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Experimental Estimates of the Impact of Malaria Treatment on Agricultural Worker Productivity, Labor Supply and Earnings

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Keywords
malaria, labor supply, labor productivity, randomized experiment

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Keywords: malaria, labor supply, labor productivity, randomized experiment
JEL codes: I12, J22, J24, O12

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1. Introduction

Agricultural productivity is often considered a key factor for economic development in low income countries. While there has been much attention for 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? Are there returns beyond the individual to firms who supply health benefits to workers? And if returns are positive, why do we not see more investment in health – i.e. what are the constraints to investment in health?

While these questions appear straight forward, trying to answer them comes with a number of challenges. Two factors play a key role. 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. Strauss and Thomas (1998) in their JEL review on health and economic development provide an overview of the growing evidence for a causal impact of health on wages and productivity in low-income settings.

A number of macroeconomic studies have also suggested that health in general, and malaria in particular, can have strong effects on economic outcomes.[1] However, studies estimating the

[1] 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

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.[2] Micro level analysis should be better at addressing these issues.[3]

To address the first challenge mentioned above, this paper focuses on one dimension of health, namely the sero-positive malarial status of a 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 and anemia and hence are likely to work fewer days and be less productive when they do work.[4] 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 using different definitions, as discussed in detail in Section 3. 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

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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.

[2] See also Ashraf, Lester an 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 (see Acemoglu and Johnson 2007; Ashraf, Lester and Weil). 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).

[3] 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).

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

work. Finally, most studies – but not all – measure malaria infection through self-reporting, which may be problematic. In this paper we address all three issues, investigating the causal effect of malarial infection, measured by blood tests, 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 in each round to ensure fairness in testing with all workers receiving one treatment over each survey round (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 with a counterfactual of workers who had not yet received the program, which is the intent to treat effect. Comparisons are also made between workers who tested positive for malaria earlier than those who tested positive for malaria in later weeks of the study period which is the average treatment effect. In our first round of data, we find intent to treat effects using a cohort comparison of treated workers on both labor supply and productivity increases which account for a 7.2 percentage point increase in monthly earnings, due to treatment in comparison to a counterfactual of workers in later cohorts who were sick in the earlier period, but not yet treated. These results reinforce that estimates of the impact of malaria can not only consider the labor supply response of ill workers as many workers continue to work even when they are sero-positive.

Our first round estimates of the average treatment effect, the effect of being treated for malaria when ill in comparison to other workers who would also later test positive, we find significant earnings effects in one of the comparison group constructions, but these results do not seem to be robust across all specifications. As the percentage of workers who fall ill with malaria ranges from 36.3% in the first round to 20.6% of workers in the second round, the power to detect changes in productivity over a four week period in such a small subsample likely explains the lack of statistically significant average treatment effect estimates in the first round. Having also repeated the study in a second year, we are able to compare across two rounds of the survey, one with high and one with low infection rates. As expected the effects are smaller in the second –

low infection – year, although low power, associated with the lower infection rates, inhibits us to draw strong conclusions.

The paper is organized to present these results as follows. The next section reviews the theoretical linkages between health and labor outcomes as well as the empirical literature which has tested these relationships. The third section provides an overview of the studies estimating the cost of malaria, and also discusses measurement issues. The fourth section describes the experimental design and identification strategy, while the fifth section presents the results. The last section concludes.

2. Health and Labor Outcomes

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.[5] 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.[6] In recent studies, reduction in exposure to malaria at an early age has increased incomes of adults (Cutler et al. 2010 and Bleakley 2010). Studies that have 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).

[5] See for example Schultz (2002).

[6] 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.

Our analytic framework starts from a simple Grossman model of health production where households 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 worker's earnings (E) 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:

$$L_{it} = L(\mu_{it}, w_{it}, \mu_{ct}, v_{it}) \tag{1}$$

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 price of time, w_{it}, firm characteristics, μ_{ct}, and unobservable determinants of labor participation, v_{it}. An individual will work if the offered wage exceeds the value of time. Individuals choose the sector of work that yields the highest return and the time spent working is given by equating the marginal value of leisure with hourly earnings.

The wage can be specified as an explicit function of observed individual health characteristics, θ_{it}, and observed relevant non-health characteristics, x_{it}, as well as firm characteristics, μ_{ct}, which determine the offer rate, by the following:

$$w_{it} = w(\theta_{it}, x_{it}, \mu_{ct}, e_{it}) \tag{2}$$

Substituting in for wage yields a labor response function that explicitly includes health terms:

$$L_{it} = L(\theta_{1it}, \theta_{2it}, \mu_{it}, x_{it}, \mu_{ct}, \varepsilon_{it}) \tag{3}$$

Where ε_{it} represents unobserved individual characteristics that determine labor outcomes (entailing v_{it} and $e_{it.}$). We further distinguish between malaria related health (θ_{1it}), which is

impacted by our intervention and other health dimensions (θ_{2it}).[7] With this formulation, we are primarily interested in the effect of a change in the first dimension of the health vector, namely malaria status and the consequent impacts as it relates to the efficiency of the metabolism of bodily energy, on each element in the labor outcome vector (i.e. the $\partial L_{it}/\partial\theta_{1it}$ terms).

Empirical tests of this health-productivity relation have remained limited.[8] 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 θ_{it} 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 θ_{2it} being uncorrelated with θ_{1it} and thus avoid this problem. Another identification problem with the use of observational data is reverse causality- not only does θ_{1it} affect L_{it} but L_{it} also affects θ_{1it}. The exogenous change in θ_{1it} induced through the intervention treatment will also control for this.

A second reason for the relative scarcity of empirical work is the remaining challenge to measure 'health' given its multidimensional nature. In this paper, we focus on one particular health deficit, namely malaria infection, which we expect to have potentially severe effects on worker productivity, and by randomizing the timing of treatment, we also randomize unobserved confounding health factors (θ_{2it}), which provide us with a strong identification strategy. 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.[9] The use of one large plantation will enable us to abstract from concerns regarding firm characteristics μ_{ct} as well as treatment heterogeneity across firms in our estimates.

[7] We define θ_{1it} as reflecting dimensions of health related to malaria, implying separability between θ_{1it} and θ_{2it}

[8] 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).

