

Full Length Research Paper

Two-Way Causality between Presumptive Malaria and Poverty in Rural South West, Nigeria

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ABSTRACT: This study examined the possibility of two-way causality between presumptive malaria and poverty in rural South West, Nigeria. Multistage sampling technique was used to obtain primary data from 395 respondent farming households using structured questionnaire. Descriptive statistics and Two-Stage Probit Least Square (2SPLS) estimated with CDSIMEQ program was employed to examine the two-way causality between presumptive malaria and poverty. The Mean Per Capita Household Expenditure (MPCHHE) for the households stood at N5605.89k with the 2/3 of MPCHHE (poverty line) amounting to N3737.26k. The Foster-Greer-Thorbecke (FGT) results reveals a poverty incidence, depth and severity of 0.425, 0.031 and of 0.004, respectively. The results of 2SPLS show that presumptive malaria significantly explained household poverty status and the

reverse effect was equally significant. The coefficient of household poverty status had positive sign ($\beta=2.3949$) and it was significant. Similarly, the coefficient of workdays lost to presumptive malaria was positive ($\beta=0.0607$) and it was statistically significant. The study established the existence of a bi-causal relationship between presumptive malaria and household poverty, suggesting that the endogeneity bias between malaria and household poverty status is attributable to reciprocal causation. It is therefore recommended that poverty reduction strategies should incorporate malaria control activities to properly address poverty just as it will also offers new areas of intervention in the battle against poverty.

Keywords: Presumptive malaria, poverty, endogeneity, CDSIMEQ, Southwest Nigeria.

INTRODUCTION

Malaria, one of the widespread communicable diseases, comes as a result of attacks on red blood cells by protozoa parasites belonging to genus *Plasmodium*. The protozoa get introduced into the human body through female anopheles mosquitoes. Human beings are infected majorly by *Plasmodium falciparum* (WHO, 2009). The early symptoms of malaria are identical and comparable with the symptoms of other febrile diseases: they include fever, chills, vomiting, headache, fatigue, muscle and joint pain, abdominal discomfort, anorexia, perspiration and lassitude. In malaria-endemic countries, people commonly assume they have malaria when sick and treat themselves accordingly (Whitty, 2008; Juma and Zurovac, 2011).

Malaria is a major public health problem in Nigeria. It remains an important cause of morbidity and mortality. Nigeria accounted for 32% of the global estimate of 655,000 malaria deaths in 2010 (WHO, 2012). An estimated 97% of the country's approximate population of 160 million residents is at risk of malaria. Children under age 5 (U5) and pregnant women are the most vulnerable to illness and death from malaria infection in Nigeria. It accounts for about 60% of all outpatient attendance and 30% of all hospital admissions (WHO, 2012). A typical bout of malaria lasts from about 10 to 14 days with 4 to 6 days of near complete incapacitation and a recuperation period of 4 to 8 days characterized by fatigues and weakness (Berman *et al.*, 1999). In addition to the direct

health impact of malaria, there are also severe economic burdens on the country as a whole, with about 480 billion Naira lost to malaria annually in the form of treatment costs, prevention efforts, loss of work time (Federal Ministry of Health, 2012).

Malaria is commonly recognized as a disease of poverty (WHO/UNICEF, 2003; Sachs and Malaney, 2002; Gallup and Sachs, 2001). Malaria thrives in poverty and also impedes economic growth and keeps households in poverty (Teklehaimanot and Mejia, 2008). According to Booyesen *et al.* (2001) and Jackson (2002), poverty contributes to malaria and malaria contributes to poverty, causation is bi-directional. The bi-causal relationships between malaria and poverty are in two folds. On one hand, poverty fosters the spread of the illness and on the other hand, the illness increases poverty of affected households. In the first case, poverty enhances the vulnerability of people to malaria infection. Apart from being associated with poor nutrition and a breakdown of immune systems, is also related to unsafe housing conditions and poor sanitation practices as a result of lack of knowledge and lack of access to means of protection like the use of mosquito nets. In the second case, several episodes of malaria can make households and individuals to move into deeper poverty where its primary impact is visible mainly on the incomes and the expenditures of individuals and households.

