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ABSTRACT

Productivity and Health: Alternative Productivity Estimates Using Physical Activity*

This paper investigates an alternative proxy for individual worker productivity in physical work settings: a direct measure of physical activity using an accelerometer. First, the paper compares worker labor outcomes, such as labor supply and daily productivity obtained from firm personnel data, with physical activity; they are strongly related. Second, the paper investigates the effect of a health intervention on physical activity, using a temporally randomized offer of malaria testing and treatment. Workers who are offered this program reallocate time from lower intensity activities in favor of higher intensity activities when they work.

JEL Classification: I12, J22, J24, O12

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

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1. Introduction

Productivity is a key determinant of economic growth, but its empirical measurement remains a challenge. Measures of labor productivity at the level of the individual worker or firm are rare and, when they occur, often noisy and/or biased.[1] Individual labor productivity is especially difficult to measure outside a piece rate setting, where most labor activity is located. Effort and time on the job are typically unobserved by a third party, difficult to recall after the fact by the respondent, and hard to link to firm or farm output. A proposed alternative measure of worker productivity is the direct measurement of physical activity, which can be a proxy for worker effort especially for physically arduous tasks. In low and middle income countries these types of tasks represent an important part of economic activity.[2] However, the validation of physical activity measures and their consistency as a proxy for worker productivity have not been well established (Bort-Roig et al. 2014).

This paper builds on previous work on the productivity costs of malaria infection conducted at a large sugarcane plantation in rural Nigeria that pays workers piece rate wages. Using the piece rate daily earnings as the direct observation of worker productivity, the previous work estimates the high economic cost of malarial infection – the offer of a workplace based malaria testing and treatment program increases worker earnings by approximately 10% over the weeks following the offer (Dillon et al. 2014). This study, conducted in a subsequent harvest season, posits physical activity measured by accelerometer as a proxy for worker productivity, and investigates the impact of access to malaria treatment on work and productivity as well as on the proposed proxy for productivity.

[1] A large literature examines both the measurement of labor productivity for an individual firm and for an individual worker. For firm level studies see, for example, Bartelsman and Doms (2000), Asker et al. (2014), Syverson (2011), and Bartelsman et al. (2013); for individual worker studies see for instance Lazear (2000), Mas and Moretti (2009), Bandiera et al. (2010), Hermann and Rockoff (2012), Ziven and Neidell (2012).

[2] In the case of Nigeria, agriculture represents close to one fourth of the economy (World Development Indicators 2016), employing about one third of the labor force, who carries out heavy physical activities including planting, sowing, harvesting, herding, which would qualify for more accurately measurement by means of accelerometers. Other sectors, like mining, quarrying, construction, include similar hard physical activities.

An earlier literature has considered the relationship between productivity, effort, and physical activity. Becker (1977, 1985) models firms as choosing a time and effort 'package' from each worker, with effort per time unit a determinant of the worker's wage.[3] Gibbons (1987) and Lazear (2000), focusing on piece rate wage settings, consider workers as maximizing expected income net of the cost of effort each day, first by choosing whether to work or not on that day, and second by deciding how much effort to deliver when working. In the context of these models, physical activity can be thought of as a proxy for overall effort, and thus a key determinant of productivity, at least for physically demanding production technologies.

The empirical focus of the paper first validates physical activity as a substitute measure for unobserved individual worker productivity. We find that physical activity is highly correlated with labor productivity and labor supply. Each active hour is associated with increased earnings of 111 naira, or 14% of the earnings standard deviation.

We then estimate the effects of a malaria testing and treatment program on worker physical activity to test the validity of this measure as a proxy for productivity. We estimate three sets of treatment effects when comparing a worker who received access to malaria testing and treatment to a counterfactual group of workers yet to receive treatment. The first is the Intention to Treat Effect (ITT), which summarizes the gains to all workers with the offer of the workplace health program. Workers who are offered this program reduce lower intensity activities in favor of moderate intensity activities, and reduce sedentary time. The Treatment Effect on the Treated (TOT) is estimated on the subset of malaria positive workers and indicates that workers' daily average sedentary and 'light' physical activity time is reduced, while 'fairly active' and 'very active' physical activity levels increased. These changes in physical activity are due to a reallocation of activity within working hours as total labor supply is largely unaffected. Finally, building on earlier work, we estimate the impact of the revelation of positive health information among workers who test malaria negative, which we call the Treatment Effect on the Medically Untreated (TmUT). This sub-group of workers also exhibits an increase in earnings and in the

[3] Becker (1977) notes, "Although the word "effort" is used throughout this paper, it cannot yet be satisfactorily measured, nor adequately defined in words. Surely, "effort" includes the expenditure of physical energy….This paper sidesteps these difficulties by defining effort analytically by its role in a model of behavior."

proportion of time spent in moderate activity levels after the receipt of diagnosis. This result is consistent with Dillon et al. (2014) who find similar results and detail how these workers switch to higher return, higher effort tasks, due to revised expectations over the perceived cost of effort. As physical activity directly proxies for effort, the effect of information on physical activity provides some evidence that the perceived cost of effort changes in response to the malaria testing and treatment program among these workers.

Together, these two validation exercises indicate that physical activity may be an attractive proxy for individual worker productivity. Monitoring physical activity with wearable technologies should be feasible in many settings where piece-rate labor does not exist, and can therefore help extend productivity research especially as accelerometer technologies continue to advance in accuracy and unit prices fall.[4]

The next section of this paper discusses the theoretical link between physical activity and productivity and reviews methods to measure physical activity. The third section describes the study setting in detail and section four discusses the malaria diagnostic and treatment protocols. The fifth and sixth sections describe the experimental design and estimation strategy. Section seven presents results, and the last section concludes.

2. Theoretical Motivation and Interpretation of Physical Activity

Becker (1977, 1985) provides a theoretical model of the relationship between effort, productivity, labor supply and earnings. In this Beckerian framework, the worker's total earnings, Y, depend on a 'package' of time, t, and total effort, E. The return to effort, or wage w, is partly a function of effort per unit time (e) from each worker, where $e = E/t$. Firms purchase packages of time from workers, monitoring their effort, so that worker's earnings are defined by the function:

$$Y = w(e)t \tag{1}$$

[4] A device with the same functions as the one used in this study can now be found for 35 USD a piece.

