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**Dr. Andrew Dillon
Dr. Oladele Akogun
Dr. Pieter Serneels
Francis Smart**

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Preventive or Curative Treatment of Malaria? Evidence from Agricultural Workers in Nigeria

Andrew Dillon
Michigan State University

Oladele Akogun
Federal University of Technology, Yola

Pieter Serneels
University of East Anglia

Francis Smart
Michigan State University

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Abstract: Investments in one's health require a comparison of the potential benefits and costs of providing either preventive or curative care. While preventive care lowers the probability of falling ill, and is often less costly than curative treatments, it does not provide full insurance against illness. An advantage of curative treatments, while more expensive, is that they do not require up-front investment. Focusing on malaria among agricultural workers in Nigeria, we study the benefits of preventive versus curative care. Using a static benchmark model to estimate the expected income to workers from adopting either preventive or curative malaria treatment in one period underlines how the tradeoff depends crucially on the unconditional probability of infection and the effectiveness of the preventive treatment. Focusing on bednet use as preventive measure the results show that workers only choose malaria prevention when using bednets reduces the probability of infection by 6 percentage points. A dynamic simulation that explicitly takes into account the epidemiological dynamics, modelling the probability of infection as a function of both preventative choices and epidemiological conditions shows higher expected incomes from adopting bednets, but income effects are consistently less than 5% of a standard deviation of a worker's earnings. The results also indicate that there are no significant gains to adopting multiple malaria prevention measures in comparison to solely adopting a bednet. The results may be driven partly by low initial adoption levels of prevention which causes infection rates to remain high even if workers use preventive measures. The findings reinforce the importance of vector control strategies to be implemented in tandem with individual or household level preventative interventions.

Keywords: malaria, labor supply, labor productivity, randomized experiment, preventive treatment, curative treatment

JEL codes: I12, J22, J24, O12

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1. Introduction

Is malaria prevention the best policy cure? From an individual's perspective, the response to this question is clouded by uncertainty over the probability of infection and the high initial costs of preventive treatments. Certainly, low adoption rates of preventive health measures, available at even nominal prices is a puzzle (Cohen and Dupas 2010). Curative treatment tends to be more expensive in the long run, if workers' lost earnings, cost of treatment and the costs of family members time for care is included. However, estimates of the effect of malaria on workers' lost earnings have been downward biased by only accounting for lost days of work, and not taking into account reductions in labor supply and productivity. A recent study shows that income, labor supply and productivity losses can be high, especially when infection rates are high (see Dillon et al. 2012). In a dynamic context, the epidemiological dimension may also be important. If adoption of preventive measures slows down the spread of the disease at a high enough rate, prevention may yield substantially higher benefits in the long term. Limited structured analysis exists that models the trade-off between prevention and curative treatment, also taking epidemiological dimensions into account.

This paper attempts to quantify the expected income of curative and preventive treatment in a population of Nigerian agricultural workers, focusing on sugarcane cutters. Earnings from these workers at a sugarcane plantation are high enough that income constraints are less likely to affect potential preventive investments. We first estimate the probability of adopting a preventive malaria measure, a bednet, based on observable individual and household characteristics. Consistent with the literature, we find that wealthier households are more likely to adopt bednets, but that household composition and on the job training potentially are also key determinants of

adoption of preventive health behaviors. We then estimate the expected income of preventive and curative treatments considering first a static and then a dynamic model. In a static model of health investment, we base expected income calculations on a range of plausible assumptions about the probability of infection from the epidemiological literature, the cost of bednet as reported in our survey data, and the full benefits of treatment from malaria infection, estimated in previous work.¹ A dynamic simulation of health investment models more explicitly how the rate of preventive health technology reduces the probability of infection for the general population and how epidemiological differences across worker villages affect the likelihood of infection. The simulation framework allows us to predict days worked, days sick and impute under various simulation scenarios the expected income effects of preventative and curative choices from the experimental data found in Dillon et al. 2012.

The paper contributes in a number of ways. First, by considering more precise estimates of the economic benefits of malaria for an individual worker, it provides a richer and more complete comparison of preventive and curative treatment for agricultural workers in a static framework. Second, making use of simulation to model dynamic outcomes, it provides new estimates for this trade off that takes the epidemiological dimension into account, including the effects of preventive treatment on mosquito breeding. Using simulation allows us to study a wide range of scenarios that are inconceivable with observational data, and as such improves our understanding beyond what is possible from existing observational data. The validity of any simulation model depends on the underlying theory and the parameter values used. Using contemporary insights on epidemiology of malaria, we extend Carter (2002)'s spatial simulation model making use of

¹ For now, we limit ourselves to costs and benefits accruing to the individual worker and make abstraction from those accruing to the household as a whole.

parameter values obtained from new studies Collins et al 2007; Killeen et al 2007), as discussed in the methods section. The findings of the study are as follows. In this benchmark model, expected income from relying on preventative treatment is higher than expected income from curative care when bednets reduce the probability of infection by 6 percentage points.

In a dynamic simulation that models the probability of infection as a function of both preventative choices and epidemiological conditions, expected incomes from adopting bednets are higher, but these income effects are consistently less than 5% of a standard deviation of a worker's earnings. Adopting multiple malaria prevention measures yield no significant gains in comparison to adopting a bednet only. These results may be driven partly by low initial adoption levels of prevention which causes infection rates to remain high even if workers use preventative measures.

These results suggest interesting implications for health policy. While prevention may be the best cure, sole emphasis on the distribution of bednets is not sufficient to promote adoption. There are potentially several determinants of the effectiveness of bednets including whether they are insecticide treated and long-lasting bednets which are more commonly promoted in recent bednet interventions. The behavioral dimension to bednet use also deserves more attention, including when, where and how bednets are used by individuals. With sugar cane workers in a large plantation as subjects in our study, the results also have important implications for the potential of work-place based health interventions. We discuss the external validity of the simulation results in the conclusion including whether a different compensation system may induce different incentives for workers and firms.

The paper is organized as follows. We first review the literature on the benefits and costs of preventive and curative treatments. In the third section, we describe the study context and data from which we will build to expected income models. The static model of health investment is described in the fourth section, while the simulation model of health investment is outlined in the fifth section. The sixth section provides a discussion of our results and the conclusions drawn from our analysis are organized in the final section.

2. Review of the Preventive and Curative Costs for Malaria

The majority of micro-level studies in public health assessing the costs related to malaria use a cost-of-illness (COI) approach and classifies costs into those directly and indirectly incurred. Direct costs are usually defined as the expenditure on prevention and treatment of malaria by households and health services. These include medical testing, drugs, consultation, special food, transportation, medical supplies, non-medical supplies, services and out-of-pocket expenditures (Akazilli et al, 2007 and Chima et al, 2003.) Indirect cost is the cost of time lost due to malaria which we discuss in the next section.

Generally, studies have concluded that these prevention and treatment costs constitute a small portion of the total direct and indirect costs that were estimated. For example, Attanyake et al. (2000) estimated that only 24% of the estimated US\$7 per malaria episode was attributable to ‘direct costs’. In Ghana this was estimated to be 29% of a total US\$1.87 per episode (Akazilli et al, 2007) and in Rwanda, this was US\$2.58 of the total US\$11.82 (Ettling & Shepard, 1991).

A study in Kenya based on household surveys and supplemented with in-depth case studies of selected households found the prevention and treatment cost of malaria incidents to be 7.1% and 5.9% of all estimated costs in the wet and dry seasons respectively (Chuma et al 2006.) This study also found that the burden of prevention and treatment cost were regressive, with malaria costs accounting for over 10% of the expenditure in the poorest households. Akazilli et al (2007) also measured costs in relation to income in Ghana and found that the poorest quintile spend 33.98% of their expenditure on malaria treatment cost, while that figure for the second poorest quintile was 8.97%. In Malawi, very low income households carried a disproportionate share of the economic burden of malaria, with total estimated cost of malaria among these households consuming 32% of annual household income compared to 4.2% among households in the low to high income categories (Ettling et al, 1994).

Some studies report components of treatment costs in more detail, especially the cost of transportation, which can vary widely depending on the location of the village and accessibility of treatment. In the case of Ethiopia, where treatment costs represent US\$1.60 of the total US\$5.86 per episode, 20.92% of the patients surveyed paid for transport to seek medical services (Deressa 2007). In Sudan, Abdel-Hameed (2001) found that transportation accounted for 24% of total estimated costs for those seeking treatment but who were not hospitalized, and in Ghana, transportation cost to health care facilities represented 13.1% and 5.9% of the total estimated costs for severe and mild febrile illnesses, respectively (Asenso-Okyere & Dzator, 1997).²

² Some studies also consider government expenditure as part of the 'direct cost', which may be in the form of eradication and prevention efforts or medical treatment subsidies. For example, in Vietnam treatment costs represent 6% of the US\$11.79 per episode, but the Government of Vietnam provides free medical services (Morel et

The non-negligible amount of prevention costs can be understood when considering the different methods of prevention in more detail. Prevention efforts can take the form of insecticide-treated nets (ITNs), intermittent preventive treatment³ (IPT), vector control and eradication initiatives, and development of vaccines. Household prevention methods may also include aerosol sprays, bednets, and mosquito repellents. A detailed comparison of estimates of monthly household expenditure on malaria prevention across a number of countries in sub-Saharan Africa reflects that costs range from US\$.05 to US\$2.10 per capita, as shown in Figure 1 (Chima 2003).

It is widely accepted that prevention can be very effective. The WHO estimates that ITNs can reduce malaria incidence by 15-20% and in most countries that are currently affected by malaria, this is the most common prevention technology. In an experimental trial, Lengeler found that ITNs could reduce episodes by 62% in areas of unstable malaria (2009). Although ITNs prove very effective in these studies, the literature clearly shows that lack of income prevents the poorest groups from benefitting. In Malawi, ITNs were disproportionately concentrated among the least poor (Mathanga & Bowie, 2007) and Matovu et al (2009) found similar results in Tanzania. In India, where Babu et al (2007) estimated household prevention costs to be US\$1.60 in rural areas, Biswas et al (2010) studied the characteristics of ITN ownership and found income to be the strongest determinant.

al, 2008.) In Rwanda, Ettling and Shepard (1991) found that treatment costs per case were equivalent to 160% of the Ministry of Health's budget per capita.

³ IPT is systematic treatment of malaria whether an individual is symptomatic or not. This approach is most commonly used in vulnerable subpopulations in highly endemic areas, particularly during pregnancy, where a case of malaria could have severe consequences.

