



Socioeconomic Determinants of Adult Mortality in Namibia Using an Event History Analysis



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Abstract

Adult mortality remains a neglected public health issue in sub-Saharan Africa, with most policy instruments concentrated on child and maternal health. In developed countries, adult mortality is negatively associated with socioeconomic factors. A similar pattern is expected in developing countries, but has not been extensively demonstrated, because of dearth of data. Understanding the hazard and factors associated with adult mortality is crucial for informing policies and for implementation of interventions aimed at improving adult survival. This paper applied a geo-additive survival model to elucidate effects of socioeconomic factors on adult mortality in Namibia, controlling for spatial frailties. Results show a clear disadvantage for adults in rural areas, for those not married and from poor households or in female-headed households. The hazard of adult mortality was highly variable with a 1.5-fold difference between areas, with highest hazard recorded in north eastern, central west and southern west parts of the country. The analysis emphasizes that, for Namibia to achieve its national development goals, targeted interventions should be aimed at poor-resourced adults, particularly in high-risk areas.

Introduction

Achieving better health has been a long-term agenda in public health. In the past two or plus decades, many health policy instruments, in most developing countries, have aimed to meet developmental issues, particularly the Millennium Development Goals (Bendavid et al. 2012; Jamison et al. 2006). Efforts in most countries have concentrated on child and maternal health as opposed to the general adult health (Bradshaw and Timaeus 2006; de Wilque and Filmer 2013). A lot has been done to improve children and maternal health, particularly the formulation of strategies, and scaling up of interventions aiming at improving health in children and mothers through disease prevention and control (Jamison et al. 2006). Little focus, though, has been drawn on adult health, specifically on adult survival and mortality (Kazembe 2013; Murray et al. 2010; Nikoi 2009; Obermeyer et al. 2010; Rajaratnam et al. 2010), yet adults are the economically active and productive group, with clear repercussions if neglected for long.

Whereas, the neglect in adult health, in part,

is due to lack of policy; on the other hand, studying adult mortality is further compounded by dearth of data, with few countries having reliable or complete civil registration and vital statistics (Mathers et al. 2005; Murray et al. 2010). In most countries, the population censuses have mostly been used in such an endeavour. However, these are limited in scope, with regards to having appropriate variables for meaningful epidemiological analysis.

What has been shown, elsewhere in Europe and the Americas, is that adult mortality is negatively associated with socioeconomic position. A similar pattern is expected in developing countries, but has not been extensively demonstrated. Literature documents a distinct relationship between adult mortality and socioeconomic factors, and the list is extensive. Particularly, socioeconomic factors contribute indirectly and/or exacerbate adult mortality. According to the theoretical framework proposed by Roger et al. (2005), socioeconomic factors are distal factors of adult survival. These factors act indirectly through proximate determinants like living

conditions, behaviour, health factors and socioeconomic and demographic variables, which, in turn, aggravate morbidity and mortality.

Studies, for example, Bassuk et al. (2002), noted an increased hazard of mortality among adults with lower education level regardless of the economic status, sex, race and neighbourhood. Nikoi (2009) observed that single adults, on average, were twice likely to die when compared to adults who were married. Sammy (2009) found that adults in the upper categories of socioeconomic status had lower hazard ratios (HR) for mortality compared to those in the poorest category. However, the differences were very small and not statistically significant. 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; Mackenbach et al. 1997; Marmot et al. 1984; Preston and Taubman 1994).

Moreover, in epidemiology or social science applications, survival data often contain geographic or spatial information such as community, district or region of residence. These factors make it possible for researchers to study the impact of the location on individual's survival, often modelled as random effects (Banerjee and Carlin 2003; McIntyre et al. 2002). The inclusion of random effects permits modelling of unmeasured and unobserved factors that have an effect on the outcome. These may act at various levels, be it at community, regional and national tiers, which may be attributed to differences in resource availability and accessibility (Magadi and Desta 2011; McIntyre et al. 2002), resulting in spatial inequalities that may negatively impact health outcomes. In random effect modelling, a possible extension is to assume that unobserved factors vary spatially to give spatial frailty survival models (Banerjee and Carlin 2003; Henderson et al. 2002). Bayesian frailty models have been used to

quantify the association between adult mortality and socioeconomic factors (Sartorius et al. 2013).

Moreover, metrical (continuous) variables may exhibit non-linearity, which should be captured if necessary. However, several models that have been applied to study adult mortality are not flexible enough to permit simultaneous estimation of fixed effects, non-linear effects and unstructured and structured random effects. The use of geo-additive survival models has been promising in this regard (Hennerfeind et al. 2006; Kazembe et al. 2007).

