Health information, treatment, and worker productivity

Andrew Dillon
Northwestern University

Jed Friedman
World Bank

Pieter Serneels
University of East Anglia

April 2020

Abstract: Agricultural and other physically demanding sectors are important sources of growth in developing countries but prevalent diseases such as malaria can adversely impact the productivity and labor supply of workers. We estimate the impact of malaria infection on worker earnings, labor supply, daily productivity, and task selection by using a phased-in design where we randomize the study week in which piece-rate workers at a large sugarcane plantation in Nigeria are offered malaria testing and treatment. Two estimation strategies indicate a significant and substantial intent to treat effect of the intervention. The program increases worker weekly earnings by 11 to 13 percent over the weeks following the offer, depending on the reference period, using a between-worker estimator that exploits the experimental design. A within-worker estimate provides similar but smaller estimates of 8 to 10 percent. We identify different pathways through which this effect occurs. For workers who test positive for malaria, the treatment of illness principally increases labor supply, leading to higher earnings. For workers who test negative, the health information leads to increased earnings via augmented daily productivity. This productivity response arises, in part, from selection into higher return tasks within their job at the plantation. The results underline the importance of medical treatment but also of improved access to information about one's health status, as the absence of either leads workers to work less or choose lower return tasks when working.

Keywords: malaria, labor supply, labor productivity, field experiment

JEL codes: I12, J22, J24, O12

The authors can be contacted at andrew.dillon@northwestern.edu, jfriedman@worldbank.org, and p.serneels@uea.ac.uk.

Acknowledgements: We would like to thank Oladele Akogun, Bashir Aliyou, Sarah Baird, Lori Beaman, Sarah Donovan, Günther Fink, Kelly Jones, Berk Ozler, Terrie Taylor, Chris Udry, Edit Velenyi, Marcos Vera-Hernández and the Nigerian Ministry of Health, Malaria Control Program, especially Dr. Toulope Olayemi Sofola for helpful comments and close collaboration. The plantation staff and sugarcane cutters welcomed us and patiently assisted us throughout the study, without which this study would not have been possible. The World Bank Research Support Board, the Spanish Impact Evaluation Fund administered by the World Bank, IFPRI, US Department of Labor, USDA National Institute of Food and Agriculture, and University of East Anglia are gratefully acknowledged for providing resources and support for the study. Practical Sampling International undertook this work in the field and we appreciate the efforts of the supervisors, enumerators, and health workers who implemented this study. Sarah Kopper and Tyler Box provided excellent research support. We would like to thank seminar participants at the Brunell Development Economics Conference, Carlos III University, CEMFI (Madrid), CSAE Development Economics Conference, DePaul University, IFPRI, Institute for Fiscal Studies, Manchester University, Midwest Development Day, Midwest International Development Economics Conference, Michigan State University, Monash University, NEUDC, Royal Economic Society Conference, University of California-Davis, University of East Anglia, University of Illinois-Urbana Champaign, University of Kent, University of Maryland, University of Minnesota, University of Otago, and the US Department of Labor. We also wish to thank the informed comments of 5 anonymous referees. This study was ethically reviewed by the National Health Research Ethics Committee, Nigeria (NHREC 01/01/2007-28/10/10/2009c), Adamawa State Health Research Ethics Committee, and IFPRI's Institutional Review Board. Publicly available dofiles and data files may be found at https://doi.org/10.7910/DVN/FTNSWN.

I. INTRODUCTION

Gains in agricultural productivity have been a key driver of economic development throughout much of world history and remain an important source of growth in developing countries today. While a great deal of attention has been devoted to the role of technological innovation and diffusion in raising labor productivity, the role of health, while recognized widely, has received less extensive consideration, at least in empirical analysis.[1] As one form of human capital, health is assuredly related to productivity; healthier workers are expected to earn more, just as higher educated workers are expected to have higher earnings. Yet health is a multidimensional construct and it is unclear which aspects of health are most important for agricultural labor productivity.

This study focuses on one disease – malaria – and its influence on earnings, labor supply, productivity and task choice among an agrarian workforce. Malaria is one of the most prevalent

[1] The literature on productivity benefits from investment in the health of able-bodied adults has taken two general directions. One explores the relationship between adult nutrition and labor outcomes - see for instance Edgerton et al. (1979) and Thomas et al. (2006) for experimental studies; Fogel (1993), Schultz (1997, 2002), Strauss and Thomas (1998) for nonexperimental studies of the effect of nutrition on labor outcomes. The other strand of the literature considers the effect of specific illnesses See Audibert and Etard (2003) for a quasi-experimental study of schistosomiaseis, Fox et al. (2004) and Thiruthmurthy etl. (2006) for careful descriptive studies of the labor effects of HIV infection and Habyarimana et al. (2010) for the effect of ARV treatment

communicable diseases in the world today. Agricultural workers and those in other physical occupations are presumed to suffer the greatest productivity declines from malaria due to the physical nature of work demanded. Studies at the individual and household level have found variable estimates of the cost of malaria (see Sauerborn et al. (1991), Shephard et al. (1991), Ettling et al. (1994), Guiguemde et al. (1994), Attanyake et al. (2000), Chima et al. (2003), Akazilli et al. (2008), or Ayieko et al. (2009) among others). While they generally estimate substantial economic losses on households and firms from malaria, most of these studies have one or more methodological limitations. They typically study association, rather than causation, as identifying exogenous variation in malaria status to attribute causality is a challenge. Fink and Masiye (2015) is an exception that studies the randomized distribution of a malaria preventive technology – bednets – among cotton farmers in Zambia which increased farmer output value by 14.7 percent. A second common methodological limitation is the imprecise measurement of individual worker productivity, which is difficult when worker performance is not directly tied to an observable output such as in piece rate work. Finally, most studies – but not all – measure malaria infection in symptomatic cases through self-reports, with the concomitant challenges of recall bias and accuracy of diagnosis.

Our study addresses all three limitations with the randomized phased-in access to a mobile health clinic with piece rate wage-workers at a large sugar plantation in Nigeria. By doing so, we identify the productivity effects of a curative malaria treatment.[2]

We estimate treatment effects in the study population using labor outcomes measured at either the daily level or aggregated to weekly averages. For robustness purposes, we explore two distinct estimators: the within worker and the between worker estimators. We first estimate a worker fixed effect specification using comparisons of the daily labor outcomes of the workers before and after their malaria testing (i.e. the within worker estimator). This within worker comparison establishes a descriptive analysis of the worker's response to treatment but is prone to temporal confounding. Second, we estimate a between worker specification with group by week fixed effects which is the preferred estimator corresponding to the phased experimental design (i.e. the between worker estimator). Exploiting the random allocation of malaria testing and treatment to study weeks, it compares weekly averages of labor outcomes of workers offered the malaria testing program to the outcomes of workers who have not yet

[2] Given the ethical considerations when providing a validated effective malaria treatment to the study population, we did not withhold treatment from a subsample of workers using a pure control group. Instead, our phased-in study design ensures all workers received access to testing and treatment over the relatively brief study period while also maintaining a standard quality of care. Achieving this quality level would not have been possible if all 800 workers had been tested on the same day or week, given the limited diagnostic clinical capacity and distance between the diagnostic clinic and plantation.

received testing. Here the test and treat (if positive) worker outcomes are assessed for the same calendar period of time as the comparison workers. The identifying assumption relies on similar rates of malaria status among workers who have not yet been tested. We examine this assumption by varying the comparison reference period, as the assumption is weaker with shorter reference periods.

The offer of a workplace-based malaria testing and treatment program increases worker earnings by 10.8 to 13.4 percent in the two to three weeks following the offer, with productivity (defined as output per day) increasing 5.9 to 8.9 percent according to the between worker estimator. Within-worker estimates provide similar but smaller estimates of 7.5 to 9.7 percent increases in worker earnings and productivity increases of 3.9 to 4.2 percent. By construction, these intent to treat effects reflect the combined effect of medical treatment (if sick) and provision of worker-specific health information, i.e. whether the worker is malaria positive or negative.

We then conduct sub-group analysis separately for those workers who test positive or negative for malaria. Focusing only on the malaria positives, we use similar within and between worker estimators. This conditioned analysis can be interpreted as an estimate of the treatment on the treated (TOT) reflecting the gains from treating malaria among malaria positive workers (compliance with the medical protocol is near universal). Gains in earnings are observed among the malaria positive primarily due to increases in labor supply. Labor supply rises in the within worker specification by 8.6 to 10.9 percent and in the between worker specifications by 6.9 to 7.0 percent depending on reference period. Increases in daily worker productivity are smaller, ranging from 3.0 to 4.2 percent for the two and three week reference periods (and not precisely estimated in the between worker specification). Overall this suggests the gains to treatment of malaria infection are substantial and largely arise through increases in labor supply. While the counterfactual assumption in the between worker estimator – that the comparison workers who test positive for malaria were also malaria positive for the preceding study period – is relatively innocuous for short reference periods, it may be less defensible for periods farther away from the test as malaria is episodic and may not persist beyond 2 to 3 weeks. We therefore test the sensitivity of the results across multiple reference periods.

A similar conditional analysis is conducted on malaria negative workers – defined as those with either no evidence of the malaria parasite in their blood or with levels low enough to fall below the clinical threshold. We term this comparison the treatment on the medically untreated (TmUT) because while malaria negative workers are not untreated in an experimental sense – they receive an information treatment – they do not receive curative care. This effect can be thought of as a variation of a Treatment on the Treated estimate, where healthy workers were 'treated' by learning about their actual good health, a potential 'good news' health information effect. As before, we apply two estimators: a within worker estimator using daily labor outcomes and a between worker estimator comparing averaged weekly outcomes. A necessary assumption in the between worker estimates is that the comparison workers who subsequently test negative constitute a valid counterfactual group for the workers given a healthy diagnosis. For both estimators, we find TmUT effects on earnings estimates primarily due to increased daily productivity and a relative reduction in lower return task selection. In contrast we do not find substantial labor supply effects as was found for the malaria positive workers, suggesting distinct pathways through which worker earnings are increased among the malaria positive and negative workers.

One explanation of the TmUT estimates is that healthy workers update their health beliefs, which in turn affects their labor decisions. Because health is multi-dimensional and not perfectly observable by the subject, workers often do not know their precise health status and often adjust behavior to health information (Dupas (2011)). In our study, only 29% and 64% of worker's positive and negative self-reports of malaria infection, respectively, were accurate in relation to their diagnostic test results.[3] As the term "malaria" is often taken in the study setting as a wider assignation of general illness, especially illness accompanied by fever, other diseases with the same symptoms (e.g. flu) can be erroneously self-diagnosed as malaria but have less severe effects on labor outcomes. It is possible that a trusted diagnosis itself affects worker behavior, especially if the test result does not conform to worker expectations, which may be conditioned by their endemic environment.[4] Workers who test negative for malaria may have expected their physical work capacity to be low (despite having few or no malaria parasites) if they felt low in energy, possibly due to other reasons but mis-ascribed to malaria, or if they perceived malaria as so widespread that it affects virtually everyone much of the time. Hence a healthy malaria diagnosis is likely to convey a broad meaning of good health for our study subjects that in turn affects their expectations related to work efficacy.

This updating of labor decisions in response to health information is consistent with the task selection choices we observe among malaria negative workers. Workers can choose every morning upon arrival at the plantation to conduct either cane-cutting, which pays a piece rate wage, or 'scrabbling', a cane bundling and loading task, which is less arduous and pays a daily fixed wage lower than the

[3] We discuss the diagnostic protocol in more detail in section three but rely on WHO (2010) and Government of Nigeria (2011) recommended diagnostic protocols. Self-reports and diagnostic results may differ due to misperceptions of a respondent's symptoms and because malaria is a parasitic infection that results in both symptomatic and asymptomatic cases. Workers may have a clinically positive parasitic level of malaria yet be asymptomatic. Many diseases including HIV, malaria, tuberculosis have asymptomatic stages which affect health.

[4] In the final results section of the paper and the paper's appendix, we discuss a theoretical framework that explores how health perceptions may affect the optimal level of daily effort supplied by a worker in a piece rate wage setting.

expected daily earnings from cane cutting. Malaria negative workers are relatively more likely to select into higher return higher effort sugarcane cutting, rather than scrabbling tasks, after their diagnosis compared to before. This interpretation is also supported by findings from additional analysis that indicate, among the workers who tested negative, a differential treatment response across factors likely to affect health expectations, namely the worker's parasite density and self-reported fatigue status. The results lead to the conjecture that surprise good health news results in a reallocation of labor and effort, but we also discuss alternative mechanisms. Extrapolating from this context to a more general setting, increased contact with a high-quality health system may have important indirect effects for the labor and investment decisions of workers.

