AN EVENT HISTORY ANALYSIS OF SOCIO-ECONOMIC DETERMINANTS OF ADULT MORTALITY IN NAMIBIA

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ABSTRACT

Adult mortality remains a neglected public issue in Sub-Sahara Africa (SSA), with most policy instruments concentrated on child and maternal health. Lack of vital registration system in SSA, further, has made it impossible to accurately estimate adult mortality. However, interest to better understand the epidemiology of HIV/AIDS, which has a greater impact on adults, has rejuvenated research in adult mortality. Understanding the hazard of and factors associated with adult mortality is crucial towards designing programmes and interventions aiming at improving the well-being of adults. The main objective of the study was to apply an event history discrete time survival analysis approach to elucidate effects of socio-economic factors on adult mortality in Namibia. Specifically I simultaneously estimated the effects of socio-economic determinants on adult mortality in Namibia; as well as investigated geographical effects of location on adult mortality in Namibia, using spatial frailty models).

The study used adult mortality data of 25,854 individuals aged 15 years and above, from the 2006/07 Namibia Demographic and Health Survey. The socio-economic factors used for the study included the type of residence (urban/rural); region; age of household head; sex of household head; marital status; education; nearest health facility; means to the nearest health; time to the nearest health facility and wealth index.

The explanatory analysis was carried out using the Kaplan Meier curves, with the log rank test used to assess significance. Further geo-additive survival models were carried out using the Bayesian framework for joint modelling of fixed, non-linear and spatial frailties. The proposed Bayesian model assumed the following prior distributions: for the fixed effects I assigned diffuse priors, while the baseline was fitted using penalized random walks priors. For unstructured random effects and the structured spatial effects, the exchangeable normal prior and conditional autoregressive prior respectively were assumed.

Results from the best model, which adjusted for the baseline, unstructured random effects, spatially structured effects as well as the fixed effects at a constituency level, showed that the overall baseline hazard of adult mortality declined constantly from age 15 up to age 40 years. The hazard of mortality subsequently increased from age 60 years. Lack of resources to improve the health, wellbeing and living standards of adult and old age people may be responsible for the increase in hazard of mortality from age 60 years.

Further, results show a clear disadvantage for adults in rural areas; for those not married as well as for those of low wealth ranking particularly the poorest, for those in female headed households. Furthermore, in terms of health factor, the result shows that adult seeking health care from hospital, as well as traveling to nearest health facility within minutes and accessing the nearest health facility by means of a car provided an advantage of better survival at old age.

In terms of the geographic effects, the hazard map, fitted at a constituency level, shows that that there was high hazard of an adult dying in the North Eastern part of the country while in the North Western and Central East there was a reduced risk in the hazard of an adult mortality.

The unstructured random effects, again fitted at a constituency level, indicated that there was spatial variation in the hazard of adult mortality at a constituency level with constituencies for Caprivi and Erongo regions in the lower hazard, while constituencies for Oshikoto and Otjozondjupa region were at the higher hazard of adult mortality.

It is hoped that this study particularly the spatial analysis section will help health planners, policy makers to identifying specific areas with high hazard of adult mortality in order to design, evaluate programmes and develop strategies aiming at improving the health and well-being of adults. Moreover, if the country is to achieve national development goals such as Vision 2030, Millennium Development Goals (MDGs) and National Development Programme 4 (NDP4), then efforts should be made to support adults in areas with high hazard of mortality while at the same time considering the impacts of socio-economic factors, since adults form part of the economic and productive age group for a population.

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DEDICATIONS

This work is dedicated to God for his guidance throughout the study. I also dedicated the work to my family for believing in me and who through thick and thin provided me all the support to make my educational dream come true.

DECLARATIONS

I, Alina Kandjimbi, hereby declare that this study is a true reflection of my own research, and that this work, or part thereof has not been submitted for a degree in any other institution of higher education.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CAR	Conditional Autoregressive
CI	Credible Interval
DHS	Demographic Health Survey
DIC	Deviance Information Criterion
DSS	Demographic Surveillance System
EHA	Event History Analysis
GLM	Generalized Linear Models
GLMM	Generalized Linear Mixed Models
HIV/AIDS	Human Immune Virus/ Acquired Immune Deficiency Syndrome
HR	Hazard Ratio
LRT	Likelihood Ratio Test
MCMC	Markov Chain Monte Carlo
MDG	Millennium Development Goals
MoHSS	Ministry of Health and Social Services
NDHS	Namibia Demographic Health Survey
NDP4	National Development Programme 4
NSA	Namibia Statistics Agency
PSU	Primary Sampling Unit

SES	Socio Economic Status
SPSS	Statistical Package for Social Science
SSA	Sub-Saharan Africa
STAR	Structured Additives Regression
UNDP	United Nations Development Programme
WHO	World Health Organization
WHS	World Health Statistics

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CHAPTER 1

INTRODUCTION

1.1 Background

Improving the health of the population has become an important undertaking of most in most developing countries, mainly now that most countries are battling to meet developmental issues particularly the Millennium Development Goals (MDGs) (Jamision et al., 2006; Bendavid et al., 2012). Most studies on adult mortality have concentrated on child and maternal mortality as compared to adult mortality (Bradshaw & Timaeus, 2006). A lot has been done to improve children and maternal health, particularly the formulation/proposal of strategies aiming at improving health in children and mothers through disease prevention and control (Jamison, Feachen, Makgoba, Bos, Baigana, Hoffman & Rodger, 2006). Little focus, though, has been drawn on adult health, specifically on adult survival and mortality (Murray et al., 2010; Rajaratnam et al., 2010; Obermeyer et al., 2010; Kazembe, 2013; Nikoi, 2009). Yet, adults are the economically active and productive group. For the purpose of this study, adult mortality is defined as the deaths of adults dying in the ages 15-60 years according to the World Health Statistics (WHS) 2012

The emergence of HIV/AIDS in recent years has made adult mortality a crucial indicator for health and development planning, since human capital at times is scarce and not easily replaceable (Bangha, 2008). Moreover, if a country has high mortality, it may imply that the health status of a country is poor. The death of prime adults has been highly associated with eroded welfare of other household members. For instance, children who have lost their parents are at risk for worse schooling and health outcome (Ainsworth, Beegle and Konda, 2005). Hence, similar to child survival, the indicators of adult mortality are fundamental in planning, monitoring and improvement of societal health status as they provide significant summary indices on the standard of living, socio-economic development, prevalence of disease as well as community health system of a country (Kaundjua, 2011).

Adult mortality is monitored within vital registration system, particularly in developed countries. However, vital registration systems are usually non-existent or rare in some SSA countries, a fact that has made it impossible to accurately estimate adult mortality (Mathers, Ma Fat & Lopez, 2005). Despite, the dearth of vital statistics to study the patterns and trends as wells as risk factors, adult mortality in SSA, is usually based on information collected about deaths in household's census. However, censuses are 10 years apart, to make meaningful updates on the trends and patterns of mortality (Bendavid et al., 2012). Therefore, in order to fill the gap, estimates and projections from the World Health Organization/United Nations Development Programme (WHO/UNDP) have been used (Jamison et al., 2006). Moreover, some countries derive adult mortality estimates from Demographic and Surveillance System (DSS), where these exist (INDEPTH et al., 2004).

Recently, many African countries have derived adult mortality estimates from the Demographic and Health Surveys (DHS), which collects data on survivorship / widowhood / siblings. Namibia has joined other SSA countries that participated in the 2006/07 round of conducting DHS, under the module "Support For Those Who have Died" which captured the household mortality data, presenting an opportunity to study adult mortality in detail (MoHSS and Macro, 2008).

Diseases have been identified as causes of adult mortality worldwide. For instance, 80% of the 35 million deaths worldwide were due to communicable disease (World Health Organization Africa, 2011). Non communicable diseases includes: obesity; diabetes, hypertension, cardio-vascular diseases, chronic respiratory conditions and many other diseases. In South Africa, for example, cardio-vascular diseases were the second leading cause of mortality among adults accounting for 40 percent (Asiki G et al., 2013). Infectious diseases particularly Human Immune Virus/ Acquired Immune Deficiency Syndrome (HIV/AIDS) have also had significant impact on adult mortality in Sub-Sahara Africa (SSA). For instance, Southern Africa had the greatest proportion of adults infected with an average of 29.2 percent infected (Ngom and Clark, 2003). The impact of HIV/AIDS on mortality has to some extent substantially affected the population structure of many African countries (Ngom and Clark, 2003; Bendavid et al., 2012).

Therefore, HIV/IDS have been a major source of adult mortality for many Sub-Sahara African countries including Namibia. As a result, the issue of adult mortality in the African region is now being recognized more widely and, a response has begun to emerge, particularly with regard to the impact of the Acquired Immune Deficiency Syndrome epidemic and high mortality due to malaria (Bradshaw and Timaeus, 2006). Consequently, by seeking for preventive measures on HIV/AIDS transmission, has resuscitated interest in adult mortality - as a whole.

Although diseases are the major causes of adult mortality in SSA, often there are myriad of factors particularly socio-economic factors that contribute indirectly and even exacerbate adult mortality (Rogers, Hummer & Krueger, 2005). For that reason, the goal of this study is to quantify the relationship between socio-economic factors and adult mortality.

This study was conducted based on a theoretical framework of Roger et al. (2005). For further explanations on the theoretical framework (see page 8) For the purpose of this study, socio-economic factors were defined as socio-economic conditions that may influence the likelihood of mortality.

Roger, Hummer and Kruger (2005) have found that socio-economic factors influence an individual's chances of dying. Roger et al. (2005) further stated that individuals at higher socio-economic position are less exposed to factors that lead to morbidity, disability and eventually mortality. This may be due to the fact that individuals with high socio-economic status may practice healthy lifestyles and behavior unlike people with low socio-economic status and hence may have higher risk of mortality particularly adult mortality.

Like other SSA countries, Namibia is not an exception when it comes to adult mortality. According to the 2006/07 Namibia Demographic and Health Survey (NDHS) report the adult mortality is increasing. The adult mortality rate for women has increased from 4.29 in 2001 to 8.29 in 2006/07 (NDHS), while the adult mortality rate for men has increased from 6.31 in 2000 to 10.38 in 2006/07 (NDHS). This increasing trends may challenge the progress towards achieving the development goals such as Millennium Development Goals (MDGs), National Development Plan 4 (NDP4) and Vision 2030. As a result, a country may be faced with high number of challenges such as poverty, hunger, diseases, and short life expectancy.

The extent to which socio-economic factors impact on adult mortality has remained largely unexplained, especially in Namibia. Hence, this study will provide a better understanding of socio-economic factors critical at explaining variations in adult mortality, thus crucial for informing policies and implementation of public health interventions aimed at reducing adult mortality and improving adult survival. In other words, the study will focus on the socio-economic determinants of adult mortality than on longevity.

1.2 Statement of the problem

Adult mortality has been neglected as a public health issue in Namibia compared to vast interest shown towards infant and maternal mortality. A few studies conducted particularly in Namibia have focused on the association between adult mortality and socio-economic factors. Thus, the study will help bridge that information gap. The impacts of socio-economic factors on adult mortality are an important public health issue that may assist to inform adult health policies and implement public health interventions. Moreover, the influences of socio-economic factors on adult mortality are a vital health issue that may assist social planning towards accelerated attainment of the country's national development goals such as Millennium Development Goals (MDGs), National Development Plan 4 (NDP4) and Vision 2030. Indeed there are quantifiable disparities in urban and /or rural areas and changes in population since independence, and the rapid urbanization registered in the 2011 Namibia Population and Housing Census indicates the need to study the effects of socio-economic determinants on adult mortality in Namibia. Thus, the study applied an event history discrete time survival analysis approach, in order to explain effects of socio-economic factors on adult mortality in Namibia.

1.3 Study Objectives

The main objective of this study is to apply an event history discrete time survival analysis approach to elucidate effects of socio-economic factors on adult mortality in Namibia.

The specific objectives of the study are:

a) To estimate the effects of socio-economic determinants on adult mortality in Namibia.

b) To investigate geographical effects of location on adult mortality in Namibia

c) To explore frailty random effects on adult mortality in Namibia.

d) To fit and assess event history models applied to adult mortality.

1.4 Significance of the study

Adult morality has impacts on the population structure and it mostly affects the economically active population of a country, thus it is important to understand how socio-economic factors affect adult mortality. Since no study has been done to investigate the effects of socio-economic factors on adult mortality in Namibia, this study will help bridge that information gap and inform adult health policies in Namibia. Moreover, the findings will be intended to assist policy makers, public health planners in designing, evaluating programmes and develop strategies for improving the well-being of adults in Namibia. Additionally, the information will be used to identify regions with poor health status for the formulation of interventions and programmes that will reduce morbidity and mortality as per NDP4 and Vision 2013. Furthermore, studies on adult mortality and socio-economic determinants are few in Namibia and the event history modelling has not been used but mostly logistic regression.