Becker assumes that firms are indifferent to the distribution of hours among workers, so that earnings are proportional to time for given effort levels. The model provides a parameter of the effort intensity of work, σ, where the return to work depends on effort intensity along with human capital and other time-invariant worker characteristics. The earnings function can be specified with a Cobb-Douglas production function such that:

$$Y = \alpha e^{\sigma} t = \alpha E^{\sigma} t^{1-\sigma} \quad (2)$$

with $\alpha = \beta h$ where h represents worker human capital and β reflects the returns to human capital conditional on effort and time, which can be thought of as a measure that includes time-invariant characteristics such as individual skill or genetic endowments. In the context of agricultural labor, worker human capital, h, includes characteristics of the worker including their health status, which varies over time. When the effort intensity of work is less than one, $\sigma < 1$, equal effort will be used per hour worked as there are diminishing returns to additional effort on earnings. Firms then choose σ and α, as well as monitoring costs, to maximize income.[5]

In our piece rate wage setting with fixed work hours, we can use the reduced form earnings function to disaggregate the effects of changes in health status on effort, measured using physical activity data, into labor supply and productivity effects.[6] Workers cannot trade off effort and hours worked in our study context, and this facilitates the identification of changes in health status on worker effort.[7] Dillon et al. (2014) defined the return to effort partly as a function of health perceptions that in turn were determined by a worker's true health status, *H,* as well as health information, *I*, since both changes in *H* and changes in *I* appeared to affect worker behavior. Incorporating this insight into the Beckerian model, health status is clearly one element in the

[5] In Becker (1977), the trade-offs between production technology and monitoring are fully derived with respect to the firm's choice of the effort intensity of work, σ, and the distribution of worker endowments, α, employed.
[6] In the theoretical model, monitoring costs and production technology are choice variables, but our single study site allows us to abstract from differences in production technology across workers and differences in monitoring, as the firm has a uniform monitoring system. Differences could arise in supervision of different groups of employees and we consider this potential source of unobserved heterogeneity in our fixed effects strategy discussed in more detail below.
[7] Workers cannot choose hours on the plantation. They are picked up from their local villages by a plantation bus and returned to their village at closing. All workers have the same hours supplied at the plantation conditional on labor supply.

human capital vector h, that is $h = h(H)$. Information about health, on the other hand, does not necessarily affect health status directly, at least in this static model, but new information about health, especially if unexpected, may affect the perceived cost of effort and hence the effort choice supplied by the worker, that is $e = e(I)$. Therefore, we can specify the return to effort (per unit time) as partly a function of health perceptions, $w(e) = \beta h(H)e(I)^{\sigma}$. The total earnings function is then a function of both health information and the worker's actual health status, as well as other dimensions of human capital.

In this randomized control trial described in more detail below, we exogenously vary access to a malaria testing and treatment intervention by randomly assigning workers to a day of testing. For malaria positive workers, the effect of the intervention provides an estimate of the impact of changes in the workers' health status and information about their malaria status. For malaria negative workers, who do not receive treatment, the sole effect of the intervention is that of health information. Becker's model motivates the experimental design, as effort alone is not the only determinant of productivity, and our discussion of worker fixed effects, particularly β and unobservable components of h, map effort into worker productivity.

Despite the theoretical attention to effort in earnings functions, the measurement of physical activity has typically generated most interest in the fields of medicine, public health, and nutrition sciences. In medical and public health studies, whether assessing the health risks associated with certain (e.g. sedentary) lifestyles, or estimating gains from health promotion activities, measurement efforts aim to capture the duration, frequency, intensity, or setting of physical activity (Bauman et al., 2006). Nutritionists tend to be interested in physical activity as a major component of individual energy needs. Calorie (food) deficits or surpluses are generally evaluated comparing estimated energy expenditure against a benchmark energy requirement. Physical activity is the most variable component of human daily energy expenditure and the second most important after the Basal Metabolic Rate (BMR) (FAO and WHO, 2001).

A number of tools are used for the measurement of physical activity that can be ranked according to their degree of practicality. Nutritionists and physiologists consider the doubly labeled water method (DLW) as the gold standard to measure energy expenditure in free-living conditions (Speakman, 1997; FAO and WHO, 2001). As an alternative to this gold standard, subjects are sometimes asked to keep diaries or logs of physical activity. While widely used in medical and nutrition studies, these methods can be cumbersome and costly to implement with large samples. More common are individual self-reports of physical activity. Instruments that have undergone international validation, including developing country settings, include the International Physical Activity Questionnaire (IPAQ) in its short- and long-form versions (Craig et al., 2003), the WHO-led Global Physical Activity Questionnaire (GPAQ), and a Sub-Saharan Africa Activity Questionnaire (Sobngwi et al., 2001). The instruments are designed to measure activities in different domains (work, travel to and from places, and recreational activities) and the intensity of these activities (e.g. low, moderate or high physical activity) rather than precisely measuring energy expenditures. While validation studies for these survey instruments exist (e.g. Craig et al., 2003), the instruments remain prone to the types of biases that may be encountered in any subjective self-report based on survey recall, and their accuracy has been called into question as it appears to often produce results that are in contradiction with objective measures (Corder and Van Slujis, 2010).

In the last decade, activity trackers have been developed as instruments that have the potential to provide sufficiently accurate estimates of physical activity and energy consumption at the individual level. Accelerometers are possibly the most commonly used type of device, but other types of sensors are also being used or tested (Baranowski et al., 2012; Storm et al., 2015).[8] Applied work making use of accelerometers has investigated the relationship between physical activity and the built environment (Sallis et al., 2016) or contrasted patterns of physical activity across countries or populations (Salvo et al., 2015). One particular challenge with this method is study subject adherence to the protocols necessary for accurate measurement – the accelerometers must be worn in a consistent fashion during waking hours for several consecutive days. Given these challenges, certain field studies have seen up to 40% of individual-day data to be invalid

[8] Most recently, a review of accelerometer studies with sample sizes greater than 400 identified accelerometry data for more than 275,000 individuals, from 76 studies and 36 countries (Wijndaele et al, 2015). Efforts have also started to develop internationally agreed protocols for accelerometer data collection, sharing, and dissemination (Cain and Geremia, 2012; Wijndaele et al, 2015).

(Sherar et al., 2011). Despite these adherence challenges that can lead to data censoring, wearable technologies including accelerometers hold a great deal of promise due to their accuracy in real-time measurement.

