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ABSTRACT

Health Information, Treatment, and Worker Productivity: Experimental Evidence from Malaria Testing and Treatment among Nigerian Sugarcane Cutters*

Agricultural and other physically demanding sectors are important sources of growth in developing countries but prevalent diseases such as malaria adversely impact the productivity, labor supply, and occupational choice of workers in these sectors by reducing physical capacity. This study identifies the impact of malaria on worker earnings, labor supply, and daily productivity by randomizing the temporal order at which piece-rate workers at a large sugarcane plantation in Nigeria are offered malaria testing and treatment. The results indicate a significant and substantial intent to treat effect of the intervention – the offer of a workplace based malaria testing and treatment program increases worker earnings by approximately 10% over the weeks following the mobile clinic visit. The study further investigates the effect of health information by contrasting program effects by workers revealed health status. For workers who test positive for malaria, the treatment of illness increases labor supply, leading to higher earnings. For workers who test negative, and especially for those workers most likely to be surprised by the healthy diagnosis, the health information also leads to increased earnings via increased productivity. Possible mechanisms for this response include selection into higher return occupations as a result of changes in the perceived cost of effort. A model of the worker labor decision that includes health perceptions in the decision to supply effort suggests that, in endemic settings with poor quality health services, inaccurate health perceptions may lead workers to misallocate labor thus resulting in sub-optimal production and occupational choice. The results underline the importance of medical treatment but also of access to improved information about one's health status, as the absence of either may lead workers to deliver lower than optimal effort levels in lower return occupations.

JEL Classification: I12, J22, J24, O12

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

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I. INTRODUCTION

Agricultural productivity has been a key driver of economic development throughout much of world history and remains 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 has received less consideration. 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 labor productivity. It is also unclear whether workers' perceptions of their own health status, which may be imperfectly related to the true state of physical health, affect effort levels at work.

Extensive research has linked the health and nutrition environment of early childhood to later adult outcomes (Strauss & Thomas (1998), Walker et al. (2007), Hoddinott et al. (2008), Cutler et al. (2010), Bleakley (2010), Heckman et al. (2010), Gertler et al. (2013)). But to what extent does productivity benefit from investment in the health of able-bodied adults? The existent literature has taken two general directions. One explores the relationship between adult nutrition and labor outcomes, the other considers the effect of specific illnesses such as HIV infection or tuberculosis.[1, 2] This study also focuses on one disease – malaria – and its influence on labor supply, productivity and occupational choice among an agrarian workforce. Malaria is one of the most prevalent communicable diseases in the world today. Adults affected by malaria suffer from lower energy levels via heightened morbidities such as fever, weakness, muscle aches, and chills, and hence are likely to work fewer days and be less productive when they do work.[3] Agricultural workers and those in other physical occupations are presumed to suffer the greatest productivity declines from malaria due to the nature of work demanded.

[1] For the nutrition literature see, for instance, Basta et al. (1979), Edgerton et al. (1979), Wolgemuth et al. (1982), Imminck and Viteri (1980), and Thomas et al. (2006) for experimental studies; Strauss (1986), Sahn and Alderman (1989), Bhargava (1997), Fogel (1997), Schultz (1997), Thomas and Strauss (1997), Strauss and Thomas (1998), Sur and Senauer (1999), Behrman and Rosenzweig (2001), Schultz (2002), and Weinberger (2003) for nonexperimental studies of the effect of nutrition on labor outcomes. Also see Deolalikar (1988) and Croppenstedt and Muller (2001) for effects of nutrition on farm output and production frontier respectively.

[2] For the disease specific literature 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 careful descriptive studies of the labor effects of HIV infection and Habyarimana, Mbakile and Pop-Ellches (2010) for the effect of ARV treatment in Kenya; Saunderson (1995) looks at tuberculosis in Uganda. Of interest is also Zivin and Neidell (2010), who find substantial effects of pollution on worker productivity in California.

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

Studies at the 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. (2007), Ayieko et al. (2009), among others). While they generally find that malaria imposes substantial economic losses on households and firms, 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. 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 such 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. Our study addresses all three limitations with the randomized temporal access to a mobile health clinic by piece rate wage-workers at a large sugar plantation in Nigeria.

Because health is multi-dimensional and not perfectly observable by the subject, workers often do not know their precise health status. Nevertheless workers have perceptions and must form expectations about their health status on which labor choices are predicated. With access to high quality clinical care, individuals presumably receive health information based on clinical standards of diagnosis. However for workers in developing countries the quality of health information tends to be poor due to both the restricted accessibility and the low quality of health care. Worker mis-perceptions about health may lead to misallocation of optimal effort affecting productivity, labor supply or occupational choice. As in the clinical setting, our intervention not only delivers medical treatment to the ill, but also provides diagnostic results to all workers. It is possible that this diagnosis itself affects worker behavior, especially if results run counter to worker expectations conditioned by their endemic environment. We thus posit that work decisions related to labor supply and effort are partly a function of health perceptions, which are closely related to but not identical with actual physical health status. In the third section of the paper, we illustrate in a theoretical model the effect of health perceptions on optimal effort supply in a piece rate wage setting following Gibbons (1987) and Lazear (2000).

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. (2011), Gong (2013), Baird et al. (2013)). 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 productivity. Furthermore, the role of health information may be especially relevant for specific diseases typically diagnosed by 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. 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)).

If workers select their 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. Specifically, in the context here, if workers underestimate their own health because of a lack of 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. We will investigate whether workers' re-evaluation of actual malaria status as a result of new health information leads to changes in occupational choice, labor supply, productivity, and eventually earnings.

We conduct three types of analyses in order to estimate three interrelated treatment effects in the study population. First, to estimate the effect of the overall intervention that provides malaria testing followed by treatment of those who are malaria positive, we compare labor outcomes of workers offered this program to a counterfactual of workers who have not yet received it. This comparison yields an estimate of the intent to treat (ITT). We find ITT effects of this workplace program for both labor supply and productivity that together account for approximately a ten-percentage point increase in earnings in the weeks following treatment. In principle, this gain reflects the effect of both medical treatment (if sick) and the provision of improved worker-specific health information.