CHAPTER 2

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

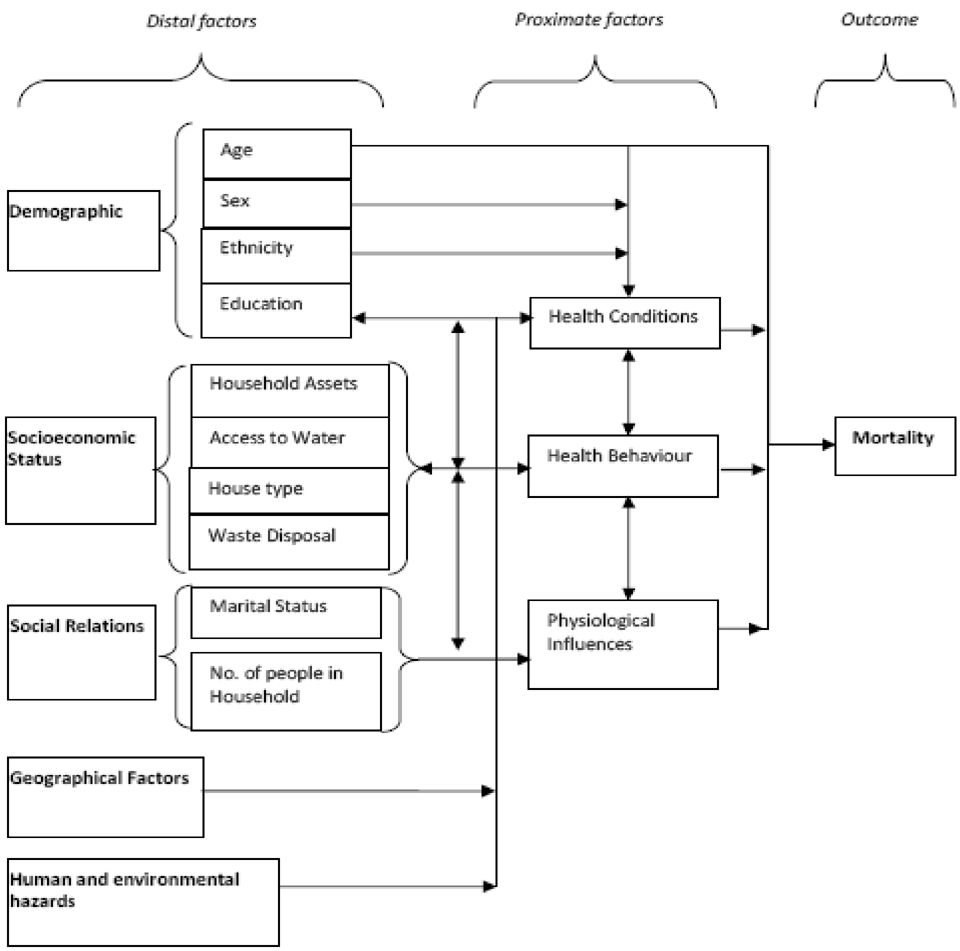
2.1 Theoretical framework

Nikoi (2009) indicated that different frameworks have been used to assess the relationship between socio-economic factors and adult mortality as far back as medieval times. For instance, during the agrarian and industrial revolution times food supply was used to establish the relationship (Malthus, 1830). Other studies have looked at only how income and earnings predict mortality (Preston, 1983). However, most epidemiologists have focused more on how the socioeconomic variable is being measured rather than giving up on the fact that socioeconomic status could predict mortality. Lopez (1984) in his classical model of adult mortality has shown that an individual's probability of dying is being primarily a function of sex, age, health, genetic endowment, and the environment, all of which determine the risk of morbidity or accident. These factors work together and are influenced by a complex and ever changing set of social and historical determinants (INDEPTH, 2002). In short, adult health which often precedes mortality according to Lopez is influenced by three main factors; the environment, human behavior and ill health carried from childhood into adulthood. If the researcher was to use Lopez model on adult mortality, there was a need to have longitudinal data i.e. making follow up on the subject of interest for the study from birth into adulthood. However, recently most SSA that conducted studies on adult mortality including Namibia derived adult mortality estimates from DHS, which is more of cross sectional data. Thus, the study was conducted based on a theoretical framework of Roger et al. (2005), which proposes that socio-economic factors, geographical factors, social relations, human and environment hazards are distal factors for mortality in adults. These factors act indirectly through proximate determinants like living conditions, behavior and health factors, socio-economic and demographic variables which in turn causes morbidity and mortality. The behavior and health factors include availability and access to health facility. The economic and social variables consist of marital status, family composition and relatives. Demographic variables consist of age and sex. These variables are further grouped into individual, household and community factors. The study set out to investigate the relationship between socio-economic factors and adult mortality taking into consideration the role of other indirect factors in this relationship.

A graphical illustration of the theoretical framework explained is shown by Figure 2.1. The theoretical concept as proposed by Roger et al. (2005) holds that, the causal pathway to adult mortality flow from distal factors such as geographical factors, human and environmental hazard and socio-economic influences. These factors flow through proximate determinants like nutrition, behavior, injury prone, living conditions, and in turn cause morbidity and mortality. Socio-economic factors determine whether or not a person will seek health care as well as able to live a healthy lifestyle, in order to improve morbidity and mortality (Mosley & Chen, 1984). Apart from these, individual with lower socio-economic status are more exposed to hazard of mortality such as environment;

chemical or biological and tend to be disadvantaged in terms of mortality hazard (House et al., 1990).

Figure 2.1 Conceptual frameworks showing the relationship between factors for adult mortality (Roger et al., 2005)



2.2 Literature Review

Literature shows little focus has been drawn on adult health than on child and maternal health. For instance, many national government and development agencies have proposed strategies of advancing service delivery to effectively fight against poor health in children and mothers through disease prevention and control (Jamison et al., 2006). Despite the fact that little has been done to improve adult health, there are a several studies that have been conducted on adult mortality and socio-economic factors aiming, at improving adult health. Some of the main indicators that are being used to measure socioeconomic status (SES) to draw out an association with morbidity and mortality include: education, household wealth (especially income), occupation, type and area of residence and lifestyle (Nikoi, 2009).

Roger et al. (2005) indicated that Benjamin Gompertz developed a mathematical formula that showed an increase in mortality with an increase in age. Age is a well-known factor that explains health and mortality. Its biological dimension is that as adults grow older, their body cells turn to weaken and suffer functional difficulties (Kaplan & Kronick, 2006; Grundy & Sloggett, 2003) thus becoming more prone to ill health and disease which often turn to morbidity and mortality. Several studies, for instance: Bassuk, Berkman, & Amick (2002) found age to be an important factor for adult mortality. Ogliari et al. (2008) indicated that, with age, the homeostasis functions and balance between the cells and body fluids are distorted, thus diseases and other health conditions become common in old age. Moreover, in old age, behaviour that enhances good health is also affected. Older people exercise less, are less active which in the end hastens the development of diseases or accidents hence higher levels of mortality as age increases.

Sudire et al. (2005) indicates that education status is an important determinant of mortality. Furthermore, low level of literacy was associated with poor management of diseases and other health conditions that may consequently results in deaths that could have been circumvented. Bassuk et al. (2002) noted an increased hazard of mortality among adults with lower education level regardless of the economic status, sex, race and neighborhood. Zhu & Xie (2007) found that educated adults were less exposed or at greater risk of adult mortality than those who were not educated.

In other studies, marital status was also found to be an important factor of mortality (Nagata, Takatsuka & Shimuzu, 2003). This was linked to improved care giving for the married people from their spouses in old age, and the psychological boost experienced from the presence of the spouse (Davis et al., 1992). Nikoi (2009) observed that single adults, on average were twice likely to die when compared to adult who were married. This can be explained by concept of social capital, such that emotional or psychological supports from partners do alleviate individuals from poor health mostly through care.

Several studies have used wealth index as a predictor of adult mortality. For example, Nikoi (2009) found that the higher socioeconomic quintile had the highest mortality rate, thus reducing the gap between the rich and the poor might not be the effective way in reducing adult mortality. In another study by Sammy (2009) it was found that those adults in the upper categories of socio-economic status had lower hazard ratios for mortality compared to those in the poorest category. However, the differences were very small and not statistically significant.

Furthermore, type of residence (urban/rural) was found to be a determinant of mortality. A study by Zimmer, Kaneda & Spess (2006) investigated the mortality of older adults across urban and rural areas in China. Zimmer et al. (2006) observed that unadjusted rural mortality was 30 percent higher than urban mortality. Several research suggest that there were a number of public health factors that made urban residents in many developing countries advantageous people's health, such as access to health services and safe water (National Research Council, 2003). Moreover, individuals living in urban areas are thought to be socioeconomically better off, earning higher incomes and obtaining higher levels of education, factors considered to be robust predictors of health (Antonovsky 1967; Marmot et al., 1984; Preston and Taubman 1994; Mackenbach et al., 1997).

Kadobera, Sartorious, Masanja, Mathew & Aiswa (2012) indicated that distance to the nearest health facility was a determinant of adult mortality. It has been documented that primary health care usage pattern declines with increasing distance or travel time to the nearest health facility. A number of studies have documented the relationship between mortality and distance or travel time to the health facility. In particular, Becher, Muller, Jahn, Gbangou, Kynast-Wolf., & Kouyate (2004) in a study in Zambia found that increasing travel time or distance to nearest health facility was associated with child mortality.

In epidemiology, economic or social science applications, survival data often contain geographic or spatial information such as type of residence, region or district. These factors make it possible for researchers to study the spatial effects of the location and so on. For instance, Henderson, Shimakura and Gortz (2002) model spatial variation in survival of acute myeloid patients in northwest England, Banerjee and Carlin (2003) apply spatial frailty model to infant mortality in Minnesota, and Li and Ryan (2002) analyze the effects of risk factors on the onset of childhood asthma with spatial data from the East Boston Asthma study. Flores, Rodriquez-Girondo, Cadarso-Suaresz, Kneib, Gomes and Casanova (2012) analyzed flexible geo-additive survival analysis of non-Hodgkin lymphoma in Peru.

Moreover, literature shows that survival regression models that received considerable attention recently are the inclusion of random effects and flexible modeling through semi-parametric and non-parametric approach (Hannagal, 2011). The inclusion of random effects permits modeling of unmeasured and observed factors in the model. These may act at family, community, regional and national level (Magadi, 2011). Bolstad & Manda (2001), found significant heterogeneity at a constituency level, which may be attributed to different availability of resources at a community level. Recent studies also assumed that unobserved factors vary spatially to give spatial frailty survival models. Bayesian geo-statistical frailty model have been used to quantify significant association between adult mortality and socio-economic factors (Sartorious, 2013). Several studies that have been conducted on adult mortality did not dwell more on adult mortality using discrete time survival models. Thus, the study will help bridge that information gap.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

An event history analysis (EHA) is a longitudinal record of the timing of the occurrence of one or more types of event (Steele, 2005). EHA is used to study the duration until the occurrence of the event of interest, where the duration is measured from time at which an individual becomes exposed to the ‘risk’ of experiencing the event. The techniques described in this section are commonly known as survival analysis in biomedical science, duration analysis in economics or hazard modeling in engineering or reliability science. Although often used interchangeably with survival analysis, the term EHA is used primarily in social science applications where events may be repeatable and an individual history of event is of interest.

Therefore, subsequent sections in this Chapter are focused on concepts of survival analysis, defining the hazard model and how is modelled. In particular, we consider discrete time survival models, baseline, flexible models and random effects for unobserved heterogeneity. We also consider the principle of model estimation and selection.

3.2 Survival models

Event history data or models of analysis that deal with EHA data have three main characteristics: (i) the dependent variable is the waiting time until the occurrence of a well-defined event (for this study, age at which the household member died), (ii) observations are censored, in the sense that for some units the event of interest has not occurred at the time the data are analysis and, (iii) there are explanatory whose effect on the event (for this study, death) we wish to control.

3.3 Survival function

When analyzing the event history data, one of the key components is the survival function. The survival function can either be of continuous or discrete time. Survival function is defined as the probability that no event has occurred before time *T* measured at *t* (Steele, 2004). Survival function is given by the formula

$$S(t) = \Pr(T \geq t) \tag{3.1}$$

whereby *S(t)* is known as the decreasing function of t with $S(t) = 1$ and $S(t) \to 0$ as

$t \to \infty$

while t denotes the survival time. The complement of the survival function is known as cumulative distribution function that is the probability that an event occurs before t. The cumulative distribution function is given by

$$F(t) = 1 - S(t) = \Pr(T < t) \tag{3.2}$$

3. 3.1 Survival analysis in continuous time

Let T denote a survival time. The distribution function of T, providing the probability of exit before time $T = t$, is then $F(\mathrm{t}) = \Pr(\mathrm{T} \leq \mathrm{t})$, while the probability of surviving beyond t is

$$F(t) = 1 - F(t) = \Pr(T > t),$$

whereby $S(\infty) = 0$. So, the density of T can be expressed as $f(t) = \frac{dF(t)}{dt} - \frac{dS(t)}{dt}$

The density $F(t)$ captures the chance of an event occurring in a short time interval

$(t, t + dt)$, given survival to t, is

$$\Pr(t \leq T < t + dt | T \geq t) = \frac{\Pr(t \leq T < t + dt | T \geq T)}{dPr(T > t)} = \frac{F(t + dt) - f(t)}{S(t)}$$

A related function is the hazard function $h(t)$,which is the instantaneous event rate, obtained as $dt \to 0$ in the ratio of the preceding probability to the length of the interval dt.

That is,

$$h(t) = \lim_{dt \to 0} \frac{F(t + dt) - F(t)}{dt} \frac{1}{S(t)} = \lim_{dt \to 0} \frac{S(t) - S(t + dt)}{dt} \frac{1}{S(t)} = \frac{f(t)}{S(t)}.$$

Since $-f(t)$ is the derivatives of $S(t)$, one obtains that $h(t) = \left(-\frac{S(t)}{S(t)}\right)$,and so,

$$h(t) = \frac{-dlogS(t)}{dt} \tag{3.3}$$

In order to obtain cumulative hazard rate, one need to integrate both sides in equation (3.3)

$$H(t) = \int_0^t h(u)du = \int_0^t \left[\frac{-dlogS(u)}{du} \right] du$$

$$= \int_0^{-\log S(t)} dlogS(u) = -\log S(t)$$

3. 3.2 Survival analysis in Discrete Time

The event history analysis data discrete time process generally record the dependent variable as a series of binary outcomes denoting whether or not the event of interest occurred at the observation point (Box-Steffensmeier & Jones, 2004). The event of interest for this study is “death”, whether a household member died or not.

The two models widely used in social sciences to estimated discrete time models are logit and probit (Box-Steffensmeier, 2004). However, there is a need to consider mathematical concepts $h(t), f(t) and\ h(t)$ underlying the discrete time model.