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

There is currently little understanding of whether the effects of health on labor productivity are sizeable and along which dimensions they vary. The scarce existing research does however provide benchmarks. Strauss and Thomas (1998) in their JEL review provide an overview of the then existing evidence for a causal impact of health on wages and productivity in low-income settings. They also concluded that much remained to be done to understand what dimensions of health matter. More than a decade later, two groups of studies have emerged: those looking at the relationship between nutrition and labour outcomes, and those considering the effect of specific illnesses on labor outcomes.[10] The first literature generally indicates a positive effect of nutrition on labor productivity.[11] Studies on specific diseases 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.[12]

3. Malaria: cost and measurement

Diagnosis of malaria depends on the demonstration of parasites 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 dehydrated and

[10] We neglect a third group of studies that looks at the effect of investments during childhood on labor outcomes later in life (see Fogel (1994), Strauss andThomas (2000), Ribero and Nunez (2000), Dercon and Porter (2010)).

[11] 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.

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

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 the 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]

[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

Pluess et al. (2009) found that on average 1.8 workdays are 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

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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 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.

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 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

[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 countries 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

reporting, which has serious shortcomings. Our study addresses these shortcomings. 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 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 may 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.

In RDT, making use of a toolkit, the patient receives a prick in the finger thereby leaving a trace of blood which is automatically analyzed resulting in a 'positive' test outcome if the parasite density is above a certain threshold. RDT is a newly recommended method by the World Health

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 the recommended approach by WHO for large scale field work.

Organization (see WHO, 2010). The third method exists of taking a blood sample from patients and carrying out microscopy analysis in the lab, counting the number of parasites.[25] 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 conduct both RDT and microscopy; however, we primarily use microscopy (gold standard) results as they provide the most accurate measurement of malaria infection.

4. Experimental Design and Identification Strategy

Taking into consideration observations from the large literature reviewed in the previous section on the relationship between health and labor outcomes, this study implemented a randomized testing and treatment program within a single large plantation that hires sugarcane cutters throughout the sugar cane cutting agricultural season (November-April) and pays them on a piece rate basis.[26] Across the plantation supervisors collect daily worker output using a standardized measuring stick. A worker's payment is based entirely on his output. The plantation's wage is 2.04 Naira per unit of output;[27] a meter of cane cut represents approximately one U.S. cent of earnings. Workers carefully observe the recording of their output as it is the basis of their monthly payments from the plantation, often maintaining their own separate ledger. The daily output data is collected for all workers throughout the entire harvest period.

We observe the entire cane cutting population of workers across the harvest season in 2010 and 2011 over the same period of time (February and March). Information collected by the plantation was linked to worker and health characteristics collected by a set of survey enumerators and health workers. The information on worker characteristics was administered by the survey enumerator including employment history, age, education, gender, place of living and

[25] During this process the sample is divided in four quadrants and the number of parasites is counted in each of the quadrants and summed up to result in the total parasite load.
[26] The plantation is 57,200 ha and employs between 600 and 800 workers for the harvest during the harvest season.
[27] Each worker's output is measured at the end of each day by his supervisor using a standardized measurement stick.

household welfare. Then the registered health worker administered the second questionnaire by first asking a brief health history and then recording the results of two tests: a Rapid Diagnostic Test (RDT) for malaria and a blood slide which is used to microscopically verify malarial status.[28] All workers who had a positive RDT or were parasitic positive according to the microscopy results from the collected slides were treated with the appropriate doses of Artemisinin Combination Therapy (ACT).

Artemisinin based combination therapy (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; and is effective for another week. 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.[29]

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, etc., 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.

Sampling of workers followed a two stage procedure where worker groups - called 'gangs' by the workers, were first selected, then workers within a group were selected.[30] A list of workers

[28] Fingerprick blood specimens (which pose minimal risk) were obtained from participating workers– less than .5 ml of blood was required from each person. Respondents were tested for malaria with the Binax Now™ RDT. This antigen-based test, which utilizes both HRP-II (a PF-specific antigen) and aldolase (a pan-Plasmodium antigen) is well validated internationally and provides accurate diagnosis for current malaria infection (particularly for the most severe form, p. falciparum), and can distinguish the infecting Plasmodium species to some extent. Results were available within about 15 minutes for RDT tests and within a few days for the blood slide test. All results were communicated directly to the participants.

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

[30] Workers are assigned to gangs by the company in no particular order. Each gang counts around 50 workers and is allocated on a weekly basis to plots that are ready to be harvested. Because the management prefers gangs to be

was obtained from the plantation before the beginning of the experiment. Selection of the order of gangs and then workers within gangs was also completed before the beginning of the experiment, so that the survey team had a predetermined number of workers from each gang to survey each day. Each week one group was provided with access to treatment implying that each worker was tested and treated if positive (and surveyed), as set out above. This process continued until all gangs of the plantation had been served and the entire workforce had received access to treatment. The order of testing and treatment was randomized over time and this provides us with an identification strategy, as explained below. 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. We focus on three labor outcomes: worker productivity, labor supply and income.

Using this information we estimate two types of treatment effects: an 'intent to treat effect' (ITT) and an 'average treatment effect' (ATE). The first effect reflects the benefits of access to treatment, comparing outcomes of workers with access to treatment to those of workers without access to 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.[31] These treatment effects are summarized in the figure below. As a robustness check, we present several different methods for constructing the ITT and ATE using different numbers of weeks to exploit the time varying worker access to malaria testing and treatment.

Figure 1: Construction of Average Treatment Effect Estimation and Intent to Treat Effects Exploiting the Time Varying Randomization Design

	Average Treatment Effect Estimation		
	Treatment Group Assignment Rule	Control Group Assignment Rule	Outcome Variable

equally productive and since the harvesting activity is strongly individual, there is no obvious reason why unobserved gang fixed effects should play an important role, except for that they also reflect the plots to which the gang 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 gangs based on health. Despite this, we control for gang(-plot) fixed effects in our analysis.

[31] 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. Our intervention will systematically test and treat malarial cases in the entire work force, rather than relying on workers presenting themselves at the health clinic.

