Productivity and Health:
Alternative Productivity Measures using Physical Activity

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May 2017
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Abstract: Individual labor productivity is difficult to measure without individually attributed worker output. This paper investigates a possible alternative proxy for individual worker productivity in physical work settings: a direct measure of physical activity using an accelerometer. We establish the validity of this measure in an agricultural labor force where workers are paid per quantity of sugar cane cut. First, we compare worker labor outcomes, including earnings, labor supply and on the job productivity with physical activity and observe that they are strongly related. Each active hours is associated with increased earnings of 111 Naira which is 14% of the earnings standard deviation. Second, we investigate the effect of a health intervention on physical activity using a temporally randomized offer of malaria testing. The intervention also provides malaria treatment when workers test positive. The treatment effect on the treated indicates that workers daily average sedentary and 'light' physical activity time is reduced, while 'fairly active' and 'very active' physical activity levels increased.

Keywords: labor productivity, productivity measurement, malaria, field experiment
JEL codes: I12, J22, J24, O12

Acknowledgements: We would like to thank Adedoyin Adesina, Bashir Aliyou, Sani Njobdi, and the Nigerian Ministry of Health, Malaria Control Program. The plantation staff and sugarcane cutters welcomed us and patiently assisted us throughout the study, without which this study would not have been possible. ESRC/DFID, Michigan State University, USDA National Institute of Food and Agriculture, and University of East Anglia are gratefully acknowledged for providing resources and support for the study. We appreciate the efforts of the supervisors, enumerators, and health workers who implemented this study. This study was ethically reviewed by the National Health Research Ethics Committee, Nigeria, Adamawa State Health Research Ethics Committee, and Michigan State University's Institutional Review Board.

1. Introduction

Productivity is a key determinant of economic growth but its empirical measurement at the micro level remains a challenge. A large literature examines both the measurement of productivity for an individual firm (for example, Bartelsman and Doms (2000), Asker et al. 2014, Syverson 2011, and Bartelsman et al. 2013) and for an individual worker (for example, Lazear (2000), Mas and Moretti (2009), Bandiera et al. (2010), Hermann and Rockoff (2012), Ziven and Neidell (2012)). Nevertheless, measures of labor productivity at the individual level are rare and, when they occur, possibly noisy or even biased, also individual labor productivity is difficult to measure outside piece rate settings. Effort and even hours worked are typically unobserved by a third party, difficult to recall by the respondent, or hard to link to firm or farm output. An alternative class of measures of worker productivity is the direct measurement of physical activity, which is a proxy for worker effort, particularly for physically arduous tasks. The validation of physical activity measures and their consistency as a proxy for productivity has not been well established (Bort-Roig et al. 2014).

This paper builds on previous work on the productivity costs of malaria infection conducted with a large sugar cane plantation in rural Nigeria that pays workers piece rate wages. Using the piece rate earnings as direct observation of worker productivity, the study confirmed 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 paper posits physical activity as a productivity proxy, and investigates the impact of access to malaria treatment on the proposed proxy for productivity. The daily physical activity data was generated by accelerometers worn by a subsample of workers in this setting during the 2013 sugarcane harvest season.

The empirical focus of the paper first validates physical activity measures as a proxy for individual worker productivity by exploring the association of physical activity with labor productivity and labor supply among a sample of agricultural workers in a piece rate wage setting. We find that physical activity is highly correlated with labor productivity and, especially, labor supply, suggesting that physical activity may be a good proxy for worker effort. The relationship between productivity, effort, and physical activity is established in an earlier literature by Becker (1977, 1985), Gibbons (1987) and Lazear (2000). Becker (1977, 1985) develops a model where firms choose a time and effort 'package' from each worker. Effort per time unit is a determinant of the worker's wage[1]. Gibbons (1987) and Lazear (2000), focusing on piece rate wage settings, develop a model where workers maximize 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 these models, physical activity estimates could be thought of as a proxy for effort, and thus a key determinant of productivity, for physically demanding production processes. Monitoring physical activity should be feasible to collect in many such settings if piece-rate labor does not exist and therefore can extend the applicable settings for productivity research. In a second test of the validity of physical activity measures to proxy for productivity we then estimate the effects of a malaria treatment and testing program on worker physical activity. We find that treating malaria, or revealing information about malaria status when healthy, substantially affects physical activity. These findings are also consistent with the theoretical framework outlined in Dillon et al. (2014) where effort is partly a function of health expectations formed by the interaction of a worker's true health state and the available health information.