This study, therefore, was aimed at estimating the effects of socioeconomic factors on adult mortality in Namibia, by applying a geo-additive survival model. Specifically, we fitted a model that jointly estimated the effects of socioeconomic and geographical factors on adult mortality in Namibia. In our analysis, we use data from a recent national sample survey to examine hazard of adult mortality in Namibia.

Methods

Study Area and Context

Namibia is located in the south-western part of Africa, surrounded by Angola, South Africa and Botswana and partly to the north by Zambia and Zimbabwe (Figure 1). The current population is 2 million, which occupies a land mass of about 800,000 km². The country is ranked as a middle-income country, with life expectancy at birth of 63 years for women and 55 years for men. Adult mortality is estimated at 340 per 1,000 population (with 356 for male and 290 for female). The distribution of burden of disease as a percentage of total disability-adjusted life years, by broader causes, was 69% for communicable diseases, 25% for non-communicable diseases and 6% for injuries, as of 2009 estimates.

Figure 1. Map of Namibia showing its 13 regions and neighbouring countries



Data

This study used data from the 2006/2007 Namibia Demographic and Health Survey (DHS), which captured the household mortality data under the module “Support For Those Who Have Died” (MoHSS [Namibia] and Macro International Inc., 2008). The Namibia DHS applied a multi-stage sampling approach. Details of the survey can be found in the survey report (MoHSS [Namibia] and Macro International Inc., 2008). In brief, at the first stage, 500 enumeration areas, which were the primary sampling units (PSUs), were randomly selected with probability proportional to size. The PSUs were selected using the sampling frame from the 2001 Namibia Population and Housing Census. At the second stage, a random sample of 40 households was systematically drawn from each PSU. Then from the selected houses, at a third stage, women and men of the

reproductive age group, 15-49 years, were invited to participate in the survey.

Further, in all participating households, all household members were enumerated and information on socioeconomic variables, demographic characteristics and healthcare factors was recorded. Table 1 shows a list of variables included in the analysis. Age and sex of the head of the household were used to measure the resource base, with female-headed households and young-aged deemed more vulnerable than otherwise. The sex of the household member permitted to capture gender differences in mortality. Wealth index, education and marital status were further measures of socioeconomic position. Access and availability of healthcare were captured through variables: nearest health facility, means to nearest health facility and time to nearest health facility.

For the response variable, we used information on deaths in the household that occurred in the past 12 months preceding the survey date, and included full information on age and sex of the deceased. The questions used to

collect mortality data were: “Has any usual member of your household died in the last 12 months,” and if yes, there was a follow-up question on: “How many members died in the past 12 months.”

Table 1. Description of key variables included in the analysis

Covariates	Description
Outcome variable	
Event	Whether any household member died (1 = member died, 0 = member still living at the time of survey).
AgeHMbr	Age (in years) of household member at the time of death or survey
Socioeconomic factors	
SexHMbr	Sex of household member (1 = male; 2 = female)
SexHHead	Sex of household head (1 = male; 2 = female)
HHage	Age of household head (in years)
Educ	Education attainment of household member (1 = none; 2 = primary; 3 = secondary or higher)
Marital	Marital status of household member [1 = never married; 2 = married; 3 = others (divorced or widowed)]
Wealth index	Index showing the well-being of the household (1 = poorest, 2 = poorer, 3 = middle, 4 = richer, 5 = richest)
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 constituencies in Namibia, in 2007
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)

Statistical Analysis

Descriptive analysis

Exploratory analysis used the Kaplan–Meier curves to assess the difference in probability of survival, for various covariates, with respect to age, assuming that the time at which the household member died was age in completed years. Log-rank test was used to assess the significance of survival at various levels of covariates.

Modelling the hazard rate and risk factors of adult mortality

In studying adult mortality, we assume T as the time to event (death), recorded as age in completed years. The probability that a survival time T is less than or equal to some value t is measured as $F(t) = P[\text{Adult dies at age} \leq t]$. A common approach, however, is to consider hazard rate or force of mortality, $h(t)$. The hazard rate describes the risk or event of “failure” (i.e., death), given that the individual has survived all along up to point t (Box-Steffensmeier and Jones 2004).

