If It Pays, It Stays: Can Agribusiness Internalize the Benefits of Malaria Control?

Richard Sedlmayr

Abstract

Might a malaria control intervention entail agricultural effects that allow a commercial agribusiness to offset its costs? The randomized allocation of 39,936 insecticide-treated mosquito nets among 81,597 smallholder cotton farming households in 1,507 clusters helps evaluate this in the context of Zambia’s cotton outgrowing industry. But despite large health impacts on treated households, no impact on cotton deliveries to the agribusiness is detected. With some caveats, the results tend to strike a discord with recent evidence on the agricultural productivity effects of malaria control.

JEL classification: C930, I390, Q120

Key words: Bed net adoption, contract farming, insecticide-treated nets, malaria, public-private partnerships

I. Background

Malaria incidence has fallen by nearly half since the year 2000 and more than half in Africa (WHO 2014). The World Health Organization cites the growing use of insecticide-treated mosquito nets as a central cause (WHO 2014); approximately 700 million nets have been distributed over the last fifteen years (Bhatt and Gething 2014). It is widespread policy to distribute nets for free (WHO 2007). One reason is that malaria control has positive externalities (Hanson 2004). Furthermore, demand for nets is low even at heavily subsidized prices, and it has been demonstrated that charging for them neither serves to induce selection of those who have the highest need, nor to increase usage rates among recipients (Cohen and Dupas 2010). Meanwhile, the distribution of free nets does not appear to dampen demand later on (Dupas 2014). Overall, there is ample evidence to suggest that decisive policy leads to higher technology adoption and better health outcomes than market solutions would.

However, if malaria control enhances economic output by increasing the availability and productivity of labor, commercial actors may be able to internalize its benefits to a degree (Roll Back Malaria 2011). The guiding idea of the research presented here is that supporting evidence could help expand malaria

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control in the private sector, thereby diminishing the risks associated with a possible waning of ongoing political support for global malaria control efforts.

Specifically, if a credible link between malaria control and agricultural output could be established in the Zambian cotton sector, at-scale opportunities for financially sustainable malaria control would present themselves. Research by the World Bank suggests that over much of last decade, 300,000 Zambian households grew cotton in contractual arrangements with private agribusinesses (Tscherl and Kabwe 2009). In these so-called outgrowing agreements, companies offer smallholder farmers agricultural inputs in exchange for a commitment to deliver crop. Even a modest increase in cotton deliveries could make the provision of mosquito nets a commercially viable intervention that might be sustained without public or philanthropic support. This study evaluates this conjecture in more detail, using a large-scale randomized trial.

It also adds a mosaic of evidence on the impact of ill health on poverty. A substantial body of cross-country literature argues that malaria is a major drag on economic growth (Bloom and Sachs 1998), (Gallup and Sachs 2001), (WHO 2001), (Sachs and Malaney 2002), (Bloom and Canning 2005); a smaller body of research tends to downplay this (Weil 2007), (Acemoglu and Johnson 2007), (Ashraf, Lester and Weil 2008). Recent experimental efforts successfully linked malaria prevention and treatment to increases in agricultural output (Dillon, Friedman and Semeels 2014); (Fink and Masiye 2015).

Context on Zambia’s Cotton Industry

As illustrated in figure 1, Zambia experiences only one rainy season, with rainfalls usually starting in early November, peaking in January, and ceasing again in April. The pronounced fluctuations strongly affect malaria transmission. The burden of the disease follows the rains with a brief time lag because the *Anopheles* mosquito—the transmitter of the *Plasmodium falciparum* parasite that is the main cause of malaria in Zambia (WHO 2014)—breeds in stagnant water.

The climactic fluctuations also determine the annual cycle of rain-fed smallholder agriculture: field work generally starts with the return of the rains in November, and most planting occurs in December. This is when contract farmers in Zambia’s cotton industry obtain the bulk of their cotton seed, as displayed in figure 1. The most labor-intensive field activities, especially weeding, continue through the peak of malaria season. Cotton harvests start in May and are followed by several months of cotton deliveries to buyer companies that bulk, process, and resell cotton.

The implementing partner in this study was Dunavant Zambia Ltd; as of 2010/11, it was the largest player in Zambia’s cotton industry, competing with half a dozen other companies. Its core business was the purchase of unprocessed seed cotton from farmers; cotton ginning (i.e., the separation of cotton lint and cotton seed); the sale of cotton lint; and to a limited extent, the processing and sale of cotton seed oil. The company managed a vast network of over 100,000 contract farmers in 2010/11. At the village level, farmers are managed by so-called distributors, who serve as a liaison between the company and the farmers. These report to local sheds—warehouses that are managed by company employees, supervise distributors, and store in- and outputs. Shed managers in turn report to one of the nine regional headquarters, each of which correspond to one of Zambia’s districts (of which there were a total of 72 in 2010/11).

The company operates a credit-based outgrowing scheme. At the beginning of a season, farmers sign contracts that allow them to obtain seed and pesticides, but occasionally also tools and other inputs, in the form of a loan from the company. The average loan size in the 2010/11 season was 39 US$2 (median: 29 US$). In return, farmers contractually commit to delivering their entire cotton output to the company at the end of the season. In the 2010/11 season, average deliveries amounted to 548 kg (median: 382 kg). In practice, farmers have the option to side-sell to other parties than the ones they originally contracted 1 In 2013, Dunavant Zambia Ltd was acquired, restructured, and rebranded.

