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Observing the Effects of Antimalarial Drug Availability on Women's Work Absenteeism

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Observing the Effects of Antimalarial Drug Availability on Women's Work Absenteeism

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1. Abstract

This study aims to provide insight on how availability of antimalarial drugs can help alleviate the economic burden of malaria. Much of the existing literature that looks into the effects of antimalarial drug availability focuses on the associated health benefits, but fails to draw a link to the economic benefits that may also be incurred. Using data from the 2015-2016 Tanzania Demographic and Health Survey and Malaria Indicator Survey, this study performs a series of multiple regressions to observe how increased availability of artemisinin-based combination therapies (ACTs), a front-line antimalarial drug in most African countries, affects likelihood of work absenteeism for women. Women living in village-clusters with higher availability of ACTs were found to have decreased likelihood of work absenteeism, with a 1% cluster-level increase in ACT availability leading to a 0.295 percentage point decrease in likelihood of absenteeism. Furthermore, ACT availability was found to have a greater effect on decreasing likelihood of absenteeism for women who were self-employed agricultural workers. A 1% cluster-level increase in ACT availability for these women would lead to a 0.5459 percentage point decrease in likelihood of absenteeism. By finding that ACTs have an effect of decreasing likelihood of absenteeism, this study confirms that ACTs can be used as a tool to both decrease the health and economic burdens of malaria. Additionally, identifying self-employed agricultural workers as a group that sees increased benefits of ACT availability can help inform policymakers on how scarce resources can best be allocated to see the most impact on alleviating the economic burden of malaria.

2. Introduction

Malaria has been, and continues to be the leading cause of death and disease in many developing countries (Cowman et al., 2016). With over 3.3 billion people across 97 countries at risk, and an estimated 200 million annual cases resulting in roughly 600,000 deaths, malaria poses a significant global health issue (Cowman et al., 2016). While the various health and economic effects of malaria have been well studied, there are still significant gaps in the existing literature.

The prevalence, health effects, and treatment of malaria have been well documented and analyzed over the past several decades. Major international organizations, such as the WHO keep detailed records of malaria incidence, mortality, and expenditures for prevention, treatment, research. (WHO, 2018). The biology of malaria is also relatively well understood, with plasmodial parasites carried by mosquito vectors known as the cause of the disease (Cowman et al., 2016). Research on the mechanisms of action for antimalarial drugs has also been extensively pursued. Currently, the biochemical mechanisms of the first-line antimalarial drug in Africa, artemisinin-based combination therapies (ACTs) are being studied, with a rudimentary understanding on how they specifically targets and kill disease parasites (Cowman et al., 2016; Cui and Su, 2009). Additionally, the effects of drug availability on malaria incidence and mortality has been studied, with increased ACT availability being attributed to decreases in malaria morbidity (Nkumama et al., 2017; Eastman and Fidock, 2009).

The economic effects of malaria have also been well researched, with existing literature looking into the direct and indirect costs of the disease at the individual, household, national, and macroeconomic levels. Direct costs include expenditure on drugs, diagnostics, and other treatments, whilst indirect costs are measured by loss of income from missing work due to either personal or familial illness (Arrow et al., 2004). Malaria is most prevalent in developing, low-income regions, which further exacerbates the economic burden of the disease (Gallup and Sachs, 2001).

Despite the well-researched field of malaria in terms of biology and economics, there remain shortcomings in bridging the gap between the two subjects. A weakness in current literature is the lack of in-depth analyses on how availability of malaria treatment affects an individual's economic well-being. Much of the existing literature that looks into the effects of availability of antimalarial drugs (most of the recent literature focusing on ACTs) primarily focuses on their effect on decreasing malaria incidence.

This study contributes to bridging the gap between the biological and economic studies of malaria by analyzing the effect of ACT availability on an individual's economic well-being. By understanding the economic benefits of malaria treatment, this study captures the downstream beneficial effects of malaria treatment that are not just limited to improved health.

To capture the individual-level economic benefits of ACTs, this study looks at the effect of ACT availability on women's absenteeism from work in Tanzania. Work absenteeism is used as an important measure of the indirect costs associated with illness from malaria, as missing work results in loss of income—an opportunity cost. Absenteeism is an indirect cost, as it is not a cost that is directly incurred from treatment of malaria, but one that arises as a downstream consequence of contracting the disease. Existing literature on the financial burden of malaria in Tanzania has analyzed the direct costs of treatment on the national and individual levels (Jowett and Miller, 2005), whilst research on the effects of ACT availability measures decreases in mortality and morbidity (Bhattari et al., 2007). After a thorough review of the literature, I was unable to find existing studies that measure the effect of ACT availability on alleviating the economic burden of malaria, which this study aims to capture.

3. Historical Background

3.1 Literature on the Economic Burden of Malaria

The economic burden of malaria has been studied and quantified on both the microeconomic and macroeconomic levels. Microeconomic studies look into both direct and indirect costs borne by individuals, households, governments, and other third-party organizations (e.g. nonprofits), tallying the total costs of prevention, treatment, and lost opportunity (Arrow et at., 2004). On the individual and household level, there have been many studies conducted across various African countries that estimate expenditures on malaria prevention, treatment, and associated loss of opportunity (Arrow et al., 2004).

Expenditures on malaria prevention vary by region and income level, but are generally spent to purchase items such as mosquito coils, sprays, repellents, and bednets (Arrow et al., 2004). Studies have found that lower-income individuals spend less on prevention, but also bear the highest economic burden of malaria (Ettling et al., 1994). In rural Malawi, individuals in very poor farming communities spent roughly $0.05 per month on malaria prevention (Ettling et al., 1994), whilst individuals in urban Cameroon had a much higher spending of $2.10 a month (Desfontaine et al., 1989).

The direct costs of malaria treatment include the cost of drugs, diagnostics, and other medical fees (Hailu et al., 2017; Onwujeke et al., 2013). Cost of treatment poses a larger burden on the poorest individuals most prone to infection, as they spend more on treatment, both in actual amount and relative to their income. A study conducted in rural Ethiopia by Hailu et al. (2017) found that direct costs of malaria treatment amongst the poorest individuals was nearly twice that of those in the wealthiest socioeconomic demographic. Other studies confirm the larger impact of direct costs on lower income households, a study by Ettling et al. (1994) finding that malaria treatment took up 28% of household income for very poor households, and only 2% for other households. Lack of spending on malaria prevention potentially contributes to higher spending on treatment, particularly if an individual more frequently contracts the disease due to lack of preventative measures. Poor individuals who cannot afford the proper prevention measures may be more prone to infection, which in turn causes them to spend more on treatment when they do become sick.

Although the direct costs of malaria pose a significant financial burden on individuals, the indirect costs prove to have a much larger effect. Indirect costs of malaria are measured by calculating the loss of income for missing work due to personal illness, or from caring for ill family members (Arrow et al., 1994; Onwujeke et al., 2013; Hailu et al., 2017). Measuring the economic burden of malaria on households in Southeast Nigeria, Onwujekwe et al. (2013) found that the direct treatment costs per household for each case of malaria was $3.05—much lower than the indirect cost of $9.11. Similar findings were observed in Ethiopia, with the total cost of $6.74 to a household per case of malaria consisting of $4.55 in indirect costs (Hailu et al., 2017). Missing work due to either personal or familial illness can cause a significant economic burden on individuals and households, particularly those who are low income, lack stable employment, or are dependent on seasonal work (e.g. harvest seasons for farmers). For these individuals, absenteeism from work results in loss of income, which in turn may cause other hardships such as inability to afford adequate food, housing, or education for their children. Thus, it is crucial that the poor prevent malaria infection as much as possible, and when they do become ill, are able to recover quickly. In the past decade, the development and wide-scale use of quick-acting and effective artemisinin-based combination therapies (ACTs) is thought to have reduced the duration of illness from malaria (Hailu et al., 2017). However, to my knowledge, there are no comprehensive studies that look at how availability and use of ACTs affect indirect costs borne by individuals and households prone to malaria.

3.2 Literature on the Biology of Malaria

The transmission and spread of malaria occurs in four steps— a mosquito vector transmits the disease parasites to a human host, the human host incubates the parasites and allows them to multiply, the disease is re-transmitted to a mosquito that bites the infected human host, and the cycle restarts when a new human is bitten (Figure 1).

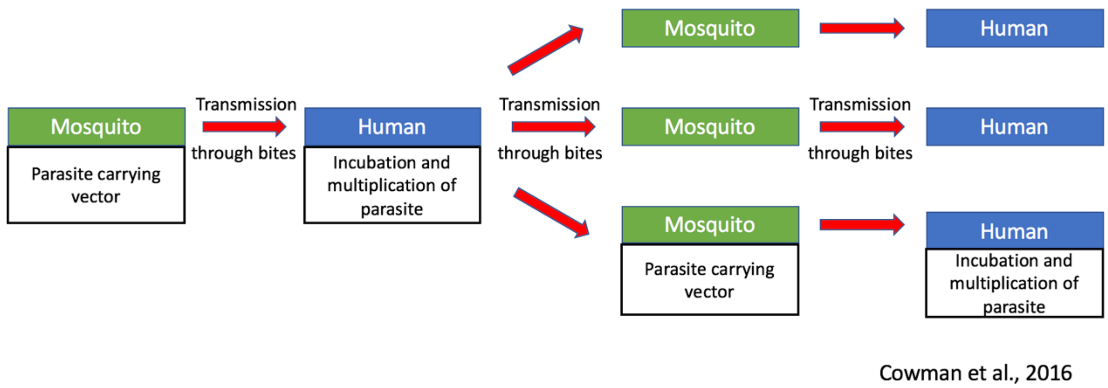


Figure 1.

