Determinants of Selecting Malaria Treatment in Rural Zimbabwe: Case Study from Mutema Rural Area*

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Abstract

This study examines the determinants of selecting malaria treatment in rural Zimbabwe, using a case study from Mutema, a rural area which is located in the eastern part of Zimbabwe in the Chipinge District. The study uses cross sectional data collected in the period between August 2009 and February 2010. The eight villages were used as clusters. The systematic random sampling was done in each cluster and a sample of 163 households was assessed. The study mainly focuses on the role played by distance to health centre, religion, education and age in influencing the choice of malaria treatment. Using a probit model, with the dependent variable being the choice of treating malaria, that is either choosing medical or self-care, five factors were found to be significant in determining the selection of malaria treatment by malaria-infected persons. These factors are the following: distance to the nearest health centre, household attained education, religion, severity of the disease and previous infection. More importantly, distance and religion with predicted probabilities of 20% and 98%, respectively, were found to be two of the prohibiting factors for people to use medical care. There is need for policy makers to implement policy measures that aim at increasing the number of health centres in rural areas to shorten the long distance people walk in order to get access to health facilities.

JEL Classification: I12, I19

Key words: Malaria treatment, probit, Zimbabwe.

1.0 Introduction

A considerably large body of literature has confirmed that good health in general can play a major role in poverty alleviation and human development (Thomas and Strauss, 1997; Odwee, Okurut and Adebua, 2006). The choice of disease treatment plays an important role in the reduction of the disease prevalence. This paper empirically examines the factors that influence patients' choice of treatment. In particular, it seeks to determine the factors that influence malaria-infected persons to either use medical care or self-treatment. In this study,

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medical care indicates receiving treatment from a hospital or health centre that has medical professionals or buying from a pharmacy, drugs that are prescribed by a medical professional. On the other hand, self-care indicates practicing traditional ways of treating malaria, buying non-prescribed drugs over the counter, receiving no treatment at all and utilizing any other forms of malaria treatment that is not suggested by medical professional.

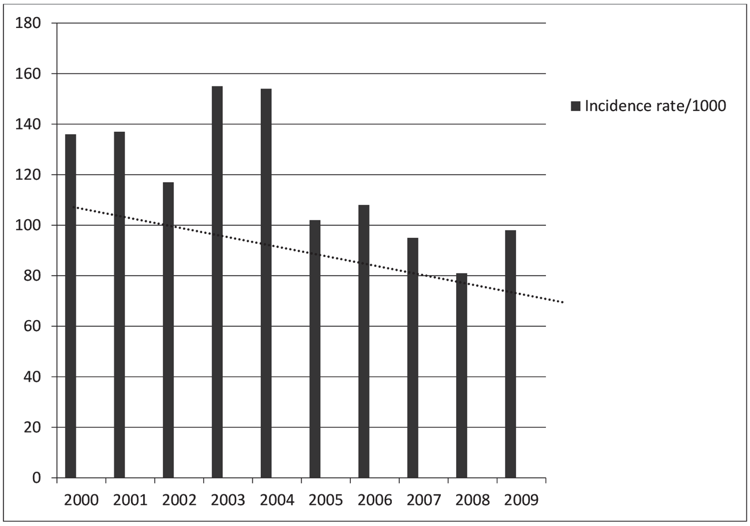
Malaria has been found to be the most widespread infectious disease and is a major public health problem in Africa particularly in Sub-Saharan Africa (Snow *et al*. 2002). Malaria is one of the major causes of death in Sub-Saharan Africa. In recent years, malaria has occurred in areas previously free of malaria, and most studies have attributed the situation to climatic change (WHO, 2008). Sachs (1995) and Sachs and Gallup (2000) established that, in Africa, the malaria risk has always been geography-specific, which means it is most intensive in tropical and sub-tropical zones where Zimbabwe is located. The poor tend to be affected the most as they usually have a limited access to health services, information and protective measures, and have less ability to avoid living or working within malaria-affected areas. As such, this paper focuses on one of the malaria-infected rural areas in Zimbabwe.

Malaria remains a major public health problem in Zimbabwe with over five million people estimated to be at risk of contracting the disease annually (MoHCW, 2009). The Ministry of Health and Child Welfare further states that an estimate of about 50% of the country's population resides in malaria endemic areas. Despite intensive campaigns to promote medical care, self-treatment options remain common in most rural areas of Zimbabwe. That poses a question of why this is the case. This paper, by analysing specifically on malaria, further develops the research of Yip *et al.* (1998) which studied the factors influencing patients' choice of medical care provider in the three-tier health care system in rural China.

1.1 Malaria in Zimbabwe

According to USAID (2009), malaria, after HIV/AIDS, is the second leading cause of death in Zimbabwe and is severe in most low veld areas of the country. According to the recent Zimbabwe population census of 2012, about 67% of the people live in rural areas, and this is the group which houses the highest percentage of the poor populace. While village clinics, health centres and even district or mission hospitals are primary providers of health care, it is not well known as to how people in the rural areas respond to most diseases and receive health services. Given that malaria is one the most common diseases in most rural areas in Zimbabwe, this paper sheds light on the choice of treatment when people in rural areas are infected by Malaria. Malaria is endemic throughout Zimbabwe and is a common cause of hospital admissions for all age groups. However, there is an ecological distribution of specific areas where malaria is most prevalently found (ZDHS, 2005/2006).