The precise technology employed in this study was chosen after market research and consultation of experts in this area, who largely emphasized reliability, immediate availability and user friendliness in the field.[9] For these reasons we chose to use the belt-worn FitBit accelerometer, a three-dimensional accelerometer which measures activity duration and intensity in minutes. The accelerometer reports time spent in four levels of activities: Sedentary Minutes, and Lightly, Fairly and Very Active Minutes. The proprietary algorithm assigns minute intervals to any activity if the assessed activity is more strenuous (in terms of estimated caloric expenditure) than a slow-paced walk. The caloric expenditure threshold is normed to the BMI of the worker, with the three partitions of activity representing increasingly greater energy expenditures. The device tracks worker physical activity continuously throughout the day and cannot be manually turned off by the worker.

3. Study Setting

The study is implemented on a single large (5,700 hectares) sugarcane plantation in rural Nigeria. The plantation employs 680 sugarcane cutters who work for the entire harvest season that stretches from mid-November to April (in this case the study year 2012-13) and 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 from local villages surrounding the plantation and are transported daily to and from the assigned work site. The cane-cutters are organized into eight work groups and each group is managed by a supervisor. Every day the supervisor and his cutters are allocated to a set

[9] Ease of use was an important consideration, and even after choosing the most user-friendly option at the time, a number of trackers were lost. One alternative approach would have been to develop one's own accelerometer. While this has the advantage over commercial products available at the time of fieldwork in that the underlying algorithms are known and available, discussions with experts in this field who are and have been developing their own devices indicated that the development is time consuming and costly, beyond the scope of our study.

of starting fields in the plantation and additional fields when the starting fields are finished. 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. The worker's day is standardized with plantation trucks collecting workers from their village and delivering them to the field sites to be cut each day, and transporting them back to their village at the end of the day. This standardized work day ensures that for each cane cutter the number of hours of work is fixed across all workers in a work group and alleviates concerns about trade-offs between work hours and effort.

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. Workers are paid monthly and they often keep track of their daily output by maintaining their own separate ledger. Disagreement between cutters and management over output amounts are rare. The work tends to be lucrative and an average day of cane cutting pays 1,156 naira, or approximately 7 USD. 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) (Nigeria National Bureau of Statistics, 2012), sugarcane cutter positions are in high demand in the local communities.

We supplement the daily productivity 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 study design permits estimation of the within-worker effect of malaria testing and treatment by comparing a worker's physical activity before and after 'treatment' which allows us to control for time invariant worker characteristics such as human capital or other worker unobservable characteristics that may also affect productivity independently of health (in equation 2). During the study period, the plantation was unexpectedly closed for cutting in weeks five and six of the eight-week study period due to an operational breakdown at the processing plant, after our sub-sample of workers had been fitted with accelerometers. This reduces the statistical power of our estimates, as we do not observe as many work days in the analysis as planned in the study design, and truncates the observation period over which we can estimate the productivity/activity impacts of treatment.

4. Malaria: Measurement and Treatment Protocol

Before describing the health intervention and its effect on physical activity in more detail, it is important to understand both the measurement and expected impact of malaria infection as the particular biology of infection informs the identification strategy. Malaria is endemic in our study setting and workers in our initial qualitative interviews described it as an important health issue. As malaria symptoms generally include fever, chills, sweats, headaches, nausea, vomiting, body aches, and general malaise, the potential for malaria infection to impact labor outcomes is high. Severe malaria can 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.[10] 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 (Najera and Hempel, 1996).

Three methods are commonly used to assess 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 generic, subjects may, through self-assessment, categorize other illnesses with similar symptoms as malaria infection.[11] 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

[10] 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).
[11] This is further enhanced for the study area by the word referring to fever in the local language being the same as that referring to malaria.

and Type II errors, making it difficult to sign the measurement bias and rendering it imprecise as a measurement approach.[12]

Our study relies on the measurement of parasites in the worker from thick film blood smears read in a dedicated laboratory. Although expensive to implement as it requires trained personnel and appropriate instruments, thick blood film microscopy is considered the diagnostic gold standard. In practice, our study team takes a blood sample from each consenting worker and conducts microscopy analysis in a lab that is two hours away (by car) from the plantation. The microscopy analysis counts the number of parasites, with workers above a specified threshold considered to be malaria positive.[13] Our adopted definition of malaria positivity is the presence of at least three parasites over the total examined fields in the blood smear. [14] This decision follows the clinical diagnostic standards in the study area (Government of Nigeria 2011). As there is no universally adopted standard for both symptomatic and asymptomatic cases in a population (Laishram et al., 2012), we rely on the clinical threshold in our study area as our objective measure following the recommendation in WHO (2010).[15]

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)).

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[12] 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 nevertheless remains a widely used approach in socio-economic and public health studies.

[13] 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 from each batch of 50 slides to verify. If discrepancies between the primary laboratory technician and the supervisor were found, the whole batch of slides was re-validated.

[14] In the medical literature studies focusing on different settings use distinct parasite density thresholds to classify malaria infection as there is no unique or universal medically established standard for population based malaria testing which includes asymptomatic malaria cases (see dalla Martha et al. (2007), Toure et al. (2006), and Rottmann et al. (2006)).

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

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 properly, had consumed the medication himself without distributing to others, and whether the worker was asymptomatic. The rate of malaria positives among the sub-sample of workers who wore the physical activity monitors was 30%. Almost no problems with compliance were reported and we assume full compliance with ACT treatment for the remainder of the analysis.

5. Study Design

While we observe labor outcomes for the entire cane cutting population of 680 workers during an eight-week study period from February to April 2013, at the peak of the harvest season, the analysis in this paper is based on a subsample of workers who were equipped with activity trackers during the study period. A random sub-sample of 83 sugarcane cutters was assigned an activity tracker. Each tracker was labeled with a unique code for the dedicated use of the same worker over the study period. Cane cutters clipped these activity trackers, approximately the same size and weight as a USB flash drive, to their pant hem, pocket, or belt. At the end of every work week, the data recorded by these trackers were synced to a notebook computer at the field survey office and the trackers were simultaneously charged. This process was carefully managed and workers received back the same tracker by the start of the new workweek. Detailed checking during the fieldwork reassured that trackers were operational, although some were lost by the workers, as discussed below.[16]

[16] The protocol was developed after a one-week intensive pilot with 10 sugarcane workers off plantation in January 2013. This pilot tested practical modalities such as data registration, battery, charging and syncing time, device functioning in high temperature and water rich environment, and exploring device location to minimize loss (arm, around the neck, belt).