The next section of this paper describes the study setting in detail. Sections three and four explain the experimental design and identification strategy, respectively. Section five presents the results, discusses possible threats to validity, and explores various robustness checks. A final section offers concluding thoughts and a basic cost-benefit assessment that indicates the economic gains from the intervention compare favorably with the cost, both for the worker and the firm.

II. STUDY SETTING

The experiment is situated on a single large sugar cane plantation (5,700 hectares) in rural Nigeria. The plantation employs 816 sugarcane cutters who work for the entire harvest season that stretches from mid-November to April. Cane-cutters are paid a piece rate wage. While there are other activities on the plantation, including a sugar processing facility, this study focuses solely on the sugarcane cutter labor force. We first describe the work environment on the plantation and then the sugarcane cutters' characteristics.

A. Plantation Work Environment

Workers are hired for the entire harvest season from local villages surrounding the plantation and are transported daily to the assigned work site. This organized transportation also serves to standardize the number of hours of cane cutting across all workers.[5] The cane-cutters are organized into eight work groups, averaging slightly more than 100 workers per group, and each group is managed by a supervisor. Every day the supervisor and his cutters are assigned a set of starting fields in the plantation and additional fields to cut when they have finished with their starting fields. Sugarcane cutters do not work in teams to complete the rows of cane they are assigned but rather work individually along a row, allocated

[5] Due to this transportation policy, our analysis of worker labor supply focuses on the extensive rather than the intensive margin as workers cannot choose to work more hours than the common transportation allows.

to them by the supervisor, until finished and are then assigned another row to harvest. Rows of cane are typically of uniform density due to mechanized planting and the irrigated nature of sugarcane that requires fields to be encompassed with water canals.[6] Due to the size of the plantation and the capacity of the processing factory on site, workers may cut as much cane as they can within a given work day. One worker's productivity does not impact other workers' earnings as additional cane rows, or even nearby fields, are always made available when workers have finished their row or field.[7]

Cane cutters are paid a piece rate of 2.04 Naira for every measured "rod" of cane cut where a "rod" (approximately two meters in length) is a physical standard carried by every work group supervisor. At the end of each day, the worker's output for that day is entered on their personal administrative record, a 'blue card', and is signed off by both the supervisor and worker. The plantation thus keeps records of the daily output (quantity cut), the days worked, and the total earnings for each worker. Disagreement between cutters and management over compensation amounts are rare. The work is lucrative as an average day of cane cutting pays 1,008 Naira, or approximately $7 USD, providing daily earnings that are substantially higher than typical local alternatives. Most workers labor on their own plot for subsistence agriculture throughout the year while devoting their efforts to cutting cane during the sugarcane harvest season.[8] With the poverty rate in the surrounding Nigerian state at 74.3% (measured at $1 USD per day (NBS 2012)), sugarcane cutter positions are in high demand in the local communities.

An unusual feature of the plantation work is that, at the start of every day, workers have the choice of two daily tasks – sugarcane cutting or 'scrabbling'. Scrabbling is a task that includes the collection of cut sugarcane rods and binding them into bundles for loading on trucks destined for processing at the factory. The scrabbling task is less physically intensive than cutting and the required worker effort more difficult to observe, therefore scrabbling pays fixed earnings of 500 Naira per day (roughly half the expected earnings of a day spent cutting). A cane cutter can choose to carry out scrabbling work on any day, through a request to the supervisor at the start of the day. There is also a dedicated separate work force of scrabblers hired and managed by the plantation, but these full-time

[6] This also means that the malaria risk is not entirely seasonal, as it would be in rain fed production areas. The existence of the water canals throughout this large plantation creates larval breeding that is uncorrelated with rainfall patterns.

[7] In other words there is no risk of shortage of cane to cut for any individual worker. Indeed, at the end of the season the firm typically brings in (old) machines to cut the remaining cane that workers have not been able to cut in time (i.e. during the window of optimal ripeness). A worker's earnings potential is therefore unaffected by other workers' productivity.

[8] 86% of workers list household farming as their main activity outside the sugar cane harvest season, 10% work for their own account in a non-agricultural sector and 4% work for someone else in agriculture or trade. The primary agricultural harvest season runs between October and November, while the sugar cane harvest occurs between January and April.

scrabblers are not part of this study. While cane-cutters choose to scrabble only infrequently, the amount of time devoted to scrabbling is not trivial – the average cane-cutter spends 5 days each week working on the plantation (with the other days of the week spent off the plantation, either inactive or in agriculture and household related activities) of which 0.6 days per week is spent on scrabbling over the 6 week intervention period.[9] This daily task choice will play an important role in the interpretation of the results, where we posit that, at the start of every workday, a worker balances the expected return of a task selection against the expected effort cost of the task.

B. Worker's Characteristics

We supplement the plantation administration records with data from worker interviews covering socio-demographic, work history, and self-reported health information. At the end of the interview we also collect blood samples to test for malaria. These three data sources will be combined at the level of worker-week or worker-day to estimate the productivity costs of malaria. The analysis focuses on four labor outcomes constructed from the firm's administrative data: daily earnings, labor supply, productivity, and task selection (the latter two conditional on labor supply).

Regarding basic workforce characteristics, workers are exclusively male and generally of prime age (a mean age of 30 years). They have previously worked on the plantation for a year on average and tend to be in good nutritional status. The mean body-mass index (BMI) is almost 24, and only 6.8% of the workers have a BMI less than 20, which can indicate undernourishment. These descriptive results are summarized in Table 1. As stated earlier, the average daily earnings are slightly more than 1000 Naira, and the average harvest season comprises 60 workdays. The typical worker elects to spend 13% of work days as a scrabbler, with the remainder devoted to cane cutting.

Appendix Table A.1 also conveys the p-value from balance tests of each measured worker characteristic across the eight work groups. Most socio-economic and demographic characteristics are balanced across work groups, except for worker education. In addition, the plantation records make clear that earnings opportunities also differ across work groups with average earnings and days worked varying significantly. As work groups are uniquely allocated to plots these differences may reflect either differing group or plot characteristics (or both).[10] Given the imbalance in average earnings and in certain characteristics that may be related to productivity, most notably years of schooling, it is important to

[9] 57% of workers did no additional work outside the plantation in the previous seven days before interview, while 18% worked on their own farm and 23% in household related business, typically agricultural or small trade,

[10] While the plantation follows a detailed harvest plan to ensure sugarcane is cut when it is ripe, some fields may have slightly riper sugarcane that can be somewhat easier to cut.

stratify the randomized exposure to treatment within work group in order to control for any such imbalance, as discussed in Section III.

Not only do earnings and related measures significantly vary across work group but they also vary across time. Appendix Table A2 presents the weekly earnings, days worked and number of days scrabbled, as well as daily earnings (worker productivity) by study week (Panel A) and then by work group (Panel B). While in a typical harvest week a worker will work 5 days and earn about 1000 Naira a day (7 USD), there is substantial temporal heterogeneity in labor outcomes. Weekly earnings, days worked, number of days scrabbled, and daily earnings (conditional on working) exhibit greater variation within than across weeks and vary more within than across workgroups. These differences across work groups and across weeks within work groups motivates the adoption of group by week fixed effects specifications which we discuss further in the next section.

III. EXPERIMENTAL DESIGN

The experiment follows a phased in randomized design, using temporally randomized exposure to testing and treatment to resolve the identification problems inherent in the joint determination of health and labor. This approach also ensures we can reach the entire population of sugarcane workers, an important ethical consideration for both the firm and research team. The formal properties of a staggered randomization approach are characterized in Athey and Imbens (2018) with empirical examples such as Miguel and Kremer (2004).

The order of worker testing and possible curative treatment followed a two-stage procedure where a randomly determined order of workers within each group were selected from a complete list of workers obtained from the plantation.[11] The randomization was implemented before the beginning of the study, so that the survey team had a predetermined number of specified workers from each work group to test and survey each study week. This design yields an approximately even distribution of workers interviewed and tested across work days within each of the six study-weeks in each of the work groups. Appendix Figure A1 summarizes the number of workers interviewed and tested, the number of workers assessed as malaria positive, and the total number of work days supplied by the plantation labor force for each of the study weeks that inform our estimates.

The phased in randomization offers both ethical and empirical advantages relative to a one period randomization of workers to treatment and control groups. It ensures that all workers have access to the

[11] Work group composition was stable over the study period. The plantation assigns workers to a work group at the beginning of the season and workers remain in the group throughout the season.

testing and treatment program which was a precondition for the firm's participation in our study (as no worker refused treatment, this approach leads to 100% take up). An additional empirical advantage is that it permits us to observe a distribution of workers' health statuses over time, rather than at one single moment, which allows effect estimation that are robust to short-term temporal variation in either labor conditions or health status.[12]

The randomization of the medical treatment also brings with it a well-known challenge. Following medical guidelines, we cannot withhold treatment or information once workers have been tested. As a result, there is not an ethical design with a 'pure' counterfactual. We cannot observe labor outcomes for workers who tested malaria positive but did not receive the test results and medical treatment, or for workers who tested malaria negative but were not told the result. We can however construct a counterfactual assuming the stability of worker's health status over short periods. Much of the subsequent robustness analysis tests the feasibility of this assumption.

In the ensuing sections, we discuss the randomization and its validation with balancing tests in more detail. We then provide a description of the worker testing and treatment protocol.

A. *Randomization and Balancing Tests*

Worker attrition, noncompliance and survey refusal on the date of interview and testing are common sources of imbalance but are minimal in our sample. To assess attrition, we need to distinguish between the within worker estimator, which is applied to the daily labor outcomes for the entire twelve weeks for which we have administrative data, and the between worker estimator which is applied to aggregated weekly data and uses labor outcomes over the six-week program implementation period. Twenty-six workers drop out of our sample and are considered attrited observations in the daily within estimation (8 in week 1, 1 in week 3, 1 in week 5 and 16 in week 7). For the weekly between worker estimation, two workers are dropped from the analysis. Attrition is lower in the between worker estimator because it is still possible to estimate a weekly average despite a missing day of observation. In terms of date-of-interview noncompliance, fifty workers were not present on their scheduled day of interview and were dropped from the daily within worker analysis. As these workers were interviewed and tested later in their scheduled week of interview, they remain in the weekly between worker estimation sample. In the Appendix Table A3 we show that workers who dropped out of the sample and those who were interviewed and tested are not significantly different from each other across a range of observable

[12] Specifically, the phased-in design gives us observations for treated and untreated workers at the same moment in time (day and week) spread across the study period.

characteristics. Only one mean difference is statistically significant (the number of rooms in the household), suggesting little to no attrition bias in our estimates.

As identification in the between estimator is principally provided by the randomization of the order of testing and treatment over time, we also investigate whether the phased within-group randomization was successful. Table 2 presents the summary results of within group balance tests conducted on worker characteristics according to the week in which the worker was interviewed and offered the malaria test. Overall, the randomization process appears to have produced a well-balanced sample. Out of 72 balancing tests – nine characteristics for each of eight work groups – only five tests (or 1 in 14) suggest some degree of significant temporal imbalance at the threshold significance level of 0.10 and none at the 0.05 level.[13] In additional robustness checks, linearly controlling for observed worker characteristics such as education, BMI, and age does not affect the effect estimates reported below.

B. *Worker Testing and Treatment Protocol*

The measurement of malaria in our study relies on the measurement of parasites in the worker from thick film blood smears read in a dedicated laboratory. Although expensive to implement as it requires trained personnel and appropriate instruments, thick blood film microscopy is considered the diagnostic gold standard when read by a trained professional in a qualified lab. In practice, our study team takes a blood sample from each consenting worker and conducts microscopy analysis in a lab two hours away (by car) from the plantation.[14] The microscopy analysis counts the number of parasites within defined ares of the slide, with workers above a specified threshold considered to be malaria positive.[15] While a high parasite load indicates malaria infection there is no medical consensus about the *exact* relationship between parasite load and malaria outbreak – a common parasite threshold has not been universally adopted.[16] Workers who have malaria parasites in their blood smears are infected with malaria

[13] We list all the control group means and mean differences between treatment and control for the balancing tests in the appendix.

[14] A free small health post to which workers have access in principle exists on the plantation but we do not expect its presence to matter for our impact estimates. The health post is perceived by the work force to be of poor quality, is far removed for most workers and has no patient follow-up. No worker reported a visit to the health post during the fieldwork period. This was confirmed through our inspection of its records. Malaria care outside the plantation was generally low quality with limited diagnostic capacity throughout the period of our study.

[15] A professional laboratory technician read all the slides to record the number of parasites in five viewing fields. After recording the parasite count, the laboratory supervisor selected random subsamples of slides to verify from each tray of 50 slides. If discrepancies were found between the counts of the primary laboratory technician and the supervisor, the whole tray of slides was re-validated.