With respect to their cost, ITNs can cost up to US\$5.50 for a long-term net; however in many countries, initiatives are underway by NGOs, donor organizations, and local governments to distribute heavily subsidized or free nets (WHO 2007). For example, under its national malaria control strategy, the Nigerian federal government is currently engaging in free mass distributions of ITN and planned to distribute 63 million ITNs by the end of 2010 (Ye et al 2012). We do not have results of this initiative, however Ye et al. sampled in Kano state, the location of the first wave of distribution, and found that net ownership had increased from 10% to 70%.

Intermittent preventive treatment is another prevention method, typically used for pregnant women, and has been shown to reduce malaria and other health risks in newborns. This method is rarely explicitly considered as a cost of malaria in the literature. In Nigeria, only 2% and .6% of urban and rural women, respectively, received IPT during an antenatal medical visit (NDHS 2003).

While most studies include prevention costs in the cost-of-illness approach to valuing the costs of malaria, Cropper et al. (2000) attempted to value the benefits of malaria control in Ethiopia by estimating a demand curve for the vaccine. Since no vaccine currently exists for malaria, this was done hypothetically by surveying heads of household their willingness to pay for a vaccine. This may more broadly capture the costs of malaria, including those that are not quantifiable, such as suffering, lost leisure time, and longer-term consequences, which the COI approach fails to encompass. Indeed, the results indicated that the annual household value of preventing malaria was 2-3 times the expected cost of illness. Cohen and Dupas (2010) also employed a demand-estimation approach in Kenya for ITNs; however, since ITNs do not guarantee

immunity, an individual's willingness to pay does not reflect the full value that a vaccine would. Furthermore, Cropper's study was based on a survey of hypothetical willingness to pay, whereas the participants in Cohen and Dupas's study were only counted if they actually purchased the ITNs, so cash availability may have reduced observed demand in the latter.

Cost of Time and Opportunities Lost Due to Malaria

'Indirect costs' in the public health literature are generally defined as the opportunity costs of malaria, or productive time lost due to illness, representing the majority of malaria costs. These costs are more difficult to quantify than the prevention and treatment costs. The potential effects of malaria lie not just in the loss of productive time by the sick, but also time spent by household members caring for the sick, loss of knowledge transfer from those affected, reduction in investments in agriculture, education and nutrition due to malaria expenses, changes in cropping patterns, and the compounding effects of these consequences over generations. The WHO (2001) also suggests that the presence of malaria may depress tourism and other investments, generating further indirect costs that are difficult to quantify.

Most studies estimate these costs using the wage rate method of measuring workdays lost due to illness multiplied by the value of a day's work. The value of a day's work is typically measured by average wage rate but other studies have utilized average daily income (Ayieko et al., 2009; Ettling et al., 1994; Guiguemde et al., 1994) or average daily output per adult (Sauerborn et al., 1991; Shephard et al., 1991). In Burkina Faso, these costs constitute 69% of the total US\$5.96 cost of malaria per case (Sauerborn et al., 1991) and 79% of the US\$6.87 in Ghana (Asenso-Okywere & Dzator, 1997.)

Most of the literature acknowledges the intangible costs that cannot be quantified and are therefore excluded from cost estimates. Akazilli et al (2007) define intangible costs as those that impact “quality of life.” For example, health can be viewed as consumption good which increases its owner’s utility. Malaria patients and their families likely experience increased pain and suffering and decreased enjoyment of life, but this is difficult to quantify and therefore none of the available literature attempts to do so, though it could be argued that the willingness-to-pay for vaccine approach mentioned above would encompass these costs.

A number of studies focus only on the work days lost due to malaria, both of the ill person and his or her relatives. Pluess et al. (2009) conducted a cross-sectional study in six villages close to the oil palm plantations of Papua New Guinea, and determined the average workdays lost to malaria to be 1.8 per episode. Households to be surveyed were selected by random sampling. In addition to the survey, researchers collected blood slides from all participants to confirm the presence of malaria. The plantations provide free health care, so access to anti-malarials may reduce the number of days lost per episode.

In Nepal, the average workdays lost ranged from 6-14 days per episode (Mills, 1993.) This study identified a sample by stratifying districts by geographical region and randomly choosing one district per region. Data was collected by a health service team who also confirmed the presence of malaria with a blood test before surveying. Free treatment was available from the service team; however, the results are based on data from 1984, which could partially account for the longer duration if treatments have since improved.

Asenso-Okyere & Dzator (1997) used a household survey in Ghana, implemented in two districts chosen for the presence of the different types of healthcare (government, mission, private, and community) and for similarities between employment types (farming was the primary occupation in both.) Surveying a random sample of 1,289 households, they found that on average 5 productive workdays were lost per episode of self reported malaria, with 64.2% of these workdays lost attributed to care taking. Seeking treatment took on average one half of a farm workday. Because the study did not take a blood test, it may include other incidences of high fever, but also miss non reported episodes.

A key factor in measuring the net workdays lost due to illness is the impact of labor substitution. For example, if a father is sick with malaria but sends his son to work in his place, then there is no net workday loss due to malaria. Labor substitution is often referred to as a coping process employed by families in attempt to reduce the impact of disease. Some studies attempt to capture such coping processes in their quantification of lost productivity. Alaba & Alaba (2006) accounted for this in a recent study of income lost due to malaria in Nigeria. Data for the study was collected using multi-stage-sampling, selecting three health zones from Oyo State as base strata, from where 4 local governments were randomly selected. The study estimated that average net workday loss, defined as patient's lost workdays minus labor substitution plus opportunity cost of substituted labor, was 10 days per episode in the agriculture sector. Cropper et al. (2000), conducting a survey in 18 villages in 2 selected districts in Ethiopia especially

designed to provide variation in malaria incidence, used the same formula to calculate an average of 21 workdays lost per malaria episode in Ethiopia.⁴

In a few other studies that took into account labor substitution in the presence of illness, no loss of production was observed. For example, Gateff et al. (1971) found that families reallocated labor within the household during bouts of malaria and schistosomiasis and production was not affected. A similar result was observed among female cotton pickers in Sudan: schistosomiasis did not reduce production because healthy family members worked more to compensate for the sick (Parker 1992).

The potential costs for employers are illustrated by two studies. A study among textile factory workers in Kenya observes a loss of 720 person-days over a ten month period, with malaria accounting for 53% of the illness episodes (Some 1991), while the above mentioned study of six villages around an oil palm plantation in Papua New Guinea finds that 9,313 workdays were lost due to malaria over a two year period (Pluess et al 2009).

Summarized, these studies agree that malaria imposes an economic cost on individuals, households and firms that is significantly above zero. At the same time Audibert et al (2009) find no relationship between malaria infection (measured from blood samples) and cocoa and coffee production in Cote d'Ivoire.

⁴ The study did not select a random sample as there was no complete list of households; therefore interviewers walked in different directions and chose every other household to survey.

While the above studies provide a wealth of information about the work days lost due to malaria, they also suffer from a number of weaknesses. First, many studies use weak data on earnings and days lost, and do not distinguish between the average and the marginal product of labor.⁵ More importantly, most studies do not provide any insight on causality. Somi et al. (2007) present evidence for dual causation between malaria and socioeconomic status, measured by asset ownership. Hong (2008), using historical census data from adult males who migrated from less to more malaria prone counties between 1850 and 1860 in the US, finds that they accumulated 9% less wealth per year, mainly due to lower labor supply with high malaria countries having 1.6 to 2.7 percentage points lower labor force participation rates in 1850 and 1860 respectively. A number of studies have also estimated other economic costs of malaria, often focusing on children, where the disease has its biggest impact resulting in infant and child mortality.⁶ So while there is good reason to expect a causal relationship between malaria on absenteeism from work, there is limited hard evidence. Finally, while the above studies provide information on absenteeism from work, as a measure for decreased labor supply, they provide little insights on losses in on-the-job productivity, which may be as important. A small number of studies find that absenteeism is followed by a number of days with reduced capacity. Picard and Mills (1992), for instance, using a pairwise comparison among Nepalese workers find that an additional 1.2 days are lost due to being partially disabled by illness. In this paper, we take into account on-the-job performance.

⁵ Many studies also make generalisations while not taking into account important dimensions like the type of work or the season of survey. Chima, Goodman and Mills (2003) provide an overview and comments on a number of studies.

⁶ Barreca (2007) estimates that in utero and post natal exposure to malaria lead to substantially lower levels of educational attainments and higher rates of poverty later in life. There is also strong evidence for negative effects of malaria on education outcomes. Cutler, Funf, Kremer and Singhal (2007), exploiting geographic variation in malaria prevalence in India prior to a nationwide eradication program in the 1950s, finds that malaria eradication resulted in gains in literacy and primary school completion of approximately 10 percentage points.

3. Data Description

We use three types of data in this paper: survey and experimental data obtained from a randomized intervention, data from a mosquito survey to determine mosquito parameter values, and data from other epidemiological studies to define values of remaining parameters in the model.

First, using results from Dillon et al (2012) which carries out a unique analysis estimating the effects of malaria treatment on income from work, considering both increased labor supply and on-the-job productivity. This randomized intervention provided testing and treatment within a single large plantation that hires sugarcane cutters throughout the sugar cane cutting season (November-April) and pays them on a piece rate basis.⁷ The daily output data is collected for all workers throughout the entire harvest period. We observe the entire cane cutting population of workers across the harvest season in 2010 and 2011 over the same period of time (February and March). Information collected by the plantation was linked to worker and health characteristics collected by a set of survey enumerators and health workers. The information on worker characteristics was administered by the survey enumerator including employment history, age, education, gender, place of living and household welfare. Then the registered health worker administered the second questionnaire by first asking a brief health history including recent treatment for illness and preventative health behaviors, and then recording the results of two

⁷ Across the plantation supervisors collect daily worker output using a standardized measuring stick. A worker's payment is based entirely on his output, as each worker's output is measured at the end of each day by his supervisor using a standardized measurement stick. The plantation's wage is 2.04 Naira per unit of output. With the exchange rate in Nigeria fluctuating over our survey rounds generally around 150 Naira=1 USD, a meter of cane cut represents approximately one U.S. cent of earnings. Workers carefully observe the recording of their output as it is the basis of their monthly payments from the plantation, often maintaining their own separate ledger.

tests: a Rapid Diagnostic Test (RDT) for malaria and a blood slide which is used to microscopically verify malarial status.⁸ All workers who had a positive RDT or were parasitic positive according to the microscopy results from the collected slides were treated with the appropriate doses of Artemisinin Combination Therapy (ACT).⁹ The treatment of groups of workers was implemented in random order, which allows estimation of treatment effects. The study finds substantial and significant average treatment effects in high incidence year, but low and insignificant average treatment effects in low incidence year, while it finds significant intent to treat effects across high and low infection years. Further description of the study design is found in Dillon et al. 2012.