Despite the general assumption of potential bi-causality relationship between malaria and poverty, there have been so few research efforts to establish such a dual relationship between malaria and poverty except the studies by de Castro and Fisher, (2012) and Somi *et al.* (2007), both in Tanzania. The two-way linkage between malaria and poverty has not been studied thus far in Nigeria. Although the causal effect of malaria on poverty in Nigeria has been increasingly documented, the empirical evidence regarding the two-way causality between malaria and poverty is still limited. Thus, the link between malaria and poverty at the household level remain unclear. Considering the prevalence of poverty, especially among the rural farming households, an examination of malaria and other critical factors affecting poverty with a rural focus is necessary. Understanding whether the malaria-poverty relationship implies causality and, if it does, the direction of causality has crucial implications for malaria control efforts, such as the Roll Back Malaria (RBM) with the ultimate goal of malaria eradication. It is also essential for developing suitable public policies and developmental interventions to fight poverty as advocated by Hakim *et al.* (2010). Also, given that malaria is endemic throughout Nigeria, and that over 69% of the country's population are living below poverty line (NBS, 2012), malaria incidence may increase significantly in Nigeria because many may not be able to afford the newly introduced drugs due to poverty (Yusuf *et al.*, 2010), except certain policies are put in place to reduce the cost of malaria treatment and prevention at

household level most especially in the rural areas as poverty in Nigeria is mostly of rural phenomenon. This study intends to examine the possibility of two-way causality between presumptive malaria as measured by workdays lost to presumptive malaria and household poverty level in rural South West, Nigeria. Specifically, the study examined:

- (i) Workdays lost to presumptive malaria and incidence of poverty among households in the study area.
- (ii) The importance of workdays lost to presumptive malaria in explaining the level of household poverty in rural South West, Nigeria.
- (iii) The significance of poverty and other determinants in the frequency of malaria attacks as measured by workdays lost to presumptive malaria.

MATERIALS AND METHODS

The study was carried out in South West, Nigeria.. Total population of the area as at 2006 was 27,581,992 (NPC, 2006). The zone is bounded in the North by Kogi and Kwara States, in the East by Edo and Delta States, in the South by Atlantic Ocean, and in the West by Republic of Benin. It composes of six states: Ekiti, Lagos, Ogun, Ondo, Osun and Oyo. There are two distinct seasons, the rainy season, which lasts from April to October and the dry season which starts from November and ends in March. The distribution of rainfall varies from about 1000mm to about 2000mm. Important cash crops such as cocoa, kolanut, citrus, coffee, rubber and oilpalm are grown in the region. Savanna parts of the region produces food crops such as tubers, grains, plantain/banana and vegetables. Although, malaria is endemic throughout Nigeria (Yusuf *et al.*, 2010), the choice of south west Nigeria is premised on the fact that the zone is lies within the rain-forest belt of Nigeria. The climate is hot and humid which favours the proliferation of the mosquito vectors (Babalola *et al.*, 2009). Nigeria Demographic and Health Survey (2013) indicated that South west is the zone with the lowest number of households with at least one Insecticide Treated Nets (ITNs) or Long-lasting Insecticidal net (LLIN) in Nigeria. Hence, poor access to an important malaria preventive measure. A multi-stage sampling technique was adopted in the study. The first stage was the random selection of Oyo and Osun states from the six states in South west, Nigeria. In the second stage, four (4) and three (3) rural Local Government Areas (LGAs) from Oyo and Osun states, respectively were randomly selected based on probability proportionate to size of rural LGAs in each of the states. The third stage was the random selection of five villages from each of the LGAs. In the fourth stage, a random selection of four hundred and twenty (420) food crop farming households from the thirty-five villages selected for the study was carried out. This was achieved

by making a list of food crop farming households in each of the selected villages from which a random selection of 10% of food crop farming households were done in each of the selected villages. Out of the four hundred and twenty (420) questionnaires administered on the respondents, twenty-five (25) were discarded for incomplete information and inconsistency. Thus, data from 395 questionnaire were analyzed for the study. This study was not an epidemiologic or clinical study of malaria. Following Leighton and Foster (1993) and Attanayake *et al.* (2000), the study focused on "perceived" or "self-reported" malaria and not with the prevalence of malaria as measured by presence of parasites in the blood that are yet to manifest in illness symptoms. During the interview, efforts were made to ensure that people reported malaria episodes based on symptoms as close as possible to accepted clinical symptoms. The following symptoms were taken as indicative of malaria: fever, headache, chills/shivering, abdominal pain, diarrhea, nausea / vomiting, bitter taste, loss of appetite (anorexia), lassitude (general body weakness), muscular pain and joints pain (Tangpukdee *et al.*, 2009; Looareesuwan, 1999).

Primary data used for this study were obtained from the respondents with the aid of structured questionnaire. The data collected from the households include socio-economic and demographic characteristics such as age and sex of household head, household size, level of education and years of farming experience of household head; farm size cultivated, food crops planted, inputs used (quantities and prices), farm output (in kg), selling price per unit output, income realized from other crops owned by the farm households such as tree crops, plantain / banana and vegetables, etc. access to agricultural credit and extension services. Malaria related information such as access to electricity, mosquito nets, cause of malaria, and mode of transmission, symptoms, attitudes and practices of households to malaria prevention were sought. Also obtained were number of presumptive malaria cases per household in 2014, type / place of treatment, distance to the nearest health centre, cost of treatments, transportation, subsistence, as well as days of incapacitation due to malaria attacks and workdays lost by the caregiver(s). Information on households' monthly expenditure on food and non-food items was also obtained.