[16] Several studies in the medical literature from different settings use distinct parasite density thresholds in classifying malaria infections as there is no unique medically established standard for population-based malaria

but may not exhibit symptoms as the body fights the parasitic infection – so called asymptomatic cases (Laishram et al. (2012), WHO (2012)). Following the WHO (2010) recommendation, our diagnostic protocol for malaria follows the clinical diagnostic standards in the study area (Government of Nigeria 2011) which is the presence of at least three parasites over the total examined fields in the blood smear.[17]

Table 3 conveys the blood slide results by presenting the distribution of the total parasite count. Only 9% of the workers have no observed parasite presence while roughly 55% have one or two parasites observed. These descriptive statistics are similar to parasite loads observed in Senegal by Bottius et al. (1996), where they diagnosed 90% of the population to be chronically infected (either symptomatic or asymptomatic). Asymptomatic malaria is common in endemic areas (Trape et al. (1987)) and it appears that many workers in our sample exhibit sub-clinical parasite threshold loads. Regarding a clinical diagnosis of malaria, more than one-third – 36% – of the work-force exceeds the adopted cut-off for a malarial diagnosis (a minimum of three parasites), with 15% having a parasite count of four or more.[18]

Workers receive their test results individually from a health worker in a confidential setting.[19] The plantation or field supervisors had no access to treatment records of workers. Workers diagnosed with malaria receive an adult dose of Artemisinin based Combination Therapy (ACT) along with clear instructions on use. ACT is the preferred first line treatment for malaria recommended by the World Health Organization, as there has been no resistance to ACT yet reported in Africa, and ACT has been proven to cure *falciparum malaria* within 7 days with few to no side effects. ACT also provides protective effects between two and four weeks after treatment (White (2005), Sowunmi et al. (2007), and Woodring et al. (2010)). Identification of intervention impact is predicated on the assumption that workers comply with the prescribed medical treatment if they test positive and are subsequently cleared of the malaria parasite. Compliance with the treatment protocol was maximized through two follow-up visits by the health workers and a small incentive (50 Naira) for the workers to return used ACT boxes to health workers. During the follow-up visits, health workers determined whether the treatment had been successful which included ascertaining whether the worker had taken the medication properly, had consumed the medication himself without distributing to others, and whether any of the worker's

testing, which typically includes asymptomatic malaria cases (see dalla Martha et al. (2007), Toure et al. (2006), and Rottmann et al. (2006)).

[17] In the absence of a universally adopted standard for both symptomatic and asymptomatic cases in a population, WHO recommends following local standards for the clinical threshold as the objective measure.

[18] Inspection of records in the closest nearby town showed that the malaria positivity rate observed in our population of workers is at a similar level to the clinical diagnostic rates found in the areas surrounding the study setting during the study months.

[19] Tested workers were informed about the overall test result but not the exact parasite count, in line with medical practice. We conduct analysis using the underlying parasite count as a robustness check.

symptoms resolved. Virtually no problems with compliance were reported and we assume full compliance with ACT treatment for the remainder of the analysis.

IV. ESTIMATION STRATEGY

We estimate three types of treatment effects: an 'intent to treat effect' (ITT), a 'treatment on the treated' effect (TOT), and a 'treatment of the medically untreated' effect (TmUT). The ITT yields an unbiased, causal estimate of the effect of the offer of the testing and treatment program on labor outcomes including earnings, labor supply, productivity and task selection. The TOT and TmUT provide a disaggregation of the ITT by malaria status that may demonstrate the pathways through which program impact works, though these estimates are not strictly causal without stronger assumptions.

For each of these estimated effects, we use two specifications and consider four reference periods over which the treatment effect might be measured (one, two, three, and four week effects) in order to document the robustness of results to the identifying assumptions of each specification. The first specification uses a within worker fixed effect estimation that compares the daily labor outcomes before and after treatment. Here, the counterfactual is the worker himself before the intervention or treatment date. Second, we estimate a between worker weekly labor outcome specification, which includes a group by week fixed effect. In this second estimation the counterfactual of workers who were yet to be interviewed and tested (or medically treated, depending on the sample restriction) were established by the phased-in randomization. We describe both specifications in detail below and discuss the merits of their identifying assumptions.

The two estimators also differ slightly in the data they use. The within worker estimator is applied to the daily labor outcomes for the entire twelve week harvest season for which we have administrative data (six week implementation period, two weeks before and four weeks after implementation). The between worker estimator is applied to aggregated weekly data and, as it exploits the experimental design, only considers labor outcomes over the six week implementation period of the program.

A. Specification 1: Within worker estimation using daily labor outcomes and including worker fixed effects

The ITT estimates the effect of access to malaria testing and treatment on labor behavior. The time indicator t is measured in days and, for each worker i, centered at date T_i, the worker's date of treatment. Using the variation in the daily labor outcomes, the within worker ITT compares the labor outcome over the interval τ, after access to treatment, with the labor outcome for the same worker over the equivalent length interval $-\tau$, before access to treatment, where τ refers to the length of the reference period (7, 14, 21, or 28 days). The reference interval before and after treatment is easily converted to weeks to provide a comparison with our second, weekly labor outcomes specification below. Since there is an average lag of three days between the collection of blood slides and the delivery of the result to the worker, along with medical treatment if the worker tested positive, the day of interview and testing, as well as the two following days, are excluded from the analysis (i.e. observations are excluded for $T_i \leq t \leq T_i + 2$).[20,21] We estimate the within worker ITT as follows:

$$L_{it}^{\tau} = \alpha + \beta^1 I(t > T_i) + F_i + \varepsilon_{it} \;\; \forall i \in M, \forall t \in (T_i - \tau \ldots T_i - 1, T_i + 2 \ldots T_i + 2 + \tau) \qquad (1)$$

where L_{it} measures the three labor outcomes of interest for worker i on day t indexed by a reference period τ: daily labor supply, daily productivity which equals daily earnings conditional on working (in log form), and daily task selection (scrabbling instead of cane cutting). Since the equation contains worker fixed effects, F_i, this is a comparison of symmetric intervals of days centered on the intervention date and subsequent 2 days over the full study interval of 2 + τ.[22] The treatment indicator is given by the function $I(t>T_i)$ which takes the value of 1 for all days that follow treatment date T_i. ε_{it} is the error term and standard errors are clustered at the worker level. β^1 is the estimate of the change in labor outcome after access to treatment for worker i, relative to his own labor outcome in the past.

In estimating the effect of access to malaria testing and treatment for the full sample of workers, M, that represents the cane-cutting workforce, β^1 aggregates the combined effect of medical treatment, and the provision of more accurate information about one's health status. Note that the content of information is distinct for the parasitemic positive and negative workers. The ITT thus reflects a combined effect of 'bad' news and medical treatment for the parasitemic positives and possible 'good' news for the parasitemic negatives. We disaggregate the effects for parasitemic positive (TOT) and parasitmemic negative (TmUT) workers in the next two regressions that restrict the sample based on the worker's malaria status.

The within worker TOT restricts the sample to those who are ill and treated, comprising daily labor before and after their treatment:

---

[20] Due to scheduled work stoppages (such as Sundays off) and other idiosyncrasies, the delivery of a diagnosis to the workers may have been as rapid as two days or delayed as long as four days.

[21] One limitation of the 21 and 28 day reference periods for workers who were interviewed in weeks one and two of the study (early February) is that work observations from three and four weeks earlier are not available because the study began two weeks after the re-start of cane cutting on the plantation in mid-January. This creates an unbalanced panel in worker days, but no expected bias in estimates due to the randomization of workers to interview dates.

[22] For example, the one week reference period compares days lagged one week after treatment and response delay with, symmetrically, the leading one week before treatment.

$$L_{it}^{\tau} = \alpha + \beta^2 I(t > T_i) + F_i + \varepsilon_{it} \;\; \forall i \in M^+, \forall t \in (T_i - \tau \dots T_i - 1, T_i + 2 \dots T_i + 2 + \tau) \quad (2)$$

The complete set of malaria positive workers are denoted as M^+. β^2 is the estimate of the change in labor outcome after worker i's positive malaria diagnosis and treatment, relative to his own labor outcome in the past.

The TmUT provides an estimate of the effect of good news health information that the test is negative, restricting the sample to those workers who were malaria negative, by comparing outcomes before and after they received information about their health status.

$$L_{it}^{\tau} = \alpha + \beta^3 I(t > T_i) + F_i + \varepsilon_{it} \;\; \forall i \in M^-, \forall t \in (T_i - \tau \dots T_i - 1, T_i + 2 \dots T_i + 2 + \tau) \quad (3)$$

The set of malaria negative workers is denoted as M^-. β^3 is the estimate of the change in labor outcome after worker i's negative malaria diagnosis was communicated to the worker, relative to his own labor outcome in the past.

An advantage of the within estimator is that it is straight forward to interpret; it also provides a useful robustness check making use of the panel dimension of the data that allows a control for time invariant worker characteristics through the worker fixed effect. The limitation of this approach is that it cannot fully account for secular temporal variation in outcomes over the study period. We have considered – and ruled out – certain causes of temporal variation that could be correlated with worker outcomes including weather and events like industrial action.[23] However we cannot rule out all possible causes. The within estimation also has a slightly higher – but still very low – attrition rate as explained in section III.A above.

B. Specification 2: Between worker estimation using weekly labor outcomes and including group by week fixed effects

Our second specification leverages the randomized temporal variation in treatment assignment described in the experimental design section. This allows us to estimate over a reference period (τ = 7, 14,

[23] As part of the field work for which our teams were on the ground every work day of the study period, we kept track of local events that could disrupt or affect labor or malaria outcomes, including weather shocks, industrial actions, cultural events, other health interventions unrelated to the study, and unexpected health shocks. No such events were registered during the harvest season. Further, no such events were reported by the plantation management in the form of the administrative data. Personal discussion with plantation management at the start and end of the field work confirmed this, including an absence of concern with weather patterns on the plantation during the harvest season. Note that in the case of the between estimator, group by week fixed effects address the influence of common weather shocks at the workgroup level (which is the main concern given the geographic concentration of work group activity).

21, or 28 days) the difference in outcomes between treated workers and their counterfactual. Here, the counterfactual is those workers not yet treated but observed over the same reference period, τ. For example, to estimate one week effects, outcomes in the 2nd week of the study period are contrasted between workers treated in the 1st week ('the treated') and the 3rd week (their 'control'), outcomes in the 3rd week of the study are contrasted across workers treated in the 2nd week and the 4th week, and so on.[24] Effects beyond the 4 week reference period (28 days) could not be measured as the program fieldwork period lasted six weeks. The weeks of treatment for both treated and comparison workers are excluded from the analysis (i.e. the four-week reference period is only estimated from workers assessed in the first and sixth week of the study).

The intent to treat effect for the between worker specification is given as:

$$L_{igt}^{\tau} = \alpha + \beta^4 I\left(T_{i,\tau-} = 1\right) + F_{gt} + \varepsilon_{igt} \quad \forall i \in \left(W\left(T_{i,\tau-} = 1\right) \cup W\left(T_{i,\tau+} = 1\right)\right), \forall t \in \tau \quad (4)$$

where L_{igt}^{τ} measures the three labor outcomes of interest that mirror those in the within estimator estimates: weekly labor supply (in logs, the number of days worked per week), weekly average of daily productivity (log weekly average of daily earnings conditional on working), and ratio of days scrabbled per week (ratio of days scrabbled to days worked per week) for worker *i* in workgroup *g* for week *t*, averaged over a reference period τ (of either 1, 2, 3, or 4 weeks). We also estimate the overall impact on weekly earnings (log unconditional daily earnings averaged over the week), which is the sum of the effects on labor supply and productivity. ε_{igt} is the worker specific error term with standard errors clustered at the worker level. The indicator function $I\left(T_{i,\tau-} = 1\right)$ conveys whether the worker *i* has been interviewed and tested before the reference period τ. The sample construction differs from equations (1) – (3) in both the unit of analysis and counterfactual. Labor outcomes are aggregated by week, as defined above. β^4 provides a treatment effect estimate of the difference in weekly labor outcome of those workers interviewed as part of the testing and treatment program relative to the labor outcomes of workers in the same reference period who had yet to be interviewed and tested. More precisely, it compares labor outcomes in the interval τ for those workers who were tested the week before τ, with the labor outcomes for workers who were treated the week after τ. The grouped sets of workers assessed before and after τ are denoted as $W\left(T_{i,\tau-} = 1\right)$ and $W\left(T_{i,\tau+} = 1\right)$. To control for the potential non-random placement of workers across workgroups and plots, as well as the natural weekly variation in work outcomes both

[24] For two week effects (i.e. the two weeks after the treatment week), outcomes in the 2nd and 3rd week are contrasted for workers treated in the 1st and 4th weeks, outcomes for the 3rd and 4th week are compared for workers treated in the 2nd and 5th weeks, and so on.

across and within workgroups, a full set of workgroup-work week fixed effects, F_{gt}, are included in the specification.