Of interest is to extend the hazard rate to captures the effect of covariates. Here we propose a more general Cox model that captures random effects including spatial frailties (Banerjee and Carlin 2003). Assume that T_{ij} is the observed number of years lived or the censoring time for j -th individual in area i . Under Cox's model, the hazard function at time $T = t$ is given by:

$$h(t|\beta, v_{ij}) = h_0(t) \exp(\beta v_{ij}) \quad (1)$$

where $h_0(t)$ is the baseline hazard at age t , and the β s are a vector of regression coefficients for the fixed and time-invariant variables (v_{ij}). As individuals are clustered in geographical regions, group-specific random frailty term, ψ_i , was introduced to augment the Cox model, that is:

$$h(t|\beta, v_{ij}, \psi_i) = h_0(t) \exp(\beta v_{ij} + \psi_i) \quad (2)$$

The above model indicated that adulthood survival was influenced by both individual-specific factors (v_{ij}) and group-specific environmental factors ψ_i . The group effects might include healthcare, socio-cultural and environmental differentials, which may impose geographical heterogeneity. We introduce two types of random effects to capture such geographical effects: (1) spatially distributed random effects, through s_i ; and (2) unstructured heterogeneity random effect, u_i , giving $\psi_i = s_i + u_i$ (Besag et al. 1991). Fitting model (2) assumed a semiparametric additive predictor, which is known as a geo-additive survival model (Hennnerfeind et al. 2006):

$$\eta_{ij}(t) = f_0(t) + \beta v_{ij} + u_i + s_i \quad (3)$$

where η_{ij} is the log-additive predictor at time (age) t for adult j in area i . The term $f_0(t) = \log(h_0(t))$ is the log baseline hazard effect at time (age) t . The other terms are as defined above.

Various models, summarized as follows, were fitted:

$$\begin{aligned} M0 &= f(\text{baseline}) \\ M1 &= f(\text{baseline}) + \beta^T v \\ M2 &= f(\text{baseline}) + f_{\text{spatial}}(\text{region}) + \beta^T v \\ M3 &= f(\text{baseline}) + f_{\text{random}}(\text{region}) + \beta^T v \\ M4 &= f(\text{baseline}) + f_{\text{spatial}}(\text{region}) + f_{\text{random}}(\text{region}) + \beta^T v \\ M5 &= f(\text{baseline}) + f_{\text{spatial}}(\text{consti}) + \beta^T v \\ M6 &= f(\text{baseline}) + f_{\text{random}}(\text{consti}) + \beta^T v \\ M7 &= f(\text{baseline}) + f_{\text{spatial}}(\text{region}) + f_{\text{random}}(\text{region}) + \beta^T v \end{aligned}$$

where M0 is the basic model with the baseline component only, and M1 adds fixed effects, while model M2 includes spatially structured effects, at regional level (*region*), to model M1. Model M3 assumed spatially unstructured random effects at the regional level, whereas model M4 combines all effects at the regional level. These models (M2–M4) are repeated in models M5–M7, substituting random effects at the regional level to be considered at the constituency level (*consti*).

This model fitting strategy is commonplace in mortality literature and allows for the interpretation of mortality differentials within a multivariate context (Rogers et al. 2005). The idea is to have a basic model, then, it is adjusted for socioeconomic factors, to measure the effect of these covariates alone, and can further be adjusted for other factors. The risk of factors is estimated as hazard ratios, with hazard ratio of above 1.0 indicating a higher risk of dying for individuals in that particular category of variables, while HR below 1.0 signifies reduced risk of mortality.

Because of the complexity of the model, we applied a fully Bayesian approach via the Markov Chain Monte Carlo simulation technique for inference. The following prior distributions were assumed. The fixed effects were assigned diffuse priors, while the smooth functions were evaluated using penalized splines with second-order random walk priors. The unstructured random effects were assumed to follow an exchangeable normal distribution with mean zero and over-dispersed variance, whereas the structured spatial effects were modelled

using the conditional autoregressive prior. All variance components were then modelled using inverse gamma with parameters $a = 0.05$ and $b = 0.01$. For all the models, 12,000 iterations were run with a burn-in of 2,000 for each model. Model choice was based on the Deviance Information Criterion (DIC) developed as a measure of goodness-of-fit and model complexity (Spiegelhalter et al. 2002). Model with the lowest DIC was chosen as the best model.

The data were analyzed in two major software packages, BayesX (Belitz et al. 2009) and R software (R Development Core Team 2011). The BayesX was used to estimate geo-additive survival models. The R software was used primarily for explanatory analysis, particularly to generate Kaplan–Meier curves, and associated statistical tests.

Results

Table 2 gives a descriptive summary of mortality by region and across various covariates. There was a clear disadvantage for those in rural areas, for those of low wealth ranking and those not married. Kavango and Karas regions had the highest prevalence of adults who died, with significant difference observed among regions ($p < 0.01$). Survival curves (given in the Appendix [online at www.longwoods.com/content/24220], together with the log-rank test in Table A1) support the fact that adult survival differed across various socioeconomic factors including marital status, education level, type of residence (urban/rural), wealth index, sex and age of household head. Furthermore, significant differences were established for the healthcare factors (Table 2).