Let the random variable T denote a discrete random variable, indicating the time of an event occurrence. Since we assume that events are observable at specific, discretely defined point,t_i, the probability mass function for a discrete random variable is

$$f(t) = P_r\ (T = t_i) \tag{3.4}$$

and denote the probability of an event occurring at time t_i . Through (3.4), it is clear that there can be multiple failures occurring at the same time. The survivor function for discrete random variable T is given by

$$S(t) = \Pr(T \geq t_i) = \sum_{j>i} f(t_j), \tag{3.5}$$

where j denotes a failure time using the results shown in 2.1a for the continuous case, the hazard rate for the discrete time case is given by

$$h(t) = \frac{F(t)}{st} \tag{3.6}$$

which demonstrate that the hazard off an event occurrence is equivalent to the ratio of the probability of failure given survival. Hence, the hazard probability for discrete case is given by

$$h(t) = \Pr(T \geq t_i | T \geq t_i) \tag{3.7}$$

3.4 Hazard function

An alternative characterization of the distribution of survival time, T, is given by the hazard function, defined as

$$\lambda(t) = \lim_{dt \to 0} \frac{\Pr(t < T \leq t + dt | T > t)}{dt} \tag{3.8}$$

whereby $\Pr(t \leq T < t + dt | T \geq t)$ is the probability that an event occurs during the interval $(t, t + dt)$, given that no event has occurred before time t. The notation $\lim_{dt \to 0}$ is the shorthand for the limit as the width of the interval gets infinitesimally small, so the hazard expresses the probability that an event occurs within a small interval of time. The conditional probability in the numerator for equation (3.10) may be written as the ratio of the joint probability that T is the interval $t, t + dt \; and \; T > t$. Thus, $\lambda(t)$may be written as

$$\lambda(t) = \frac{f(t)}{S(t)} \tag{3.9}$$

The cumulative hazard (cumulative risk) is denoted by

$$\Lambda(t) = \int_0^t \lambda(x)dx \tag{3.10}$$

whereby $\Lambda(t)$ is defined as the sum of the risks one may face going from duration 0 to t.

3.5 Censoring and the likelihood function

In cases where for some units the event of interests has occurred and therefore the exact time is known, whereas for some units the event of interest has not occurred and it is know that the waiting time exceeds the observation time is referred to as censoring (Rodriquez, 2007).

3.6 Types of censoring

Right censoring occurs when the subject leaves the study before an event can occurs, or the study ends before the event has occurred. Left censoring occurs when the event of interest has already occurred before the study begins. Interval censoring occurs when time to event of interest occurs within an interval.

3.7 Unobserved heterogeneity

This section considers survival models with a random effect representing unobserved heterogeneity of frailty. The term frailty was introduced by Vaupel et al. (1979), to indicate that different individuals are at risk even though they appear to be similar with respect to measurable attributes such as age, sex and weigh (Hanagal, 2011). Frailties are group specific factors acting on an adult survival, which together with other individual factors may protect or accelerate death (Vaupel et al., 1979). The term frailty is used to represent unobservable random effects shared by subjects with similar (unmeasured) risk in the analysis of mortality. The unobserved random effects can be modelled either as structured or unstructured random effects. The unstructured random effect is concerned with fitting uncorrelated random effects while the structured fit the correlated random effects. Thus, the inclusion of random effects which permits modelling of unmeasured and unobserved factors, which may either act at a family, individual, regional or constituency level. Those operating at individual, family, community and regional level may have a direct or intermediate effect on the outcome (Kazembe et al., 2013). Models that incorporate random effects are commonly called Generalized Linear Mixed Models (GLMM) and those that account for non-linearity are refered to as Generalized Additive Models (GAM) and when extend to include random effects they are known as Generalized Additives Mixed Models (GAMM) (Hennerfeind, Brezger & Fahmeier, 2006)

When it comes to model fitting, models constructed in terms of group level frailties are sometimes referred to as shared frailty models because observations within sub-group share unmeasured risk factors that prompt them to exit earlier (or later) than other sub groups in the population (Box-Steffensmeier & Jones, 2004). Models based on individual level frailties (i.e. each observation in the sample has potentially its own unique frailty) are referred to as frailty models or individual level frailty models.

3. 7.1 Individual frailty

Box-Steffensmeier & Jones (2004) defined individual frailty as follow: suppose, a sample of j observations are more failure prone due to reasons unknown (or unmeasured).The hazard rate is given by

$$h(t_j) = h_o(t)\exp(\beta' x_j) \tag{3.11}$$

However, if there are unmeasured frailties among individuals in the sample, then the hazard rate shown above will not only be the function of the covariates, but also a function of the frailties associated with j individuals. In this case, hazard could be expressed as

$$h(t_j) = h_0(t)\exp(\beta' x_j + \Psi_j) \tag{3.12}$$

whereby Ψ_j are the frailties and are assumed to be an independent sample from a distribution with mean =0 and variance =1.

3. 7.2 Shared frailty model

Box-Steffensmeier & Jones (2004) defined shared frailty as follow: suppose we have j observations and i subgroups (for repeated measures data, the j observations will simply be the period- specific records of data for the individual. The hazard rate for the $j.th$ individual in the $i.th$ subgroup (with frailties) is:

$$h(t_{ij}) = h_0(t)\exp\,(\beta' x_{ij} + \Psi_{wi}\,) \qquad (3.13)$$

where w_i are the subgroups of the frailties which are assumed to be an independent sample from a distribution with mean =0 and variance=1.

If $\Psi = 0$ we can re-express the equation (2.8) as

$$h_{ij}(t)|(\beta, x_{ij}, v_i) = h_0(t)v_i\ \exp(\beta' x_{ij}) \qquad (3.14)$$

whereby, $v_i = \exp(\Psi\, w_i)$ denotes the shared frailty.

Recent studies that looked at frailty models showed a significant heterogeneity at community level, which may be attributed to differential availability of resources at community level (Bolstad & Manda, 2002).

3.7.3 Spatially correlated frailties

Research on survival analysis has increased since the seminal work by Cox in the 1970s (Cox, 1972) to include spatially correlated frailties. This should be seen as an extension to the shared frailties as overviewed in Section 3.7.2, and are generally referred to as geo-additive survival models (Similar to the shared frailties (Section 3.7.2), we assume that T is the number of years lived or the censoring time for the jth adult in the area I, the hazard function at time $T = t$ is given by

$$h(t|\beta, v_{ij}, \Psi_i) = h_0(t) \exp(\beta v_{ij} + \Psi_i) \tag{3.15}$$

Since the individual used for the study were clustered in geographical regions, a random frailty term Ψ_i was introduced to augment for cox model in equation (3.15). The model indicates that adult survival is influenced by individual specific factors v_{ij} as well as by group specific

environment factors Ψ_i that are approximated by geographic location. We expand this concept in the sections to follow.

3. 8 Geo-additive regression models

The classical tool for analyzing the effects of covariates ν on continuous survival time is the Cox proportional hazard model (Cox, 1972) is given by

$$\lambda_i(t, v) = \lambda_o(t)\exp\,(v_i T\,\gamma) \tag{3.16}$$

Whereby γ is defined as parameter considered as a random variable. However, at times this specification is not flexible for modeling variables affecting Thus, several study uses structured geoadditive survival models (Hennerfeind et al., 2006; Kneib and Fahrmeir, 2007), which is a flexible spatial generalization of the cox model.

The geoaditive hazard regression model is given by: $\lambda_i(t) = \exp(n_{it})$ (Hennerfeind, Brezger and Fahmeir, 2006), whereby,

$$n_{it} = g_0(t) + g_1(t)u_i + \cdots f_1(z_{it1}) + \cdots f_k(z_{itk}) + f_{spatial}(s_i) \tag{3.17}$$

$g_0(t)$ = log-baseline hazard rate;

z_{itk} = linear effects of continuous covariates;

$f_{spatial}(s_i)$ = Spatial effects

$g_1(t)u_i$ = non linear effects of covariates

The non-parametric effects, including the log-baseline hazard are modeled using penalized splines (P-splines, Eilers and Marx, 1996). The spatial effect is split into a structured and an unstructured part given by

$$f_{spatial}(s_i) = f_{str}(s_i) + f_{unstr}(s_i) \tag{3.18}$$

Equation (3.12) will enable us to distinguish between two types of geographical influential factor. The structured effect refers to general smooth spatial effect along the whole studied area, while the unstructured effects accounts for possible effects that maybe present only at locally (Rodriguez-Girondo, Cadaro-Suarez, Kneib, Gomez and Casanova, 2012).

The structured spatial effects are modeled by means of Markov random field, assuming that the effect of an area s_i is conditionally Gausian.

3.9 Bayesian statistical modeling

3. 9.1 Prior distribution for covariates

In Bayesian approach, prior knowledge is incorporated in order to come up with new estimates. The idea is to update observed data with prior knowledge in order to come up with posterior beliefs that may be used for inference. The priors can be expressed in the pairwise difference form as

$$p(f|\tau_t^2 \propto \exp[\frac{\tau_t^2}{2}\sum_{t=3}^{T}(f_t - 2f_{t-1} + f_{t-2})^2 \tag{3.19}$$

The spatially structured component s_i was assigned a conditional autoregressive (CAR) prior.

The CAR prior assumes that the mean for each area, s_i conditional on the neighbouring area, has normal distribution with its mean equal to the average of neighbouring areas, s_i and variance inversely proportional to the number of neighbours, m_i. The CAR prior has the form

$$p(s_i|s_i; l\ neighbouring\ i) \sim N(\frac{1}{s_i}\sum_{l\ adj\ i} s_i, \frac{\tau_s^2}{m_i})$$

whereby $l\ adj\ i$ denotes the adjacent areas and τ_s^2 is the spatial variance.

For the unstructured spatial heterogeneity term u_i is assumed to follow an exchangeable Gaussian prior with zero mean and variance, τ_s^2, that is,

$$u_{i\sim}N(0, \tau_u^2)$$

3. 9.2 Posterior distribution

Fully Bayesian inference is based on the analysis of posterior distribution of the model parameters. Posterior distribution based on conditional independent assumption is given by

$$p(\beta, \tau^2, \gamma|data) \alpha \ L(data|\beta, \tau^2, \gamma) p(\beta, \tau^2, \gamma)$$

$$= L(data|\beta, \tau^2, g) x\{\prod_{i=1}^{\infty} p(\beta_j \,|\tau_j^2) p(\tau_j^2)\} p(\gamma) \qquad (3.20)$$

whereby,

$p(\beta, \tau_2, \gamma\,|data)$ is the posterior density function

while $L(data|\beta, \tau^2, \gamma)$ gives the likelihood for the data.

3. 9.3 Markov Chain Monte Carlo (MCMC) method

Posterior inferiors inference may be difficult due to intractability of integrals is highly analytical difficult, which makes direct inferences almost impossible. This problem is solved by using MCMC simulation. The utilization of the MCMC simulation techniques since the 1990s is on the increase. These methods combined the Monte Carlo simulation and Markov chain ideas hence the name ((Hennerfeind et al., 2006; Kneib and Fahrmeir, 2007; Rodriquez et al., 2012).

Ntzoufras (2011) defined Markov chain is defined as stochastic process (

$\theta^{(1)}, \theta^{(2)} \ldots\ldots, \theta^{T}$)

such that

$$f\left(\theta^{(t+1)}\middle|\theta^{(t)},\dots,\theta^{(1)}\right) = f(\theta^{(t+1)}|\theta^{(t)}) \tag{3.21}$$

The MCMC method simulates draws from the complex distribution of interest which is usually the posterior distribution. To compute the posterior mean for example, the following integral has to be evaluated

$$E(\theta|y) = \int_{\theta} \theta p(\theta|y)d\theta$$

In order to make inference about the posterior, a sequence of T random draws are made from different prior and hyper prior distribution. Then the posterior estimator θ of is computed as a mean of the T draws. The integral above was evaluated through Monte Carlo integration while the simulation is through Markov chains that is,

$$E(\theta|y) = \frac{1}{T}\sum_{t=1}^{T}\theta(t)$$

3.10 Model selection

The need to select a model is of great importance in statistics in order to ensure goodness of fit and adjust or penalize for model complexity. The observed data is usually from an unknown probability distribution. As a result, several models are fitted in order to find the best. The models that are not very close to the actual distribution have to be discarded. Below are different statistics that are commonly used in the model selection.

3. 10.1 The likelihood ratio test

A likelihood ratio test is a statistical test used to compare the fit of two models. The test is based on the likelihood ratio, which expresses how many times more likely the data are under one model than the other. This likelihood ratio, or equivalently its logarithm, can then be used to compute a p-value, or compared to a critical value to decide whether to reject the null model in favour of the alternative model.

LRT is based on the joint probability density function of observable random variables. At the null model, subsequent updated model are estimated and it is viewed as the function of parameters given the realized random variables. The LRT then uses the Chi-square test to assess if any updated model offers an improvement in goodness of fit against the null model.

3. 10.2 Akaike Information Criterion (AIC)

The AIC is one of the statistics used to select the best model. It is defined as

$$AIC = 2k - 2ln(L) \tag{3.22}$$

whereby k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model. The AIC is calculated for each model under consideration using the same data and the model with the lowest AIC is chosen. The term $2k$ is a penalty to be paid for over fitting and this discourages adding too many variables in the models which always leads to a smaller likelihood. This provides the trade-off between over fitting and optimum model fit.

3. 10.3 Bayesian Information Criterion (BIC)

The BIC is another model selection in statistic that was introduced by Schwarz (1978) is based on the empirical log-likelihood and it does not require the specifications of priors. Due to this fact, the BIC is favoured in situations where the priors are difficult to set. It is related to the AIC and both statistics penalize model complexity. The best model fitted is identified by the minimum value of BIC. Mathematically, the BIC is given by

The BIC is given by

$$BIC = -2\ln(L) + kln(n) \tag{3.23}$$

whereby L= the maximized value of the likelihood function of the model and

k= the number of free parameters to be estimated

n= the number of observations, or equivalently or the sample size

The penalty term in the BIC is more stringent that the penalty term of AIC for $n > 8, kln(n)$

exceeds 2k and this leads to BIC favoring smaller models than the AIC.