Following a similar approach to the ITT estimation, the TOT on malaria positives for the between estimator is estimated by comparing labor outcomes over reference period τ for those workers who had access to treatment before the reference period and were treated if ill (and are therefore presumed healthy over τ) with the labor outcomes for workers who were not tested until the week after τ and at that point found to be malaria positive (and thus assumed sick over τ). We estimate:

$$L_{igt}^{\tau} = \alpha + \beta^5 I(T_{i,\tau-} = 1) + F_{gt} + \varepsilon_{igt} \quad \forall i \in M^+ \cap \left(W\left(T_{i,\tau-} = 1\right) \cup W\left(T_{i,\tau+} = 0\right)\right), \forall t \in \tau \quad (5)$$

L_{igt}^{τ} measures the same labor outcomes of interest as for the ITT. The TOT reflects the combined effect of receiving an illness diagnosis and medical treatment for such a diagnosis.

The TmUT estimation for the between approach compares labor outcomes for those workers who tested malaria negative with those workers not yet tested but assumed negative based on the results of subsequent tests.

$$L_{igt}^{\tau} = \alpha + \beta^6 I(T_{i,\tau-} = 1) + F_{gt} + \varepsilon_{igt} \quad \forall i \in M^- \cap \left(W(T_{i,\tau-} = 1) \cup W(T_{i,\tau+} = 0)\right), \forall t \in \tau \qquad (6)$$

The TmUT is estimated for the same labor outcomes as the ITT and TOT and reflects the effect of receiving positive health news (a malaria negative diagnosis).

Because the TOT and TmUT compare outcomes across workers, it is useful to further assess balance for each of the TOT and TmUT estimations. We therefore re-estimated balance tests that we applied to the full sample (presented in Table 1) for each of the subsamples underlying the estimation of the TOT or TmUT. The results presented in Table 2 confirm balance on worker covariates across work groups and study weeks.

The strength of the between worker estimator is that it compares labor outcomes for treated and comparison workers during the same span of calendar time. Therefore, the between worker estimate is, by construction, not correlated with unobserved time effects. As randomization to treatment was implemented at the worker level, within workgroup, these estimates are not subject to confounders due to imbalance across workgroups (or the plots to which working groups are allocated). The workgroup by week fixed effects included in the specification further absorb any common shocks operating at that level. Possible confounders in this setup instead relate to the dynamics of illness – for example a worker assumed healthy over period τ is actually sick – or anticipation effects – i.e. workers may lower their labor outcomes in anticipation of future treatment. The influence of possible confounders will be assessed later in the results section.

V. RESULTS

We report in the subsequent sections the three types of treatment effects: an 'intent to treat effect' (ITT), a 'treatment on the treated' effect (TOT), and a 'treatment of the medically untreated' effect (TmUT) over four reference periods, and for the within and between worker specifications.[25] After reporting these results, we discuss the internal validity and the interpretation of results with a series of robustness tests and supplementary analysis including a placebo test to confirm the identifying assumptions where possible.

A. Intent to treat effect – the joint effect of malaria testing and treatment

Table 4 presents the results of Equations (1) and (4) estimated for all workers. We analyze the three labor outcomes for both specifications, as well as total earnings for the between specification; all variables converted to log quantities except for daily labor supply, which is represented by a simple binary indicator variable.[26,27] The within worker fixed effects results, reported in Columns (1), (2), and (3) of Table 4, indicate a daily labor supply, daily productivity (conditional on working), and daily scrabbling response to the intervention. As the reference period increases, the labor supply, productivity and scrabbling effect sizes increase which suggests the effects of treatment grow over the reference period. Estimates, vary from 4.9% to 10.0% for the daily labor supply response, 3.1% to 4.6% for the daily earnings or productivity response, and 2.9% to 7.0% for the scrabbling response. As the rates of scrabbling increase at roughly half the rate of the general labor supply response (and as this scrabbling increase is estimated from a lower base level) the results indicate a relative decline in the proportion of work time spent scrabbling. To be clear, this relative decline occurs against a backdrop of absolute

[25] Throughout, standard errors are clustered at the worker level for all estimated treatment effects. For our weekly estimation approach, data is aggregated at the weekly level, two-way clustering at both the worker and week level is not feasible since the number of study weeks is restricted to the program duration of six weeks, which makes it difficult to disentangle correlated temporal shocks that vary across individuals. Such small number of clusters may also lead to downward biased standard errors (see Cameron et al. (2008)). Athey and Imbens (2018) note that the standard Liang-Zeger adjusted standard errors which we estimate in this paper are overly conservative for a phased-in randomized design.

[26] Results in levels are available in the online appendix Table A8 and are similar to the main results.

[27] Throughout the discussion 'daily earnings' refers to daily earnings from both cane cutting and scrabbling by the cane cutting work force. Earnings from cane cutting are obtained as daily worker output multiplied by the piece rate, and earnings from scrabbling reflect the corresponding fixed wage. Earnings estimations are at the worker-day or worker-week level, with worker productivity conditional on being present at work but incorporating earnings from either cane cutting or scrabbling activities. This approach permits us to decompose earnings into labor supply and productivity effects.

increases both in the rate of working overall and (a proportionally smaller increase) in the total number of days devoted to scrabbling.

The between worker estimates at the weekly level, reported in Columns (4)-(7) of Table 4, confirm a clear, albeit somewhat delayed, response to treatment. In the first week after treatment, earnings increase by 4.3%, although this effect is not precisely estimated. Due to the intervention logistics, we may not expect to see large effects in the first week after treatment – the microscopy analysis and relay of diagnosis took an average of three days (and medicinal efficacy requires another two to three days). Larger impacts emerge in the two- and three-week reference period, confirming a delayed response (consistent with the within worker estimates). Overall, these estimates show sizeable between worker impact. The largest impacts occur in the two- and three-week reference period, at which point all treated workers should have received a diagnosis and possible medication as well as taken the full ACT course. Weekly earnings are on average 10.8% higher in the two weeks following the malaria testing and treatment and rise to 13.4% higher in the three-week period. These gains in earnings are divided between increases in both weekly labor supply and daily productivity. In both the two- and three-week reference period, the days worked increases by approximately 5%. Productivity, measured by daily earnings conditional on labor supply, increases by 6-9% in the two- and three-week reference period. Consistent with the within-estimator results above the results indicate a relative decline in work time spent scrabbling: the ratio of days scrabbled to cutting cane declines by 8 to 15% in the two- and three-week reference periods. Estimated gains to earnings, labor supply, productivity, and scrabbling all lose precision in the 4-week reference period, possibly due to the truncated sample for which we observe four-week impacts, and most coefficients decline in magnitude.

Despite the different estimation frameworks of the within and between worker specifications, the two estimated impacts of the intervention are consistent with one another for labor supply, daily earnings conditional on labor supply, and proportion of work time spent scrabbling. As the descriptive statistics in Table A1, Panel A suggest an overall increasing trend in scrabbling incidence over the study weeks (and no apparent trends in the other outcomes considered), the findings indicate a relative decline in scrabbling incidence for treated workers against a backdrop of generally rising amount of time allocated to scrabbling.

B. Treatment on the treated – the joint effect of testing and treatment for the malaria positives

The estimates reported in Table 5 focus on the effects of treatment on malaria positive workers. The within worker fixed effects estimates (equation 3), reported in Columns (1) to (3) of Table 5, indicate a labor supply response that varies between 5.9% in the one-week reference period to 11.1% in the four-week reference period. The rates of scrabbling also increase but at roughly 60% the rate of the general labor supply response. Daily earnings effects are substantial and estimated more precisely for longer reference periods (3.7% and 4.3% in the three- and four-week references respectively). The daily productivity responses reported in Column (2) are also consistent with workers who are treated for malaria requiring some time to regain strength before they can provide higher levels of effort on the job.

The between worker estimates, reported in Columns (4) to (7) of Table 5, are generally less precise than the between worker ITT estimates, as statistical power is reduced due to the sample restriction to malaria positive workers. It is also no longer possible to estimate impacts for a four-week reference period due to insufficient numbers of malaria positive workers in the comparison group for that period. Nevertheless, a weekly earnings response in the two- and three-week estimates (Column 4) is apparent and of a similar order of magnitude – 9.1% to 11.2% of total earnings – as the ITT estimates in Table 4. The proximity in magnitude of the two estimates (the ITT and the TOT) suggests that the earnings benefit from the intervention occurs not only for the malaria positive workers but also to those who test negative, as we investigate in sub-section C below.

The gains in weekly earnings for those previously infected arise primarily from an increase in labor supply, consistent with the daily within worker estimates. The number of days per week worked after treatment with ACT increases by about 7% in the between worker specification, at the lower end of the within estimates (5.9-11.1%). There may also be a marginal gain in the productivity of each day worked – on the order of 2% to 4% for the two- and three-week reference periods respectively, but these are not precisely estimated at standard levels of significance. We do not find a TOT effect on the ratio of days worked in scrabbling in the between specification, the point estimates are lower in magnitude than the ITT estimates in Table 4 and not precisely estimated.

C. Treatment on the medically untreated - the effect of testing for malaria negatives

A comparison of estimated coefficients for the ITT (Table 4) and TOT (Table 5) suggests that not all benefits measured by the ITT estimates accrue solely to malaria positive workers. Since the intervention consists of both medical treatment and health information, estimates of Equation 3 and 6 provide evidence on the role of health information – in this case ‘good news’ – in the worker’s daily and weekly labor decisions. These results are presented in Table 6. A good news effect can be isolated because we know that medical response to treatment is not a plausible mechanism among the malaria negative workers – these workers were not treated with ACT.

The within worker fixed effects estimates, reported in Columns (1) to (3) of Table 6, indicate positive labor supply and productivity responses. The labor supply responses range from 4.4% to 9.4% depending on the reference period, which are of 15%-25% smaller magnitude then the TOT estimates. While the magnitude of the labor supply response does not dramatically differ between the malaria positive and negative, the malaria negative point estimates suggest a somewhat different response to the program. The rate of task selection into scrabbling also increases but at a lower rate than the observed increase for malaria positive workers. The relatively muted labor supply and scrabbling responses in the TmUT, when compared with the TOT, suggest that a possible good news effect operates through a different channel than the response to a malaria positive diagnosis and subsequent drug treatment. The good news also impacts daily productivity for which the response is relatively consistent (4.3% to 4.8%) across reference periods.

The between worker results, reported in Columns (4) to (7) of Table 6, extend and strengthen the conclusions based on the within results. Changes in weekly earnings for this group of workers are precisely estimated in the 2- and 3-week reference period, and the magnitude of 11.7% to 14.2% is even higher than the ITT estimates of Table 4. While the coefficients for the labor supply response are positive (but not precisely estimated), it is apparent that most of the gains in earnings arise through higher daily productivity. The estimated productivity among malaria negative workers are of the order of 7.4% to 11.2% for the two- and three-week reference periods. This differs from the earnings gains of malaria positive workers, discussed above, who experienced a rise in earnings largely due to the labor supply response. The between worker results also confirm that healthy workers, upon receiving good news, are relatively less likely to opt for scrabbling, conditional on working (Column 7). This relative decline in scrabbling incidence occurs against the increasing temporal trend of scrabbling incidence within the full sample, as described earlier. Taken together, the results suggest that worker expectations of their own health can influence not only the decision to supply labor but also the choice of task. They also indicate that the productivity and earnings gains from good news estimated in Table 6 are at least partially due to switching into piece rate work from scrabbling, a job with lower earnings in expectation.

To assess whether the relative decline in scrabbling constitutes the entire mechanism of the "good news" effect of a healthy diagnosis, the first panel in Appendix Table A6 re-estimates Equation (6) but now restricts the sample only to worker-week observations with no scrabbling whatsoever. While the point estimates in the table are not as precisely estimated as for the whole sample (due to fewer worker-weeks in this analysis), the results indicate that even when restricting estimates to non-scrabbling worker-weeks, earnings are still significantly higher, implying that while task selection is an important component, it is not the full explanation for the productivity effects among malaria negative workers.

A small but growing literature explores the potential effect of health information on behavior (see Madejewicz et al. (2007), Jalan & Somanathan (2008), Thornton (2008), Dupas (2011), Cohen et al. (2015), Gong (2015, Baird et al. (2014)). Typically, these studies concentrate on the effects of specific health risk revelation on health behavior such as the adoption of new medicines or risky sexual practices. There is little research to date investigating whether and how health information affects short-term work decisions like daily labor supply and effort. Furthermore, the role of health information may be especially relevant for specific diseases typically diagnosed through general symptoms, like malaria, that can therefore be easily misdiagnosed. The endemic nature of such diseases may further bias general expectations, as similar symptoms may be too quickly attributed to the disease when in fact arising from other causes (Das et al., 2013). In our study context, the local language for 'fever' and 'malaria' are referred to by the same words whereas fever may be due to other infections or diseases (D'Acremont et al., 2014).