Assignment Rule:	Malaria Positive in study weeks	Malaria Positive in study weeks	Earnings, Days Worked, Productivity in study weeks
2 week reference	1,2	5,6	3,4
3 week reference	1,2,3	4,5,6	4,5,6
4 week reference	1,2,3	4,5,6	3,4,5,6

Intent to Treat Effect Estimation

	Treatment Group Assignment Rule	Control Group Assignment Rule	Outcome Variable
Assignment Rule:	Interviewed in study weeks	Interviewed in study weeks	Earnings, Days Worked, Productivity in study weeks
2 week reference	1,2	5,6	3,4
3 week reference	1,2,3	4,5,6	4,5,6
4 week reference	1,2,3	4,5,6	3,4,5,6

As an econometric specification, the ATE is estimated by comparing labor outcomes at time t+a for those workers who were tested positive at time t (and were treated at t and are therefore healthy at t+a), with the labor outcomes for workers who test positive after t+a (i.e., in t+a+b) and are assumed to also be ill at time t+a[32]. This difference reflects the effect of treatment of malaria, as it compares the output of a random subsample of workers who are treated with that of a random subsample of worker who are ill, within the same season. We estimate:

$$L_{i(t+a)} = \alpha + \beta T_{it} + \gamma X_i + \delta G_i + \lambda R_i + \varepsilon_{it} \quad \forall i \in T_t \cup T_{t+a} \tag{4}$$

where $L_{i(t+a)}$ reflects the three labor outcomes of interest: earnings, labor supply and productivity respectively. T_{it} indicates whether the worker was treated for malaria at time t, X_i are worker and household characteristics, G_i is an indicator for the worker's gang and R_i is an indicator for the round of data (included only in the pooled analysis), and ε_{it} are the unobservables.

As indicated the estimation sample consists of those infected and treated at time t (T_t) and those infected and treated at time t+a (T_{t+a}).[33] Accounting for a time lag (a) is necessary because it takes time for workers to be cured and bounce back to their 'normal' energy levels. We also exploit that ACT, while being a curative medicine, creates a hostile environment for the parasite,

[32] For further clarification, see Appendix Figure 1 which provides a visual representation of an example of how worker's data is used to construct treatment and comparison groups.

[33] In our design we split the sample between those who have access to treatment at time t (A_t) and those who do not have access at time t (NA_t). The first group contains both those infected at time t (I_t) and those not infected at time t (NI_t)

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 time lag a, as described later.

Following a similar approach, the ITT is estimated by comparing labor outcomes at time t+a for those workers who had access to treatment at time t (and were treated at t if ill and are therefore healthy at t+a), with the labor outcomes for workers who had access at t+a. 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 the same season. Equation 4 is estimated where T_t now represents having access to treatment at time t.

In principle, equation 4 could be estimated exclusively with independent variable T, but not the other variables, yielding unbiased estimates of the ITT and ATE due to the random allocation of workers to treatment cohorts. In our preferred estimates, we also include the additional gang indicators and worker and household characteristics. The set of worker and household characteristics include worker age, experience at the plantation, schooling, household size and estimated household expenditure. 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.[34]

A potential concern with the identification strategy as set out above is that there may be contamination between treatment and control groups. We distinguish two types of spillovers. A first type of spillovers stems from the construction of our identification strategy, as workers in the control group may have been treated before and may therefore be less likely to suffer from

[34] 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.

malaria. To address this we inspect the robustness of our results varying the time lag a, as described in Figure 1 above.

A second type of spillovers arises across time and space for epidemiological reasons and stems from the spread of the parasite being slowed down in the control group due to intervention in the treatment group. While this is a valid theoretical point, the large size of the plantation combined with the modest size of each gang treated in one go, makes these spillovers unlikely.

To estimate equation 4, we consider several different strategies to construct the reference period maximizing statistical power and minimizing potential contamination of the effects of treatment across the treatment and control group. In Figure 1, the design which has the least statistical power, as well as the least potential contamination of treatment is the '2 week reference' treatment and control group comparison where we estimate the ITT and ATE effects comparing earnings, labor supply and productivity effects over weeks 3 and 4 of the study among workers who were interviewed/treated in weeks 1 and 2 compared with those interviewed/treated in weeks 5 and 6. This comparison yields the least statistical power as the sample is subdivided with a third not used. Another down side of this approach is that infection in week 3 and 4 (at time t+a) for the control group is proxied by measurement further in the future, namely in week 5 and 6 (at time t+a+b). Because workers who are infected in weeks 5 and 6 may have been negative in weeks 3 and 4, these estimates are likely to be biased downwards, providing us with a lower bound.

In contrast, the 3 and 4 week reference use the full sample, but are potentially contaminated by workers in later rounds who have been treated biasing the treatment effect also downward as their recovery from malaria will potentially increase their earnings, labor supply and productivity while they are being classified as the control group.

As the results section illustrates, the ITT results are relatively robust to the control group construction. Because of potential contamination effects in the 3 and 4 week reference analysis, it may be the case that productivity and labor supply effects are increasing over time as a worker becomes well after treatment and regains their strength from illness. Therefore the 4 week

reference, which includes the outcomes at week 3, if found to be robust to alternative control group constructions, may be the best estimate of the impact of malaria treatment, and is our preferred estimation.[35]

Before estimating these equations, we present some evidence that randomized variation in timing of testing and treatment of workers actually produced a sample of balanced observable characteristics consistent with our sample design. We investigate whether there are statistically significant differences across time of interview and subsequently across gangs as the choice of gang was the first stage of the sampling procedure. In Table 1 and 2, we regress respectively the month of interview and the set of gang indicators on a set of observable worker and household characteristics and test whether the coefficients estimated are statistically different than zero.[36] We report the means of the observable characteristics by time of interview and then the p value of the coefficient test. The results in Table 1 indicate that the observable characteristics are primarily balanced over the period of the interview at the 5% level of statistical significance with the exception of the experience of the worker in round 1 and hemoglobin in round 2. The number of rooms variable is also unbalanced between timing of the interview in both rounds (2.5 rooms in the first phase of the study versus 2.8 rooms in the second phase of the study) and results in predicted household expenditures being slightly unbalanced. The number of cattle is also unbalanced in round 2. These covariates will be included as controls in the treatment effect estimation. It is important to note that most observable characteristics are balanced between study periods and rounds. In Table 2, we also observe that the observable worker and household characteristics are balanced across gangs at the 5% level of statistical significance with the exception of the worker's BMI in the first round. However, to ensure that our estimates are not biased by observable covariate imbalance or unobservables in the allocation of workers to gangs, sampling, or absenteeism of workers, we include gang indicators in all of our estimates to account for potential between gang differences.

[35] We plan to address this in future work. If this recovery path is individual specific, we can investigate whether controlling for individual worker fixed effects generates the same results for the subsample of workers for whom we have panel data across the two years

[36] While we refer to gang indicators, this are actually gang*plot indicators since gangs are allocated to plots as explained before.