2 Nominal 2011 US$. The exchange rate of ZMK / US$ = 4,785.47 is applied throughout this paper.
with, as buyers may compete in overlapping territories. Detecting side-selling is difficult, and contract enforcement is usually not viable. Strategic default (which would be associated with 100% side-selling) was uncommon in the 2010/11 season; the median farmer repays the loan in full, and average defaults amount to little over one dollar. For more details on the outgrowing contract, see appendix A.

Study Rationale
As illustrated in appendix B, the company’s central challenge is to process a sufficient volume of cotton to offset fixed costs and achieve profitability. The company’s budgeting systems model expected profitability by multiplying cotton volume by a fixed contribution margin (i.e., the monetary amount that one kilogram of delivered farmgate cotton contributes to marginal profit). Both fixed costs and the contribution margin are substantial: in other words, cotton outgrowing is a volume-driven business with high operating leverage. This creates demand for innovations that have the potential to increase cotton deliveries. For a number of reasons, insecticide-treated nets may plausibly be counted among the candidates:

First, they have proven effective in preventing malaria (Lengeler 2004), which is endemic throughout Zambia’s cotton growing regions (WHO 2014), and there is ample literature highlighting the costs of malaria on agricultural output via labor hours and productivity (Conly 1972), (Sauerborn, et al. 1991), (Attanayake, Fox-Rushby and Mills 2000). Studies variably define time costs as including the opportunity cost of time spent sick; of time caring for others who are sick; and of productivity impairments...
before full recovery. Partly because of differences in definitions, and potentially because of differences in terms the type of labor, the type of parasite, available treatment options, acquired resistance, and other contextual factors, time cost estimates vary widely (Shephard, et al. 1991); (Chima RI 2003), (Ayieko, et al. 2009); (Fink and Masiye 2015). Overall, 5–6 work days (i.e., one work week) of household labor lost per household malaria episode appears to be a plausible working assumption in the context at hand.

Second, Zambian cotton farmers are (given the company’s input financing system) not constrained in their access to inputs, and only rarely report being constrained in terms of available land; consistent with literature on the economics of smallholder farming (Cleave 1974), Zambian cotton farmers typically identify labor constraints as the primary factor in determining plot size. Weeding is a labor-intensive activity, and as both the growth of weeds on the cotton fields and the growth of malaria incidence are driven by annual rainfall patterns (see fig. 1) and peak at the same time, it is plausible that malaria control could relieve binding labor constraints.

Third, given their extensive preexisting infrastructure, cotton outgrowing companies are exceptionally well positioned to conduct even remote household-level distributions of insecticide-treated mosquito nets at very low marginal cost. In the context of this study, the marginal cost of procuring and distributing insecticide-treated mosquito nets was 5 US$ (Sedlmayr, et al. 2013).

The central purpose of this study was therefore to evaluate if independent private sector malaria control efforts would be viable for Zambia’s cotton industry, which had not traditionally been involved in such operations. A valuation was performed to establish the financial impact, and it was agreed that if the intervention would prove commercially viable based on the research results and this tool, the company would purchase mosquito nets and distribute them to its contract farmers for free in future seasons. The most plausible mechanism involved expected increases in cotton yields. Dividing the marginal cost of one insecticide-treated net (5 US$) by the contribution margin derived and quantified in appendix B (in US$ / kg) yields 21.74 kg; this is the threshold increase in overall cotton deliveries that would suffice to offset the cost of one net. Appendix B also demonstrates that costs could be further defrayed by a reduction in loan defaults; 5.38 kg in additional deliveries from delinquent farmers would suffice to offset the cost of one net.

The validation of protocol adherence in net delivery and the measurement of health impacts—both critical links in the theory of change—allowed for the simultaneous data collection on the impacts on maize farming. In 2010–11, the company did not have a commercial interest in maize and did not collect data on this crop. However, as 99% of surveyed farmers grow maize, effects are of theoretical interest. Though maize is (like cotton) a rain-fed crop in the study context, farmers report that it requires less weeding, so effects on maize yields were more speculative.

II. Study Design

The study population was composed of all farmers having a standing contract farming agreement with the company for the 2010/11 season on December 23, 2010. By this time, 81,597 annual contracts associated with 1,507 distributors were registered in the company’s database (see fig. 2). Farmers whose contracts had not been processed by the cutoff date in December 2010 were not recruited into the study.

Data

This study uses two data sources. The first is an administrative database owned and operated by the cotton outgrowing company. This database identifies farmers and the region, shed, and distributor they work with, and captures their annual input loans and cotton output.

The primary outcome measure, as registered in the public trial registry, is: “Farmer’s cotton yields (kg delivered per household), as defined in the routine data collection system of the participating cotton outgrowing agribusiness” [Notes: Time frame 2010–2011 season.] Two qualifications are in order. First,
Second, the yields captured in the database are cotton deliveries received by the company. These are not necessarily identical to farmer’s true cotton yields because farmers have the option to side-sell a share of their cotton to other buyers in breach of their contract. For the core purpose of the study, which is to determine the commercial viability of the intervention from the company’s perspective, cotton deliveries to the company are more relevant than their true cotton yields. Also, honest survey responses on true cotton yield would be are likely difficult to obtain in an environment of side-selling. Nonetheless, this variable is of theoretical interest and will be revisited in the discussion section.

