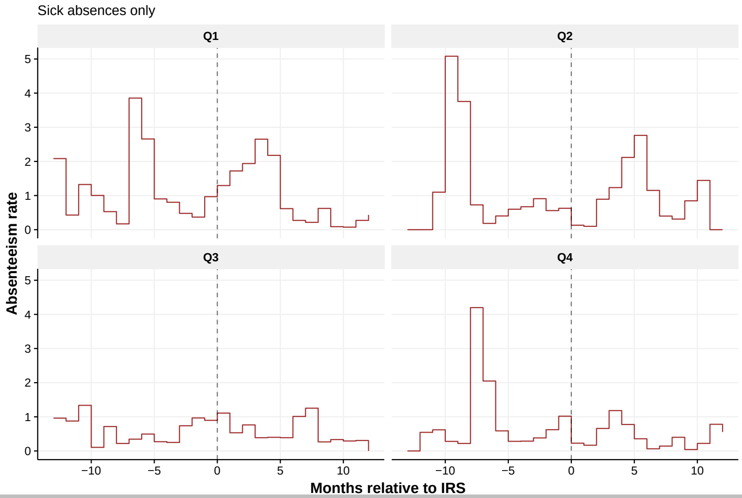
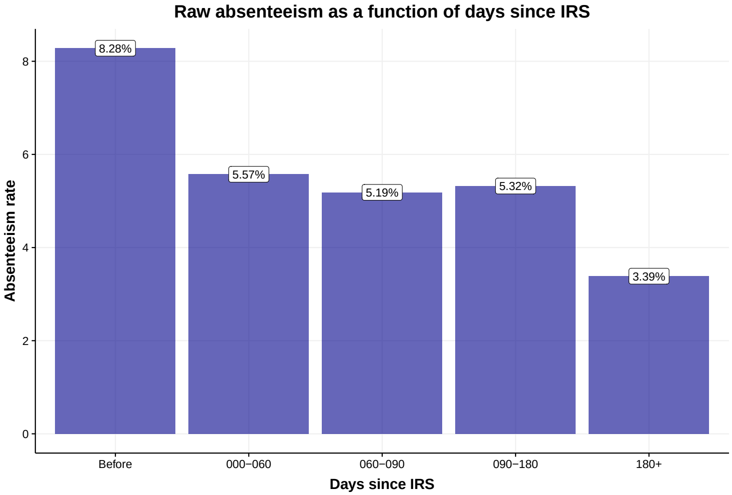
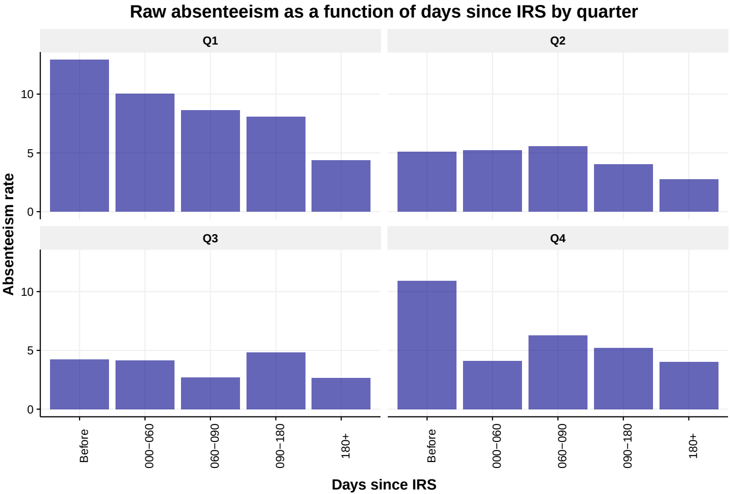


Descriptive: absenteeism in binned time period



Descriptive: absenteeism in binned time periods by season



Modeling after matching I

Having now created a matched sample of 6790 workers, of which 50% received IRS and 50% did not, we can confidently carry out our analysis on this sample. Since the propensity score matching effectively cancels out demographic differences, our model only need take into account those differences which are not at the person-level. In our case, these include seasonality (defined here by quarter) (later, will add other factors).