Based on this discussion we see several possible explanations for the good news response estimated in our data. One such explanation focuses on the choice of worker effort in response to expectations of their own health. We formalize this explanation in Annex 1. Here we summarize the main intuition. The starting point is that workers deliver effort based in part on expectations for their own health, which may at least partly diverge from their actual physical health. Especially in endemic settings where information is poor, malaria negative workers can underestimate their own health as malaria is believed prevalent and self-diagnosis is based on general symptoms leaving ample opportunity for misdiagnosis. The good news of a malaria negative diagnosis will thus affect worker expectations of current and future productivity that can in turn lead to higher labor supply, higher productivity, and possibly differential task choice.

If workers select their daily labor supply and effort level based in part on their health perceptions, inaccurate information will lead to suboptimal labor choices. New information about one's health may then lead to health belief updating and possibly revised labor supply and effort. If workers underestimate their own health because of a lack of trusted and individual specific information in a generally endemic environment, they may increase their effort levels and labor supply once their true (improved) health status has been revealed. Alternative models of task selection and labor response to health information, such as those with an explicitly dynamic setting, may also be consistent with these empirical findings. Unfortunately, the relatively short time period does not allow us to disentangle predictions from such alternative dynamic models.

D. Potential threats to the validity of impact estimates

Potential threats to the validity of ITT estimates

As discussed in Section II, we chose as a study design the randomized staggered adoption of treatment. Athey and Imbens (2018) characterize this estimator and the various assumptions necessary for identification. Foremost among the assumptions is an absence of anticipation effects. We now explore and discuss various forms of possible worker anticipation concerns.

One concern is whether workers interviewed and tested later in the study are differentially affected by the *announcement* of the malaria testing and treatment at the start of the program. In principle, notification of the program may raise worker's health awareness and, in particular, awareness of malaria symptoms, which in turn can lead to anticipatory behavior such as increased health care seeking. If workers interviewed and tested later in the study were more likely to seek health care on their own prior to interview, the malaria positivity rate would be lower in later weeks and these workers would be healthier. The balancing tests in Table 7 Panel A evaluate the null hypothesis that the malaria positivity rate, formal and informal health seeking behavior, reports of any morbidity, and malaria self-reports increase over time and finds near uniform balance within work groups across study weeks. Of the 40 presented balance tests, only six suggest temporal imbalance at the 0.10 level – slightly higher than the number we would expect if the temporal differences are driven by chance. We note that the malaria positivity rate is balanced across study weeks and groups with the exception of group 8. Additional descriptive statistics for the sample indicate only 1% of workers report seeking formal health care and 2% sought out informal health care over the six-week study period.[28] The results largely rule out the concern of a care-seeking response to program announcement. The null hypothesis of balance over time with respect to formal health care seeking behavior of workers cannot be rejected for any work group. The null hypothesis of balance with respect to informal health care seeking behavior is rejected in only one work group. Malaria/fever self-reports and reports of other illness are imbalanced within three work groups in total across study weeks. A sensitivity analysis, that estimates program effects when sequentially

[28] Workers may not necessarily leave malaria untreated. They may self-treat by purchasing medication in the market or making use of traditional medicine. Formal care and reliable testing can be expensive and is not always available. In an endemic area, adult workers have experience with malaria and may not perceive the need for formal medical advice. At the same time, knowledge about treatment may be limited. Knowledge tests administered to workers at the same plantation in a later season (with some workers overlapping across rounds) demonstrates that workers were quite well informed about symptoms of malaria, but much less about treatment.

excluding each work group, indicates that the few instances where the null hypothesis of balance over time is rejected in Table 7 Panel A do not alter the main findings.[29]

A further threat to the internal validity of the between worker estimate is the potential correlation between assigned interview date and anticipatory health seeking behavior. Even though workers were not informed when they would be interviewed and tested, as the weeks of the study increase, the expectation of the yet untreated workers to receive treatment in the near future increases, and this change in expectations may affect health related behaviors. The tests in Table 7 Panel B investigate balance with respect to two further groups, namely workers who were selected in the first three weeks of the study relative to the last three weeks of the study, and workers selected in weeks 1 and 2, compared to those selected in weeks 3 and 4, and those selected in weeks 5 and 6. Testing equality across the three periods, we find no systematic temporal variation in the probability a worker is malaria positive, any reports of illness or fever, or any health care seeking either in the public health system or through informal care or self-treatment such as procurement of malarial medications in the market. We conclude that the intervention did not differentially affect the health-related behavior of workers treated early or late in the study period.

Another possible concern is that workers whose labor outcomes are observed for the study interval, but who are not yet assessed for malaria, may adjust work effort in anticipation of a subsequent test. This anticipatory effect, should it arise, would affect the labor outcomes of the control group. To explore this possibility, we estimate a placebo test using lags of treatment on worker labor supply and productivity. The lagged treatment placebo tests utilize the within worker estimator with daily data to explore the presence or absence of placebo "treatment effects" at points in time other than the actual date of the start of treatment. The absence of any estimated placebo impact would lend further confidence that the actual impact estimates identify a real behavioral response to treatment. Table 8 reports the results from these tests using 3 alternative placebo dates: 7, 14, and 21 days before the actual date of treatment, and then compares the average daily outcomes in a symmetric range of days before and after the placebo interview date. A comparison of the full placebo estimates with the impact estimates suggest that the changes in labor outcomes are indeed a response to the malaria testing and offered treatment rather than

[29] The temporally randomized results were re-estimated omitting each of the eight work groups in turn to assess sensitivity. Specifically, two-week intent to treat impacts on earnings, labor supply, productivity and ratio of days scrabbling were estimated eight times over, with each iteration leaving out one of the eight work groups. None of these estimates are significantly different from the main results reported in the paper. In another check the results were re-estimated by omitting each of the study weeks in turn to assess the two-week intent to treat impact. In only three out of the 24 tests (the ITT, TOT, and TmUT were estimated for 4 outcomes – earnings, labor supply, daily productivity, and task choice) the statistical significance of the result drops below the standard 10% p-value, though the coefficients remain similar to the reported estimates.

attributable to some other factor such as anticipatory behavior. The majority of placebo tests yield imprecise placebo impact estimates that are low in magnitude. Only 1 of 6 labor supply estimates and 2 of 6 daily productivity estimates are precisely estimated. In these cases the placebo estimate is lower than the equivalent actual estimate and one estimate is negative. We conclude there is little evidence to suggest that workers altered labor outcomes in anticipation of treatment.

Another type of treatment spillover that can bias the impact estimate arises if the intervention itself leads to epidemiological changes in the disease environment. It is theoretically possible that the intervention reduces parasite prevalence in any comparison group as a result of successful parasite elimination in the treatment group. While a valid concern in theory, the majority of malaria transmission occurs in the evening and night hours when the workers are off the plantation in geographically dispersed home villages and presumably exposed to a much larger parasite reservoir in the local population. As shown in Table 7 Panel A and B, the measured malaria positivity rate shows no decline over the weeks of study in 7 out of 8 groups, indicating little evidence for disease transmission spillovers.

Finally, on the behavioral side, we need to consider whether the treatment of a random subset of workers induces a peer response in the workers yet to be treated. Mas and Moretti (2009) identify peer effects under a particular setting where the low productivity of peers in salaried supermarket work induced customers to shift to a quicker clerk. Our study setting is less likely to produce these types of effects as, given the piece rate wage offer and fixed daily work schedule, a fall in productivity by a particular worker does not affect the effort required of other workers or the number of hours they can work. Bandiera et al. (2010) also identify peer-effects, this time for the more similar piece rate wage environment of seasonal fruit pickers. They find that the presence of social peer networks equalizes individual output with more productive workers exerting less effort and less productive workers exerting more effort when working alongside peers. If this peer effect is present in our setting, it would serve to bias downward any estimate of malaria impact as the temporal order of treatment is random with respect to pre-existing social networks. That we still identify any impact underscores the robustness of our main results.[30]

[30] The group size in our study setting is large (typically around 100 workers per group) and the number of groups is unfortunately small (8). There was no scope for the design to alter group composition or size to investigate possible peer effects. In previous research that identifies peer effects, the composition of the peer group is smaller and workers directly observe the productivity of their peers. In our setting, workers are each assigned a row of sugarcane to cut to start with, and then another row once this is finished. 100 workers across a large sugarcane field makes it difficult for workers to observe the productivity of their peers. Further, we control for group effects in the weekly analysis in part to account for unobservable differences in peer networks across groups. The setting also does not allow the study of general equilibrium effects such as a possible shift in the relative wage between scrabbling and

<u>*Additional potential threats to the validity of TOT and TmUT estimates*</u>

To identify the TOT and TmUT effects an additional necessary assumption is that a worker's health state does not change over the concerned time interval. In case of the TOT estimates in the between worker approach, described in equation (5), the key assumption required for the counterfactual is that malaria positive workers who tested positive in a later study week were also malaria positive just before, during the study interval τ. The within worker TOT specification requires a similar but distinct assumption, namely that the worker himself was malaria positive in the days considered in the reference period previous to their testing date. Since the malaria status of workers is only assessed at one point in time, unfortunately the health status stability assumption cannot be directly verified with our data. However, it is defensible when we consider the biology of malaria infection. An outbreak of malaria lasts an average of 14-17 days with parasite loads maximizing in the blood one to three days before emergence of symptoms (White (2005), Sowunmi et al. (2007), and Woodring et al. (2010)). Because of these particular dynamics of illness, the one- and two-week reference periods are likely to contrast malaria positive treated workers with workers who are also malaria positive. Even for the three-week reference period, a large proportion of workers who subsequently test positive are expected to be positive during the observation period.

In additional results in the appendix, we also test the robustness of the stability of infection assumption by comparing impacts between workers who are likely to be suffering more severely versus less severely from malaria as proxied by the measured parasite count in the blood. If the estimated TOT effect does capture the labor gains from treating malaria, then workers with more severe cases should respond more strongly to treatment. We investigate this in Appendix Table A5 by disaggregating the TOT response for two groups: those with a parasite count of 3 and those with a parasite count of 4 or more.[31] While the difference in point estimates for the two groups are not precisely estimated (as we have split an already small sample), the results are suggestive. Both the earnings and labor supply response are far larger in magnitude for those workers with more severe malaria (and indeed are only significantly different from zero for that group). For those with a parasite count of 4 or more, the three-week gain in earnings is estimated to be 18.4%, almost entirely arising through a labor supply response (15.4%). This differential pattern by disease intensity is consistent with the conjecture that the main TOT estimate captures the results of malaria treatment rather than confounding from an invalid counterfactual group. It

---

cane-cutting if the demand for cane-cutting simultaneously increases in the entire labor force. This is because the relative wage between scrabbling and cane-cutting was fixed for the study period.

[31] In an alternative specification, we allow parasite count to be a continuous variable and interact it with the treatment effect; this approach gives similar results.

also further supports the finding that much of the gain from malaria treatment manifests through increased labor supply and not increases in productivity while at work.

The TmUT estimations in equation (3) and (6) rely on a similar health assumption. The estimates obtained from the between worker specifications require that those tested negative in later study weeks are also negative over the reference period. The within worker specification relies on the assumption that the worker was malaria negative in the reference period before their testing date. We believe these assumptions to be largely valid for the same reason as mentioned above – the dynamics of malaria illness. Nevertheless, the robustness of this assumption is explored in several ways through complementary analysis presented in the appendices.

The first analytic extension restricts the analysis to the subset of malaria negative workers who also report no symptoms of any illness in the previous four weeks. Even though self-reports are an imperfect measure of health, as shown earlier specifically with respect to malaria self-reported morbidity, these estimates may be informative. We find that the earnings impact among the restricted sample of workers who report no morbidity of any kind, are virtually the same as in the full sample (Appendix Table A6, panel B). This suggests that, to the best that we can investigate with self-reported information, the misattribution of sick workers to a healthy comparison group does not appear to confound the estimated earnings gains to diagnosed malaria negative workers.

Further, if there is a behavioral response to the 'good news' of a healthy diagnosis, we expect it to be more pronounced among those workers who find this news more surprising and hence revise expectations of physical work capacity, in line with the proposed theoretical framework discussed above and detailed in Annex 1. We investigate in Appendix Table A7, possible differential response to treatment across factors likely to affect health expectations, namely the parasite load (as malaria negative workers can still have sub-clinical levels of parasites in the blood and may suffer from malaria related sub-clinical symptoms) and whether the worker reports fatigue at the end of the workday. Both the between and within results (reported in Table A7 Panel A and B respectively) support the idea that good health news leads to increased daily worker productivity: malaria negative workers with parasites (but below the diagnostic threshold) exhibit a significant daily earnings response yet those with no parasites do not. Similarly, those who report fatigue at the end of the day respond with increased daily worker productivity after being told they are malaria negative – in contrast to those who report no fatigue.[32]

[32] In general, the sub-group analysis does not yield group specific coefficients significantly different from each other, at least partially due to the smaller number of workers per sub-group. Nevertheless the relative magnitude and

Taken all together, these results provide further evidence of a treatment response in labor outcomes for the malaria positives, who are treated and tested, in terms of increases in labor supply, and for the malaria negatives, who receive ‘good news’, in terms of increases in daily productivity and switching into higher earning tasks. They underline the relevance of both medical treatment and health information for the labor response decisions of workers in this context.