Separately, a survey team of enumerators and health workers employed by the project collected information on worker and health characteristics from all workers. Worker information included employment history, demographic information, place of living, and household characteristics. The registered health worker first asked the worker a brief health history and then prepared a blood slide which was used to microscopically verify his malarial status. All workers who were parasitic positive according to the microscopy results from the collected slides were treated with the appropriate doses of Artemisinin Combination Therapy (ACT).[17]

At the end of the fieldwork the activity information collected from the trackers was linked to plantation labor data, the worker and health information from the survey and the malaria test, producing a data set that enables the envisaged two-part analysis carried out below. In the first part we analyze the relationship of physical activity with both labor supply and productivity. The second part estimates the short-run effects of malaria testing and treatment on direct measures of physical activity, as well as labor supply and earnings.

Worker sampling and order of treatment

Two stages of worker selection were undertaken for this study, the second of which is most relevant to the analysis in this paper. The first concerns the offer of malaria testing and treatment, which was temporally randomized over an eight-week period for the entire worker population, stratified by work group. The second sampling activity determines the subsample of workers to receive an accelerometer to wear throughout the study period, forming the sample of interest for this paper.

Selected workers for the accelerometer sample totaled 83. Given a previous positivity rate (35%) from an earlier round of the study (Dillon et al. 2014), we oversampled malaria positive workers due to the ex-ante concern of low power to detect the effects of malaria infection.[18] Given

[17] ACT treatment consists of a set of pills to be taken twice a day for three days in a row. Diagnosis was completed and reported to the worker within two days of the blood draw.
[18] As a result of this sampling strategy, sample weights are calculated to reweight to the worker population based on the selection probabilities and the malaria positivity rate. Our regression results presented below do not change substantially if the sample weights are omitted.

this concern, a malaria positive worker was approximately 50% more likely to be selected into the study sample. All workers who were allocated an accelerometer received the device in week 1, and wore the same device until the end of the field period, unless it was lost. Workers could not change or transfer trackers through the study period as each tracker was uniquely identified.

Table 1 presents a comparison of worker health and household characteristics for the sample that received an accelerometer and the sample of workers who did not. Workers' characteristics including age, BMI and hemoglobin score were well balanced between the tracked and non-tracked samples. In the tracked sample, malaria positive cases were significantly higher as intended given the selection strategy. The second panel shows that human capital indicators including literacy, numeracy, school attendance, level of school completed, and plantation experience are all balanced between the tracked and non-tracked sample. The household characteristics of workers are also balanced in terms of household composition including number of spouses, children, and total household size, as well as a household asset index. [19]

Work Disruption and Tracker Loss

The nature of the production process together with the daily working order of processing machinery partially determine harvest activity on any given workday at the plantation. Since sugarcane has an optimal time to be harvested (in order to maximize sugar content), and needs to be processed on the same workday by the sugar factory on the plantation, past planting schedule and current factory activity affect whether sugarcane cutters work on a given day. During our study period, an unexpected mechanical failure at the processing factory resulted in a temporary stoppage of harvest activity during study weeks 5 and 6. Since all workers who had been allocated an accelerometer were already treated by this time, this does not affect our identification strategy,

[19] The asset index reflects household expenditures which are not measured but rather predicted using the method suggested by Grosh and Baker (1995) and Ahmed and Bouis (2002). The questionnaire 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 weighted regression on the NLSS 2010 data.

and still allows us to estimate treatment impacts on worker physical activity, but it does reduce the power of the study from our initial expectations. It also limits the time window over which we can investigate the effects of treatment.

While 83 workers were allocated activity trackers at the beginning of the study, 25 accelerometers were lost over the eight-week study period, resulting in 58 devices being returned at the end of the study.[20] This analysis utilizes the daily data generated by all trackers, until the point that they were lost. Figure 1 presents the frequency of tracker loss by the number of days until the tracker was lost by the worker. Tracker loss does not seem to occur at any particular point in time, though loss increases in the first week after assignment and during weeks 5 and 6 of the study when the plantation was unexpectedly closed and workers were monitored less closely.

Because workers who lost their accelerometer may have different characteristics, thus possibly resulting in biased estimates, we assess the correlates of the probability of losing the tracker device.[21] In Table 2, worker characteristics and health status are regressed on an accelerometer loss indicator. No statistically significant relationships are found between tracker loss and any of the observed individual, household or health characteristics, including age, experience, schooling, household composition, assets, malaria test result status, BMI, and hemoglobin. All estimated coefficients are also very close to zero in magnitude.

Balancing tests

The identification of the relation between health and physical activity relies on the temporally randomized exposure to a malaria testing and treatment program. The assignment of workers into treatment or comparison group is described in detail in the next section. To avoid confounding the impact of treatment with possible interactions between worker characteristics, we

[20] We investigated and carried out qualitative interviews to assess whether these devices were stolen, but there is no reason to believe so. Given the relatively high earnings from cane cutting, workers are keen to keep a good reputation with the plantation, and they were fully aware that the device was not useful without the complementary workstation and log in password to download and read the information, which they did not have access to.

[21] Selective loss may introduce a selection bias in later estimation results. For instance: if workers who had more physical capacity were more likely to lose their tracker due to greater physical activity, then this would likely bias activity measures downwards. If workers who were more educated or wealthier were more careful with their tracker, then this differential probability of tracker loss might also potentially bias the estimates.

investigate here whether there are statistically significant differences between treatment and comparison workers across observable worker and household characteristics – work experience, education, household size, asset index, hemoglobin and body mass index. Table 3 reports the standardized mean difference in characteristics for each pairwise comparison as well as the p-value of the standard t-test of difference. None of the standardized mean-differences exceed the 25 percent threshold suggested by Imbens and Wooldridge (2009) to signal possible sample imbalance. No mean differences are also significantly different at conventional levels as determined by traditional t-tests of equality.

6. Econometric Strategy

To assess the relationship between physical activity and the worker's daily labor supply and output, as recorded by the plantation, we first estimate the conditional association between labor outcomes and each of the measured levels of physical activity (sedentary, light, medium and high intensity minutes):

$$L_{id} = \alpha_i + \sum_j \beta_j A_{jid} + \varepsilon_{id} \quad (3)$$

In this equation L is either labor supply (days worked), which can be thought of a measure of productivity at the extensive margin, or by daily earnings, which provide a measure of productivity at the intensive margin (as daily earnings is a linear transformation of rods cut, i.e. a direct measure of output). A_{jid} is the activity measure for intensity j - i.e. number of minutes (or hours) by the intensity level of the activity (lightly active, fairly active, very active) observed for worker i on day d (note that these minutes along with sedentary minutes sum to the total minutes in a 24-hour period). The ratio of time in each of the intensity categories relative to the total time spent in activity is also used as an outcome to assess the distributional change of time across intensity levels. The specification includes an individual fixed effect to control for time invariant worker characteristics, such as worker skill, that help translate physical activity and effort into output. Becker's model motivates the potential effect of unobservable components in either the transformation of human capital, β_i or human capital itself, h_i in specifying the relationship between effort and productivity. Standard errors are clustered at the work group level. These regression estimates serve as a validation test for the use of physical activity as a proxy for labor variables in our study context.