Table 1 provides descriptive statistics of worker characteristics for each study round separately, as well as for the pooled sample. The average worker was 30 years old, had 5 years experience in this type of work (in round 1), has attended some schooling, with close to three quarters having completed secondary school or below. Household wealth is measured by a normalized asset index.

This data also contain information on bednet use. Bednet use is by far the most used preventive technology in the area, and we therefore focus our analysis on this type of prevention. We

⁸ Fingerprick blood specimens (which pose minimal risk) were obtained from participating workers— less than .5 ml of blood was required from each person. Respondents were tested for malaria with the Binax Now™ RDT. This antigen-based test, which utilizes both HRP-II (a PF-specific antigen) and aldolase (a pan-Plasmodium antigen) is well validated internationally and provides accurate diagnosis for current malaria infection (particularly for the most severe form, *p. falciparum*), and can distinguish the infecting Plasmodium species to some extent. Results were available within about 15 minutes for RDT tests and within a few days for the blood slide test. All results were communicated directly to the participants.

⁹ Artemisinin based combination therapy (ACT) is the preferred first line treatment for malaria recommended by the World Health Organization, as there has been no resistance to ACT yet reported in Africa, and ACT has been proven to cure *falciparum malaria* within 7 days with few to no side effects; and is effective for another week. Compliance with the treatment protocol was maximized through follow-up visits by the health workers and a small incentive (50 Naira) to return used ACT boxes to health workers who would conduct a short follow up visit to ensure compliance. (ACT exist of a pills to be taken twice a day for three days in a row.)

measure bednet use by the worker in the previous night, as well as whether the worker's house contained window screening to prevent insect entry. Almost 50 percent of the workers make use of bednets in the previous night across the pooled sample, with some indication that its use has increased from round 1 to round 2.¹⁰ Unconditional infection rates in our sample also vary between the two rounds, with an average infection rate of 36% in round 1 and 14% in round 2 using microscopic diagnosis.¹¹ These infection rates may be correlated with increased bednet usage, but may also be due to inter-seasonal variation in epidemiological disease transmission factors such as temperature, rainfall, and other vector control measures.

Table 2 provides a summary of worker's earnings, days worked and daily wage by month and by round. These earnings statistics provide the benchmark for the expected income calculations for both preventive and curative treatment. Earnings and labor supply vary both between months of the agricultural season, but also between rounds. This is in large part due to the interlinked production process whereby sugarcane is harvested and then must be directly processed in the plantations sugar refinery. Production disruptions at the refinery may result in suspensions of sugarcane cutting in the field which may explain some variation in these data. For the purposes of our model, we used pooled monthly earnings for workers in February, as this was the month when most workers were interviewed across the two rounds.

A second source of data provides information on epidemiological variables. As part of the second survey round, a detailed epidemiological study was conducted for a subsample of three

¹⁰ It is unclear at this point why this increase has occurred. The higher incidence in the first year may have invited adapted delayed behavioral response. It is also possible that our first round of survey work raised awareness about the importance of protection against malaria. There also seem to have been some government interventions in the villages surrounding the plantation which may have increased use, although documentation of there is limited documentation of these programmes.

¹¹ Thick blood slide microscopy is the gold standard method to measure malaria infection.

worker villages. In addition to information on health facilities, survey teams collected information on mosquito breeding locations and performed an immature stages collection. The immature stages collection provides information on intra-village variation on the numbers of breeding sites, but also the number of larvae and pupae who were identified through a separate laboratory examination to be anopheles mosquitos. The epidemiological survey teams also conducted a household Indoor Adult Pyrethrum Spray Survey in these three villages to identify the number and types of mosquitos found in residential housing in the workers villages. We exploit this data to create a simulation of the epidemiological environment in which the workers reside including the mosquito lifecycle, and the probability of becoming infected from a mosquito¹².

This data provides a set of descriptive variables used in the simulations to account for variations in the epidemiological environment across worker villages. In Table 3, descriptive statistics from the three sites are presented. The data indicates variation across the three village sites in the percentage of mosquitos with bloodmeal and sporozoites, as well as the number of female mosquitos which vary between 4.8 and 6.3 per sleeping site¹³. These variables are important in calibrating our simulation and providing realistic parameters for the worker's epidemiological environment. We now turn to describing both the static and dynamic simulation to assess the expected income from preventative and curative health investments.

¹² Killeen et al. model the probability of a mosquito being killed by its prey at 10% and that of being killed by a bednet at 40%. Collins & Jeffery (2007) provided an essential resource for the parameterization of the life cycle of *plaxmodium malariae*.

¹³ These different types of mosquitos are of importance as female mosquitos transfer malaria, and mosquitos found with bloodmeal have eaten recently and contain infective cells, sporozoites, which can be transferred to humans.

Existing epidemiological studies form the third source of data. Remaining parameters are defined based on insights from the literature, including Carter (2002), Killeen (2007) and studies surveyed in Williams (2002). Appendix provides an overview of specific sources for different parameters.

4. A Static Framework of Health Investment

Building on the above studies which assess the cost of illness and prevention, we examine the individual's decision problem to invest in preventive versus curative treatment for malaria using a static model where workers compare the expected income from preventive and curative treatments before choosing the method that provides the highest payoff. We focus on the worker population on one large sugarcane plantation in Nigeria, also making use of insights from our previous study that estimates the effects of malaria on labor outcomes (Dillon et al. 2012), as discussed in the data section.

In a rational agent model, which provides a useful benchmark, individuals compare the net benefits of preventive versus curative treatment before choosing an investment option. Figure 2 provides a systematic presentation of this choice. Workers can either choose preventive measures, such as bednets, to reduce the unconditional probability of infection, r , to a conditional probability of infection, $q \equiv P(\text{Infection}|\text{Prevention})$, where $r \geq q > 0$. We can write $q = (1 - \phi)r$, where ϕ reflects the effectiveness of the preventive treatment with $0 < \phi \leq 1$.¹⁴ The adoption of preventive measures while lowering the risk of infection if the preventive measure is used properly, is not a sufficient condition to reduce the probability of infection to

¹⁴ This effectiveness is driven by both the technical qualities of the technology as well as the behavioural modalities of its implementation.

zero. Most agricultural workers are not able to protect themselves entirely from malaria using bednets as they are exposed to malaria at the workplace as irrigated agricultural land provides an ideal breeding ground for mosquitos. In our case, the workers at the plantation are exposed to a large scale irrigated system that is conducive to mosquito exposure, especially in the early morning when the workers' shifts begin at the plantation. Preventive measures require workers to incur costs, C_p . They also incur costs of curative treatments if they fall ill, C_c . If workers do not choose to adopt preventive measures, they may either be infected or remain well. A novelty of this approach is the recognition that workers who fall ill do not have the same expected income as workers who are well. Income from ill workers is discounted by θ where $0 \leq \theta < 1$.

The expected utility of choosing prevention is the sum of the payoffs that occur when the worker falls ill or not after,

$$U_p = q(\theta y - C_p - C_c) + (1 - q)(y - C_p) \quad (1)$$

where we assume that workers take curative care if they fall ill. If workers do not choose prevention, the expected utility is:

$$U_c = r(\theta y - C_c) + (1 - r)y \quad (2)$$

A worker will choose preventive care if and only if $U_p > U_c$, which we call the preventative care condition. To calculate whether this condition holds, we abstract from differences in health care supply and prices. Since our study focuses on workers from one plantation, who mostly come from the surrounding villages, the workers in our sample face the same costs and availability of preventive care. Based on local prices, we determined the average monthly cost of prevention

(C_p) and curative treatments (C_c) over the course of an agricultural season¹⁵. The parameter, θ , the income discount for ill workers compared to healthy workers, is proxied in our data by the estimated cost of malaria infection on worker income. This is the complement of the average treatment effect (ATE) on earnings from the preferred specification in our previous work (Dillon et al. 2012), for this purpose expressed as a percentage of total earnings, $\theta = 1 - ATE$.¹⁶

To estimate the preventative care condition in a static framework, we must make assumptions about ϕ based on the literature. As ϕ potentially varies across individuals and is determined by unobservables such as adherence to proper bednet usage as well as preventative adoption decisions of others in the worker's community, we can estimate the determinants of preventative care and the correlation based on unobservables across preventative care decisions. This would provide evidence that a static model may provide biased expected income estimates if unobservables are significant determinants of preventative choices.

We can write the ratio of choosing preventive over curative as

$$\frac{U_p}{U_c} = \frac{(1 - \phi)r(\theta y - C_p - C_c) + (1 - (1 - \phi)r)(y - C_p)}{r(\theta y - C_c) + (1 - r)y} > 1 \quad (3)$$

where the left hand side is the ratio of the relative the pay offs when choosing no prevention versus when using prevention. Using i for individual and j for household subscripts, this can be presented more generally as:

¹⁵ Local prices indicate the cost of a bednet to be USD 5 and the cost of curative treatment to be USD 7, which is consistent with costs mentioned elsewhere in the literature.

¹⁶ Dillon et al 2012 conduct a randomized experiment that tested and treated workers if they were infected with malaria. This average treatment effect reflects the benefit to workers from having been treated for malaria when they would have otherwise been ill. Hence, this reflects the earnings benefit of absence of illness, or, alternatively the cost of illness.

$$P\left(\frac{U_p}{U_c} > 1\right) = f(y_i, \theta, C_c, C_p, r_{ij}, \phi_{ij}, \varepsilon_i) \quad (4)$$

where the likelihood of using preventive care is a function of the individual's income, which depends on individual characteristics, as well as foregone productivity on the job and the costs of curative and preventive care, which are all considered exogenous¹⁷, and the rate of infection and effectiveness of preventive care. The latter two depend on individual and household characteristics and behavior such as, living conditions including proximity to water and housing materials, as well as number of other household members and their frequency and accuracy of bednet use, etc.