After the data collection, all completed questionnaire were checked properly for any error and edited. Statistical tools used in data analysis include descriptive analysis, Foster-Greer-Thorbecke (FGT) and two-stage probit least square (*ivprobit*) models. The descriptive statistics included frequency, means, percentages and standard deviation. FGT model was used to generate the poverty indices while the *ivprobit* model (estimated with *cdsimeq* program) was used to investigate the correlates of malaria and poverty as well as the possibility of two-way causality between presumptive malaria and

household poverty.

Econometric specification

Two-way causality in the association between presumptive malaria and households' poverty status

Somi *et al.* (2007), and de Castro and Fisher (2012), pointed out the possibility of two-way relationship between malaria and poverty and, therefore, the presence of 'endogeneity'. Following Hassan and Birungi (2011) and Tenzin *et al.* (2013) presumptive malaria is proposed to increase the workdays lost to malaria illness and increases household expenditure on malaria treatment. Thus, increases poverty. In some cases, the household poverty will expose household members to malaria illness and also reduce the strength of households to attends promptly to their health needs which will increase the workdays lost to the illness. The first equation of workdays lost to presumptive malaria (y_1) as a function (f) of poverty status (y_2) is as shown in equation 1:

$$y_1 = g(y_2, x_1) \quad (1)$$

Where x_1 is a vector of other independent variables

In the same manner, presumptive malaria is assumed to increase the workdays lost to malaria illness and increases household expenditure on malaria treatment, thus, promotes poverty. The equation of poverty status (y_2) as a function (f) of workdays lost to presumptive malaria (x_1) is as shown in equation 2 below:

$$y_2 = f(y_1, x_2) \quad (2)$$

Where x_2 is a vector of the other independent variables.

These two equations above suggested a reversed causality of household poverty and presumptive malaria and therefore raise the question of endogeneity and simultaneity problems as claimed by Nasution *et al.* (2015) and Tenzin *et al.* (2013). Without rectifying the problem the application of 'ordinary least squares' is not suitable, as the results will be incorrect, inconsistent and the estimators biased (Hassan and Birungi, 2011). The usual remedy for the existence of an endogeneity problem is the adoption of an instrumental variable (IV) estimation or a two-stage least squares (2SLS) estimation. In this case, one of the endogenous variables is dichotomous, while the other endogenous variable is continuous. Therefore, this study employed a two-stage probit least squares (2SPLS) regression (*ivprobit*) model which is recommended for such a simultaneous equation model (Alvarez and Glasgow, 1999; Hassan and Birungi, 2011; Tenzin *et al.*, 2013; Keshk, 2003). Keshk (2003) CDSIMEQ method was applied to estimate the model.

The `cdsimeq` method implements the two-stage estimation method described in Maddala (1983) for simultaneous equations model in which one of the endogenous variables is continuous and the other endogenous variable is dichotomous. In this case, the workdays lost to presumptive malaria is a continuous variable while the household poverty status is dichotomous. The `cdsimeq` command implements all the necessary procedures for obtaining consistent estimates for the coefficients, as well as their corrected standard errors. The two-equation generic econometric model was considered following (Gujarati, 2003):

$$y_1^* = \gamma_1 y_2^* + \beta_1' X_1 + \varepsilon_1 \tag{3}$$

$$y_2^* = \gamma_2 y_1^* + \beta_2' X_2 + \varepsilon_2 \tag{4}$$

Where:

If y_1^* and y_2^* are observed as follows:

$$y_1 = y_1^*$$

$$y_2 = 1 \text{ if } y_2^* > 0$$

$$y_2 = 0 \text{ otherwise}$$

Neither γ_1 nor γ_2 equal zero, indicating a non-recursive model for which `cdsimeq` is designed.

If we begin the analysis with our simultaneous equation model:

$$y_1 = \gamma_1 y_2^* + \beta_1' X_1 + \varepsilon_1 \tag{5}$$

$$y_2^* = \gamma_2 y_1 + \beta_2' X_2 + \varepsilon_2 \tag{6}$$

y_1 is a continuous endogenous variable, y_2^* is a dichotomous endogenous variable which is observed as 1 if $y_2^* > 0$, and 0 otherwise, X_1 and X_2 are matrices of exogenous variables in equations 5 and 6. β_1' and β_2' are vectors of parameters in equations 5 and 6, γ_1 and γ_2 are the parameters of the endogenous variables in equations 5 and 6, ε_1 and ε_2 are the error terms of equations 5 and 6. Because y_2^* is not observed, the structural equations 5 and 6 are rewritten as:

$$y_1 = \gamma_1 \sigma_2 y_2^{**} + \beta_1' X_1 + \varepsilon_1 \tag{7}$$

$$y_2^{**} = \frac{\gamma_2}{\sigma_2} y_1 + \frac{\beta_2'}{\sigma_2} X_2 + \frac{\varepsilon_2}{\sigma_2} \tag{8}$$

The estimation follows the typical two-stage estimation process. In the first stage, the following two models are fitted using all of the exogenous variables (i.e., the exogenous variables in both (7) and (8),

$$y_1 = \Pi_1' X + u_1 \tag{9}$$

$$y_2^{**} = \Pi_2' X + u_2 \tag{10}$$

Where

X is a matrix of all the exogenous variables in (7) and (8), Π_1 and Π_2 are vectors of parameters to be estimated, u_1 and u_2 are error terms.