In the second phase of analysis, we estimate the impact of malaria testing and treatment directly on physical activity (which, given the relationship estimated above, further implies malaria impacts on earnings and possibly labor supply). The primary econometric specification estimates the Intention to Treat Effect, which compares daily labor outcomes over some observation period, *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 yet to be tested. To control for the potential non-random placement of workers across workgroups, a full set of workgroup fixed effects, F_g , are included in the specification. Specifically, we estimate:

$$L_{igt} = \alpha + \beta T_{igt-} + F_g + \varepsilon_{it}, \forall i \in W_{t-} \cup W_{t+} \qquad (4)$$

where L_{igt} measures the three labor outcomes of interest: labor supply, daily productivity, and physical activity for worker *i* in work group *g*, and ε_{it} is the worker specific error term.

Given the limited weeks of valid data in our study period (due to the factory break down as discussed above), we set the observation period *t* to be a seven-day reference period to maximize the number of worker days in the analysis. This implies that all workers assessed on day *t* are assigned to the treated group whereas workers assessed on day $t+7$ are assigned to the counterfactual comparison group. The observation period for the outcomes of interest extend from day *t* to day $t+7$.

The set of workers assessed, *W*, are also determined through clinical testing to be either positive, *P* or negative, *N*. Disaggregating the sample of tracked workers between positive and negative malaria cases, separate estimates of the impact on malaria positives and negatives are obtained as well – the TOT and TmUT effects as described earlier.

The TOT on malaria positives is estimated by comparing labor outcomes at time interval 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 (4) is re-estimated but now for the subset of workers P who have tested positive, as given in Equation (5):

$$L_{igt} = \alpha + \beta T_{igt-} + F_g + \varepsilon_{it}, \forall i \in P_{t-} \cup P_{t+} \tag{5}$$

as before, L_{igt} reflects the labor outcomes of interest: labor supply, productivity, and physical activity. The TOT reflects the combined effect of receiving an illness diagnosis and medical treatment for such a diagnosis. This is a valid TOT estimate if those workers assessed positive on day $t+7$ are also malaria positive over the interval from day t to day $t+7$.

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 (6):

$$L_{igt} = \alpha + \beta T_{igt-} + F_g + \varepsilon_{it}, \forall i \in N_{t-} \cup N_{t+} \tag{6}$$

The medically untreated are an interesting subgroup. They do not receive any medicine (as they are malaria "free") but do receive information on their health status. Dillon et al. (2014) find that this group responds to the diagnosis by both increasing productivity (effort) within occupation as well as switching into sugarcane cutting from lower return occupations. The study rules out many alternative explanations for this behavioral response and finds that workers most likely to be surprised by a healthy diagnosis based on pre-test expectations respond the strongest. The Treatment on the Medically Untreated, TmUT, analysis in this paper tests again this hypothesis of the effect of 'positive' health information on a worker's physical activity.[22] Similar to the above, this is a valid TmUT estimate if those workers assessed negative on day *t+7* are also malaria free over the interval from day *t* to day *t+7*.

7. Results

The paper presents two sets of results. First, we present the conditional correlations of labor outcomes and physical activity to validate the use of physical activity data as a proxy measure of productivity. Then we present the results for the estimated effects of a malaria treatment and testing program on worker physical activity.

Relationship between physical activity and worker individual labor supply and output

Table 4 presents summary statistics for the tracked subsample including the physical activity outcome variables sedentary, light intensity, medium intensity, and high intensity minutes of activity (labelled 'lightly', 'fairly' and 'very active', respectively). As described earlier, applications of the accelerometer technology can result in a high degree of respondent non-compliance, and this study is no exception. In order to distinguish valid observation days from invalid days in the analysis, the three following trimming criteria were adopted: (1) We delete an observation day if there was a reporting error in the accelerometer data identified because it did not sum to 24 hours in that day. (2) We stipulate a cut-off for a valid day of data by establishing thresholds on total time devoted to activity (of any level). A day is deemed invalid if the activity tracker measures active time of less than three hours on work days or less than 1.5 hours on non-work days. Figure 2 presents the histograms of sedentary time per day for both (plantation) work days and non-work days. The degree of non-adherence is readily apparent in the right tails of both histograms, and especially that for non-work days.[23] (3) The remaining days are trimmed at the 1st

[22] One key difference with previous seasons is that the plantation did not allow cutters to switch between different cutting and scrabbling in the current season. This study therefore does not investigate task or occupational switching.

[23] Any classification threshold for a valid day will include some proportion of false positives and false negatives. We believe the chosen thresholds are conservative in that they likely include a relatively larger number of invalid days. However, the presented results are robust to other cut-offs in either direction at 30 minute increments.

and 99th percentile of the rods cut per active hour distribution in order to further reduce the influence of likely measurement error in both daily productivity and daily activity measures.

By comparing the first and second panels of Table 4, we can see that roughly 1/3 of worker-days do not meet the criteria of a valid day of observation. We see that adherence to protocols is relatively worse on non-work-days as a greater proportion of worker-day observations do not meet the trimming thresholds and are therefore excluded.

The thresholds used to delineate the different levels of intensity of activity were pre-programmed in the accelerometer using a proprietary algorithm. Total active minutes is also included in the descriptive statistics in Table 4. Among all worker-days registered using the activity monitors, workers spent on an average day 18.8 hours in sedentary activity, 2.4 hours in light intensity activity, 2.1 hours in fairly intensity activity and 0.4 hours in high intensity activity. These activity levels increase with the trimmed data (as expected) to 6.8 hours of physical activity per day, again mostly in the light or fairly active categories. Workers are certainly more active on the days when they cut cane: 7.6 hours in contrast with 5.8 hours of activity when off the plantation. The table also reports the percent of days worked among the sugarcane cutters and their conditional daily earnings, 1,154 naira or approximately 7 USD.

These descriptive statistics provide a physical activity profile of the workers. Of particular interest for this study is the relationship between physical activity and individual worker labor supply and output recorded by the plantation. Table 5 presents the estimates of equation 3, reflecting the relationship between workers' labor outcomes and minutes in physical activity levels (sedentary, low, medium and high activity levels). In the first panel, we pool all active minutes, while in the second and third panels we disaggregate different levels of intensity to demonstrate the relation of effort intensity with labor supply, unconditional daily earnings, and daily earnings conditional on working that day.[24]

[24] Since 'very active' only represents a very small proportion of activity, we first pool 'fairly active' and 'very active' together.