Because we consider several preventive technologies, for which the application is likely to be co-determined by unobserved factors, we jointly estimate the likelihood of choosing each of these preventive treatments. Focusing on two preventive treatments, namely bednet use and window screen protection, we use a bi-probit model, using the following set of equations:

$$\begin{cases} \Phi(P_i^1) = \beta_0^1 + \beta_1^1 x_{1i} + \dots + \beta_n^1 x_{ni} + \beta_{n+1}^1 x_{1j} + \dots + \beta_{n+m}^1 x_{mj} + \varepsilon_{1i} \\ \Phi(P_i^2) = \beta_0^2 + \beta_1^2 x_{1i} + \dots + \beta_n^2 x_{ni} + \beta_{n+1}^2 x_{1j} + \dots + \beta_{n+m}^2 x_{mj} + \varepsilon_{2i} \end{cases} \quad (5)$$

where ε_{1i} and ε_{2i} follow a joint distribution. The joint estimation of use of both prevention technologies also allows for estimation of the unobserved factors affecting the choices to use both technologies. If the correlation in technology choice, ρ is positive and significant,

¹⁷ We can make these depending on individual characteristics, but our estimations in other work suggest that variation in on the job productivity losses are limited, while the literature also suggests that while individual costs for treatment, like transport, may vary across individuals, they represent only a limited fraction of the total cost, as discussed in section 2.

unobserved factors play an important role in preventative health choices. In the next section, we develop a dynamic simulation approach to estimate how the conditional and unconditional probabilities of infection may change if some of the potential unobservables in preventative technology adoption are explicitly modeled.

5. A Dynamic Simulation of Health Investment

In the static model of health investment, a worker chooses preventative or curative behavior, falls ill or not, and then realizes expected income. This approach is a first step in understanding the expected income from preventative choices. However, the results depend on how infection rates respond to preventative health behaviors and the efficacy of preventative treatment. In principle, a dynamic model would permit the infection rate to be endogenously determined in the model based on the interaction between individual choices and the epidemiological environment.

We introduce epidemiological features in a simulation model to predict the probability of infection for workers and explicitly model the spillovers from individual worker preventative behavior on the reduction of the population probability of infection over time. We use information from a separate detailed epidemiological study in a subsample of three worker villages, as described in more detail in the data section.

The simulation uses a spatial multi-agent setup similar to Carter (2002) which features a prime mosquito ecological zone in the center of a population grid. Those in the center of the ecological zone are more likely to be infected with malaria by virtue of them being more frequently fed

upon. Transmission occurs on a round by round basis.¹⁸ Unlike Carter (2002), our simulation explicitly tracks each mosquito within the population grid.¹⁹ This allows for technologies such as insecticide treated bednets that kill mosquitos to directly limit the spread of malaria in addition to reducing the probability of infection. The simulation also shares components with Killeen et al. (2007) which explicitly models the life cycle of malaria through the interaction with mosquitos and humans, but our approach diverges in that models on an individual level mosquitos and humans, and makes use of dynamic infection rates within these populations.²⁰ We also uses insights from Collins to incorporate the time dimension.²¹ Our simulation model does not assume that all mosquitos are infectious, but rather that mosquitos and humans jointly infect and re-infect each other over repeated periods. In Figure 3, we present the simulation

¹⁸ Carter's (2000) model considers a human population of 348 distributed across 45 square kilometers and uses a 1 kilometer perimeter around which an infected person can infect another person by means of a mosquito vector. The breeding area of the mosquitos is centered and about 35 km (78% of the area). Each infected individual remains infected for 100 days and transmits an infection vector of on average 6 or less, meaning each person will transmit malaria to up to six people within the 1 km radius. Carter's simulation shows that a vaccine that inhibits the transmission of malaria could effectively contain or eradicate malaria in the long run in a population at rates of effectiveness or either 90%, 95%, or 99%. These immunity rates are much higher than the leading vaccine RTS (about 50% effectiveness).

¹⁹ We diverge from Carter (2000) by including individual mosquitos. The primary purpose is to represent the tenuous nature of the individual mosquitos life in order to characterize how technology such as insecticide treated bednets might not only reduce the rate of infection by the individual but also the population through directly decreasing the life expectancy of human feeding mosquitos. Other differences with Carter (2000) are that our simulation does not specify a unit (ie. km or meters) of measurement, the populated grid being between 0 and 1. To specify greater distances between individuals is to specify a greater density of the grid. Carter (2000) also has only the barest sketch of a time component, with mosquitos not modeled explicitly and no time delay in transmission from one individual to a mosquito to another human. This makes the limited mosquito ecology the primary restriction that contains malaria from being spread throughout the entire population in the absence of vaccination. (Individuals outside of the mosquito ecology do not transmit malaria though they may become infected by someone within the malaria ecology.)

²⁰ Killeen et al (2007) present a simulation study of the potential community and individual effects of low to moderate levels of community bednet usage. The simulation explicitly models the mosquito life cycle with the direct effect of intervention a reduction in the number of bites accompanied by a response in malaria levels.

²¹ Providing a survey of what is known about the life cycle of *plasmodium malriae*, a strain of the parasite that causes the disease, Collins (2007) provides key insights that allow refinement of the time aspect of malaria transmission in our model, describing how mosquitos are contagious 2 to 3 weeks after a having a bloodmeal of a contagious individual. Once contagious the mosquito once encountering a human may transmit sporozoites (one of the many forms of the malaria parasite) to a human which will mature in approximately 15 days and on average 3 days later merozoites are released into the blood stream that are available to be taken by mosquitos and the cycle begins again. Collins also describes the prepatent period which is defined as the time it takes before the parasites are detected on a thick blood film, summarizing a number of studies stating that the earliest period observable is among a west African strain with a period of 16 days, while there is a wide range among mosquito transmitted malaria (16-59 days).

steps in estimating the epidemiological transmission of malaria between mosquitos and humans. Using this simulation, we estimate the probability of that a mosquito feeds (bloodmeal) based on several human conditions (dwelling characteristics and prevention such as bednets) and environmental conditions (hazards). Focusing on the preventative conditions, the determinants of a mosquito having bloodmeal are summarized such that:

$$P(b_t^m) = f(dwelling^m, prevention^m, hazards^m) \quad (6)$$

Figure 4 provides the linkage within the simulation between the environmental and human systems where the probability of infection is determined in part by mosquitos having bloodmeal conditional on their infection in previous periods of the simulation.

$$P(I^h) = f(b_t^m | infected\ b_{t-1}^m) \quad (7)$$

Equation 7 is in large part determined by unobserved variables in a static formulation that can now be taken into account in a dynamic simulation. Details on the simulation methodology, including initializing conditions, daily mosquito emergence and routine, and mosquito infection cycle as well as model parameters are described in detail in Appendix.

After the initial period, infection rates in both the mosquito and human population depend jointly on epidemiological conditions which affect the mosquito's reproduction rate and lifecycle as well as the preventive and health-seeking curative behavior of humans. This is the mechanism through which spillovers are explicitly modeled in the simulation. For example, a worker who does not adopt a preventative health technology such as a bednet, increases their own probability

of infection and the total number of infectious mosquitos in the population by passing back to the mosquito population more malarial parasites if the worker did become ill in the previous period.

A central feature of our simulation is that workers make decisions about the use of bednets, household screened windows, the use of both preventative measures or neither. They also make decisions about whether to seek curative care or not (at a hospital), and if so when (i.e. the amount of time to taken before seeking care). Both preventive technology investment and health-seeking decisions are predicted from the experimental data based on the worker's observable characteristics.

There are two parameters which vary within the simulation and on which we have to make explicit assumptions. These are the effectiveness of prevention technologies at repelling or killing mosquitos. As cited above, the World Health Organization has provided some estimates of the efficacy of bednets on the infection rate, but we found much less literature on the efficacy of screened household windows on the probability of infection. If workers in the simulation use window screens then there is a chance the mosquito will be repelled, just as if they used an insecticide treated bednet. However, for insecticide treated bednets, a mosquito may also be killed if it comes in contact with the net. We vary the bednet 'kill rate' in the simulation, as a robustness check. If a worker uses both preventative technologies, the probability of a mosquito biting is greatly reduced in the simulation. In all scenarios, we assume this probability to be 5%²². In the epidemiological simulation, the mosquito not repelled has a chance of infecting the person with malaria or itself becoming infected with malaria.

²² This number is intentionally low because the per mosquito effectiveness of insecticide treated nets is uncertain when nets may be older than 6 months and many workers may choose not to be under their nets and therefore

Given the worker's probability of infection in any given period, we can estimate under different simulation scenarios the number of days the worker may fall ill. These simulation results can then be linked to our experimental data to calculate expected worker productivity, labor supply and income under these different scenarios. These results are presented in the following section after presentation of the initial static model results.

6. Results

Static Model Results of the Expected Income from Preventative versus Curative Health Investments

In the static model formulation, we compare expected utility from adopting preventative health behavior to expected utility from using a curative approach (Equations 1 and 2) which we proxy using expected income. To calculate these expected income levels, we make two cost assumptions, informed by our survey data. First, we assume that the cost of curative treatment is USD 7, based on the cost diagnostic and prophylactic costs of administering this treatment that we incurred in the field. Second, we assume that the cost of a bednet is USD 5 based on market information in the vicinity of the plantation. As a bednet is durable throughout the agricultural season and we use monthly expected income in our calculation, we discount the bednet cost over the course of the agricultural season²³.

unprotected at the times when mosquitos are primarily feeding. Killeen et al. (2007: figure 2) model mosquito death rates at 50% as a result of contact with an ITN and 10% with contact without an ITN.

²³ Monthly earnings are 18309 if well and 17240 if ill.

The next step is attribute effectiveness to bednet use. Based on a Cochrane review of five community-randomized trials, full coverage with ITNs in the community reduced malaria infections by 50% on average across the studies (WHO 2007). These treatment effects were estimated with full community compliance which is unlikely without a health intervention. With average bednet usage in our data of 49% across the two rounds, we conservatively assume less than half the effect of the controlled trial estimates since we have about half the population coverage and cannot ensure full compliance. This yields a conservative estimate of close to 20% incidence reduction rate in the static model²⁴ which we use for illustrative purposes. Using a 20 percentage reduction in probability as our benchmark, we compare expected income from curative treatment with a 30% probability of infection to preventive expected income. Calculating the preventative infection rate with a 20% reduction in infection gives a preventative infection rate of 24% ($.8 \times 30\%$). Using these probabilities, cost estimates and income estimates from the survey data, we calculate that expected monthly income due to prevention is 17,693 Naira while expected income due to a curative strategy yields 17,673 Naira. If other factors such as credit constraints reduce an individual's ability to make larger purchases such as a bednet, the expected income difference may not be large enough to induce adoption of preventive health measures. Alternatively, other unobserved factors may account for individual adoption if there are spillovers from others adopting within communities, as the expected income gap between those who choose preventative versus curative treatment is not large.