Equation (9) is estimated via OLS and equation (10) via probit. From these reduced-form estimates, the predicted

values from each model are obtained for use in the second stage.

$$\hat{y}_1 = \hat{\Pi}_1' X \tag{11}$$

$$\hat{y}_2^{**} = \hat{\Pi}_2' X \tag{12}$$

In the second stage, the original endogenous variables in (7) and (8) are replaced by their respective fitted values in (11) and (12). Thus, in the second stage, the following two models are fitted:

$$y_1 = \gamma_1 \hat{y}_2^{**} + \beta_1' X_1 + \varepsilon_1 \tag{13}$$

$$y_2^{**} = \gamma_2 \hat{y}_1 + \beta_2' X_2 + \varepsilon_2 \tag{14}$$

Again, (13) is estimated via OLS and (14) is estimated via probit. The final step in the procedure is the correction of the standard errors. This is necessary because, as can be seen from (13) and (14), the outputted standard errors for each model in the second stage will be based on \hat{y}_2^{**} and \hat{y}_1 and not on the appropriate y_2^{**} and y_1 . Thus, the estimated standard errors in (13) and (14) will be incorrect. The correction that needs to be implemented on the variance-covariance matrices α_1 and α_2 , which are the variance-covariance matrices of (13) and (14), respectively, are as follow:

First define the following:

$$\alpha_1 = (\gamma_1, \sigma_2, \beta_1')$$

$$\alpha_2 = \begin{pmatrix} \gamma_2 & \beta_2' \\ \sigma_2 & \sigma_2 \end{pmatrix}$$

$$c = \sigma_1^2 - 2\gamma_1\sigma_{12}$$

$$d = \frac{\gamma_2}{\sigma_2} \sigma_1^2 - 2\frac{\gamma_2}{\sigma_2} \frac{\sigma_{12}}{\sigma_2}$$

$$H = (\Pi_2, J_1) \tag{15}$$

$$G = (\Pi_1, J_2) \tag{16}$$

$$V_0 = \text{Var}(\hat{\Pi}_2) \tag{17}$$

With these definitions at hand, and noting that in probit models σ_2 is normalized to 1, the corrected variances of α_1 and α_2 can be obtained as follows:

$$V(\hat{\alpha}_1) = c(H' X' XH)^{-1} + (\gamma_1 \sigma_2)^2 (H' X' XH)^{-1} H' X' V_0 X' XH (H' X' XH)^{-1} \tag{18}$$

$$V(\hat{\alpha}_2) = (G' V_0^{-1} G)^{-1} + d(G' V_0^{-1} G)^{-1} G' V_0^{-1} (X' X)^{-1} V_0^{-1} G (G' V_0^{-1} G)^{-1} \tag{19}$$

Everything defined above is easily obtainable from built-in Stata procedures.

Explanatory variables for the equation of workdays lost to presumptive malaria

- X_1 =Household poverty status (if poor is 1, non-poor is 0)
- X_2 =Household size (number)
- X_3 =Housing type (1=if poor or bad, 1 if good)
- X_4 =Room density (number of people per room)

X₅=Environmental sanitation (1 if done regularly, 0= otherwise)

X₆=Time taken to fetch water (in minutes)

X₇=Time taken to fetch firewood (in minutes)

X₈=Preventive cost in Naira

X₉=Access to mosquito nets (ITNs or LLINs) 1=access, 0=otherwise

X₁₀=Distance to health centre (km)

X₁₁=If ever participated in malaria awareness campaign before (if participated=1,0=otherwise)

X₁₂=Use of herb (1 if used, 0=otherwise)

X₁₃=Access to electricity (1=if access, 0=otherwise)

Explanatory variables for the poverty equation

X₁=Workdays lost to presumptive malaria (manday)

X₂=Age of household head (years)

X₃ = Age squared of household head (years)

X₄= Household size (in number)

X₅= Dependency ratio (number)

X₆= Room density (number)

X₇ =Years of schooling of household head (number of years)

X₈=Years of farming experience (years)

X₉=Farm size cultivated by the household (hectares)

X₁₀=Access to extension services (if access=1, 0=otherwise)

X₁₁= Access to credit (if access=1, 0=otherwise)

X₁₂=Connected to electricity (If connected=1, 0=if otherwise)

X₁₃ =Malaria financial cost to the household (direct cost) in Naira.

