Malaria Infection, Health Information and Productivity: Experimental estimates from Nigerian sugarcane cutters

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Abstract: Vector borne diseases such as malaria can adversely impact the health and, consequently, the productivity and labor supply of workers. While the biological process that transmits malaria is well known, the economic consequences of malaria infection on a worker's daily functioning is less understood primarily because of the simultaneous determination of health and labor supply. This study analyzes the effects of malarial infection on sugarcane cutters' earnings, labor supply, and productivity through the introduction of a mobile health facility at a large sugarcane plantation in Nigeria. The treatment effect is identified through the randomized order over time at which workers are offered malaria testing and treatment. We find a significant and substantial intent to treat effect - the offer of a workplace based malaria testing and treatment program increases worker earnings by approximately 10% over the following weeks. Interestingly, there appears to be economic benefit from receiving a negative test result as well as from the treatment of illness if the worker tests positive. Possible mechanisms are discussed.

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

JEL codes: I12, J22, J24, O12

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1. Introduction and motivation

Agricultural productivity is often considered a key factor for economic development in low-income countries. While there has been much attention devoted to the role of technological innovation for increasing productivity, the role of health in raising labor productivity has received less attention. Do investments in health increase labor productivity; and if so, by how much? This study investigates the role of one dimension of health – the presence of malaria parasites in the bloodstream – in both the decision to supply labor and in the productivity of labor supplied.

From a micro perspective, the relationship between health and labor productivity has been studied both from a theoretical and empirical perspective. The fundamental insight in this literature is that health is a key component of human capital, and therefore workers with superior health are more productive.[1] Healthier workers are thus expected to earn more, just as higher educated workers would also be expected to have higher earnings. However, in contrast to the relationship between education and labor outcomes, the health - labor nexus has traditionally received less attention. Strauss and Thomas (1998) conclude that there is clear evidence for the causal impact of health on labor productivity, but that much remains to be done in order to understand what dimensions of health matter, and under which circumstances the effect is important.[2] More than a decade later, two groups of studies have emerged: those looking at the relationship between nutrition and labor outcomes, and those considering the effect of specific illnesses on labor outcomes. The first literature generally indicates a positive effect of nutrition on labor productivity.[3] Studies with a specific disease focus include descriptive, experimental and quasi-experimental studies on the effect of schistosomiasis; on HIV infection and ARV treatment; and tuberculosis, and also find positive effects of absence of illness on labor outcomes.[4] Studies that have

[1] See for example Schultz (2002).

[2] The majority of papers focuses on the relationship between nutrition and labor outcomes, see for example Bhargava (1997), Fogel (1997), Schultz (1997), Thomas and Strauss (1997), Strauss and Thomas (1998), Behrman and Rosenzweig (2001), Swaminathan and Lillard (2001), Schultz (2002). A number of papers also look at other aspects of health, see for example Swaminathan and Lillard (2000) for Indonesia.

[3] See for instance Basta (1979), Edgerton et al (1979), Wolgemuth et al (1982), Immink and Viteri (1980), Thomas et al (2006), for experimental studies; Sahn and Alderman (1989), Thomas and Strauss (1997), Strauss (1986), Sur and Senauer (2000), Weinberger (2003) for nonexperimental studies of the effect of health on labor outcomes; Deolalikar (1988) and Croppenstedt and Muller for effects of nutrition on farm output and production frontier respectively.

[4] See Fenwick and Figenshou (1971), Baldwin and Weisbrod (1974) for descriptive studies and Audibert and Etard (2003) for a quasi-experimental study of Schistosomiaseis in Santa Lucio, Tanzania and Mali respectivelv; Fox et al. (2004) and Thirumurthy, Graff, Zivin and Goldstein (2006)) for carefull descriptive studies of the labor effects of HIV infection and (Habyarimana, Mbakile and Pop-Ellches (2010) for ARV treatment in Kenya; see Saunderson (1995) for tuberculosis in Uganda. Of interest is also Zivin and Neidell (2010), who find substantial effects of pollution on worker productivity in California. Only a few of these studies make use of exogenous variation to identify causality, typically following an experimental or quasi experimental approach. In the absence of exogenous

investigated the labor productivity effects of anemic or HIV positive workers have generally found significant effects from these illnesses (Thomas et al. 2004, Fox et al. 2004). In recent studies on malaria, reduction in exposure to malaria at an early age has increased incomes of adults (Cutler et al. 2010 and Bleakley 2010).

A number of macroeconomic studies have also suggested that health in general, and malaria in particular, can have strong effects on economic outcomes.[5] However, studies estimating the effect of health on growth using cross-country analysis may well lead to biased results as the regressions suffer from both omitted variable bias and reverse causality problems.[6]

Carefully designed micro-level studies may be better at addressing these difficulties of identification.[7] However, in order to do so, empirical microeconomic studies must confront two potentially important confounding factors in their research design. First, the multidimensional nature of health raises the complexity of the analysis and challenges attribution. Second, identifying the direction of causation is a challenge. While the role of health for productivity may be clear from a theoretical perspective, carrying out empirical tests to identify causality is more challenging because health may lead to higher productivity, and higher productivity may lead to higher income and access to better health care.

This paper focuses on one dimension of health, namely the sero-positive malarial status of an adult male worker. Vector borne diseases, such as malaria, cause direct impacts on the health and indirect impacts on the productivity, labor supply and earnings of workers. Adults who are affected by malaria suffer from lower energy levels via heightened morbidity such as fever, weakness, muscle aches, and

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variation it is not possible to exclude that the differences in labor outcomes are driven by other unobserved health factors.

[5] McCarthy, Wolf and Wu (2000) find a strong negative association between malaria morbidity and GDP growth per capita. Gallup and Sachs (2001) confirm these results and estimate that countries with intensive malaria had 1.3% lower per capita growth rates. Sachs and Malaney (2002) make the same argument, as do Sachs (2003) and Carsten and Gundlach (2006), who consider the joint role of institutions and malaria and find that both matter. Bhattacharyya (2009) follows a similar approach specifically focusing on Africa, and concludes that differences in malaria explain most of the variation in economic growth; they find malaria also has a strong effect on savings. Azemar and Desbordes (2009), concentrating on the effects of low health and education outcomes on FDI, estimate that net FDI inflows in SSA would have been one sixth higher during the 2000-4 period alone if there would not have been malaria.

[6] See also Ashraf, Lester and Weil (2008) for a discussion on this. Recent work on the general effects of health on economic growth try to address this and find that the effect of malaria may be lower when including regional dummy variables (Acemoglu, Johnson and Robinson (2001). Weil (2007), comparing the results obtained from macro and micro analysis finds a similar upward bias for the cross country analysis, and this is confirmed for African countries specifically (Weil 2010).

[7] Moreover, effects at the macro level are not very informative about effects at the micro level. For instance, a small effect of ill health on aggregate household income and labor supply may occur as a consequence of other households stepping in when the main laborer falls ill. Limited average effects may also hide considerable heterogeneity across groups. And even if observed effects are small, it may be that the reverse effect of income on health are substantial, and this may lead to a poverty trap, as argued by Gollin and Zimmerman (2007), and more recently Bonds, Keenan, Rohani and Sachs (2011).

chills and hence are likely to work fewer days and be less productive when they do work.[8] Agricultural workers and others in physical occupations likely suffer the greatest productivity declines from malaria.

Studies at the household level have found variable estimates of the cost of malaria, as discussed in detail below. Summarized, these studies agree that malaria imposes an economic cost on households and firms that is significantly above zero. Most of these studies have one or more of the following limitations. They typically study association, rather than causation, as identifying causality is a challenge. Health may lead to higher productivity, but higher productivity may also lead to higher income and access to better health care. A second weakness is the imprecise measurement of individual worker productivity, which is difficult when worker performance is not directly tied to an observable output as in piece rate work. Finally, most studies – but not all – measure malaria infection through self-reporting with the concomitant challenges of recall bias and accuracy of diagnosis.

In this paper we address the abovementioned identification problems, investigating the causal effect of malarial testing, as assessed through blood tests, and treatment on agricultural worker earnings, labor supply and productivity by introducing a randomized testing and treatment scheme at a large sugarcane plantation in Nigeria. Sugarcane cutters on the plantation are paid a fixed rate per quantity of sugarcane that they cut. The plantation records worker output each day and pays workers monthly according to their output. The experimental design randomized the order in which workers are tested and treated over time to ensure fairness with all workers receiving one test (and treatment if positive) over the survey period (6 weeks). The study then exploits the exogenous variation in the timing of access to testing and treatment for malaria to identify the effects of treatment on workers who had access to the testing and treatment as compared to a counterfactual of workers who had not yet received the program. This comparison yields an estimate of the intent to treat effect of a workplace program that tests workers for malaria and treats workers that are found positive. We find ITT effects for both labor supply and productivity increases that together account for approximately a ten-percentage point increase in earnings in the weeks following treatment.