²⁴ Based on improved information on the efficacy of bednets, different estimates from our tables can be used by comparing different differences in the expected income levels from different probabilities of infection.

Jointly investigating at bednet and window screen use, we apply a biprobit model to estimate the probability of preventive technology use using equation 5. Given the geographical focus of our analysis, we expect differences in bednet use to occur predominantly due to differences in household and individual behavior.²⁵ As mentioned earlier, the joint estimation of both prevention technologies allows for an estimate of the unobserved factors affecting the choices to use both technologies. All else equal, the deployment of one form of prevention technology should reduce the return and therefore likelihood of using the alternative technology. The correlation in technology choice, presented in Table 4 as ρ is positive, significant, and large indicating that there is a large amount of unobserved heterogeneity, or that unobserved factors driving the correlation in technology choices even after controlling for the effects of education, wealth, and family size, are important.

The results, presented in Table 4, indicate that workers who received more on the job training are substantially (and significantly) more likely to use bednets as well as install window screens. Because this training refers to work place related training, the result indicates that those with higher firm specific human capital make more use of prevention technologies.²⁶ More highly trained workers with firm specific human capital may want to keep their high return jobs, as there is turnover in the worker population, and may therefore invest in prevention technologies to ensure continued employment. General education, on the other hand, is not strongly associated with bednet use for workers in our sample: while all coefficients on education variables are positive only high school education or more has strong predictive effects on bednet use. This is in contrast to window screen usage for which education has large and significant effects at all

²⁵ In future analysis we plan to also take past behaviour and experience with malaria, including past illness, of both the individual and other household members into account.

²⁶ Training may also proxy (some types of) ability, with the firm providing training to the most able workers.

levels of achievement except nursery or primary school. Having more spouses increases the probability of using a bednet. Since all harvest workers on the plantation (and thus in our data) are male, this may indicate that shifts in decision power within the household affect bednet use. As Thomas (1997) observes, higher income shares of women within the household may affect the distribution of health resources to children and the household more generally. The number of spouses predicts decreases in the use of window screens while the number of children predict increases window screen usage with an effect size approximately the same as that of number of spouses when scaled by the respective standard deviations. Household wealth (asset index) is not significantly associated with use of bednets or window screens after controlling for survey round.

These results, particularly the large and statistically significant correlation in preventative choices suggests that investigating a dynamic approach where preventative choices directly affect the probability of infection via reduction in the prevalence of malaria could provide additional evidence on adoption decisions.

Dynamic Simulation Results from Preventative and Curative Health Investment

Epidemiological modeling allows us to estimate how the probability of infection changes as more individuals adopt preventative behavior and if they choose to be treated when they fall ill with malaria. We present the results of three simulations where we compare the expected incomes and payoff to prevention from adopting the use of a bednet in comparison to using no preventative technology, the use of window screens in comparison to using no preventative

technology, and using both bednets and screens in comparison to using no preventative technology.

In the first simulation (Table 5, Simulation 1), workers will choose not to use bednets until the repellent power of bednets causes protection against 70% of the mosquitos they encounter in the epidemiological environment. This implies that bednets must be highly effective for individuals to adopt. As the efficacy of bednets increases, spillovers in the form of reduced expected population infection rates also raises expected income in the group of workers that does not choose to adopt. Therefore, there is a free rider problem whereby workers who do not adopt the preventative technology have higher incomes due to the reduced population probability of infection. This reinforces the importance of health policy interventions in promoting efficacious preventative technologies from a social welfare perspective when individuals may not have the proper incentives.

In the second simulation (Table 5, Simulation 2), window screens are only adopted at very high levels of efficacy²⁷. From the individual worker's perspective, screens with the same repellent power provide less individual protection than for a bednet since bednets also have a 30% probability of killing the mosquito. From a population perspective there are competing externalities associated with using screens. This is because if a mosquito is repelled then the positive externality is that it will not infect the human which in turn may infect a mosquito which will infect a different human, thus lowering expected infection rates. However households without preventative technology face a higher concentration of mosquitos than they would if

²⁷ Schreck & Self (1985) report people using bednets having only 5% of the bites of those not using nets though they suggest that bednets are probably more effective for children who go to sleep earlier.

preventative households did not use screens. This is because screens only prevent infection, but do not kill mosquitos as bednets do. Effectively, curative households face an additional population of mosquitos that are repelled by a screen and survive other methods of mosquito extermination (e.g., killed by an individual, 10% chance, or killed by a bednet, 30% chance).

For those who use both technologies (Table 5, Simulation 3), the likelihood of being bit and potentially contracting malaria can be dramatically affected. Adoption of both technologies still require efficacy near 90%. It may be surprising that at all levels of prevention technology efficacy between adopter and non-adopters that the number of days ill is not larger. This however is explained by the high rate of mosquito born malaria in the population. From the epidemiological descriptive variables in Table 3, we see that there are between 5 and 6 female mosquitos per night in each room. The simulation targets a number of mosquitos per human a little under 2 per night since the number of sleepers per room is on average greater than 2. At the extreme of 90% prevention technology efficacy, the probability of one mosquito being repelled is 99% but the probability of 50 mosquitos (approximately the average over 30 days) being repelled is only around 60%. However, at 90% prevention technology efficacy, expected net income is higher for joint technology deployment than all other technology choices available. This is because each of the technologies has the repellent power specified, thus making it nearly twice as effective, allowing the individual to capture a higher returns through reduction in the probability of infection.

As a robustness check, Table 6 explores what happens if bednets are more effective at killing mosquitos than a 30% rate. Using a moderate rate of repellent power for bednets (50%) one

need only increase the bednet kill rate to 50% before owning a bednet becomes profitable. Under scenarios in which the effectiveness of bednets at killing mosquitos becomes large the payoff to using a bednet uniformly increases as its kill rate increases. In addition to individual net benefits of using bednets being large, payoffs to society also become large as the worker not using be bednet has higher expected net returns as well.

7. Conclusion

Making use of new data from our previous study (Dillon et al. 2012) which provides estimates of the effect of malaria treatment on income from labor among agricultural workers, this paper presents the results of a cost-benefit analysis comparing preventive with curative treatment using a static and simulated expected income approach. Considering a rational decision model to benchmark future modeling, the paper analyses what the preferred treatment would be for agricultural workers if they are purely self-interested and make health investment decisions based on key costs and benefits only. While this rational model has shortcomings, it also provides a good benchmark as it helps to understand the rational part of the decision making process. The simulation estimates the expected earnings for different infection rates making use of predicted probabilities for preventive care obtained from the same data on agricultural workers, and focusing on bednet use.

Under both static and dynamic models, if bednets reduce the probability of infection by the WHO suggested effect size of 20 percentage points, the expected income from preventive treatment is higher than curative treatment. This presumed effect size may be predicated on

many other factors, including the individuals own correct use of the bednet during times of the day where vector transmission is potentially the highest. The use of preventive and curative treatment by other household members may also contribute to the prevalence of the vector in the individual's community and the effectiveness of bednets in reducing overall transmission rates. Bednets are likely more effective in highly endemic areas. As we have suggested above, the cost of preventive care may also be a relevant factor as expected income differences between the preventive and curative care are relatively small.

Overall workers do not have a strong incentive to use prevention technologies so long as their effect sizes are modest. Additionally it is unlikely that the effectiveness of either technologies at repelling mosquitos will increase much above 50-70% without a corresponding change in behavior since workers are frequently not within the protected enclosures created by prevention technologies during primary feeding times. Despite this, the simulation implies several routes to improving the net benefits of prevention technologies. The most direct route to improving earnings for both users and non-users of ITNs is to increase the effectiveness of the bednet insecticide. Improved insecticide in bednets results in mosquitos having shorter life expectancies and smaller probabilities of passing on malaria. In the simulation, bednets are assumed to only be effective for one season. If however, bednets were more durable and effective for two seasons, then bednets would provide a positive return at all levels of repellent power according to our estimates.

In future work, it would be interesting to investigate alternative types of preventative treatment available to workers including those measures that may be taken at work as opposed to

household based preventative measures. Our results should not be taken as an indication that all preventative measures have similar expected income effects. Certainly, different types of prevention in different epidemiological environments may have significantly different returns. More research into the adoption of preventative methods at the individual, firm and community level and their effectiveness is necessary to further assess the impacts of preventative versus curative treatments. This paper provides one piece of evidence for this larger research program.

Figures and Tables

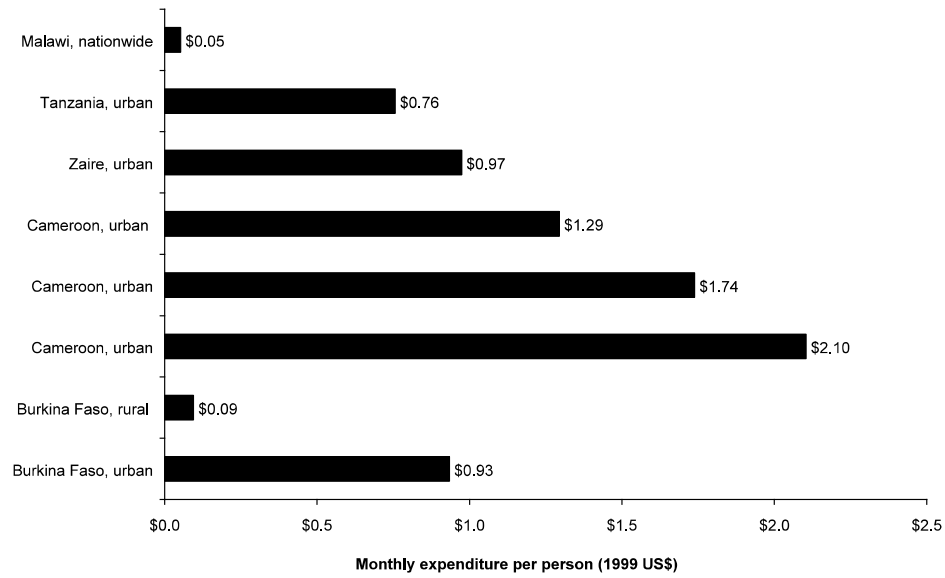


Fig. 1. Monthly per capita expenditure by households on malaria prevention-related activities. Source: Updated from Mills (1998) [84], with data drawn from Ettling et al. 1994, Evans, 1994, Zandu et al. 1991, Louis et al. 1992, Desfontaine et al. 1989, Desfontaine et al. 1990, CNLP 1995, and Guiguemde et al., 1994 [3,9,10,85–89].