Table 2. Descriptive summary of demographic, socioeconomic and healthcare factors of adult mortality based on the χ^2 test

Variable	Percentage died	n	χ^2 test	p^*
Region				
Zambezi	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	2,550		
Khomas	4.1	2,752		
Kunene	7.4	1,299		
Ohangwena	12.5	2,334		
Omaheke	5.5	1,433		
Omusati	8	2,259		
Oshana	7.7	2,312		
Oshikoto	9.6	2,261		
Otjozondjupa	5.7	1,911		
Residence				
Urban	5.4	10,829	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		

Table 2. Continued

Variable	Percentage died	n	χ^2 test	p^*
Age of household member				
15–24	9.5	8,508	99.7	<0.01
25–34	6.6	6,264		
35–44	5.8	4,187		
45–54	6.6	2,846		
55–64	8.8	1,819		
65+	10.6	2,169		
Sex of household head				
Male	6	15,019	181.5	<0.01
Female	10.6	10,774		
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		
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	4,215	299.2	<0.001
Poorer	9.8	4,785		
Middle	8.8	6,126		
Richer	6.5	6,134		
Richest	2.9	4,533		
Time to nearest health facility				
Minutes	6.6	16,730	136	<0.01
Hour	10.6	8,174		
Days	12.1	612		
Nearest health facility				
Hospital	6.3	5,531	27	<0.01
Health centre	8.4	1,933		
Clinic	8.5	17,909		
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		

*Test was carried out at $p < 0.05$

Figure 2 shows geographical distribution, at the constituency level, on percentage of adults who died in Namibia, 2006/2007, ranging between 0 and 8% at the sub-regional 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 parts of the country. Evidently, these confirm the results in Table 2, showing regional disparities, but further reveal that large areas conceal the intra-regional variation as shown in Figure 2.

Figure 2. Prevalence of adult mortality at the constituency level in Namibia

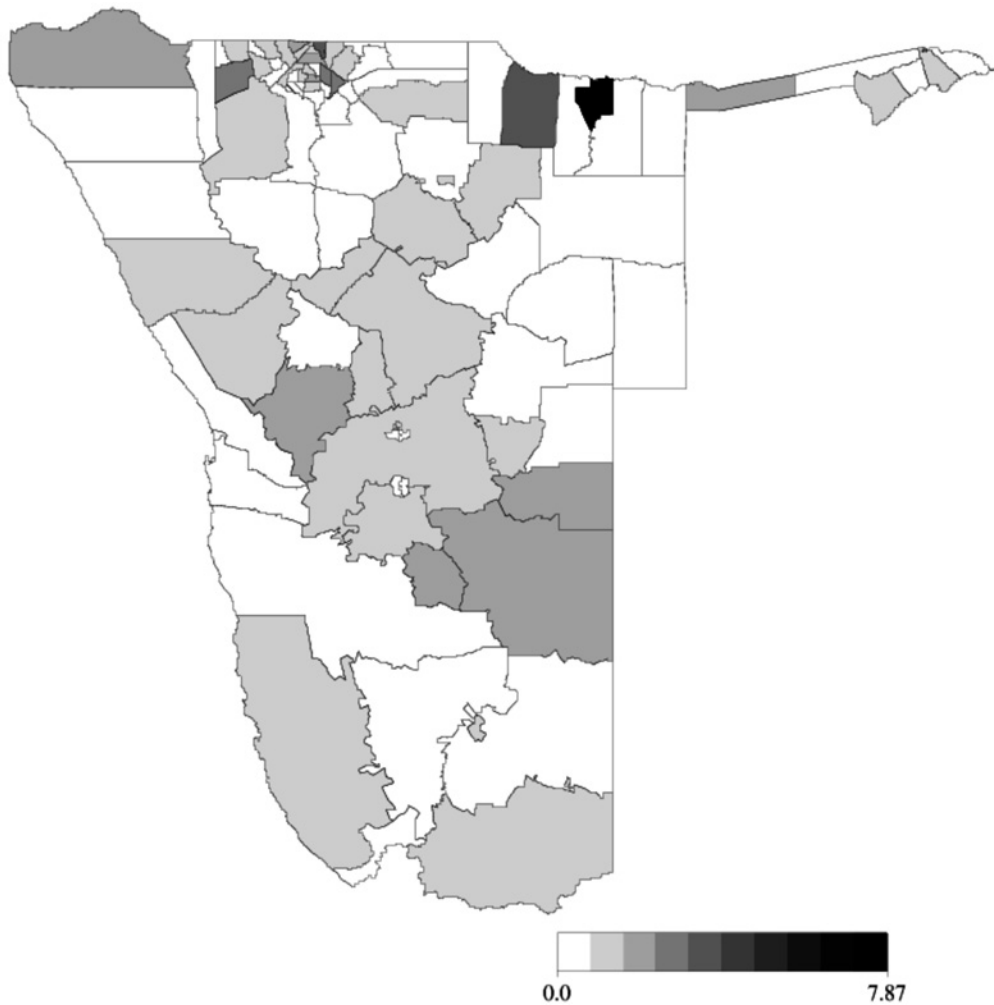


Table 3 presents the DIC values. The results indicate that Model 7 (M7) had the lowest DIC value. M7 incorporated the baseline, fixed effects, unstructured random effects and