The administrative database is also used for the collection of a secondary outcome defined in the registration as “Defaults on input loans, as defined in the routine data collection system of the participating cotton outgrowing agribusiness. [Notes: Time Frame 2010–2011 season; Odds ratios calculated in accordance with NIH guidance].” As described above, a categorical default variable is merely a proxy indicator for the purposes of evaluating the commercial impact on lending operations; as described in appendix B, a more accurate (if less intuitive) indicator is the absolute growth in loan repayments among delinquent farmers, defined in kg of cotton.

Beyond the administrative database of the company, a second data source for this study was the aforementioned survey, collected in one single round between June 20th and July 11th 2011 in a randomly selected subset of clusters. The central purpose of this survey was to validate the adherence to the distribution protocol and evaluate health impacts; but it also allowed for the collection of further secondary outcome variables, as well as explanatory variables about adverse events on farmers’ plots.

Short of using blood samples, malaria parasitemia are difficult to measure accurately. The current public health literature accepts self-reported estimates of fever and self-reported estimates of malaria as
outcome variables in impact studies on malaria (Sedlmayr, et al. 2013). The survey therefore asked respondents to list cases of fever (i.e., suspected malaria) in the household over the course of the last two weeks and used recall about diagnostic procedures to identify those cases where a malaria diagnosis had been confirmed by health workers. Both are used to describe the outcome of “Self-reported malaria incidence over two weeks before interview. [Notes: Time Frame 2010–2011 season; Odds ratios calculated in accordance with NIH guidance].”

The survey also allowed for the collection of land productivity data on maize plots, both in the year of the survey and in the year before it. This allowed for a construction of an outcome called “Increase in self-reported maize productivity (yield on maize plots divided by size of maize plots), calculated as maize productivity 2010–11 minus maize productivity 2009–10, measured in bags” [Notes: Time Frame: 2009–2010 and 2010–2011 seasons; bags are ordinarily 50 kg, but kg measure not specified].

Experimental Design
As illustrated in figure 2, the study used a randomized design that clustered treatment at the distributor level. In order to ensure a balanced roll-out across regions, the 62 sheds were treated as separate strata in the randomization. Nets were delivered to the shed level, and shed managers were trained on the training of distributors to ensure protocol adherence.

Following the randomization, bed nets were distributed between January 20th and January 28th 2011. As a fair and simple distribution rule, it was determined that each treatment household would be eligible for exactly one bed net through the program. Building on the aforementioned literature on bed net adoption, it was expected that smallholder’s willingness to pay would be minimal, so nets were distributed for free. No information on the purpose of nets was provided; as indicated in table 1, households in the region already often owned one net. However, distributors were encouraged to help recipients hang the nets, and provided with string to do so.

Table 1. Balance Checks

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations (^{(1)})</th>
<th>Not selected for treatment</th>
<th>Selected for treatment</th>
<th>Differences</th>
<th>p-value (^{(2)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH members aged under 5</td>
<td>894</td>
<td>0.98</td>
<td>0.99</td>
<td>0.01</td>
<td>0.894</td>
</tr>
<tr>
<td>HH members aged 5 - 14</td>
<td>894</td>
<td>2.04</td>
<td>1.98</td>
<td>-0.05</td>
<td>0.695</td>
</tr>
<tr>
<td>HH members aged 15 &amp; over</td>
<td>894</td>
<td>3.47</td>
<td>3.29</td>
<td>-0.17</td>
<td>0.312</td>
</tr>
<tr>
<td>Cotton area (h) 2010/11</td>
<td>799</td>
<td>1.23</td>
<td>1.15</td>
<td>-0.08</td>
<td>0.455</td>
</tr>
<tr>
<td>Maize area (h) 2010/11</td>
<td>798</td>
<td>1.87</td>
<td>1.79</td>
<td>-0.08</td>
<td>0.673</td>
</tr>
<tr>
<td>Mosquito nets owned</td>
<td>894</td>
<td>1.17</td>
<td>2.04</td>
<td>0.87***</td>
<td>&gt;0.001</td>
</tr>
<tr>
<td>Seed Loan (ZMK)</td>
<td>81,472</td>
<td>39,203</td>
<td>38,522</td>
<td>-681</td>
<td>0.301</td>
</tr>
<tr>
<td>Pesticide Loan (ZMK)</td>
<td>81,472</td>
<td>129,994</td>
<td>128,643</td>
<td>-1,351</td>
<td>0.528</td>
</tr>
</tbody>
</table>

Notes: (1) Differences in available observations stem from the following:
(a) loan data are available in the standard administrative database, while the other variables were collected through the survey; and
(b) over 10% of survey respondents answered “don’t know” in response to questions about maize and cotton plot areas.
(2) *** denotes p < 0.01. To adjust for the spatial correlation of regression residuals, standard errors were clustered at the distributor level. Source: Analysis by the author based on data described in the text; Sedlmayr, Fink, Miller, Earle, & Steketee (2013).