Malaria is caused by unicellular eukaryotes of the *plasmodium* genus, six species of which present health risks to humans: *Plasmodium falciparum, P. vivax, P. ovale curtisi, P. ovale wallikeri, P. malariae,* and *P. knowlesi*. *P. falciparum* and *P. vivax* are the two primary species considered as the highest risk for humans (Cowman et al., 2016). Despite the relatively widespread distribution of malaria in tropical regions, the effects of the disease are largely concentrated in certain regions, with over 90% of deaths occurring in Africa (Cowman et al., 2016).

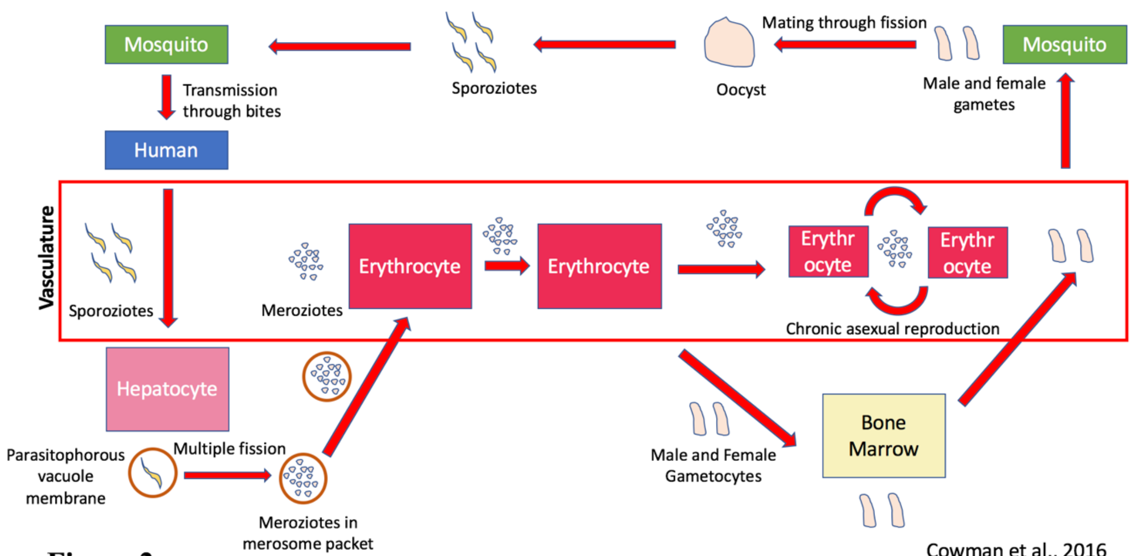


Figure 2.

Figure 2 above shows the development and spread of malaria in human and mosquito hosts. Human infection of malaria begins when an individual is bitten by a feeding mosquito, which serves as a vector for the parasite. Only female mosquitoes of certain species in the *Anopheles* genus are carriers of the disease (WHO 2016). When the feeding mosquito penetrates the skin, infection is initiated as sporozoites are injected into the individual's body (Cowman et al., 2016). Sporozoites are the malaria parasite in a spore-like "migratory mode," which enter the vasculature (vascular system) of the host until they are transported to the liver (Cowman et al., 2016). Upon entering the liver, the sporozoites exit blood vessels and enter hepatocytes (liver cells) through Kupffer or endothelial cells, both which serve as barriers between the bloodstream and the liver (Cowman et al., 2016). When a suitable hepatocyte is found, sporozoites form a parasitophorous vacuole membrane (PVM), which allows the parasites to create a protective membrane around themselves against the hepatocyte's defense mechanisms (Ward et al., 1993; Cowman et al., 2016). Once a PVM is formed, the sporozoites asexually reproduce by multiple fission until tens of thousands of daughter cells are produced in the form of merozoites (Cowman et al., 2016). Merozoites are released from the infected hepatocyte back into the vasculature in packets called merosomes, where they encounter and infect erythrocytes (red blood cells) (Cowman et al., 2016). Once in the vasculature and in contact with erythrocytes, merozoites continue a chronic cycle of asexual reproduction as they continuously take over erythrocytes and exponentially multiply in number, infecting more and more erythrocytes (Cowman et al., 2016).

Retransmission of malaria from humans to mosquitoes occurs after the chronic cycle of merozoite reproduction in the vasculature begins. During the process of asexual reproduction in the bloodstream, a portion of merozoites undergo a change which reprograms them to form male or female gametocytes, specialized cells that can form gametes through meiotic division (Cowman et al., 2016). Once the merozoites undergo change into gametocytes, they sequester in bone marrow for several days, until they have developed into a stage to be infectious to mosquitoes (Cowman et al., 2016). At this stage, they re-enter the vasculature and infect mosquitoes feeding on the human host (Cowman et al., 2016). Within the mosquito vector, the gametocytes emerge as male or female gametes, mate through fusion, and undergo several developmental stages until they become sporozoites that can be re-transmitted to humans through feeding mosquitoes (Cowman et al., 2016). This restarts the entire cycle of infection once more.

3.4 Literature on Epidemiology of Malaria

Malaria is present in 97 countries, and its transmission is primarily limited by environmental effects, in particular temperature, which limits mosquito vectors from sustaining parasite development (Cowman et al., 2016). In regions with malaria, disease incidence is determined by the frequency of contact between infected mosquitoes and humans (Cowman et al., 2016). Regions with high mosquito and human density result in more frequent contact, causing in higher infection rates.

Regions with endemic malaria that have high frequency of transmission tend to have fewer cases of severe malaria and death in adults, with most of the severe disease burden resting on children (Cowman et al., 2016). This is due to the naturally acquired immunity that develops in individuals that have been infected multiple times (Cowman et al., 2016). It is hypothesized that individuals who have been infected multiple times develop immune responses through antibodies against the parasite, which drastically reduces the risk of severe disease and death, resulting in non-life-threatening (albeit still problematic) symptoms (Cowman et al., 2016). Thus, those at the highest risk of death are children who have yet to build up this natural immunity to the disease.

Early stage symptoms of malaria are primarily febrile (fever-related), accompanied by rigors, headache, nausea, and muscle pains (Cowman et al., 2016). Treatment at this stage with appropriate drugs can allow a patient to remit in several days, however, treated individuals are usually exhausted (Cowman et al., 2016). The symptoms and post treatment state of infected individuals provides an insight on how malaria poses a substantial economic burden. In the non-severe early stages of infection, and even after complete treatment, individuals are in no position to work at the level of a healthy individual, or work at all.

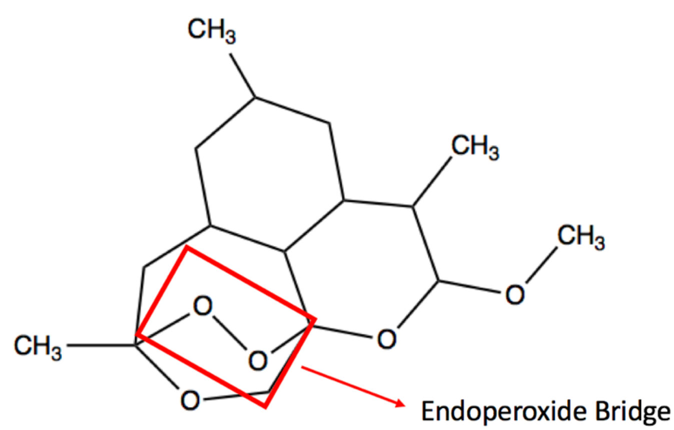
Severe or complicated malaria occurs when an infected individual is left untreated or only partially treated, and can lead to death (Cowman et al., 2016). Broadly, there are three syndromes that mark severe malaria: severe anemia, cerebral malaria (comas induced by the disease), and respiratory distress, which can occur individually or together (Cowman et al., 2016). These severe symptoms frequently result in death of children and adults who have not acquired immunity.

The symptoms of malaria are caused by exponential parasite growth, microvascular obstruction due to parasite adherence to blood vessels, and endothelial activation (inflammation of blood vessels) (Cowman et al., 2016). Once merozoites enter the chronic cycle of asexual reproduction in the vasculature, they can increase in number tenfold over 48 hours, resulting in a quick parasite infection of the entire body (Cowman et al., 2016). Parasite buildup causes acute inflammatory responses by the body, as parasite biomass impairs tissue blood flow, causing acid buildup and organ damage, most prominently in the brain (Cowman et al., 2016).