spatially structured effects at the constituency level. Our subsequent reporting of results will be based on estimates from the best model (M7).

Table 3. Model comparison based on DIC for the models of adult mortality

Model	Deviance	pD	DIC	Δ DIC
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

Figure 3 displays the baseline hazard for adult mortality in Namibia. The hazard of dying dropped from 15 years to about age 40 years, and then rose to age 80. At age 25–55,

the hazard remained overly below the HR of 1.0. Further, result shows that the intervals in the probability of dying widen from age 80.

Figure 3. The baseline hazard lines for the best model (M7).

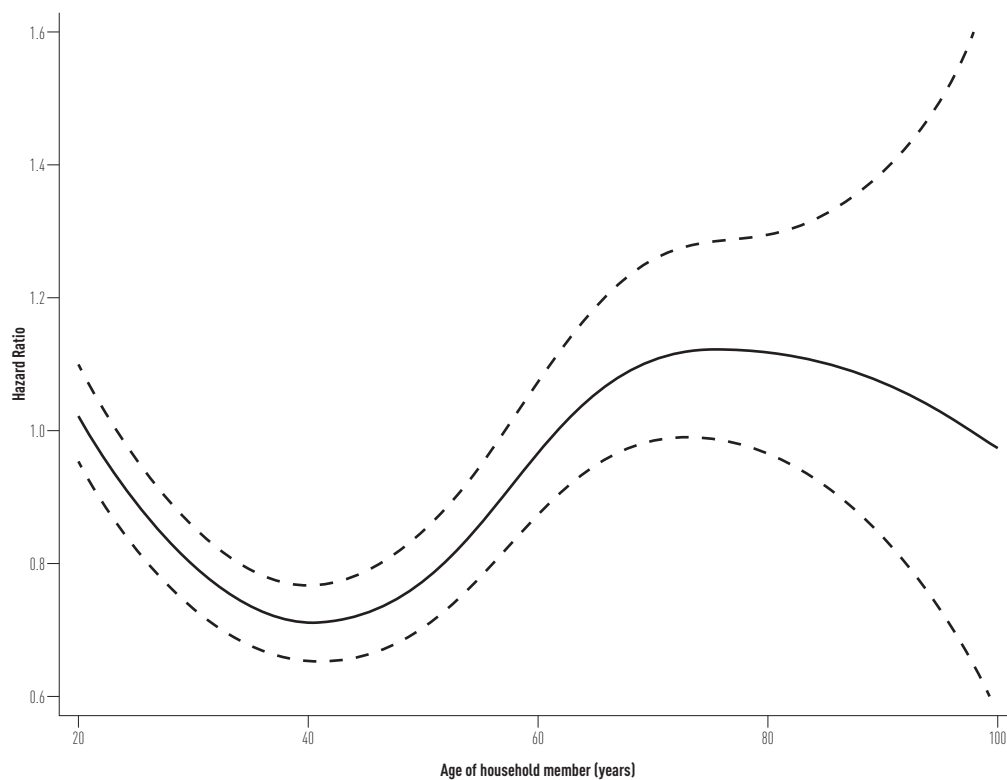


Figure 4 displays age curve for the household head, with age fitted as a non-linear smooth function. In the panel, the risk of mortality increased between 15 and 20 years and then decreased up to age 30 years, then rose again steadily up to age 65 years, with a little dip at age 50 years. A similar pattern of up and down continued from age of 65 to 70

years, with a final decrease at age of 80 years. From age of 15 to 55 years, the risk of death lay below zero, suggesting a reduced mortality risk in such households, whereas at 60 years to the end, we observed a risk of above 0, indicating an increased risk of mortality. Overall the dip in risk was at age of 30 years, and a peak in risk was at 65 years.