Ethical considerations

Written informed consent was obtained from all the heads of the households participated in the data collection process and assurance given to them that all information received would be handled confidentially. They were informed that participation is voluntary and also assured of their right to withdraw from the interview at any time they would wish during the interview. The survey was also anonymized so that household or individual information is not identifiable. Ethical clearance for the study was obtained from the Osun State Specialist Hospital Osogbo Health Research Ethics Committee (Clearance number: HREC/27/04/2015/SSHO/027).

RESULTS AND DISCUSSION

Socio-demographic and economic characteristics of the respondents

As shown in (Table 1), 88.6% of the households' head were male, age was 56.41±9.34 years, 88.4% were

married, household size was 7±2 persons and farm size was 1.72±0.56. Years of schooling were 4.80±4.65 which is far below the universal basic education of at least 6 years (primary school) with 37.0% of them had no formal education. Years of farming experience was found to be 29.53±10.78. It was also found that only 45.6% and 24.6% had access to extension services and credit, respectively. The annual farm income was ₦452,711.70±153,704.70 (equivalent to ₦37725.97 per month).

Determination of poverty line and Foster-Greer-Thorbecke (FGT) decomposition results

Table 2 shows the summary of households' expenditure on food and other non-food basic items in the study area. The Mean Per Capita Household Expenditure (MPCHHE) for the households stood at ₦5605.89 with the 2/3 of MPCHHE amounting to ₦3737.26. Hence, households were classified as poor if their MPCHHE fall below ₦3737.26k.

Poverty decomposition

The FGT results reveals a poverty incidence, depth and severity of 0.425, 0.031 and of 0.004, respectively (Table 3). It implies that 42.5% of the households were poor. Poverty depth value of 0.031 implies that an averagely poor household in the study area had 3.1% deprivation of income (that is, had to mobilize resources up to 3.1% of the poverty line more per person per day in order to break out from poverty). The severity of poverty index with value of 0.004 shows the seriousness of poverty. It implies that the core poor were about 0.4% worse off compared to the averagely poor. Therefore, the study has found that poverty is prominent amongst the sampled households in the study area.

Distribution of poverty incidence by workdays lost to presumptive malaria

Table 4 shows the variation observed in the poverty incidence as workdays lost to presumptive malaria increases. It was observed that as workdays lost to presumptive malaria increased, poverty incidence also increased. This implying a direct relationship between workdays lost to malaria and poverty incidence among the food crop farming households in the study area. Households who lost less than 40 workdays, between 40 and 59; 60 and 79; 80 and 99; and more than 99 workdays had poverty incidence of 26%, 38%, 40%, 44.8% and 55.9%, respectively. These findings concur with Ochi *et al* (2015) who linked increased poverty

Table 1: Socio-Economic Characteristics of Food Crop Farming Households (n=395)

Variables	Frequency	Percentage	Mean	S.D
Sex of the household head				
Male	350	88.6		
Female	45	11.4		
Age of Household head (years)				
< 45	49	12.4		
45-54	106	26.8		
55-64	152	38.5	56.41	9.34
> 64	88	22.3		
Marital status of household head				
Married	349	88.4		
Widow/Widower	45	11.4		
Single	1	0.3		
Household size				
2-5	111	28.1		
6-9	266	67.3	6.518	1.63
>9	18	4.6		
Household head's years of Schooling				
0 (No formal education)	146	37.0		
1-6	142	36.0		
7-12	100	25.3	4.80	4.65
>12	7	1.8		
Farming experience (years)				
1-10	11	2.8		
11-20	96	24.3		
21-30	93	23.5	29.53	10.78
31-40	142	36.0		
>40	53	13.4		
Farm size (Hectares) cultivated				
< 1	13	3.3		
1-1.5	120	30.4		
1.6-2.0	193	48.9	1.722	0.5569
2.1-3.0	57	14.4		
> 3	12	3.0		
Household access to extension services				
Access	178	45.1		
No access	217	54.9		
Household access to credit				
Access	97	24.6		
No access	298	75.4		
Household's farm income (₦ / Annum)				
Less than 200,000	8	2.0		
200,000-299,999	58	14.7		
300,000-399,999	97	24.6		
400,000-499,999	100	25.3	452711.70	153704.70
500,000-599,999	68	17.2		
600,000-699,999	35	8.9		
700,000 and above	29	7.3		

Source: Field Survey, 2015.

among households in agricultural communities with an increase in workdays lost to malaria illness.

Bi-causality relationship between presumptive malaria and household poverty

Table 5 presents the results of the 2SPLS (ivprobit) regression analysis achieved with the CDSIMEQ method.