Comparisons are also made between workers who tested positive for malaria with workers who subsequently test positive for malaria in later study weeks. This conditioned analysis can be interpreted, as an estimate of the treatment on the treated among the malaria positive. In other words, this analysis yields an estimate of the productivity gains from treating malaria. Gains in earnings of roughly the same magnitude as the ITT estimates are observed among the malaria positive (but now entirely due to increases in labor supply), suggesting the gains to treatment of malaria infection are not trivial. A similar

[8] Potentially severe complications include mortality, although in endemic areas these complications are much more common for children under five than adults.

conditioning analysis is conducted on those that test negative to investigate whether there is a benefit to the receipt of a healthy diagnosis. We find effects of the same magnitude as the ITT estimates when we restrict our analysis to workers who are told they are malaria free. health information on subsequent behavior in the labor market. In endemic settings, general awareness of malaria is widespread and often the term “malaria” is used as a wider assignation of general illness, especially illness accompanied by fever (cites). In our setting, workers who are parasitemic-negative may still expect their physical work capacity to be low (despite having no malaria parasites) if they generally feel low in energy, perhaps due to other illness but mis-ascribed to malaria, or if they perceive 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 can affect their expectations related to work efficacy.

This updating of health (and subsequently earnings) expectations is likely a key component determining the observed behavioral response to a health diagnosis. A small literature (Madejewicz et al. (2007); Jalan & Somanathan (2008); Dupas (2011); Cohen et al. (2011); Gong (2012)) investigates the effects of health information on subsequent health behavior. Typically these studies investigate the revelation of specific health risks in regards to longer-term behavior such as risky sexual practices, however there is little evidence to date that health information can influence short-term work decisions of the type investigated here. We will investigate whether an individual’s re-evaluation of actual malaria status as a result of new health information leads to changes in labor behavior.

The paper is organized to present these results as follows. The next section describes the study setting followed by a section that introduced the relevant theoretical framework. The fourth section provides an overview of previous studies that estimate the cost of malaria, and also discusses measurement issues. The fifth section describes the experimental design and identification strategy, while the sixth section presents the results. A final section offers some concluding thoughts.

2. Study setting

The study setting is one large (5700 hectares) sugar cane plantation in rural Nigeria. The plantation employs approximately 800 sugarcane cutters who work for the entire harvest season that stretches from mid-December to mid-March. While there are other activities on the plantation, including a sugar processing facility, this study focuses solely on the sugarcane cutter labor force.

Workers are hired for the entire harvest season from local villages surrounding the large plantation and are transported daily to the assigned work site, which varies as plots are cleared of ripe sugar cane and the workforce moves on to the next assigned plot. Workers are organized into eight work groups, averaging slightly more than 100 workers per group, and each group is managed by a supervisor. Each day the supervisor and his workers are assigned a set of starting fields in the plantation and additional fields to cut if the work group is particularly productive. Sugarcane cutters work individually along a row until finished and at that point supervisors will then allocate another row to cut. Rows of cane are of uniform density within a field due to mechanized planting and the irrigated nature of sugarcane that requires fields to be encompassed with water canals. Workers do not work in teams to complete rows. The plantation is so large that it is not uncommon for a work groups to remain isolated for an entire week and not encounter workers from another group.

Cane cutters are paid a piece rate of 2.04 Naira for every measured “rod” of cane cut. A “rod” is a physical standard carried by every work group supervisor and a meter of cane cut represents approximately one U.S. cent of earnings. The plantation records the daily output (quantity cut), the days worked, and the total earnings for each worker. While workers are paid monthly, they also keep track of their daily output, often maintaining their own separate ledger, and seldom are there worker-plantation disagreements over monthly payments. The work tends to be lucrative and an average day of cane cutting pays 1132 Naira, or approximately US$7.55 – a daily wage substantially higher than most local alternatives – hence sugarcane cutter positions are in high demand in the surrounding communities.

One unusual feature of the plantation work is that at the start of every work day each worker has a choice of two daily occupations – sugarcane cutting or ‘scrabbling’. Scrabbling is an occupation that requires the collection of cut sugarcane rods and the binding of them into bundles for loading on trucks destined for processing at the factory. Less physically intensive than sugar cane cutting, and more difficult to observe individual output, scrabbling pays a fixed wage of 500 Naira per day (roughly half the expected earnings of a day spent cutting). Scrabbling can be selected by a cane cutter if he is not feeling at full strength since scrabbling work is less arduous. There is a dedicated separate work force of scrabblers hired and managed by the plantation and these full-time scrabblers are not part of this study. However cane-cutters are given the option of serving as a temporary scrabbler in a given day (through a request to the supervisor) if they do not feel physically up to cutting activities. While cane-cutters seldom choose to scrabble, the amount of time devoted to scrabbling is not trivial – the average cane-cutter spends 3.5 days of the week cutting cane and 0.5 days scrabbling.

The plantation logbooks on individual worker daily productivity are one key source of information for our analysis. These daily logs record for each worker the presence of the worker on the plantation, the occupational choice (cane-cutting or scrabbling), the physical amount of cane cut, and the daily earnings. We supplement this information with worker interviews that cover socio-demographic, work, and self-reported health information. We also collect blood samples during the interview to test for malaria.

Table 1 presents selected mean individual and household characteristics of the workforce.[9] Workers are exclusively male and generally of prime age (a mean age of 30 years). Workers have previously worked on the plantation for an average of 4 or 5 years and tend to be in good nutritional status. The mean body-mass index is almost 24, and only 6.8% of the workers have a BMI less than 20, a threshold below which can indicate undernourishment. As stated earlier, the average daily earnings are slightly more than 1000 Naira, and a typical work season is comprised of 66 workdays. An average worker elects to spend 12% of the work season as a scrabbler, with the remainder devoted to cane cutting.

Table 1 also conveys the p-value from a test of the balance of each measured worker characteristic across the eight work groups. Most socio-economic and demographic characteristics are fairly equal across work groups, with the notable exception of worker education and BMI. In addition it is clear that earnings opportunities also vary across gangs with average earnings and days worked varying significantly. Given the imbalance in average earnings and certain characteristics that may be related to productivity, most notably the body mass index (BMI), the importance for the study design to stratify the randomized exposure to treatment within work group is clear.

Earnings and related measures do not only significantly vary across gang but also across time, even within gang. Table 2 lists the mean days worked and daily earnings for the entire harvest period, averaged over all workers and then for two selected gangs. In a typical harvest week, a worker will work 3.97 days and earn about 1000 Naira a day. However Table 2 makes clear the high degree of temporal heterogeneity in the days worked and earnings – heterogeneity that is specific to each gang. As the experiment will compare outcomes in a given week between workers randomly offered treatment and those not yet offered, controlling for the natural temporal variation in outcomes will be critical.

3. Theoretical framework

[9] We use the method suggested by Grosh and Baker (1995) and Ahmed and Bouis (2001) to predict household expenditure. In our questionnaire we included questions on asset ownership drawn from the Nigerian Living Standard Survey 2009, a nationally representative survey, conducted by the National Bureau of Statistics, which collects detailed data on household consumption and expenditures. We run the weighted regression $Exp_i = \sum_{a=1}^{p}(\alpha^a D_i^a + u_i)$ on the NLSS 2010 data to obtain estimates of $\widehat{\alpha^a}$, the coefficient for each asset, which we then use to predict EXPi for our own sample. Where D_i represents a dummy variable indicating whether the asset is present in the household. The regression uses population weights as calculated by the BoS. Since the estimates of the coefficients are relatively sensitive to outliers, we exclude the richest 10% of households in our prediction.

In our plantation setting, the worker's problem is to maximize expected income in any day of work by selecting into one of three occupations with different returns and levels of effort on either our sugarcane plantation study site or off-site work alternative (home production, nonfarm or off-plantation agricultural job). The insights of Schultz and Grossman on health and labor productivity can be applied to extend the Autor and Handel (2012) model of task-specific human capital.

In a simple Grossman model of health production, individuals allocate time across various activities including work, the production of health, and the production of other commodities. Subject to a time and budget constraint, the earnings (E) of worker *i* at time *t* are a function of both labor supply (L) and wages (*W*) such that a logarithmic transformation yields $\ln(E_{it}) = \ln(L_{it}) + \ln(W_{it})$.