Figure 4. Non-linear effect of the age of the head of household

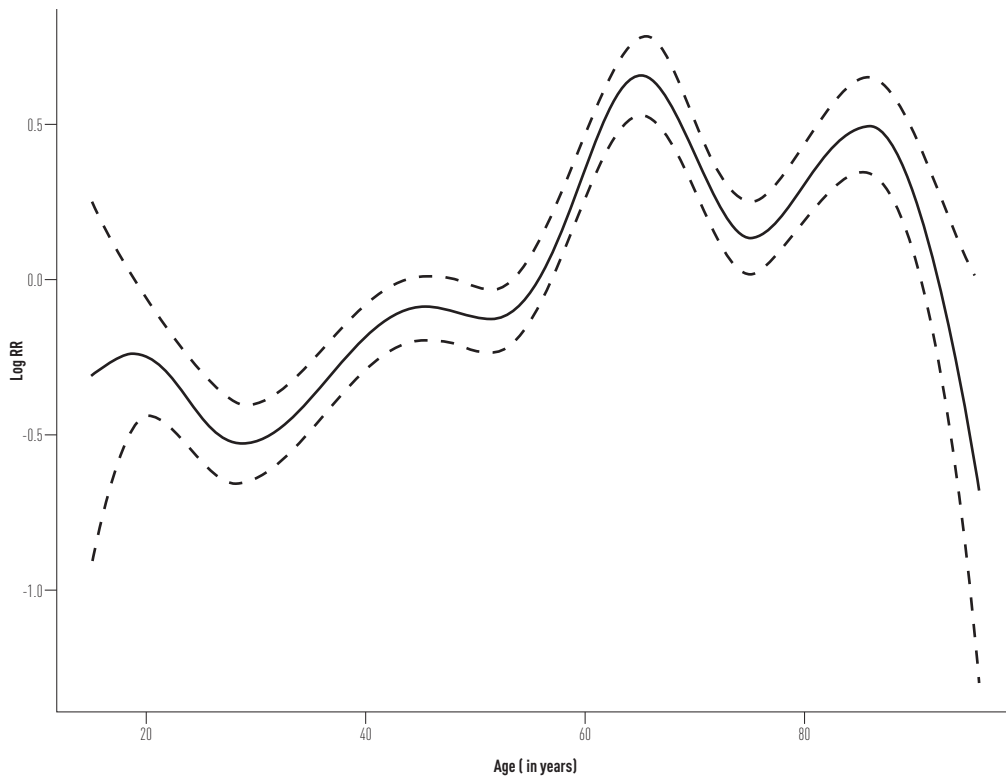


Table 4 shows risk factor of adult mortality. Generally the hazard of adult mortality was lower, as indicated by the intercept (HR = 0.02, 95% CI: 0.01–0.03). With regards to the sex of the head of the household, the

risk of adult mortality was likely to be lower for male-headed households than for female-headed households (HR = 0.65, 95% CI: 0.59–0.72).

Table 4. Fixed effects summary for the best model (M7)

Covariates	HR (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 of household member	
No education	0.99 (0.85, 1.17)
Primary education	1.22 (1.09, 1.36)
Secondary/higher education (REF)	1.00
Marital status of household member	
Never married	0.82 (0.70, 0.99)
Married	0.62 (0.53, 0.73)
Others (REF)	1.00
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 (REF)	1.00
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 (REF)	1.00
Nearest health facility	
Hospital	0.95 (0.82, 1.10)
Health centre	0.91 (0.73, 1.14)
Clinic (REF)	1.00
Means to nearest health facility	
Car/motorcycle	0.87 (0.72, 1.06)
Public transport/animal cart	1.04 (0.90, 1.19)
Walking (REF)	1.00

Regarding the education level for a household member, for adults who had no education, there was a decrease in hazard of an adult dying than those with secondary/higher education (HR = 0.99, 95% CI: 0.85–1.17); nevertheless, the decrease was not significant. In contrast, comparing adults with primary education to those with secondary education or higher, it was observed that there was a 22% increase in hazard (HR = 1.22, 95% CI: 1.09–1.36). Turning to marital status, for married adults, compared to the other marital categories (widowed and divorced), we observed a lower hazard (HR = 0.62, 95% CI: 0.53–0.73), which was much lower than that for the never-married compared to the others (HR = 0.82, 95% CI: 0.70–0.99).

In terms of the wealth status of a household, there was a significant increase in risk of an adult dying across all four levels compared to the highest level (richest household). For the poorest household, the risk was HR = 2.03; for the poor household, hazard ratio was

estimated at 1.78; for the middle quintile, we obtained an HR = 2.00; and for the richer quintile, we established a hazard ratio of 1.76 (Table 4). In general, there was a non-linear pattern in risk of adult mortality associated with wealth. As for the urban versus rural place of residence, we did not find any significant association, although urban areas were associated with reduced risk (HR = 0.91). Furthermore, there was no evidence of association between accessibility and availability of healthcare and adult mortality (Table 4).