3. 10.4 Deviance Information Criterion (DIC)

The DIC (Spiegelhalter et al., 2002) is a generalization of the AIC and the BIC and is widely used in model selection where MCMC simulation is used. The DIC only works when the posterior is approximately distributed as multivariate normal. The deviance is given as:

$$D(\theta) = -2\log\big(p(y|\theta)\big) + C, \tag{3.24}$$

whereby y are the data, θ are the unknown parameters of the model and $p(y|\theta)$is the likelihood function. C is a constant that cancels out in all calculations that compare different models, and which therefore does not need to be known. The effective number of parameters of the model is computed as

$$pD = \bar{D} - D(\bar{\theta}) \tag{3.25}$$

whereby $\bar{\theta}$ is the expectation of θ and p_D is the effective number of parameters. Thus, DIC is then calculated as

$$DIC = pD + \bar{D} \tag{3.26}$$

In model selection, the general rule is that models with smaller DIC be preferred over models with a larger DIC.

CHAPTER 4

DATA, ANALYSIS AND RESULTS

4.1 Study area characteristics

Namibia is a country in Southern Africa whose western border is Atlantic Ocean. It shares borders with Angola and Zambia to the North, Botswana to the East and South Africa to the South and East. During the time when the 2006/07 Namibia Demographic and Health Survey (NDHS) was conducted, Namibia was divided into thirteen administratively regions, which were further sub dived into 107 constituencies.

As of 2011, the total population for Namibia increased to 2.1 million from 1.8 million in 2001 (Namibia Statistics Agency [NSA], 2013). A large proportion of Namibia lives in the rural areas compared to the population that lives in urban areas (NSA, 2013).

4.2 Research design

The study is based on a quantitative cross-section design collected from the 2006/07 NDHS, to carry out data analysis of deaths and socio-economic determinants of adult mortality in Namibia.

4.3 Study population

The study population was all adults from ages 15 - 60 years from the 2006/07 NDHS data.

4.4 Sample

A representative sample of 10,000 households was selected for the 2006/07 NDHS. A multi stage sampling approach was used with primary sampling units (PSUs) as the first stage and households as the second stage sampling units. A total of 500 PSUs were selected with probability proportional to size, the size being the number of households enumerated in 2001 Namibia Population and Housing Census. In each PSU, 40 households were selected systematically. The sample size used for this study is smaller because it only used records for household members aged between 15 years and above. Thus, only a sample of 25,854 individuals aged between 15 years and above where included in the study. It should be noted that the total number of 25,854 individuals is greater than the 10,000 households because of multiple records within the selected households.

4.5 Data collection

The 2006/07 NDHS data was collected by 28 teams, each consisting of a team supervisor, a field editor, four interviewers and a driver. The majority of team supervisors and editors were staff from the Ministry of Health and Social Services. The assignment of field work took into consideration the person's proficiency in major language spoken in Namibia.

Quality assurance was maintained by national and regional supervisors through monitoring during field work. The questionnaires were edited by field editors and verified by team supervisors. National and regional supervisors ensured quality control through editing of questionnaires and observation of interviewers (NDHS, 2008).

During data collection, all women and men aged 15 years and above, who were permanent residents of the households, in the 2006/07 NDHS or visitors present in the household on the night before the surveys, were eligible to be interviewed. Respondents were asked whether any usual household member died in the last 12 months. The time to event is age in completed years at which the household member died was recorded.

The explanatory variables used for the study includes type of residence (urban/rural), region, marital status, education level, age of household head, sex of household head, time to nearest health facility, nearest health facility, time to nearest health facility and wealth index. The choice of socio-economic factors used for the study was guided by literature, see Roger et.al (2005).

4.6 Ethical considerations

The permission to use 2006/07 NDHS data was granted by Macro international.

4.7 Data management

Several categories of certain variables were grouped, since some categories had few recorded cases. Data cleaning was carried out using Statistical Package for Social Sciences (SPSS) as well as in excel in order to remove missing data. The data was then exported to BayesX and R for further analysis. One aspect of the data cleaning was to reduce the number of variables in the dataset, in order to remain with variables of interest that are essential for the analysis of the study. Dummy variables for all explanatory variables of interest for the study were created and modeled as binary variables.

4.8 Description of key variables

The outcome variable for this study is age at which a household member died. We assume that this age is right/interval censored. In addition, we have socio-economic variables. Table 4.1 shows variables used in the modeling.

Table 4.1 Description of key variables

Covariates	Description
Outcome variable	
Event	Whether any household member died
Agehmbr	Age of household member
Socio-economic factors	
Sexhmbr	Sex of household member
SexHead	Sex of household head
Hhage	Age of household head
Educ	Education attainment of household members
Marital	Marital status of household member
Wealth index	Index showing the well-being of the household (1=poorest, 2=poorer, 3= middle, 4=richer, 5=richest)

Table 4.1 Description of key variables

Covariates	Description
Spatial factors	
Reg	The region in which the household is situated (1=Caprivi, 2=Erongo, 3= Hardap, 4=Karas, 5=Kavango, 6= Khomas, 7=Kunene, 8= Ohangwena, 9=Omaheke, 10=Omusati, 11=Oshana, 12=Oshikoto and 13= Otjozondjupa)
Urbanrural	Type of residence (1=urban and 2=rural)
Constituency	Administrative boundaries , there were 107 constituency in Namibia
Other factors	
TimeHF	Time to nearest health facility (1=minutes,2=hours and 3=days)
NearestHF	Nearest health facility (1=hospital, 2=health centre and 3=clinic)
MeansHF	Means to nearest health facility (1=car/motorcycle, 2=public transport, 3= walking)

4.9 Data Analysis

The data is analyzed in two major software packages, BayesX (Belitz et al., 2009) and R software (R Development Core Team, 2011). The BayesX was used to formulate and estimate geo-additive hazard models using the STAR approach. The R software was used primarily for explanatory analysis particularly for the product of Kaplan-Meier curves, Chi-square test as well as the log-rank test.

4.9.1 Exploratory Analysis

The study uses the Kaplan-Meier curves as well as the log-rank test in examining the issues around socio-economic risk factors on adult mortality assuming the time (age) at which the household member died in completed years. The Kaplan Meier curves was used to assess the difference in probability of survival with respect to difference in socio-economic and health care factors while the log rank test was used to assess for the significance difference of socio-economic and health care factors with respect to adult mortality.

4.9.2 Geoadditive Survival Model Specification

In order to improve the models that were fitted, spatial frailty models at regional level, constituency level as well as the combination of spatial frailties at regional and constituency level were fitted. These models were additional to those with fixed effects only. Thus, eight models of different specification were fitted. The fitted models are as follow:

$$M_0 = f(baseline)$$

$$M_1 = f(baseline) + \gamma' \omega$$

$$M_2 = f(baseline) + f_{spatial}(reg) + \gamma' \omega$$

$$M_3 = f(baseline) + f_{random}(reg) + \gamma' \omega$$

$$M_4 = f(baseline) + f_{random}(reg) + f_{spatial}(reg) + \gamma' \omega$$

$$M_5 = f(baseline) + f_{random}(const) + \gamma' \omega$$

$$M_6 = f(baseline) + f_{spatial}(const) + \gamma' \omega$$

$$M_7 = f(baseline) + f_{random}(const) + f_{spatial}(const) + \gamma' \omega$$

$$M_8 = f(baseline) + f_{spatial}(const) + f_{random}(const) + \gamma' \omega$$

Below is the descriptions for the models for the study as listed above, $\gamma' \omega$ refers to fixed effects

M_0: Fitted the baseline only;

M_1: Fitted the baseline plus the fixed effects (*refer to Table 4.1 for fixed effects*);

M_2: Fitted the baseline plus the spatially structured random effects and fixed effects at regional level;

M_3: Fitted the baseline plus unstructured random effects and fixed effects at regional level;

M_4: Fitted the baseline plus the unstructured random effects plus spatially structured random effects and fixed effects at regional level;

M_5: Fitted the baseline plus unstructured random effects and fixed effects at constituency level;

M_6: Fitted the baseline plus spatially structured random effects and fixed effects at constituency level;

M_7: Fitted the baseline plus the unstructured random effects and spatial structured effects and fixed effects both at constituency level;

M_8: Fitted the baseline plus the structured random effects and unstructured random effects and fixed effects both at regional level.

We applied a fully Bayesian approach based on Markov Priors and using the Markov Chain Monte Carlo (MCMC) techniques for inference and model checking. For model choice, we used the Deviance Information Criterion (DIC) developed as a measure of fit and model complexity (Spiegelhalter et al., 2012). The analysis was carried out using version 2.1 of the BayesX software package which permits Bayesian inference based on MCMC simulation techniques. For all the models, 12000 iterations were run with a burn of 2000 for each model. Model selection using DIC was carried out at the end to choose the best model which could be used for inference. Model with the lowest DIC was chosen as the best model.

4.10 Descriptive data analysis

This section presents the results of the descriptive data analysis results before moving on to make further inferences based on models built. Table 4.2 gives a summary of the selected covariates. Explanatory analysis shows a clear disadvantage for those in rural areas, for those of low wealth ranking and those not married. Kavango and Karas had the highest percentage of adults that died.

Table 4.2 Summary of the selected socio-economic factors of adult mortality based on the Chi-square (X^2 tests)

Variable	Percentage died	Total	X^2 test	p-value*
Region				
Caprivi	9.2	1 588	287.6	<0.01
Erongo	4.5	1 915		
Hardap	7.7	1 647		
Karas	5.9	1 532		
Kavango	13.0	2 550		
Khomas	4.1	2 752		
Kunene	7.4	1 299		
Ohangwena	12.5	2 334		
Omaheke	5.5	1 433		
Omusati	8.0	2 259		
Oshana	7.7	2 312		
Oshikoto	9.6	2 261		
Otjozondjupa	5.7	1 911		

***Note**: * Test was carried out at p<0.01*

Table 4.2 Summary of the selected socio-economic factors of adult mortality based on the Chi-square (X^2 tests) Cont….

Variable	Percentage died	Total	X^2 test	p-value*
Residence				
Urban	5.4	10829	157.7	<0.01
Rural	9.7	14 964		
Sex of household members				
Male	7.3	12 020	12.8	<0.01
Female	8.5	13 773		
Age of household member				
15-24	9.5	8508	99.7	<0.01
25-34	6.6	6264		
35-44	5.8	4187		
45-54	6.6	2846		
55-64	8.8	1819		
65+	10.6	2169		
Sex of household head				
Male	6.0	15019	181.5	<0.01
Female	10.6	10774		
Age of household head				
15-24	6.5	1 081	340.2	<0.01
25-34	4.4	4 546		
35-44	5.5	5 763		
45-54	7.1	5 197		
55-64	10.7	3 772		
65+	12.7	5 434		
Time to nearest health facility				
Minutes	6.6	16 730	136.0	<0.01
Hour	10.6	8 174		
Days	12.1	612		
Nearest health facility				
Hospital	6.3	5 531	27.0	<0.01
Health centre	8.4	1 933		
Clinic	8.5	17 909		

Note*: * Test was carried out at $p<0.01$*

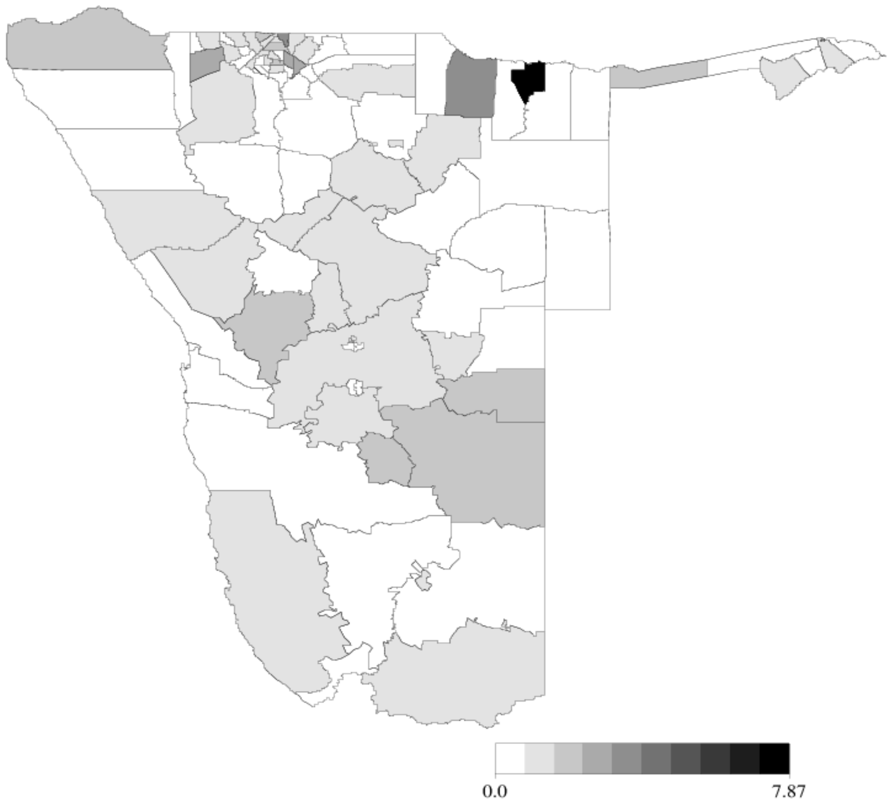
Table 4.2 Summary of the selected socio-economic factors of adult mortality based on the Chi-square (X^2 tests) Cont….