Empirical Strategy
While the trial registration defines outcomes, it does not involve a discussion of econometric specifications, leaving intact many degrees of freedom remain for the analysis. The analysis of the impact on the
primary outcome is therefore initiated with the most basic plausible specification, which is the following linear intent-to-treat model:

\[ Q_{ij} = \alpha + \beta T_j + \epsilon_{ij} \]

The dependent variable \( Q_{ij} \) is defined as the quantity of cotton deliveries, in kg, by farmer \( i \) in cluster \( j \). \( T_j \) is a binary variable that defines distributor-level assignment to treatment and is coded to 1 for farmers in clusters that had been selected for treatment and to 0 for farmers in the control group. For secondary analyses, the dependent variable is replaced with the secondary outcomes (e.g., cotton deliveries for loan repayments, land productivity on maize plots). In cases where these are categorical variables, logistic regression is used. Alternative specifications that pursue emerging questions and insights are also explored.

### III. Experimental Results

#### Balance Checks, Protocol Adherence, and Bed Net Adoption

Treatment and control groups are well balanced with regards to baseline characteristics (see table 1). However, clear differences emerge in net ownership, with households in the treatment group owning 0.87 more mosquito nets on average than households in the control group. The fact that this number is not equal to one is only partially explained by leakage in the distribution process: 4.6% of households in the treatment group reported not having received a net from the company (see table 2). The propensity to replace, sell, or gift nets may have increased in the treatment group.

<table>
<thead>
<tr>
<th>Survey Question: “Did this household receive a mosquito net from Dunavant this season?”</th>
<th>Not selected for treatment</th>
<th>Selected for treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>3 (0.7%)</td>
<td>413 (94.3%)</td>
</tr>
<tr>
<td>No</td>
<td>452 (98.7%)</td>
<td>20 (4.6%)</td>
</tr>
<tr>
<td>No response / don’t know</td>
<td>3 (0.7%)</td>
<td>5 (1.1%)</td>
</tr>
<tr>
<td>Total</td>
<td>458 (100%)</td>
<td>438 (100%)</td>
</tr>
</tbody>
</table>

Source: Reproduced from Sedlmayr, Fink, Miller, Earle, & Steketee (2013).

Figure 3 illustrates bed net usage patterns across age groups in both treatment and control groups. It also compares these to the results from a nationally representative survey. Baseline mosquito net usage (as approximated by the control group) is substantially below the Zambian average; treatment shifts it to slightly above-average rates.

#### Health Impacts

Over the course of the study period, the average rates of self-reported fever and malaria incidence among individual household members were 24% and 12% in the control group. There is a 42% reduction in the odds of self-reported fever (\( p < .001 \)) and a 49% reduction in the odds of self-reported malaria (\( p = .002 \)) (see table 3). The respective rates of fever and malaria incidence are 15% and 6% in the treatment group. A more detailed discussion of the health effects by (e.g., by age group) can be found in a separate publication (Sedlmayr, et al. 2013).

#### Impacts on Cotton Output

Cotton deliveries are lower in the treatment group by 4.05 kg. The effect is insignificant using the basic linear model, which was described above and is defined as specification (1) in table 4. The upper bound...
of the 95% confidence interval for coefficient $\beta$ is 23.15 kg, which would equate a 4.2% increase. While this suggests that very meaningful effects are not likely, an effect equal to the critical threshold of 21.74 kg (i.e., a 4% increase) cannot be dismissed.

One concern is that robust standard errors of the treatment effect are relatively high. As seed and pesticide loans were made before the nets were distributed and are therefore exogenous, and as they are simultaneously plausible determinants of output, they are added as covariates to the regression, as demonstrated in specification (2) of table 4. Indeed, the coefficients for seed and pesticide loans are highly significant, and their inclusion reduces the robust standard error of the treatment effect. However, a 4% increase in deliveries continues to lie within the confidence interval.

Density functions are depicted in figure 4; a number of insights can be gleaned from them. First, the distribution of cotton deliveries in the treatment and control groups is virtually identical; differences can barely be discerned. Second, the distribution is highly skewed, which can be addressed through logarithmic transformation. Rerunning specifications (1) and (2) in log-transformed form leads to specifications (3) and (4) in table 4. With upper bounds of 2.8% and 2.9%, respectively, these specifications allow for the dismissal of a 4% increase in deliveries.
### Table 4. Impact on Cotton Deliveries

<table>
<thead>
<tr>
<th>Linear specifications</th>
<th></th>
<th>Logarithmic specifications</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) deliveries</td>
<td>(2) deliveries</td>
<td>(3) ln(deliveries)</td>
</tr>
<tr>
<td>selected for treatment</td>
<td>-4.05</td>
<td>2.14</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(13.88)</td>
<td>(11.38)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>seed loan</td>
<td>21.22***</td>
<td>0.392***</td>
<td>11.26***</td>
</tr>
<tr>
<td></td>
<td>(4.25)</td>
<td>(0.015)</td>
<td>(1.71)</td>
</tr>
<tr>
<td>pesticide loan</td>
<td>548.35***</td>
<td>68.70***</td>
<td>6.007***</td>
</tr>
<tr>
<td></td>
<td>(10.52)</td>
<td>(16.99)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>constant</td>
<td>n</td>
<td>n</td>
<td>n</td>
</tr>
<tr>
<td></td>
<td>81,472</td>
<td>81,472</td>
<td>72,446</td>
</tr>
</tbody>
</table>