5. Results

Before discussing the results in detail, we first provide some descriptive evidence about malaria rates in the worker population and the reliability of alternative diagnostic approaches. Table 3a presents differences between the microscopic results, the RDT results and the self-reported results of workers who were tested for malaria. The microscopic results yield a 36% positive rate in Round 1. This is more than four times the rate of positive diagnosis found in the RDT tests, which reports 8.5% of tested workers.[37] Workers' self-reports yield a 8% infection rate for round 1. Given that the microscopic analysis is the gold standard in diagnosing malaria (WHO 2009), and RDT are relatively new, we primarily use the microscopy results to identify malaria infection. In round 2, we observed a much lower sero-positive rate, 20.6% from the microscopy and a 5% from the RDT. It is not uncommon for malaria rates to fluctuate across seasons, including in malaria endemic areas, depending on environmental factors that may influence the number of malaria cases.[38]

In contrast to the clinical measures, self reported infection increased to 12.6% in round 2, illustrating the potential measurement bias and low correlation with objective measures of malaria, as discussed before. To further illustrate this point, Table 3b presents a cross-tabulation of malaria diagnosis of the self reported versus microscopy results. The table illustrates the wide misperceptions that respondents hold about their own malaria status, likely due to both the overlap of malaria symptoms with those from other illnesses and the possible habituation to some symptoms. According to Table 3b, 60 and 72 percent of respondents in rounds 1 and 2, respectively, identified themselves correctly as either malaria positive with a confirmed parasitemic positive microscopy results or malaria negative with a confirmed parasitemic negative microscopy results. However, the rate of positive malaria self reports that were actually correct was only 6% in round 1 and 13% in round 2. Moreover, in our context, the average bias seems to be one of underreporting, as much more of the infected misclassify themselves as

[37] Workers were deemed to be parasitic positive if the microscopic analysis detected four or more malarial parasites in one of the five viewing fields, following standard medical practice in examining blood slides for malaria. Slides were read initially by one microscopist and verified independently by another microscopist in a laboratory at the Federal University of Technology, Yola.

[38] Note that our results are consistent across the two clinical measures; lower microscopy and RDT results are correlated. It also fits with evidence collected from local clinics showing that the number of malaria cases observed during the second round was considerably lower than during the first round. We collected additional data on precautions and prevention and plan to study in future work whether this also contributed to lower infection rates.

negative compared to noninfected misclassifying themselves as positive. For this reason, we rely on microscopic diagnosis of malaria to avoid misclassification bias.[39]

Another factor which could attenuate our results is lack of compliance with prescribed treatment. To ensure compliance, a health supervisor was assigned to monitor any parasitemic positive cases on both the day after treatment was provided and the day following the end of treatment. A small incentive of 50 naira was provided to workers to return the ACT container to the health supervisor which facilitated a short compliance interview with the worker. Over 75% of workers who were parasitemic positive completed a post-treatment interview where we were able to confirm compliance.

Table 4 reports the descriptive statistics for the labor outcomes: earnings, days worked and daily productivity, for each of the two rounds. Earnings and labor supply vary both between months of the agricultural season, but also between rounds. Average worker earnings range between 11,179 and 22,402 Naira (75 USD and 150 USD) in survey round 1 and 13,952 and 22,182 Naira (93 USD and 148 USD) in survey round 2. The variance of earnings and days worked is higher in round 2 which is in large part due to the interlinked production process whereby sugarcane is harvested and then must be directly processed in the plantations sugar refinery. Production disruptions at the refinery, especially in round 2, halt sugarcane cutting in the field which may explain some variation in these data.

ITT and ATE estimates

The ITT estimates for each round are presented in Table 5 and illustrate the benefits of access to treatment, comparing outcomes of workers with access to treatment to those of workers without

[39] Another factor which could attenuate our results is lack of compliance with prescribed treatment. To ensure compliance, a health supervisor was assigned to monitor any parasitemic positive cases on both the day after treatment was provided and the day following the end of treatment. A small incentive of 50 naira was provided to workers to return the ACT container to the health supervisor which facilitated a short compliance interview with the worker. Over 75% of workers who were parasitemic positive completed a post-treatment interview where we were able to confirm compliance.

access to treatment (and who may or may not have fallen ill).[40] Table 5 presents estimates of β from eq (4) when L_{it} is the natural log of earnings, days of work (i.e., labor supply) and wages (i.e., productivity). In round 1, we estimate increased earnings effects of 15.5% , labor supply effects of 8%, and productivity increases of 7% in the 2 week reference approach. In both the 3 and 4 week reference approach, we continue to find statistically significant intent to treat effects on worker earnings of 7-8%, a productivity effect between 4-5%, but no labor supply effect. We find no statistically significant ITT effect on worker earnings, labor supply or productivity in round 2, when infection rates are considerably lower.

In summary, access to treatment did yield productivity gains in the full worker population when we consider all differing reference periods and when infection rates are higher. This provides some evidence that workplace based malaria interventions can yield significant benefits to the worker population both in substantially larger worker earnings and productivity. These results also illustrate that previous estimates that do not consider productivity effects of malaria in estimating its effects of workers omit substantial loses that workers incur when they work while suffering from malaria.

The ATE estimates by round are reported in Table 6 and illustrate the effect of testing and treatment of workers in comparison to a counterfactual of workers that later tests positive for malaria. We find similar estimates on earnings, labor supply and productivity in round 1, but these effects are not statistically significant. A similar absence of effect is detected in round 2 for ATE estimates as we found for ITT estimates. Treated workers in the two week comparison group had 18.8% higher earnings than the counterfactual of workers in round 1 which was statistically significant. However, the statistical insignificance of the round by round ATE estimates are likely due to small sample size and low statistical power.

Table 7 presents the pooled ITT and ATE estimates. The ITT estimates confirm across all control group constructions a statistically significant productivity effect of having access to malaria treatment of between 4-5%. For the ATE estimates, it is observed that the larger sample size from pooling does not increase the precision of the estimates enough to detect statistically significant effects. Both the ITT and ATE estimates do suggest that the majority of earnings

[40] Table 5 presents estimates of β from eq (1) when L_{it} is the natural log of earnings, days of work (i.e., labor supply) and wages (i.e., productivity).

gains due to malaria testing and treatment programs are due to productivity and not labor supply effects.

These results underscore that studies that do not account for the productivity loses associated with malaria infection likely miss many of the costs of malaria, as many workers continue to work despite being ill. Further, many of the previously cited studies only account for workers who self-report malaria (or self-report and seek treatment). Our results, using the microscopy gold standard to identify malaria cases, rather than self-reports, and testing for malaria within an entire worker population, indicate that access treatment can have considerable effects on worker productivity, providing significant benefits both to workers and firms that employ them.