For the purposes of this first pass, we "bin" IRS exposure into 5 groups: before IRS (includes IRS $>$ 365 days ago), 180$+$ days ago, 90-80 days, 60-90 days, and in the last 60 days.

Having estimated our binomial logistic regression model, we examine the odds ratios for absence as a function of our predictive variables.

Modeling after matching II

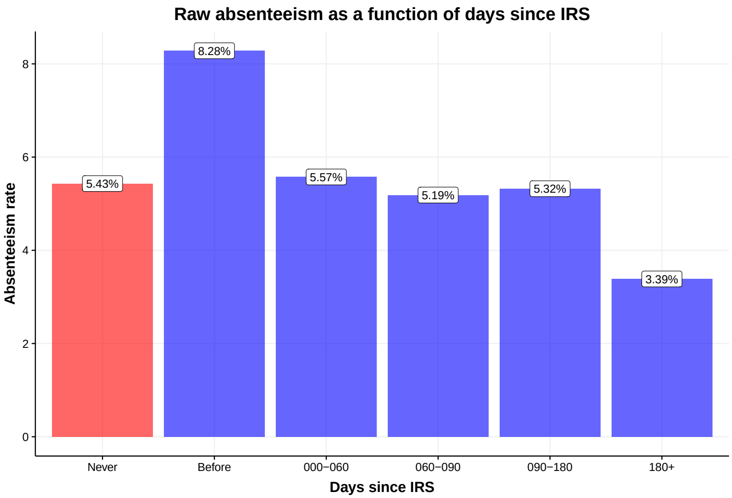
All absence:

	Variable	OR	Lower	Upper
(Intercept)	(Intercept)	0.1453572	0.1398927	0.1509910
days_since000-060	days_since000-060	0.6762597	0.6381616	0.7162830
days_since060-090	days_since060-090	0.6669767	0.6144421	0.7229558
days_since090-180	days_since090-180	0.6264072	0.5929128	0.6615467
days_since180+	days_since180+	0.4103491	0.3866648	0.4352378
quarter2	quarter2	0.4316940	0.4071196	0.4575924
quarter3	quarter3	0.3868169	0.3654818	0.4092827
quarter4	quarter4	0.6866548	0.6538714	0.7210702

Sick absence only:

	Variable	OR	Lower	Upper
(Intercept)	(Intercept)	0.0122875	0.0109890	0.0136983
days_since000-060	days_since000-060	0.8171294	0.6943435	0.9578084
days_since060-090	days_since060-090	1.1444964	0.9421297	1.3801122
days_since090-180	days_since090-180	1.3149744	1.1537264	1.4972210
days_since180+	days_since180+	0.5220637	0.4425079	0.6132913
quarter2	quarter2	0.9261983	0.8093301	1.0599349
quarter3	quarter3	0.5732323	0.4957100	0.6623028
quarter4	quarter4	0.4912209	0.4236313	0.5690253

Ever IRS'ers compared with never-IRS'ers



ARIMA / Discontinuity analysis (not using propoensity score matching) I

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Discussion

General

- 30-40% reduction in absenteeism in the 6 months after IRS, adjusting for seasonality.
- Both propensity score matching and discontinuity approaches give similar results.

Implications

- Reduction is large and significant.
- Depending on detailed cost data (pending), IRS may be effective even from a purely financial point of view.

Limitations

- No analysis yet of different worker types (agricultural vs. industrial).
- For the question at-hand (effectiveness of IRS), not sure if the methodology is best.
- Have not yet ventured at all into side-analyses (effect on employment, tonnage, etc.).
- Sick absenteeism seems to track absenteeism poorly: possibility of other clinics being used.

Thank you

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