**Source:** Author’s analysis as described in the text.

**Notes:**
- Deliveries are denominated in kg, loans in US$.
- To adjust for the spatial correlation of regression residuals, standard errors were clustered at the distributor level.
- Robust standard errors are in brackets.
- Sample sizes change in logarithmic specifications because of observations with zero values.
- *** denotes p < 0.01

### Figure 4. Cotton Deliveries (81,472 Observations)

![Cotton Deliveries Graph](https://example.com/cotton-deliveries-graph.png)

**Source:** Author’s analysis based on data described in the text.
To further evaluate the robustness of the result, the sensitivity of specification (1) to outliers is evaluated. Figure 5 depicts treatment coefficients and confidence intervals for subsamples that exclude the highest and lowest observations. While confidence intervals narrow substantially with the progressive restriction of the subsample, the findings prove very robust.

Figure 5. Sensitivity of Outliers on Estimated Cotton Delivery Impact

Source: Author’s analysis based on data described in the text.
Notes: (1) Involves the progressive removal of the remaining observations with the highest and lowest values. For multiple observations with the same value, selection for removal occurs at random.

Finally, Fischer’s nonparametric permutation test (or “randomization inference”) is used to test the “sharp null hypothesis” that the true treatment effect is zero for all subjects (see Table 5). If the true treatment effect is assumed to have been null for all subjects, nearly a quarter of alternative randomizations would have resulted in an estimated treatment effect below the one that was measured. The sharp null hypothesis cannot be dismissed.

Table 5. Randomization Inference

<table>
<thead>
<tr>
<th>True treatment effect (in kg)</th>
<th>1st</th>
<th>5th</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>95th</th>
<th>99th</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) –4.05</td>
<td>–17.1</td>
<td>–13.1</td>
<td>–7.7</td>
<td>–4.0</td>
<td>–0.0</td>
<td>5.4</td>
<td>9.5</td>
</tr>
<tr>
<td>(2) 0</td>
<td>–12.8</td>
<td>–9.1</td>
<td>–3.8</td>
<td>0.0</td>
<td>3.8</td>
<td>9.2</td>
<td>12.9</td>
</tr>
</tbody>
</table>

Notes: Randomization inference involves the assumption of a ‘true’ treatment effect that is presumed to hold not only on average, but for every study subject. This allows for the computation of both actual and potential outcomes for each subject, which in turn allows error terms to be derived from multiple randomization simulations (10,000 in the cases above). For illustration purposes, one may assume that the true treatment effect is equal to the measured treatment effect of -4.05 kg, and use simulation to explore how alternative randomizations might have fared; the resulting error terms allow for the construction of confidence intervals. As can be seen above in specification (1), these intervals are substantially narrower than those presented in Table 4. Specification (2) derives a distribution of errors on the assumption that the ‘true’ treatment effect is zero. This tests the ‘sharp null hypothesis’ (p = 0.23).
Impact on Loan Defaults
The registration does not specify the definition of defaults in unambiguous detail. To evaluate impact on loan repayments in absolute terms, the basic linear model is chosen; no impact is detected (see table 6). To estimate the impact of treatment on the incidence of loan default rates, logarithmic regression is used (see table 7). The coefficients are not significantly different from one: here too, no impact is detected.

Table 6. Impact on Loan Repayments

<table>
<thead>
<tr>
<th></th>
<th>Cotton deliveries made for loan repayment (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>selected for treatment</td>
<td>-0.44(0.96)</td>
</tr>
<tr>
<td>constant</td>
<td>56.48</td>
</tr>
<tr>
<td>n</td>
<td>81,231</td>
</tr>
</tbody>
</table>

Source: Author’s analysis based on data described in the text.

Table 7. Impact on Default Rates

<table>
<thead>
<tr>
<th></th>
<th>Full default (OR)</th>
<th>Partial default (OR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>selected for treatment</td>
<td>0.887</td>
<td>1.031</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.715-1.099</td>
<td>0.827-1.286</td>
</tr>
<tr>
<td>n</td>
<td>81,472</td>
<td>81,472</td>
</tr>
</tbody>
</table>

Source: Author’s analysis based on data described in the text.
Note: Coefficients are odds ratios.

Impact on Maize
Specification (1) in table 8 illustrates the application of the basic linear model on maize plot productivity gains. As registered, this variable requires recall of both 2009/10 and 2010/11 plot size, as well as recall of maize harvest in both years. Approximately one quarter of respondents are unable able to recall all of these. Specification (2) uses survey responses on adverse events as dummy control variables, further reducing the number of observations with complete recall. Less restrictive specifications (3)–(8) involve higher recall rates but differ from the registered outcome variable. No single specification suggests an impact on maize; however, it is worth noting that effects can be picked up on other potential explanatory variables, such as the incidence of reported crop damage by pests and by people (i.e., theft or vandalism).