3.5 Literature on Malaria Treatment through Artemisinin-based Combination Therapies

There exist two primary categories of drugs used to treat malaria: chloroquine (CQ) and artemisinin. Beginning in the 1940s, chloroquine was the most frequently used drug to treat the disease due to its high efficacy, safety, and low cost (Flegg et al., 2013). However, after several decades of use, trends of CQ resistance in parasites became more prominent, and in the 1960s, sulphadoxine-pyrimethamine (SP) was used in many countries as the first-line treatment for malaria (Flegg et al., 2013). Intensive use of SP saw a quick rise of parasite resistance against the drug, and the rapid decline in efficacy led to withdrawal of its usage in many regions by the early 2000s (Flegg et al., 2013).

At this time, many African countries began transitioning away from use of CQ and SP to a new treatment as the first-line policy for treatment of malaria—artemisinin-based combination therapies (ACTs) (Cowman et al., 2016; Flegg et al., 2013). ACTs are a combination based therapy that pairs an artemisinin-derivative (ART) drug with another drug, utilizing the combined effects to quickly and thoroughly treat malaria (Eastman and Fidock, 2009). Artemisinin derivatives currently used include artemether, artesunate, and dihydroartemisinin, all characterized by a lactone containing an endoperoxide bridge, seen in Figure 3.(Eastman and Fidock, 2009).



Eastman and Fidock, 2009

Artemether

Figure 3.

Partner drugs used alongside ARTs include lumefantrine, mefloquine, amodiaquine, and piperaquine (Eastman and Fidock, 2009). The reason ARTs are combined with a partner drug is due to their short half-lives, which are between 45 minutes to 3 hours (Eastman and Fidock, 2009). Although the ARTs are able to clear out a substantial amount of parasite biomass when active, they are unable to completely eradicate all parasites during their short half-life, thus require a longer lasting partner drug to continue killing parasites once they are no longer functional (Eastman and Fidock, 2009).

The exact action of ARTs against malaria parasites is not completely understood, but there are three primary hypotheses regarding the action of ARTs against malaria parasites: targeting heme polymerization, protein function, and mitochondria function (Cui and Su, 2009).

Malaria parasites that feed on and digest hemoglobin in the bloodstream generate heme, a toxic chemical and must be converted through polymerization to a non-toxic ‘hemozoin’ form (Cui and Su, 2009). In-vitro, ARTs are shown to react with heme to form heme-artemisinin compounds, which inhibit heme-polymerizing proteins from functioning (Cui and Su, 2009). Thus, it is possible that ARTs react and form complexes with heme that disallows it from being detoxified in the parasite, and results in death.

ARTs may also interact with certain amino acid residues on key proteins within the parasite cell, interfering with normal functions and causing death (Cui and Su, 2009). Two potential targets for this interference are cysteine proteases, which degrade ingested hemoglobin, and P-type ATPases which perform key phosphorylating activities required for cell function (Cui and Su, 2009). Inhibiting the activity of these two proteins causes a catastrophic failure of key functions within the parasite, killing it.

Finally, ARTs may also disrupt the respiratory chain of mitochondria within parasite cells, disallowing them from functioning properly to generate energy needed for cellular activities (Cui and Su, 2009).

Studies have found that there has been an overall decline in malaria burden (measured through parasite prevalence in children aged 2-10) over the past two decades across Africa, with the improved availability of ACTs being a crucial factor contributing to this decline (Nkumama et al., 2017). In Tanzania, a study conducted from 2003 – 2006 which increased ACT availability to sick children by providing the drug free of charge saw a significant decline in morbidity and mortality within two years (Bhattarai et al., 2007). This suggests that ACTs are an effective driver for reducing the health burden of malaria when made available to individuals in endemic regions.

In terms of the economic benefits associated with increased ACT availability, a study in Ethiopia found a decrease in overall costs spent on treatment of malaria in the past decade, likely attributed availability of ACTs (Hailu et al., 2017). The quick action of ACTs decreases the duration of illness, which in turn reduces both direct costs of prolonged treatment, and indirect costs of missing longer periods of work (Hailu et al., 2017). Thus, it can by hypothesized that increased ACT availability results in access to faster treatment and improved recovery, which decreases time missed from work, and increases overall economic well-being. However, to the extent of my research, there exist no studies that directly link decreased economic disease burden to availability ACTs, which this thesis aims to prove.

Some other considerations that may contribute to decreased malaria burden and economic costs of the disease to an individual include improved malaria control strategies through increased usage of insecticide treated nets (ITNs) and indoor residual spraying (IRS) (Nkumama et al., 2017). Both of these strategies decrease the contact between mosquito disease vectors and humans, the former continuously mitigating contact during the vulnerable stage of sleep, and the latter eradicating the vectors altogether.

3.6 Literature on Barriers to Access of Artemisinin-based Combination Therapies

The efficacy of ACTs in malaria treatment has led most governments in Africa to create national policies designating them as the recommended drug for antimalarial treatment (Cohen et al., 2013). However, despite being the front-line drug, ACT usage has been limited due to high prices in the private sector, frequent stock-outs in the public sector, and inaccessibility in rural regions (Cohen et al., 2013). ACTs are priced 20 to 40 times higher than other conventional antimalarial treatments such as amodiaquine and sulphadoxine-pyrimethamine (SP) (Cohen et al., 2010). A price difference of this magnitude provides a barrier to access for many individuals, particularly those of lower socioeconomic status, who turn to cheaper and less effective alternatives for treatment. In the public sector, poor stock flow management, misunderstanding of procurement needs, and limited funding cause severe shortages in ACT availability (Kangwana et al., 2009). A study in Kenya found that on average, 25.6% of government facilities were out of stock of ACTs, with the median time for the shortage being 52 days (Kangwana et al., 2009). Thus, despite national policy designating ACTs as the go-to antimalarial treatment, the drugs themselves were not available to patients for significant amounts of time. Populations living in rural areas also face barriers to access of ACTs. In Nigeria, despite ACTs being the government's designated first-line antimalarial treatment, rural populations had limited access and consumption of the drug compared to urban dwellers (Onwujekwe et al., 2009)

4. Methods and Data

4.1 Methods

This study uses a series of multiple regressions to capture the effect of ACT availability on likelihood of women's work absenteeism in Tanzania. The regression model is built out by adding variables that were determined to be important using my knowledge and research on the biology and epidemiology of malaria, in addition to development economics. The regression analysis primarily focuses on the relationship between the two variables of interest, the dependent variable of work absenteeism, and the independent variable of ACT availability. Control variables that may affect likelihood of absenteeism are also added to create a robust model.

To further capture the effects of potentially omitted variables on absenteeism and ACT availability, the study sample was segmented into two groups at certain cutoff levels of ACT availability. A series of chi-squared tests and simple regressions were then run on segmented groups of high ACT availability and low ACT availability to see if certain population indicators such as urban/rural status, education level, and wealth were significantly different between the two groups. Variables found to be significantly different between the two groups were then included in the regression as additional controls.

Finally, an interaction variable between ACT availability and agricultural occupation was created to measure if ACT availability had a different effect on likelihood of absenteeism for agricultural workers as opposed to non-agricultural workers. A subsequent set of regressions was also run with an interaction variable between ACT availability and self-employed agricultural workers (a subset of agricultural workers) to observe if the drugs had a significantly different effect on likelihood of absenteeism for specific groups within the population.

Through the regression analyses, the effect that ACT availability and other variables have on likelihood of work absenteeism can be observed.

4.2 Data

Data used in this study was taken from the 2015-2016 Tanzania Demographic and Health Survey and Malaria Indicator Survey, conducted by the Tanzanian Ministry of Health. The survey was conducted across 30 regions in Tanzania (25 on the mainland, 5 on Zanzibar), included 608 village clusters (with 22 households per cluster), and interviewed 13,266 women between the ages of 15-49. This data set was chosen as it measured a variable of interest that could represent the indirect cost of malaria (absenteeism from work in past 7 days) and ACT availability (ACTs available at closest health facility). Additionally, it contained a number of control variables that could either affect likelihood of work absenteeism by affecting likelihood of contracting malaria, or directly affect likelihood of work absenteeism. The variables influencing malaria transmission were usage of insecticide treated bed nets (ITNs) and anti-mosquito spraying conducted in the household in the past 12 months. Other control variables included marital status, pregnancy status, number of children under 5 in the household, occupation, education level, urban-rural status, and wealth quintiles.[1]

[1] Reasoning for choice of these variables is provided in *Section 4.4 Variable Definitions and Choice*

4.3 Data Cutting

Despite the large sample size of 13,266 women in the original survey, a significant amount of data had to be dropped to conduct the analysis measuring the effect of ACT availability on likelihood of work absenteeism. Three main cuts were made to prepare a sample suitable for the study. The first cut dropped all individuals who were marked as "missing" or "not in universe" in their response to having missed work in the past week (job absenteeism). "Missing" indicates that the response was not recorded for the individual, whilst "not in universe" indicates that the question was not asked to the individual. These individuals were dropped from the data set, as job absenteeism is the indicator variable for the indirect cost of malaria. Thus, individuals who do not have the associated data for this variable cannot be used in this study. It is possible that dropping these individuals could have an effect on the results of this study.[2] The second data cut dropped all individuals whose occupation status was "not currently working," as individuals who were not working are unable to be used in an analysis measuring job absenteeism. Similar to dropping "missing and "not in universe" individuals for job absenteeism, removing these individuals from the sample could influence the results observed in this study.[3] The final data cut dropped all individuals who indicated they "did not know" if ACTs were available at the closest health facility or pharmacy.[4] Between the three data cuts, the sample was reduced from 13,266 to 1,308 individuals.