The paper first establishes the correlation between physical activity as a proxy for effort and labor outcomes. We compare worker labor outcomes, including earnings, labor supply and on the job productivity with physical activity and observe that they are strongly related. Each active hours is associated with increased earnings of 111 Naira which is 14% of the earnings standard deviation. The paper then estimates three sets of treatment effects, to comparing worker's pre-interview with post-interview daily physical activity while controlling for unobserved worker heterogeneity such as health endowments using worker fixed effects. First, the estimate of the effect of the malaria testing and treatment program indicates a significant increase in physical activity. The treatment effect on the treated indicates that workers daily average sedentary and 'light' physical activity time is reduced, while 'fairly active' and 'very active' physical activity

[1] 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."

levels increased. These changes in physical activity are due to a reallocation of activity within working hours as total labor supply is largely unaffected. Physical activity effects on the workers who test negative for malaria are also found to be significant. This result is again consistent with Dillon et al. (2014) who find the effect of untreated health diagnosis on the malaria negative results in these workers switching to higher return, higher effort tasks. 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.

The paper proceeds in the next section by reviewing methods to measure physical activity as well as discussing the link between physical activity and productivity. Section three describes the study setting in detail while section four discusses the malaria diagnostic and treatment protocols. The fifth and sixth sections describe the experimental design and the econometric strategy. Section seven presents results, while the last section concludes.

2. The Measurement and Interpretation of Physical Activity

Becker (1977, 1985) provides a theoretical model of the relationship between effort, productivity, labor supply and earnings which motivates our interest in validating physical activity as a proxy for labor productivity and our randomized control trial. The worker's earnings, I, depends on a 'package' of time, t_m, and effort per unit time from the worker, $e_m = E_m/t_m$. Income is then defined by the function:

$$I = w(e_m)t_m \tag{1}$$

The model provides a parameter of the effort intensity of work, σ_m, where Becker defines:

$$I = \alpha_m e_m^{\sigma_m} t_m = \alpha_m E_m^{\sigma_m} t_m^{1-\sigma_m} \tag{2}$$

with $\alpha_m = \beta_m h_m$ where h_m represents worker human capital and σ_m. In our piece rate wage setting, we can use this reduced form to disaggregate labor supply and productivity effects of changes in health status on effort measured using physical activity data or productivity measured using piece rate wage data in addition to daily labor supply data. Dillon et al. (2014) defined effort as a function of health perceptions, $\widetilde{H}$, that were determined by a worker's health status and their health information, $\widetilde{H} = g(H, I)$. In our randomized control trial, we provide a malaria testing and treatment intervention to estimate the effect of changes in health status and information for those workers who test positive and the effect of health information on worker's who test negative for malaria on their earnings, labor supply, productivity, and physical activity.

While measuring earnings and labor supply is fundamental to empirical analysis in labor economics, the measurement of physical activity has typically generated most interest in the medical and nutrition fields. In medical studies, whether assessing the risk factors associated with certain (e.g. sedentary) lifestyles, or in health promotion studies aiming at measuring the potential benefits or impacts of specific health policy interventions, the measurement aims 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) needs 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 ordered in relation to their degree of practicality. Nutritionists and physiologists consider the doubly labelled water method (DLW) as the gold standard to measure energy expenditure (Speakman, 1997; FAO and WHO, 2001) in free-living conditions. 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 are 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)[2] in its short- and long-form versions (Craig et al., 2003), the WHO-led Global Physical Activity Questionnaire (GPAQ)[3], and a Sub-Saharan Africa Activity

[2] www.ipaq.ki.se
[3] http://www.who.int/chp/steps/GPAQ/en/

Questionnaire (Sobngwi et al., 2001). These instruments have been developed for physical activity surveillance, and allow collecting subjective, self-reported information on activity levels and are fairly compact (7-23 questions). The instruments are designed to measure activities in different domains (work, travel to and from places, and recreational activities) and 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 do exist (e.g. Craig et al., 2003), the instruments remain prone to the type 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 estimate of 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).[4]

The precise technology employed in this study was chosen after market research and consultation of experts in this area, because of its stated reliability, immediate availability and user friendliness in the field.[5] For these reasons we choose to use the FitBit accelerometer, a three-dimensional accelerometer which measures activity duration and intensity in minutes and an estimated activity score based on a proprietary algorithm. The accelerometer reports time spent in four levels of activities: Sedentary Minutes, and Lightly, Fairly and Very Active Minutes. The device tracks worker physical activity continuously throughout the day and can not be manually turned off by the worker when worn.[6]

[4] Most recently, a review of accelerometer studies with sample sizes greater than 400 identified accelerometry data for more than 275 thousand 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).

[5] Ease of use was an important consideration, and even after choosing the most user friendly option, 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 that the underlying algorithms are known and available, discussions with medical experts in this field who are and have been developing their own devices, indicated that the development is costly and time consuming and was beyond the scope of our study.

[6] This standardizes across workers the minutes reported across the four activity categories.

3. Study Setting

The experiment is situated on a single large (5,700 hectares) sugar cane plantation in rural Nigeria. The plantation employs 680 sugarcane cutters who work for the entire harvest season that stretches from mid-November to April. Cane-cutters are paid a piece rate wage. While there are other activities on the plantation, including a sugar processing facility, this study focuses solely on the sugarcane cutter labor force.