The incidence of malaria from year 2000 to 2009 shown in the Figure 1 below, shows that the incidence rate of malaria has been very high, ranging from above 130 to about 150 per 1000 between the year 2000 and 2004, with only 2002 marginally below the range. The incidence rate dropped to as low as 80 per 1000 temporarily in 2008, but returned to a high range again in 2009 approaching nearly 100 per 1000. The re-emergence of the high incidence rate of the disease shows that mitigation of the disease is still a challenge in Zimbabwe. The rate of progress required to achieve the 2015 MDG target of "62 people per 1000" is shown as the dotted line in the Figure 1. This target has yet to be met.



Note: The dotted line represents the rate of progress which was required to reach the MDG goal deadline.

Source: Ministry of Health and Child Welfare-National health Strategy for Zimbabwe, 2009.

Figure 1: National Malaria Incidence Rates in Zimbabwe.

1.2 Economic Burden of Malaria

The economic burden of malaria is the total loss or reduction in output (Gross Domestic Product) that is associated with malaria-driven morbidity and mortality (WHO, 2006). Most malaria-driven deaths occur in Africa, particularly in the South of Sahara, where malaria causes major obstacles to social and economic development. Generally, the costs of malaria can be measured by the number of lives lost, the time spent being ill with fever, economic/financial burdens from preventing and treating malaria, and the indirect costs generated from the lost wages and lost productive time while caring for the sick.

Malaria causes deterioration of both health and wealth of individuals as well as the whole economy. Malaria affects households through repeated absence from work, which then has an effect of income reduction. Most agricultural communities suffer from malaria because household members may have to forego work when illness strikes. Given that rural areas are affected the most by this disease, this paper targets appropriate sample groups. A reduction in household income also means a reduction in household expenditure on basic goods, and consequently, such households get trapped in a poverty circle.

First, a malaria-free environment encourages spatial labour mobility, an aspect that is conducive to diffusion of new technologies in society. Second, a malaria-free country would attract investments in tourist industries, and thus help reduce unemployment. Third, in a malaria-free environment, resources that would otherwise have been spent on treating malaria are put into other uses that enhance productivity such as schooling or farm investments (Mwabu, 2002). Apart from endemicity, factors specific to geographic areas, which may generate differences in economic effects of malaria in the country, include healthcare seeking behaviour which in some instances is a cause and a consequence of drug resistance of particular strains of malaria (Musonda and Mangai, 2007).

Health economics has emerged as one of many fields in economics where few studies especially in Zimbabwe have been carried out. Malaria as one component of health economics, is a very deadly disease if not treated early and correctly[1]. It is one of the major diseases, and leaving it uncontrolled may impede economic growth. Thus, an improved understanding of the factors that influence health care seeking behaviour pertaining to malaria is necessary in order to enhance the effectiveness of current malaria control strategies, reduce deaths associated with the disease and reduce the negative socio-economic impact of the disease.

Understanding malaria treatment patterns and behaviours is important, but not much has been done to this nascent area of health economics especially at the grassroots level which represents the actual affected populace. Medical care has for long been recommended as the best treatment choice of malaria. Nonetheless, self-treatment has also been common, which means there is more to be known about the behaviour of the affected population in order to devise better and effective ways of reducing this burden. On a macro scale, understanding the determinants of malaria treatment choice will help the government expend efficiently in health and also determine whether to put more health resources on health institutions or to concentrate on peripheral health services, such as village health posts and dispensaries.

The following sections of the paper include: i) theoretical and empirical literature reviews which provide a brief explanation along with its related literature, methodology and data; ii) methodology which shows the econometric model (probit model) and data used; iii) results; and iv) conclusion.

2.0 Theoretical Literature Review

2.1.1 The Grossman Model (2000)

The central assumptions of Grossman are that (i) individuals are producers of health; (ii) individuals are born with a level of health stock that depreciates with time, such that when health stock deteriorates below a certain point then death occurs and people have full knowledge of the health production function; (iii) individuals are also assumed to have an infinite planning horizon for their health investment decisions. The resultant model is shown below:

$$W = \int_0^T e^{-\rho\tau} U\{t^s(\tau), X(\tau)\} dt \qquad \text{.......(1)}$$

From the above model W is the total utility of the individual, $U\ \{t^s(\tau), X(\tau)\}$ is the individual's utility function which depends on sickness time, $t^s(\tau)$, and the consumption of other goods, $X(\tau)$. An individual derives disutility from sick time $t^s(\tau)$, while deriving utility from consumption goods $X(\tau)$. This gives rise to the following derivatives

1) Medical care is considered the better way of treating malaria due to better diagnosis of the disease by medical professionals as compared to self-treatment.

also $\frac{\partial U}{\partial t^s(\tau)} \leq 0,$..................$(2a)$ $\frac{\partial U}{\partial X(\tau)} \geq 0,$................ (2b)

$$\frac{\partial t^s(\tau)}{\partial H(\tau)} \prec 0 \text{..................} (3)$$

The negative derivative for equation (2a) above shows the disutility that sickness time yields to an individual while in equation (2b) the positive sign is indicative of the utility increases derived from consumption goods. Equation (3) reflects that sick time ($t^s(\tau)$) is lower the higher the health stock ($H(\tau)$). Continuous discounting of future utility flows uses a subjective discount rate (ρ) as shown by the term $e^{-\rho\tau}$ in equation (1).