[2] Analysis on how dropping these individuals may have affected the results is discussed in *Section 6: Discussion*
[3] See above
[4] See above

To increase the sample size after the three cuts were made, and to convert ACT availability into a more measurable metric, data regarding ACT availability was changed from a "yes-no" 0-1 variable into a continuous variable within the original sample of 13,266. This was done by taking the number of "yes" responses from a village cluster as a percentage of total responses. Thus, if a cluster of 10 individuals had 8 "yes" responses, and 2 "no" responses, all individuals in the cluster would be assigned a new ACT availability value of 0.80, or 80%. The continuous variable is interpreted as cluster-level ACT availability to an individual, however, this is not the only possible interpretation of this variable.[5] By creating a continuous variable as proportion of "yes" responses within a cluster, some individuals who had met the response criteria for absenteeism and were currently working, but had indicated "don't know" for ACT availability could be added back into the study's sample from the original sample. They were added back by being assigned the value for proportion of ACT availability calculated from other respondents responses in their clusters. Thus, the "don't know" respondents' ACT availability was represented by the proportion of "yes" to "no" responses by other individuals in their cluster. This process added 106 individuals back into the sample, and the final sample size used in this study's analysis was 1,414 individuals.

To identify differences in population indicators between the original sample of 13,266 and the cut sample of 1,414, a series of chi-squared tests were run on several variables of interest. The population indicator variables used were urban-rural status, level of education, and level of wealth. Chi-squared tests compared the difference in

[5] The possible interpretations of this variable, and how they affect analysis of the results is discussed in *Section 6 Discussion*

proportion of individuals of urban status between the original and cut samples, proportion individuals with high level of education, and proportion of individuals with high level of wealth.

There was no statistically significant difference between proportion of individuals of urban status, indicated by the variable *U*, between the two samples, with 31.18% of individuals being of urban status in the original sample, and 31.75% of individuals being of urban status in the cut sample.

Level of education was measured by creating a variable for high level of education (*HE*) from an existing variable in the survey—"level of education completed." Individuals who had completed secondary or higher education were put in the high education group, whilst those who had not were not included. A chi-squared analysis found that the proportion of individuals in the high education group significantly declined between the original sample, of which they made up 27.78%, and the cut sample, of which they made up 23.76%. It is unclear which data cut(s) could have shifted this proportion, as dropping unemployed/not currently working individuals intuitively would have had the opposite effect of increasing the proportion of educated and employable individuals.

Level of wealth was measured by creating a variable (*TW*) for top two quintile designations of wealth, created from an existing variable in the survey which assigned an individual a wealth quintile score based on their socioeconomic status. A note here is that the wealth quintile scores were not broken up into fifths within the original sample, as the wealth quintile score was relative to the rest of Tanzania's population. Individuals in the top two wealth quintiles were put in the top wealth group, whilst all others were not included. A chi-squared analysis found that the proportion of individuals in the top two wealth quintiles did not significantly differ between the original and cut samples, making up 48.98% and 50.42% of their respective samples. The lack of significant difference in the proportion of wealthier individuals following the cuts was interesting, as intuitively dropping unemployed individuals would have increased the proportion of individuals with an income, thus, the proportion of wealthy individuals.

The statistically significant difference in education level between the original sample and the cut sample could have some implications regarding the external validity of the results from this study.[6] It is important to keep in mind the effects of cutting data to create a usable sample for an analysis, as it potentially affects the external validity, thus generalizability of the findings of the study.

[6] How the differences in education level may affect external validity is discussed in *Section 6: Discussion*

4.4 Variable Definitions, Choice, and Summary Statistics

Table 1

Variables	Sample Mean (Standard Dev.)	Max	Min	Observations
Absenteeism (overall sample)	0.59 (0.49)			1414
Absenteeism (self-employed agricultural worker)	0.50 (0.50)			636
ACT Availability for Village Cluster	0.94 (0.10)	1	0.3	1414
ITN Usage	0.60 (0.49)			1414
Anti-Mosquito Spraying of Dwelling in past 12 months	0.11 (0.31)			1414
Married	0.70 (0.46)			1414
Pregnant	0.14 (0.35)			1414
Number of Children under 5 in Household	1.52 (1.59)	16	0	1414
Working in an Agricultural Occupation	0.49 (0.50)			1414
Working as a Self-Employed Agricultural Worker	0.45 (0.50)			1414
Living in Urban Region	0.32 (0.47)			1414
Completed Secondary or Higher Education	0.24 (0.43)			1414
Total Years of Education	6.33 (3.44)	16	0	1414
In Top 2 Quintiles of Wealth	0.50 (0.50)			1414

Key Variables of Interest and Control Variables From Survey Data

The variable used in this study to measure the indirect cost and economic burden of malaria is work absenteeism. Individuals miss work due to being sick from malaria infection, or if they need to take care of family members who have the disease (Arrow et al., 2004). Missing work results in a loss of income, whether the individual works as a wage earner who does not get paid when not present, or as an agricultural worker who is unable to grow and harvest crops. The data used contains a variable for absenteeism which signifies if an individual has a job from which she was absent in the past week, coded as 1, or 0 if she has not missed work. In this analysis, the variable for absenteeism was designated as *A*. As seen in Table 1 the mean for value for *A* was 0.59, thus 59% of individuals indicated they had missed work in the past week. The reason for the individual missing work in the past week is not necessarily only attributable to malaria, thus, a variety of control variables were also included in the regression.

The primary regressor of interest in this study was the availability of ACTs, for which the continuous variable *ACT*, which represented ACT availability for an individual at the village cluster level, was created from an existing variable in the data. The original variable in the survey measured if there were ACTs available at the closest health facility or pharmacy to an individual, with responses coded as 1 for "yes", 0 for "no." This variable was then converted into a continuous variable from 0 to 1 through the process described in section *4.3 Data Cutting*, by taking the percentage of individuals who responded "yes" within a cluster, and assigning all individuals within that cluster the new variable for ACT availability. This new variable is used to signify ACT availability at the cluster level, under the assumption that although an individual may have answered "no" to ACTs being available at the closest health facility of pharmacy, if a majority of other respondents in her cluster responded "yes," the individual lives in a cluster that has high availability of ACTs. The mean value for *ACT* was 0.94, signifying that the average cluster level ACT availability was 94%. There were no clusters in the sample that had no ACT availability, with the minimum being 0.3 and the maximum being 1(Table 1).

While ACT availability is the primary variable of interest in this study, there are a number of other variables that are accounted for as controls, as they can influence likelihood of work absenteeism either by prevention of malaria, or other causes. The two control variables that accounted for increased prevention of malaria were ITN usage (*ITN)* and anti-mosquito spraying of the household in the past 12 months (*S*). ITNs decrease malaria risk by providing a protective barrier between sleeping individuals and mosquito disease vectors, whilst anti-mosquito spraying decreases malaria risk by eliminating the disease vectors themselves. ITN use frequency by individuals in the sample was 59% (Table 1). A majority of individuals did not have their dwellings sprayed against mosquitoes in the past 12 months, with only 11% of individuals indicating spraying had occurred (Table 1).

Other control variables included from the survey data were marital status (*M*), pregnancy (*P*), number of children under 5 (*C*), and agricultural occupation (*Ag*). Marital status was included as a control, as married women may have more flexibility in missing work due to illness or other causes, particularly if their spouse generates income. 70% of individuals in the sample were married (Table 1). Pregnancy status was included as a control to account for the effects of pregnancy on an individuals' ability to work, particularly in the later terms of pregnancy, as heavily pregnant women may miss work more frequently. Individuals who were pregnant at the time of the survey made up a small proportion of the sample at 14% (Table 1). Number of children under 5 was included as a control, as caring for ill children (including those with malaria) has been well documented as a reason for work absenteeism (Mukasa et al., 2019; Arrow et al., 2004). As see in Table 1, the sample average for number of children under 5 in the household was 1.52, with a maximum of 16 and minimum of 0 (it is possible that a woman had multiple families' children under 5 living in her household). Agricultural occupation type was included as a control, as an individual's type of employment can affect her likelihood of absenteeism. The occupation categories from the survey were Professional, Technical, or Managerial, Clerical or Sales, Self-Employed Agricultural Worker, Agricultural Employee, Household and Domestic Worker, Services Worker, Unskilled Manual Worker, and Skilled Manual Worker. Agricultural occupations in particular may influence likelihood of absenteeism, as crop harvests and farming activities are dependent on continuous and timely work. Individuals working in agriculture may have more incentive to not miss work despite illness or other reasons, as their income is more dependent on lack of absenteeism. Thus, a variable for agricultural occupation (*Ag*)*consisting* of individuals who were Self-Employed Agricultural Workers and Agricultural Employees was created. Additionally, by splitting individuals into agricultural and non-agricultural categories, the sample was relatively evenly split with 49% having agricultural occupations and 51% being in other occupations (Table 1). This was beneficial, as some of the occupation categories contained very small numbers of individuals, thus it may have been difficult to measure their independent effect on likelihood of absenteeism.