A labor response function derived from this model can be specified as:

$$L_{it} = L(\mu_{it}, \omega(\theta)_{it}, f_t, \nu_{it}) \tag{1}$$

where *L* is the labor outcome vector of individual *i* at time *t*. This vector can include such outcomes as labor force participation, sector of work, occupation, time spent working, productivity, income from work, and number of jobs worked. Inputs into the labor supply function include an array of individual characteristics, μ_{it}, the wage price of time, w_{it}, which is in part a function of worker health, theta, firm characteristics, f_t, and unobservable determinants of labor participation, v_{it}. An individual will work if the offered wage exceeds the value of time. Individuals choose the occupation of work that yields the highest return and the time spent working is given by equating the marginal value of leisure with hourly earnings.

A theoretical model that characterizes the occupational choice of a worker as a function of expected health and productivity can be derived from the Autor and Handel (2012) framework of task specific efficiencies. Each worker *i* has a vector of task efficiencies $\Phi_i = \{\varphi_{i1}, \varphi_{i2}, \ldots., \varphi_{iK}\}$ whose elements are strictly positive values and can be thought of as the efficiency of the worker at a particular task. This efficiency is determined by worker endowments, including potentially different dimensions of their health such as malaria status and BMI, their human capital, experience on the job, innate skills, effort required, supervision and other firm specific effects, and other worker-task specific characteristics. The task efficiency vector characterizes the contribution of each characteristic to the productivity of worker *i* in task *k*.

Different occupations at the plantation produce different outputs using the vector of K tasks. The output of worker *i* in occupation *j* is summarized by the production function:

$$Y_{ij} = e^{\alpha_j + \sum_K \lambda_{jk}\varphi_{ik} + \mu_i} \tag{2}$$

Where $\lambda_{jk} \geq 0 \; \forall \; j, k$ and μ_i is the worker specific error term. Autor and Handel (2012) normalize the output price of each vector to unity. The production structure of occupation *j* is represented by the vector $\Lambda_j = \{\alpha_j, \lambda_{j1}\lambda_{j2}, \ldots., \lambda_{jk}\}$. The daily marginal product of worker *i* in occupation *j* is the log wage in a competitive labor market equilibrium such that

$$w_{ij} = \alpha_j + \sum_K \lambda_{jk}\varphi_{ik} + \mu_i \quad (3)$$

Workers can be ordered along a continuum, a closed unit interval [0,1] denoted T, according to their highest daily expected productivity, w_{ij}^*, which is a point in the nonnegative orthant Ω in Euclidean space R^n.

Workers at our study site have three potential occupations from which to choose that include off-plantation work, sugarcane cutting or 'scrabbling'. The expected productivity ordering provides the daily distribution of workers by occupation which we can categorize into four distinct groups: sugarcane cutters, scrabblers, off-plantation workers, and a set of workers whose expected productivity in scrabbling and cane cutting is in an inframarginal range where potential perturbations of expected task efficiencies alter rankings on a day to day basis. We call this set of workers on the continuum, 'switchers', because they potentially switch between occupations within a workweek.[10] Sugarcane cutting is more physically demanding and pays a fixed piece rate wage, while scrabbling is paid a fixed daily wage.

Given the theoretical framework above, worker *i* chooses his occupation to maximize expected income. Workers in the higher effort occupation, cane cutting, exert an additional physical cost, which is included in the vector of task efficiencies. Workers choose cane cutting which we denote as occupation *cut* when it has a higher expected return than the alternative occupation, scrabbling. As the return for scrabbling is fixed, in equilibrium, the worker's marginal product in scrabbling must be less than or equal to the daily fixed wage, $\overline{w}_{scrab}$. Cane cutting is chosen by workers when the expected daily return exceeds the scrabbling wage

$$\alpha_{cut} + E_i(\Phi_{icut})\Lambda_{cut} > \overline{w}_{scrab} \quad (4)$$

In our intervention, the access to testing and resultant health information, as well as malaria treatment when a worker is positive, may alter the actual health status or the perceived health status of the worker. There are two potential pathways given this theoretical framework. The first pathway is via treatment. When sick workers are ill, their task efficiency decreases and their potential productivity and labor supply effects will vary depending on how the worker manages physical fatigue. Some workers may

[10] We do not formally model switching from either scrabbling or cane cutting and the third occupation, off-plantation work. Theoretically, we assume that the return to off-plantation is lower than the expected wage on the plantation. This is substantiated by the high demand for work on the plantation and high rural poverty rates in the surrounding areas where the plantation is located.

take off days of work to recuperate (a labor supply effect), while others may spread their work effort more uniformly across the work-week or work less productively on days when they normally work (productivity effect). The second pathway is via information about their worker's health status. When workers receive health information, it may change their expectations about their future physical work capacity which may also affect their task efficiency. A worker who lives in an endemic area may believe they are sick, but upon positive health information realize that their physical work capacity is higher than they originally believed. Health information potentially increases worker motivation and actual work capacity if the difference between actual health status and perceived health status is large.

Empirical tests of this health-productivity relation have remained limited.[11] The above formulation also makes clear the usefulness of an experimental framework in order to identify the role that health plays in labor outcomes. The econometric problems in identifying the influence of health on labor outcomes in such an approach include the possibility that a worker's heath status in the task efficiency vector may be correlated with ε_{it} through endowment effects. This study's randomization of subjects into treatment and control groups will result in ε_{it} and malaria health status being uncorrelated with worker health endowments or other confounding health factors (μ_{it}) and thus avoid this problem. Another identification problem with the use of observational data is reverse causality between malaria status and labor. The exogenous change in malaria status induced through the intervention treatment will also control for this. Lastly, differences across firms in management or scale of operations affect worker productivity, while differences in firm policies regarding absenteeism and the provision of health care to workers may influence the effect of malaria treatment on productivity.[12] The use of one large plantation will enable us to abstract from concerns regarding firm characteristics f_t as well as treatment heterogeneity across firms in our estimates.

4. Malaria: cost and measurement

Diagnosis of malaria depends on the demonstration of either parasites or the presence of anti-bodies in the blood. Symptoms generally include fever, chills, sweats, headaches, nausea, vomiting, body aches, general malaise, and increased respiratory rate. Severe malaria can also impair consciousness, cause seizures, and result in coma (CDC and Najera/WHO). Individuals affected are also often

[11] Empirical work that has attempted to test the theory includes Immink and Viteri (1981), Wolgemuth et al. (1982), Strauss (1986), and Thomas et al. (2004). For more discussion, see also Strauss and Thomas (1998).
[12] Firm fixed effects are found to be important determinants of worker productivity, especially in developing countries (see for instance Soderbom and Teal 2004).

dehydrated and hypovolemic (Miller et al 2002.) The duration of an episode of malaria varies widely.[13] Hempel and Najera (1996) indicate that an episode of malaria lasts up to 14 days, with an average of 4-6 days of total incapacitation and the partially incapacitated days characterized by nausea, headaches, and fatigue. Abdel-Hameed found that in Sudan, the mean hospitalization time per episode was 9 days.

The cost of malaria to individual workers has been studied in the public health literature, mostly using a cost-of-illness (COI) approach. Distinguishing between 'direct' and 'indirect' costs, direct costs, in this literature, refer to expenditures on prevention and treatment of malaria by households,[14] and typically constitute a small proportion of the total costs.[15] Indirect cost, in this literature, refers to the cost of time lost due to malaria, and is also one focus of this paper. Studies estimating the 'indirect costs' usually measure workdays lost due to self-reported illness multiplied by the going wage.[16] These estimates are typically carried out at the household level, and measure the work days lost due to malaria of both the ill person and his or her relatives.[17] Pluess et al. (2009) found that on average 1.8 workdays are

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[13] It may among others depend on the endemicity level of malaria in the area. Highly endemic areas may, for instance, have higher levels of immunity, and episodes may be longer in areas with less stable malaria presence (Deressa 2007).

[14] These include medical testing, drugs, consultation, special food, transportation, medical supplies, non-medical supplies, services and out-of-pocket expenditures (Akazilli et al, 2007 and Chima et al, 2003.)