Second, to assess the effect of medical treatment among malaria positives we also compare outcomes from workers who tested positive for malaria with outcomes from workers who did not yet have access to treatment but are assumed sick as they test positive in the following weeks. This conditioned analysis can be interpreted as an estimate of the treatment on the treated (TOT) in so far as it yields an estimate of the productivity gains from treating malaria among malaria positive workers, as compliance is near universal. 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. Overall this suggests the gains to treatment of malaria infection are substantial. While the counterfactual assumption necessary for this interpretation may be relatively innocuous for time periods proximate to the introduction of testing and treatment among the sick, it may be less defensible for periods that are farther away from the point in time of the intervention. We therefore test the sensitivity of the results across multiple reference periods.

A third comparison focuses on the isolated effect of providing possibly new and unexpected information regarding one's own health status to those who test negative for malaria. To do this, a similar conditional analysis, the treatment on the medically untreated (TmUT)[4], is conducted on malaria negative workers – those with either no evidence of the malaria parasite in their blood or with levels low enough to fall below the clinical threshold. Again a necessary assumption for this analysis is that the workers who subsequently test negative constitute a valid counterfactual group for the workers given 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, suggesting that even healthy workers update their health beliefs and modify their labor decisions. As the term "malaria" is often used as a wider assignation of general illness, especially illness accompanied by fever, other diseases with the same symptoms (e.g. flu) can be self-diagnosed as malaria but have less severe effects on labor outcomes. Workers who are parasitemic negative may therefore expect their physical work capacity to be low (despite having few or no malaria parasites) if they feel out of shape, or low in energy, possibly due to other reasons 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 affects the perception of their own health and their expectations related to work efficacy.

Again, the critical assumption for this interpretation, given our temporal randomization, is that workers who ultimately test negative a short period in the future constitute a valid counterfactual for those workers already informed of their negative diagnosis. The validity of this assumption is explored in a variety of ways including a test of differential response by workers who may be more surprised by a negative diagnosis – for example those workers who report fatigue at the end of the workday or those who carry subclinical levels of the malaria parasite in their blood (and hence feel weaker) but nevertheless do not meet the diagnostic threshold of malaria positivity.

Mechanisms for the increased earnings and productivity among workers who test negative include a selection into higher return occupations. We interpret this selection to be a result of changes in the perceived cost of effort due to revised health expectations. These findings underline the importance of both medical treatment and access to improved information about one's health status, as the absence of either may lead workers to deliver lower than optimal effort levels. Our study also suggests that the productivity costs of malaria are not only attributable to reductions in the labor supply and productivity of the worker but also to the potential suboptimal allocation of workers across occupations in these endemic settings.

[4] The TmUT refers to workers who were malaria negative and therefore not prescribed malaria medication, though all workers received health information about their malaria status. In this paper, we call this effect the treatment on the medically untreated. Strictly speaking malaria negative workers are not untreated, but our conditional analysis is used to reveal the effect of this information in this subsample of the worker population.

The next section of this paper describes the study setting, followed by a section introducing a theoretical framework. Section Four discusses our diagnostic approach as well as other measurement issues. The fifth section describes the experimental design and identification strategy, while section six presents the results. A final section offers concluding thoughts.

II. STUDY SETTING

The experiment is situated on a single large (5,700 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-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.

Workers are hired for the entire harvest season from local villages surrounding the plantation and are transported daily to the assigned work site. 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 if the work group is particularly productive. Sugarcane cutters do not work in teams to complete the rows of cane but rather work individually along a row until finished and are then assigned by the supervisor to 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.

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 his personal '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. Laborers are paid monthly and they often keep track of their daily output by maintaining their own separate ledger. Disagreement between cutters and management over compensation amounts are rare. The work tends to be lucrative and an average day of cane cutting pays 1,020 Naira, or approximately US$7. This daily wage is substantially higher than most local alternatives. 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 occupations – sugarcane cutting or 'scrabbling'. Scrabbling is an occupation that includes the collection of cut sugarcane rods and then binding of them into bundles for loading on trucks destined for processing at the factory. Less physically intensive than cutting, and more difficult to observe individual effort, scrabbling pays a fixed wage of 500 Naira per day (roughly half the expected earnings of a day spent cutting). Scrabbling work can be selected by a cane cutter if he is not feeling at full strength that day through a request to the supervisor. There is also a dedicated separate work force of scrabblers hired and managed by the plantation but these full-time 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 3.5 days of the week cutting cane and 0.5 day scrabbling (with the other days of the week spent off the plantation). This daily occupational choice will play a role in the results to come.

The plantation records on individual worker daily productivity and job choice are one key source of information for our analysis. We supplement this information with data from worker interviews covering socio-demographic, work history, and self-reported health information. We also collect blood samples during the interview to test for malaria. The experimental design randomizes the order in which workers are tested and treated over time with all workers receiving one test (and treatment if positive) over the survey period of six weeks. The study then exploits the exogenous variation in the timing of access to testing and treatment for malaria to identify the effects of the intervention.[5] To do this we construct a time-series of worker-week observations that permits us to compare the labor outcomes of treated and untreated workers for the same weeks of observation.

Table 1 presents selected mean individual and household characteristics of the workforce.[6] 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 to 5 years 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. As stated earlier, the average daily earnings are slightly

[5] A free health clinic to which workers have access already exists on the plantation but we do not expect the presence of this clinic to confound our impact estimates. The clinic is believed by the work force to be of poor quality. There is no patient follow up and the facility is far removed for most workers. Virtually no worker has reported a visit to the clinic during the field work period, and this has been confirmed through inspection of the clinic's records.

[6] These characteristics include household expenditure which are not measured but rather predicted using the method suggested by Grosh and Baker (1995) and Ahmed and Bouis (2001) . 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 (NBS), 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 EXP_i for our own sample. Where D_i^a represents a dummy variable indicating whether asset a is present in the household. The regression uses population weights as calculated by the NBS. Since the estimates of the coefficients are relatively sensitive to outliers, we exclude the richest 10% of households in our prediction.

more than 1000 Naira, and the average harvest season comprises 66 workdays. The typical 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 balance tests of each measured worker characteristic across the eight work groups. As work groups are uniquely allocated to plots these differences may reflect differing group or plot characteristics.[7] Most socio-economic and demographic characteristics are fairly equal across work groups, with the notable exception of worker education and BMI. In addition the plantation records make clear that earnings opportunities also differ across work groups with average earnings and days worked varying significantly. Given the imbalance in average earnings and in certain characteristics that may be related to productivity, most notably BMI, it will be important to stratify the randomized exposure to treatment within work group in order to control for any such imbalance.