Figure 5 shows the unstructured random effects for adult mortality at the constituency level. There was heterogeneity across constituencies in the hazard of an adult dying. Some constituencies had hazard of adult mortality above 1.00, while others had hazard of adult mortality below 1.00, suggesting significant variability in the hazard ratio across constituencies (sub-regions) in Namibia. These results agree with Figure 1, which shows adult mortality map at the constituency level.

Figure 5. Unstructured random effects at the constituency level in Namibia, based on the best model (M7)

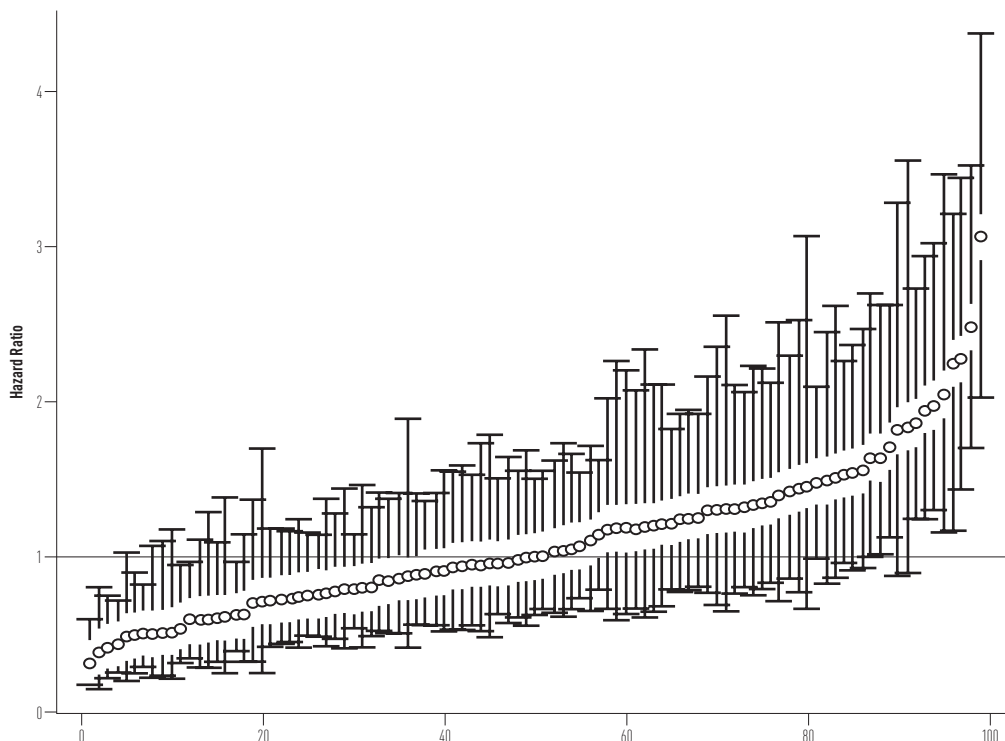
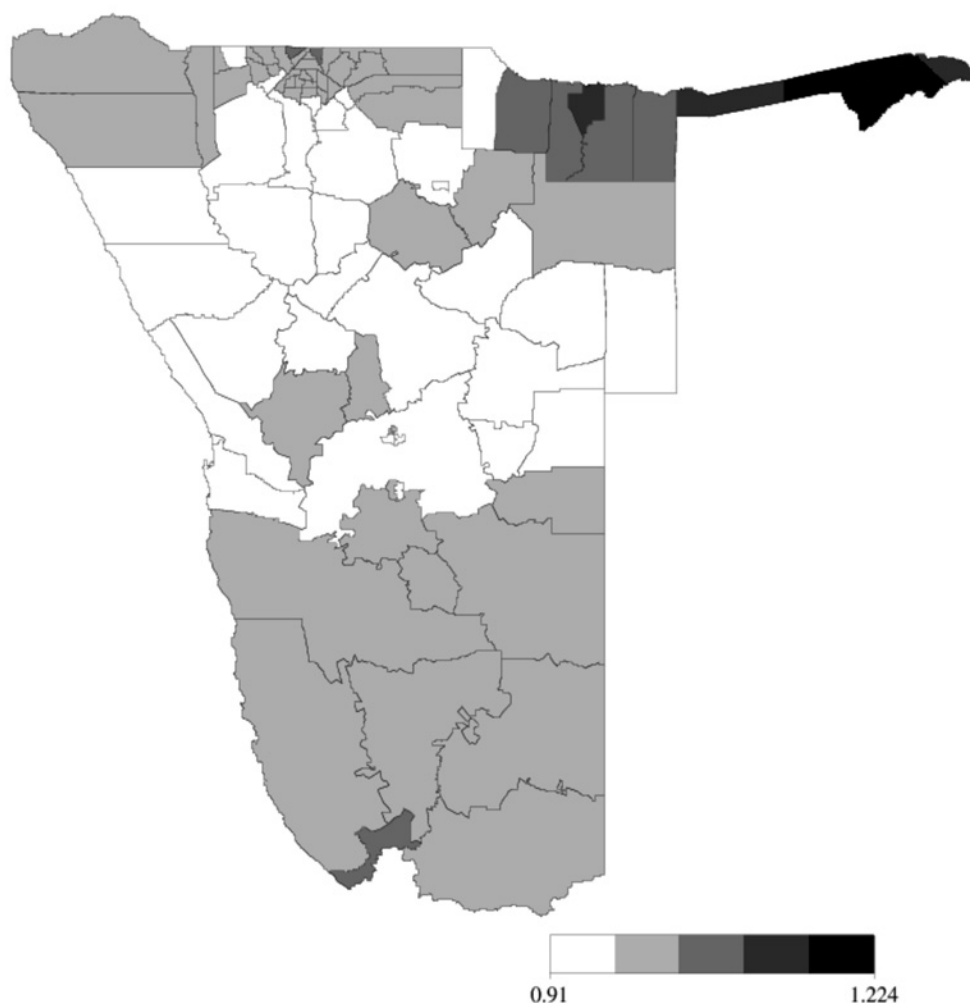