[15] For example, Attanyake et all (2000) estimated that only 24% of the estimated US$7 per malaria episode was attributable to 'direct costs'. In Ghana this was estimated to be 29% of a total US$1.87 per episode (Akazilli et al, 2007) and in Rwanda, this was US$2.58 of the total US11.82 (Ettling & Shepard, 1991). A study in Kenya based on household surveys and supplemented with in-depth case studies of selected households found the prevention and treatment cost of malaria incidents to be 7.1% and 5.9% of all estimated costs in the wet and dry seasons respectively (Chuma et al 2006.) This study also found that the burden of prevention and treatment cost were regressive, with malaria costs accounting for over 10% of the expenditure in the poorest households. Akazilli et al (2007) also measured costs in relation to income in Ghana and found that the poorest quintile spend 33.98% of their expenditure on malaria treatment cost, while that figure for the second poorest quintile was 8.97%. In Malawi, very low income households carried a disproportionate share of the economic burden of malaria, with total estimated cost of malaria among these households consuming 32% of annual household income compared to 4.2% among households in the low to high income categories (Ettling et al, 1994). Some studies report components of treatment costs in more detail, especially the cost of transportation, which can vary widely depending on the location of the village and accessibility of treatment. In the case of Ethiopia, where treatment costs represent US$1.60 of the total US$5.86 per episode, 20.92% of the patients surveyed paid for transport to seek medical services (Deressa 2007). In Sudan, Abdel-Hameed (2001) found that transportation accounted for 24% of total estimated costs for those seeking treatment but who were not hospitalized, and in Ghana, transportation cost to health care facilities represented 13.1% and 5.9% of the total estimated costs for severe and mild febrile illnesses, respectively (Asenso-Okyere & Dzator, 1997).

[16] The going wage is typically proxied by average wage rate in the village. Some studies also use average daily income in the household (Ayieko et al., 2009; Ettling et al., 1994; Guiguemde et al., 1994); or average daily output per adult in the household (Sauerborn et al., 1991; Shephard et al., 1991)

[17] A complication when measuring workdays lost due to illness at the household level is that there is important labor substitution. For example, if a father is sick with malaria but sends his son to work in his place, then there is no net workday loss due to malaria. Labor substitution is often referred to as a coping process employed by families in attempt to reduce the impact of disease. Some studies attempt to capture such coping processes in their quantification of lost productivity. Alaba & Alaba (2006) accounted for this in a recent study of income lost due to malaria in Nigeria. Data for the study was collected using multi-stage-sampling, selecting three health zones from Oyo State as base strata, from where 4 local governments were randomly selected. The study estimated that average

lost per episode due to malaria, measured by blood test in Papua New Guinea, and consider this as a lower bound because the plantations provide free health care. Mills (1993) find that average workdays lost from malaria, measured by blood tests, ranged from 6 to 14 days per episode in Nepal. Asenso-Okyere & Dzator (1997) found that on average 5 productive workdays were lost per episode of self-reported malaria in Ghana.[18] Because the study did not take a blood test, it may include other incidences of high fever, but also miss non-reported episodes. Other studies also find substantial losses of working time, for instance up to 5 days per episode in Burkina Faso and up to 11 days in Sudan.

The value of work time is usually estimated using the prevailing local wage rate and studies suggest a cost per episode varying from 18 USD for Chad (Shepard et al 1991), to 13 USD for Rwanda (Ettling and Shepard 1991) and 8 USD for the Congo (Shepard et al 1991).[19] When also taking the time cost of other household members as well as medical costs into account, the costs increase further, with one study for Ethiopia showing a cost of up to 31 USD per episode (see Cropper et al. 2004).

A handful of studies go beyond absenteeism from work, and provide insight on losses in on-the-job productivity. Leighton (1993) conducting qualitative interviews estimate that 50% of Kenyan agricultural laborers work two of the days they are sick with malaria and that productivity is reduced by 50%-75% on those days, estimating the value of workdays and productivity lost due to malaria at 3% to 13% of the total annual value of the agriculture sector. Nur (1993), concentrating on Sudan, measured the percentage change in normal productivity when a worker was weakened due to malaria but not fully incapacitated and estimates a productivity lost equivalent to 2.55 workdays per episode on average, in addition to the 6.16 days lost to total incapacitation. In a study of irrigated vegetable farming in Côte d'Ivoire, Girardin et al (2004) find that farmers sick with malaria for more than 2 days produce 47% lower yields than those sick less than 2 days during one cabbage production cycle. Picard and Mills (1992) find that an additional 1.2 days are lost due to being partially disabled by illness. At the same time

net workday loss, defined as patient's lost workdays minus labor substitution plus opportunity cost of substituted labor, was 10 days per episode in the agriculture sector. Cropper et al. (2000), conducting a survey in 18 villages in 2 selected districts in Ethiopia especially designed to provide variation in malaria incidence, used the same formula to calculate an average of 21 workdays lost per malaria episode in Ethiopia. Other studies that took into account labor substitution observed no loss of production. For example, Gateff at all (1971) found that families reallocated labor within the household during bouts of malaria and schistosomiasis and production was not affected. A similar result was observed among female cotton pickers in Sudan: schistosomiasis did not reduce production because healthy family members worked more to compensate for the sick (Parker 1992). The advantage of analysis at the household level is that costs to other members other than the infected members are taken into account. Our study abstracts from these focusing on the consequences for the infected individual.

[18] 64.2% of these workdays lost were attributed to care taking. Seeking treatment took on average one half of a farm workday.

[19] These are all in 1997 USD. More careful estimation distinguishes between gender and seasons and observes similar magnitudes (up to 6 USD for Burkina Faso 1985 USD). For other examples see Ettling et al. (1994) for Malawi, Asenso-Okyere and Dzator (1997) for Ghana, and Jowett and Miller (2005) for Tanzania.

Audibert et al (2009) find no relationship between malaria infection (measured from blood samples) and cocoa and coffee production in Cote d'Ivoire. [20, 21]

These studies provide valuable information about economic costs associated with malaria; they also suffer from important weaknesses. Many of the studies use weak data on earnings and days lost, and do not distinguish between the average and the marginal product of labor;[22] they also do not identify causality.[23] Most – but not all – studies also measure malaria infection through self-reporting, which has serious shortcomings. Our study addresses these weaknesses. Focusing on a setting where pay is tied to performance, labor productivity is perfectly observed in our study, as discussed in more detail in Section 4. Causality is addressed by randomizing the order of treatment, as also discussed in Section 4. In the next paragraph, we discuss the measurement of malaria found in the literature.

Three methods are commonly used to measure malaria infection in large-scale surveys: self-reporting, Rapid Diagnostic Testing (RDT), and microscopy.[24] While self reported malaria is often used

[20] Sallares (2002), studying the history of malaria in ancient Rome, finds evidence that what is now thought to be malaria, increased the cost of constructing a villa by 25%, due to among other lower productivity of the workers (see Packard 2009). There is also anecdotal evidence from the international football world. Chelsea striker Drogba, an Ivory Coast international, complained about feeling unwell and he had to forego playing at two important matches due to fever (the Premier League draw at Aston Villa on 16 October 2010 and the following week's Champions League trip to Spartak Moscow). He was then tested and found out to have malaria. His trainer argued "He has this virus and, obviously, he lost power and training." And added " but he will be firing on all cylinders within days". The story also illustrates the challenges of identifying malaria: "We ran tests on all the tropical diseases and viruses but because it was dormant, there was not enough parasitic activity in his blood to pick up malaria in the initial tests."

[21] Two studies also estimate the potential cost of malaria for employers. A study among textile factory workers in Kenya observes a loss of 720 person-days over a ten month period, with malaria accounting for 53% of the illness episodes (Some 1991), while Pluess et al (2009) find that 9,313 workdays were lost due to malaria over a two year period in oil palm plantation in Papua New Guinea. In the presence of performance pay, one might argue that the cost of illness is entirely borne by workers. This is not the case if transaction costs of hiring and firing are nonzero or if there are externalities.

[22] Many studies also make generalisations while not taking into account important dimensions like the type of work or the season of survey. Chima, Goodman and Mills (2003) provide an overview and comments on a number of studies.

[23] Two exceptions are Somi et al. (2007) present evidence for dual causation between malaria and socioeconomic status, measured by asset ownership. Hong (2008), using historical census data from adult males who migrated from less to more malaria prone counties between 1850 and 1860 in the US, finds that they accumulated 9% less wealth per year, mainly because due to lower labor supply with high malaria counties having 1.6 to 2.7 percentage points lower labor force participation rates in 1850 and 1860 respectively. A number of studies have also estimated other economic costs of malaria, often focusing on children, where the disease has its biggest impact resulting in infant and child mortality. Barreca (2007) estimates that in utero and post-natal exposure to malaria lead to substantially lower levels of educational attainments and higher rates of poverty later in life. There is also strong evidence for negative effects of malaria on education outcomes. Cutler, Funf, Kremer and Singhal (2007), exploiting geographic variation in malaria prevalence in India prior to a nationwide eradication program in the 1950s, finds that malaria eradication resulted in gains in literacy and primary school completion of approximately 10 percentage points.