Workers are hired for the entire harvest season (in this case the 2013 harvest season) from local villages surrounding the plantation and are transported daily to the assigned work site. The cane-cutters are organized into eight work groups and each group is managed by a supervisor. Every day the supervisor and his cutters are assigned a set of starting fields in the plantation and additional fields to cut if the work group has finished these starting fields. 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 delivering workers to the field sites to be cut each day and transporting them off the plantation at the end of the day. This standardized work day ensures that for each cane cutter the number of hours of work is fixed and alleviates concerns about tradeoffs 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 compensation 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 (NBS 2012)), sugarcane cutter positions are in high demand in the local communities.

The plantation records individual worker daily productivity, a key source of information for our analysis. We supplement this information with data from worker interviews covering socio-demographic, work history, and self-reported health information. We also collect blood samples during the interview to test for malaria. The 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 closed for cutting in weeks five and six of the study due to an operational breakdown at the plantation's processing plant, after our sub-sample of workers had been fitted with accelerometers. Several robustness tests are described below to assess the sensitivity of our results. Because all workers were interviewed and treated if positive before the temporary cutting stoppage, the effect of this event primarily 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.

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 also impair consciousness, cause seizures, and result in coma (Najera and Hempel 1996). Individuals affected are also often dehydrated and hypovolemic (Miller et al., 2002). The duration of an episode of malaria varies widely.[7] Najera and Hempel (1996) indicate that an episode of malaria lasts up to 14 days, with an average of 4-6 days of total incapacitation and the partially incapacitated days characterized by nausea, headaches, and fatigue.

Three methods are commonly used to 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.[8] At the same time, especially in areas where malaria and diseases with similar symptoms are endemic, habituation to these symptoms may lead to underreporting of malaria infection. Self-reported malaria can therefore suffer from both Type I and Type II errors, making it difficult to sign the measurement bias and rendering it imprecise as a measurement approach.[9]

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 2 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.[10] While a high parasite load indicates malaria infection there is no medical consensus about the *exact* relationship between parasite load and malaria outbreak. Laishram et al. (2012) discuss asymptomatic malaria, noting that a common parasite threshold has not been

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[7] 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).
[8] This is further enhanced for the study area by the word referring to fever being the same as that referring to malaria in the local language.
[9] 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.
[10] A professional laboratory technician read all the slides to record the number of parasites in five viewing fields. After recording the parasite count, the laboratory supervisor selected random subsamples of slides to verify from each batch of 50 slides. If discrepancies between the primary laboratory technician and the supervisor were found, the whole batch of slides was re-validated.

universally adopted. Our adopted definition of malaria positivity is the presence of at least three parasites over the total examined fields in the blood smear. [11] 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, we rely on the clinical threshold in our study area as our objective measure following the recommendation in WHO (2010). This protocol is slightly more conservative than the CDC recommendation of 4 malaria parasites over viewed fields (CDC 2014). 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.

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

[11] Several studies in the medical literature from different settings use distinct parasite density thresholds in classifying malaria infections as there is no unique medically established standard for population based malaria testing which includes asymptomatic malaria cases (see dalla Martha et al. (2007), Toure et al. (2006), and Rottmann et al. (2006)).

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 sugar cane cutters was assigned an activity tracker. Each tracker was labelled with a number that was assigned to 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 pockets or belts. At the end of every work week, the data recorded by these trackers was synced to a computer at the field survey office and the trackers were simultaneously charged. This process was carefully managed and workers received back the same tracker. Careful checking during the field work reassured that trackers were operational, although some were lost by the workers, as discussed below.

Separately, a survey team of enumerators and health workers employed by the project collected information on worker and health characteristics from all workers. The former included employment history, demographic information, place of living and household welfare. Registered health worker administered the second questionnaire by first asking a brief health history and then prepared a blood slide which was used to microscopically verify 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).[12]

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 rich data set that enables the envisaged two part analysis carried out below. In a first part the study investigates the relationship between physical activity with both labor supply and productivity. A 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. The within worker effect of malaria testing and treatment is estimated by comparing a worker's physical activity before and

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

after 'treatment' which allows us to abstract from unobserved worker characteristics like ability or baseline physical condition that may be correlated with worker physical activity or productivity. By focusing on one large plantation we abstract from potential firm fixed effects - which may play an important role as different firms follow different approaches towards illness and illness related absenteeism.

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 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 who receive an accelerometer to wear throughout the study period, forming the sample of interest for this paper.

Selected workers for the accelerometer sample were made up of two groups which totaled 83 workers. The first group of workers comprised the first 25 workers who tested positive for malaria during the health survey administered as part of the temporally randomized roll-out of the malaria test over the entire worker population. Given a previous positivity rate (35%) from an earlier round of the study (Dillon et al. 2014), this 'oversampling' of malaria positive workers stemmed from the ex-ante concern of low power to detect malaria effects, as malaria incidence varies seasonally. The second group of workers enrolled in the activity study were randomly selected in equal proportions from the workers who were to be tested in weeks 2, 3 and 4 of the study. All workers who were allocated an accelerometer received the device in week 1, and wore it until the end of the field period, unless the accelerometer 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 sample. 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. [13]

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 affects whether sugarcane cutters work on a given day. This is an exogenous source of variation in the level of worker activity and is fixed across workers.[14] 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, and still allows us to estimate treatment impacts on worker physical activity (although it does reduce the power of the study from our initial expectations).