The estimates reflect a strong relationship between labor outcomes and the activity measures, both on the extensive and intensive margins. An additional hour of (any) activity increases the likelihood of a plantation work day by 8 percentage points. It is actually time spent in light activity that has the strongest association with a work day (a marginal effect of 10 percentage points per hour of light activity) followed by moderate activity (7.5 percentage points) and then heavy activity (6 percentage points). On the job productivity, proxied by daily earnings in this piece rate setting, is also strongly related to physical activity as shown by the results in column 3 of Table 5, which depicts the correlations with earnings on days worked. Broadly speaking, about 60% of the activity association with earnings is driven by showing up for work and 40% by the association with more intensive activity levels.[25] For workdays on the plantation, light activity is no longer associated with earnings, again highlighting the arduous nature of the production process. While not as precisely estimated (in part due to the reduction in observations) the point estimates suggest that moderate activity is most clearly associated with daily productivity, followed by heavy activity. This is not necessarily surprising since heavy activity captures relatively extreme physical exertion such as running, while cane-cutting, while arduous, is typically conducted at a slower pace.

Effects of malaria testing and treatment on physical activity and labor outcomes

Tables 6, 7, and 8 report the physical activity treatment effects from the malaria testing and treatment program for all workers (ITT), the malaria positives (TOT), and the malaria negatives (TmUT) respectively. We also report outcomes of the ITT, TOT and TmUT on daily labor supply, daily earnings and daily rods cut. In panel A of each table we include all worker-day observations, while in panel B, we restrict to those days where workers worked on the plantation. Each column of the tables presents program treatment effects on labor outcomes (columns 1-3), physical activity hours by intensity level (columns 4-7) and the ratio of hours in each intensity level relative to the total number of active hours of the worker (columns 8-10).

[25] This reflects the estimated coefficient in Panel A for earnings on days worked, which is roughly 40% of the unconditional association between earnings and activity.

In the full sample of workers (Table 6), the overall effect of the malaria program tends to increase labor supply, earnings and daily rods cut, although these results are not precisely estimated (Col 1-3). The program also appears to decrease sedentary hours and light work hours among workers (Col 4,5) as well as increase time spent in more vigorous activity; however, the results are again not precisely estimated. Since the number of hours per day is fixed, we also look at the proportion of time spent at different levels of activity by estimating the ITT using the ratios of intensity hours relative to total active hours. We find statistically significant shifts from the proportion of light to fairly active time.

In panel B, we observe the intent to treat effects on daily earnings and daily rods cut conditional on working, which are more precisely estimated than the unconditional estimates. Reflecting the relatively arduous nature of cane cutting, light activity has no longer any association with productivity and an additional hour of moderate or heavy activity is associated with an additional 65 naira of earnings. Average hourly earnings for cane cutters are on the order of 150-200 naira, so a shift of one hour from light to moderate or heavy activity represents a significant proportional increase in output and earnings. The physical activity specifications also result in larger and more precise estimates of time substitution across intensity levels of physical activity. The results suggest that the testing and treatment lead to a shift from light to fairly or very active time on the order of 1.6 hours per work day. This shift in activity is also associated with an increase in daily earnings of 316 naira on the basis of an additional 141 rods cut – approximately a 25% increase in output.

Focusing on workers who are diagnosed with malaria (Table 7), the effect sizes of TOT estimates are larger than the above ITT estimates, but again estimated imprecisely. Malaria infected and treated workers tend to have higher daily earnings and more rods cut, and tend to supply less labor (Panel A Columns 1-3); they are also less engaged in light activity and tend to be more engaged in fairly active physical activity (Panel A Columns 4-7).

The physical activity effects (Column 4-7) are largest conditional on labor supply (Panel B), with daily fairly active hours increasing by 1.4 hours and very active hours increase by 0.3 (although this increase is not precisely estimated). The increase in physical activity is roughly twice the increase estimated in the above ITT estimates, suggesting that the largest gains (over seven days) of the malaria testing and treatment program accrue to the malaria positives, as perhaps to be expected given the efficacious treatment offered. This activity increase corresponds well with statistically significant increases in daily earnings and rods cut (Panel B Columns 2-3).

A similar pattern emerges when we estimate the TOT on the ratio of intensity level hours divided by the total active hours (Panel B, Columns 8-10). The TOT on these ratios indicates a shift from light to fairly active levels of activity. Note that the number of worker-day observations decreases considerably when we restrict the sample to the malaria positives, decreasing statistical power, yet we find significant changes in the intensity of physical activity.

The treatment effects on the medically untreated (TmUT) are reported in Table 8 and represent the effect of the worker learning that he is malaria negative. In line with earlier results for the same setting, which identified a 'good news' effect on worker earnings and productivity, the estimates suggest a positive effect of health information on physical activity, though coefficient estimates are smaller than in the malaria positive subsample. The TMuT estimates on physical activity are consistent in suggesting a reduction of sedentary and light work hours with corresponding increases in fairly active and very active hours (Columns 4-7 of Panel A and B). The ratios of these intensity levels relative to total active minutes indicates a significant shift from light (negative effect) to fairly and very active time (positive effects) (Columns 8-10 of Panel A and B). As with the TOT, these substitution effects across activity levels correspond to objective measures of productivity, daily rods cut, and daily earnings (Columns 1-3 of panel A and B). In an endemic area, the effect of unanticipated health information may cause workers to revise their expectations of short-run work capacity, consistent with previous findings in the same setting (Dillon et al. 2014).

8. Conclusion

The empirical measurement of labor productivity at the micro level is a severe challenge in many settings, especially when effort and hours worked are unobserved, difficult to recall, or hard to link to firm or farm output. Nevertheless, productivity remains of central interest as it is a key determinant of welfare. It is also a presumably important channel through which health affects wellbeing. This study investigates whether a direct measure of physical activity can be a valid proxy for productivity, particularly for agricultural workers and, specifically in this case, cane cutting in Nigeria.