6. Conclusions

This paper provides experimental evidence on the effects of malarial 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 and potentially also to increasing firm productivity. Accounting for both labor supply and productivity effects suggests a much larger estimate of the cost of malaria than previously reported in studies (for example, Ettling and Shepard 1991, Ettling et al. 1994, Cropper et al. 2004).

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.[41] 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.[42] The positive correlation between the agro-ecological environment of those areas with high growth potential and malarial breeding may diminish the gains from increased agricultural productivity.

Our results also provide empirical evidence with respect to one of the mechanisms through which increased health affects worker earnings. Much of the theoretical motivation in examining the effects of health and labor outcomes dates to efficiency wage theories (Liebenstein 1957), which posits that if increased nutrition increases productivity then employers should raise wages to induce productivity gains. This paper provides evidence of a causal productivity effect that supports efficiency wage claims that we disentangle from labor supply effects on earnings. In this sense, further research into the design of employer and/or government based health initiatives to test and treat malaria is necessary to increase worker welfare and firm productivity, especially in the agricultural sector. A low cost employer-based testing and treatment program could provide large benefits at low cost, since workers are often inhibited from visiting health clinics due to distance and the cost of treatment. However, the design of employer based programs should also take into account the intrahousehold implications of the distribution of efficiency wages within the household and labor substitution effects among household members to ensure that productivity gains and unattended secondary effects do not mitigate the treatment of malaria among workers.[43] What is less clear is why workers do not internalize the gains from increased health by seeking additional healthcare. Given the large earnings effects and the

[41]Due to this high incidence of malaria, The World Bank proposed in December 2006 to allocate 180 million USD for malarial interventions in Nigeria.

[42] 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.

[43] See for example Genicot (2005) for a theoretical model of the relationship between efficiency wages and child labor.

relatively low cost of treatment, future research on the behaviorial aspects of worker behavior might yield important insights.

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Tables

Table 1: Randomization Test: Variation across timing of interview

	Round 1			Round 2		
	Interviewed in 1st 3 weeks	Interviewed in 2nd 3 weeks	pvalue	Interviewed in 1st 3 weeks	Interviewed in 2nd 3 weeks	pvalue
Worker Characteristics						
Worker age	30.1	30.0	0.804	31.1	31.0	0.787
Ln experience in years	1.0	1.2	0.011	1.2	1.2	0.271
Percentage schooled	0.9	0.9	0.991	0.9	0.9	0.355
Hemoglobin	14.1	14.1	0.872	14.3	14.0	0.001
Body mass index	23.6	23.6	0.952	23.0	23.0	0.900
Household Characteristics						
HH size	4.8	5.1	0.407	6.2	7.0	0.355
Number of rooms	2.5	2.8	0.041	3.0	3.3	0.017
Number of cattle	1.2	1.0	0.387	3.4	2.8	0.022
Number of poultry	6.5	6.9	0.644	9.2	11.0	0.116
Predicted Hh Exp	11999.8	13031.3	0.022	16229.5	16265.5	0.036
Number of observations	263	500		326	334	

Table 2: Randomization Test: Variation across gangs

	P value for test of equality across gangs	
	Round 1	Round 2
Worker Characteristics		
Worker age	0.286	0.041
Ln experience in years	0.566	0.575
Percentage schooled	0.073	0.602
Hemoglobin	0.141	0.494
Body mass index	0.021	0.110
Household Characteristics		
HH size	0.247	0.365
Number of rooms	0.183	0.518
Number of cattle	0.788	0.356
Number of poultry	0.568	0.072
Predicted HH Exp.	0.453	0.078
Number of Observations	763	660

Table 3a: Positive Rates of Diagnostic Tools for Malaria

	Round 1			Round 2		
	Microscopy	RDT	Self-Reports	Microscopy	RDT	Self-Reports
% Positive	36.3	8.5	8.0	20.6	5.0	12.6
N		763			659	

Table 3b: Cross-tabulation of Positive and Negative Malaria Cases Diagnosed by Self-Report and Microscopy

		Round 1		Round 2	
		Microscopy Results		Microscopy Results	
		Positive	Negative	Positive	Negative
Self-Reported Cases	Positive	18	43	18	65
	Negative	259	443	118	458

Table 4: Worker Earnings, Days Worked and Wages by Round

	Earnings	Days Worked	Daily Wage
Round 1 (N=763)			
January	17,838	17	1,048
	(7,281)	(4)	(286)
February	22,402	20	1,139
	(8,110)	(4)	(292)
March	16,286	15	1,096
	(7,159)	(4)	(314)
April	11,179	12	889
	(5,026)	(4)	(217)
Round 2 (N=645)			
January	20,106	24	862
	(43,710)	(57)	(477)
February	15,508	20	789
	(37,354)	(50)	(616)
March	13,952	16	897
	(32,065)	(39)	(210)
April	22,182	22	1,010
	(49,561)	(54)	(544)

Note: Means are reported with standard deviations in parenthesis.

Table 5: Intent to Treat Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Ln:	Earnings	Days worked	Wage	Earnings	Days worked	Wage
	Round 1			Round 2		
2 week reference						
Health interview in phase 1 (1=Yes)	0.155*	0.082*	0.073*	0.026	0.002	0.024
	(0.079)	(0.045)	(0.044)	(0.092)	(0.068)	(0.035)
Constant	8.674***	1.886***	6.788***	7.856***	1.000***	6.856***
	(0.105)	(0.063)	(0.090)	(0.197)	(0.118)	(0.099)
Observations	401	401	401	465	465	465
3 week reference						
Health interview in phase 1 (1=Yes)	0.083**	0.033	0.050*	0.014	-0.027	0.040
	(0.039)	(0.024)	(0.028)	(0.048)	(0.026)	(0.032)
Constant	9.503***	2.629***	6.874***	9.013***	2.280***	6.734***
	(0.037)	(0.015)	(0.038)	(0.067)	(0.038)	(0.061)
Observations	684	684	684	547	547	547
4 week reference						
Health interview in phase 1 (1=Yes)	0.072**	0.035	0.041*	0.018	-0.027	0.045
	(0.034)	(0.023)	(0.024)	(0.051)	(0.027)	(0.034)
Constant	9.673***	2.829***	6.850***	9.008***	2.285***	6.723***
	(0.025)	(0.017)	(0.038)	(0.070)	(0.037)	(0.066)
Observations	683	683	683	547	547	547