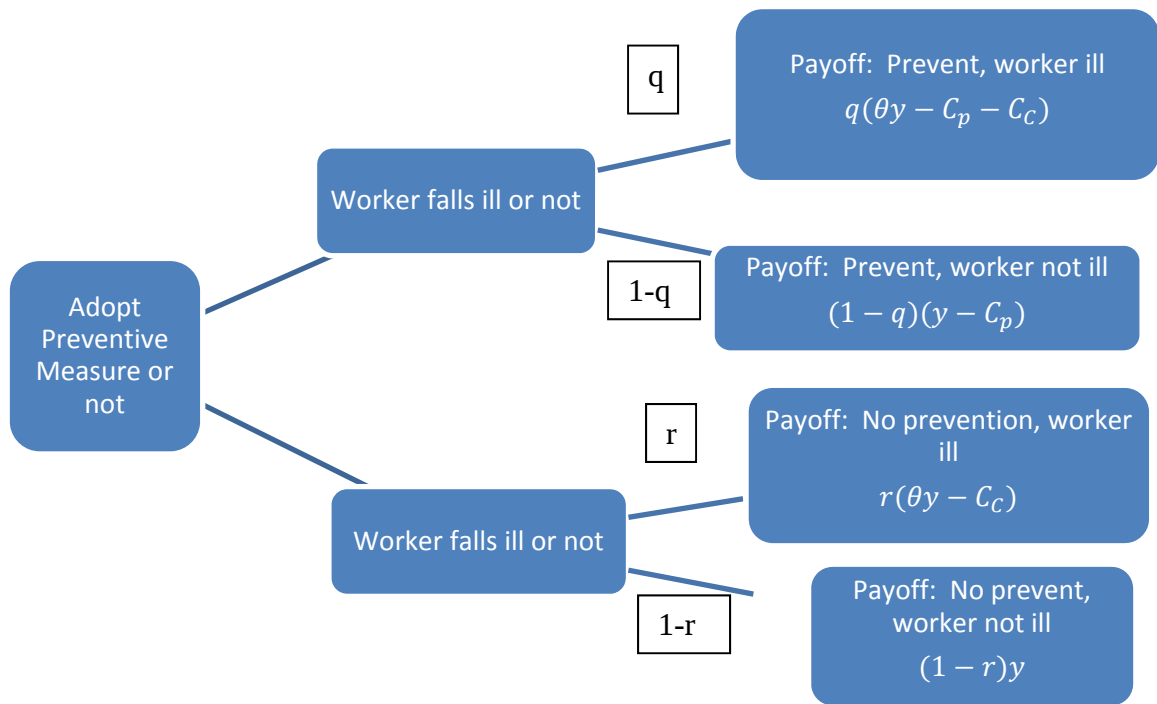


Figure 2: Decision Tree of Workers in Comparing Preventive versus Curative Treatment

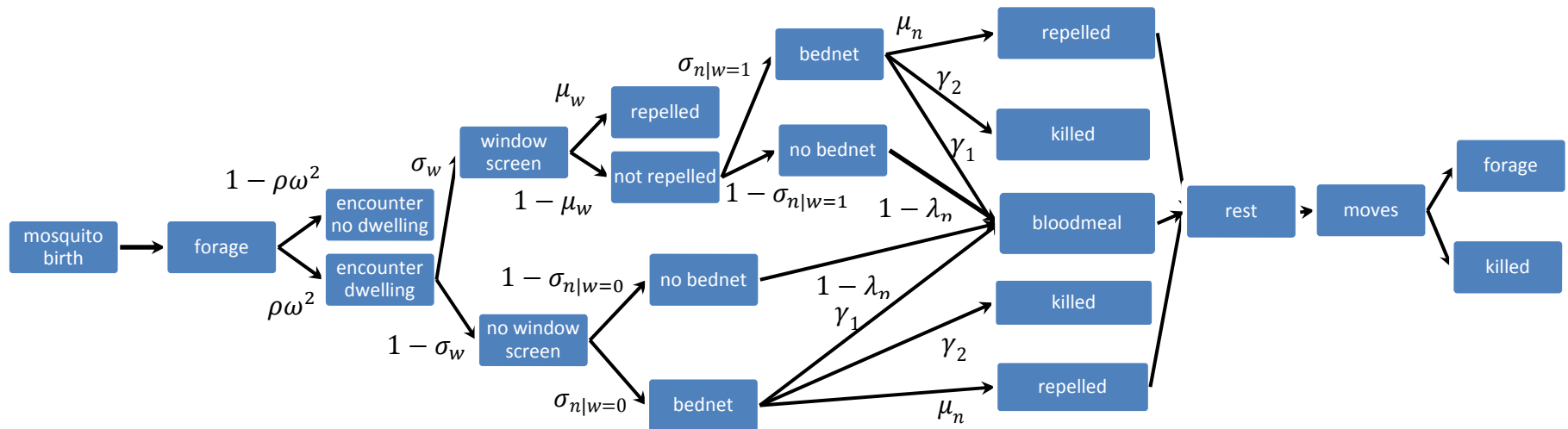


Figure 3: Modeling malaria environments to estimate the probability of blood meal for a mosquito.
 $P(b_t^m) = f(dwelling^m, prevention^m, hazards^m)$

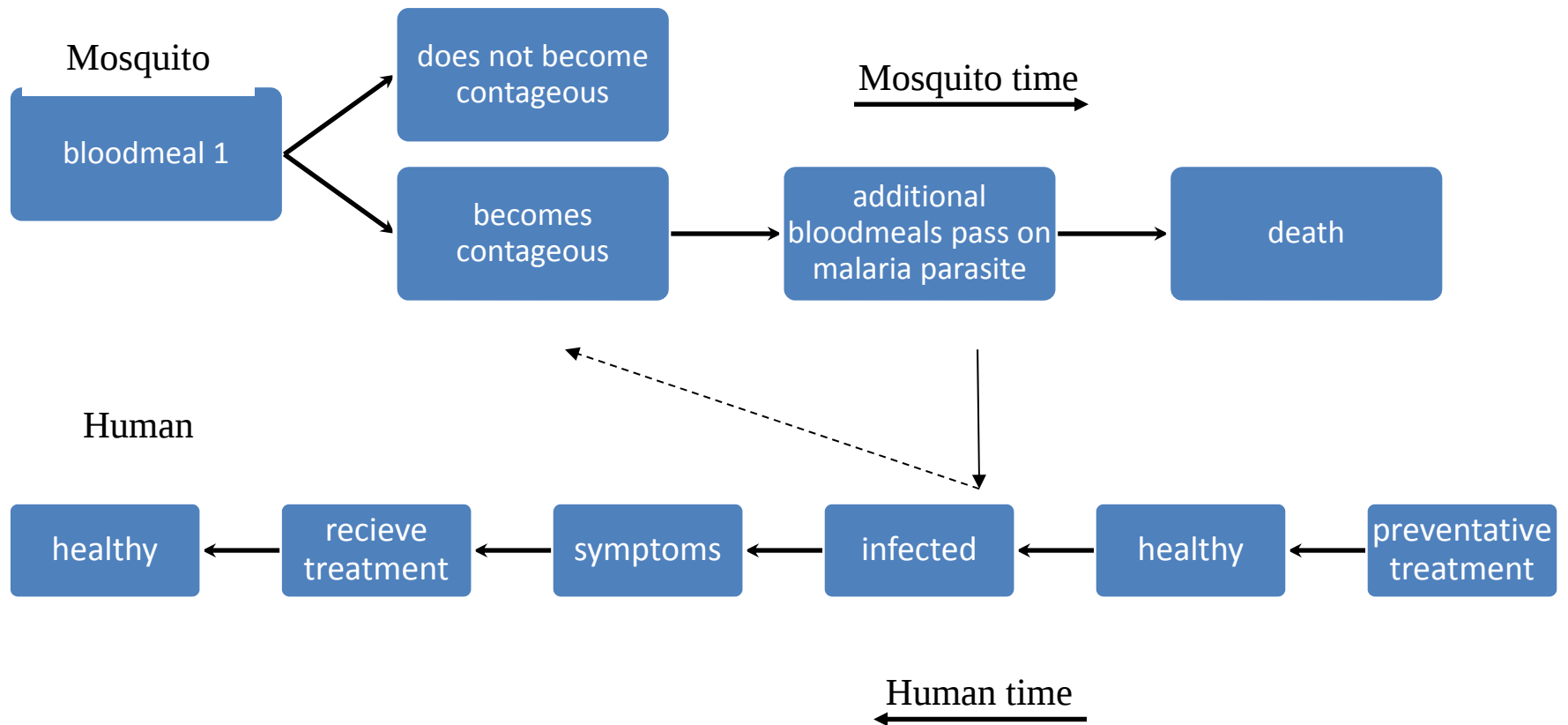


Figure 4: Modelling the probability of a mosquito infecting a human. $P(I^h) = f(b_t^m | \text{infected } b_{t-1}^m)$

Table 1: Summary Statistics of Worker Individual and Household Characteristics by Round

	Round 1 (n=804)		Round 2 (n=897)		Pooled (1,701)	
	mean	Sd	mean	sd	mean	sd
Bednet Use Last Night (%)	22%		74%		49%	
Worker Age	30.096	(8.135)	29.988	(6.986)	30.039	(7.549)
Worker is Casual Worker	1.000	(0.000)	1.000	(0.000)	1.000	(0.000)
Number of Years of Experience	5.416	(6.556)	6.236	(5.251)	5.848	(5.916)
Attend Formal Schooling	0.858	(0.349)	0.862	(0.345)	0.860	(0.347)
Highest Level of Education						
Nursery School	0.006	(0.079)	0.003	(0.058)	0.005	(0.068)
Primary School	0.108	(0.311)	0.117	(0.322)	0.113	(0.317)
Junior High	0.150	(0.358)	0.147	(0.354)	0.149	(0.356)
High School	0.470	(0.499)	0.478	(0.500)	0.474	(0.499)
More Than High School	0.071	(0.257)	0.041	(0.199)	0.055	(0.229)
Received on the Job Training	0.393	(0.489)	0.524	(0.500)	0.462	(0.499)
Family Size - living in the same dwelling						
# of Spouses	0.756	(0.675)	0.866	(0.671)	0.814	(0.675)
# of Children	2.378	(2.576)	2.857	(2.681)	2.631	(2.642)
# of Others	1.180	(3.993)	1.579	(2.568)	1.390	(3.324)
Total	5.315	(5.106)	6.302	(4.028)	5.835	(4.594)
# of Workers in Gang from Same Village	13.750	(16.259)	12.407	(12.098)	13.042	(14.229)
Household Asset Index (Normalized)	-0.343	(0.999)	0.318	(0.899)	0.006	(1.003)

Table 2: Worker Earnings, Days Worked and Wages by Round

	Earnings	Days Worked	Wage
<i>Round 1 (N=816)</i>			
January	17,773	17	1,023
	7,103	5	299
February	21,926	20	1,103
	8,075	4	315
March	16,248	16	1,053
	6,889	6	334
April	11,432	13	862
	4,941	6	230
<i>Round 2 (N=745)</i>			
January	20,106	24	862
	(43,710)	57	477
February	15,508	20	789
	(37,354)	50	616
March	13,952	16	897
	(32,065)	39	210
April	22,182	22	1,010
	49,561	54	544

Note: Means are reported with standard deviations in parenthesis. Sample differences between Tables 1 and 2 result from merging data collected in the field and firm records where some workers identifiers in either of the datasets does not permit matching.