Furthermore, a variable for self-employed agricultural occupation (*SelfAg)* was also created, and used in place of agricultural occupation to run an identical set of analyses (described later in the *Methods* section). The original variable of agricultural occupation consisted of both agricultural employees as well as self-employed agricultural workers, whilst the new variable was just the latter individuals. This variable was created, as it is possible that agricultural employees, who presumably work for an employer, may have increased likelihood of absenteeism in comparison to self-employed agricultural workers for several reasons. Working for an employer could provide these individuals with benefits such as sick days off, which may incentivize them to miss work should they have reason to do so. Additionally, working for an employer may mean that there are other employees that can still tend to crops should an individual have to miss work, decreasing the negative consequences of absenteeism. Self-employed agricultural workers tending to their own land do not have benefits such as sick days off, and as they may be the only person working their land, missing work can have dire consequences on their crop yield and income. Thus, self-employed agricultural workers may have less likelihood of absenteeism in comparison to agricultural employees. Self-employed agricultural workers made up a significant portion of 45% of the sample (Table 1).

Population Indicator Control Variables

In addition to control variables taken directly from the survey data, several other population indicator variables for urban status (*U*), high level of education (*HE*), years of education *(Edyrs*), and high level of wealth (*TW*) were included in the regression upon finding that they significantly differed between high ACT availability clusters and low

ACT availability clusters.[7] These variables were included as they otherwise might have been omitted variables that both influence availability of ACTs and likelihood of absenteeism. 32% of the sample had urban status (Table 1). Higher educated individuals only made up 24% of the sample (Table 1). For total years of education the mean was 6.33 years, with a maximum of 16 years and a minimum of 0 years (Table 1). The proportion of individuals in the top two wealth quintiles was 50% (Table 1).

Interaction Variables

Interaction variables were created between the occupation variable *Ag* and ACT availability variable *ACT* to observe if ACT availability had a significantly different impact on agricultural workers' likelihood of absenteeism compared to non-agricultural workers' likelihood of absenteeism. The new interaction variable was *Ag*ACT*. This was also done for the occupation variable *SelfAg* representing self-employed agricultural workers in place of the agricultural occupation variable (*Ag*) and creating the interaction variable *SelfAg*ACT*. These interaction variables were subsequently and independently included in the regression analysis.

[7] The process of testing for significant differences these variables had between high ACT availability clusters and low ACT availability clusters, and the relationships they have with high ACT availability clusters can be found in *Section 9: Appendix*

5. Analysis and Results

5.1. Regression Buildup with Variables from Survey

To begin analyzing the effects of ACT availability on likelihood of absenteeism, a series of regressions were performed, starting with a simple regression of *A* on *ACT*, and adding controls until all variables were included in a multiple regression. Standard errors were clustered at the village cluster level, as the data for individuals was clustered as such. The regression buildup was modeled by the following equations:

(1) $A_i = \alpha + \beta_1 ACT_j + \varepsilon_{ij}$

(2) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \varepsilon_{ij}$

(3) $Am_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \varepsilon_{ij}$

(4) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \varepsilon_{ij}$

(5) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \varepsilon_{ij}$

(6) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \varepsilon_{ij}$

(7) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 Ag_i + \varepsilon_{ij}$

In the regression equations, the subscript *i* denotes the individual level variables within the sample, *j* denotes cluster level variables assigned to an individual within a cluster and ε_{ij} is the clustered standard error.

Table 2

VARIABLES	(1) absenteeism	(2) absenteeism	(3) absenteeism	(4) absenteeism	(5) absenteeism	(6) absenteeism	(7) absenteeism
ACT Availability	-0.401*** (0.143)	-0.408*** (0.142)	-0.348** (0.141)	-0.334** (0.142)	-0.334** (0.142)	-0.331** (0.142)	-0.295** (0.135)
ITN Usage		0.0563* (0.0296)	0.0540* (0.0294)	0.0474 (0.0300)	0.0475 (0.0300)	0.0461 (0.0301)	0.0192 (0.0296)
Anti-Mosquito Spraying in past 12 months			0.0597 (0.0433)	0.0670 (0.0429)	0.0671 (0.0429)	0.0657 (0.0430)	0.0491 (0.0429)
Marital Status				0.0560* (0.0303)	0.0554* (0.0309)	0.0603* (0.0316)	0.0920*** (0.0318)
Pregnant					0.00537 (0.0372)	0.00337 (0.0372)	0.00615 (0.0369)
Number of Children under 5						-0.00976 (0.00862)	0.00461 (0.00878)
Agricultural Occupation							-0.199*** (0.0297)
Constant	0.969*** (0.134)	0.942*** (0.134)	0.881*** (0.135)	0.832*** (0.139)	0.831*** (0.139)	0.841*** (0.138)	0.878*** (0.132)
Observations	1,414	1,414	1,414	1,414	1,414	1,414	1,414
R-squared	0.007	0.010	0.012	0.014	0.014	0.015	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 shows that ACT availability has a significant and negative effect on likelihood of absenteeism across all regressions, although the significance and magnitude of its effect decreases as more controls are added. This result is in line with the initial hypothesis that higher availability of ACTs has economic benefits of decreased likelihood of absenteeism.

ACT availability may decrease likelihood of absenteeism through several channels. ACTs may directly improve the health of the individual through their quick action in eliminating malaria biomass and reducing length of illness, which allows a sick individual to recover faster (Hailu et al., 2017). Faster recovery means an individual is able to return to work faster if she contracts malaria, or may not need to miss work at all. A possible indirect benefit of living in a high ACT availability cluster is reduced timeframe that other humans serve as disease vectors. As malaria is transmitted by mosquitoes which have bitten infected human hosts, by reducing the timeframe humans are infected, the number of mosquito disease vectors also decreases. Reduced number of mosquito disease vectors reduces the likelihood an individual contracts malaria, thus decreases the likelihood of absenteeism from work due to malaria-related illness.

The final regression output in Column 7 shows that ACT availability had a coefficient of -0.295, statistically significant at the 5% level. This means that as ACT availability for an individual's cluster increases by 1%, her likelihood for missing work in the past 7 days would decrease by 0.295 percentage points. This is particularly interesting, as cluster wide effects of improved ACT availability can significantly decrease individual level likelihood of absenteeism. Thus, even if an individual does not have easy access to ACTs herself, if she lives in a cluster with high ACT availability she may see some indirect benefits. As the mean value of absenteeism in the sample was 0.59 (Table 1), if cluster level ACT availability goes from 0% to 100%, individuals living in the cluster would see a decrease of mean absenteeism to 0.295—a 50% decrease.

The lack of statistical significance of the effect of ITN usage on likelihood of absenteeism, and the positive, albeit insignificant effect was surprising. ITNs prevent an individual from contracting malaria by serving as a protective barrier against mosquito disease vectors. Thus, increased ITN usage should reduce the likelihood of contracting malaria, which reduces risk of illness, and consequently absenteeism. A reason for ITN usage having an insignificant effect on likelihood of work absenteeism in a regression including ACT availability may be that individuals are still contracting malaria despite sleeping under bednets. It is possible that sleeping under a bednet is not significantly decreasing incidence of malaria, and it is the treatment once malaria is contracted that has a more meaningful impact on work absenteeism.

Lack of significance for anti-mosquito spraying was not as surprising of a finding, mostly due to the fact that such as small proportion of the sample (~11%) had their dwellings sprayed in the past 12 months. It is possible that this proportion was too small to capture any beneficial effects in reducing risk of malaria. Additionally, as timespan for spraying was the past 12 months, quite a long time period, it is possible that the beneficial effects of anti-mosquito spraying were not captured as the effects may have diminished after several months and mosquitoes may have returned to the dwellings.

Marital status had a positive and significant effect on likelihood of absenteeism. This makes intuitive sense, as women who have a spouse who is also presumably working may feel less pressure to go to work if they need to be absent. Having another source of income in the household provides a financial buffer that reduces the economic burden of missing work, providing some leeway for an individual to miss work if they have a reason to do so. In the final regression (Table 2, Column 7), marital status had a coefficient of 0.0920, statistically significant at the 1% level. Thus, being married increased the likelihood of absenteeism for an individual by 9.20 percentage points.

Number of children under 5 did not have a statistically significant effect on likelihood of absenteeism, although it did have a positive coefficient, which was predicted. Previous studies have found that caring for young children who are sick or require care for some reason is a cause for work absenteeism (Mukasa et al., 2019).

Being in an agricultural occupation was statistically significant in decreasing the likelihood of absenteeism, which was expected. Agricultural work requires planting, care, and harvests must be conducted in a time-sensitive and continuous manner. Thus, agricultural workers may be more inclined to not miss work, even if they have reasons to do so, as missing work may have drastically negative consequences on their livelihoods compared to other occupations. Additionally, as a substantial proportion of the agricultural workers were self-employed agricultural workers, they may have easier access to their workplace, particularly if their farms are in close proximity to their homes, thus are less likely to miss work.

The coefficient for the variable of being an agricultural worker is -0.199, statistically significant at the 1% level (Table 2, Column 7). This means that being an agricultural worker decreases the likelihood of an individual missing work in the past week by 19.9 percentage points. In addition to the potential reasons mentioned above for why agricultural workers may be incentivized to not miss work, it is possible that other occupations working in the formal sector (such as Services Workers, Professional or Managerial Workers, Clerical or Sales Workers) may have employee benefits such as sick days, which may incentivize individuals to miss work if they have a reason to do so.