An important component of the Grossman model is the equation which shows the trajectory of health stock with time. From the assumptions of the model, health stock depreciates with time up to a level where death occurs. This is algebraically shown below

$$\nabla H = \dot{H} = I(\tau) - \delta\{\tau, X(\tau)H(\tau)\} \text{...} (4)$$

As individuals invest in health, health stock (H) increases. Moreover, if investment in health had an incremental effect only then the rate of change of health stock ($\dot{H}$) would be positive causing health to improve with age but due to depreciation, at a rate δ, health decreases with time (τ).
Outcomes from equation (4) would be generalized using the derivatives below:

$$\frac{\partial \delta(\tau)}{\partial \tau} \succ 0 \text{..} (5)$$

$$\frac{\partial \delta(\tau)}{\partial X(\tau)} \prec or \succ 0 \text{..} (6)$$

Grossman hypothesized that depreciation increases with time (equation 5) and from equation (6) consumption goods have an ambiguous effect on health depreciation, that is depreciation may increase or decrease with consumption of goods. Therefore, some commodities and lifestyles increase depreciation, for instance tobacco and bad eating habits, while some commodities, like proper nutritional foods, reduce depreciation. In a nutshell, the conceptual contribution of Grossman is to treat health as capital.

Muurinen (1982) and Wagstaff (1986) decomposed the Grossman model into consumption and production versions. Investment in health has returns, in terms of added labour income and wealth, so health is seen as a commodity that is not valued *per se* but only for its impact on labour productivity and wealth. In this regard, this is known as the pure investment variant of the Grossman model. Similarly to consumption in goods, health is valued because of the enjoyment it brings into life. For instance, the absence of sickness in itself gives utility to individuals and it can also be argued that going to a zoo, for instance, is much more enjoyable when one is in good health than otherwise.

The theoretical results of the Grossman model, according to Zweifel (2000), are that health and wealth are interrelated assets whose values are controlled by the individual over time. The basic predictions are based on age, education and wages. In both variants of the Grossman model age is inversely related to health demand. The demand for health therefore decreases with aging because payoffs from health stock decreases with time. In addition to this, depreciation increases with age thereby pushing up the marginal cost of holding an additional unit of health. Further, lifetime wages reduce the demand for health in the consumption version because the higher the wage the lower the marginal incentive to keep health as a consumption good. On the other hand, lifetime wages increases the incentive to work and the incentive to be healthy by increasing the return to health capital. Higher-wage workers will tend to increase their optimal health capital stock.

An increase in education, which was used by Grossman to capture knowledge, increases the production of health. In this connection, people with more years of schooling are likely to produce more health than those with less years of schooling. Hence, education is positively related to demand for health in the consumption and production variants. This is so because education enables one to select a consumption bundle ($X(\tau)$) that will optimise health while at the same time education enables one to become a more productive worker. Education will be one of the factors that is going to be tested in this study whether it has been having a positive impact on demand for malaria treatment in Mutema.

According to Grossman's individual production function, income also had a positive relationship with demand for health and health care, which is as income increase, people's demand for good health will also increase since they can now afford to meet medical expenses. The Grossman model shows that females tend to demand more medical services than the males. This is because females need maternal care which males do not demand. The probability of reporting illness in a female headed household is higher than the male headed. This paper also considers the effect on determining malaria treatment choice by either female headed household or male headed.

However, some of the assumptions made by the Grossman model are not realistic, for instance, the assumption that people have full knowledge of the health production function. In addition, the model assumes with certainty that as wages increases, demand for health also increases but the relative price of health may increase as wages increase and opposite results may be experienced.

2.1.2 Behavioural Model of Health Services (Andersen, 1968)

This is one of the major models explaining the demand in health services and goods that can be used in explaining the selection of malaria treatment by villagers. This is a comprehensive model for health services which concentrates on the individual's determinants of utilization behaviour. In this model, an individual's decision to utilize medical services depends on a sequence of conditions, which can be grouped into three components:

a) Predisposing component

This is further divided into demographic, social structure and belief sub-components.

- Demographic: includes variables for describing individual factors that are indirectly associated with utilization and are not considered to be a specific reason for using health care. The variables are age, sex, marital status and past illness.
- Social structure: these are variables that may influence the physical and social environment of an individual. The variables are race, occupation, family size, education, ethnicity, religion and residential mobility.
- Belief: these are variables that are likely to influence illness, attitudes towards health services and knowledge about disease.

b) Enabling component

These are variables that allow an individual to have the means to seek care. This component is divided into family resources and community resources.