VI. CONCLUSIONS

While adult health is believed an important determinant of labor supply and productivity, especially in agrarian settings, few studies have been able to causally identify such a relation. We estimate the labor response of malaria infection among a population of sugarcane workers through the phased-in randomized introduction of a mobile health clinic in this piece rate wage setting. The results, concordantly estimated by two complementary empirical approaches, indicate that there are earnings and labor supply gains on the order of 10% in the weeks following treatment for malaria.[33] In the relatively high wage environment of the Nigerian sugarcane plantation that we consider, these estimated productivity costs likely exceed the private costs for malaria diagnosis and treatment, as illustrated below. It is important to note that our results only represent estimates of gains from treatment and information over a two- to four-week reference period – the gains from malaria treatment may well extend beyond our reference period.

Our study also finds that treatment of diagnosed illness is not the only cause of gains in earnings. Revised expectations about one’s own health appears to be another factor, at least among workers given a malaria-free diagnosis. Workers who were informed of a healthy diagnosis increased their productivity after receipt of health information, in part due to shifting out of a lower-return fixed wage task and into the piece rate work of cane cutters where greater effort is required for higher average returns. In endemic situations, it is quite possible that there are real returns to health information, especially if the information is received as a surprise. Workers who were most responsive to the healthy diagnosis did indeed have some parasite presence in their blood, but at sub-clinical levels; they were also more likely to report that

precision of the estimated coefficients are consistent with the channel of revised expectations driving changes in labor behavior among workers who received a healthy diagnosis.

[33] These estimates are of a similar order of magnitude as those observed by Fink and Masiye (2015) who find increases in average farm output value of 14.7% associated with the randomized introduction of preventive bed nets, among small scale cotton farmers in Zambia over a six-month period. The authors attribute these observed improvements in productivity mostly to changes in labor supply. The study collected limited information on production inputs but estimates that labor supply increased on average 3.6 days due to treatment, with large variation across farmers. About 60% of this effect seems to stem from reduced absence from work because of the farmer’s own improved health and about 40% seems to come from less time spent on taking care of other ill household members.

they felt tired at the end of the workday. These correlations suggest that unanticipated good news – resulting in a change in expectations of earnings potential – are a key mechanism to worker's labor response to malaria testing.[34] Although previous work has documented behavioral responses to surprise health information, these findings are largely confined to longer-run health outcomes that area a function of risky behaviors such as unprotected sex. To our knowledge, no previous study has investigated the effect of health information on participants' subjective health beliefs and consequent changes in day-to-day work behavior. As a result, the existent literature on health and productivity may undervalue the effect of positive health information on worker effort and income.

Turning to the specific context of malaria, the WHO estimates that Nigeria alone accounts for over 30% of worldwide malaria cases (WHO 2012). Because the agricultural sector has the highest poverty rate (62.7%) of any occupational group in Nigeria (NLSS 2003/4), increasing agricultural productivity is a key component of Nigeria's poverty reduction strategy. However, areas that have high potential for agricultural growth because of their favorable agro-ecological conditions (i.e. good rainfall, proximity to rivers or lakes) or previous agricultural investments (i.e. irrigation) are also likely to be breeding areas for mosquitoes that pass on malaria.[35] The positive correlation between the agro-ecological environment of those areas with high growth potential and malarial breeding may diminish the gains from increased agricultural productivity either directly through an elevated infection rate or indirectly through raised perceptions of widespread ill health.

Previous work that attempted to monetize the cost of adult ill health due to malaria looked solely at the impacts on the malaria infected and their caretakers. If we apply this strategy to our results and ascribe the labor benefit solely to the treatment of disease among malaria positive workers, we would estimate the labor supply and productivity gains from treating malaria to be 37% of earnings over a 3-week period, or approximately US$ 37, split roughly equally between gains arising from increases in labor supply and daily productivity. [36] This estimate is far higher than most existing findings (see Sauerborn et al. (1991), Shephard et al. (1991), Ettling et al. (1994); Guiguemde et al. (1994), Attanyake et al. (2000), Chima et al. (2003), Akazilli et al. (2008), Ayieko et al. (2009), or Fink and Masiye (2015)).

[34] Two additional channels through which the good news effect translates to higher earnings could be failing self-discipline as considered in a dual self model as in Thaler and Sherfin (1981) or gift exchange motives as set out by Akerlof (1982). We discuss both in the Theoretical framework in Appendix A.1.

[35] For example, Harb et al. (1993) and Thompson et al. (1996) observed an increase in the mosquito population with the use of irrigation in the Nile Delta. Ghebreyesus et al. (1999) observed a seven-fold increase in the incidence of malaria with the use of microdams and irrigation in a region in Ethiopia.

[36] The Wald estimator is calculated as the between worker estimate of the ITT for the three week reference period (0.134) divided by the incidence of malaria: 0.134/0.36= 0.37. Valued at average daily earnings and average days worked, this gives 37 USD per three week period (0.37*6.72 USD/day*4.9 days per week*3 weeks=37 USD).

In part this value is higher because our estimate also includes productivity effects conditional on working, which are often absent in other studies. However, this ‘naïve’ estimate overlooks potential gains from a worker behavioral response to the testing information itself. As the intervention is a combination of health information and pharmacologic treatment for the sick, the ITT estimates cannot distinguish between these two channels of possible impact and it would be in error to load the benefit from treatment solely on the malaria positives. Our study results confirm that there is an earnings effect of testing and treatment for workers who tested positive and a ‘good news effect’ for workers who tested negative that result from two different responses, a large labor supply response for malaria positive workers and a large increase in productivity for workers who were malaria negative.

How do these worker-level economic impacts compare to the costs of the intervention? Using the 3-week between worker estimate as a benchmark, treatment increases earnings by 13.4% over the reference period.[37] This gain translates into 1,986 Naira, or approximately 13.2 USD when evaluated at daily average earnings across the workforce. Turning to the cost side, the pharmaceutical expense of one treatment with ACT in our rural setting was 7 USD at the time of implementation. The total costs of the testing program include the wage of health workers, which amounts to 30 USD per day to test approximately 20 workers, and the total additional cost of testing (i.e. lancets, slides, rubber gloves, slide transport, laboratory staff), which comes to 6 USD per worker based on the study’s accounts. For a worker population of 800 workers in season with a 36% positivity rate, the benefit-cost ratio is 1.3.[38] These are only the monetized gain over three weeks – gains may well extend beyond that period, but we are unable to observe them. There may also be positive spillovers to the household in terms of reduced disease transmission. Prices of ACT have fallen since the field work implementation, which would further increase the benefit-cost ratio. For example, Palafox et al. (2016) report median ACT prices in Nigeria as 4 USD from a recent national survey.

We also estimate net program benefits for the employer, stemming from a reduction in production costs due to a smaller and more reliable workforce, requiring less materials and management, as well as an increase in aggregate productivity. Appendix A.2 provides details of this estimation. It appears likely, in our study setting, that the value to the firm of a workplace-based malaria testing and treatment program exceeds the cost.

[37] The three-week reference period is the preferred reference period as ACT clears the blood from parasites within 7 days and provides protective effects between two and four weeks after treatment (White 2005).

[38] With average benefit per worker of 13.2 USD and average cost per worker of 7 USD*0.36+1.5 USD+6USD=10.02 USD, this gives a cost benefit ratio of 1.32.

From a national health policy perspective, our empirical results expand the beneficiary base beyond the subset of workers who suffer malaria infection. While the earnings loss among the sick is substantial, the results imply that the full costs of malaria to the economy are not only among the confirmed infected. Workers living in endemic areas, particularly those in physical occupations, may reserve work effort and select lower return tasks under uncertainty surrounding their health status. These results are broadly consistent with the wider economic development literature that investigates how constrained individuals manage risk, i.e. the risk averse poor select low return investments that in turn perpetuate poverty (for example, Zimmerman and Carter (2003) and Lybbert et al. (2004) among others). In our case, workers in endemic areas with uncertain information about their own health and, perhaps, expectations of poor health, can remain trapped in a low-level equilibrium via occupation choice (see Banerjee and Newman (1993) for an early discussion). Future research that implements comprehensive testing, not only of symptomatic but also of asymptomatic individuals, may yield further gains in understanding the productivity costs of ill health in a low information environment.

REFERENCES

Akazili, J., Aikins, M., & Binka, F. N. (2008). Malaria treatment in Northern Ghana: What is the treatment cost per case to households? *African Journal of Health Sciences, 14*(1): 70-79.

Akerlof, G. A. 1982. "Labor contracts as partial gift exchange." *The Quarterly Journal of Economics*, *97*(4): 543-569.

Athey, S. and Imbens, G. 2018. "*Design-based Analysis in Difference-In-Differences Settings with Staggered Adoption*" NBER working paper (24963). http://www.nber.org/papers/w24963.

Audibert, M., and Etard, J.F. 1998. "Impact of schistosomiasis on rice output and farm inputs in Mali." *Journal of African Economies,* 7(2):185-207.

Baldwin, R. E. and Weisbrod, B. A. 1974. "Disease and Labor Productivity." *Economic Development and Cultural Change,* 22(3): 414-435.

Baird, S., Gong, E., McIntosh, C., and Ozler, B. 2014. "The heterogeneous effects of HIV testing". *Journal of Health Economics*, 37(1): 98-112.

Banerjee, A. V. and Newman, A. F. 1993. "Occupational Choice and the Process of Development," *Journal of Political Economy,* 101(2): 274-98.

Bandiera, O, Barankay, I., and Rasul, I. 2010. "Social Incentives in the Workplace". *Review of Economic Studies*, 77(2): 417-458.

Bottius, E., Guanzirolli, A., Trape, J. F., Rogier, C., Konate, L., and Druilhe, P. 1996. "Malaria: Even more Chronic in Nature than Previously Thought; Evidence for Subpatent Parasitaemia Detectable by the Polymerase Chain Reaction." *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 90(1): 15-19.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414-427.

Cohen, J., Dupas, P., and Schaner, S. G. 2015. "Price Subsidies, Diagnostic Tests and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial" *American Economic Review*, Vol 105, 2, p 609-645.

Chima, R. I., Goodman, C. A. and Mills, A. 2003. "The Economic Impact of Malaria in Africa: A Critical View of the Evidence". *Health Policy and Planning* 63:17–36.

D'Acremont, V., Kilowoko, M., Kyungu, E., Philipina, S., Sangu, W., Kahama-Maro, J., Lengeler, C., Cherpillod, P., Kaiser, L. and Genton, B. 2014. "Beyond Malaria: Etiologies of Fever in Tanzanian Children Attending Outpatient Clinics." *New England Journal of Medicine*. forthcoming.

dalla Martha RC, Tada MS, Ferreira RG, da Silva LH, Wunderlich G. 2007. "Microsatellite characterization of Plasmodium falciparum from symptomatic and non-symptomatic infections from the Western Amazon reveals the existence of non-symptomatic infection-associated genotypes. *Memórias do Instituto Oswaldo Cruz* 102:293-298.

Das, A., Das Gupta, R. K., Friedman, J., Pradhan, M. M., Mohapatra, C. C., & Sandhibigraha, D. (2013). “Community perceptions on malaria and care-seeking practices in endemic Indian settings: policy implications for the malaria control programme” *Malaria Journal*, *12*(39): 10-1186.

Deressa, T. 2007. “Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian approach”. World Bank Policy Research Paper No. 4342. Washington D.C.: World Bank.

Dupas, P. 2011. “Health Behavior in Developing Countries.” *Annual Review of Economics*., 3(1), 425-449.

Dupas, P. 2011. “Do Teenagers Respond to HIV Risk Information? Evidence from a Field Experiment in Kenya.” *American Economic Journal: Applied Economics* 3: 1-34.

Edgerton, V. R., Gardner, G. W., Ohira, Y., Gunawardena, K. A., and Senewiratne, B. 1979. “Iron-deficiency Anaemia and its Effect on Worker Productivity and Activity Patterns.” *British Medical Journal*, *2*(6204), 1546.

Ettling, M., Mcfarland, D.A., Schulz, L.J. and Chitsulo, L.. 1994. “Economic impact of Malaria in Malawian Households.” *Tropical Medical and Parasitology*. 45. Supplement 1. 74-79.

Fink, G. and F. Masiye. 2015. “Health and Agricultural Productivity: Evidence from Zambia”, Journal of Health Economics, Vol 42, July 2015, P 151-164.