5.2. Regression with Population Indicator Controls

Table 3

VARIABLES	(1) absenteeism
ACT Availability	-0.310**
	(0.137)
ITN Usage	0.0156
	(0.0294)
Anti-Mosquito Spraying in past 12 months	0.0530
	(0.0437)
Marital Status	0.0914***
	(0.0320)
Pregnant	0.00445
	(0.0369)
Number of Children under 5	0.00447
	(0.00888)
Agricultural Occupation	-0.189***
	(0.0339)
Urban Status	0.0448
	(0.0363)
Higher Education	0.0260
	(0.0425)
Total Years of Education	-0.00505
	(0.00491)
Top Two Wealth Quintiles	-0.00653
	(0.0352)
Constant	0.904***
	(0.134)
Observations	1,414
R-squared	0.054

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A subsequent regression was run including the population indicator controls that were significantly different between high ACT availability and low ACT availability clusters. The variables for urban status (*Urban)*, higher education level (*HE)*, total years of education (*Edyrs*), and higher level of wealth (*TW*) were included to control for any omitted variables, deepening the analysis on other potential drivers that may have affected likelihood of absenteeism and ACT availability. The regression analysis run was modeled by the following equation:

$$(1)\quad A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 Ag_i + \beta_9 U_j + \beta_{10} HE_i + \beta_{11} EdYrs_i + \beta_{12} TW_i + \varepsilon_{ij}$$

Table 3 shows the regression output when the population indicator variables are included as controls. All four controls are not statistically significant, thus have no significant effect on likelihood of absenteeism for an individual.

5.3. Regressions with Interaction Variable

Table 4

VARIABLES	(1) absenteeism
ACT Availability	-0.253
	(0.165)
ITN Usage	0.0187
	(0.0296)
Anti-Mosquito Spraying in past 12 months	0.0497
	(0.0432)
Marital Status	0.0925***
	(0.0318)
Pregnant	0.00555
	(0.0370)
Number of Children under 5	0.00477
	(0.00878)
Agricultural Occupation	-0.116
	(0.254)
Agricultural Occupation*ACT Availability	-0.0894
	(0.268)
Constant	0.839***
	(0.159)
Observations	1,414
R-squared	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the regression output for the regression analysis takes the interaction between ACT availability and agricultural occupation into account through the interaction variable $Ag*ACT$. The regression analysis was modeled by the following equation:

$$A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 Ag + \beta_9 Ag*ACT_i + \varepsilon_{ij}$$

The interaction variable was not statistically significant in itself, suggesting that the effect of ACT availability on likelihood of absenteeism for individuals with agricultural occupations was not significantly different from the effect of ACT availability on individuals in other occupations. An F-test was run to see if there was a significant effect of ACT availability on likelihood of absenteeism for individuals with agricultural occupations but found no significant effect.

A subsequent regression was run with the interaction variable between ACT availability and agricultural occupation this time including population indicator controls, with results displayed below in Table 5. The regression analysis was modeled by the following equation:

$$A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_6 C_i + \beta_7 Ag_i + \beta_8 Ag{*}ACT_i + \beta_9 U_i + \beta_{10} HE_i + \beta_{11} EdYrs_i + \beta_{12} TW_i + \varepsilon_{ij}$$

Table 5

VARIABLES	(1) absenteeism
ACT Availability	-0.278*
	(0.166)
ITN Usage	0.0153
	(0.0294)
Anti-Mosquito Spraying in past 12 months	0.0533
	(0.0440)
Marital Status	0.0918***
	(0.0320)
Pregnant	0.00397
	(0.0370)
Number of children under 5	0.00457
	(0.00888)
Agricultural Occupation	-0.128
	(0.254)
Urban Status	0.0439
	(0.0362)
Higher Education	0.0270
	(0.0428)
Total Years of Education	-0.00510
	(0.00494)
Top Two Wealth Quintiles	-0.00667
	(0.0352)
Agricultural Occupation*ACT Availability	-0.0658
	(0.269)
Constant	0.875***
	(0.157)
Observations	1,414
R-squared	0.054

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Again, the interaction variable was not statistically significant in itself. An F-test was run to see if the effect of ACT availability on likelihood of absenteeism had a significant effect for individuals with agricultural occupations, but found no significance. Thus, adding the population indicator controls did not lead to a difference in how ACTs affect likelihood of absenteeism for individuals in agricultural occupations.

5.4. Regressions with Self-Employed Agricultural Occupation

Table 6 below shows the output of all the previous regression analyses, but with the variable for agricultural occupation (*Ag*) replaced with self-employed agricultural occupation (*SelfAg*). The primary goal of running this new set of regressions was to see if ACTs had different effects on decreasing likelihood of absenteeism for certain groups of individuals. To test this, an interaction variable between ACT availability and self-employed agricultural occupation was created. Observing how ACTs may benefit certain segments of the population can better inform us on which groups benefit most from their availability.

Table 6

VARIABLES	(1) absenteeism	(2) absenteeism	(3) absenteeism	(4) absenteeism
ACT Availability	-0.267*	-0.283**	-0.0979	-0.108
	(0.137)	(0.138)	(0.171)	(0.175)
ITN Usage	0.0266	0.0214	0.0238	0.0195
	(0.0299)	(0.0296)	(0.0300)	(0.0298)
Anti-Mosquito Spraying in past 12 months	0.0452	0.0498	0.0504	0.0542
	(0.0436)	(0.0441)	(0.0432)	(0.0437)
Marital Status	0.0864***	0.0872***	0.0896***	0.0901***
	(0.0316)	(0.0318)	(0.0317)	(0.0319)
Pregnant	0.00880	0.00692	0.00524	0.00315
	(0.0371)	(0.0369)	(0.0370)	(0.0369)
Number of Children under 5	0.00485	0.00496	0.00546	0.00544
	(0.00878)	(0.00888)	(0.00883)	(0.00893)
Self-Employed Agricultural Occupation	-0.185***	-0.167***	0.235	0.249
	(0.0294)	(0.0341)	(0.253)	(0.249)
Urban Status		0.0499		0.0457
		(0.0359)		(0.0361)
Higher Education		0.0317		0.0375
		(0.0425)		(0.0429)
Total Years of Education		-0.00409		-0.00496
		(0.00499)		(0.00502)
Top Two Wealth Quintiles		-0.00249		-0.00326
		(0.0356)		(0.0354)
Self-Employed Agricultural Occupation * ACT Availability			-0.448*	-0.447*
			(0.266)	(0.264)
ACT Availability on Self-Employed Agricultural Occupation			-0.5459	-0.555
[*F-test p-value*]			[0.0134]	[0.0128]
Constant	0.837***	0.850***	0.679***	0.693***
	(0.133)	(0.137)	(0.165)	(0.168)
Observations	1,414	1,414	1,414	1,414
R-squared	0.046	0.049	0.049	0.051

The first regression run was modeled by the equation:

$$(1)\ A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 SelfAg_i + \varepsilon_{ij}$$

Table 6, Column 1 shows that being a self-employed agricultural worker has a significant and negative effect on likelihood of absenteeism, with a coefficient of -0.185 significant at the 1% level. Being a self-employed agricultural worker may have a negative effect on likelihood of absenteeism for similar reasons to why agricultural occupations in general have a decreased likelihood of absenteeism. Compared to the effect of agricultural occupation in the first set of regressions run (Table 2, Column 7) the variable for self-employed agricultural occupation had the same 1% statistical significance, but the magnitude of the coefficient was smaller (-0.185 vs. -0.199). Thus, being a self-employed agricultural worker does not further decrease the likelihood of absenteeism compared to being in an agricultural occupation in general.

The next regression included the population indicator controls included in the first set of regression analyses, modeled by the equation:

$$(2)\ A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 SelfAg_i + \beta_9 U_j + \beta_{10} HE_i + \beta_{11} EdYrs_i + \beta_{12} TW_i + \varepsilon_{ij}$$

Replacing agricultural occupation with self-employed agricultural occupation did not make any of the previously non-statistically significant population control indicators have statistically significant effects on likelihood of absenteeism, which was expected as they presumably have independent effects on likelihood of absenteeism.