- Family resources: these variables are income, health insurance and regular source of care.
- Community resources: this shows the ratio of health personnel and facilities per population, region of country and rural or urban character.

c) Perceived component

These include medical need.

- Perceived need: this is measured by self-reported health status or number of sick days,
- Evaluated need: estimated by clinical diagnosis.

Each component of the model is correlated with families' use of health services. More importantly, the need component is the one of the most closely associated with use followed by the predisposing component represented by the family composition variables, such as large families, families with young children, families headed by younger persons and married persons tend to be higher users (Sorkin, 1984). Andersen' s behavioural model of health services demand for healthcare varies across household, since it's a function of patient, provider, and household, the nature of the illness and community characteristics. The patient's and provider's characteristics will both determine the choice of treatment, thus demand for healthcare is not uniquely depending on the factors that interact to determine choice of a healthcare provider.

2.1.3 Health Belief Model (HBM)

According to Hochbaum (1956), the HBM model was developed in the 1950s as a way to try to explain why medical screening programs offered by the United States Public Health Service were not very successful. The main concept of the HBM model is that health behaviour is determined by personal beliefs or perceptions about a disease and the strategies available to decrease its occurrence. The following are the four constructs of the model: (1) perceived seriousness, (2) perceived susceptibility, (3) perceived benefits and (4) perceived barriers. Each of these perceptions, individually or in combination can be used to explain health behaviour such as the selection behaviour of malaria treatment

In general, from above brief theoretical explanations, this paper adopts the concepts that malaria treatment can be affected by factors such as education, income and distance to the nearest health facility. As outlined by Grossman model, age is inversely related to health demand. The demand for healthcare therefore decreases with aging because payoffs from health stock decreases with time. In an empirical manner, this paper strives to put data analysis while using a case of Zimbabwe's rural area.

2.2 Empirical Literature Review

Flores *et al*. (2001) used a binomial logistic regression to analyse people's response to illness in Mexico. Their objective was to analyse illness factors associated with the form of attention (self-care or medical care) used to resolve health problems in Mexico. A descriptive analysis was conducted to study demographic and socioeconomic characteristics, access to medical services, perception of seriousness of the illness, treatment received, and reasons why medical care was not sought and sixty-one percent of the sample was self-attended. Another study by Wakgari *et al*. (2003) was done about self-treatment in rural communities, Butajira in southern Ethiopia. The objective of their study was to quantify the use of self-treatment and to determine the actions taken to manage malaria illness. A cross-sectional study was undertaken in six peasant associations in Butajira district, southern Ethiopia. Simple random sampling was used to select a sample of 630 households with malaria cases within the last six months. Self-treatment at home was found as a major action taken to manage malaria disease. Like de Bartolome *et al.* (1995), distance to the health facility was found to be statistically significant in influencing malaria-infected people to use self-treatment, however sex, age and religion were statistically insignificant. Yip *et al.* (1998) examined the determinants of patients choice of medical provider in the three tier health care system in rural China, Shunyi country of Beijing. One of their conclusion after using multinomial logit model is that, patients with high income are more likely to use medical care. Mwifadhi *et al.* (2007) analysed factors affecting decision to seek medical care and self-treatment in rural Tanzania in the context of maternal services. They found that women who lived in male-headed households were less likely to deliver in a health facility than women in female-headed households (this is in line with Grossman model discussed above). Mothers with primary and higher education were more likely to deliver at a health facility.

In another study by Nyamongo (2002), who investigated health care switching behaviour of malaria patients in a Kenyan rural community, concluded that patients usually use several sources of health care for the treatment of malaria. Factors such as knowledge and duration of sickness, the anticipated cost of treatment, and a patient's judgment of the intensity of sickness[2)] determined their choice of treatment. The findings by Nyamongo (2002) concurs with an earlier study by Ruebush *et al*. (1995) conducted in the same country of Kenya which also highlights the importance of the patient's judgment of the intensity of the malaria sickness when deciding on the malaria treatment choice. They concluded that self-treatment was exceptionally common and of 138 incidences of febrile illness, 60% were treated at home with herbal remedies or medicines purchased at local shops, and only 18% received treatment at a health centre or hospital.

A cross sectional study conducted in another rural set up by Simsekand *et al*., (2005) showed significant relationship between knowledge of malaria and treatment choice. As part of their results, 89% of respondents from Sanliurfa province of Turkey knew at least one of the classical symptoms of malaria, and fever and chills were the most commonly reported symptoms (79%). Malik *et al*. (2006) analysed treatment-seeking behaviour for malaria in children under five years of age in Sudan. The data was obtained by interviewing 96 mothers who had brought their febrile children to selected health facilities. They discovered that self-treatment was common and some of the reasons included people's ability to recognize malaria, the cost of travel and, in some occasions, the lack of health care facilities.