[24] Thick blood film microscopy is considered the gold standard but is expensive to implement as it requires trained personnel and appropriate instruments. Because detection of low concentration of parasites remains difficult, even for the best expert microscopist (Nkrumah et al 2010), RDT has become a recommended approach by WHO for large scale field work.

as a proxy – particularly in socio-economic studies – careful measurement of malaria infection requires testing of a blood sample, as the diagnosis of malaria depends on the demonstration of parasites in the blood. As self-reporting relies on subjective self-assessment, it is not necessarily reliable. Because the symptoms of malaria are very generic, subjects may categorize other illnesses with similar symptoms (like cold, flu) as malaria infection. At the same time, especially in areas where malaria (or diseases with similar symptoms) are endemic, habituation to these symptoms may lead to underreporting of malaria infection. Self reported malaria can therefore suffer from both Type I and Type II measurement errors, making it difficult to sign the measurement bias and rendering it imprecise as a measurement approach. Strauss and Thomas (2000) present evidence that self-reported health information could either be positively or negatively attenuated, and that the direction of the bias may be correlated with respondent characteristics. Self reported health remains nevertheless a widely used approach in socio-economic studies.

The measurement method this study adopts consists of taking a blood sample from workers and carrying out microscopy analysis in the lab, counting the number of parasites above which a specified threshold the worker is considered malaria positive. Thick blood samples provide the gold standard for malaria infection measurement. While parasite load indicates malaria infection, which is positively related to malaria outbreak, there is no medical consensus about the *exact* relationship between parasite load and malaria outbreak. In this paper, we rely on microscopy as it provides the most accurate measurement of malaria infection and yields an estimate of parasite severity. Our adopted definition of malaria positive is the presence of at least 3 parasites in at least one examined field in the blood smear. This decision follows the clinical diagnostic standards in the study area.

Table 3 conveys the blood slide results by presenting the distribution of the maximum parasite count. Only 9% of the workers have no observed presence of parasites while roughly 55% have had 1 or 2 parasites observed. Asymptomatic malaria is common in endemic areas (get cites) and it appears that many workers in our sample exhibit sub-clinical parasite threshold loads. The cut-off for a malarial diagnosis is a minimum of 3 parasites in at least one blood field, and 36% of the work-force exceeds this threshold, with 15% having a parasite count of at least 4.

In our study, all workers diagnosed with malaria receive an adult dose of Artemisinin based combination therapy (ACT). 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 for another week afterwards. Compliance with the treatment protocol was maximized through follow-up visits by the health workers and a small incentive (50 Naira) to return used ACT boxes to health workers who would conduct a short follow up visit to ensure compliance.[25]

5. Experimental Design and Identification Strategy

Our experimental design uses time varying randomization to resolve some of the potential identification problems suggested by the previous literature. A time varying randomization was chosen so that all workers would have access to the testing and treatment program in a relatively short window of time. All workers who were parasitic positive according to the microscopy results from the collected slides were treated with the appropriate doses of Artemisinin Combination Therapy (ACT) upon the receipt of a diagnosis. On average there was a time lag of three days between the collection of blood slides and the delivery of the result to the worker, along with medicine if the worker tested positive.

By combining the output data with the data from the survey and the malaria test, we obtain a rich data set that enables the study of the effects of malaria on labor outcomes. The randomized timing of exposure to our intervention allows us to abstract from unobserved worker characteristics like ability, physical condition, or health endowments, in our analysis, as spelled out in Section 2. By focusing on one large plantation, rather than many small farmers, we abstract from potential contaminating firm fixed interaction effects - which may play an important role as different firms follow different approaches towards illness and illness related absenteeism.

The worker treatment order followed a two-stage procedure where first a randomized order of worker groups were determined, then a randomized order of workers within each group.[26] A list of workers was obtained from the plantation before the beginning of the experiment. Selection of the order of work groups and then workers was completed before the beginning of the study, so that the survey team had a predetermined number of workers from each work group to test and survey each day. IN most of the study weeks, some workers from each work group were treated with the interview and malaria test, so there is a relatively smooth distribution of workers interviewed across time within each work group.

[25] ACT treatment exists of a set of pills to be taken twice a day for three days in a row.

[26] Workers are assigned to worker groups by the company in no particular order but based on geographical proximity of residence. Each worker group counts around 80-100 workers and is allocated on a weekly basis to plots that are ready to be harvested. Because the management prefers worker groups to be equally productive and since the harvesting activity is strongly individual, there is no obvious reason why unobserved worker group fixed effects should play an important role, except for that they also reflect the plots to which the worker group has been allocated. There was no pre-screening of workers for illness by the plantation and based on the company records and the large number of workers, there does not appear to be any systematic selection of workers to worker groups based on health. Despite this, we control for worker group fixed effects in our analysis.

This process continued until all work groups of the plantation had been served and the entire workforce had received access to treatment. As the order of testing and treatment was randomized over time, this provides us with an identification strategy. Combining this data with the daily measurement of output of all plantation workers permits us to estimate the causal impact of malaria treatment on labor outcomes. Figure 1 conveys both the sources and the timing of data collected. In terms of labor outcomes recorded daily by the plantation, we focus on three: worker productivity, labor supply and income.

Table 4 presents the summary results of balance tests conducted on worker characteristics according to the week in which the worker was randomly offered the malaria test. In principle, randomization will guarantee balance but in practice, with approximately 100 workers per work group, the success of the randomization in ensuring balance needs to be checked. Overall, the randomization process appears successful, out of 72 balancing tests – 9 characteristics in each of 8 gangs – only 5 suggest some degree of significant temporal imbalance at a threshold significance level of .10. No characteristic diverges within work group across week. In additional robustness results, presented in the in the appendix, linearly controlling for observed worker characteristics such as education, BMI, and a quadratic in age doesn't affect the main results.

Combining the sources of data in Figure 1, we estimate two types of treatment effects: an 'intent to treat effect' (ITT) and an 'treatment on the treated' (TOT). The first effect reflects the benefits of access to malaria testing and treatment, comparing outcomes of workers with access to treatment to those of workers yet without access to testing and treatment (and who may or may not have fallen ill). The second effect compares outcomes of those who are ill and treated to those who are ill but not yet treated due to their later randomly allocated testing date.[27] These treatment effects are summarized in the equations below. As a robustness check, we present several different estimates of the ITT and TOT using different durations for the observation period.

As an econometric specification, the ITT is estimated by comparing labor outcomes in some period of weeks, *t*, for those workers who were tested at time *t*-, a period before the observation period *t*. with the labor outcomes for workers who are tested at point *t*+ after the observation week *t*. We denote the sets of workers assessed at *t*- and *t*+ as W_{t-} and W_{t+}. This difference in outcomes over period *t* represents the effect of testing and treating for malaria, as it compares the output of a randomly selected subsample of workers who are tested with a randomly selected subsample of worker who are yet to be tested. To control for the potential non-random placement of workers across workgroups, as well as the

[27] A free health clinic to which workers have access already exists on the plantation. However, there is no individual worker follow up and the facility is far removed for some workers. Virtually no worker has reported access to the clinic.

natural weekly variation in work outcomes, we also include a full set of workgroup-workweek fixed effects, F_{gt}. We estimate:

$$L_{igt} = \alpha + \beta T_{igt-} + F_{gt} + \varepsilon_{it}, \quad \forall i \in W_{t-} \cup W_{t+} \qquad (5)$$

where L_{igt} reflects the three labor outcomes of interest: earnings, labor supply and productivity respectively for worker *i* in work group *g* at period *t*, and ε_{it} is the worker specific error term.

Following a similar approach, the TOT is estimated by comparing labor outcomes at time *t* for those workers who had access to treatment at time *t*- and were treated if ill and are therefore healthy over the period *t*, with the labor outcomes for workers who were not tested until time *t*+. Differences between the two groups reflect the effect of access to treatment, as it compares the output of a random subsample of workers who had access with that of a random subsample of worker who had no access to treatment in period of observation (but assumed sick). To estimate the TOT, Equation 4 is re-estimated but now for the subset of workers P who have tested positive, as given in Equation (6):

$$L_{igt} = \alpha + \beta T_{igt-} + F_{gt} + \varepsilon_{it}, \quad \forall i \in P_{t-} \cup P_{t+} \qquad (6)$$

as before, L_{igt} reflects the three labor outcomes of interest: earnings, labor supply and productivity respectively.