Not only do earnings and related measures significantly vary across work group but they also vary across time, even within a work group. Table 2 lists the mean days worked and daily earnings for the entire harvest period, in the first panel averaged over all workers and then for two selected work groups. While in a typical harvest week a worker will work 3.97 days and earn about 1000 Naira a day, Table 2 makes clear the high degree of group-specific temporal heterogeneity in days worked and earnings. As the experiment will compare outcomes in a given week between workers randomly offered treatment and those not yet offered, controlling for the work-group specific temporal variation in outcomes will also be critical.

III. THEORETICAL FRAMEWORK

A brief theoretical framework serves to highlight the role of health perceptions in the individual worker labor decision by incorporating into a piece rate wage model insights from the health production literature on the potential effect of health perceptions on worker effort. The model also motivates our identification strategy described in the next section.

In our plantation setting, the worker's decision is to maximize expected income net of cost of effort for any day of work by deciding (a) whether to work on the plantation or not, (b) which job to carry out on the plantation and (c) how much effort to deliver. Each possible job – cane cutting or scrabbling on the plantation or off-site work (such as home production, nonfarm work, or off-plantation agricultural job) – will have different returns and requires different levels of effort. Our theoretical model characterizes this choice as a function of expected returns to effort, relying on the literature on piece rate wage contracts including Gibbons (1987) and Lazear (2000). Given the possibility of health information effects

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

on subsequent behavior, we further enrich the model by allowing health perceptions to affect subsequent labor decisions. The worker's problem is then to maximize a utility function *U=U(Y,e)* where *Y* is income, *e* is work effort.[8] The worker's output *x* in a physical occupation depends on ability, *A*, and effort. Effort partly depends on the workers' own perceived physical work capacity, which we denote as the worker's perceived health $\widetilde{H}$, due to the influence of health perception on the expected cost of effort. We denote the worker output function as:

$$x = f(e(\widetilde{H}), A) \tag{1}$$

where $f_1, f_2 > 0$. Perceived health, in turn, is an unknown function of actual health, *H*, and information about one's own health, *I*:

$$\widetilde{H} = g(H, I) \tag{2}$$

A worker's effort thus depends not only on the more familiar constructs of motivation and the offered wage but also on health self-perception, which is a function of actual health as well as the content and trustworthiness of information received from outside. Workers with perceptions of more robust health will deliver more effort.

For the fixed-wage scrabbling occupation, denote the minimum level of output needed to maintain employability as x_0, where x_0 can be attained by various combinations of effort, e_0, and ability, A_0:

$$x_0 = f\left(e_O(\widetilde{H}), A_0\right) \tag{3}$$

If scrabbling is to be a viable option for a worker on any given day, the expected utility from scrabbling need exceed the utility from off-plantation work which we norm to zero. Specifically

$$U\left(w_{scrab}, e_O(\widetilde{H})\right) \geq U(0,0) \tag{4}$$

where w_{scrab} is the fixed daily wage for scrabbling. Figure 1 conveys the possible combinations of effort and ability at which the worker is indifferent between scrabbling and off-plantation work with the curve denoted U_{x0}. If a particular worker combination of chosen effort and ability falls below this curve, the worker selects either leisure or work off the plantation. Workers who scrabble typically earn rents by scrabbling since they are only required to produce x_0 of output in order to receive w_{scrab} but are likely capable of greater effort.

[8] We assume that the utility function has a strictly positive (negative) first derivative and strictly negative (positive) second derivative in income (effort). Other elements may enter the worker's utility such as physical health itself, but these elements are suppressed at no loss of generalizability.

However a second occupational choice confronts plantation workers. For any ability level A, cane cutting requires greater effort than scrabbling in order to earn a sufficient differential to compensate for the higher costs of effort demanded. The worker who selects into cane cutting receives piece rate compensation, $w_{cut} = Rx$, where R is the piece rate. A risk neutral worker will then select cane cutting when the expected utility from this work exceeds that of scrabbling. We denote the set of possible abilities and effort levels by which a worker prefers cane cutting to scrabbling as $(e_*(\widetilde{H}), A_*)$, where:

$$U\left(Rf\left(e_*(\widetilde{H}), A_*\right), e_*(\widetilde{H})\right) \geq U\left(w_{scrab}, e_O(\widetilde{H})\right) \tag{5}$$

The U_{x*} curve in Figure 1 denotes the combinations of ability and effort by which a worker is just indifferent between scrabbling and cane cutting.

With this framework we can categorize plantation workers into three distinct groups: workers who always cut cane, workers who always scrabble, and workers who switch between the two occupations (we ignore workers off the plantation). This latter group of workers, the switchers, is located in an inframarginal area in Figure 1 where potential perturbations of daily productivity due to perceived health may alter their preferred choice on a day to day basis. We call this set of workers 'switchers', because they switch between occupations within a harvest season, sometimes repeatedly so. A switcher is denoted in the figure by S_1, where a change in health expectations has increased the expected net returns from cane cutting to a degree that this occupation is now preferred. Contrast this movement with that of worker S_2 who also experiences a change in health expectations of the same magnitude. However the lower ability endowment of this worker is such that scrabbling remains the preferred occupation.[9]

In principle this framework allows us to assess the effect of physical health and information about one's health on different labor outcomes. First workers supply labor to work on the plantation (or not) if this effort provides higher returns than off plantation work, conditional on health and available information. As mentioned earlier, all workers who were selected from the surrounding villages to work on the plantation take up the job, but workers can be absent on any given day, typically for health related reasons. Second, each day when supplying labor to the plantation workers choose to cut cane or scrabble depending on their own perceived health. Third, workers decide how much effort to deliver on the job, which is also a function of their perceived health. This is particularly relevant for cane cutters, whose earnings directly depend on effort. Fourth, workers' total earnings in a period can be assessed as a product of their daily labor supply, their occupational choice, and on the job effort. We specify a labor response function derived from this model as:

[9] Note that a corollary of this decision framework is that workers at higher ability levels are more likely to switch from scrabbling to cane cutting when health expectations are revised upward. This corollary will be investigated later.

$$L_{it} = L(A_{it}, e(g(H_{it}, I_{it})), R, \overline{w}_{scrab}, \mu_{it}, \nu_{it}) \quad (6)$$

where L is the labor outcome vector of individual i at time t. This vector includes such outcomes as labor supply (days worked), occupational choice, productivity, and earnings from work. μ_{it} reflects unobserved individual characteristics while ν_{it} reflects work group or plot characteristics.