Robust standard errors in parentheses. Regressions include gang indicators and worker characteristics. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Average Treatment Effect Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Ln:	Earnings	Days worked	Wage	Earnings	Days worked	Wage
	Round 1			Round 2		
2 week reference						
Health interview in phase 1 (1=Yes)	0.188*	0.136	0.052	0.007	-0.112	0.119
	(0.103)	(0.086)	(0.056)	(0.269)	(0.206)	(0.085)
Constant	8.686***	1.875***	6.810***	8.483***	1.450***	7.032***
	(0.108)	(0.067)	(0.128)	(0.807)	(0.532)	(0.351)
Observations	140	140	140	107	107	107
3 week reference						
Health interview in phase 1 (1=Yes)	0.077	0.037	0.040	-0.009	-0.013	0.005
	(0.066)	(0.044)	(0.037)	(0.102)	(0.052)	(0.081)
Constant	9.553***	2.658***	6.895***	9.183***	2.364***	6.819***
	(0.080)	(0.050)	(0.054)	(0.292)	(0.142)	(0.204)
Observations	250	250	250	120	120	120
4 week reference						
Health interview in phase 1 (1=Yes)	0.066	0.032	0.033	0.009	-0.008	0.018
	(0.055)	(0.038)	(0.037)	(0.112)	(0.052)	(0.090)
Constant	9.681***	2.813***	6.867***	9.157***	2.364***	6.793***
	(0.075)	(0.055)	(0.047)	(0.316)	(0.148)	(0.219)
Observations	248	248	248	120	120	120

Robust standard errors in parentheses. Regressions include gang indicators and worker characteristics. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Pooled ITT and ATE Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Ln:	Earnings	Days worked	Wage	Earnings	Days worked	Wage
	ITT			ATE		
2 week reference						
Health interview in phase 1 (1=Yes)	0.071	0.025	0.047*	0.064	0.008	0.056
	(0.067)	(0.044)	(0.026)	(0.149)	(0.102)	(0.056)
Constant	8.864***	2.056***	6.808***	9.007***	2.171***	6.836***
	(0.131)	(0.068)	(0.084)	(0.294)	(0.197)	(0.134)
Observations	866	866	866	247	247	247
3 week reference						
Health interview in phase 1 (1=Yes)	0.046	0.003	0.043*	0.044	0.014	0.030
	(0.037)	(0.016)	(0.023)	(0.063)	(0.029)	(0.045)
Constant	9.548***	2.624***	6.924***	9.572***	2.654***	6.918***
	(0.052)	(0.025)	(0.051)	(0.093)	(0.050)	(0.063)
Observations	1,233	1,233	1,233	370	370	370
4 week reference						
Health interview in phase 1 (1=Yes)	0.044	0.005	0.042**	0.049	0.007	0.042
	(0.033)	(0.015)	(0.020)	(0.051)	(0.020)	(0.037)
Constant	9.762***	2.897***	6.863***	9.772***	2.892***	6.880***
	(0.045)	(0.015)	(0.034)	(0.049)	(0.017)	(0.035)
Observations	1,274	1,275	1,274	383	383	383

Robust standard errors in parentheses. Regressions include gang indicators and worker characteristics. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Appendix Figure 1: Data Example: Worker Interviewed in Week 5

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.

Appendix: Tables with detailed results

Appendix Table 6a: Intent to Treat Estimates: 2 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Interviewed (1=Yes)	0.155*	0.082*	0.073*	0.026	0.002	0.024
	(0.079)	(0.045)	(0.044)	(0.092)	(0.068)	(0.035)
Age	0.001	0.004***	-0.002	0.002	0.003	-0.001
	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)
Experience in Years (ln)	0.000	-0.023*	0.023*	-0.027	-0.023	-0.004
	(0.016)	(0.013)	(0.012)	(0.035)	(0.027)	(0.027)
Read (1=Yes)	0.053	0.028	0.025	-0.221	-0.182	-0.039
	(0.109)	(0.078)	(0.080)	(0.147)	(0.120)	(0.053)
Write (1=Yes)	-0.059	-0.036	-0.024	0.141	0.050	0.091**
	(0.114)	(0.081)	(0.080)	(0.119)	(0.119)	(0.037)
HH Size	0.009*	0.006	0.003	0.005	0.003	0.002
	(0.005)	(0.004)	(0.003)	(0.009)	(0.008)	(0.005)
HH Asset Index	0.000	0.000	0.000	0.000**	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.349***	0.266***	0.083***	0.003	-0.030*	0.032***
	(0.007)	(0.007)	(0.003)	(0.022)	(0.017)	(0.010)
Gang 3 Indicator	0.500***	0.242***	0.258***	0.198***	0.024	0.174***
	(0.015)	(0.007)	(0.008)	(0.016)	(0.017)	(0.010)
Gang 4 Indicator	0.118***	0.064***	0.054***	-0.247***	-0.164***	-0.083***
	(0.021)	(0.011)	(0.015)	(0.038)	(0.029)	(0.013)
Gang 5 Indicator	0.341***	0.227***	0.114***	0.275***	0.161***	0.114***

	(0.015)	(0.010)	(0.008)	(0.009)	(0.008)	(0.007)
Gang 6 Indicator	0.186***	0.219***	-0.032***	0.018	-0.136***	0.154***
	(0.008)	(0.005)	(0.007)	(0.028)	(0.020)	(0.011)
Gang 7 Indicator	0.291***	0.330***	-0.039***	0.146***	0.191***	-0.045***
	(0.024)	(0.015)	(0.012)	(0.045)	(0.036)	(0.014)
Gang 8 Indicator	0.379***	0.256***	0.123***	-0.164***	0.020	-0.184***
	(0.020)	(0.012)	(0.011)	(0.012)	(0.014)	(0.008)
Constant	8.674***	1.886***	6.788***	7.856***	1.000***	6.856***
	(0.105)	(0.063)	(0.090)	(0.197)	(0.118)	(0.099)
Number of observations	401	401	401	465	465	465