Allowing for a short time lag after treatment is necessary because it takes an average of three days for workers to receive diagnosis, take the 3-day course of medicine, and to be cured and return to their ‘normal’ energy levels. For this reason we will want to look at impacts that may emerge fully one week after the initial test. We also exploit that ACT, while being a curative medicine, creates a hostile environment for the parasite, and keeps patients protected against malaria for some time after treatment, estimated between two to four weeks (White 2005). We test the robustness of our findings by varying the length of the period of observation, as described later.

A potential concern with the identification strategy, especially for the ITT estimates, as set out above is that of disease spillovers arising across time and space for epidemiological reasons and stems from possible reduced parasite prevalence in the control group due to intervention in the treatment group. While a valid concern in theory, the large size of the plantation (5,700 hectares) and the relatively small total number of workers infected over the study period makes these spillovers less likely. Furthermore, most of the transmission of malaria 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. Additionally, the measured malaria positivity rate shows no decline over the weeks of study suggesting the absence of significant spillover effects.

To estimate equation (5), we consider several different strategies to construct the reference period in which to compare treated workers with workers yet to be treated. We estimate the effects estimated for the first week after treatment, the second week after, the third week, and fourth. Given the constrained timing of the intervention in order to accommodate the wishes of the plantation, effects beyond four weeks could not be measured as the fieldwork period lasted only six weeks and the weeks of observation for both treatment and comparison workers need be excluded (i.e. the four week reference period is only estimated from workers assessed in the first and sixth week of the study). Also, a more reduced form approach to measure impact that maximizes power is highlighted. In this approach we pool the week-long outcomes over four windows of increasing duration: one week, two weeks, three weeks, and four. Results from both approaches (week-by-week or pooled) will present complementary pictures: the week-by-week capturing the dynamics of gains from testing and treatment, while the pooled weeks give summary measures that maximize power.

To identify the TOT estimates described in equation (6), we must make an assumption about the malaria status of the comparison workers, and that is malaria positive workers tested in later study weeks were malaria positive for the earlier observation weeks. This is an assumption that unfortunately is not verifiable with our data since we only assess the malaria status of workers at one point in time. The expected length of illness can potentially vary by worker. However, an outbreak of malaria lasts an average of 14-16 days with parasite loads maximizing in the blood 1 to 3 days before emergence of symptoms. 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 are expected to be positive. We do not estimate a TOT result over a four-week reference period due to the relatively small number of malaria positive workers. Robustness analysis on sub-groups will further provide evidence supporting our identifying assumption.

6. Results

ITT estimates

Table 5 presents the results of equation (5) estimated on the total sample of workers for weekly earnings, days worked, and the daily wage. The results suggest that in the first week after treatment, earnings increase by 4%, although this effect is not significantly different from zero. Days worked also increases by 4%, now significant at the 10% level. There appears to be no effect on daily productivity.

Larger impacts are estimated when using a two and three week reference period that are less sensitive to the time lag between observation, diagnosis, treatment, and medical efficacy. The two week pooled reference period indicates that weekly earnings average almost 11% more in the two weeks following the malaria testing and treatment, rising to 13% per week in the three week period. These gains in earnings are approximately evenly divided between increases in labor supply and increases in the daily wage. In both the two and three week reference period the days worked increases by approximately 5%, while the daily wage increases by 6-9% depending on the recall period. The earnings gains begin to diminish by the fourth week, although it is difficult to determine whether this is due to an eventual decline in the efficacy of the intervention or partly due to the truncated sample for which we can observe 4-week impacts.

The week-by-week estimates largely echo this pooled reference period results, with earnings effects peaking two weeks after the malaria test. By the third week there appears to be no effect on labor supply, although daily wages are still 11% higher.

These ITT estimates summarize the worker benefit of the testing and treatment regime we implement for the average cane-cutter. If the benefit were solely due to the treatment of malaria among the positive workers, we can adopt a Wald estimator to calculate the work and productivity costs of malaria. Given that 35.6% of the workers test positive for malaria, the two-week pooled point estimates would indicate a 30% gain in earnings for treating malaria, which yields a far higher earnings and productivity effect than other studies cited above. Of course the actual intervention itself is a combination of health information and pharmacologic treatment for the sick, and the ITT estimates cannot distinguish between these two channels. We next turn to a re-estimate of equation (5), but this time only among the workers that test positive for malaria. With the assumptions discussed above, this approach yields an estimate of the TOT for workers sick with malaria.

Results for the malaria positives

Table 6 conveys the same basic estimation framework but only for those workers who were determined to have tested positive for malaria and subsequently administered ACT. Since the worker sample is now truncated to approximately one-third the total sample, precision suffers. Nevertheless an earnings response in the two- and three-week pooled estimates is quite apparent and roughly on the same order of magnitude – 9% to 11% of total earnings – as the ITT estimates in Table 5. The similarity of the two estimates (ITT and TOT) suggests that not all of the earnings benefit from the intervention accrues to the malaria positive workers alone, though we may be concerned about the identifying assumption which assumes a counterfactual of later sero-positive workers discussed above.

Nevertheless there appears to be an earnings effect from treating malaria, with most of the response arising from an increase in the labor supply. The days worked after treatment with ACT increase on the order of 7%. There may also be a marginal gain in the productivity of each day worked – on the order of 2% - 4% as suggested in the point estimates – but these estimates are not precisely estimated at standard levels. The total estimated earnings benefit from malaria treatment that accrues over a three week reference period, estimated at the average daily wage for the workforce, comes to 1345 Naira, or approximately $US 9. While less than the naïve Wald estimator guess of a $30 gain, the estimated gain is still greater than the market cost of ACT which currently stands at $5-$7.

Of course to interpret the estimates in Table 6 as the benefit from treating malaria positive workers with ACT, we must make several assumptions. For one, as stated before, we assume that the workers who subsequently test positive for malaria in later weeks are a valid counterfactual for the positive "treated" workers in the earlier weeks. We also must assume that the workers comply with the ACT treatment protocol. Regarding compliance, workers were incentivized to return the empty blister packages, and on a follow-up visit to positive workers, compliance information was sought. While the information is self-reported by the worker, and hence not verifiable, the results suggest a high-degree of compliance (Appendix Table).

If the benefits measured for the malaria positive workers represent an estimate of economic gains from curing malaria through ACT treatment, then we may observe greater benefits accruing to those workers with more severe cases of malaria, that is those with higher parasite loads. Table 7 disaggregates the TOT response by disease intensity by stratifying the positive sample into two groups: those with a parasite count of 3 and those with a parasite count of 4 or more. While the point estimates are not significantly different from each other, the results are quite suggestive. The earnings response and the labor supply response are larger in magnitude for those workers with more severe malaria, supporting the interpretation that the results in Table 5 actually capture the economic benefits for treating malaria illness in this population.

Results for the malaria negatives

A comparison of Tables 5 and 6 suggests that not all of the benefits implied by the ITT estimates accrue to the malaria positives. Might it be possible that the labor market behavior of workers respond to the good news of a negative malaria test? Table 8 investigates this possibility by presenting the results from Equation (5) but this time estimated only on the sub-sample of workers who test negative. Changes in earnings for this group of workers are precisely estimated, at least for the 2 and 3 week reference period pooled results, and in magnitude are even higher than the ITT estimates of Table 5. While the coefficients for the labor supply response are positive (but not significantly different from zero), it is apparent that most of the gains to earnings arise from an increase in the daily wages earned by the workers. These wage effects are on the order of 7%-11% depending on the reference period. There are several possible explanations for this response. As mentioned above, the good news of a malaria negative diagnosis may significantly affect worker expectations of productivity that in turn lead to higher labor supply and differential occupation choice. Other potential explanations include a "meaning" effect (Moerman, 2011) from a healthy diagnosis. Related to the more familiar placebo effect, the meaning effect implies that workers respond to the healthy diagnosis by changing their own subjective perceptions of their health and vitality and hence work harder.[28]

One proposed mechanism – a change in earnings expectations as a result of (surprise) good news – can manifest through worker decisions to switch out of scrabbling and into piece rate work. This is investigated in Table 9 that regresses the proportion of workdays in the week devoted to scrabbling on the treatment indicator, separately for malaria negatives and positives. There is no noticeable change in the scrabbling rate for malaria positives, but healthy workers are significantly more likely to switch out of scrabbling into piece-rate work. This empirical result is consistent with theoretical model derived in section 2 and the view that good health news affects the expectations of earnings even in the very short run. This also indicates that the wage gains estimated in Table 8 is at least partially due to switching into piece rate work from a lower fixed wage.