The result of the second stage regressions with corrected standard errors is as presented in the (Table 5). The coefficient of household poverty status had the anticipated positive sign ($\beta=2.3949$) and it was significant. This implies that being poor has a direct effect on workdays lost to malaria. That is, the poor households lost more workdays than their counterparts' non-poor households. Similarly, the coefficient of workdays lost to presumptive malaria was positive ($\beta=0.0607$) and it was

Table 2: Determination of household poverty line.

Monthly Expenditure	Average value (₦)	Percentage
Food	20945.57	60.0
Health care	2133.08	6.1
Rent allowance	1022.36	2.9
Clothing	1667.09	4.8
Children education	2483.80	7.1
Transport	2758.73	7.9
Water	147.80	0.4
Electricity	431.77	1.2
Kerosene	1011.24	2.9
Fuel / Gas / Charcoal	146.33	0.4
Petrol for generator	99.49	0.3
Batteries for radio / torchlight	188.38	0.5
Toiletries	545.16	1.6
GSM maintenance	1131.09	3.2
Other expenses	207.09	0.6
Total Non-food expenditure	13973.41	40.0
TOTAL (Food + Non-Food)	34,918. 98	100
Mean Per Capita Household Expenditure (MPCHHHE)	5605.89	
Poverty line (2/3 PCHHE)	3737.26	

Source: Field survey, 2015.

Table 3: Poverty incidence, depth and severity among the households (FGT model result).

Poverty index	Value
Poverty incidence (P_0)	0.425
Poverty depth (P_1)	0.031
Poverty severity (P_2)	0.004

Source: Field survey, 2015.

Table 4: Workdays lost to presumptive malaria and incidence of poverty among households.

Workdays lost to Presumptive malaria	Number of Respondents	Poverty Incidence P(0)
Less than 40	23	0.260870
40-59	89	0.382022
60-79	139	0.402878
80-99	87	0.448276
Above 99	57	0.578947
Total	395	

Source: Field survey, 2015.

statistically significant, implying that an increase in workdays lost to presumptive malaria increases the probability of households being in poverty. The result shows that malaria significantly explained household poverty status and household poverty equally explain malaria (proxied by workdays lost to presumptive malaria). It suggests further that the endogeneity bias between malaria and household poverty status is attributable to reciprocal causation. This finding is in consonance with de Castro and Fisher (2012). The age and age squared of household head, dependency ratio, extension services, connected to electricity, distance to

health center, and use of mosquito nets were the variables that significantly affect the number of workdays lost to presumptive malaria. The coefficient of age of household head was negative ($\beta=-4.9046$) and significant at 1%. This implies that when the age of household head increased by one unit, the workdays lost to malaria decreased by 4.9%. This is possible because of the likelihood of increasing immunity due to recurrent bouts of malaria. However, the coefficient of age squared of household head was positive ($\beta=0.0470$) and significant at 1%, implying that the inverse association of age with workdays lost to presumptive malaria were weakened

Table 5: Results from the 2 stage probit least squares estimation CDSIMEQ second stage regressions with corrected standard errors.

Workdays lost to presumptive malaria	Coefficient	Std Error	t	P-value
poverty status	2.3949**	1.1641	2.06	0.040
Household size	3.4337***	0.8288	4.14	0.000
Housing type	-3.4344*	2.0567	-1.67	0.096
Room density	-1.6625	2.2541	-0.74	0.461
Environmental sanitation	-5.8447***	2.2432	-2.61	0.010
Time taken to fetch water	-0.5367***	0.1492	-3.60	0.000
Time taken to fetch firewood	0.0351*	0.0211	1.66	0.097
Preventive cost in Naira	-0.0005**	0.0002	-2.36	0.019
Access to mosquito nets (ITNs or LLINs)	-22.7899***	3.7533	-6.07	0.000
Distance to health centre	1.2592***	0.2855	4.41	0.000
Malaria awareness campaign	19.4372***	7.4884	2.60	0.010
Use of herb	2.0683	2.4523	0.84	0.400
Access to electricity	-2.7029	2.0407	-1.32	0.186
Constant	66.6066	6.4702	10.29	0.000
Household poverty status	coefficient	Std Error	z	P-value
workdays lost to presumptive malaria	0.0607**	0.0308	1.97	0.049
Age	0.3900**	0.1877	2.08	0.038
Age squared	-0.0031*	0.0017	-1.82	0.069
Household size	0.4979***	0.0756	6.58	0.000
Dependency ratio	1.3296	1.3752	0.97	0.334
Years of schooling	-0.0516	0.0401	-1.29	0.198
Room density	-0.7210**	0.2968	-2.43	0.015
Farm size	-0.5474**	0.2283	-2.40	0.017
Farming experience	-0.0188	0.0205	0.91	0.361
Access to extension	-1.1004**	0.4492	-2.45	0.014
Access to credit	0.2642	0.2857	0.92	0.355
Access to electricity	0.1800	0.2766	0.65	0.515
Malaria financial cost	-0.0001**	0.00005	-2.27	0.023
Constant	-14.4236	6.0013	-2.40	0.016

NB. *, ** and ***; Significant at 10%, 5% and 1%, respectively.