To observe if ACTs had a significantly different effect on self-employed agricultural workers' likelihood of absenteeism compared to individuals with other occupations, an interaction variable between ACT availability and self-employed agricultural occupation, $SelfAg{*}ACT_i$ was created and included the regression analysis. This was modeled by the equation:

(3) $A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_7 C_i + \beta_8 SelfAg_i + \beta_9 SelfAg{*}ACT_i + \varepsilon_{ij}$

Table 6, Column 3 above shows that the interaction variable has a negative and significant effect on likelihood of absenteeism. The coefficient for the interaction variable was -0.448, statistically significant at the 10% level. This suggests a 1% cluster-level increase in ACT availability would decrease likelihood of absenteeism for self-employed agricultural workers an additional 0.448 percentage points compared to other occupations. To see if the effect of ACT availability on decreasing likelihood of absenteeism for self-employed agricultural workers was significant, an F-test was conducted and found significance at the 5% level (Table 6, Column 3). The coefficient for *ACT* (effect of ACTs on decreasing likelihood of absenteeism for individuals who are not self-employed agricultural workers) was -0.0979. Thus, ACTs have an effect of decreasing likelihood of absenteeism for self-employed agricultural workers by -0.5459 (-.0979 + -0.448). For every 1% increase in cluster-level ACT availability, a self-employed agricultural worker's likelihood of absenteeism decreases by 0.5459 percentage points. If an individual were in a cluster with 0% ACT availability, and cluster level ACT availability rose to 100%, her likelihood of absenteeism would decrease by 54.59 percentage points—a massive decrease. There was one inconclusive finding in the results of the effect of ACT availability on likelihood of absenteeism for self-employed agricultural workers. The mean value of absenteeism for self-employed agricultural workers was 0.50 (Table 1), however, the effect of ACT availability on decreasing likelihood of absenteeism for agricultural workers is -0.5459. Thus when its effect is applied to the average absenteeism rate for self-employed agricultural workers, it leads to a negative absenteeism value.

Population indicator control variables were subsequently added to the regression with the interaction variable, modeled by the equation:

$$A_i = \alpha + \beta_1 ACT_j + \beta_2 ITN_i + \beta_3 S_i + \beta_4 M_i + \beta_5 P_i + \beta_6 C_i + \beta_7 SelfAg_i + \beta_8 SelfAg*ACT_i + \beta_9 U_j + \beta_{10} HE_i + \beta_{11} EdYrs_i + \beta_{12} TW_i + \varepsilon_{ij}$$

Addition of the population indicator control variables did not substantially change the magnitude or significance of the interaction variable's effect on likelihood of absenteeism (Table 6, Column 4). When an F-test was conducted, significance in the effect of ACT availability on likelihood of absenteeism for self-employed agricultural workers remained at the 5% level.

It is understandable that ACTs have a greater effect on decreasing likelihood of absenteeism for individuals who are self-employed agricultural workers. Self-employed agricultural workers may further benefit from the availability of ACTs as they may be more prone to contracting malaria, as their work is outdoors, which exposes them to more mosquito vectors. Additionally, as self-employed agricultural workers' livelihoods are more dependent on their continuous and timely work (for they may be the only person working on their farm), they may have increased incentives to not miss work should ACTs reduce the severity of their illness. Thus, availability of ACTs and improved treatment may have a greater effect of decreasing likelihood of absenteeism for such individuals compared to individuals in other occupations who may face less risk of malaria and have livelihoods less dependent on not missing work.

6. Discussion

6.1 Possible Interpretations of ACT Availability Variable

There exist several possibilities on how the variable for ACT availability, *ACT*, can be interpreted, each with differing implications on how policymakers can look to alleviate the economic burden of malaria. The two primary interpretations I considered were measuring physical ACT availability, and level of accessibility driven by cost.

The interpretation of physical availability assumes that individuals who indicated that ACTs were not available at the closest health facility or pharmacy did so because ACTs were physically were not available. Thus, for a village cluster that has 0.70 ACT availability, 30% of the individuals in the cluster live near a health facility or pharmacy that physically does not carry ACTs. For the results found in the first regression analysis for the effect of ACT availability on all individuals' likelihood of absenteeism, the coefficient for *ACT* of -0.295 (Table 2, Column 7) indicates that if an individual's cluster goes from having no health facilities or pharmacies that carry ACTs, to all health facilities or pharmacies carrying ACTs, her likelihood of absenteeism will decrease by 29.5 percentage points. The effect of ACT availability on likelihood of absenteeism for self-employed agricultural workers of -0.5459 (Table 6, Column 3) suggests that for a self-employed agricultural worker, if her village went from having no health facilities or pharmacies that carry ACTs to all health facilities or pharmacies carrying ACTs, her likelihood of absenteeism would decrease by 54.59 percentage points.

The policy implications of this interpretation of physical ACT availability should focus on improving physical distribution of the drugs across all clusters. If ACTs are physically available for a higher percentage of individuals in a cluster, individuals living in the cluster should see decreased likelihood of absenteeism.

The alternate interpretation of the ACT availability variable is as a measure of access, likely driven by cost. Cost has been found by many studies to be a major barrier to access for ACTs (Chuma et al., 2010). This interpretation assumes that individuals who responded “no” to whether ACTs were available at the closest health facility or pharmacy did so because they could not afford the drugs. In this case, the assumption is made that ACTs are physically available, but individuals are faced with cost barriers to accessing them. If a village cluster has an ACT availability value of 0.70, this means 30% of its population does not have access to ACTs because they cannot afford to buy them. In interpreting the results found in this study for the effect of ACT availability on likelihood of absenteeism for all individuals (Table 2, Column 7), the coefficient for *ACT* of -0.295 indicates that if in individual’s cluster goes from having everyone facing cost barriers to accessing ACTs to nobody facing cost barriers to accessing ACTs, her likelihood of absenteeism decreases by 29.5 percentage points. For self-employed agricultural workers, the effect of ACT availability of -0.5459 on likelihood of absenteeism indicates that a self-employed agricultural worker will see a 54.59 percentage point decrease in likelihood of absenteeism.

Policy implications for this interpretation of accessibility to ACTs driven by cost should focus on decreasing cost barriers and allowing more individuals to access the benefits of ACTs. Making ACTs accessible to a higher proportion of a cluster will lead to decreased likelihood of absenteeism for individuals within the cluster.

6.2 Reverse Causality

Reverse causality is unlikely between likelihood of absenteeism and ACT availability. It is unlikely that likelihood of absenteeism of an individual has an effect on whether or not ACTs are available at the closest health facility or pharmacy to their dwelling. Additionally, as the variable for ACT availability for each individual was created as a continuous variable calculated from the average ACT availability in the cluster they lived in, the likelihood of reverse causality further decreases. This is because likelihood of absenteeism is an individual level variable, whilst ACT availability now becomes a cluster level variable. It is highly unlikely that an individual's likelihood of missing work has an effect of ACT availability at a cluster level.

6.3 Omitted Variable Bias

Omitted variables and background bias could be reducing the magnitude of the effect ACT availability has on decreasing likelihood of absenteeism found in this study.

This could be occurring due to the omitted variable of an individual or someone in the individual's family recently getting malaria. Recently having malaria could lead to an individual purchasing ACTs, which would increase the likelihood that they indicate that ACTs are available at the closest health facility or pharmacy. This would increase their cluster's overall value for ACT availability. However, getting malaria, or having a family member contract malaria would also increase likelihood of absenteeism. Thus, this background bias could lead to an increased value for ACT availability and also increase likelihood of absenteeism. Despite this, the results still find that increased ACT availability has a negative effect on likelihood of absenteeism, thus it is possible that this background bias could be reducing the magnitude of the actual effects of decreased absenteeism that ACT availability has.

After much thought on other omitted variables that could potentially influence both likelihood of absenteeism and ACT availability, I was unable to think of other variables that were not already included in the analysis. It is, however, possible that there are other variables unaccounted for in this study that may have background bias effects on the results.

6.5 Data Cutting Effects on Results

The three data cuts made from the original sample to create the sample used in this study could have affected the results by skewing the sample population in certain directions. Drops were made of individuals who had missing data for job absenteeism, individuals who were not currently working, and individuals who did not know if ACTs were available at the closest health facility or pharmacy. The group for whom the variable of job absenteeism was missing could have been listed as such because they had not missed work in so long that the question was unwarranted. If this was the case, and they had not been missing work due to the benefits of ACTs, the magnitude and significance in effect of ACTs would be much higher.

Dropping individuals who were not currently working could have affected the results found in this study based on the reason they were not currently working. Including individuals who might have responded “not currently working” because they were at home ill with malaria may have decreased the effect that ACT availability has on absenteeism, particularly if they had been absent from work due to not seeing benefits from ACTs.

Finally, dropping individuals who did not know if ACTs were available at the closest health facility of pharmacy could have affected the results. These individuals were added back into the sample and assigned an ACT availability value based on other individuals’ responses in their cluster. Had they accurately been able to provide information on ACT availability they would have shifted ACT availability level up or down in their cluster. This would have had an effect on how ACT availability would affect likelihood of absenteeism.

7. Conclusion

This study aimed to measure the effect of ACT availability on decreasing the likelihood of work absenteeism. Through the regression analysis conducted, it found that individuals living in clusters with higher ACT availability had decreased likelihood of work absenteeism. This suggests that ACTs do, in fact, have beneficial effects of preventing individuals from missing work and bearing the indirect costs of malaria. For every 1% increase in cluster-level ACT availability, an individual would see a 0.295 percentage point decrease in likelihood of absenteeism. Furthermore, the analysis found that self-employed agricultural workers saw greater effects of ACT availability leading to decreased likelihood of absenteeism. For self-employed agricultural workers, a cluster level ACT availability increase of 1% would lead to a 0.5459 percentage point decrease in likelihood of absenteeism.