Table 3: Household Indoor Adult Pyrethrum Spray Survey

	Village 1 (N=98)		Village 2 (N=133)		Village 3 (N=135)		Total (N=366)	
	mean	sd	mean	Sd	mean	sd	mean	sd
Mosquitos had bloodmeal	0.698	0.463	0.691	0.465	0.903	0.297	0.785	0.412
Mosquitos had sporozoites	0.189	0.395	0.191	0.396	0.086	0.282	0.145	0.353
# of female mosquitos	5.396	7.091	6.324	4.148	4.871	3.536	5.463	4.846
# of sleepers in room	3.113	1.396	4.529	1.607	3.452	2.008	3.710	1.833

Table 4: Determinants of Preventive Technology Use

Dependent Variable (1=Yes)	Worker slept the previous night under bednet	Worker has screens on his windows	Correlation in Technology Choice (ρ)
Worker Age	0.00254 (0.00556)	-0.00706 (0.00530)	
Number of Years of Experience	0.000167 (0.00783)	-0.00375 (0.00758)	
Highest Educational Achievement			
Nursery or Primary School	0.151 (0.123)	0.190 (0.118)	
Junior High School	0.158 (0.117)	0.273** (0.111)	
High School or More	0.178* (0.0934)	0.419*** (0.0892)	
Received on the Job Training	0.162** (0.0692)	0.296*** (0.0661)	
# of Spouses	0.130** (0.0597)	-0.164*** (0.0576)	
# of Children	-0.0225 (0.0162)	0.0329** (0.0158)	
Asset Index	0.0382 (0.0365)	0.0489 (0.0344)	
Round****	1.417*** (0.0727)	0.786*** (0.0693)	
Constant	-1.196 (0.436)	-0.022 (0.420)	0.336*** (0.0451)
Observations	1,705	1,705	1,705

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**** Dummies for local government area were also included

Table 5: Expected Income in Naira from Preventative and Curative Treatment Choices from Epidemiological Simulation

Simulation 1:				Curative Non-Users			
Bednet Only Users							
Repellant Power	# days ill	# treatments	Net Earnings	# days ill	# treatments	Net Earnings	Prevention Payoff
10%	1.45	0.80	17462	1.96	0.83	17514	-52
30%	1.45	0.77	17480	1.95	0.82	17520	-41
50%	1.38	0.74	17508	1.93	0.81	17527	-19
70%	1.29	0.68	17558	1.90	0.80	17539	19
90%	1.02	0.52	17693	1.88	0.79	17553	140

Simulation 2:				Curative Non-Users			
Window Screen Only Users							
Repellant Power	# days ill	# treatments	Net Earnings	# days ill	# treatments	Net Earnings	Prevention Payoff
10%	1.74	0.77	17453	1.86	0.78	17557	-104
30%	1.78	0.78	17444	1.89	0.79	17546	-102
50%	1.76	0.78	17447	1.91	0.80	17535	-88
70%	1.72	0.76	17468	1.93	0.81	17527	-59
90%	1.55	0.66	17543	1.94	0.82	17522	21

Simulation 3:				Curative Non-Users			
Bednet and Window Screen Users							
Repellant Power	# days ill	# treatments	Net Earnings	# days ill	# treatments	Net Earnings	Prevention Payoff
10%	1.46	0.74	17377	1.91	0.80	17532	-155
30%	1.43	0.73	17390	1.88	0.79	17543	-153
50%	1.36	0.68	17428	1.91	0.80	17534	-106
70%	1.18	0.56	17525	1.90	0.80	17539	-14
90%	0.70	0.26	17792	1.91	0.81	17532	260

Bednets kill at 30%. Screens repel at 70% and bednets at 50% when not otherwise specified.

** Cost of bednets is 5 USD or 750 Naira divided over 6 months (one working period).

*** Cost of screens is 20 USD or 3000 Naira divided over 12 months (two working periods).

Note: Maximum monthly earnings is 18309 if well and minimum is 17240 if ill.

Table 6: Expected Income in Naira from Varying the Efficacy of Insecticide treated bednets.

Bednet Kill Rate	Bednet Only Users			Curative Non-Users			
	# days ill	# treatments	Net Earnings	# days ill	# treatments	Net Earnings	Prevention Payoff
10%	1.56	0.85	17413	1.99	0.84	17532	-119
30%	1.38	0.74	17508	1.95	0.82	17520	-41
50%	1.08	0.57	17649	1.83	0.76	17534	115
70%	0.78	0.37	17820	1.68	0.69	17539	281
90%	0.48	0.18	17987	1.60	0.63	17666	321

** Cost of bednets is 5 USD or 806 Naira divided over 6 months (one working period).

Note: Maximum monthly earnings is 18309 and minimum is 17240.

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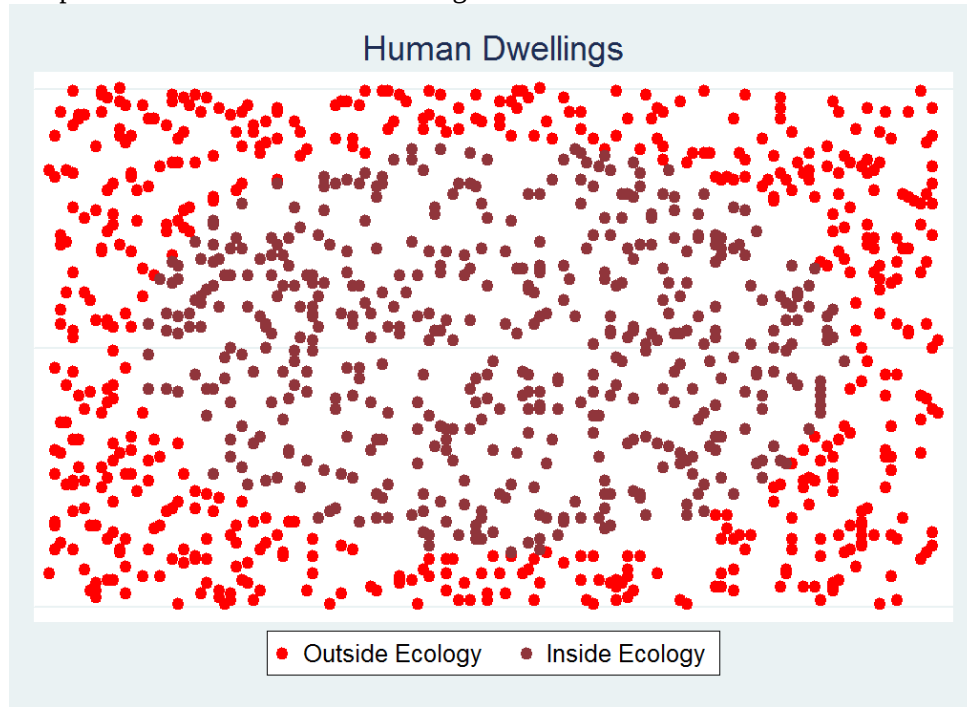
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Appendix 1: Simulation Methodology

1.1 Initialization Conditions

There are initially ρ humans distributed from a uniform distribution throughout a two dimensional (0,1) grid²⁸. The grid is pixelated into a matrix for which the width of pixels is defined as ω and consequentially the number of pixels is calculated as ω^{-2} . Each individual is forced to occupy a unique pixel. Within the grid there is a central ecologic zone with a radius r . The proportion of the total grid space that is part of the ecologic zone is $E = 1 - \pi r^2: 0 \leq r \leq .5$. Infection rates among humans are initially ι_h and among mosquitos ι_m . These rates are arbitrarily chosen and unimportant for the steady state outcome so long as they are sufficiently high to ensure that malaria exists among the long run population. About 50% of humans and mosquitos initially infected with malaria are contagious.