Well-identified empirical tests of the health-productivity relation remain limited in the literature.[10] The above labor response function makes clear the usefulness of an experimental approach to measure the role that health plays in labor outcomes. Observational studies suffer from a range of econometric problems in identifying this effect. Focusing on the effect of actual health (H), these studies do not account for the possibility that a worker's heath status may be correlated with μ_{it} through endowment effects. This study's randomization of subjects into treatment and control groups results in an exogenous change in malaria health status due to medical treatment of those who are infected and thus avoids this problem. Another identification problem with the use of observational data is the possibility of reverse causality between health status and labor. The exogenous change in malaria status induced through medical treatment rules out this possibility. To address concerns that unobserved differences in management or scale of operations across firms affect worker productivity, as firm policies regarding absenteeism and the provision of health care to workers may influence the effect of malaria treatment on productivity,[11] the study focuses on workers within one large plantation.

Our study approach also provides the opportunity to study the role of information and perceptions of one's own health for labor outcomes as our intervention is a combined treatment of health information and possible curative care, thus creating exogenous variation both in the worker's actual health and/or information about his own health. More formally, the effect on labor outcomes of the exogenous change in perceived health offered by our intervention is the derivative of the labor response function to a change in the cost of effort. With perceived health a function of actual health and information, as set out above, this is a combination of two partial effects:

$$\frac{\partial \mathrm{L}}{\partial \mathrm{e}} = \frac{\partial \mathrm{L}}{\partial \mathrm{e}}\left(\frac{\partial \mathrm{e}}{\partial \widetilde{\mathrm{H}}}\frac{\partial \widetilde{\mathrm{H}}}{\partial \mathrm{H}} + \frac{\partial \mathrm{e}}{\partial \widetilde{\mathrm{H}}}\frac{\partial \widetilde{\mathrm{H}}}{\partial \mathrm{I}}\right) \quad ` \quad (7)$$

where the first term reflects the impact of a change in actual health on effort, while the second term reflects the effect of improved information regarding one's own perceived health on effort. While for those tested negative the first term will be zero, allowing separate identification of the information effect, the estimated impact for those who test positive will reflect a combined health and information effect.

[10]See Footnote 1 and 2.

[11] Firm fixed effects are found to be important determinants of worker productivity, especially in developing countries (see for instance Soderbom and Teal 2004).

IV. MALARIA: IMPACT AND MEASUREMENT

Before describing the intervention in more detail, it is important to understand both the measurement and expected impact of malaria infection as the particular biology of infection informs our identification strategy and subsequent robustness analysis. As malaria symptoms generally include fever, chills, sweats, headaches, nausea, vomiting, body aches, general malaise, and increased respiratory rate the potential for malaria infection to impact labor productivity is high. Severe malaria can also impair consciousness, cause seizures, and result in coma (Najera and Hempel 1996). Individuals affected are also often dehydrated and hypovolemic (Miller et al., 2002). The duration of an episode of malaria varies widely.[12] Najera and Hempel (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.

Three methods are commonly used to measure malaria infection in large-scale surveys: self-report, Rapid Diagnostic Testing (RDT), and microscopy. While self-reported malaria is often used as a proxy, 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. Because the symptoms of malaria are very generic, subjects may, through self-assessment, categorize other illnesses with similar symptoms as malaria infection. At the same time, especially in areas where malaria and 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. [13]

Our study relies on the measurement of parasites in the worker from thick film blood smears, which were read in a laboratory. Although expensive to implement as it requires trained personnel and appropriate instruments, thick blood film microscopy is considered the diagnostic gold standard. The study team takes a blood sample from each consenting worker and carry out microscopy analysis in a nearby lab, counting the number of parasites, with workers above a specified threshold considered malaria positive.[14] While a high parasite load indicates malaria infection there is no medical consensus about the

[12] Duration may 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).

[13] 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 and public health studies.

[14] 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 the batch. If discrepencies between the primary laboratory technician and the supervisor were found, the whole batch of slides was re-validated.

exact relationship between parasite load and malaria outbreak. Laishram et al. (2012) discuss asymptomatic malaria, noting that a common parasite threshold has not been universally adopted. [15] Our adopted definition of malaria positivity is the presence of at least three parasites over the total examined fields in the blood smear. This decision follows the clinical diagnostic standards in the study area. However we also conduct analysis with the underlying parasite count and not only the binary diagnostic measure.

Table 3 conveys the blood slide results by presenting the distribution of the total parasite count across blood fields. Only 9% of the workers have no observed presence of parasites while roughly 55% have had one or two parasites observed. These descriptive statistics are similar to parasite loads observed in endemic settings in Senegal by Bottius et al. (1996), where they diagnosed 90% of their sample with chronic asymptomatic malaria. 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. 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.

All 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) 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 dosage properly, had consumed the medication himself without distributing to others, and whether the worker was asymptomatic. Almost no problems with compliance were reported and we assume full compliance with ACT treatment for the remainder of the analysis.

[15] Different studies in the medical literature use distinct parasite density thresholds in classifying malaria infections as there is not a medically established standard for population based malaria testing which includes asymptomatic malaria cases (dalla Martha et al. (2007), Toure et al. (2006), and Rottmann et al. (2006)).

V. EXPERIMENTAL DESIGN AND IDENTIFICATION STRATEGY

The study design uses temporally randomized exposure to treatment to resolve the identification problems inherent when observationally relating health and labor. We chose this approach to ensure that all workers would have access to the testing and treatment program. Workers deemed malaria positive according to microscopy are treated with the appropriate doses of Artemisinin Combination Therapy (ACT) upon the receipt of a diagnosis. There is a 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 order of worker testing and possible curative treatment followed a two-stage procedure where workers were first stratified by group, followed by a randomly determined order of workers within each group. A list of workers was obtained from the plantation and the stratified randomized order of treatment was decided 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 every study week, a subset of workers from each work group were assessed for malaria so there is a relatively even distribution of workers interviewed across time within each work group.

The randomization of the order of testing and treatment over time 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 testing and treatment on labor outcomes. Both the sources and the timing of data collection are depicted in Figure 2. In terms of labor outcomes recorded daily by the plantation, the analysis focuses primarily on three outcomes: worker productivity (average daily earnings within a given week of observation), labor supply (days worked), and total weekly earnings, but also considers the effects on occupational choice where relevant.