Due to the magnitude and statistical significance of the effect that ACT availability has on decreasing likelihood of absenteeism for self-employed agricultural workers, it is likely that the overall beneficial effects of ACTs are being largely driven by this subcategory. This is an important finding, as it identifies a subset of the population which particularly benefits from ACT availability. Self-employed agricultural workers see the most benefit of increased ACT availability leading to decreased likelihood of absenteeism, thus provide a target group to which scarce ACT resources can be allocated. Thus, policies may look to divert more resources to these individuals when looking to most impactfully alleviate the economic burden of malaria.

The different interpretations of the ACT availability variable also call for different policy strategies. In interpreting ACT availability as physical availability of ACTs, improvements in distribution of the drugs should be a key focus to spread their benefit. This could mean improving drug supply chain logistics for remote regions that are known face low availability (Onwujekwe et al., 2009), or providing incentives for health facilities/pharmacies to carry the drugs. In interpreting ACT availability as accessibility to individuals driven by cost, decreasing cost barriers becomes the primary policy objective. ACTs are known to be prohibitively expensive in the private sector (Cohen et al., 2010) and public facilities that are intended to make them more accessible face severe shortages (Kangwana et al., 2009). Thus, policies can be implemented to either provide subsidies to help purchase drugs in private sector, or improve drug stock management in the public sector.

There are several future avenues of research that can be pursued considering the findings of this study. One avenue of research is looking into what is truly driving cluster level ACT availability. Determining if ACT availability is physical availability, accessibility determined by cost, or a combination of the two can inform policymakers on how to best increase ACT availability. Another avenue for future research is to see if any other subgroups of the population see particularly large benefits from ACTs decreasing their likelihood of absenteeism. Although self-employed agricultural workers were identified in this study as a group that sees increased benefits from ACTs compared to the rest of the population, it is quite likely that there exist other subgroups in the population that see the same effect. By identifying these groups, policymakers can strategize how to best utilize scarce resources to provide the most impact in helping alleviate the economic burden of malaria.

The findings of this study prove that ACTs can help alleviate the indirect costs of malaria by decreasing the likelihood of absenteeism. Existing literature primarily focuses on the impact ACTs have on malaria morbidity and mortality. There still remains much research to be done regarding the impact of ACTs on the economic well-being of individuals who live in malaria endemic regions. By finding that ACTs can help decrease the indirect costs of malaria, this study provides evidence that they are a tool that can be used to help alleviate both the health and economic burdens of malaria on the most vulnerable people on the planet.

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9. Appendix

Appendix Table 1

VARIABLES	(1) Urban Status	(2) Urban Status	(3) High Education Level	(4) High Education Level	(5) Total Years of Education	(6) Total Years of Education	(7) High Wealth Level	(8) High Wealth Level
100% ACT availability cutoff	0.0890*		-0.140***		-0.340		-0.0575	
	(0.0533)		(0.0314)		(0.275)		(0.0534)	
90% ACT availability cutoff		0.157***		-0.239***		-0.742**		-0.120**
		(0.0576)		(0.0390)		(0.300)		(0.0548)
Constant	0.270***	0.197***	0.312***	0.422***	6.509***	6.898***	0.535***	0.597***
	(0.0354)	(0.0479)	(0.0255)	(0.0357)	(0.182)	(0.253)	(0.0358)	(0.0445)
Observations	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414
R-squared	0.009	0.020	0.027	0.056	0.002	0.008	0.003	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

9.1 Measuring Differences in Population Indicator Control Variables Between High ACT Availability and Low ACT Availability Clusters

Similar to the chi-squared tests run in *Section 4.3 Data Cutting* to find differences in population indicators between the original sample and cut sample, differences in population indicators between individuals in clusters with high ACT availability and low ACT availability were measured. This was done by creating a threshold for cluster-level ACT availability (*ACT*), and conducting chi-squared tests on population indicators for individuals above and below the threshold level. Additionally, simple regressions were run, regressing the population indicator variable on the ACT availability cutoff groups to see if there was any relationship between the two. Standard errors were clustered at the village cluster level to account for variables interacting at the cluster level.

Two threshold levels for ACT availability were used to measure differences in population indicators between high ACT availability and low ACT availability clusters, ensuring that any relevant differences were captured. An ACT availability threshold of 100% found a relatively even split in the sample, with 758 individuals being in clusters where all members indicated ACTs were available at the closest health facility or pharmacy, and 656 being in clusters with ACT availability below 100%. When the ACT availability threshold was decreased to 90%, far more individuals had access to ACTs at or above the threshold, with 1,089 individuals in clusters at or above 90%, and 325 below the threshold. By testing at the two threshold levels with vastly different proportions of individuals above and below, any population indicator that was significantly different for both thresholds would likely be a relevant difference that existed between high ACT availability clusters and low ACT availability clusters.

For the 100% threshold level, a chi-squared test and simple regression[8] found that the proportion of individuals of urban status was significantly different between clusters with 100% ACT availability and clusters with below 100% ACT availability. The chi-squared test found the difference to be significant at the 1% level, while the simple regression found a positive relationship between urban status and 100% ACT availability significant at the 10% level. Similarly, chi-squared tests found significant differences in the proportion of individuals with high levels of education (significant at the 1% level) and high levels of wealth (significant at the 5% level) between clusters with 100% ACT availability and clusters with below 100% ACT availability. A simple regression analysis found a negative relationship between higher levels of education and 100% ACT availability (significant at the 1% level), but no significant relationship between higher levels of wealth and 100% ACT availability. In addition to an individual having a higher level of education, an individual's total years of education was also tested using a simple regression to see if it had a relationship with 100% ACT availability (a chi-squared test could not be conducted, as years of education is a continuous variable). No significant relationship was found between years of education and 100% ACT availability.

Comparing clusters with 90% ACT availability or above, and clusters below 90% ACT availability, chi-squared tests found significant differences at the 1% level in proportion of individuals with urban status, and proportion of individuals with higher levels of education. Simple regressions found a positive relationship between urban status and clusters with 90% ACT availability or above (significant at the 1% level), and a

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[8] See Appendix Table 1 for simple regression outputs of relationship between population indicator variables and threshold levels for ACT availability

negative relationship between higher levels of education and clusters with 90% ACT availability or above (significant at the 1% level).[9] Additionally, a chi-squared test found that the proportion of individuals of higher wealth significantly differed between the two cluster groups at the 1% level, whilst a simple regression found a negative significant relationship between higher levels of wealth and clusters with 90% ACT availability or above (significant at the 5% level). Total years of education was also found to have a negative significant relationship with clusters at 90% ACT availability or above (significant at the 5% level).

Appendix Table 2:

Variable	Proportion in Clusters with 100% ACT Availability	Proportion in Clusters below 100% ACT Availability
Living in Urban Region	35.88%	26.98%
Completed Secondary or Higher Education	17.28%	31.25%
In Top 2 Quintiles of Wealth	47.76%	53.51%

Appendix Table 3:

Variable	Proportion Clusters at or above 90% ACT availability	Proportion in Clusters below 90% ACT availability
Living in Urban Region	35.35%	19.69%
Completed Secondary or Higher Education	18.27%	42.15%
In Top 2 Quintiles of Wealth	47.66%	59.69%

[9] See Appendix Table 1 for simple regression outputs of relationship between population indicator variables and threshold levels for ACT availability

For urban vs. rural status, the proportion of urban individuals was higher for individuals in clusters with 100% ACT availability, making up 35.88% of the group, compared to a far lower 26.98% of the clusters under the threshold level (Appendix Table 2). Results were similar for the 90% threshold level as seen in Appendix Table 3. It is understandable why clusters with higher ACT availability consist of more urban individuals, as these regions have better supply chain logistics, bigger and newer health facilities with more inventory, and higher demand of diverse products due to more population density, which may contribute to higher levels of ACT availability.

As seen in Appendix Table 2, clusters with 100% ACT availability had a smaller proportion of individuals with secondary and higher education, making up only 17.28 % of this group, while making up 31.25% of the clusters below the 100% threshold. Results were similar for the 90% cutoff level (Appendix Table 3). It is surprising that individuals with higher levels of education make up a smaller proportion of the group with 100% ACT availability, as higher education usually represents higher wages, thus increased likelihood of living in proximity to better healthcare facilities or pharmacies that carry ACTs. Similarly, a regression between years of education and clusters with 90% ACT availability or above found that there was a significantly negative relationship between the two (Appendix Table 1, Column 6). Again, it is unclear why years of education has a negative relationship to ACT availability level.

Clusters with 100% ACT availability had a lower proportion of individuals in the top 2 wealth quintiles, who made up 47.76% of that group, as opposed to 53.51% of the group below the threshold level (Appendix Table 2). Similar differences in proportions were observed at the 90% threshold level as seen in Appendix Table 3. A simple regression found that there was no statistically significant relationship between high wealth level and clusters with 100% ACT availability. There was, however, a negative significant relationship (at the 5% level) between high wealth level and clusters with 90% ACT availability or more. It is surprising that those who are wealthier make up a smaller relative proportion of the clusters that have high ACT availability compared to clusters that have low ACT availability, as wealth would intuitively signify proximity to better stocked health facilities and pharmacies. One possible explanation for this may be that wealthier individuals live in suburban areas that have smaller health facilities/pharmacies which may not carry the same diversity of medications that can be found in large urban health facilities/pharmacies, or rural health facilities/pharmacies that must carry everything, as they are the only source of medication in their rural setting.