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.[15] This analysis utilizes the daily data generated by all trackers, until the

[13] The asset index reflects household expenditure which are not measured but rather predicted using the method suggested by Grosh and Baker (1995) and Ahmed and Bouis (2002). In our questionnaire we included questions on asset ownership drawn from the Nigerian Living Standard Survey 2009, a nationally representative survey, conducted by the National Bureau of Statistics (NBS), which collects detailed data on household consumption and expenditures. We run the weighted regression $Exp_i = \sum_{a=1}^{p}(\alpha^a D_i^a + u_i)$ on the NLSS 2010 data to obtain estimates of $\widehat{\alpha^a}$, the coefficient for each asset, which we then use to predict EXP_i for our own sample. Where D_i^a represents a dummy variable indicating whether asset a is present in the household. The regression uses population weights as calculated by the NBS. Since the estimates of the coefficients are relatively sensitive to outliers, we exclude the richest 10% of households in our weighted regression on the NLSS 2010 data.

[14] Workers are collected from their villages by truck and all start and stop their workday at the same time.

[15] We investigated and carried out qualitative research 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 station and log in password to download and read the information

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, particularly 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 resulting in biased estimates of impact, we assess the correlates of the probability of losing the tracker device.[16] In Table 2, worker characteristics and health status is 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.

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 investigate the correlation between each level of activity and labor supply and productivity, respectively. Recall that the latter is used as the base for the workers' payment, and is carefully checked by both worker and supervisor. We then carry out regression analysis to estimate the conditional association between labor outcomes and each of the levels of physical activity (sedentary, light, medium and high intensity minutes). These regression estimates provide a validation test for the use of physical activity as a proxy for labor variables in our study context.

$$L_{id} = \alpha_i + \sum_j \beta_j A_{jid} + \varepsilon_{id} \tag{3}$$

[16] Selecctive 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 estimates downwards. If workers who were more educated or wealthier were more careful with their tracker, then this differential probability of tracker loss would potentially bias estimates upwards. The results from Table 2 minimize these concerns with respect to these types of attrition biases.

In equation one above, L is either labor supply (day worked), which can be thought of a measure of productivity at the extensive margin, or on the job productivity, reflected 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_j is the activity measure for activity j - i.e. number of minutes 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 specification also includes a worker fixed effect to control for individual factors that help translate physical activity and effort into output. Standard errors are clustered at the work group level.

In the next phase of analysis we estimate the impact of malaria testing and treatment on physical activity (which, given the relationship estimated above, implies malaria impacts on earnings and possibly labor supply). Restricting our analysis to the activity tracked subsample, the primary econometric specification uses the daily physical activity data comparing the set of daily outcomes for worker i over periods of time before, $t+$, and after, t-, the worker was tested (or received the diagnosis, in an alternative definition of the timing of treatment) at day $d = 0$. The first set of treatment effect estimates is the treatment effect of the program on worker's physical activity for both malaria positive and malaria negative workers. Given the few weeks in our study period, we set t to be a seven day reference period. The set of workers assessed, W, are then 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 can also be estimated. Effects of malaria status on worker's physical activity are estimated in addition to labor outcomes including daily earnings, daily labor supply and daily rods cut.

The overall treatment effect estimates use the regressions specification found in equation 4, which include a worker fixed effect, while the treatment effects for the positives and negatives are estimated separately.

$$A_{id} = \alpha + \beta T_{i0} + F_i + \varepsilon_{id}, \forall i \in W \tag{4}$$

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 higher return cane-cutting from scrabbling. 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. Our subsequent analysis will again test this hypothesis of the effect of 'positive' health information on a worker's physical activity. As workers are exposed to treatment on a temporally randomized basis over a four-week period, sampling variation or fieldwork anomalies could also produce imbalance in worker characteristics across study weeks or be associated with work groups with differential productive possibilities.[17]

7. Results

The paper presents three sets of results. First, we conduct balancing tests on the worker sample. Second, the correlations of labor outcomes and physical activity among agricultural workers in a piece rate wage setting are presented to validate the use of physical activity data as a proxy measure of productivity. Third, we present the results for the estimated effects of a malaria treatment and testing program on worker physical activity.