De Bartolome *et al.* (1995) found that people who live in rural areas of Brazil opted for self-care as compared to those in urban areas and this was discovered since the long distance from the health facility was one of the reason for the difference. Cost of treatment and wealth were found to be significant in influencing the choice to choose between the two. Lindelow (2002) used multinomial logistic regression model in analysing the demand for health care in rural Mozambique. Females were found to be more likely to seek treatment from either hospital or health post than from the traditional medical care.

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2) This is in line with the health belief model which acknowledges that the way the patient sees the intensity or severity of disease is likely to influence healthcare decisions of that particular person.

The previous literature shows that there is variation in treatment seeking patterns of malaria-infected people across countries. Some of the variables that contributed to this variation are: age, sex, severity of malaria, cost of malaria treatment and distance to the medical facility. However, this paper differs from the above studies as it is the first of this kind, at least according to my knowledge, to be carried in rural Zimbabwe which is also one of the countries greatly affected by the burden of Malaria. Furthermore, by doing this research, it is somehow possible to do a comparative analysis using previous studies in this issue regarding health studies and population.

3.0 Methodology

The objective of this study is to model the choice of malaria treatment in rural area of Zimbabwe. When a person is infected with malaria, he or she can either use medical treatment or self-treatment. In this sense, the study will therefore have an option of using either the probit or the logit regression model, since an individual is faced with two distinct choices of malaria treatment thus the dependant variable is a binary variable; in other words Malaria treatment choice is a discrete decision which is in line with qualitative choice models. However, in this paper, the individual is faced with two options, to choose whether to use self-treatment or medical treatment under guidance of medical professionals. The choice of malaria patients especially in the rural area depends on a number of characteristic among them such as proximity, income, severity, education, severity. It is the utility derived from each alternative that makes individuals choose certain choices.

The Probit and Logit regression models can be used for this study since they are based on the method of maximum likelihood estimation (MLE). According to Aldrich and Nelson (1984), the MLE is concerned with picking parameter estimates that imply the highest probability or likelihood of having obtained the observed sample. They further explain that the objective of the maximum likelihood estimation is to choose the estimates of the coefficients that make the likelihood of observing a particular outcome of the dependant variable as large as possible. According to Wooldridge (2004), these binary response models are such that equation (7), as X_i (explanatory variable) increases, $P_i = E(Y = 1/X)$ increases but never steps outside the zero-one interval, and the relationship between P_i and X_i is nonlinear. As Wooldridge (2004) states, these binary models are given by models of the form:

$$P(Y = 1/X) = G(\beta_0 + \beta_1 X_1 + ... + \beta_k X_{k)} = G(\beta_0 + X\beta) \qquad (7)$$

Where X denotes a full set of explanatory variables and G is a function taking on values strictly between zero and one that is $0 < G(z) < 1$ for all real numbers z. The function G can take various nonlinear functions. Wooldridge furthers explains that G can follow a logistic function thereby yielding to the logit model or it can follow a standard normal cumulative distribution function which results in a probit model. As supported by Gujarati (2004) and Wooldridge (2004), this study will adopt the probit model because of the normality assumption for error term. Estimation of binary outcomes has been done using either probit or logit techniques and there is often little difference between the predicted probabilities from these two techniques hence the question of which one to adopt is a matter of choice (Gujarati, 2004). In the Probit model, the function G can, therefore, be stated as follows:

$$G(z) = \phi(z) \equiv \int_{-\infty}^{z} \phi(v)\,dv \quad \text{.......(8)}$$

Where $\phi(z)$ is the standard normal density:

$$\phi(z) = (2\pi)^{-1/2} \exp(-z^2/2) \quad \text{.......(9)}$$

The model relies on calculus in order to find the partial effect of roughly continuous variables on the response probability, if X_i is a roughly continuous variable, its partial effect on $p(x) = p(Y = 1/x)$ is obtained from the following partial derivative:

$$\frac{\partial p(x)}{\partial x_i} = g(B_0 + x\beta)\beta_j$$

Where:

$$g(z) \equiv \frac{\partial G}{\partial z}(z) \quad \text{.......(10)}$$

3.1 Empirical Model Specification

As highlighted above, the probit parameters will be estimated using the maximum likelihood estimation (MLE) method. The empirical methodology is specified as follows:

CHOICE = F (Age, Hsex, Hedu, Hsize, Dist, Inc, Pinfect, Relig, Sever)

Or equivalently,

$$P(CHOICE = 1/X) = F(\beta_0 + \beta_1 Age + \beta_2 Hsex + \beta_3 Hedu + \beta_4 Dist + \beta_5 Inc + \beta_6 relig + \beta_7 previn + \beta_8 Sever + \beta_9 Hsize + \varepsilon) \quad \text{.......(5)}$$

Where:

$P(CHOICE = 1/X)$ is the probability that an individual will use self-treatment given the vector of observable characteristics;

F is a function taking on values strictly between zero and one and shows that the conditional probability is a non- linear function of explanatory variables;

Hsex is household head sex and is a dummy variable;

Hedu is household head education and is a dummy variable;

Hsize is household size;

Dist is distance which is a dummy variable;

Inc is income and is a dummy variable;

relig is religion which is a dummy variable;

previn is previous infection;

Sever is severity; and

ε is the error term.