Does the switch out of scrabbling constitute the entire mechanism of the "good news" effect of a healthy diagnosis? Table 10 investigates this by restricting the sample only to worker-week observations with no scrabbling whatsoever. While the point estimates in the table are not as precisely estimated as in the whole sample, the results indicate that even when restricting estimates to non-scrabbling worker-weeks, earnings are still significantly higher. Why might this be so? Changing expectations leading to occupation switching is apparently not the full story. Another possible explanation is that our analysis confounds healthy workers who just received a good test, with sick workers who have yet to be tested (and who may clear the disease on their own and subsequently test negative). The second panel in Table 10 investigates this possibility by restricting the analysis to the subset of malaria negative workers who also report no symptoms of illness (any illness) in the last four weeks. Even with this restriction, the earnings impacts are virtually the same as in Table 8 – the misattribution of sick workers to a healthy control group is likely not a factor behind the earnings gains to treated malaria negative workers.

The final table explores how the worker response to good news varies with select characteristics such as the parasite load (malaria negative workers still may have a sub-clinical level of parasites in the blood and may even suffer from malaria related sub-clinical symptoms) and whether the worker feels

[28] Alternative explanations such as gift exchange or misattribution of healthy workers are unlikely.

tired at the end of the work day. The results in Table 11 support the conjecture that not only good health news, but surprise good health news, engenders an earnings response: those with some parasites (but below the diagnostic threshold) respond, those with no parasites do not. Similarly those who report fatigue at end of day respond to being told they are malaria negative, but those without subjective reports of fatigue show no statistically significant earnings, labor supply or productivity responses.

6. Conclusions

This paper provides experimental evidence on the effects of malaria infection on agricultural worker's earnings, labor supply and productivity. While the previous literature examining health and labor outcomes has reinforced the theoretical linkages between health and labor supply as well as productivity (Strauss and Thomas 1997), difficulties in measuring productivity or plausible establishing exogenous variation in worker's health have inhibited the estimation of malaria's effect on worker's earnings. The implementation of our mobile malaria health clinics on earnings and productivity appear to have statistically significant effects for workers which potentially increases firm productivity. Accounting for both labor supply and productivity effects suggests an estimate of the cost of malaria on those infected that is of a similar magnitude to those reported in previous studies (for example, Ettling and Shepard 1991, Ettling et al. 1994, Cropper et al. 2004). Similar to those earlier studies, the gain in the treatment of malaria appears to accrue mainly on the extensive margin of days worked rather than the intensive margin of productive capacity conditional on work.

In the context of Nigeria alone, a country of approximately 124 million people, malaria was the leading disease reported over the past year with 51% of individuals reporting illness due to malaria, according to the Nigeria Living Standards Survey (NLSS) 2003/04. The World Bank estimates that Nigeria accounts for 20% of worldwide malaria cases. 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.[29] The positive correlation between the agro-ecological

[29] For example, Harb et al. (1993), Thompson et al (1996) observed an increase in the mosquito population with the use of irrigation in the Nile Delta, (see Asenso-Okyere p298). 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.

environment of those areas with high growth potential and malarial breeding may diminish the gains from increased agricultural productivity.

Alongside gains to malaria treatment among sick workers, we find evidence that workers who were informed of a healthy diagnosis increase their productivity after receipt of health information, in part due to shifting out of a lower-return complementary occupation and into the piece-rate work of cane cutters. Although previous work has documented behavioral response to surprise health information, these findings are largely confined to longer-run outcomes and risky behavior such as unprotected sex or smoking. To our knowledge, no previous study has investigated the effect of malaria testing on participants' subjective health beliefs and consequent changes in day-to-day work behavior. Hence, the existent malaria literature may undervalue the effect of positive health information on worker effort and hence family income.

A low cost employer-based testing and treatment program could provide large net benefits, since workers are often inhibited from visiting health clinics due to distance and the cost of treatment. However the gains to the implementation of a work-place clinic for malaria testing and treatment do not only occur for workers with diagnosed malaria, but also to healthy workers who receive the diagnosis that they are malaria free. In endemic situations, it is quite possible that there are real returns to health information, especially if the information is interpreted as a surprise. In our study setting, good health news induced a switch out of the fixed wage alternative occupation on the plantation to the piece-rate cane-cutting and to higher earnings. There was also a corresponding increase in labor supplied to the plantation. Workers who were most responsive to the negative diagnosis did indeed have some parasite presence in their blood, but at sub-clinical levels. Responsive workers were also more likely to report that they felt tired at the end of the work-day. These correlations suggest that surprise good news – resulting in a change in expectations of earnings potential – plays a causal role. However there may be additional channels through which the good news effect translates into higher earnings, such as a "meaning" response to the diagnosis that increases a general sense of well-being and optimism. Our study, designed to measure the productivity costs of malaria infection, cannot definitively identify the causal mechanisms behind the "good news" effect.

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Figure 1. Data structure and identification of impact

A: Worker interviewed in week 5 tests positive for malaria

	Week Number					
	1	2	3	4	5	6
L_{it}	Observed L_{i1}	Observed L_{i2}	Observed L_{i3}	Observed L_{i4}	Observed L_{i1}	Observed L_{i6}
X_{it}	<------------------------- Inferred $X_{it} = X\text{-}_{i5}$ ------------------------->				Observed X_{i5}	Inferred $X\text{-}_{i6} = X_{i5}$
Malaria Status	<------------------------- Inferred Status: **Sick?** --------------------->				Observed Sick	Inferred Status: **Well**

B: Worker interviewed in week 5 tests negative for malaria

	Week Number					
	1	2	3	4	5	6
L_{it}	Observed L_{i1}	Observed L_{i2}	Observed L_{i3}	Observed L_{i4}	Observed L_{i1}	Observed L_{i6}
X_{it}	<------------------------- Inferred $X_{it} = X\text{-}_{i5}$ ------------------------->				Observed X_{i5}	Inferred $X\text{-}_{i6} = X_{i5}$
Malaria Status	<------------------------- Inferred Status: **Well?** --------------------->				Observed Well	Inferred Status: **Well**

NOTE: L_{it} represents earnings, days worked and wages and are collected from daily employment and output records kept by the plantation. $X\text{--}_{it}$ are workers characteristics collected once over the six weeks by the survey enumerator. These data are either known to be constant over the six week period (e.g., gender) or assumed constant (e.g., place of living). Malaria status is collected once over the six weeks by a registered health worker. Sick workers are assumed to be sick during the weeks prior to testing, and assumed well during the weeks following testing (and treatment). Workers who test negative are assumed to be well during the weeks leading up to testing and well during the weeks that follow testing.

Table 1. Worker socio-economic characteristics and balance of characteristics across work groups

	Worker Covariates and Balance Test P-value		
	Mean	Std. Dev.	P value
Individual characteristics			
Age	30.0	8.1	0.142
Years of experience	4.4	4.1	0.990
Year of education	8.2	4.3	0.001
Body mass index	23.8	2.6	0.026
Household characteristics			
HH size	5.4	4.5	0.172
Number of rooms in house	2.8	1.7	0.128
Number of cattle	1.1	4.2	0.311
Number of poultry	7.4	12.0	0.733
Imputed monthly PCE	12543.2	6264.5	0.253
Work characteristics			
Average daily earnings (Naira)	1019.9	243.5	0.001
Total days worked	66.7	15.6	0.001
Propotion of time spent scrabbling	0.12	0.19	0.001

Note: The pvalue is from the balancing test of the covariate across worker groups.