Variable	**Percentage died**	**Total**	**X^2 test**	**p-value***
Means to nearest hospital				
Car	4.8	4 013	67.9	<0.01
Public transport/ Animal cart	7.9	4 968		
Walking	8.7	16 021		
Education of household member				
None	8.5	3 876	80.6	<0.01
Primary	9.9	8 230		
Secondary/ Higher	6.5	13 283		
Marital status of household member				
Never married	8.8	13 796	186.6	<0.001
Married	5.4	9 464		
Other	13.4	2 162		
Wealth index				
Poorest	12.0	4215	299.2	<0.001
Poorer	9.8	4785		
Middle	8.8	6126		
Richer	6.5	6134		
Richest	2.9	4533		

***Note**: * Test was carried out at p<0.01*

Figure 4.1 assess the hazard of adult mortality without considering the impacts of socio-economic or any other factor that may affect adult mortality. The results show that there were geographical discrepancies at 95% credible bands in the hazard of adult mortality at a constituency level. The percentage of adult mortality was high for constituencies in the North Eastern, Central West of Namibia as well as in the Southern West part of the country, while, the percentage of adult mortality was lowest for the constituencies in the Northern East, North West and Southern part of the country.

Figure 4.1 Map of adult mortality at a constituency level showing the percentage dead in each area.



4.10.1 Differentials in adult mortality hazard

Figure 4.2 shows the hazard and the survival function. It was evident that there was a general decline in the probability of an adult surviving as the age of household member increased, while the probability of adult dying increased as age of household member increased. This finding is similar with what was found by Bassuk, Berkman, & Amick (2002), that age is an important factor for adult mortality.

Figure 4.2 Survival and hazard function of adult mortality in Namibia

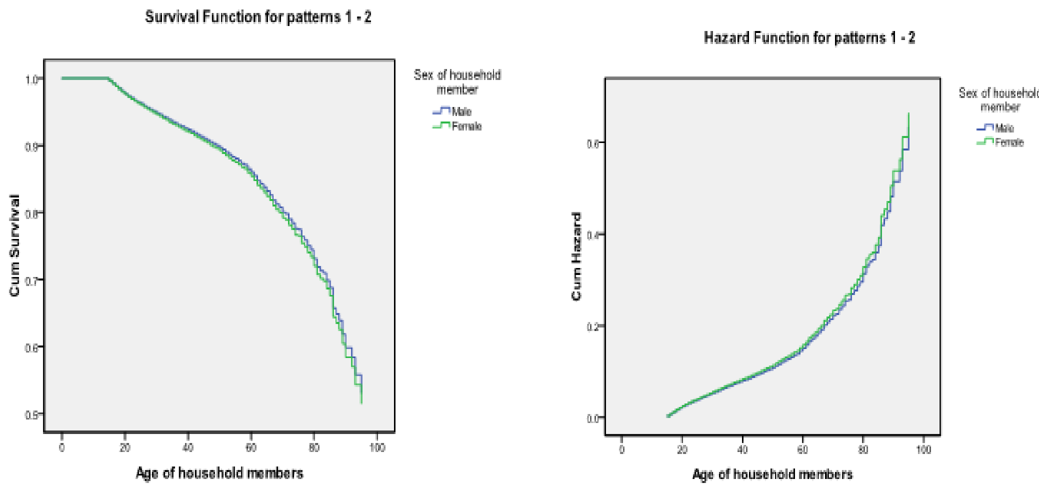


Table 4.3 shows a summary of the covariates used for the study based on the log rank test. In terms of the socio-economic factors, the results shows a significant difference in the probability of survival for adults and old age people with respect to marital status, education level, type of residence (urban/rural), wealth index, sex and age of household head. The health care factors particularly the means and time to nearest health facility shows a significant difference unlike the nearest health facility.

Table 4.3 Summary of the selected socio-economic factors based on the log-rank test

Covariates	log-rank test	p-value*
Marital status of household member	1050.4	0.00
Education of household member	181.5	0.00
Residence	10.5	0.00
Wealth index	143	0.00
Sex of household head	11.2	0.00
Age of household head	113.8	0.00
Nearest health facility	1.9	0.38
Means to nearest hospital	100.1	0.00
Time to nearest health facility	18.6	0.00

Note*: * Test was carried out at p<0.05*

Figure 4.3 shows how the probability of survival changes with respect to age. Furthermore, it was observed that the probability of survival was constant for ages less than 15 years. Moreover, it was observed that the risk of an adult dying declined constantly up to age 60. Furthermore, the study shows that intervals in the probability of dying are wide from age 80 and above

Figure 4.3 Survival function of adult mortality in Namibia

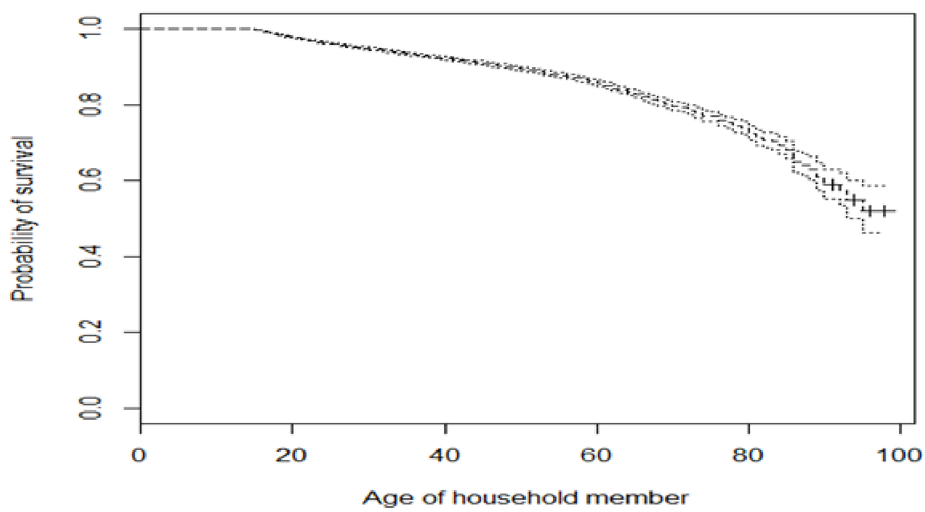


Figure 4.4 shows how adult and old age mortality hazard varies with marital status. It was evident that the never married adults have low probability of survival compared to adults who were married or in other marital status. For this study others in terms of marital status includes divorced and widowed. It can be observed that the probability of survival for married adults was close to 1.0 even at age 60, while a drastic decline in the probability of survival for the never married adults was observed after age 80 years and above. The log rank test (*Table 4.2*) shows that marital status was significant. Thus,

there were disparities in the probability of survival for adults and old age people in terms of their marital status.

Figure 4.4 Survival of adults and old age people in terms of their marital status

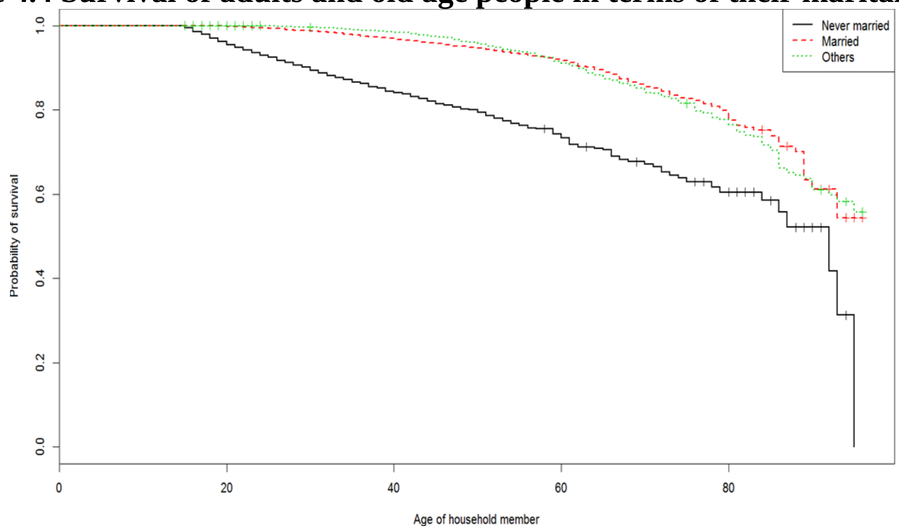


Figure 4.5 shows that the probability of survival for adults and old age people with no education was higher compared to adults with pre-primary and secondary/higher education.

Furthermore, it was also observed there was a sharp decline in the probability of survival for adults and old age people with secondary/higher education after age 60. However, the results are counter-intuitive, but there may be some possible interaction with other variable. The log rank test (*Table 4.2*) shows that education was significant. Thus, there were differences in the probability of survival for adults and old age people in terms of their in the education level.

Figure 4.5 Survival of adults and old age people in terms of education

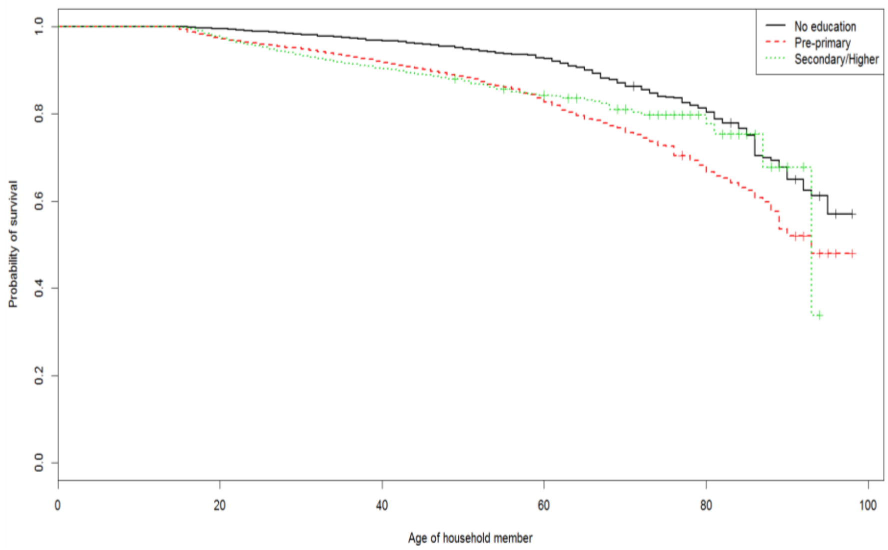


Figure 4.6 show that there was a slight difference in the probability of survival for adults and old age people that lives in urban/rural areas. For instance, the probability of survival for adults and old age people in urban area was slightly higher for some age group particularly from age 15 - 65 years. Furthermore, it was observed that the probability of survival for adults and old age people in urban areas remained constant after age 80 years and above compared to rural areas. Thus, there were differences in the survival probabilities for adults and old age people that lives in urban and rural areas. The log rank test (T*able 4.2*) shows that type of residence (urban/rural) is significant. Thus, there were disparities in the probability of survival for adults and old age people in terms of their type of residence (urban/rural).

Figure 4.6 Survival of adults and old age people in terms of their types of residence (urban/rural)

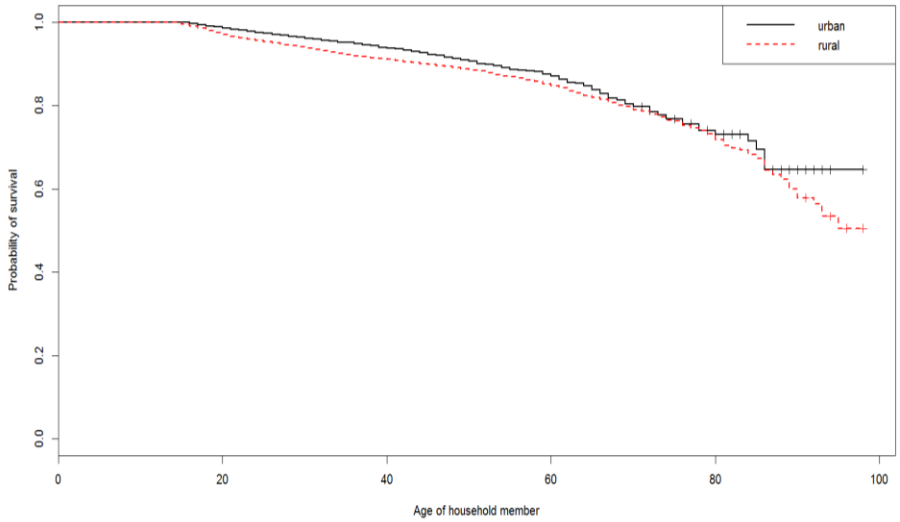


Figure 4.7 shows how adult mortality risk varies with the wealth status for the household. It was evident that the probability of survival for adults and old age people increases as the wealth status of a household improves. Result shows that probability of survival was lowest among poorest adults and old age people while for richest adults and old age people the probability of survival was close to 1.0 even after age 60 years. The log rank test (T*able 4.2*) shows that wealth index was significant. Thus, wealth index was a determinant of adult and old age mortality.

Figure 4.7 Wealth index as a determinant of adult and old age mortality

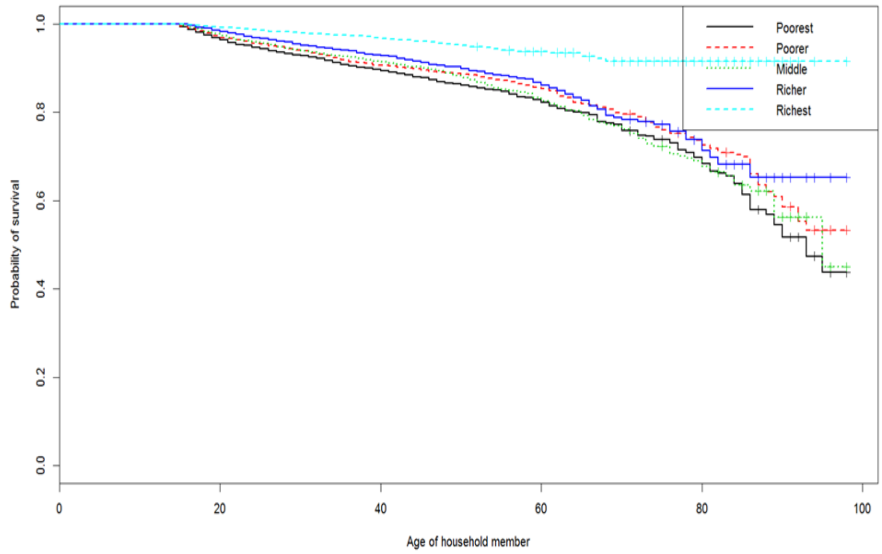


Figure 4.8 shows that the probability of survival for adults and old age people was higher for male headed households compared to female headed households. This was particularly true for ages between 20 to 65 years. The log rank test (*Table 4.2*) shows that sex of head of the household was significant. Thus, there was no evidence to state that there are disparities in the survival of adults and old age people in terms of the sex of head of the household.