Table 4 presents the summary results of balance tests conducted on worker characteristics according to the week in which the worker was interviewed and offered the malaria test. In principle, randomization will guarantee balance of covariates, but in practice, with approximately 100 workers in each of eight work groups, the success of the randomized draw in ensuring balance needs to be validated. Overall, the randomization process appears to produce a well-balanced sample. Out of 72 balancing tests – nine characteristics in 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. In additional robustness checks, linearly controlling for observed worker characteristics such as education, BMI, and age does not affect the main results.

We estimate three types of treatment effects for the offer of malaria testing and treatment: an ‘intent to treat effect’ (ITT) a ‘treatment on the treated’ effect (TOT), and a ‘treatment of the medically untreated’ effect (TmUT). The first effect reflects the benefits of access to malaria testing and treatment, comparing outcomes of workers *with* access to testing and treatment to those of workers *yet without* access to testing and treatment (and who may or may not have fallen ill from malaria). The second effect compares outcomes of those who are ill and treated to those who are ill but not yet treated due to their randomly allocated later testing date. The third effect considers the sole effect of health information on labor outcomes (operating presumably through the mechanism of updated health perceptions) for those workers who test malaria negative. We do this by comparing labor outcomes for those workers who are tested and informed to be malaria negative with those workers not yet tested but assumed negative based on the results of subsequent tests. This effect can be thought of as a TOT estimate of the information component of the intervention where healthy workers learn about their actual good health, a potential 'good news' effect. However to distinguish these estimates from the TOT for those workers who are malaria positive, we adopt the TmUT. As a robustness check, we present several different estimates of these effects using different durations for the observation reference period. We now discuss each of these estimates in more detail.

The ITT effect is estimated by comparing labor outcomes over some observation 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 *t+*, after the observation period *t*. The sets of workers assessed at *t*- and *t+* are denoted as W_{t-} and W_{t+}. The difference in outcomes over period *t* represents the combined 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 natural weekly variation in work outcomes both across and within workgroups, a full set of workgroup-workweek fixed effects, F_{gt}, are included in the specification. Specifically we estimate:

$$L_{igt} = \alpha + \beta T_{igt-} + F_{gt} + \varepsilon_{it}, \forall i \in W_{t-} \cup W_{t+} \quad (8)$$

where L_{igt} measures the three labor outcomes of interest in log form: earnings, labor supply and daily productivity for worker *i* in work group g at period *t*, and ε_{it} is the worker specific error term. Where relevant, we also consider a fourth labor outcome, namely occupational choice, which is measured as the proportion of work days per week devoted to scrabbling. In terms of the theoretical framework set out in Section 3, β captures the effect of a change in perceived health in parasitemic negative workers, or the combined effect of a change in actual health (as a result of treatment) and the provision of more accurate information about the worker's health status in parasitemic positive workers. Note that the content of information is distinct for the two groups. The ITT thus reflects a combined effect of good news for the parasitemic negatives and bad news and medical treatment for the parasitemic positives.

Following a similar approach, the TOT on malaria positives 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+ but at that point found to be malaria positive (and thus assumed sick over the period *t*). To estimate the TOT, Equation (8) is re-estimated but now for the subset of workers P who have tested positive, as given in Equation (9):

$$L_{igt} = \alpha + \beta T_{igt-} + F_{gt} + \varepsilon_{it}, \forall i \in P_{t-} \cup P_{t+} \tag{9}$$

as before, L_{igt} reflects the log labor outcomes of interest: earnings, labor supply, and productivity. The TOT reflects the combined effect of receiving an illness diagnosis and medical treatment for such a diagnosis.

Finally, we estimate a possible 'good news' effect by comparing labor outcomes at time *t* for those workers who were tested and found negative at time *t*- with the labor outcomes for workers who were not tested until time t+, but found to be negative at that point. This is estimated for the subset of workers N who have tested negative, as given in Equation (10):

$$L_{igt} = \alpha + \beta T_{igt-} + F_{gt} + \varepsilon_{it}, \forall i \in N_{t-} \cup N_{t+} \tag{10}$$

To estimate Equations (8) – (10), several different strategies to construct the reference period are used to compare treated workers with workers yet to be treated. Allowing for a short time lag after treatment is necessary because it takes an average of three days for workers to receive diagnosis and then take the additional 3-day course of ACT to clear the body of malaria parasites and return to 'normal' energy levels. Thus the week in which the actual blood test is drawn (*t*-) is excluded from the analysis. The identification strategy also exploits the pharmacologic properties of ACT that, while being a curative medicine also protects patients against malaria reinfection for some time after treatment, estimated between two to four weeks. The robustness of our findings are tested by varying *t*, the length of the period of observation.

Treatment effects are estimated for the first week after treatment, the second week after, the third week, and the fourth. To estimate one week effects, outcomes in the 2nd week of the study period are contrasted across workers treated in the first week ('the treated') and the third week (their 'control'), outcomes in the 3rd week of the study are contrasted across workers treated in the second week and the fourth week, and so on. For second week effects, outcomes in the 3rd week are contrasted for workers treated in the 1st and 4th weeks, information for the 4th week is used for workers treated in the 2nd and 5th weeks, and so on. Given the constrained timing of the intervention in order to accommodate the wishes of plantation management, effects beyond the 4th week could not be measured as the fieldwork period lasted six weeks and the weeks of observation for both treatment and comparison workers are excluded from the analysis (i.e. the fourth week after treatment effect is only estimated from workers assessed in the first and sixth week of the study). Also in parallel analysis, in order to maximize the number of worker-week observations, outcomes are averaged over four windows of increasing duration: one week, two weeks, three weeks, and four. Results from both approaches (week-by-week or pooled over weeks) 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.

The ITT estimates can be biased if the treatment itself leads to biological or behavioral worker responses. One biological concern with the identification strategy is the possibility of a disease transmission spillover through time due to the possible reduction in parasite prevalence in the control group as a result of successful parasite elimination in the treatment group. While a valid concern in theory, the vast 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. In addition, the measured malaria positivity rate shows no decline over the weeks of study, counter to expectations in the presence of significant spillover effects. We do not expect such a spillover possibility to affect our estimates.

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 set of working conditions that are likely to be highly important to peer productivity effects. Our study setting is less likely to produce peer productivity effects for two important reasons. First, peer productivity effects require that the work of peers is observable to other workers. In our study, a work group contains approximately 100 workers distributed across large stretches of the sugarcane plantation. Second, unlike the Mas and Moretti setting where the low productivity of peers in salaried supermarket work induces more customers to shift to a quicker clerk, in our piece rate wage setting with a fixed daily work schedule any drop in productivity by a particular worker does not affect the effort required of other workers or the number of hours they can work. For these reasons, we find it unlikely that peer effects are a significant source of bias in our ITT estimates.