Balancing tests

To avoid confounding the impact of treatment with possible interactions between worker characteristics or work group with particularly productive weeks, we investigate whether there are statistically significant differences in a set of observable worker and household characteristics– age, work experience, education, household size, asset index, hemoglobin and body mass index - across interview weeks and work groups. In Table 3, Panel A, most characteristics are balanced

[17] Recall that work groups are allocated to plots following a pre-harvest plan, so group effects actually reflect matched group-plot effects.

across interview weeks and workgroups, respectively, with the exception that hemoglobin is unbalanced across interview weeks, while experience is imbalanced between workgroups. Only 2 of the 14 balancing tests are rejected at the 5% level of statistical significance. Table 3, Panel B presents a stronger set of balancing tests for our 83 worker sample in examining work group by week balancing tests. Household size is not balanced in week 4 of the study while hemoglobin and BMI are imbalanced across workgroups in week 2, but the other covariates are well balanced across workgroups by study weeks. Of the 28 mean equivalence tests, the null hypothesis is rejected in 3 tests at the 5% level.

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. Physical activity data was trimmed to ensure internal consistency and user compliance. We trimmed data if there was a reporting error in the accelerometer data if it did not sum to 24 hours in each recorded day. The data was trimmed using the sedentary activity data if total activity was less than three hours on work days or less than 1.5 hours on non-work days given the distributions observed in Figure 2. The data was then Winsorized using the rods per hours active variable and the 1% tails were trimmed from the distribution.

The thresholds used to delineate intensity by category 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-work-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 0.43 hours in high intensity activity. The table also reports the percent of days worked among the sugarcane cutters and their unconditional daily earnings, 642 Naira or USD 4.28. For work days on the plantation hours of activity increase relative to days off the plantation on non-work days as expected. Most of the change in the activity intensity on work days is captured in the lightly active and fairly active categories of physical activity which increase in both categories by approximately an hour per category.

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 different levels of intensity are pooled to demonstrate the robustness of hours and intensity on labor supply, daily earnings, and conditional daily earnings. The coefficients reflect a strong relationship between minutes of lightly active and fairly active, and to some extent minutes very active, with labor supply and on the job productivity.

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

Tables 6, 7, and 8 report the pooled physical activity treatment effects from the malaria testing and treatment program for the pooled sample of 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 the worker-day observations to those days where workers worked on the plantation.

In the pooled sample of workers (Table 6), the overall effect of the malaria program decreases sedentary hours and light work hours among workers on a daily basis, comparing the seven days preceding the interview and after the interview. Pooling fairly active and very active hours yields a positive estimate of the malaria testing and treatment program on workers' physical activity, but the effect is not precisely measured. Comparing with workers' daily labor supply, earnings, and rods cut, the ITT for the labor outcomes is also positive, but not precisely measured. These results are obtained after including worker fixed effects to control for worker unobservable characteristics that may be correlated with physical activity. In panel B, we observe the conditional intent to treat effects on labor outcomes including daily earnings and rods cut which are precisely estimated. The physical activity specifications also result in more precise estimates of the substitution of workers across intensity levels of physical activity. A larger, negative substitution effect is precisely measured for light hours of work, while a larger, positive effect of the testing and treatment program is measured on fairly active and very active hours, though it is not precisely measured.

Among those workers who are diagnosed with malaria (Table 7), the effect sizes are larger than the pooled ITT estimates. Malaria infected and treated workers are less sedentary, less engaged in light physical activity, and more engaged in fairly active and very active physical activity. The physical activity substitution effects are largest conditional on labor supply. Though these effects are not statistically significant, sedentary hours decrease by 1.3 hours while fairly active and very active hours increase by 1.4 hours. This corresponds well with statistically significant increases in daily earnings and rods cut among this subsample. The number of worker-day observations decreases considerably when we restrict the sample to the malaria positives, decreasing statistical power.

The treatment effects on the medically untreated 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 an effect of negative malaria status information on subsequent 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. In an endemic area, the effect of surprising health information may cause workers to revise their expectations of short-run work capacity. Workers who discover they are malaria negative in this endemic area reduce sedentary and light activity time while fairly active and very active hours increase. The daily earnings and daily rods cut specifications are also statistically significant and positive in response to the malaria information for the malaria negatives. .

Sensitivity Analysis

The specification for the above results include worker fixed effects, but one concern with the use of the within worker specification is the potential influence of temporally imbalanced worker or work-group characteristics interacted with week specific common productivity shocks. Though the sample appears to have characteristic balance across work groups and interview weeks, as presented in Table 2, we conduct two sets of sensitivity analyses. First, to address the potential effect of work group we re-estimate the above specification using work group fixed effects. This leads to very similar results (results not presented but available upon request). Second, we re-estimate the impact estimates, for all workers as well as separately by malaria status, for each separate interview week subsample. While this significantly reduces the sample size for each weekly estimate, the impact estimates are consistent across weeks (again, results available upon request).

8. Conclusion

The empirical measurement of productivity at the micro level remains a challenge, though improving worker productivity is central to improving worker welfare and a key variable in many empirical investigations of the effect of health on individual well being. Labor productivity is difficult to measure at the individual worker level outside piece rate settings, when effort and hours worked are unobserved, difficult to recall, or hard to link to firm or farm output. This study investigates whether a direct measure of physical activity can be a valid proxy for productivity, particularly for agricultural workers, in this case cane cutting in Nigeria.