The paper first explores the association of physical activity with labor productivity and labor supply among agricultural workers in a piece rate wage setting, and finds a strong association. Each active hour is associated with increased earnings of 111 naira which is 14% of the earnings standard deviation. To further validate physical activity as a measure of worker productivity, the study estimates the impact of a malaria testing and treatment program on physical activity, building on previous work. If physical activity is a good proxy for worker productivity in this setting we expect to see an impact, in line with earlier study results that find an effect of malaria testing and treatment on worker output and labor supply. The results indicate that workers daily average sedentary time and light physical activity reduced after treatment, while fairly active and very active physical activity levels increased, with larger impacts among the malaria positives.

We also estimate statistically significant effects of malaria information on workers who test negative, in line with results from a previous study (Dillon et al. 2014). Workers who receive information that they are malaria negative respond with higher levels of physical activity. This provides complementary evidence that workers shift effort in response to health perceptions (Dillon et al., 2014), and is further evidence of general behavioral responses to health information (see Madejewicz et al. (2007), Jalan & Somanathan (2008), Thornton (2008), Dupas (2011), Cohen et al. (2015), Gong (2014), Baird et al. (2014)).

Taken together, the results indicate that physical activity can be a good proxy for individual worker productivity in arduous agricultural tasks, and possibly similar heavy activities in other sectors. Nevertheless, several empirical challenges remain. One challenge is subject adherence to study design. Further attention to participant compliance in future studies using physical activity will strengthen this conclusion. A second challenge faced in the field was the specification of where the accelerometer should be worn by the participant. Future work validating the location of the accelerometer as well as whether a single or multiple accelerometer might provide the most accurate measure of productivity, conditional on specific tasks, would be a welcome advance to this field of study.

As individual productivity effects are central to many theoretical applications outside the fields of health, labor and agricultural economics, this paper confirms that physical activity can be a useful proxy for individual labor productivity when other measures of output are unavailable or costly to observe.

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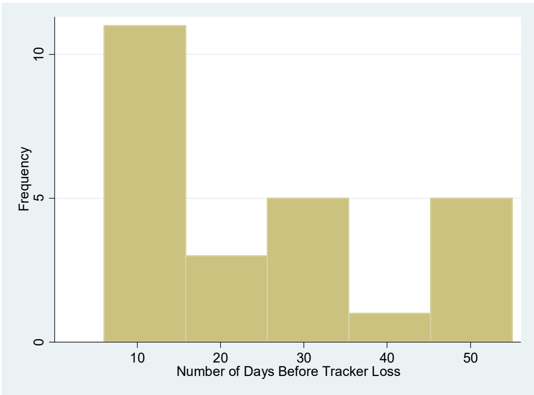
Figure 1: Days Before Tracker Loss



Figures 2: Minutes Sedentary and Compliance

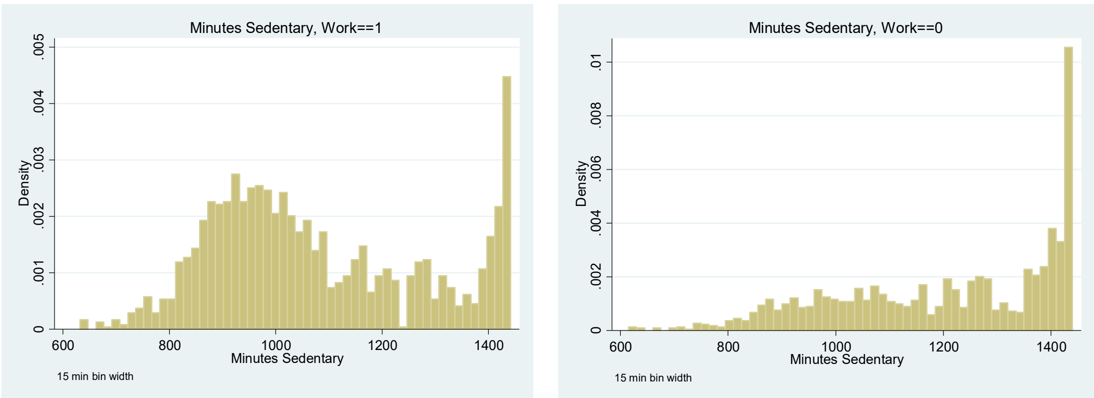


Table 1: Characteristics of Accelerometer Tracked and Non-Tracked Subsamples

	Non-Tracked Workers Mean	Tracked Workers Mean	P-value
Plantation experience	1.39	1.67	0.172
	(0.92)	(0.73)	
Attended school (%)	84	83	0.749
Primary (%)	10	8	0.677
Junior secondary (%)	6	6	0.922
Senior Secondary (%)	62	66	0.490
BMI	22.43	22.66	0.405
	(2.40)	(2.30)	
Malaria incidence (% positive)	20	30	0.027
	(40)	(46)	
Hemoglobin score	13.85	13.71	0.273
	(1.06)	(1.28)	
Household Size	5.69	6.08	0.427
	(4.05)	(5.24)	
Asset Index	13,628	12,943	0.439
	(7,519)	(7,690)	

Note: These descriptive statistics are computed for the entire sample of 587 non-tracked workers and 83 tracked workers. The p-value results from a t-test of mean differences. Standard errors are reported in parentheses below the means.

Table 2: Determinants of Accelerometer Loss

VARIABLES	Accelerometer lost
Age	0.00
	(0.005)
	(0.001)
Any school indicator	0.00
	(0.003)
Years of plantation experience	-0.01
	(0.007)
N. Children	-0.01
	(0.006)
Monogamous indicator	0.02
	(0.034)
Polygamous indicator	-0.03
	(0.031)
N. cattle owned	-0.00
	(0.003)
N. poultry owned	-0.00
	(-0.001)
Number of Rooms	-0.01
	(0.010)
Hemoglobin (Hb/dec)	0.02
	(0.021)
Malaria positive (1=Yes)	-0.01
	(0.051)
Body Mass Index	0.00
	(0.007)
Constant	-0.29
	(0.308)
Worker observations	83
R-squared	0.069

Estimates based on a linear probability model.