To identify the TOT estimates described in equation (9), a key additional assumption about the malaria status of the counterfactual worker group is necessary, namely that 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 malaria status of workers is only assessed at one point in time. However, an outbreak of malaria lasts an average of 14-17 days with parasite loads maximizing in the blood 1 to 3 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. A TOT estimate over a four-week reference period cannot be reliably estimated due to the small number of malaria positive workers assessed in the 6^{th} week of the intervention.

The estimation of the information effect on the workers who test malaria negative in equation (10) relies on a similar assumption, namely that those tested negative in later study weeks are also negative during the observation period. We believe this assumption to be valid for the same reason – the dynamics of malaria illness – as mentioned above. Nevertheless the robustness of this assumption is explored in several ways through complementary analysis including the restriction of analysis to workers who report no physical morbidities over the previous 4 weeks (a presumably healthier group). We also test the good news effect by contrasting results between workers with no parasites or those that report no fatigue at the end of the day with workers who have subclinical parasite levels or who report fatigue. It is these latter groups who are more likely to be surprised by a healthy diagnosis and thus revise their health expectations.

VI. RESULTS

We report 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). Throughout the analysis we focus on the three labor outcomes of primary interest: worker productivity worker productivity, labor supply, and total weekly earnings; where relevant we also discuss occupational choice.

VI.A. Intent to treat estimates – the joint effect of malaria testing and treatment on labor outcomes

Table 5 presents the results of equation (8) estimated on the total sample of workers. We analyze three outcomes all converted to log quantities: weekly earnings, days worked, and the daily wage. The results depict a clear, albeit somewhat delayed, response to treatment. In the first week after treatment, earnings increase by 4%, although this effect is not precisely estimated. Days worked also increases by 4%, significant at the 10% level. From these results, there appears to be no effect on daily output. Due to intervention timing we may not expect to see large effects in the first week after treatment as the microscopy analysis and relay of diagnosis took an average of three days (and medicinal efficacy requires another two to three days), so workers assessed towards the end of the interview week may not receive diagnosis (and medication if applicable) until the middle of the second week of observation.

Larger impacts emerge in the two and three week reference period (at this point all treated workers should have received a diagnosis and possible medication). The two week pooled reference period indicates that weekly earnings average 11% more in the two weeks following the malaria testing and treatment. Earnings rise to 14% higher in the three week period. These gains in earnings are divided between increases in both labor supply and the daily wage. In both the two and three week reference period the days worked increases by approximately 5%, although the gain in labor supply is no longer significant in the three week period. The daily wage increases by 6-9% depending on the observation period. Gains to earnings, labor supply, and wages all begin to decline in the pooled 4-week reference period and any gain is no longer statistically significant, 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 that capture the short-run dynamic impacts of treatment largely echo the pooled reference period results. Earning gains peak two weeks after the malaria test at a precisely estimated 14%. Both labor supply and productivity increase with labor supply gains peaking in the second week at 8% and productivity in the third week at 11%. By the fourth week effects are no longer significantly different from zero.

These ITT estimates summarize the average worker benefit of the combined testing and curative treatment offered to every worker. If the labor benefit were solely due to the treatment of disease among malaria positive workers, we can apply a Wald estimator to calculate the labor supply and productivity costs of malaria. Given that 36% of the workers test positive for malaria, the two-week pooled point estimates would indicate a 30% gain in earnings for treating malaria, or $US 30, split roughly equally between gains in labor supply and daily productivity. This estimate is far higher than most findings summarized in 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. (2007), or Ayieko et al. (2009), perhaps because our estimate also includes productivity effects conditional on working, which are often absent in other studies. However this 'naïve' Wald estimate overlooks the possibility of 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 potential impact. We attempt to do so in the subsequent analysis.

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

The next set of estimates in Table 6 focuses on the effects of treatment on malaria positives (equation (9)). Precision suffers in comparison to Table 5 since the worker sample is now truncated to approximately one-third of the total sample. It is also no longer possible to estimate a four-week reference period due to insufficient numbers of malaria positive workers in the control group for that period. Nevertheless an earnings response in the two- and three-week pooled estimates is 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 (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 later.

Most of the gains in earnings for those infected arise from an increase in labor supply. The number of days worked after treatment with ACT increase on the order of 7%-8%. There may also be a marginal gain in the productivity of each day worked – on the order of 2% to 3% as suggested in the point estimates – but these productivity numbers 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 1,345 Naira, or approximately $US 9. While less than the naïve Wald estimator gain of $30, the estimated gain is still greater than the market cost of ACT which currently stands at $5 to $7. And of course this is only the monetized gain over three weeks – gains may well extend beyond that period but we are unable to observe them.

As discussed earlier, workers receive immunity after treatment, so we don't expect treated workers to be re-infected in the following weeks. However for this approach to yield a valid estimate of the TOT for workers sick with malaria we must assume that the workers who later test positive are also positive with malaria during the period of observation. While this is a reasonable assumption for the weeks immediately before health assessment that we focus on in this study, we further test this assumption by exploring heterogeneity in treatment impact with respect to disease intensity. If the estimated 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 Table 7 by disaggregating the TOT response into two groups: those with a parasite count of 3 and those with a parasite count of 4 or more.

While the point estimates for the two groups are not significantly different from each other (as we have split an already small sample), the results are suggestive as 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 19%, almost entirely arising through a labor supply response.

This differential pattern by disease intensity is consistent with the conjecture that the main TOT estimate captures the successful treatment of malaria infection rather than bias from an invalid counterfactual group. Further it is suggestive that much of the gain from malaria treatment manifests through increased labor supply and not increases in productivity while at work.

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

A comparison of response coefficients in Tables 5 and 6 suggests that not all benefits measured by the ITT estimates accrue solely to malaria positive workers. Since the intervention consists of both health information and medical treatment, estimates of Equation (10) provide the first evidence on the role of a worker's own health information – in this case 'good news' – in labor decisions. Results in Table 8 are estimated only on the sub-sample of workers who test negative and then receive this information in the following days. Changes in earnings for this group of workers are precisely estimated in the 2 and 3 week reference period pooled results, and the magnitude of 12%-15% is 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% to 12% depending on the reference period.