The paper first investigates the association of physical activity with labor productivity and labor supply among the sample of agricultural workers in a piece rate wage setting, and finds a strong relationship (Table 5). Each active hours 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 further builds on previous work (Dillon et al. (2014)) to estimate the impact of a malaria testing and treatment program on physical activity. If the latter is a good proxy for worker productivity 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. Moreover, treatment effects for the malaria positives using measures of physical activity indicated that workers daily average time sedentary time in light physical activity reduced while and fairly active and very active physical activity levels increased for the average treated worker with higher response rates 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 survey round (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 smooth effort in response to health perceptions as argued in Dillon et al. (2014) and other recent papers on the effect of health information including (Madejewicz et al. (2007), Jalan & Somanathan (2008), Thornton (2008), Dupas (2011), Cohen et al. (2015), Gong (2014), Baird et al. (2014)).

Taken together, these study results indicate that physical activity can be a good proxy for individual worker productivity for arduous agricultural labor. The results also confirm a main causal channel, physical capacity, through which malaria affects worker earnings and productivity. As individual productivity effects are central to many theoretical applications outside of the health and labor literature, the paper also provides confirmation that increases in productivity can be proxied by physical activity data, today easier to collect with new wearable tracking technologies, when individual specific measures of output are unavailable or costly to observe.

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Tables

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

	Non-Tracked Workers Mean	Tracked Workers Mean	P-value
Age	32.44	30.96	0.127
	(8.38)	(7.34)	
BMI	22.43	22.66	0.405
	(2.40)	(2.30)	
Malaria incidence (% positive)	0.20	0.30	0.027
	(0.40)	(0.46)	
Hemoglobin score	13.85	13.71	0.273
	(1.06)	(1.28)	

Panel B: Worker Education

	Non-Tracked Workers Mean	Tracked Workers Mean	P-value
Can read English (%)	72	65	0.200
Can write in English (%)	72	65	0.224
Math calculations (%)	89	86	0.290
Attended school (%)	84	83	0.749
Primary (%)	10	8	0.677
Junior secondary (%)	6	6	0.922
Senior Secondary (%)	62	66	0.490
Plantation experience	1.39	1.67	0.172
	(0.92)	(0.73)	

Panel C: Household Characteristics

	Non-Tracked Workers Mean	Tracked Workers Mean	P-Value
Spouses	1.0	1.14	0.360
	(1.32)	(1.14)	
Children	2.85	3.00	0.625
	(2.65)	(2.59)	
Household Size	5.69	6.08	0.427
	(4.05)	(5.24)	
Asset Index	13,627.92	12,943.21	0.439
	(7,518.87)	(7,690.44)	

Note: These descriptive statistics are computed for the entire sample of 587 non-tracked workers and 83 trackers. Standard errors are reported in parentheses below the means.

Table 2: Determinants of Accelerometer Loss

VARIABLES	Accelerometer lost
Age	0.00
	(0.005)
N. cattle owned	-0.00
	(0.003)
N. poultry owned	-0.00
	(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)
Number of Rooms	-0.01
	(0.010)
Hemoglobin (Hb/dec)	0.02
	(0.021)
Treatment Indicator	-0.01
	(0.051)
Body Mass Index	0.00
	(0.007)
Constant	-0.29
	(0.308)
Worker observations	83
R-squared	0.069

Standard errors clustered at the worker level.

Table 3: Activity Monitor Subsample Balancing Tests

Panel A: Balance across Workgroups & Interview Weeks

	Interview Weeks	Workgroups
Age		
Experience		0.036
Education		
HH Size		
Asset Index		
Hemoglobin	0.029	
BMI		

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

Panel B: Balance across Workgroup within Interview Weeks for Full Sample

	Age	Experience	Schooling	HH Size	Asset Index	Hemoglobin	BMI
Week 1							
Week 2						0.002	0.023
Week 3							
Week 4				0.045			

P-values are reported when the null hypothesis of balance across categories is rejected at the 5% level of significance given the smaller sub-sample size.

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)			
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)			
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	Daily earnings (conditional)
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 for Labor and Physical Activity

	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active and Very Active Hours
			Panel A: Full Sample			
Program Offer	0.038	235.041	104.909	-0.257	-0.260**	0.517
(1=Yes)	(0.089)	(163.412)	(72.944)	(0.533)	(0.129)	(0.471)
Constant	0.545***	758.622***	338.685***	16.896***	3.263***	3.841***
	(0.066)	(121.182)	(54.094)	(0.256)	(0.062)	(0.227)
Number of Worker-Day Observations	833	833	833	503	503	503
		Panel B: Sample Restriction to Work-Day Observations where Labor Supply==1				
Program Offer	----	312.146***	139.312***	-0.349	-0.318*	0.667
(1=Yes)		(115.783)	(51.682)	(0.763)	(0.185)	(0.651)
Constant	----	312.146***	139.312***	-0.349	-0.318*	0.667
		(115.783)	(51.682)	(0.763)	(0.185)	(0.651)
Number of Worker-Day Observations		501	501	333	333	333