IV. Discussion
Two insights can be clearly gleaned from the results.
First, the intervention had a substantial health impact. Given the low administrative cost of the targeting and distribution approach, cost-effectiveness (in terms of cost per case averted) was very high (Sedlmayr, et al. 2013).
Second, despite these health effects, there is no indication that the intervention was commercially viable for the agribusiness. The program failed to meet the benchmarks set out by the valuation model. The use of Zambian cotton outgrowing companies as a channel for sustained malaria prevention would likely require philanthropic or public subsidies.
From a broader development research perspective, the results pose a puzzle. To recap, the intervention averted more than one malaria case per household per month on average, adding one estimated week of available labor to treated households each time, which would translate into a 15% (10%) increase in labor.
availability for a household with two (three) field workers; the study period coincided with the most labor-intensive farming period for rain-fed cotton and maize, which are the dominant sources of economic value among Zambian cotton farmers; and yet, neither cotton deliveries nor maize production appear to have changed significantly. In the case of cotton, a 3% impact can be dismissed. The results are puzzling in the light of (Fink and Masiye 2015), who evaluate a free program in a very similar context and identify a 25% increase in cotton yields and a 12% increase in maize yields. This begs an explanation.

Explanation 1: Differences in Treatment Intensity

One notable difference between the net program evaluated here and the free net program evaluated by Fink and Masiye is the intensity of household-level treatment. Their free net program complied more closely with WHO guidelines on universal coverage (WHO 2007) by aiming to offer one net per uncovered sleeping space to households in the treatment group, while the study presented here aimed for one single net. WHO compliance per se is not a satisfactory explanation for the absence of economic effects: recall that the desired health effects did materialize in the trial at hand. Indeed, these health effects are so substantial, and the intervention was so cost-effective, that one may question the virtues of universal coverage: it appears that opportunities to reduce malaria incidence at the margin through ad hoc net distributions—even in the absence of reliable household-level net coverage data—can be worthwhile).

But as a consequence of their distribution rule, the number of nets successfully transferred in Fink and Masiye’s free net program amounted to 2.41 per treatment household on average, substantially more than the 0.94 nets studied here. This helps explain the majority of the divergence in economic impacts. That said, the same paper also evaluates a program that provides nets on loan and achieves a much lower

Table 8. Impact on Maize

<table>
<thead>
<tr>
<th>Specification</th>
<th>(1) bags/h increase</th>
<th>(2) bags/h increase</th>
<th>(3) bags/h</th>
<th>(4) bags/h increase</th>
<th>(5) bags/h increase</th>
<th>(6) bags increase</th>
<th>(7) bags</th>
<th>(8) bags</th>
</tr>
</thead>
<tbody>
<tr>
<td>selected for treatment</td>
<td>−0.009</td>
<td>−0.083</td>
<td>−3.66</td>
<td>−2.99</td>
<td>0.068</td>
<td>−0.014</td>
<td>−5.21</td>
<td>−0.96</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.096)</td>
<td>(3.23)</td>
<td>(3.78)</td>
<td>(0.099)</td>
<td>(0.105)</td>
<td>(9.72)</td>
<td>(13.31)</td>
</tr>
<tr>
<td>damage - flood or drought</td>
<td>−0.177</td>
<td>3.72</td>
<td>−0.166</td>
<td>−16.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(4.15)</td>
<td>(0.144)</td>
<td>(20.11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>damage - animals</td>
<td>−0.072</td>
<td>1.72</td>
<td>0.007</td>
<td>−3.94</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(5.31)</td>
<td>(0.123)</td>
<td>(13.90)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>damage - pests</td>
<td>−0.258**</td>
<td>1.40</td>
<td>−0.290**</td>
<td>−6.72</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(4.39)</td>
<td>(0.140)</td>
<td>(16.59)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>damage - people</td>
<td>0.058</td>
<td>29.99</td>
<td>−0.722**</td>
<td>−13.73</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.551)</td>
<td>(24.12)</td>
<td>(0.350)</td>
<td>(32.68)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>damage - other</td>
<td>0.052</td>
<td>−2.15</td>
<td>0.000</td>
<td>16.33</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.112)</td>
<td>(4.13)</td>
<td>(0.138)</td>
<td>(17.56)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>0.204***</td>
<td>0.385**</td>
<td>36.04***</td>
<td>31.61***</td>
<td>0.207***</td>
<td>0.364**</td>
<td>58.97***</td>
<td>62.19***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.147)</td>
<td>(2.51)</td>
<td>(4.56)</td>
<td>(0.051)</td>
<td>(0.144)</td>
<td>(6.06)</td>
<td>(14.80)</td>
</tr>
<tr>
<td>n</td>
<td>651</td>
<td>449</td>
<td>700</td>
<td>485</td>
<td>715</td>
<td>494</td>
<td>787</td>
<td>574</td>
</tr>
</tbody>
</table>

Source: Author’s analysis based on data described in the text.

Notes: - The variable bags quantifies the numbers of bags of maize harvested by the survey respondent’s household in the 2010/11 season.
- The variable bags increase quantifies the increase in the aforementioned variable between the 2009/10 and 2010/11 seasons.
- The variable bags/h quantifies the numbers of bags of maize harvested per hectare by the survey respondent’s household in the 2010-11 season.
- The variable bags/h increase quantifies the increase in the aforementioned variable between the 2009/10 and 2010/11 seasons. This is the registered outcome variable.
- Damage variables are dummies that are coded to 1 if the household reported a damage of this type to its farming plot during the 2010/11 season, and 0 otherwise. Specifications (2), (4), (6), and (8) use these as control variables.
- ** denotes p < 0.05; *** denotes p < 0.01.
take-up (0.81 nets per household on average), while the estimated impact on cotton yields remains in the vicinity of 25%. (Maize impacts drop from 12% to 6%).