Fogel R.W. “New Findings on Secular Trends in Nutrition and Mortality: Some Implications for Population Theory.” In: Rosenzweig M. R. and Stark O., eds. *Handbook of Population and Family Economics*, Vol 1A. Amsterdam, Elsevier, 433–481. 1993

Fox, M., Rosen, S., MacLeod, W., Wasunna, M. , Bii, M., Fogliam, G. and Simon, G. 2004. “The Impact of HIV/AIDS on Labor Productivity in Kenya.” *Tropical Medicine and International Health* 9 (3): 318-324.

Ghebreyesus, T. A., Haile, M., Witten, K. H., Getachew, A., Yohannes, Ambachew M., Yohannes, M., Teklehaimanot, H. D., Lindsay, S. W. and Byass, P. 1999. "Incidence of Malaria among Children Living near Dams in Northern Ethiopia: Community based Incidence Survey." *British Medical Journal* 319 (7211): 663-666.

Gong, E. 2015. “HIV Testing and Risky Sexual Behavior.” *The Economic Journal*, Vol 125, Issue 582, p 32-60.

Guiguemde, T., 1994. “Household Expenditure on Malaria Prevention and Treatment for Families in The Town Of Bobo-Dioulasso, Burkina Faso.” *Transactions of the Royal Society of Tropical Medicine and Hygiene* 88(3), 285–292.

Habyarimana, J., Mbakile, B. and Pop-Eleches, C. 2010. “The Impact of HIV/AIDS and ARV Treatment on Worker Absenteeism: Implications for African Firms.” *Journal of Human Resources* 45(4): 809–839.

Harb, M., Faris, R., Gad, A. M., Hafez, O. N., Ramzy, R., and Buck, A. A. 1993. “The Resurgence of Lymphatic Filariasis in the Nile Delta.” *Bulletin of the World Health Organization*, 71(1), 49.

Kremer, M. and Miguel, E. 2004. “Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities.” *Econometrica*, 72(1), 159-217.

Jalan, J., and Somanathan, E. 2008. “The Importance of Being Informed: Experimental Evidence on Demand for Environmental Quality.” *Journal of Development Economics*, 87(1), 14-28.

Laishram, D. D., Sutton, P. L., Nanda, N., Sharma, V. L., Sobti, R. C., Carlton, J. M., and Joshi, H. (2012). “The Complexities of Malaria Disease Manifestations with a Focus on Asymptomatic Malaria.” *Malaria Journal*, 11(1): 29.

Lybbert, T. J., Barrett, C. B., Desta, S., and Coppock, D. L. 2004. Stochastic Wealth Dynamics and Risk Management among a Poor Population, *The Economic Journal* 114 (October): 750-777.

Mas, A. and Moretti, E. 2009. “Peers at Work” *American Economic Review* 99 (1), 112-145.

Miller, L. H., Baruch, D. I., Marsh, K., and Doumbo, O. K. (2002). “The Pathogenic Basis of Malaria.” *Nature*, 415(6872), 673-679.

Palafox B, Patouillard E, Tougher S, et al. Prices and mark-ups on antimalarials: evidence from nationally representative studies in six malaria-endemic countries. *Health Policy and Planning*. 2016;31(2):148-160.

Rottmann, M., Lavstsen, T., Mugasa, J. P., Kaestli, M., Jensen, A. T. R., Müller, D., Theander, T. and Beck, H-P. 2006. "Differential expression of var gene groups is associated with morbidity caused by Plasmodium falciparum infection in Tanzanian children." *Infection and immunity* 74 (7): 3904-3911.

Sauerborn, R., D. S. Shepard, M. B. Ettling, U. Brinkmann, A. Nougtara, and Diesfeld, H. J.. 1991. "Estimating The Direct and Indirect Economic Costs of Malaria in a Rural District Of Burkina Faso." *Tropical Medicine And Parasitology,* 42(3): 219-223.

Schultz, T. P. and Tansel, A. 1997. “Wage and Labor Supply Effects of Illness in Côte d’Ivoire and Ghana: Instrumental Variable. *Journal of Development Economics* 54: 251–286.

Schultz, T.P. 2002. "Wage Gains Associated with Height as a Form of Health Human Capital," *American Economic Review,* American Economic Association, 92(2), 349-353.

Shepard, D. S., Ettling, M. B., Brinkmann, U. and Sauerborn, R. 1991. "The Economic Cost of Malaria in Africa." *Tropical Medicine and Parasitology,* 42 (3): 199. Some, E. S. 1992. "The Pattern of Morbidity and its Effects on Productivity of Factory Workers in Kenya." *East African Medical Journal* 69(11): 622-6.

Sowunmi, A., Gbotosho, G. et al, 2007. Therapeutic Efficacy and Effects of Artemether-Lumefantrine and Amodiaquine-Sulfalene-Pyrimethamine on Gametocyte Carriage in Children with Uncomplicated *Plasmodium falciparum* Malaria in Southwestern Nigeria. *American Journal of Tropical Medicine and Hygiene* 77: 235-241.

Strauss, J. and Thomas, D. 1998. “Health, Nutrition, and Economic Development.” *Journal of Economic Literature*, 36 (2):766-817

Thaler, R. and Shefrin, H. 1981. "An Economic Theory of Self-Control," *Journal of Political Economy* 89(2): 392-406.

Thirumurthy, H., Graff -Zivin, J. and Goldstein, M. 2008. "The Economic Impact of AIDS Treatment: Labor Supply in Western Kenya," *Journal of Human Resources,* 43(3), 511-552.

Thomas, D., Frankenberg, E., Friedman, J., Habicht, J. P., Ingwersen, N., Jaswadi, N. Jones, McKelvey, C., Pelto, G., Sikoki, B., Seeman, T., Smith, J., Sumantari, C., Suriastini, W. and Wilopo, S. 2006. “Causal Effect of Health on Labor Market Outcomes: Experimental Evidence," Mimeo.

Thompson, D. F., Malone, J. B., Harb, M., Faris, R., Huh, O. K., Buck, A. A., and Cline, B. L. 1996. “Bancroftian Filariasis Distribution and Diurnal Temperature Differences in the Southern Nile Delta.” *Emerging Infectious Diseases*, 2(3), 234.

Thornton, R. L. 2008. “The Demand for, and Impact of, Learning HIV Status.” *American Economic Review*, 98(5): 1829.

Toure FS, Bisseye C, Mavoungou E. 2006. Imbalanced distribution of Plasmodium falciparum EBA-175 genotypes related to clinical status in children from Bakoumba, Gabon. *Clinical Medicine and Research,* 4:7-11.

Trape, J. F., Zoulani, A., and Quinet, M. C. 1987. “Assessment of the Incidence and Prevalence of Clinical Malaria in Semi-immune Children Exposed to Intense and Perennial Transmission.” *American Journal of Epidemiology*, 126(2), 193-201.

White, N.J. 2005. “Intermittent Presumptive Treatment for Malaria”. PLoS Medicine 2: 1-63.

WHO. 2010, *Guidelines for the Treatment of Malaria (2e).* 2nd Edition. Geneva: World Health Organisation.

WHO. 2012. *World Malaria Report 2012.* Geneva: World Health Organisation.

Woodring, J. V., Ogutu, B. Schnabel, D., Waitumbi, J. N., Olsen, C. H., Walsh, D. S., Heppner Jr, D. G. and Polhemus, M. E.. 2010. Evaluation of Recurrent Parasitemia after Artemether-Lumefantrine Treatment for Uncomplicated Malaria in Children in Western Kenya. *American Journal of Tropical Medicine and Hygiene* 83: 458-464.

Zimmerman, F.J. and Carter, M.R. 2003. “Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints.” *Journal of Development Economics* 71: 233– 260.

Table 1: Within work-group balance of worker characteristics across week of treatment

Work group	Number of Workers	Age	Years of experience in cane cutting	Years of schooling	BMI	Household size	Num. rooms in house	Number of cattle	Number of poultry	Imputed monthly PC Expenditures
1	98	0.379	0.921	0.658	0.558	0.809	0.408	0.724	0.906	0.979
		[30.36]	[1.15]	[8.64]	[23.60]	[5.71]	[2.62]	[0.88]	[6.77]	[12980.53]
2	95	0.395	0.122	0.61	0.293	0.573	0.608	0.783	0.238	0.917
		[29.537]	[1.200]	[9.063]	[24.054]	[5.063]	[2.989]	[1.768]	[9.589]	[13202.090]
3	111	0.905	0.535	0.564	0.956	0.356	0.735	0.473	0.544	0.725
		[31.473]	[1.042]	[7.250]	[23.565]	[6.277]	[3.036]	[1.071]	[7.196]	[12408.406]
4	110	0.053	0.931	0.283	0.088	0.519	0.842	0.943	0.607	0.673
		[28.464]	[1.214]	[8.391]	[23.960]	[3.955]	[2.536]	[1.955]	[7.200]	[12006.972]
5	107	0.683	0.611	0.937	0.371	0.879	0.031	0.628	0.105	0.56
		[29.280]	[1.188]	[9.318]	[23.737]	[4.907]	[2.991]	[1.280]	[6.972]	[12662.625]
6	103	0.708	0.031	0.87	0.481	0.775	0.24	0.865	0.498	0.886
		[30.243]	[1.133]	[8.078]	[23.829]	[6.320]	[2.592]	[0.728]	[8.019]	[11550.639]
7	99	0.536	0.183	0.071	0.013	0.797	0.699	0.095	0.637	0.593
		[30.929]	[1.072]	[7.071]	[23.258]	[5.616]	[3.091]	[0.909]	[6.879]	[13669.150]
8	91	0.537	0.466	0.755	0.187	0.116	0.311	0.627	0.663	0.545
		[29.359]	[1.145]	[8.022]	[23.952]	[5.011]	[2.402]	[1.543]	[6.728]	[11962.626]

The reported p-values results from an F-test that tests the equality of coefficients across the survey weeks in a regression of each of the individual characteristics on week indicator for each work group. The mean for each group is reported in brackets. Two workers were dropped from the balancing tests as their complete set of observables was not completed when merged with the administrative earnings data.

Table 2. P-values and means for balancing tests, by malaria status sub-group

Panel A: **Restricted sample of malaria positive workers, for treatment on treated analysis**

Work group	Number of Workers	Age	Years of experience in cane cutting	Years of schooling	BMI	Household size	Num. rooms in house	Number of cattle	Number of poultry	Imputed monthly PC Expenditures
1	35	0.466	0.57	0.512	0.017	0.697	0.308	0.983	0.651	0.308
		[29.80]	[1.03]	[9.43]	[23.79]	[5.89]	[2.26]	[0.97]	[7.14]	[14015.64]
2	33	0.165	0.417	0.475	0.039	0.621	0.737	0.725	0.532	0.584
		[28.79]	[1.17]	[8.70]	[24.22]	[4.18]	[3.48]	[1.97]	[11.82]	[14032.92]
3	42	0.605	0.947	0.947	0.497	0.97	0.85	0.987	0.767	0.914
		[31.76]	[0.90]	[7.67]	[23.45]	[5.93]	[2.95]	[1.00]	[7.71]	[12379.67]
4	41	0.454	0.899	0.596	0.786	0.235	0.187	0.023	0.321	0.484
		[28.24]	[1.40]	[8.59]	[23.89]	[3.41]	[2.51]	[1.76]	[6.63]	[12714.36]
5	31	0.912	0.154	0.886	0.783	0.472	0.212	0.226	0.515	0.15
		[29.74]	[1.34]	[8.97]	[23.62]	[4.45]	[3.00]	[1.13]	[7.48]	[12779.72]
6	39	0.198	0.304	0.562	0.356	0.839	0.52	0.639	0.326	0.891
		[30.26]	[1.28]	[8.28]	[23.76]	[5.62]	[2.82]	[0.74]	[7.85]	[11445.38]
7	42	0.44	0.236	0.231	0.16	0.805	0.689	0.935	0.791	0.226
		[29.80]	[1.03]	[9.43]	[23.79]	[5.89]	[2.26]	[0.97]	[7.14]	[14015.64]
8	30	0.996	0.448	0.226	0.894	0.264	0.825	0.195	0.599	0.817
		[30.45]	[1.00]	[7.57]	[23.11]	[5.50]	[2.74]	[0.81]	[6.81]	[12879.51]

The reported p-values results from an F-test that tests the equality of coefficients across the survey weeks in a regression of each of the individual characteristics on week indicator for each work group. The mean for each group is reported in brackets.