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

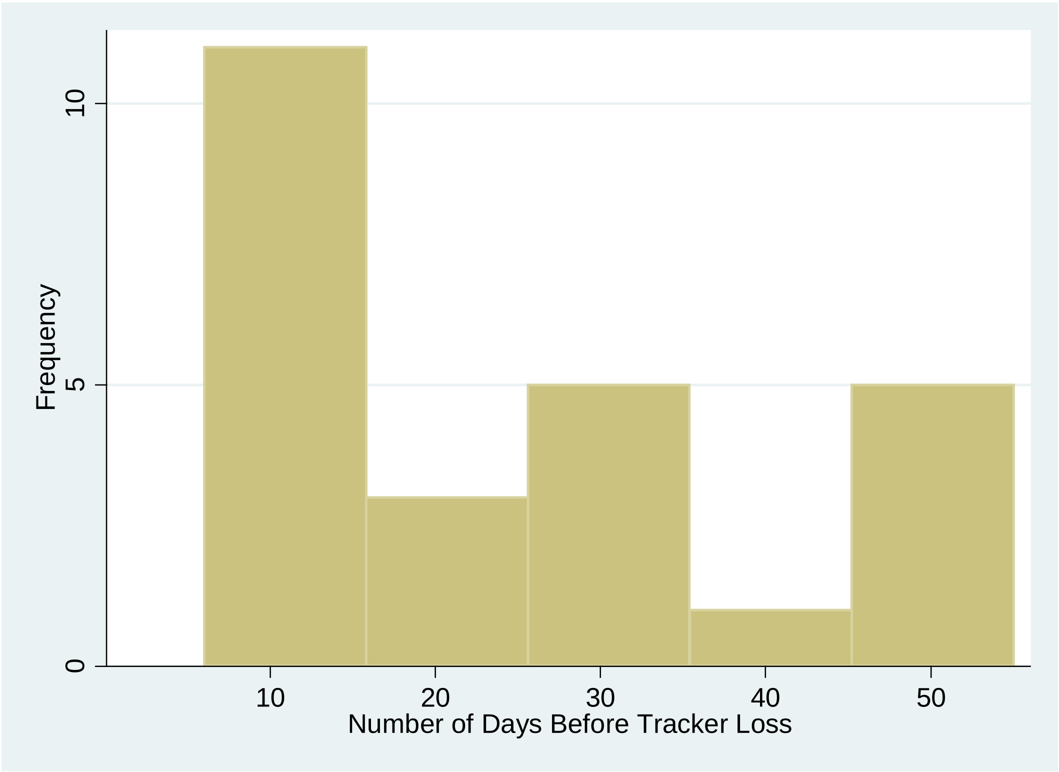
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active and Very Active Hours
			Panel A: Full Sample			
Malaria Positive (1=Yes)	-0.065	217.359	96.947	-0.320	-0.414**	0.734
	(0.168)	(310.211)	(138.457)	(1.023)	(0.206)	(0.855)
Constant	0.481***	292.241	130.553	18.150***	2.784***	3.067***
	(0.168)	(310.211)	(138.457)	(0.454)	(0.091)	(0.380)
Number of Worker-Day Observations	234	234	234	146	146	146
		Panel B: Sample Restriction to Work-Day Observations where Labor Supply==1				
Malaria Positive (1=Yes)	----	537.812**	239.910**	-1.260	-0.158	1.418
		(263.730)	(117.761)	(1.132)	(0.324)	(0.887)
Constant	----	685.228***	306.090***	19.906***	2.255***	1.839***
		(263.730)	(117.761)	(0.679)	(0.194)	(0.532)
Number of Worker-Day Observations		145	145	107	107	107