Explanation 2: Differences in Yield Measurement
This paper measures maize output similarly to Fink and Masiye. However, it relies on administrative sources for cotton deliveries, while Fink and Masiye use household surveys that elicit self-reported cotton yields. As mentioned above, cotton deliveries may not be equivalent to true cotton yield: any household could choose to side-sell a share of their cotton output instead of honoring their contractual obligation with the company. As illustrated in appendix A, the company rewards surplus volumes with higher prices because it assumes sideselling to be positively associated with cotton production. If this is true, it may help explain the divergence in results to a degree: increases in cotton yield could have materialized, but then been side-sold before delivery.

Figure 6 juxtaposes survey data from Fink and Masiye with administrative data on deliveries to the outgrowing company in the same year (which is available for approximately 90% of the farmers in their sample). While survey data on cotton yields are approximately 15% higher than delivery data on average (which may provide a sense of the volume of side-selling)\(^3\), the rate of apparent side-selling does not appear to be clearly associated with cotton volumes. The sample had not been on the precipice of some threshold volume typically associated with high rates of side-selling; there is no indication that the propensity to side-sell should have increased in the treatment group.\(^4\)

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**Figure 6. Cotton Output per Farmer: Administrative Delivery Data vs. Survey Data, 2009/10 Season**

Source: Author’s analysis based on data provided by Fink Masiye.

Notes: This chart juxtaposes the data underlying Fink Masiye (2015) with the same farmers’ deliveries (in kg) to the cotton buying company in the same year, where available. Deliveries are translated from bales into kilos using the average weight of 80kg per bale. Values are not log-transformed in order to retain observations with values equal to zero. To visualize the majority of observations that lie below 1,000 kg, a subset of the data is displayed on the right.

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3 One caveat is that this assumes honest survey responses in the presence of side-selling. A second caveat is that any possible side-“buying” is not quantified, so the data technically refer to net side selling.

4 Indeed, behavioral reasoning suggests that treatment could reduce the propensity to side-sell by triggering reciprocity. The opposite may hold for the 4.6% of treatment households who had been allocated to the treatment group but did not end up receiving a net. Indeed, leakage is negatively associated with cotton deliveries. However, this may be a matter of selection bias, and controlling for leakage does not render treatment effects significant.
That said, side-selling does diminish the returns that the company can expect to reap from any investments in farmer productivity (including the health investment studied here). It leads to the inefficient contract described in appendix A and more generally contributes to an apparent cycle of low investment and low productivity. The nonmarket alternative of buyer coordination and the outright formation of monopsonies in diverse African countries is also associated with diverse failures (Short, Barreiro-Hurle and Balié 2014). There may be substantial promise in microeconomic innovations that improve contractual design, and in behavioral innovations that improve relationships between farmers and buyers. Examples may include improved loan enforcement through farmer identification (Giné, Goldberg and Yang 2012) or collateralization (Jack, et al. 2016); the introduction of savings and/or commitment devices (Casaburi and Macchiavello 2016); and more broadly the stimulation of loyalty (Casaburi and Macchiavello 2015).

Explanation 3: Unexplained Differences, Implies Failed Replication

The above explanations provide some intuition for why the cotton output effects measured here might have been expected to fall below those of previous research. However, even when both explanations are considered jointly, they fail to explain the magnitude of the difference in results. Ultimately, this paper does strike a sobering discord with recent encouraging evidence on the agricultural productivity effects of malaria control. It appears that hidden factors moderate these effects, and that the nature of these moderators is not yet well understood.

From a theoretical standpoint, there are numerous reasons for why labor shocks (such as the health effects discussed above) may fail to translate into an impact on cotton yield.

For instance, in the presence of complete and competitive markets, the health intervention should not translate into changes in the household’s agricultural output, as the household’s supply and demand decisions would be separable (Krishna 1964). Apparent labor market imperfections are one frequently cited violation of the assumptions underlying separation, but the hypothesis that farm labor allocation is independent of household structure has withstood empirical scrutiny (Benjamin 1992). Separation is commonly invoked in empirical studies of agricultural production in poor countries, and has been presented as robust to the nonexistence of some markets (Udry 1999).

The possible absence of labor markets does not negate that households have more than one option for how to invest their time. Even if these options were extremely limited (say, to farming and the production of home-made goods), the rational allocation of labor would entail the assimilation of marginal returns to labor across these activities. In such an environment, the rational response to a labor shock may be to disproportionately reduce labor allocation to that activity for which output reacts less elastically. In other words, it may be precisely because cotton output reacts elastically to weeding activities that farmers may dampen shocks on this activity at the cost of less time-sensitive ones. While the extent of the production of home-made goods in the sample and during the farming season is not known, the season does overlap with the school year, so school-age household members may be one source of labor in times of urgent need.