Figure 4.8 Survival for adults and old age people in terms of sex of head of the household

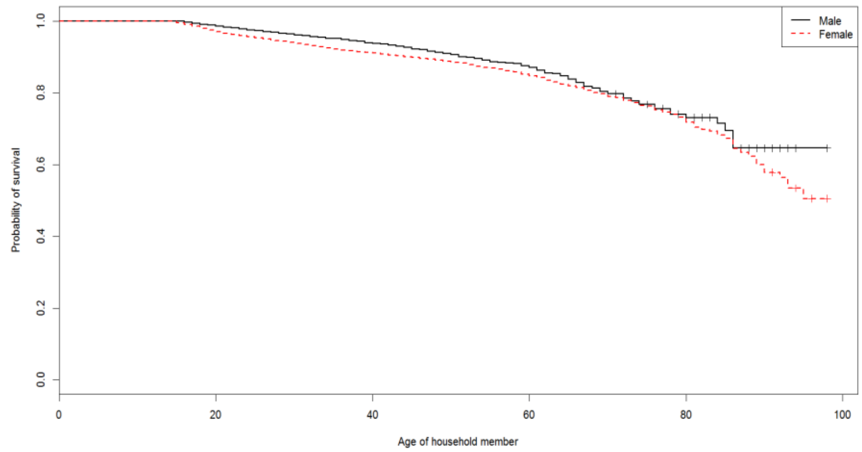


Figure 4.9 shows that the probability of survival was higher for adult and old people who visited hospital as the nearest health facility as compared to the probability of survival for those that visited the health centre or clinic. The log rank test (*Table 4.2*) shows that nearest health facility was significant. Thus, there are disparities in the survival of adults and old age people in terms of the nearest to the health facility.

Figure 4.9 Survival for adult and old age people in terms of nearest health facility

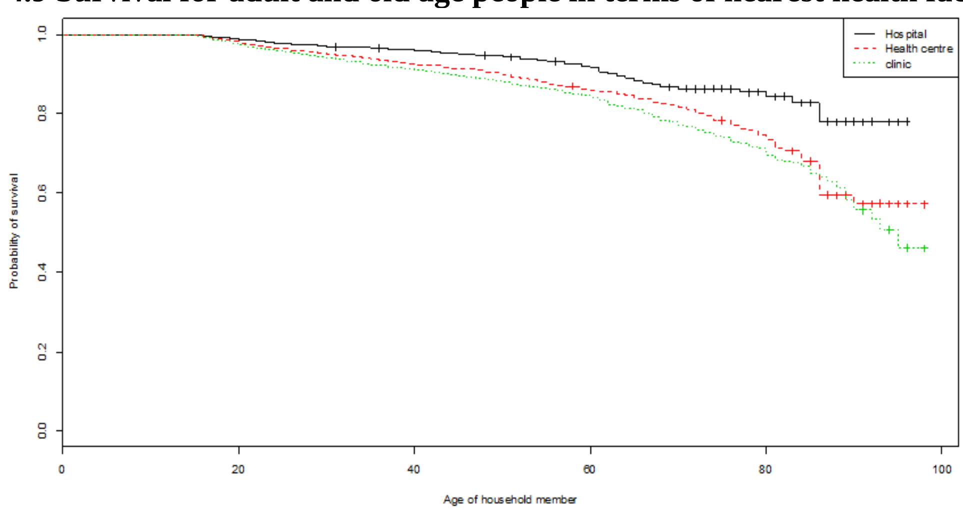


Figure 4.10 shows that the probability of survival was high for adults and old age people that access the nearest health facility by means of car compared to those that access the health facility by walking, means of public transport or animal cart. The log rank test (*Table 4.2*) show that means to nearest health facility was significant. Thus, there were disparities in the survival of adults and old age people in terms of their means to the nearest health facility.

Figure 4.10 Survival of adults and old age people in terms of the means to nearest health facility

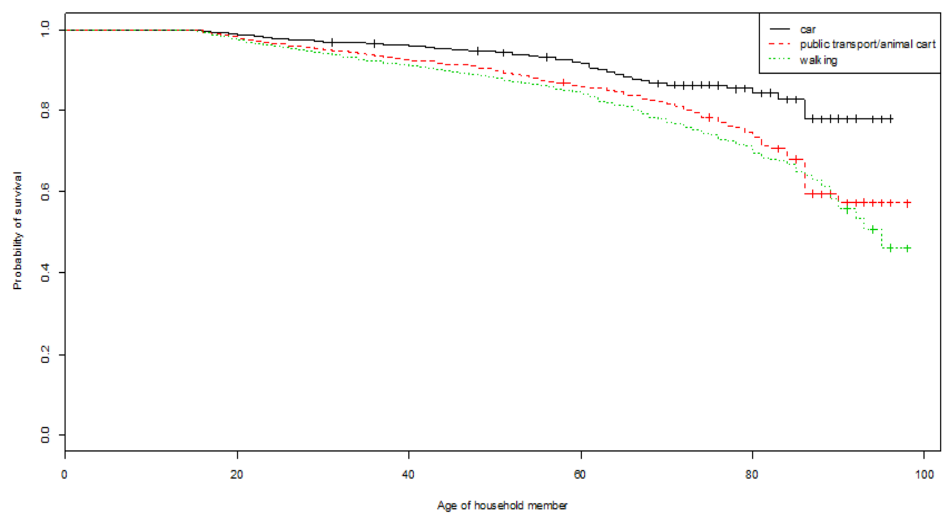
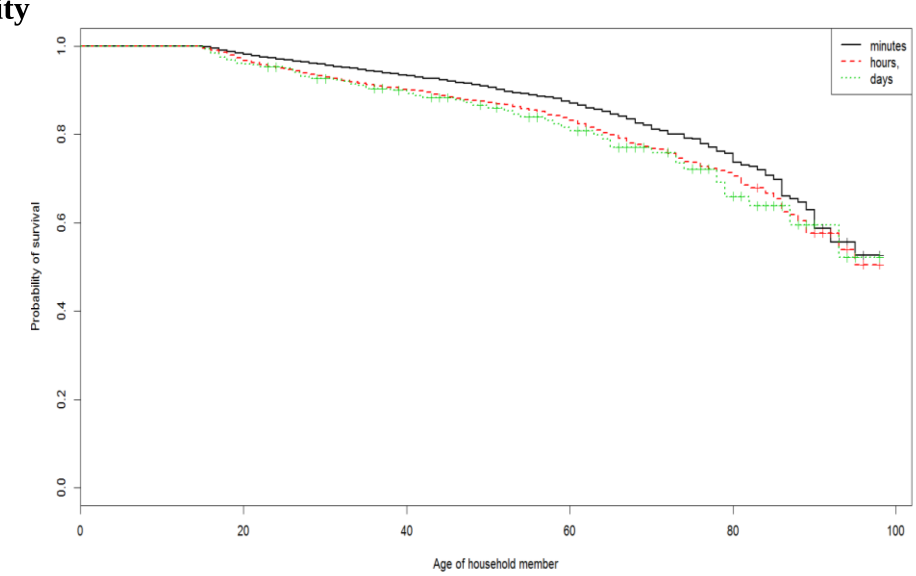


Figure 4.11 shows that the probability of survival was high for adults and old age people that take minutes to get to the nearest health facility as compared to those that takes hours or days to get to the nearest health facility. The log rank test (*Table 4.2*) shows that time to nearest health facility was not significant. Thus, there was no evidence to state that there is a difference in the probability of survival for adult and old age people with respect to time to nearest health facility.

Figure 4.11 Survival of adults and old age people in terms of time to nearest health facility



4.11 Geo-additives discrete time hazard model

These section deals with model comparison, baseline hazard, fixed effects as well as the random effects .

4.11.1 Model comparison

Table 4.4 presents the model selection values for the discrete-time survival models. The model selection values are given in terms of the deviance, effective number of parameters as well as the deviance information criterion. The result shows that model 7 (M7) had the lowest DIC value. M7 incorporated the baseline, fixed effects, unstructured random effects and spatially structured effects both at constituency level. Looking at the DIC values for models that were fitted at a regional level, it may be concluded that constituencies explained the hazard of dying better than considering the effects of region or at combined region and constituency.

Table 4.4 Model comparison based on Deviance Information Criterion (DIC) for the models

Model*	Deviance	pD	DIC	ΔDIC
M0	14176.2	6.59	14189.4	993.01
M1	13416.5	33.92	13484.3	287.92
M2	13418.2	33.15	13484.5	288.14
M3	13417.8	32.74	13483.2	286.84
M4	13418	32.85	13483.7	287.25
M5	13002.5	97.62	13197.7	1.3
M6	13010.8	95.83	13202.5	6.09
M7	13001.7	97.36	**13196.4**	0
M8	13012.1	95.58	13203.2	6.81

Note: model descriptions provided on page 45*

4.11.2 Baseline hazard

This section compares the two types of baseline models, specifically M0 and M7. The M0 looks at overall baseline hazard without adjusting for any variable, while the M7 model adjusted for fixed effect and random effect. The two models show how adult mortality varies with age.

Figure 4.12 evidently shows a nonlinear variation in hazard adult and old age mortality. There was a decline in hazard up to age 40 and then rises from age 60. Lack of resources to improve the health, wellbeing and living standards of adult and old age people may be responsible for the increase in hazard in old age. At age 25 to 55, the hazard remained overly below 1.0 mark. Further, result shows that the intervals in the probability of dying widen from age 80 and this may be due to fewer death cases reported for these age groups.

Figure 4.12 Baseline for null model. The centre line is the hazard rate while the other lines are the 80% and 90% credible bands respectively.

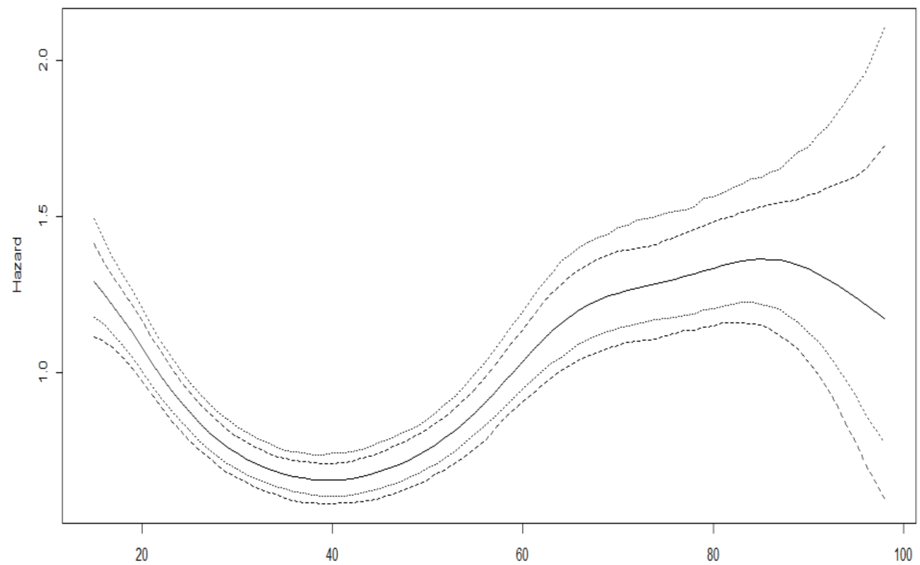
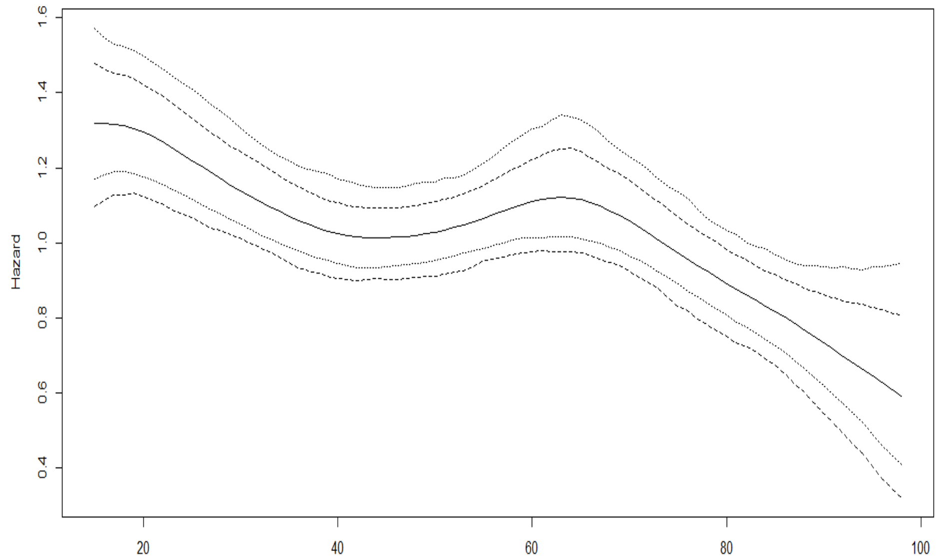


Figure 4.13 evidently shows that there was a nonlinear relationship between the hazards of an adult mortality for the best model (M7). Furthermore, there was a decline in hazard up to age 40 and then rises from age 60. This maybe because the model (M7) adjusted for baseline, fixed effects, random effect as well the structured effects at a constituency level. Thus, it may be concluded that other factors explained the hazard of adult mortality better than considering the effects of region or as presented in Figure 4.12.