There are several possible explanations for this response. As discussed above, workers may deliver effort based in part on the perception of their own health, which is at least partly distinct from their actual health. Especially in endemic settings where information is poor, healthy workers may 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 may significantly affect worker expectations of productivity that in turn lead to higher labor supply, higher productivity, and possibly differential occupation choice.[16]

Another possible explanation is of course that the identifying assumption in equation (10) does not hold – some fraction of control workers who subsequently test negative may in fact be suffering from malaria during the period of observation thus contaminating the comparison. Subsequent robustness analysis explores this likelihood through several complimentary channels: (a) investigating occupational

[16] A competing explanation for this observation may be a type of "gift exchange" (Akerlof (1982)). In this explanation, cane-cutters are grateful to management for the attention expressed through the mobile health clinic and work harder in response. We find this explanation unlikely in a piece-rate setting where effort is already measured and priced. Based on statements overheard during the study period, both before and after a worker received testing and treatment, worker satisfaction with management at the time of the survey appears to be uniformly and rather low with little gratitude expressed.

choice made after the receipt of good health news, (b) limiting analysis to workers who report no recent illness (of any kind), and (c) exploring differential response to treatment by characteristic such as parasite count that capture whether the negative diagnosis runs counter to pre-test worker expectations.

One proposed mechanism through which workers maximize their earnings (net of effort) is by switching occupation, as suggested in the theoretical framework. In principle this switch can occur in response to improved information or improvements in actual health status that lead the worker to revise perceptions of the cost of effort. As previously discussed, workers may choose to work as scrabblers on days when they anticipate that the effort required to earn the same amount (or more) as the scrabbling wage through cane cutting will be more costly (in terms of effort). Conversely, workers who revise their health perceptions on the basis of a negative diagnosis may be more likely to opt for cane-cutting. This is investigated in Table 9 where the proportion of workdays in the week devoted to scrabbling is regressed on the treatment indicator in a similar specification as Equation (8). The first panel reports the results for workers who tested malaria positive only, and indicate there is no noticeable change in the scrabbling rate for malaria positives after receipt of diagnosis.

The results for malaria negatives - reported in Columns 3 and 4 of Table 9 - reveal that healthy workers, upon receiving good news, are significantly more likely to switch out of scrabbling into piece-rate work. This suggests the importance of worker *perceptions* about their own health that influence not only the decision to supply labor but also the choice of occupation.[17] These results also indicate that the productivity/wage gains from good news estimated in Table 8 are at least partially due to switching into piece rate work from a lower fixed wage. To assess whether switching out of scrabbling constitutes the entire mechanism of the "good news" effect of a healthy diagnosis, Table 10 re-estimates Equation (9) 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 – occupational selection is an important component but not the full story.

A possible confounder to the good news effect is the potential misattribution of good health in our comparison group due to the phased nature of the study design. To test whether the results stem from comparing healthy workers who just received a good test with some proportion of sick workers who have

[17] The theoretical framework of Section 3 also suggests that workers with greater ability may be more likely to switch into piece-rate work given a change in health expectations as a result of the negative diagnosis. Of course we do not observe ability directly in the data but proxy for it with worker age or BMI as cane-cutting is an extremely physical occupation. Consistent with the theoretical prediction, the analysis finds that younger workers and workers with higher BMI are somewhat more likely to switch into piece-rate work after the receipt of a health diagnosis (results available upon request).

yet to be tested (and who may clear the disease on their own and subsequently test negative) in our analysis, the second panel in Table 10 further restricts 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, further indicating that misattribution of sick workers to a healthy control group is unlikely to be a factor behind the earnings gains to diagnosed malaria negative workers.

If there is a behavioral response to the 'good news' of a healthy diagnosis, it should be stronger for those who find this news surprising and hence revise expectations of physical work capacity. Here we investigate possible differential response across factors likely to determine health perceptions - 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. The results in Table 11 support the conjecture that especially *surprise* good health news, leads to an earnings response: negative workers with parasites (but below the diagnostic threshold) exhibit a significant earnings and wage response yet those with no parasites do not. Similarly those who report fatigue at end of day respond with an increased labor supply after being told they are malaria negative, but those without subjective reports of fatigue show no change in labor supply.[18]

VII. CONCLUSIONS

While adult health is believed an important determinant of labor supply and productivity, especially in agrarian settings, few studies have been able to identify and measure such a relation. This study, investigating the labor costs of malaria infection, is able to do so through the temporally randomized introduction of a mobile health clinic in a piece rate wage setting. The results indicate that there are earnings and labor supply gains on the order of 10% in the weeks following treatment for malaria. In the relatively high wage environment of this Nigerian sugarcane plantation, these estimated productivity costs likely exceed the private costs for malaria diagnosis and treatment. It is important to note that our results only represent estimates of gains from treatment and information over a two or three week reference period – the gains from malaria treatment may extend beyond our reference period. However treatment of diagnosed illness is not the only cause of such gains in earnings. Another factor appears to be the perceptions about one's own health.

[18] The point estimates do suggest a change in wages for the non-fatigued group but this response is not precisely estimated. In general this sub-group analysis does not yield group specific coefficients significantly different from each other, due in large part to the smaller number of workers per sub-group. Nevertheless the relative magnitude and precision of the estimated coefficients are consistent with the channel of revised expectations driving changes in labor behavior among workers who received a health 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 complementary occupation and into the piece-rate work of cane cutters where higher effort is required for positive returns. Although previous work has documented behavioral response to surprise health information, these findings are largely confined to longer-run outcomes and risk-taking behavior 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 family 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.[19] The positive correlation between the agro-ecological environment of those areas with high growth potential and malarial breeding can diminish the gains from increased agricultural productivity either through directly increasing the infection rate or concurrently raising the perception of the infection rate.

A low cost employer-based testing and treatment program appears to provide large worker 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. In endemic situations, it is quite possible that there are real returns to health information, especially if the information is interpreted as a surprise. Workers who were most responsive to the negative diagnosis did indeed have some parasite presence in their blood, but at sub-clinical levels. This is consistent with findings by Laishram et al. (2012) who review the potential impact of asymptomatic malaria on health. 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 dual-self model that is tempted to postpone effort (Thaler and Shefrin 1981). Our study, designed to measure the productivity costs of malaria infection, cannot definitively identify the causal mechanisms behind the

[19] 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.

“good news” effect. The study does illustrate that the commonly held belief that productivity losses due to workers working when sick is likely a less important bias in estimates of the cost of malaria than the effect of health perceptions which induce suboptimal occupation sorting.