Source: Field survey, 2015.

over time due to a decrease in immunity or tolerance level with age; thus, they become more susceptible to malaria attack. Access to extension services was found to be positive ($\beta=12.0908$) and significantly associated with workdays lost to presumptive malaria; this is because the more farming households had contacts with extension services, the likelihood of increasing farming activities, and the greater the exposure to mosquito bites and malaria attacks, hence the more workdays lost to malaria attacks. Conversely, the coefficient of access to electricity was negative ($\beta=-7.2031$) and significantly related to workdays lost to malaria. This implies that access to electricity reduced the number of workdays lost to malaria. This might not be unconnected with the fact that availability of electricity to power electric fans improves comfort inside bed nets (Von Seidlein *et al.*, 2012; Hughes, 2014). Heat inside bed is the reason given by some people in the previous researches for poor usage of mosquito nets (Pulford *et al.*, 2011). Also, electric fans drive away mosquitoes before reaching their

intended victim (Hughes, 2014), hence reducing the frequency of mosquito bites and malaria episodes reported by the household. Distance to health centre had negative coefficient ($\beta=-0.3600$) and significant at 10% level. This is contrary to the *a priori* expectation that the longer the distance to the health centre, the more difficult for people to access health services, hence the more the prevalence of malaria. It however implies that some of the health centres in the study area were either ill-equipped or had no competent personnel. Also, some of the rural people might not even go to the health centres when they perceived malaria but resorted to self-medication which eventually prolonged the workdays lost to malaria. Access to mosquito nets had negative coefficient ($\beta=-10.4898$) and significant at 1% level. Access to and sleeping under mosquito nets (ITNs or LLINs) reduced the frequency of mosquito bites; hence, less malaria attacks and reduced workdays lost to malaria. The coefficient on financial cost of malaria was positive ($\beta=0.0015$) and significant at 1%. An indication

that households who were more exposed to malaria, lost more workdays to malaria and would have spent more on malaria treatment. The result showed further that an increase in age of household head, household size and access to electricity increased the likelihood of household being in poverty. However, age squared of household head, room density, farm size, access to extension services, and malaria financial cost are the variables that have significant reduction effect on household poverty in the study area. The exorbitant electricity tariff being paid, especially the estimated billing (arbitrary billing of electricity consumers) and those on direct lines might be responsible for the direct effect of being connected to electricity and increasing the likelihood of such households being in poverty.

Conclusion and Recommendations

The study established the existence of a bi-causal relationship (two-way causality) between presumptive malaria and household poverty. Workdays lost to presumptive malaria was significantly explained by household poverty status and the household poverty status equally explained workdays lost to presumptive malaria. This study concluded that an increase in workdays lost to presumptive malaria increased the probability of household becoming poor and being poor increase the number of workdays lost to presumptive malaria. This suggests that the endogeneity bias between malaria and household poverty status is attributable to reciprocal causation. The bi-causal relationship between presumptive malaria and household poverty status has significant implications on malaria control and poverty reduction strategies. Therefore, poverty reduction strategies should integrate malaria control activities to appropriately address poverty. Similarly, malaria control will also be taken as poverty reduction strategies in addition to being seen as health interventions. Hence, this study suggested that poverty interventions should appropriately integrate malaria control into their designs and models, especially in malaria endemic areas.