Figure 4.13 Baseline for the best model (M7). The hazard is given at the centre with 80% and 95% credible bands.



.11.3 Fixed effects

From the best model, we produced the summaries of the factors considered in this study to explain influences of covariates to adult mortality. Table 4.5 provides estimates of the Hazard Rate (HR) and 95% Credible Interval (CI) from the model with the best fit.

The result shows that, in terms of sex of head of the household, for male headed household there was a decrease in hazard of an adult dying (HR=0.65, 95% CI: 0.59 to 0.72), than for female headed households. It was observed that, there was a significant decrease in the hazard of an adult dying for male headed households.

On age of household head, there was a general increase in the hazard of an adult dying (HR=1.02). The hazard of an adult dying increases as age of head of the household increases. There was a significant increase in the hazard of an adult dying as the age of head increases.

Regarding the education level for household member, for adults who had no education, there was a decrease in hazard of an adult dying (HR= 0.99, 95% CI: 0.85, 1.17), than those with secondary/higher education. Comparing adults with no education with those with primary education (HR=1.22, 95% CI: 1.09 to 1.36), it was observed that there was an increase in hazard with 23 units. Although there was a decrease in hazard, the decrease is not significant.

On marital status, the never married adults had a decrease in hazard of dying (HR=0.82, 95% CI: 0.70 to 0.99), than adults with other types of marital status. Other types of marital status, for this study includes divorced and widowed. Comparing never married and married adult (HR= 0.62, 95% CI: 0.53 to 0.73), there was a slight decrease in hazard with only 0.2 units. The decrease in hazard for marital status was not significant.

Table 4.5 Fixed effects summary for the best model (M7)

Covariates	**Hazard Ratio (95% Credible Interval)**
Intercept	0.02 (0.01 , 0.03)
Sex of household head	
Male	0.65 (0.59, 0.72)
Female (Ref)	1.00
Age of head of the household	1.02 (1.02 , 1.02)
Education level	
No education	0.99 (0.85 ,1.17)
Primary education	1.22 (1.09, 1.36)
Secondary/higher education (Ref)	1.00

Note: Ref refers to Reference

Table 4.5 Fixed effects summary for the best model (M7) Cont….

Covariates	Hazard Ratio (95% Credible Interval)
Marital status	
Never married	0.82 (0.70, 0.99)
Married	0.62 (0.53, 0.73)
Others (Ref)	1
Wealth index	
Poorest	2.03 (1.51, 2.72)
Poorer	1.78 (1.37, 2.31)
Middle	2.00 (1.54, 2.54)
Richer	1.78 (1.44, 2.23)
Richest (Ref)	1.00
Type of residence	
Urban	0.91 (0.76,1.10)
Rural	1
Time to nearest health facility	
Time in minutes	1.14 (0.80 , 1.60)
Time hours	1.53 (1.09, 2.18)
Time in days	1
Nearest health facility	
Nearest health facility (hospital)	0.95 (0.82, 1.10)
Nearest health facility (health centre)	0.91 (0.73, 1.14)
Nearest health facility (clinic)	1
Means to nearest health facility	
Means to the nearest health facility (car/motorcycle)	0.87 (0.72 ,1.06)
Means to the nearest health facility (public transport/animal cart)	1.04 (0.90, 1.19)
Means to nearest health facility (walking)	1

Note: Ref refers to Reference

In terms of the wealth status of a household, there was an increase in hazard of an adult dying (HR =2.03 CI: 151 to 2.72) in poorest household compared to the adults in richest households. Although there was an increase in hazard of an adult dying with respect to the wealth status of a household, this increase was not significant.

For urban area, there was a decrease in hazard of an adult dying in urban (HR=0.91, 95% CI: 0.76 to 1.10) than in rural area. The decrease in hazard of an adult dying in urban area was not significant.

The results show that, for adults who travel to health facility in minutes, there was an increase in hazard of an adult dying (HR= 1.4, 95% C.I: 0.80 to1.60), than for those who travelled in days. Comparing those who travelled in minutes with those who travelled in hours (HR=1.53 95% CI: 1.09 to 2.18), there was an increase in hazard of 39 units. Although, there was an increase in hazard of an adult dying for those who travelled in minutes and hours, this increase was not significant.

In terms of nearest health facility, for adults who visited hospital as their nearest health facility, there was a decrease in hazard of an adult dying (HR=0.95, 95% CI: 0.82 to 1.10), than for those who visited a clinic. Comparing those who visited hospital and health centre (HR=0.91, 95% CI: 0.73 to 1.14), there was a slight decrease in hazard with only 0.04 units. This decrease was not significant.

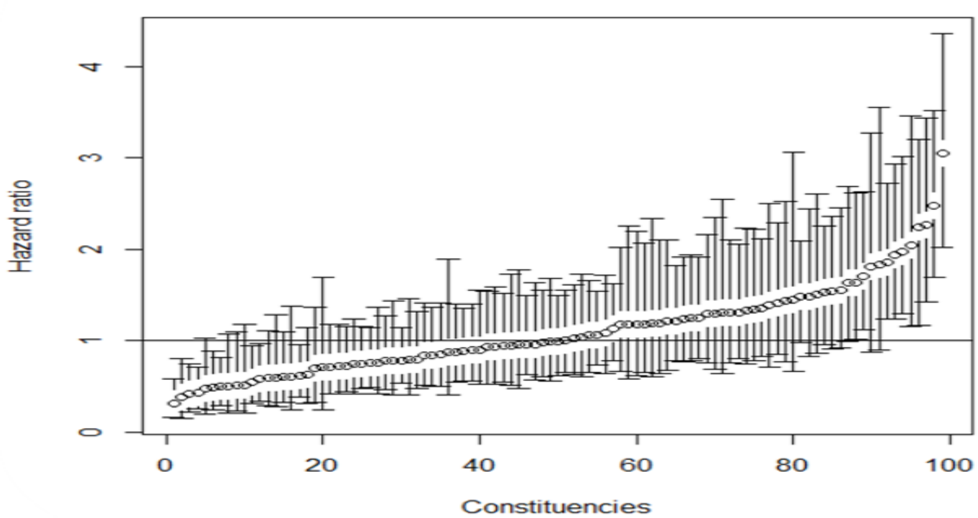
Regarding the means of transportation to nearest health facility, it was observed that adults who uses car/motorcycle as means to the nearest health facility, had a decrease in hazard of an adult dying (HR=0.87 95% CI: 0.72, 1.06), than those who walks. Comparing those who uses car/motorcycle and public transport/animal cart (HR=1.04

95% CI: 0.90 to 1.19), there was a decrease in hazard with 0.17 unit. Although there was a decrease in hazard, this decrease is not significant.

4.11.4 Random effects

The unstructured random effects for adult mortality at constituency level were also fitted. Figure 4.14 shows that there were spatial variations in the hazard of an adult dying in all constituencies. Some constituencies has hazard of adult mortality above 1, while other constituencies had hazard of adult mortality below 1, suggesting discrepancies in the hazard ratio at constituency level in Namibia. For instance, Caprivi and Erongo constituencies were at the lower end [1-10] while constituencies for Oshikoto & Otjozondjupa at the other end [9-102]. These results agree with Figure 4.1 that shows adult mortality map at a constituency level.

Figure 4.14 Caterpillar plot for the unstructured random effects based on best model



4.11.5 Spatial effects

The spatial effects estimates were interpreted using maps generated in BayesX using the Bayesian approach. Maps presented in darker colour signify constituencies/region with high hazard of adult mortality while lighter colour show constituencies/region with low hazard of dying. Figure 4.15 shows the spatial variability of hazards of dying at 80% and 95% credible bands. The North Eastern part of the country, Central North of the country and down Southern part of the country shows high hazard of an adult dying (presented in black colour) while areas of reduced risk (presented in lighter colour) are commonly found in the North West, Central North, Central and towards Eastern part of the country.

Figure 4.15 Spatial structured and unstructured effects (given as Hazard Ratios) of adult mortality at constituency level at 80% and 95% credible bands

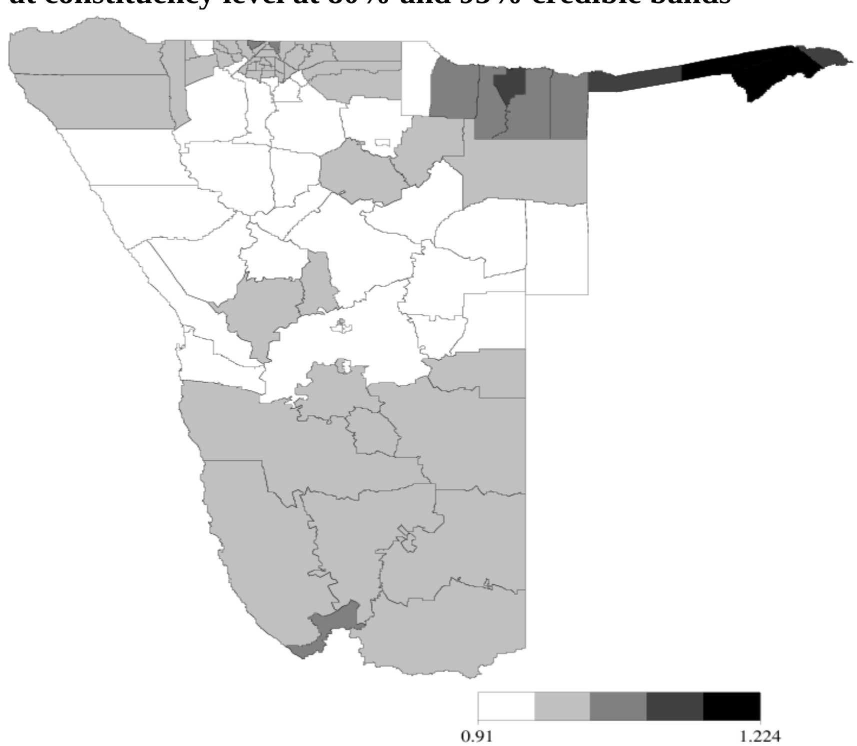
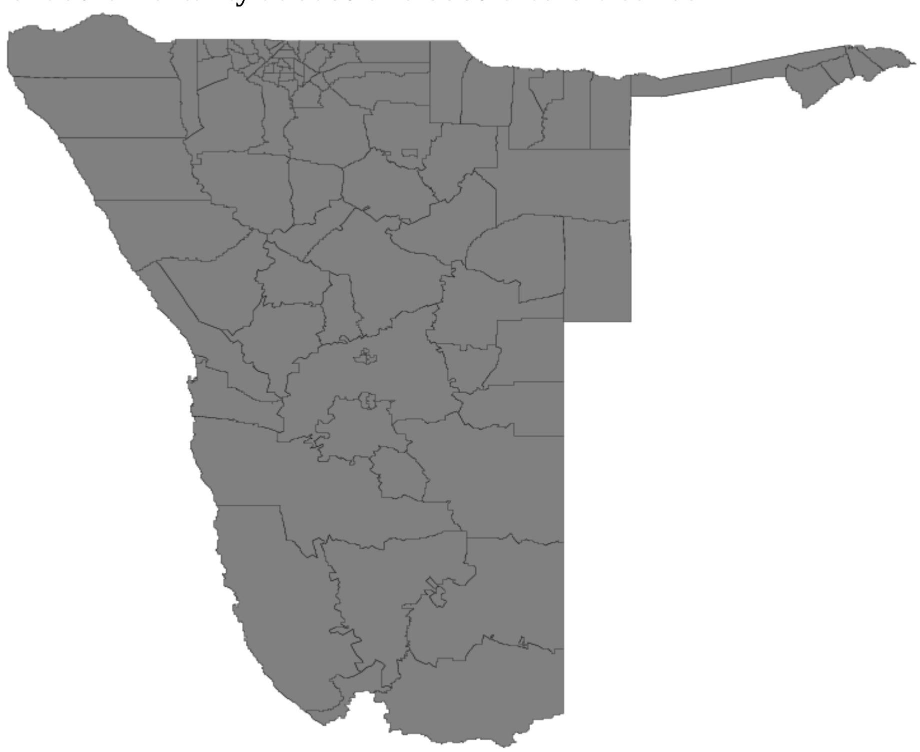


Figure 4.16 shows the probability map at 80% and 95% credible bands. Grey colour signifies no significant increased hazard while white colour indicates the reduced hazard of dying. The result shows no significance in hazard of an adult dying in terms of the spatial structured and unstructured effects at constituency level.

Figure 4.16 Spatial structured and unstructured effects with other significant covariates of adult mortality at 80% and 95% credible bands



CHAPTER 5

DISSCUSSION AND CONCLUSIONS

5.1 Discussion

The aim of the study was to apply an event history discrete time survival analysis in order to explain effects of socio-economic factors on adult mortality in Namibia. We fitted geoadditive survival models using the Bayesian framework for joint modeling of fixed, non-linear and spatial frailties. The proposed model assumed discrete time survival analysis which permits modification of Cox model which handles continous survival data for survey data, which is not always the case. Any ties which may arise due to heaping for instance can be handled using this model (Bolstad and Manda, 2002). Bear as it maybe, the particular model only used one type of interval censoring of 5 years grouping. The ideal situation would have been to use several types of interval censoring. However, in many demographic smoothing a 5 year interval censoring is the commonly used method (Peduzzi, Henderson, Hartigan & Lavori, 2002).