Whichever mechanism is driving selection into low return occupations, the results imply that the full costs of malaria to the economy are clearly not only among the confirmed infected. Workers living in endemic areas, particularly those in physical occupations, may reserve work effort under the perception that they are symptomatic. Our population based study, as opposed to a selective sample of ill workers, the foundation of previous empirical work on the costs of malaria, illustrates that asymptomatic malaria may have real costs to agricultural productivity via selection into low return work. These results are not uncommon to the development literature which illustrate that the risk averse poor make low return investments which perpetuate their poverty (for example, Zimmerman and Carter (2003) and Lybbert et al. (2004) among others). In our case, workers in endemic areas with low health perceptions may remain trapped in low level equilibria via occupation choice (Banerjee and Newman (1993). Further research in sub-populations that implement extensive testing not only of symptomatic, but also asymptomatic individuals may yield further gains in understanding the productivity costs of malaria and other diseases.

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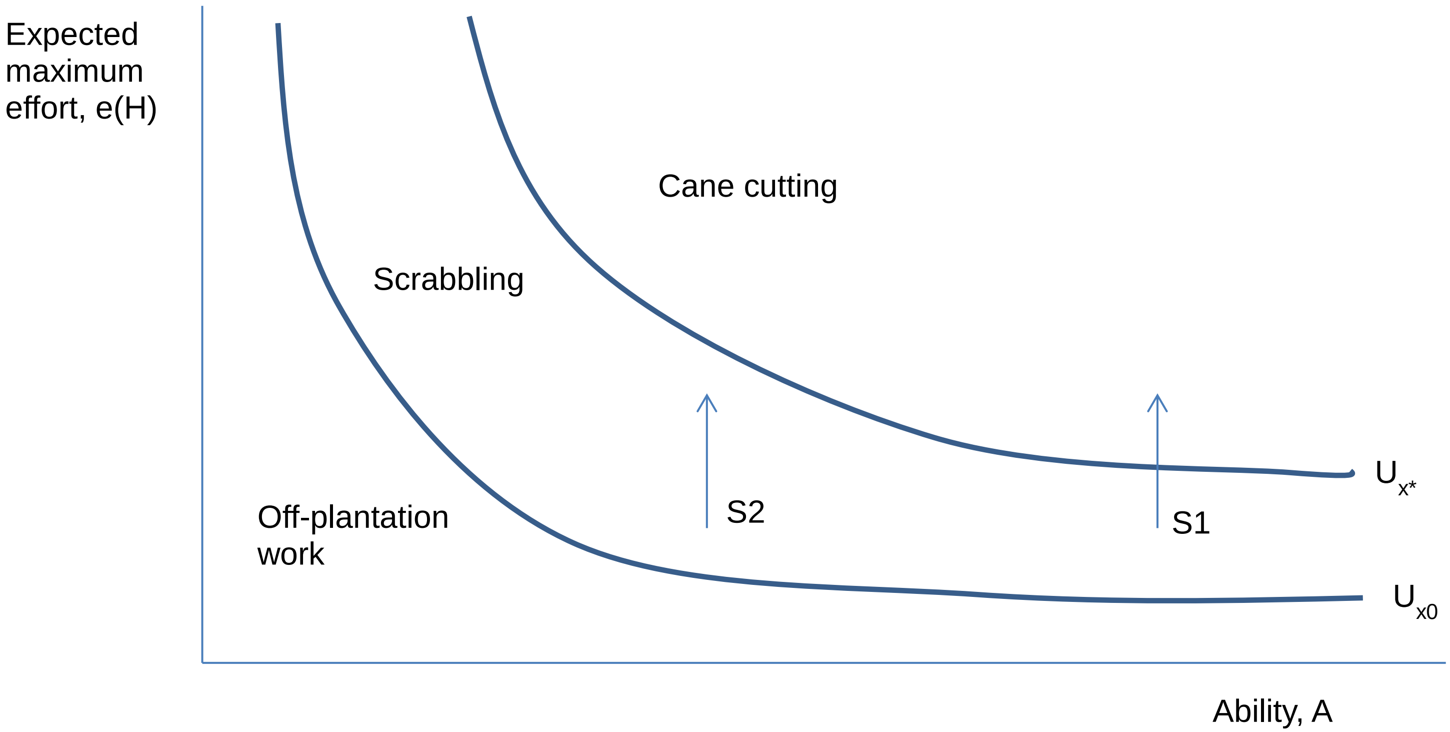
Figure 1. Occupational selection as a function of ability and expected cost of effort



Note: the expected maximum effort for workers S1 and S2 increases due to equal revisions of health beliefs as a result of new information. S1 now believes cane cutting is a profitable choice due to high ability endowment. S2 remains with his choice of scrabbling.

Figure 2. Example of data types and sources utilized, by week of observation or inference

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 $X_{it} = X_{i5}$ ------------------------->				Observed X_{i5}	Inferred $X_{i6} = X_{i5}$
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 $X_{it} = X_{i5}$ ------------------------->				Observed X_{i5}	Inferred $X_{i6} = X_{i5}$
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_{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
Years 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
Proportion of time spent scrabbling	0.12	0.19	0.001

Note: The p-value is from the balancing test of the covariate across work groups.

Table 2: Earnings, days worked and daily wage by week of harvest for all workers and selected groups

Harvest week		All workers		Group 4		Group 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

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

	Parasite count	# of workers	Percentage of total
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

Table 4. Within workgroup balance tests across survey week

Work group	Age	Years of experience	Years of schooling	BMI	HH size	Num. 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 (ITT) estimates, by pooled reference period and 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 workgroup 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 on treated (TOT) 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 workgroup 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 malaria positive control workers to estimate the four week reference. ***p<.01 **p<.05 *p<.10

Table 7. TOT 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 workgroup 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 malaria positive control workers to estimate the four week reference. ***p<.01 **p<.05 *p<.10

Table 8. Treatment on the medically untreated (TmUT) 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 workgroup 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 per week devoted to scrabbling after receipt of malaria test, by worker malaria status

Reference period	Malaria positives		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 workgroup by week fixed effects. ***p<.01 **p<.05 *p<.10

Table 10. Robust sub-sample analysis of TmUT

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 workgroup by week fixed effects. ***p<.01 **p<.05 *p<.10

Table 11. TmUT estimates by malaria negative worker parasite count or fatigue status at end of day

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 workgroup by week fixed effects.
***p<.01 **p<.05 *p<.10