3.2 Data and Variables

Data

This study relies on both secondary and primary data. Secondary data is from the Zimbabwe Demographic Health Survey (ZDHS) 2010/11 which is administered by Zimbabwe National Statistics Agency (ZIMSTAT) while primary data, using 163 previously Malaria affected households from Mutema rural area, was from a survey which was conducted in Zimbabwe in Chipinge District. For this analysis, cross sectional data between August 2009 and February 2010 (summer season) was used. The survey was carried out in March 2010, a self-administered questionnaire instrument was used for data collection, and the response rate rate was around 93%. Moreover, the tool captured socio economic factors that influence human behaviour in treating the disease.

On another note, Mutema rural area in located in the Eastern part of Zimbabwe in the low veld along Save River. An average of twenty households were interviewed in each of the villages (clusters) to extract the necessary information for the study. The eight villages were referred to as clusters with random population. The systematic random sampling was applied since it is easier to perform in the field and hence is less subject to selection errors by researchers than either simple or stratified sampling. In this context, this sampling technique provides greater information per unit cost than simple random can provide systematic sample is generally spread more uniformly over the entire population and thus provide more information about the population than an equivalent amount of data contained in the simple random sample (Scheaffer *et al*. 1990)

Dependent Variable

CHOICE is a dummy variable that takes the value of 1, if the person has used self-treatment on malaria, and the value 0 otherwise. When a person chooses self-treatment, he or she borrow medication from friends and relatives, use traditional practice and use no medication at all. However, if one gets prescription from the professional health person it will be taken as medical care.

Explanatory Variables

Following the previous literature, this research establishes that people's decision to choose between self-treatment and medical treatment (in the event that the person has been infected with malaria) is likely to depend on variables like: age of household head, household size, sex of household head, education of household head, distance to the nearest health facility, income, number of previous infections, religion and perceived severity of malaria. In this connection, this study intends to test if these variables are significant in explaining the selection of malaria treatment in rural Zimbabwe.

Age of Household Head (Age)

The age of the household head is measured in years and this variable plays crucial role in people's decisions to choose between self-treatment of malaria and medical treatment. Low cases of self-treatment of malaria are expected when the household head is still young as he or she has low experience in managing the disease. The study expects to see households seeking self-treatment when the household head is old and medical treatment when the household head is young. The age is coded as follows: 18-29 years as 0, 30-39 years as 1, and 40 years and above as 2.

Sex of Household Head (Hsex)

This variable intends to establish if there are any differences in malaria treatment choices determined by difference in sex of the household head sex. Theoretically, it has been proven that women are more likely to report illnesses and hence demand medical services more than men Grossman (1972). The study expects to find consistent results to the previous literature. Women will be assigned the value 1 and otherwise 0.

Education of Household Head (HEdu)

This variable represents the highest level of formal education attained by the head of each given household. It is coded as follows: No education = 3, Primary education = 2, Secondary = 1 and Tertiary education=0. In line with the Grossman model[3)], this study expects to find household heads with no education to be more likely to use self-treatment. More educated household heads, on the other hand, are expected to demand more healthcare as compared to less educated household heads. Educated households are also expected to be more knowledgeable about the symptoms and various (effective) methods to cure malaria.

Distance to the Nearest Health Facility (Dist)

The distance to the nearest health facility is in kilometres. According to empirical evidence, most studies found a strong positive relationship between self-treatment and distance. Households that do not stay near medical facilities such as clinics are more likely to adopt self-treatment strategies unlike those that stay close to medical facilities.

Average Household Income (Inc)

Generally, individual's income heavily influences the demand for medical care. Both empirical and theoretical evidence show a positive relationship between an individual's income and demand for medical care. This study expects to find households with more income to use medical treatment and households with less income to use self-treatment. This variable will be coded as follows: household monthly income ranging from USD$0-USD$50 is coded 0; USD$51-USD$100 is coded 1 and above US$100 is coded 2. The coding relies on the fact that malaria treatment is subsidized to try and promote the use of medical care by malaria patients.

Number of Previous Infections (previn)

Previous number of malaria cases household has dealt with for the past seven months from the time of data collection are expected to play a significant role in explaining the decision to self-treat or use medical care. The study expects to find a positive relationship between self-treatment and the number of previous malaria cases. A person who contracts malaria for the first time is expected to seek medical treatment and when that same individual is attacked by malaria for more than once, it is highly probable that the patient will adopt self-treatment methods due to the fact that, infected individuals now have more malaria knowledge and experience.

Household Size (Hsize)

The household size may determine the size of resources that can be committed to treatment. For instance, a bigger household is likely going to self-treat, relative to a smaller household, due to income and resource constraints. This study expects a priori that household size will be negatively related to medical care.

Religion (relig)

Religion also plays a major role in determining malaria treatment choice and demand for health care in general. In most rural areas in Zimbabwe, people can be categorized into the following religions: Traditional religion, Apostolic sects, Roman Catholics, Protestants, Pentecostals and other Christians. From this study it is expected to see those from the traditional religion and the apostolic sects to use self-treatment methods

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3) See Grossman (2000).