Table 3: Activity Monitor Subsample Balancing Tests

Balance Statistics across Treated and Comparison Workers

	Normalized mean difference (Comparison-Treatment)	P-value
Plantation experience	-0.19	0.77
Attended School (%)	-0.04	0.51
Primary (%)	-0.03	0.21
Junior Secondary (%)	-0.01	0.88
Senior Secondary (%)	0.13	0.13
Household size	0.63	0.53
Asset index	.12	0.93
BMI	0.17	0.71
Hemoglobin score	0.19	0.41

P-values are reported when the null hypothesis of balance across categories is rejected. N=83

Table 4: Labor & Activity Summary Stats

	N (Worker-day)	Mean	SD
All worker-day observations			
Work day	3162	0.52	0.50
Daily earnings	3162	641.42	1101.80
Hours sedentary	3162	18.77	3.80
Hours lightly active	3162	2.43	1.69
Hours fairly active	3162	2.11	1.73
Hours very active	3162	0.43	0.51
Trimmed observatons			
Work day	2106	0.57	0.50
Daily earnings	2106	652.00	810.55
Hours sedentary	2106	17.18	2.42
Hours lightly active	2106	3.27	1.29
Hours fairly active	2106	2.93	1.43
Hours very active	2106	0.61	0.52
Work days (on plantation) for trimmed observations			
Work day	1190	1.00	0.00
Daily earnings	1190	1153.87	763.90
Hours sedentary	1190	16.42	2.01
Hours lightly active	1190	3.57	1.17
Hours fairly active	1190	3.30	1.36
Hours very active	1190	0.70	0.49
Non-work days (off-plantation) for trimmed observations			
Work day	916	0.00	0.00
Daily earnings	916	0.00	0.00
Hours sedentary	916	18.17	2.55
Hours lightly active	916	2.87	1.33
Hours fairly active	916	2.45	1.37
Hours very active	916	0.51	0.55

Table 5: Relationship between Labor Outcomes and Physical Activity

	Work day	Daily earnings (unconditional on working)	Daily earnings (conditional on working)
Hours active	0.082***	111.599***	44.013***
	(0.005)	(11.883)	(14.327)
Hours lightly active	0.101***	105.142***	-0.123
	(0.013)	(23.225)	(27.016)
Hours fairly or very active	0.072***	115.277***	65.302***
	(0.009)	(13.850)	(13.060)
Hours lightly active	0.100***	103.310***	-2.047
	(0.012)	(23.709)	(25.471)
Hours fairly active	0.075***	121.336***	70.910*
	(0.011)	(22.796)	(38.397)
Hours very active	0.063*	95.534*	44.756
	(0.034)	(49.033)	(97.658)
Number of worker-days	2106	2106	1190
Number of workers	83	83	83

Note: *** p<0.01, ** p<0.05, * p<0.1 Regressions include worker fixed effects. Standard errors clustered at work group level.

Table 6. Intent to Treat Effects on Labor Outcomes and Physical Activity

	Panel A: Full Sample									
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Program Offer	0.040	233.330	104.144	-0.452	-0.151	0.507	0.096	-0.058*	0.044*	0.014
(1=Yes)	(0.119)	(203.907)	(91.022)	(0.499)	(0.152)	(0.353)	(0.090)	(0.034)	(0.026)	(0.009)
Constant	0.524***	678.264***	302.806***	13.590***	3.629***	4.844***	1.937***	0.370***	0.467***	0.163***
	(0.057)	(96.997)	(43.299)	(0.483)	(0.296)	(0.293)	(0.095)	(0.034)	(0.028)	(0.009)
Number of Worker-Day Observations		559			503				503	
	Panel B: Work-Day Observations where Labor Supply==1									
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
Program Offer		315.619**	140.859**	-0.684	-0.198	0.740*	0.142	-0.087**	0.068**	0.019
(1=Yes)		(126.165)	(56.322)	(0.632)	(0.209)	(0.421)	(0.127)	(0.041)	(0.031)	(0.012)
Constant		1,248.736***	557.499***	16.816***	3.833***	2.770***	0.581***	0.579***	0.359***	0.062***
		(81.797)	(36.515)	(0.474)	(0.160)	(0.304)	(0.102)	(0.031)	(0.022)	(0.010)
Number of Worker-Day Observations		333			333				333	

Table 7. Treatment on the Treated Effects on Labor Outcomes and Physical Activity

	Panel A: Full Sample									
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Program Offer (1=Yes)	-0.110	316.129	141.006	-0.441	-0.390*	0.651	0.180	-0.093	0.065	0.027
	(0.238)	(472.771)	(211.032)	(1.234)	(0.232)	(0.830)	(0.223)	(0.069)	(0.053)	(0.019)
Constant	0.605***	615.871***	274.997***	13.952***	3.040***	5.094***	1.914***	0.345***	0.489***	0.166***
	(0.106)	(210.121)	(93.792)	(0.846)	(0.702)	(0.610)	(0.220)	(0.066)	(0.045)	(0.023)
Number of Worker-Day Observations	165			146				146		

	Panel B: Work-Day Observations where Labor Supply==1									
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
Program Offer (1=Yes)		861.404*	384.303*	-1.663	-0.075	1.432**	0.306	-0.136**	0.105***	0.031
		(478.515)	(213.703)	(1.208)	(0.315)	(0.701)	(0.245)	(0.055)	(0.036)	(0.023)
Constant		213.796	95.697	17.160***	3.680***	2.643***	0.517***	0.587***	0.357***	0.056***
		(478.515)	(213.703)	(0.958)	(0.250)	(0.556)	(0.194)	(0.044)	(0.029)	(0.018)
Number of Worker-Day Observations		107		107				107		

Table 8. Treatment on the Medically Untreated on Labor Outcomes and Physical Activity

Panel A: Full Sample										
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Program Offer	0.073	202.535	90.416	-0.445	-0.087	0.443	0.089	-0.049	0.036	0.013
(1=Yes)	(0.104)	(183.931)	(82.111)	(0.381)	(0.177)	(0.288)	(0.068)	(0.031)	(0.025)	(0.008)
Constant	0.507***	695.865***	310.655***	17.483***	3.692***	2.372***	0.453***	0.595***	0.352***	0.053***
	(0.050)	(88.134)	(39.345)	(0.300)	(0.146)	(0.199)	(0.055)	(0.021)	(0.017)	(0.006)
Number of Worker-Day Observations		394				357			357	

Panel B: Work-Day Observations where Labor Supply==1										
	Labor Outcomes			*Physical Activity*				*Distribution of Activity*		
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active Hours	Very Active Hours	Light/ Active Hours	Fair/ Active Hours	Very/ Active Hours
Program Offer		178.475*	79.675*	-0.469	-0.216	0.558	0.127	-0.077*	0.058*	0.019*
(1=Yes)		(95.750)	(42.745)	(0.520)	(0.218)	(0.389)	(0.102)	(0.042)	(0.034)	(0.011)
Constant		1,688.380***	753.741***	17.016***	3.894***	2.553***	0.538***	0.596***	0.345***	0.059***
		(25.779)	(11.508)	(0.372)	(0.160)	(0.260)	(0.085)	(0.029)	(0.022)	(0.009)
Number of Worker-Day Observations		226				226			226	