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

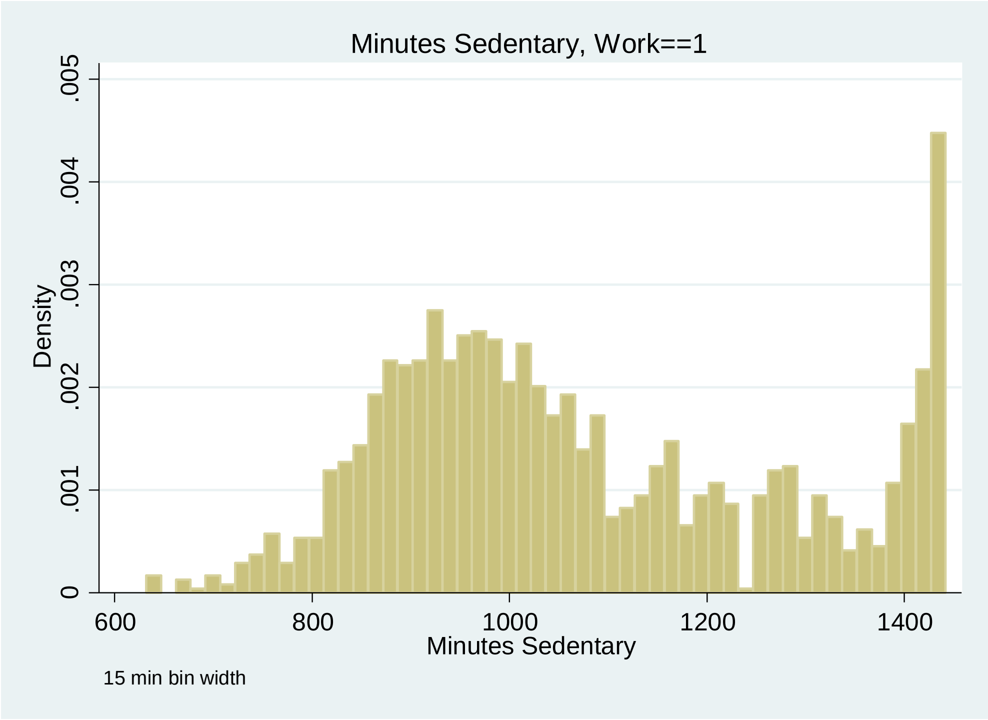
	Daily Labor Supply (1=Worked)	Daily Earnings (Naira)	Daily Rods Cut	Sedentary Hours	Light Work Hours	Fairly Active and Very Active Hours
			Panel A: Full Sample			
Malaria Negative (1=Yes)	0.075	233.999*	104.463*	-0.231	-0.149	0.380
	(0.066)	(134.964)	(60.251)	(0.396)	(0.131)	(0.395)
Constant	0.525***	838.887***	374.498***	16.627***	3.323***	4.050***
	(0.033)	(67.482)	(30.126)	(0.193)	(0.064)	(0.193)
Number of Worker-Day Observations	599	599	599	357	357	357
		Panel B: Sample Restriction to Work-Day Observations where Labor Supply==1				
Malaria Negative (1=Yes)	----	231.753**	103.460**	-0.085	-0.312**	0.397
		(109.343)	(48.813)	(0.672)	(0.147)	(0.648)
Constant	----	1,397.546***	623.905***	15.289***	4.216***	4.495***
		(40.004)	(17.858)	(0.181)	(0.040)	(0.174)
Number of Worker-Day Observations		356	356	226	226	226

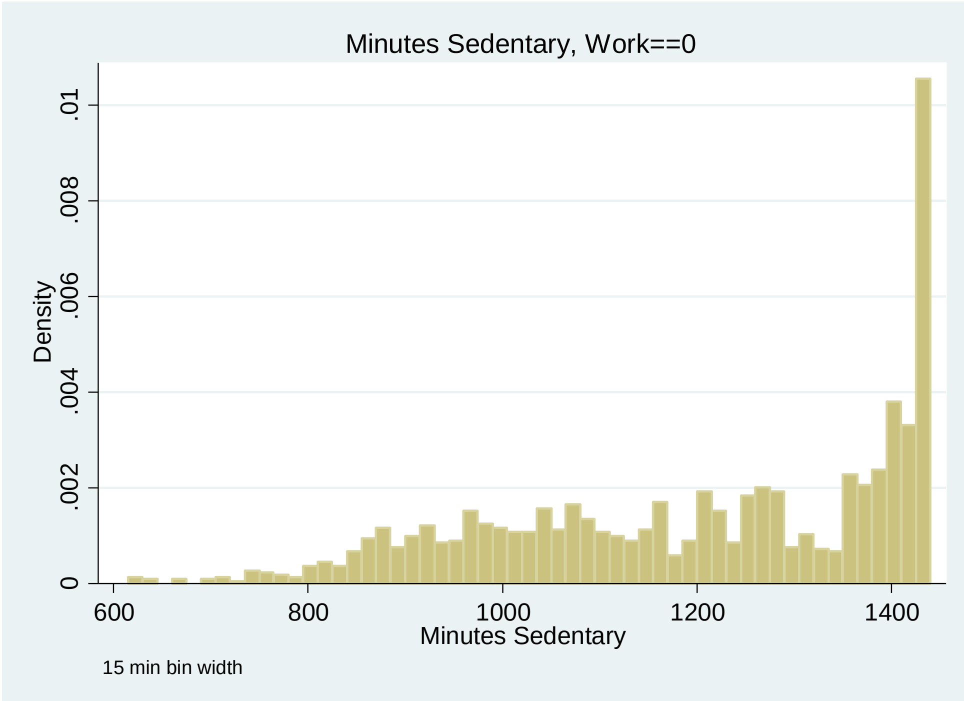
Figures

Figure 1: Days Before Tracker Loss



Figures 2: Minutes Sedentary and Compliance




Minutes Sedentary, Work==0
Density
0
.002
.004
.006
.008
.01
600
800
1000
1200
1400
Minutes Sedentary
15 min bin width