Table 1　Probit Regression Results

VARIABLES CHOICE	1 Restricted Probit	2 Restricted Probit	3 Restricted Probit	4 Unrestricted Probit
Distance	1.401***	1.402***	1.364***	1.354***
	(0.368)	(0.382)	(0.375)	(0.390)
Previous Infection	-1.036**	-0.976**	-1.023**	-1.027**
	(0.454)	(0.482)	(0.508)	(0.500)
Severity	-1.614***	-1.720***	-1.623***	-1.612***
	(0.455)	(0.423)	(0.429)	(0.425)
religion	2.012***	1.992***	1.805***	1.796***
	(0.506)	(0.512)	(0.510)	(0.496)
Highest Education	1.017***	0.917**	0.932**	0.928**
	(0.382)	(0.392)	(0.389)	(0.375)
Household size	0.199**	0.160*	0.154*	0.152**
	(0.0891)	(0.0841)	(0.0850)	(0.0763)
Age		0.361	0.385	0.393
		(0.297)	(0.286)	(0.263)
Household head sex			-0.481	-0.495
			(0.410)	(0.422)
Income				-0.0235
				(0.243)
Constant	-5.740***	-5.785***	-5.313***	-5.266***
	(1.453)	(1.443)	(1.474)	(1.394)
Observations	163	163	163	163

**** p<0.01, ** p<0.05, * p<0.1 denotes Significant at 1%, 5% and 10% respectively.*

as compared to the other religions. These groups will be coded as follows: Traditional religion =3, Apostolic sect=2, Other Christianity[4] =1 and Other[5]=0.

Severity of Malaria (Sever)

This is another variable that plays a significant role in malaria treatment choice. When people find malaria to be a severe and dangerous disease such that they spend a lot of time in bed or even death, they are likely to seek medical treatment. Those that perceive malaria as minor ailment that has minimal impact to their health are more likely to adopt self-treatment methods for malaria. The severity of malaria is coded as 1 for bed ridden and 0 for those who were not bed ridden.

4.0 Results

This section presents the results. Having specified the model which is going to be used in investigating the determinants of malaria treatment choice, this chapter focuses on the estimation, presentation and analysis of empirical findings. In explain the results, this paper also makes use of predicted probabilities based on the probit model.

4) All Christians except apostolic sect are recorded as ‘ Other Christianity ’.
5) All the respondents that do not belong into any of the main categories will be recorded as ‘ other ’.

Table 2　Marginal Effects of Restricted Probit Model[8]

VARIABLES	dy/dx
Distance*	0.144**
	(0.068)
Previous infection*	-0.101*
	(0.064)
Severity*	-0.201***
	(0.074)
religion	0.153*
	(0.089)
Highest education	0.077*
	(0.044)
Household size	0.015
	(0.01)

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Severity (*sever*)

The variable *sever* is statistically different from zero at 1% level of significance. The negative coefficient implies that a person who has been severely attacked by malaria is less likely to use self-treatment by about 20%[6] as compared to one who has mildly attacked. This result is in support of the findings by Baume *et al*. (2000) and Lindelow (2002) who found a negative relationship between the perceived severity of the disease and self-treatment. In this study, the predicted probability for opting for self-treatment for a person who was suffering from malaria but at the same time able to carry out day to day activities is 0.2306. Those who were bed ridden have a probability of opting for self-treatment of only 0.0074[7].

Distance (*dist*)

The variable is statistically significant at 1% level of significance in the restricted regression in column 1 of Table 1. This is a very important variable in explaining the determination of malaria treatment choice. The positive coefficient of distance shows that people who reside far from the health centre and have to travel for more than 3 kilometres from the health centre are more likely to self-treat malaria than those who stay within the radius of less than 3 kilometres. The marginal effects show that, a unit increase in distance moving away from the health centre is more likely to increase the probability of using self-treatment by about 14% as shown in Table 2. Using Predicted probabilities, households who stay more than 3 kilometres away from the health centre have a higher predicted probability of 0.2031 of using self-treatment which is higher than those staying less than 3 kilometres (0.0054). These results are in harmony with previous studies by de Bartolome *et al.* (1995) who found out that more people used private treatment as the distance to the health facility increased and that of Wakgari *et al*. (2003) who got distance as a statistically significant factor in determining use of self-

6) See Table 2.
7) See Table 3.
8) Marginal effects from restricted Probit model in column 1 of Table 1

treatment for malaria in Southern Ethiopia.

Household Head Education (*hedu*)

This variable is statistically significant at 10% level. Theory postulates that there should be a positive relationship between education and the medical care (Grossman, 1972). The positive link between medical care and education is clearly explained by the predicted probabilities for sub categories of 0.3612, 0.1244, 0.0255 and 0.0030 representing no education, primary education, secondary education and tertiary education categories respectively. The probabilities depict the concept that as people get more educated the probability of using medical care also increases. These results are in support of the findings by Grossman (1972) which stated that education is positively related to demand for health.