Panel B: **Restricted sample of malaria negative workers, for treatment on malaria untreated analysis**

Work group	Number of Workers	Age	Years of experience in cane cutting	Years of schooling	BMI	Household size	Num. rooms in house	Number of cattle	Number of poultry	Imputed monthly PC Expenditures
1	63	0.268	0.307	0.95	0.31	0.926	0.489	0.583	0.907	0.689
		[30.67]	[1.22]	[8.21]	[23.49]	[5.62]	[2.83]	[0.83]	[6.56]	[12405.47]
2	62	0.598	0.285	0.936	0.103	0.575	0.352	0.658	0.02	0.927
		[29.94]	[1.22]	[9.26]	[23.97]	[5.53]	[2.73]	[1.66]	[8.40]	[12759.88]
3	69	0.48	0.171	0.606	0.746	0.374	0.654	0.376	0.84	0.592
		[31.30]	[1.13]	[7.00]	[23.63]	[6.49]	[3.09]	[1.11]	[6.89]	[12425.65]
4	69	0.02	0.968	0.321	0.069	0.444	0.373	0.93	0.619	0.777
		[28.59]	[1.11]	[8.28]	[24.00]	[4.28]	[2.55]	[2.07]	[7.54]	[11586.64]
5	76	0.75	0.946	0.85	0.267	0.932	0.134	0.845	0.243	0.78
		[29.09]	[1.13]	[9.46]	[23.78]	[5.09]	[2.99]	[1.34]	[6.76]	[12614.86]
6	64	0.719	0.053	0.997	0.245	0.825	0.04	0.759	0.646	0.961
		[30.23]	[1.04]	[7.95]	[23.87]	[6.75]	[2.45]	[0.72]	[8.13]	[11614.78]
7	57	0.462	0.378	0.217	0.541	0.936	0.717	0.008	0.393	0.441
		[31.28]	[1.13]	[6.70]	[23.37]	[5.70]	[3.35]	[0.98]	[6.93]	[14250.99]
8	61	0.201	0.391	0.594	0.158	0.078	0.218	0.807	0.429	0.592
		[29.53]	[1.16]	[7.92]	[24.06]	[5.08]	[2.42]	[1.94]	[5.61]	[11713.52]

The reported p-values results from an F-test that tests the equality of coefficients across the survey weeks in a regression of each of the individual characteristics on week indicator for each work group. The mean for each group is reported in brackets.

Table 3. Distribution of malaria parasite count as determined by microscopy

	Parasite count	# of workers	Percentage of total workers
Malaria negative rate = 64.1%	0	73	8.95
	1	187	22.92
	2	263	32.23
Malaria positive rate = 35.9%	3	167	20.47
	4	86	10.54
	5+	40	4.9

816 workers assessed. Parasite count refers to the total number of parasites observed in 5 randomly selected fields situated in the blood smear slide.

Table 4. Intent to treat (ITT) estimates

	Within worker estimation using daily data			Between worker estimation using weekly data			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Daily labor supply	Daily productivity	Daily scrabbling	Weekly earnings	Weekly labor supply	Weekly average of daily productivity	Ratio of days scrabbled
One week reference	0.049***	0.031**	0.029***	0.043	0.042*	0.001	-0.001

	[0.009]	[0.013]	[0.007]	[0.033]	[0.024]	[0.022]	[0.019]
Two week reference	0.075***	0.039***	0.044***	0.108***	0.049**	0.059***	-0.148**
	[0.008]	[0.010]	[0.006]	[0.031]	[0.021]	[0.022]	[0.020]
Three week reference	0.097***	0.042***	0.058***	0.134***	0.045*	0.089***	-0.077**
	[0.008]	[0.008]	[0.006]	[0.040]	[0.027]	[0.030]	[0.030]
Four week reference	0.100***	0.046***	0.070***	0.066	0.030	0.037	-0.049
	[0.008]	[0.008]	[0.006]	[0.101]	[0.062]	[0.062]	[0.058]
Fixed Effects	Worker			Group by week			

Labor outcomes are defined as follows: Daily labor supply takes the value 1 when working; Daily productivity is Ln(daily earnings) conditional on working;

Daily scrabbling is an indicator that takes the value 1 when scrabbling, unconditional on working; Weekly earnings is Ln(unconditional earnings per day, weekly average); Weekly labor supply is Ln(number of days worked in week);Weekly average of daily productivity is Ln weekly average of daily earnings conditional on working; Ratio of days scrabbled per week is Ratio of days scrabbled to days worked per week

The estimations use robust standard errors clustered at worker level.

The within estimates have 8,200 worker-day observations for the one week reference, 15,645 worker-day observations for the two week reference, 22,537 worker-day observations for the three week reference, and 28,458 worker-day observations for the four week reference using daily labor data from the full agricultural season (15 weeks). The between estimates have 801 worker observations for the one week reference, 808 worker observations for the two week reference, 467 worker observations for the three week reference, and 157 worker observations for the four week comparison using weekly labor data from the study period (6 weeks). A few workers that were assessed drop out in the fixed effects specification. ***p<.01 **p<.05 *p<.10. Level effects are presented in Appendix Table A8.

Table 5. Treatment on treated (TOT) estimates for workers testing positive for malaria

	Within worker estimation using daily data			Between worker estimation using weekly data			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reference period	Daily labor supply	Daily productivity	Daily scrabbling	Weekly earnings	Weekly labor supply	Weekly average of daily productivity	Ratio of days scrabbled

One week reference	0.059*** [0.016]	0.007 [0.021]	0.033*** [0.012]	0.007 [0.047]	0.023 [0.037]	-0.015 [0.037]	0.029 [0.029]
Two week reference	0.086*** [0.013]	0.030* [0.016]	0.047*** [0.011]	0.091** [0.044]	0.069** [0.034]	0.022 [0.036]	-0.016 [0.031]
Three week reference	0.109*** [0.013]	0.037*** [0.013]	0.060*** [0.010]	0.112* [0.056]	0.070 [0.045]	0.042 [0.050]	-0.042 [0.049]
Four week reference	0.111***	0.043***	0.072***				
Fixed Effects	Worker			Group by week			

Labor outcomes are defined as follows: Daily labor supply takes the value 1 when working; Daily productivity is Ln(daily earnings) conditional on working; Daily scrabbling is an indicator that takes the value 1 when scrabbling, unconditional on working; Weekly earnings is Ln(unconditional earnings per day, weekly average); Weekly labor supply is Ln(number of days worked in week);Weekly average of daily productivity is Ln weekly average of daily earnings conditional on working; Ratio of days scrabbled per week is Ratio of days scrabbled to days worked per week

The estimations use robust standard errors clustered at worker level.

The within estimates have 2,984 worker-day observations for the one week reference, 5,651 worker-day observations for the two week reference, 8,098 worker-day observations for the three week reference, and 10,181 worker-day observations for the four week reference using daily labor data from the full agricultural season (15 weeks). The between estimates have 292 workers contributes to the one and two week, and 162 workers to the three week reference period using weekly labor data from the study period (6 weeks). There are not sufficient numbers of malaria positive control workers to estimate the four week reference. A few workers that were assessed drop out in the fixed effects specification. Level effects are presented in Appendix Table A.9. ***p<.01 **p<.05 *p<.10

Table 6. Treatment on the medically untreated (TmUT) estimates for workers testing negative for malaria

	Within worker estimation using daily data			Between worker estimation using weekly data			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reference period	Daily labor supply	Daily productivity	Daily scrabbling	Weekly earnings	Weekly labor supply	Weekly average of daily productivity	Ratio of days scrabbled per week
One week reference	0.044*** [0.012]	0.045*** [0.016]	0.026*** [0.008]	0.056 [0.045]	0.050 [0.032]	0.004 [0.029]	-0.017 [0.025]
Two week reference	0.069*** [0.010]	0.043*** [0.013]	0.042*** [0.007]	0.117*** [0.042]	0.043 [0.028]	0.074*** [0.028]	-0.061** [0.025]
Three week reference	0.090*** [0.010]	0.045*** [0.011]	0.056*** [0.007]	0.142*** [0.052]	0.031 [0.034]	0.112*** [0.037]	-0.093** [0.039]
Four week reference	0.094*** [0.010]	0.048*** [0.011]	0.069*** [0.007]	0.167 [0.129]	0.104 [0.077]	0.063 [0.082]	-0.041 [0.077]
Fixed Effects	Worker			Group by week			

Labor outcomes are defined as follows: Daily labor supply takes the value 1 when working; Daily productivity is Ln(daily earnings) conditional on working;

Daily scrabbling is an indicator that takes the value 1 when scrabbling, unconditional on working;Weekly earnings is Ln(unconditional earnings per day, weekly average); Weekly labor supply is Ln(number of days worked in week);Weekly average of daily productivity is Ln weekly average of daily earnings conditional on working; Ratio of days scrabbled per week is Ratio of days scrabbled to days worked per week

The estimations use robust standard errors clustered at worker level.

The within estimates have 5,216 worker-day observations for the one week reference, 9,994 worker-day observations for the two week reference, 14,439 worker-day observations for the three week reference, and 18,277 worker-day observations for the four week reference using daily labor data from the full agricultural season (15 weeks). The between estimates have 512 workers contributes to the one week reference, 516 to the two week reference, 306 to the three week, and 108 to the four week using weekly labor data from the study period (6 weeks). Level effects are presented in Appendix Table A.10. ***p<.01 **p<.05 *p<.10

Table 7: Balance of worker health and health seeking behavior over time

Panel A: **Within work-group balance of worker health and health behaviors across week of treatment**

Work group	Number of Workers	Malaria Positive	Fever Self-Report	Formal Health Care Seeking	Informal Health Care Seeking	Any self-reported morbidity	Other Illness Self-Report
1	98	0.395	0.078	.	0.953	0.456	0.739
		[0.36]	[0.09]	[0]	[0.03]	[0.06]	[0.02]
2	95	0.703	0.776	0.515	0.91	0.147	0.681
		[0.35]	[0.03]	[0.02]	[0.02]	[0.12]	[0.09]
3	111	0.647	0.758	0.233	0.571	0.234	0.857
		[0.38]	[0.05]	[0.02]	[0.01]	[0.18]	[0.09]
4	110	0.376	0.73	.	0.917	0.97	0.857
		[0.37]	[0.07]	[0]	[0.01]	[0.14]	[0.04]
5	107	0.718	0.583	0.945	0.033	0.058	0.461
		[0.29]	[0.04]	[0.01]	[0.03]	[0.10]	[0.08]
6	103	0.72	0.012	0.953	0.791	0.504	0.04
		[0.38]	[0.06]	[0.03]	[0.03]	[0.17]	[0.06]
7	99	0.466	0.578	.	0.843	0.615	0.111
		[0.42]	[0.09]	[0]	[0.02]	[0.11]	[0.03]
8	91	0.031	0.583	0.138	0.858	0.938	0.002
		[0.33]	[0.11]	[0.01]	[0.01]	[0.07]	[0.02]

The p-value results from an F-test that tests the equality of coefficients across the survey weeks in a regression of each of the health behaviors on week indicator for each work group. The mean for each group is reported in brackets. All health variables reported in Panel A concern symptoms or health seeking since the beginning of the study period. Missing p-values indicate there was no worker in the work group that reported seeking formal health care.

Panel B: **P-values for difference in mean health seeking behavior by timing of interview**

Comparison	Number of Workers	Malaria Positive	Fever Self-Report	Formal Health Care Seeking	Informal Health Care Seeking	Any self-reported morbidity	Other Illness Self-Report
Workers selected in the first half vs workers selected in the second half of study	814	0.76	0.255	0.344	0.88	0.806	0.298
		[0.36]	[0.07]	[0.01]	[0.02]	[0.12]	[0.06]
Worker selected by the terciles of study weeks	814	0.381	0.563	0.662	0.251	0.638	0.035
		[0.36]	[0.31]	[0.12]	[0.01]	[0.02]	[0.07]

The p-value results from an F-test that tests the equality of coefficients for the given comparison cited in the table. All health variables reported in Panel B concern symptoms or health seeking since the beginning of the study period. The p-value of the mean for each group is reported in brackets.

Table 8: Placebo test using lags of treatment date as placebo treatment

	Daily labor supply			Daily productivity		
	21 days before	14 days before	7 days before	21 days before	14 days before	7 days before
One-week reference	0.001	-0.010	0.033***	0.023	-0.004	-0.021*
	[0.014]	[0.010]	[0.008]	[0.019]	[0.014]	[0.012]
# observations (worker-days)	5,029	8,143	11,281	3,700	5,910	8,371
Two-week reference	-0.021	0.006		0.033*	-0.002	
	[0.013]	[0.009]		[0.017]	[0.013]	
# observations (worker-days)	9,733	14,850		7,129	10,989	
Three-week reference	-0.009			0.027		
	[0.013]			[0.017]		
# observations(worker-days)	15,219			11,297		

Labor outcomes are defined as follows: Daily labor supply takes the value 1 when working; Daily productivity is ln(daily earnings) conditional on working.

The columns report estimates for alternative placebo treatment days 7, 14, and 21 days before actual treatment date.