5.1.1 Socio-economic factors and adult mortality

The study found results which were consistent with what has been reported previously. For instance, in our analysis, the death hazard observed among the different age groups showed dramatic increases in the hazard with increasing age. This was indicated earlier in the conceptual framework, Roger et al. (2005), who emphasised the importance of age in any research on human, thus this finding was as expected. Age is a well know factor that explains health and mortality. Kaplan & Kronick, 2006; Grundy & Sloggett, 2005) indicated that as adults grow older, their body cells turn to weaken and suffer functional difficulties, thus, becoming more prone to ill health and disease which often results in morbidity and eventually mortality.

The analysis further indicated that the hazard of adult mortality varied with marital status. The analysis further indicated that the hazard of adult mortality varied with marital status. These finding agreed with Nikoi (2009) who observed that single adults, on average were twice likely to die when compared to adult who were married. The findings of the study also agrees with Davis et al. (1992), who indicated that married old people received care from their spouses and as a result their probability of surviving is higher compared to the never married adults.

The study also found that the probability of survival for adults and old age people in urban was slightly higher than for adults in rural areas. These findings agree with what was observed by Zimmer et al. (2006) who found that unadjusted rural mortality was 30 percent higher than urban mortality. National Research Council (2003) indicated that there were a number of public health factors that made urban residents survive better than rural people. Namely, availability of health services and access to safe water in urban areas which often are lacking in rural areas, may contribute to higher chances of survival for adults in urban areas.

Regarding education, the study found that the probability of survival for adults and old age people with no education was higher compared to adults with pre-primary and secondary/higher education. These findings differ from what was found in literature. For instance, Bassuk et al. (2002), who noted an increased hazard of mortality among adults with lower education, level regardless of the economic status, sex, race and neighborhood. Sudore et al. (2006) found that low level of literacy was associated with poor management of diseases and other health conditions that may consequently results in deaths.

The study also looked at the impact of household wealth on adult mortality. The findings show that, probability of survival was lowest among poorest adults and old age people while for richest adults and old age people the probability of survival was high. This situation may be attributed due to lack of resources that may impede poorest adults and old age people to access health facilities and many basic needs that are essential for improving the health, wellbeing and living standards of adult people. This finding agrees with what was found by (Sammy, 2009), that adults in the upper categories of socio-economic status had lower hazard ratios for mortality compared to those in the poorest category

In terms of the health factors, the result indicated that probability of survival was higher for adult and old age people who visited hospital as the nearest health facility as compared to the probability of survival for those that visited the health centre or clinic.

This could be the case because hospitals provide quality health services compared to other health facilities. Moreover, this may be due to the fact that normally hospitals have adequate number of staffs compared to other health facilities.

Furthermore, the result shows that the probability of survival was high for adults and old age people that access the nearest health facility by means of car compared to those that access the health facility by walking, means of public transport or animal cart. These could be because accessing the health facility by means of walking, public transport or animal cart might take longer to reach the health facility compared to when accessing the health facility by means of private car. As result, adults who access the health facility by means of private car survives better than other adults who travelled by other means of transport.

Moreover, the findings show that the probability of survival was high for adults and old age people that take minutes to get to the nearest health facility as compared to those that takes hours or days to get to the nearest health facility. These findings agrees with Becher (2004) in a study in Zambia who has observed that increasing travel time or distance to nearest health facility was associated with child mortality.

In terms of the spatial effects, we used the neighborhood structure of binary (0, 1) using intrinsic conditional autoregressive (CAR). However, fairly complex spatial structure for instance, distal factors such as access to health facility, availability of health facilities may be used , which may either benefit adults or put them at increased hazard of mortality or may represent other factors such as disease prevalence (Lawson, 2008). In our spatial analysis, it was found that, that geographic location has an impact on the hazard of adult mortality.

The hazard map that was fitted at a constituency level, shows that that there was high hazard of an adult dying in the North Eastern part of the country while in the North Western and Central East there was a reduced risk in the hazard of an adult mortality. The unstructured random effects, again fitted at a constituency level, indicated that there was spatial variation in the hazard of adult mortality at a constituency level with constituencies for Caprivi and Erongo regions in the lower hazard, while constituencies for Oshikoto and Otjozondjupa region were at the higher hazard of adult mortality.

5.1.2 Limitations

The study also had several limitations. For instance, although the study was carefully planned there are some inevitable limitations to be acknowledged. For instance, firstly, these are self-reported data, thus we cannot disregard the likelihood that mortality outcomes maybe influenced by the respondent's ability to recall. Secondly, the 2006 NDHS did not collect information for all variables such as income of household head, behavior and habit factors such as smoking and alcohol consumption which may be considered important in measuring the impacts of socio-economic factors on adult mortality. Thirdly, the data used for the study was collected in 2006/2007, thus the findings might give a different picture on adult mortality and socio-economic factors from the current situation on the ground. Lastly, we assumed single hazard for all regions. Thus, there is a need to have region-specific hazard modeling.

5.2 Conclusion

The analysis shows that there are socio-economic disparities with respects to adult mortality in Namibia. Some of the findings from the study were consistent with what has been reported previously. For instance, the study age of household member, marital status and type of residence (urban/rural), were some of the important factors in determining adult mortality. It is hoped that this study particularly the spatial analysis section will help health planners, policy makers to identifying specific areas with high hazard of adult mortality in order to design, evaluate programmes and develop strategies aiming at improving the health and well-being of adults. Adults are the economically active and productive age group for a population, thus if the government is to meet national development goals such as NDP4 or vision 2030, then adult mortality taking into consideration socio-economic factors should be considered as major public issue than concentrating only on infant and maternal health as documented in other studies. Furthermore, support should be made to adults, such as stipends particularly for the never married adults; adults from poorest households; adults with no hospital as the nearest health facility as well as adults who travel for days to the nearest health facility, in order to improve the well-being of these particular adults.

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ANNEXURE A: R codes

This is a freely available statistical package and is the software used for the explanatory analysis of this thesis. The R software can be freely downloaded from the site (http://www.r-project.org/.)

Below is some of the R syntax used for the explanatory analysis for the thesis:

```
> dhsNAM<-read.spss(file.choose(),to.data.frame=T, use.value.labels=F)

> names(dhsNAM)

>dhs.surv<-survfit(Surv(HV105, HV249) ~ 1,data=dhsNAM)

> plot(dhs.surv)


> dhs.surv.marital<-survfit(Surv(HV105, HV249) ~
Current_Marital_Status,data=dhsNAM)

> plot(dhs.surv.marital, lty=1:3)

> legend("topright", lty=1:3, c("Never married","Married", "None"))


> dhs.surv.educ<-survfit(Surv(HV105, HV249) ~ education_level,data=dhsNAM)

> plot(dhs.surv.educ, lty=1:3)

> legend("topright", lty=1:3, c("None","Primary", "Secondary and Higher"))
```

```
> dhs.surv.urban<-survfit(Surv(HV105, HV249) ~ HV025,data=dhsNAM)
> plot(dhs.surv.urban, lty=1:2, xlab="Age of household member",ylab="Probability of Survival", col=1:2,lwd=c(2,2))
> legend("topright", col=1:2, c("Urban","Rural"))

> dhs.surv.windex<-survfit(Surv(HV105, HV249) ~ HV270,data=dhsNAM)
> plot(dhs.surv.windex, lty=1:5, xlab="Age of household member",ylab="Probability of Survival", col=1:5,lwd=c(2,2))
> legend("topright", col=1:5, c("Lowest","Low","Medium","High","Highest"),lty=1:5)

> dhs.surv.sexhead<-survfit(Surv(HV105, HV249) ~ HV219,data=dhsNAM)
> plot(dhs.surv.sexhead, lty=1:2, xlab="Age of household member",ylab="Probability of Survival", col=1:2,lwd=c(2,2))
> legend("topright", col=1:2, c("Male,"Female"))

> dhs.surv.nearHF<-survfit(Surv(HV105, HV249) ~ Nearest_Health_Facility,data=dhsNAM)
> plot(dhs.surv.nearHF, lty=1:3, xlab="Age of household member",ylab="Probability of Survival", col=1:3,lwd=c(2,2))
> legend("topright", col=1:3, c("Hospital","Health Centre","Clinic"),lty=1:3)
```

```
> dhs.surv.accesTreat<-survfit(Surv(HV105, HV249) ~
Means_To_Nearest_HealthFacility,data=dhsNAM)
> plot(dhs.surv.accesTreat, lty=1:3, xlab="Age of household member",ylab="Probability
of Survival", col=1:3,lwd=c(2,2))
> legend("topright", col=1:3, c("Car","Public Transport","Walking"),lty=1:3)
```

```
> dhs.surv.accesTime<-survfit(Surv(HV105, HV249) ~
Timegrp_to_Hfacility,data=dhsNAM)
> plot(dhs.surv.accesTime, lty=1:3, xlab="Age of household member",ylab="Probability
of Survival", col=1:3,lwd=c(2,2))
> legend("topright", col=1:3, c("Minutes","Hours","Days"),lty=1:3)
```

Codes for the baseline:

```
library(BayesX)
```

a) **Baseline for the null model:**

```
>plotnonp("C:/namreg/M0_f_agehmbr_pspline.res",xlab="age",ylab="Hazard",main
=         "Baseline for null model",y=c("hr","cilo95","cilo80","ciup80","ciup95"))
```

b) **Baseline for the best model:**

```
>plotnonp("C:/namSW/M7_f_agehmbr_pspline.res",xlab="age",ylab="Hazard",mai
n= "Baseline for best model",y=c("hr","cilo95","cilo80","ciup80","ciup95"))
```

Codes for the Random effects_ Caterpillar plots:

```
>Library(gplots)
>ra<-read.table(file.choose(),header=T)
>attach(ra)
>plotCI(x=hr,ui=ciiup95,li=cilo95, ylab="Hazard ratio",xlab="Constituencies")
>abline(h=1)
```

ANNEXURE B: BayesX code

BayesX is the software for Bayesian Inference in Structured Additives Regression Models and is the software used for spatial analysis for this thesis. BayesX is free software and it can be downloaded from the site (http://www.stat.uni-muenchen.de/~bayesx/). The BayesX used for this thesis is version 2.1 and was developed in (07.05.2012) and it permits Bayesian Inference on Markov Chain Monte Carlo simulation techniques.

Below is the list of sytanx used for full Bayesian for the study:

```
> dataset dhs
> dhs.infile using c:\namreg\dhs.txt
> map m1
> m1.infile using  C:\namreg\MAP\namibia-regions.csv
> m.reorder
```

a) **Codes used to fit models at a regional level**

```
> bayesreg M0
> M0.outfile=C:\namreg\M0
> M0.regress event=agehmbr(psplinerw2), family=binomial iterations=12000
burnin=2000 step =10 predict using dhs
```

```
> bayesreg M1
> M1.outfile=C:\namreg\M1
> M1.regress
event=agehmbr(psplinerw2)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+
nevermarr+married+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+midd
le+richer+caprivi+erongo+hardap+karas+kavango+khomas+kunene+ohangwena+omah
eke+omusati+oshana+oshikoto, family=binomial iterations=12000 burnin=2000 step
=10 predict using dhs

> bayesreg M2
> M2.outfile=C:\namreg\M2
> M2.regress event=agehmbr(psplinerw2)+reg(spatial,
map=m1)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+nevermarr+marrie
d+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+middle+richer,
family=binomial iterations=12000 burnin=2000 step =10 predict using dhs

> bayesreg M3
> M3.outfile=C:\namreg\M3
> M3.regress
event=agehmbr(psplinerw2)+reg(random)+timehf1+timehf2+nearhf1+nearhf2+meanshf
1+meanshf2+nevermarr+married+hhmale+hhage+noeduc+primaryeduc+urban+poorest
```

+poorer+middle+richer, family=binomial iterations=12000 burnin=2000 step =10 predict using dhs

> bayesreg M4

> M4.outfile=C:\namreg\M4

> M4.regress event=agehmbr(psplinerw2)+reg(random)+reg(spatial, map=m1)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+nevermarr+married+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+middle+richer, family=binomial iterations=12000 burnin=2000 step =10 predict using dhs

b) **Codes used to fit models at a constituency level:**

> bayesreg M5

> M5.outfile=C:\namSW\M5

> M5.regress

event=agehmbr(psplinerw2)+const(random)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+nevermarr+married+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+middle+richer, family=binomial iterations=12000 burnin=2000 step =10 predict using dhs

> bayesreg M6

> M6.outfile=C:\namSW\M6

> M6.regress event=agehmbr(psplinerw2)+const(spatial, map=m)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+nevermarr+married

```
+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+middle+richer,
family=binomial iterations=12000 burnin=2000 step =10 predict using dhs > bayesreg
M7
> M7.outfile=C:\namSW\M7
> M7.regress event=agehmbr(psplinerw2)+const(random)+const(spatial,
    map=m)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2+nevermarr+
    married+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poorer+middle+r
    icher, family=binomial iterations=12000 burnin=2000 step =10 predict using dhs

> bayesreg M8
> M8.outfile=C:\namSW\M8
> M8.regress event=agehmbr(psplinerw2)+const(spatial,
    map=m)+reg(random)+timehf1+timehf2+nearhf1+nearhf2+meanshf1+meanshf2
    +nevermarr+married+hhmale+hhage+noeduc+primaryeduc+urban+poorest+poor
    er+middle+richer, family=binomial iterations=12000 burnin=2000 step =10
    predict using dhs
```

Codes used to map adult mortality at a constituency level

```
> dataset d
> d.infile using c:\aspatialR\diedconst.txt
> map m
> m.infile using c:\aspatialR\nam-SW.csv
> graph g
```

> g.drawmap died const, map=m swapcolors nrcolors=10 using d

Codes for spatial effects

> dataset d1

> d1.infile using C:\namSW\M7_f_const_spatial.res

> map m

> m.infile using C:\namSW\MAP\nam-SW.csv

> m.reorder

> graph g

Random effects and spatial effects for best model

> g.drawmap hr const,map=m swapcolors nrcolors=5 using d1

Probability map

> g.drawmap pcat95 const,map=m swapcolors nolegend using d1