Previous Infection (*previn*)

The coefficient of the variable previn is statistically different from zero at 10% level of significance as shown in Table 2. In contrast to economic theory, there is a negative relationship between the number of malaria cases a household has dealt with and self-treatment of malaria. Results from the table of marginal effects show that a unit increase in number of previous malaria infection will decrease the probability of using self-care by around 10%. This implies that households that had dealt with more previous malaria infections are less likely to use self-treatment methods to cure malaria. Households that have experienced malaria cases once or never from the last season have a predicted probability of 0.0914[9] of using self-treatment whilst households that have dealt with malaria cases more than once a predicted probability of 0.0168. These results could have resulted from the fact that there are other dominating factors such as perceived severity of malaria. Households might have experience with large number of malaria cases before and have the knowhow of self-treating malaria but may opt to seek medical treatment if they had been severely attacked by malaria before.

Religion (*relig*)

This variable is significant at 1% level of significance and has a positive coefficient showing a positive relationship between religion and malaria treatment choice behaviour. Traditional and apostolic sects have predicted probabilities of 0.9807 and 0.4668 respectively and the two have higher probabilities of using self-treatment in treating malaria than other Christians. The apostolic sect followers are restricted to use medical facilities by their church regulations. This result is not in support to Wakgari *et al*. (2003) who found religion as a statistically insignificant variable in influencing a malaria-infected person to use self-care in Ethiopia. The religion variable is important especially in the rural areas where most people are aligned to the apostolic religion which in most cases ban the use of medical care according to their doctrine.

In summary, factors such as previous infection, severity of the malaria, distance to the nearest health centre, household head education and religion are significant in determining the selection of malaria treatment in rural Zimbabwe, specifically in Mutema rural area, however, other variables such as income, age, household head sex and household size were statistically insignificant, while showing that they are of less importance accordingly. The cost of getting malaria treatment at most health centres in the area under study are subsidised leaving it at affordable fee of about US$ 1 and this might be the reason for obtaining income as a statistically insignificant variable in influencing the treatment choice behaviour. More people staying near the health

9) See Table 3.

facility opted for medical care as compared to those residing away from the facility. Additionally, Table 4 shows the correlation matrix of variable used in this paper.

5. Conclusion

This study investigated the determinants of choosing malaria treatment in Zimbabwe using a case study from Mutema, a rural area which lies in the low veld of Chipinge District. The main stimulus for such an analysis lies on the need to improve the understanding of how changes in the socio-economic variables would affect the malaria treatment behaviour. The dependant variable was categorized into two characteristics, either the malaria-infected person used medical or self-care whilst nine socio-economic factors were used as explanatory variables. The results from the probit regression illustrate the relevance of factors like previous infection, severity, distance, household head attained education and religion, as statistically significant determinants that affect the choice of malaria treatment in Mutema. Nonetheless, income, household head sex, age and household size were found to be statistically insignificant in influencing the method of treating malaria. Several policy recommendations can be drawn from empirical results of this study. In this regard, distance was found to be one of the prohibiting factors for people to use medical care, there is, however, need for policy makers to put policy measures that aims at increasing the number of health centres especially in rural areas, such as introducing mobile clinics, to shorten long distances for people to walk in accessing the health facilities. The model results indicate that people affiliated to the apostolic sect and traditional religions have the highest predicted probability of opting for self-treatment instead of going for medical treatment. Policies, targeting these groups, that highlight the benefits of using medical treatment whilst at the same time highlight the drawbacks of using self-care, have to be put in place so that they can encourage people to mobilize and receive medical care. Similarly, the apostolic and traditional leaders should be included in the policy formulation and implementation processes with regards to treatments for malaria and other curable pandemic diseases.

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Appendix

Table 3 Predicted Probabilities.

Previous Infection	**Prediction**
0	0.0914
1	0.0168
Severity	**Prediction**
0	0.2306
1	0.0074
Distance	**Prediction**
0	0.0054
1	0.2031
Highest Education Level	**Prediction**
0	0.0030
1	0.0255
2	0.1244
3	0.3612
Age	**Prediction**
0	0.0063
1	0.0256
2	0.0801
Religion	**Prediction**
0	0.0000
1	0.0127
2	0.4668
3	0.9807

Table 4 Correlation Matrix

	choice	previn	sever	dist	hsex	hedu	hsize	age	inc	relig
choice	1									
previn	-0.501	1								
sever	-0.558	0.333	1							
dist	0.521	-0.322	-0.369	1						
hsex	-0.400	0.142	0.313	-0.25	1					
hedu	0.463	-0.336	-0.38	0.373	-0.085	1				
hsize	0.439	-0.116	-0.22	0.287	-0.224	0.151	1			
age	0.389	-0.12	-0.19	0.263	-0.146	0.247	0.226	1		
inc	-0.410	0.287	0.375	-0.48	-0.02	-0.481	-0.181	-0.185	1	
relig	0.689	-0.364	-0.36	0.365	-0.261	0.332	0.356	0.298	-0.37	1

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