Furthermore, even farmers who are subject to labor constraints may still have the capacity to mobilize substantial labor reserves in times of need. Fafchamps (1993) plausibly assumes that farmers value leisure and views labor choices as the result of a dynamic optimization process in response to a series of exogenous shocks. The model can be taken as a basis for arguing that malaria predominantly enters the production function not via actual, but via expected labor constraints (for which farmers make allowances in the process of determining plot size); and by extension, that the nets in in the study at hand may have arrived at a time when plot sizes had been determined—too late to have a large impact on the production of most farmers in the study season 2010/11. While this is plausible, one might expect the treatment group to anticipate reduced labor constraints, plant more aggressively, and achieve higher yields in the coming season—and this is not borne out: to the extent it is possible to identify study farmers in the
A behavioral explanation for the results could be grounded in reference-dependent, non-optimizing behavior in the spirit of *satisficing* (Simon 1956). Farmers may only aspire to limited yields, but if illness triggers an experience of perceived shortfall or loss, they may compensate aggressively and with little concern for leisure (Selten 1998). Unlike Fafchamps (1993), this does not imply that yields should rise in future seasons.

V. Conclusion

It appears clear that the investment was not profitable for the company. Meanwhile, as farmers experienced reduced sickness, benefits for them are beyond doubt. How gains in available time were allocated among diverse activities remains unclear, but these activities do not appear to have predominantly involved cotton or maize farming. Multiple strands of previous research can help make sense of this result, though even neoclassical reasoning encounters no puzzle in it.

While neoclassical reasoning also provides a parsimonious explanation for why Zambia’s cotton industry has not independently provided mosquito nets to its farmers in the past, it struggles to illuminate why farmers rarely adopt them independently (Dupas 2014).

Overall, while the results can be reconciled with previous microeconomic research on the smallholder labor and technology adoption, they tend to strike a discord with literature that draws unqualified links between health and economic performance. The conditions under which health shocks reduce agricultural output may not yet be adequately understood.

Appendix A. The Outgrowing Contract

Contract farmers receive loan $L$ from the company at the outset of the season and in return contractually commit to delivering their entire cotton output $Q$ to the company at the end of the season. While the pricing of inputs is set by the company, loans do not nominally accrue interest over time. Still, the company’s purchasing and lending operations are not easily separable, as farmgate cotton prices are a function of loan volumes. The initial portion of farmgate crop deliveries is used to repay the loan, using farmgate loan repayment price $p_l$ per kilogram of cotton. For any crop volume beyond that, farmers get paid in cash, receiving farmgate cash price $p_c$ per kilogram of cotton.

Farmers who deliver no cotton, or insufficient cotton to repay their loans in full, are considered to be in default and received no payment from the company. The cash payment $C$ to any given farmer $i$ is therefore defined as

$$C_i = \begin{cases} (Q_i - \frac{L_i}{p_l})p_c & \text{if } Q_i > \frac{L_i}{p_l} \\ 0 & \text{otherwise} \end{cases}$$

In the 2010/11 season, price $p_l$ was 0.67 US$, $p_c$ was 0.70 US$, and the average cash payment $C$ was 344 US$ (median: 237 US$). The difference in the two farmgate prices can be attributed to the company’s judgment that farmers are more likely to side-sell quantities beyond those required to cover the loan, as the perceived moral burden of doing so may be lower. As $p_l$ is regarded as a mental anchor, a small bonus implicit in the higher $p_c$ was meant to nudge farmers to honor their 2010/11 contract in full.

5 48,272 study subjects (24,501 of control subjects and 23,771 of treatment subjects, i.e., 59% of both) can be matched between the two databases via national registration card numbers.
The risk of side-selling leads the company to refrain from committing to forward prices at the outset of the season, although this is when farmers make investment decisions and obtain loans. Announcing forward prices would make it easier for competitors to outbid the company if world spot prices end up being high at the time of harvest, while it would create a liability for the company if world spot prices end up being low. Any costs of hedging world price risk at the outset of the season would not accrue to competitors, thereby enhancing their relative competitiveness as buyers. As a consequence, farmgate prices end up being largely determined by the world spot price for processed cotton. In an apparent market failure, this shifts price risk to the farmers, likely reducing their willingness to specialize on cotton. It helps explain why virtually all farmers in the sample grow maize as well.

Appendix B. The Economic Interpretation of a Contract Farming Business

The studied company’s budgeting systems describe the company’s aggregate profit $P$ as a function of the cotton deliveries $Q_i$ of each of its $n$ farmers; the world spot price for processed cotton $p_w$; processing, transportation, and other variable costs $c$; the cash payment $C_i$ that is made to farmers in exchange for their deliveries; as well as fixed costs $F$, which encompasses all sunk costs associated with the initiation of seasonal cotton outgrowing operations:

$$P = \sum_{i=1}^{n} Q_i (p_w - c) - C_i - F$$

Assuming that farmer $x$ has repaid the loan and is entitled to cash payment $C_x(Q_x, p_c)$, the marginal profit that the company generates from a kilogram of cotton delivered by this farmer equals $\partial P / \partial Q_x = p_w - c - p_c$. In management accounting terms, this is the contribution margin; it was 1,100 ZMK (0.23 US$) in the 2010/11 season. For farmers who have not fully repaid the loan and are not entitled to cash payment $C_x(Q_x, p_c)$, the contribution margin is higher, at $\partial P / \partial Q_x = p_w - c$. However, because of the low loan volumes and high repayment rates, loan defaults are not a significant factor in overall profitability.

References