note: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6b: Intent to Treat Estimates: 3 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Interviewed (1=Yes)	0.083**	0.033	0.050*	0.014	-0.027	0.040
	(0.039)	(0.024)	(0.028)	(0.048)	(0.026)	(0.032)
Age	-0.001	0.002***	-0.003***	-0.000	0.004***	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Experience in Years (ln)	0.007	-0.020**	0.026*	0.001	-0.020**	0.021**
	(0.020)	(0.009)	(0.015)	(0.014)	(0.009)	(0.009)
Read (1=Yes)	-0.115	-0.095	-0.020	-0.111	-0.072	-0.038
	(0.098)	(0.058)	(0.061)	(0.102)	(0.047)	(0.060)
Write (1=Yes)	0.114	0.083	0.031	0.098	0.064	0.035
	(0.082)	(0.054)	(0.049)	(0.075)	(0.046)	(0.037)
HH Size	0.009***	0.001	0.008***	0.007	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
HH Asset Index	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.136***	0.023***	0.113***	0.136***	0.090***	0.046***
	(0.003)	(0.002)	(0.002)	(0.007)	(0.008)	(0.003)
Gang 3 Indicator	0.342***	-0.032***	0.374***	0.250***	0.016	0.235***
	(0.006)	(0.004)	(0.004)	(0.009)	(0.010)	(0.004)
Gang 4 Indicator	0.194***	-0.053***	0.247***	-0.155***	-0.141***	-0.013
	(0.006)	(0.004)	(0.005)	(0.025)	(0.013)	(0.017)
Gang 5 Indicator	0.104***	0.011***	0.092***	0.216***	0.092***	0.123***
	(0.004)	(0.003)	(0.003)	(0.010)	(0.006)	(0.006)
Gang 6 Indicator	-0.051***	0.007***	-0.059***	0.237***	0.097***	0.140***

	(0.003)	(0.002)	(0.002)	(0.008)	(0.008)	(0.005)
Gang 7 Indicator	0.042***	0.043***	-0.001	0.319***	0.197***	0.122***
	(0.005)	(0.005)	(0.003)	(0.011)	(0.006)	(0.005)
Gang 8 Indicator	0.208***	-0.012***	0.220***	0.037***	0.079***	-0.042***
	(0.003)	(0.002)	(0.003)	(0.007)	(0.007)	(0.005)
Constant	9.503***	2.629***	6.874***	9.013***	2.280***	6.734***
	(0.037)	(0.015)	(0.038)	(0.067)	(0.038)	(0.061)
Number of observations	684	684	684	547	547	547

note: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6c: Intent to Treat Estimates: 4 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Interviewed (1=Yes)	0.072**	0.035	0.041*	0.018	-0.027	0.045
	(0.034)	(0.023)	(0.024)	(0.051)	(0.027)	(0.034)
Age	0.001	0.003***	-0.003***	-0.000	0.004***	-0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Experience in Years (ln)	0.008	-0.023***	0.028*	0.001	-0.020**	0.022**
	(0.021)	(0.008)	(0.016)	(0.014)	(0.009)	(0.009)
Read (1=Yes)	-0.082	-0.078	-0.007	-0.114	-0.074	-0.040
	(0.081)	(0.049)	(0.051)	(0.103)	(0.046)	(0.061)
Write (1=Yes)	0.078	0.056	0.021	0.104	0.068	0.037
	(0.065)	(0.043)	(0.038)	(0.077)	(0.046)	(0.039)
HH Size	0.008***	-0.000	0.008***	0.006	0.003	0.003
	(0.003)	(0.002)	(0.001)	(0.005)	(0.003)	(0.003)
HH Asset Index	0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.151***	0.080***	0.071***	0.132***	0.083***	0.049***
	(0.002)	(0.001)	(0.002)	(0.007)	(0.008)	(0.003)
Gang 3 Indicator	0.354***	0.007***	0.346***	0.248***	0.010	0.238***
	(0.005)	(0.002)	(0.004)	(0.009)	(0.010)	(0.004)
Gang 4 Indicator	0.166***	-0.043***	0.207***	-0.159***	-0.148***	-0.011
	(0.006)	(0.003)	(0.004)	(0.026)	(0.014)	(0.018)
Gang 5 Indicator	0.129***	0.053***	0.076***	0.214***	0.086***	0.127***
	(0.003)	(0.002)	(0.002)	(0.010)	(0.006)	(0.006)
Gang 6 Indicator	-0.059***	0.021***	-0.081***	0.286***	0.110***	0.176***

	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.006)
Gang 7 Indicator	0.003	-0.009**	-0.002	0.315***	0.190***	0.125***
	(0.004)	(0.005)	(0.003)	(0.011)	(0.007)	(0.006)
Gang 8 Indicator	0.225***	0.008***	0.217***	0.035***	0.072***	-0.038***
	(0.003)	(0.002)	(0.003)	(0.007)	(0.007)	(0.005)
Constant	9.673***	2.829***	6.850***	9.008***	2.285***	6.723***
	(0.025)	(0.017)	(0.038)	(0.070)	(0.037)	(0.066)
Number of observations	683	684	683	547	547	547

note: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7a: Average Treatment Effect: 2 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Treated for Malaria (1=Yes)	0.188*	0.136	0.052	0.007	-0.112	0.119
	(0.103)	(0.086)	(0.056)	(0.269)	(0.206)	(0.085)
Age	0.000	0.001	-0.001	-0.003	-0.003	0.000
	(0.004)	(0.002)	(0.004)	(0.012)	(0.008)	(0.006)
Experience in Years (ln)	0.035	0.020**	0.015	0.153*	0.115	0.039*
	(0.041)	(0.010)	(0.035)	(0.087)	(0.076)	(0.023)
Read (1=Yes)	0.142	-0.009	0.151**	-0.425	-0.084	-0.341**
	(0.112)	(0.110)	(0.074)	(0.360)	(0.244)	(0.136)
Write (1=Yes)	-0.120	0.012	-0.132	0.192	-0.148	0.340***
	(0.104)	(0.104)	(0.090)	(0.191)	(0.140)	(0.068)
HH Size	0.007	0.009**	-0.002	-0.010	-0.008	-0.001
	(0.007)	(0.004)	(0.005)	(0.014)	(0.010)	(0.005)
HH Asset Index	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.330***	0.225***	0.104***	-0.416***	-0.045	-0.371***
	(0.022)	(0.014)	(0.013)	(0.119)	(0.096)	(0.054)
Gang 3 Indicator	0.442***	0.259***	0.183***	0.060	0.062	-0.002
	(0.050)	(0.033)	(0.027)	(0.073)	(0.065)	(0.022)
Gang 4 Indicator	-0.017	-0.015	-0.002	0.132	0.235	-0.102
	(0.038)	(0.032)	(0.031)	(0.264)	(0.188)	(0.094)
Gang 5 Indicator	0.156***	0.116***	0.040	0.140	0.205**	-0.066
	(0.033)	(0.012)	(0.025)	(0.102)	(0.080)	(0.043)
Gang 6 Indicator	0.077***	0.163***	-0.086***	-0.081	0.057	-0.138***