REFERENCES

- Alvarez RN, Glasgow G (1999). Two Stage Estimation of Non-Recursive Choice Models. *Political Analysis*: 8(2): 147-165.
- Attanayake N, Julia Fox-Rushby J, Mills A (2000). Household costs of 'malaria' morbidity: a study in Matale district, Sri Lanka. *Tropical Medicine and International Health volume 5 no 9 p. 595-606*.
- Babalola DA, Awoyemi TT, Awoyinka YA (2009). Effects of Malaria on Rural Farming Household Labour Supply: The Case of Ikenne Local Government, Ogun State, Nigeria. *Acta Satech 3(1): 19-24*.
- Booyens F, Rensburg D, Van Bachmann M, Engelbeecht M, Steyn F (2001). The socio-economic impact of HIV-AIDS on households in South Africa, Medical Research Council of South Africa, South Africa.
- DeCastro MC, Fisher MG (2012). Is malaria illness among young children a cause or a consequence of low socioeconomic status? Evidence from the united Republic of Tanzania. *Malaria Journal, 11:161*.
- Federal Ministry of Health (2012). Malaria advocacy brief for policy makers. Abuja, Nigeria: Federal Ministry of Health.
- Foster J, Greer J, Thorbecke E (1984). Class of Decomposable Poverty Measures: *Econometrica*, 52(3): 761-765.
- Gallup JL, Sachs JD (2001). The Economic burden of Malaria. *Am. J. Trop. Med. Hyg. 64(1-2 Suppl):85-96*.
- Gujarati DN (2003). *Basic Econometrics*. New York: McGraw Hill Book Co.
- Hakim RA, Razak NAA, Ismail R (2010). Does social capital reduce poverty? A case study of rural households in Malaysia. *European Journal of Social Sciences*, 14(4):556-566.
- Hassan R, Birungi P (2011). Social capital and poverty in Uganda. *Development Southern Africa*, 28(1):19-37. <http://dx.doi.org/10.1080/0376835X.2011.545168>.
- Hughes GB (2014). Bed Net Project (Internet). (cited 2016 Jun 14). http://www.youtube.com/watch?v=bCcXe4_CHRs.
- Jackson H (2002). *Continent in Crisis, SAfAIDS*, Avundule, Harare, Zimbabwe.
- Juma E, Zurovac D (2011). Changes in health workers' malaria diagnosis and treatment practices in Kenya. *Malaria Journal*, 10:1doi:10.1186/1475-2875-10-1.
- Keshk OM (2003). CDSIMEQ: A program to implement two-stage probit least squares. *The Stata Journal*, 3(2):1-11.
- Leighton C, Foster R (1993). Economic Impact of Malaria in Kenya and Nigeria. Major Applied Research Paper No. 6.
- Looareesuwan S (1999). Malaria. In: Looareesuwan S, Wilairatana P eds, *Clinical Tropical Medicine*. 1sted. Bangkok, Thailand. *Medical Media*, p. 5-10.
- Maddala GS (1983). *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press, p. 9-23.
- National Bureau of Statistics (2012). *Nigeria Poverty Profile Report 2010*.
- National Population Commission (2006). *Population facts*, Abuja.
- Nasution A, Rustiadi E, Juanda B, Hadi S (2015). Two-Way Causality between Social Capital and Poverty in Rural Indonesia. *Asian Social Science; Vol. 11, No. 13. P.139-150*.
- Nigeria Demographic and Health Survey (2013). National Population Commission (2014). P.565.
- Ochi JE, Madaki MJ, Murtala N (2015). Economic and Social Linkages Between Malaria Illness and Crop Production In Yobe State, Nigeria. Paper presented at the 29th International Conference of Agricultural Economists, held in Milan, Italy, August 9-14, 2015.
- Pulford J, Hetzel MW, Bryant M, Siba PM, Mueller I (2011). Reported reasons for not using a mosquito net when one is available: a review of the published literature. *Malar J. 2011; 10:83*.
- Sachs J, Malaney p (2002). The economic and social burden of malaria: nature 415: 680-685 (medline).
- Somi MF, Butler JRG, Vahid F (2007). Is there evidence for dual causation between malaria and socioeconomic status? Findings from rural Tanzania. *Am. J. Trop. Med. Hyg. 77: 1020-1027*.
- Tangpukdee N, Duangdee C, Wilairatana P, Krudsood S (2009). Malaria Diagnosis: A Brief Review. *Korean Journal Parasitology. Vol. 47, No. 2: 93-102. MINI-REVIEW*.
- Teklehaimanot A, Mejia P (2008). Malaria and Poverty. *Ann . N.Y. Acad. Sci. 1136:32-37*. New York Academy of Science. [Doi: 10.1196/annals.1425.037](https://doi.org/10.1196/annals.1425.037).
- Tenzin G, Otsuka K, Natsuda K (2013). *Impact of Social Capital on Poverty: A Case of Rural Households in Eastern Bhutan*. Ritsumeikan Center for Asia Pacific Studies (RCAPS) Working Paper Series, RWP-13004.
- Von Seidlein L, Ikonomidis K, Bruun R (2012). Airflow attenuation and bed net utilization: Observations from Africa and Asia. *Malar. J.;11:200*.
- Whitty CJM, Hopkins H, Ansah E, Leslie T, Reyburn H (2008). Opportunities and Threats in Targeting Anti-malarials for the AMFm. The Role of Diagnostics. Discussion Paper. RFF DP 08- 41.
- World Health Organization (2012). World Malaria Report fact sheet available at www.who.int/malaria accessed April 15th 2015.
- World Health Organization / UNICEF (2003). *Africa Malaria Report*. WHO/CDS/MAL/2003. 1093.2003.Geneva.
- World Health Organization (2009). *World Malaria Report*. Geneva.
- Yusuf OB, Adeoye BW, Oladepo OO, Peters DH, Bishai D (2010). Poverty and Fever Vulnerability in Nigeria: A multilevel Analysis. *Malaria Journal, 9: 235*.