Figure 1: A sample distribution of human dwellings



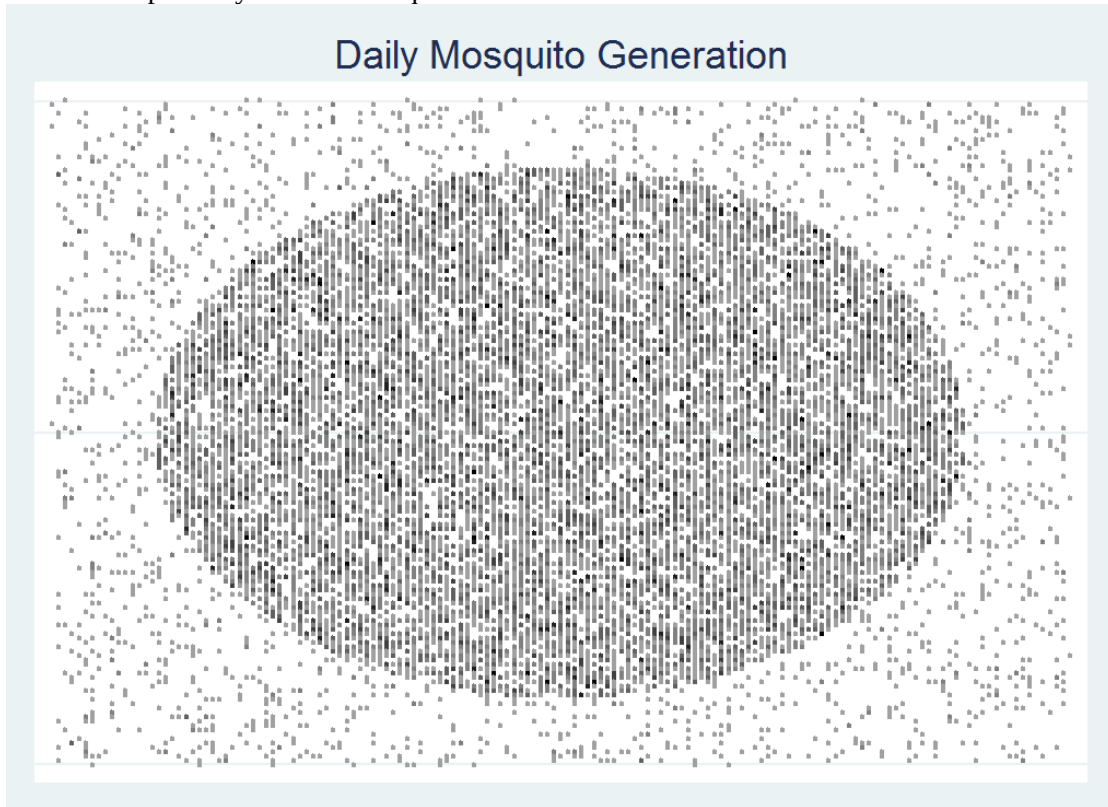
$\omega = .0067, \rho = 1000, r = .4$

1.2 Daily Mosquito Emergence

²⁸ Such a generic grid space is meant to represent any size of square homogenous space which the user may desire to define.

Each day, a total potential number of mosquitos emerging τ . Outside of the non-ecologic zone, per-pixel λ_0 percentage of mosquitos emerge relative to the ecological zone. Thus the total expected number of mosquitos emerging per day is $T = \tau(\pi r^2 + \lambda_0(1 - \pi r^2))$. Each potential mosquito occupies a pixel space uniformly distributed. If a mosquito is potentially going to emerge outside of the ecological zone then that mosquito has a λ_0 chance of being immediately dropped from the simulation. Through this mechanism mosquitos have higher densities within the ecological zone. The population T is added to the surviving mosquito population from the previous day.

Figure 2A: A sample daily draw of mosquitos.



A little over 19 thousand mosquitos emerge daily. Darker dots represent more than one mosquito for that pixel. $\omega = .067$, $r = .4$, $\lambda_0 = .1$, $\tau = 35,000$, $T = 19,333$

1.3 Daily Mosquito Routine

Each day a percentage λ_d of the previous days population dies to predation or mishap. Mosquitos begin in whatever position they ended the previous day in. Each mosquito moves from their starting position in the x direction a single draw from $N(0, \beta)$ and in the y direction a single draw from $N(0, \beta)$. Mosquitos end their movement in the center of whatever pixel their final position places them in.

If a mosquito ends its movement on the same pixel as a human dwelling then that mosquito is considered to have encountered that dwelling and will attempt to bite the occupant. If the dwelling has a window screen then the mosquito is turned away with a probability of μ_w . If the occupant uses a bed net then the mosquito is turned away at a rate μ_n and killed at a rate λ_n . If the mosquito is successful at getting past the window screen and bed net and surviving the bed net then the mosquito has the probability λ_p of being killed by its prey while attempting to feed (before transferring sporozoites).

1.4 Human Infection Cycle

Humans first exposed to malaria (via mosquito bite) have a chance of immediately fighting off the exposure at a rate indicated by *human resistance*. If malaria is not fought off they have a number of days identified as the *human precontagious period* in which the human is infected with malaria but is not producing contagious gametocytes. Likewise, humans have a number of number of days since being first infected before coming down with symptoms, labeled the *prepatent period*. Once past the prepatent period, humans enter the *symptomatic period*, experiencing fever every f days (starting the first day of the symptomatic period). For each episode of fever, that person decides to seek treatment at a probability predicted from the survey data (around 80%). If the person decides to seek treatment, that person delays a number of days also predicted from the survey data (around 3 days). Once treatment is taken the person immediately enters the *immunity period* in which he is no longer infectious and can no longer be infected.

1.5 Mosquito Infection Cycle

Mosquitos emerge uninfected each day and join the general population of mosquitos. If an uninfected mosquito bites a contagious human that human that mosquito has a chance of not becoming infected at a rate indicated by *mosquito resistance*. If the mosquito becomes infected the mosquito enters the *mosquito precontagious period* in which the mosquito is infected but is not yet emitting contagious sporozoites. Once contagious, the mosquito continues to pass on infectious sporozoites until its death. The upper limit of the life expectancy of a mosquito can be approximated with a negative binomial distribution $E(\text{life expectancy}) = \lambda_d / (1 - \lambda_d)$.

1.6 Calculating Daily Mosquito Population and Pixel Size

A number of back of the envelope calculations were used to calculate the daily mosquito population and the pixel size. The total annual mosquito population was taken as 9×10^6 annually from Killeen et al. (2007). Since we are only modeling half the year, we reduce this number to 4.5×10^6 . Dividing that population into daily values ($4.5/180$) we get 25,000. Since $[T = \tau(\pi r^2 + \lambda_0(1 - \pi r^2))$ and $T = 25 \times 10^3, r = .4, \lambda_0 = .1]$ therefore $\tau \approx 35,000$. Finally we need to calculate the expected number of mosquitoes alive at a given time. As $t \rightarrow \infty$ the upper limit of the number of expected number of mosquitoes living at time t can be expressed as the upper limit of the life expectancy of mosquitos times the number of mosquitos emerging daily. The upper limit of life expectancy can be represented as the mean of a negative binomial distribution with probability of success (survival) equal to $1 - \lambda_0 = .8$ yielding a life expectancy of 4 days per mosquito²⁹. Thus the total expected number of mosquitos currently living at time t given t is large is equal to $E\left(\sum_{i=0}^t TP_i(t)\right)$

with P_i representing the probability that a mosquito emerging in period i will survive to period t and T representing the expected number of mosquitos emerging during day i . Pulling out the constant T from

²⁹ This is an upper limit because it only calculates the probability that the mosquito population will experience mortality resulting from predation. Other mechanisms though less important, such as bet nets and death by prey, exist as well.

outside the expected value we are left with $E\left(\sum_{i=0}^t P_i(t)\right)$ which approaches from below mosquito life expectancy as $t \rightarrow \infty$. Thus we can expect to have about 77,000 mosquitos ($4*19,333$) living during any given day (assuming t is large).

From the household mosquito traps we have an estimated number of mosquitos per dwelling at 6 per night. The expected number of mosquitos encountering a dwelling is roughly the number of mosquitoos currently living divided by the number of pixels in our grid. That is $E(\text{mosquitos}) = 6 = 77,000/\omega^2$. Solving for ω we find the optimal grid size of .0088.

Table 1A: Model Parameters

Parameter	Definition	Value	Source
r	Radius of ecological zone.	.4	Model Calibration Parameter ³⁰
ι_m	Initial infection rate among mosquitos.	30%	Model Calibration Parameter ³¹
ι_h	Initial infection rate among humans.	30%	Model Calibration Parameter
ρ	Population of humans	1000	Killeen et al. 2007
ω	Pixel height and width. ³²	.005	Section 1.4
T	Total number of mosquitos emerging daily. ³³	19,333	Killeen et al. 2007
τ	Total potential number of mosquitos emerging daily.	35,000	Section 1.6
λ_0	% of mosquitos emerging per pixel in non-ecological zones relative to ecological zones.	10%	Model Calibration Parameter ³⁴
λ_d	% of existing mosquito population killed daily by predation/mishap.	20%	Killeen et al. 2007
λ_n	Base % of mosquitos killed by net when encountered.	40%	Killeen et al. 2007
λ_p	% of mosquitos killed by prey when encountered.	10%	Killeen et al. 2007
β	Movement speed of mosquitos $x_{t+1} = x_t + N(0, \beta)$ and $y_{t+1} = y_t + N(0, \beta)$	.005	Sensitivity Analysis
μ_w	Base % of mosquitos turned away by window screens.	60%	Model Variable
μ_n	Base % of mosquitos turned away by bed nets.	60%	Model Variable
<i>Human resistance</i>	% of contagious bites for which infection to an uninfected human is unsuccessful	25%	Model Calibration ³⁵

³⁰ A radius of .4 produces a scenario in which about half the zone is ecological zone for mosquitoes. This seems similar to Collins 2006.

³¹ The initial rate of infection among mosquitos and humans is somewhat unimportant since the model quickly converges on a steady state characterized by the other parameters in the model.

³² See subsection on calculating mosquito population and number of pixels..

³³ See subsection on calculating mosquito population and number of pixels.

³⁴ Including an ecological zone in which mosquitos have higher reproduction rates was inspired by Carter 2002. Further work needs be done to see if the relative returns to preventative technology may vary as a function of mosquito ecology. A value of 0 to 20% were experimented with resulting in little variation in the results of the model.

<i>Human precontagious period</i>	# of days since being first infected before the human becomes contagious.	15	Collins 2006
<i>Human Prepatent Period</i>	# of days since being first infected before the human become symptomatic.	21	Collins 2006
<i>Immunity Period</i>	# of days since taking the antibiotic that the human is immune to reinfection by malaria.	7	White (2010)
<i>Mosquito precontagious period</i>	# of days since first feeding on a human before becoming contagious.	8	Killeen 2007
σ_w	% of population with window screen ³⁶	variable	Drawn from Survey Sample
$\sigma_{n w=0}$	% of population with bednet given no window screen in use	variable	Drawn from Survey Sample
$\sigma_{n w=1}$	% of population with bednet given there is a window screen in use	variable	Drawn from Survey Sample

³⁵ This is a largely unknown value and a somewhat free value to vary in an attempt to calibrate the model so as to produce results that are properly calibrated. Values between 1% and 80% were experimented with resulting in at time greatly decreased rates of malaria infection. Based on this result a relatively low natural resistance seemed appropriate though one too low seemed infeasible.

³⁶ See pie chart on technology choice.