	(0.020)	(0.009)	(0.017)	(0.160)	(0.135)	(0.050)
Gang 7 Indicator	0.276***	0.287***	-0.011	-0.465***	0.144	-0.609***
	(0.033)	(0.023)	(0.017)	(0.163)	(0.138)	(0.061)
Gang 8 Indicator	0.376***	0.276***	0.100***	-0.380***	-0.093	-0.287***
	(0.036)	(0.025)	(0.020)	(0.096)	(0.081)	(0.031)
Constant	8.686***	1.875***	6.810***	8.483***	1.450***	7.032***
	(0.108)	(0.067)	(0.128)	(0.807)	(0.532)	(0.351)
Number of observations	140	140	140	107	107	107

note: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7b: Average Treatment Effects: 3 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Interviewed (1=Yes)	0.077	0.037	0.040	-0.009	-0.013	0.005
	(0.066)	(0.044)	(0.037)	(0.102)	(0.052)	(0.081)
Age	-0.004	0.001	-0.005**	0.000	0.002	-0.002
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Experience in Years (ln)	0.036	-0.015	0.051*	0.087	0.026	0.060**
	(0.043)	(0.025)	(0.026)	(0.055)	(0.045)	(0.027)
Read (1=Yes)	-0.103	-0.088	-0.015	-0.066	-0.095	0.029
	(0.147)	(0.099)	(0.056)	(0.292)	(0.108)	(0.199)
Write (1=Yes)	0.118	0.080	0.038	0.035	0.114	-0.079
	(0.132)	(0.090)	(0.052)	(0.250)	(0.096)	(0.186)
HH Size	0.006	0.000	0.006*	0.001	0.005	-0.003
	(0.009)	(0.006)	(0.003)	(0.009)	(0.006)	(0.004)
HH Asset Index	0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.013	-0.052***	0.065***	-0.066	0.055	-0.121***
	(0.010)	(0.010)	(0.006)	(0.050)	(0.034)	(0.030)
Gang 3 Indicator	0.350***	-0.026***	0.376***	0.229***	0.006	0.223***
	(0.014)	(0.006)	(0.011)	(0.052)	(0.039)	(0.029)
Gang 4 Indicator	0.189***	-0.038***	0.227***	-0.242***	-0.243***	0.001
	(0.017)	(0.010)	(0.012)	(0.089)	(0.067)	(0.059)
Gang 5 Indicator	0.038***	-0.009	0.046***	0.156***	0.092***	0.064
	(0.014)	(0.013)	(0.006)	(0.057)	(0.026)	(0.042)
Gang 6 Indicator	-0.133***	-0.041***	-0.092***	0.141**	0.045	0.095

	(0.006)	(0.004)	(0.005)	(0.066)	(0.038)	(0.060)
Gang 7 Indicator	0.045***	0.036***	0.009	0.064	0.097**	-0.033
	(0.015)	(0.010)	(0.006)	(0.056)	(0.048)	(0.048)
Gang 8 Indicator	0.219***	0.014***	0.204***	-0.166***	-0.071**	-0.096**
	(0.005)	(0.004)	(0.003)	(0.055)	(0.034)	(0.037)
Constant	9.553***	2.658***	6.895***	9.183***	2.364***	6.819***
	(0.080)	(0.050)	(0.054)	(0.292)	(0.142)	(0.204)
Number of observations	250	250	250	120	120	120

note: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7c: Average Treatment Effects: 4 Week Reference Period

	Round 1			Round 2		
	Earnings	Days Worked	Daily Wage	Earnings	Days Worked	Daily Wage
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Interviewed (1=Yes)	0.066	0.032	0.033	0.009	-0.008	0.018
	(0.055)	(0.038)	(0.037)	(0.112)	(0.052)	(0.090)
Age	-0.001	0.003	-0.004*	0.001	0.003	-0.001
	(0.004)	(0.002)	(0.002)	(0.005)	(0.002)	(0.003)
Experience in Years (ln)	0.035	-0.011	0.046	0.105*	0.033	0.072**
	(0.039)	(0.018)	(0.029)	(0.055)	(0.044)	(0.028)
Read (1=Yes)	-0.053	-0.047	-0.006	-0.086	-0.105	0.019
	(0.149)	(0.103)	(0.050)	(0.293)	(0.108)	(0.199)
Write (1=Yes)	0.102	0.061	0.041	0.050	0.124	-0.074
	(0.122)	(0.087)	(0.040)	(0.253)	(0.095)	(0.187)
HH Size	0.005	0.000	0.005	-0.003	0.004	-0.007
	(0.007)	(0.004)	(0.003)	(0.009)	(0.006)	(0.004)
HH Asset Index	0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gang 2 Indicator	0.053***	0.036***	0.017**	-0.092*	0.036	-0.128***
	(0.008)	(0.008)	(0.007)	(0.052)	(0.033)	(0.033)
Gang 3 Indicator	0.367***	0.030***	0.338***	0.214***	-0.009	0.223***
	(0.013)	(0.006)	(0.010)	(0.054)	(0.039)	(0.030)
Gang 4 Indicator	0.144***	-0.036***	0.180***	-0.249***	-0.256***	0.007
	(0.017)	(0.007)	(0.013)	(0.092)	(0.068)	(0.060)
Gang 5 Indicator	0.079***	0.040***	0.040***	0.138**	0.076***	0.063
	(0.013)	(0.010)	(0.008)	(0.057)	(0.024)	(0.044)
Gang 6 Indicator	-0.142***	-0.026***	-0.116***	0.235***	0.069*	0.166***

	(0.007)	(0.005)	(0.006)	(0.069)	(0.037)	(0.063)
Gang 7 Indicator	0.023	0.013	0.010	0.042	0.079*	-0.037
	(0.015)	(0.010)	(0.007)	(0.062)	(0.047)	(0.054)
Gang 8 Indicator	0.259***	0.074***	0.186***	-0.167***	-0.082**	-0.085**
	(0.005)	(0.004)	(0.003)	(0.053)	(0.033)	(0.034)
Constant	9.681***	2.813***	6.867***	9.157***	2.364***	6.793***
	(0.075)	(0.055)	(0.047)	(0.316)	(0.148)	(0.219)
Number of observations	248	248	248	120	120	120

note: *** p<0.01, ** p<0.05, * p<0.1