Table 2: Earnings, days worked and wage by week and for selected gangs

Study Week		All workers		Gang 4		Gang 7	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	Earnings	711	304	668	295	633	204
1	Days Worked	5	1	5	1	5	1
	Wage	1,016	382	991	392	817	246
	Earnings	927	415	1,094	485	797	290
2	Days Worked	6	2	6	1	6	2
	Wage	1,152	466	1,316	531	945	338
	Earnings	727	318	672	261	685	277
3	Days Worked	5	1	5	1	5	2
	Wage	1,046	358	980	329	898	352
	Earnings	721	326	686	344	627	243
4	Days Worked	5	2	5	2	6	2
	Wage	941	332	1,024	421	743	254
	Earnings	983	432	1,149	502	902	461
5	Days Worked	6	1	6	1	6	2
	Wage	1,166	456	1,372	529	1,002	470
	Earnings	691	301	739	292	543	241
6	Days Worked	4	1	4	1	4	2
	Wage	1,202	503	1,318	508	923	404
	Earnings	593	278	519	278	555	201
7	Days Worked	4	2	4	2	5	2
	Wage	948	345	908	320	873	298
	Earnings	465	246	350	210	438	196
8	Days Worked	4	2	3	2	5	2
	Wage	823	390	770	391	671	270
	Earnings	553	272	499	231	521	198
9	Days Worked	4	1	4	2	5	1
	Wage	896	361	868	328	778	249
	Earnings	528	317	527	313	534	267
10	Days Worked	3	1	2	1	3	2
	Wage	1,478	767	1,520	687	1,278	621
	Earnings	202	207	209	212	200	184
11	Days Worked	1	2	1	2	2	2
	Wage	1,176	1,303	1,235	1,337	956	909
	Earnings	410	224	383	220	436	153
12	Days Worked	3	2	3	2	4	2
	Wage	979	452	1,022	462	847	311
	Earnings	414	229	368	242	486	219
13	Days Worked	3	1	3	1	4	2
	Wage	869	401	795	414	859	379
	Earnings	543	248	525	301	583	202
14	Days Worked	5	2	4	2	5	1
	Wage	789	282	783	344	766	250
	Earnings	335	173	308	185	339	127
15	Days Worked	2	1	2	1	3	1
	Wage	642	293	611	334	622	209

Table 3. Summary results of maximum parasite count by microscopy

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

Table 4. Within gang balance tests across survey week

Gang	Age	Years of experience	Years of schooling	BMI	HH size	Number of rooms in house	Number of cattle	Number of poultry	Imputed monthly PCE
1				0.095					
2									
3									
4	0.053			0.095					
5									
6									
7			0.071				0.095		
8									

The p-value of the balance test across survey weeks within work group is given if value falls below .10 and otherwise left blank.

Table 5. Intent to treat estimates, by pooled reference period and by week by week

Reference period	Earnings		Labor supply		Wage	
	coef	se	coef	se	coef	se
Pooled estimates						
One week reference	0.043	0.033	0.042*	0.024	0.001	0.022
Two week reference	0.110***	0.032	0.051**	0.021	0.059***	0.022
Three week reference	0.136***	0.041	0.045	0.028	0.091***	0.031
Four week reference	0.077	0.163	0.041	0.105	0.036	0.087
Week by week estimates						
First week after health test	0.043	0.033	0.042*	0.024	0.001	0.022
Second week after	0.139***	0.049	0.084**	0.036	0.055*	0.029
Third week after	0.102	0.090	-0.009	0.062	0.111**	0.053
Fourth week after	0.023	0.119	-0.036	0.078	0.059	0.096

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. Information from 801 workers contributes to the one week reference, 808 to the two week reference, 467 to the three week, and 157 to the four week. ***p<.01 **p<.05 *p<.10

Table 6. Treatment estimates for workers testing positive for malaria

Reference period	Earnings		Labor supply		Wage	
	coef	se	coef	se	coef	se
Pooled estimates						
One week reference	0.007	0.047	0.023	0.037	-0.015	0.037
Two week reference	0.097**	0.045	0.073**	0.034	0.024	0.037
Three week reference	0.110*	0.060	0.079*	0.046	0.030	0.054
Four week reference	--	--	--	--	--	--
Week by week estimates						
First week after health test	0.007	0.047	0.023	0.037	-0.015	0.037
Second week after	0.087	0.069	0.088*	0.052	-0.001	0.052
Third week after	0.059	0.109	0.054	0.076	0.005	0.097
Fourth week after	--	--	--	--	--	--

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. Information from 292 workers contributes to the one and two week, and 162 workers to the threee week, reference periods. There are not sufficient numbers of positive control workers to estimate the four week reference. ***p<.01 **p<.05 *p<.10

Table 7. Treatment estimates for workers testing positive for malaria, by parasite count

Reference period	Earnings				Labor supply				Wage			
	Parasite count = 3		Parasite count >= 4		Parasite count = 3		Parasite count >= 4		Parasite count = 3		Parasite count >= 4	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
One week reference	-0.007	0.063	0.063	0.077	0.001	0.055	0.071	0.047	-0.008	0.048	-0.008	0.068
Two week reference	0.077	0.055	0.131*	0.079	0.036	0.048	0.120**	0.053	0.041	0.052	0.012	0.061
Three week reference	0.080	0.068	0.189*	0.112	0.013	0.053	0.166**	0.085	0.066	0.076	0.023	0.084

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. Information from 292 workers contributes to the one and two week reference period (166 with a parasite count of 3 and 126 with a count of 4 or more), and 161 workers (91 with a parasite count of 3 and 70 with a count of 4 or more) contributes to the threee week reference period. There are not sufficient numbers of positive control workers to estimate the four week reference. ***p<.01 **p<.05 *p<.10

Table 8. Treatment estimates for workers testing negative for malaria

Reference period	Earnings		Labor supply		Wage	
	coef	se	coef	se	coef	se
Pooled estimates						
One week reference	0.056	0.045	0.050	0.032	0.004	0.029
Two week reference	0.116***	0.042	0.043	0.028	0.074***	0.028
Three week reference	0.148***	0.053	0.027	0.035	0.121***	0.038
Four week reference	0.126	0.187	0.057	0.122	0.069	0.098
Week by week estimates						
First week after health test	0.056	0.045	0.050	0.032	0.004	0.029
Second week after	0.166**	0.065	0.092*	0.047	0.074**	0.037
Third week after	0.139	0.123	-0.025	0.087	0.163**	0.064
Fourth week after	0.051	0.145	-0.038	0.094	0.090	0.108

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. Information from 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. ***p<.01 **p<.05 *p<.10

Table 9. Ratio of work days devoted to scrabbling after receipt of malaria test

Reference period	Malaria postives		Malaria negatives	
	coef	se	coef	se
Pooled estimates				
One week reference	0.029	0.029	-0.017	0.025
Two week reference	-0.013	0.032	-0.058**	0.025
Three week reference	-0.033	0.054	-0.102**	0.040
Four week reference	--	--	-0.013	0.070
Week by week estimates				
First week after health test	0.029	0.029	-0.017	0.025
Second week after	0.008	0.046	-0.074**	0.034
Third week after	-0.111	0.093	-0.167**	0.069
Fourth week after	--	--	-0.079	0.122

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. ***p<.01 **p<.05 *p<.10

Table 10. Treatment estimates for workers testing negative for malaria, robust sub-sample analysis

Reference period	Earnings		Labor supply		Wage	
	coef	se	coef	se	coef	se
Only workers-weeks with no days devoted to scrabbling						
One week reference	0.034	0.048	0.046	0.034	-0.014	0.031
Two week reference	0.095*	0.050	0.052	0.033	0.044	0.029
Three week reference	0.125**	0.063	0.056	0.040	0.069*	0.037
Four week reference	0.147	0.209	0.053	0.122	0.094	0.100
Only workers who report no recent illness						
One week reference	0.069	0.051	0.064*	0.036	0.003	0.032
Two week reference	0.129***	0.046	0.049	0.030	0.081**	0.032
Three week reference	0.178***	0.059	0.035	0.039	0.143***	0.044
Four week reference	0.334	0.229	0.205	0.129	0.129	0.116

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. ***p<.01 **p<.05 *p<.10

Table 11. Treatment estimates for workers testing negative for malaria, by select worker characteristics

Reference period	Earnings				Labor supply				Wage			
	Parasite count = 0		Parasite count = 1 or 2		Parasite count = 0		Parasite count = 1 or 2		Parasite count = 0		Parasite count = 1 or 2	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
One week reference	-0.065	0.089	0.063	0.049	0.046	0.066	0.042	0.035	-0.111	0.073	0.019	0.031
Two week reference	-0.043	0.114	0.131***	0.046	-0.047	0.094	0.045	0.030	0.004	0.095	0.086***	0.030
Three week reference	0.019	0.133	0.146**	0.058	-0.161*	0.089	0.029	0.038	0.181	0.147	0.117***	0.041
	Not tired at end of day		Tired		Not tired at end of day		Tired		Not tired at end of day		Tired	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
One week reference	-0.047	0.148	0.084*	0.050	0.029	0.085	0.060*	0.035	-0.076	0.139	0.022	0.031
Two week reference	0.081	0.107	0.134***	0.045	-0.066	0.069	0.055*	0.030	0.148	0.100	0.080***	0.030
Three week reference	0.051	0.086	0.169***	0.058	-0.116	0.086	0.043	0.038	0.167	0.129	0.126***	0.040

Robust standard errors clustered at worker level. Regressions include gang by week fixed effects. ***p<.01 **p<.05 *p<.10