Figure 6 shows the spatial variability of hazards of adult mortality, with darker colours in the map signifying constituencies with increased hazard of adult mortality, while lighter colours show constituencies with reduced hazard. The force of mortality ranged between 0.91 and 1.23. The north eastern part of the country, north of the country and down

in the southern part of the country show high hazard of an adult dying, whereas areas of reduced risk are commonly found in the north west, central and towards eastern part of the country. Nevertheless, these effects were not significant after controlling for socioeconomic and demographic fixed effects in the model.

Figure 6. Spatial structured random effects (given as hazard ratios) of adult mortality at the constituency level in Namibia



Discussion

The aim of the study was to apply an event history discrete time survival analysis to explain effects of socioeconomic factors on adult mortality in Namibia. We fitted geo-additive survival models using the Bayesian

framework for joint modelling of fixed, non-linear effects and spatial frailties.

Keeping in mind the general objective, this study first adopted the conceptual framework by Rogers et al. (2005) for understanding socioeconomic differences in adult mortality

in Namibia. Second, we documented the basic patterns of association between socioeconomic and adult mortality using survey data. Third, we give substantial attention to how the risk of adult mortality varies in space. The study found results that were consistent with what has been reported previously. The force of mortality, in our analysis, varied with marital status, place of residence, educational level, wealth ranking and availability and accessibility of healthcare (Bassuk et al. 2002; Davis et al. 1992; Nikoi 2009; Sudore et al. 2006).

In general, evidence shows that the poor are at more risk, a fact which may be attributed 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, well-being and living standards of adult people (Sammy 2009; Zhi and Xie 2007). On the contrary, we observed high risk of adult mortality at all levels of wealth, similar to what was reported by de Walque and Filmer (2013), a fact that still need to be investigated. Similarly, although we did not find significant association with urban/rural, studies generally find a higher mortality in rural than urban areas. This has been attributed to easy availability and accessibility of healthcare resources (Becher 2004). Often low level of literacy was associated with poor management of diseases and other health conditions that may consequently result in deaths (Sudore et al. 2006).

In addition to evaluating socioeconomic factors, this paper exploited the effects of geographical location on adult mortality by assuming structured spatial effects. Although we did not find significant differences in risk, our argument is that contextual neighbourhood factors may play a part in attenuating or exacerbating the effects of socioeconomic status on adult mortality. Area promotes or inhibits health, over and above individual socioeconomic characteristics (McIntyre et al. 2002; Ross and Mirowsky 2001). In their study “neighbourhoods and health,” Diez-Roux and

Mair (2010) re-emphasized existence of effects of neighbourhood physical and social environments on health of residents of any community or location. They further indicated that a better understanding of health or disease distribution requires both individual characteristics and characteristics of groups or of contexts to which individuals belong.

Although the study was carefully planned, there are some inevitable limitations that need to be acknowledged. First, we used self-reported data, which are subject to measurement error arising from the respondent’s recall bias. Such recall tends to decrease with time, with distant past events often under-reported. To limit this error, this study was designed to record deaths that occurred only within 24 months preceding the survey year. Second, the 2006 NDHS did not collect information for all variables such as income of household head, behaviour and habit factors such as smoking and alcohol consumption, which may be considered important in measuring the impacts of socioeconomic factors on adult mortality. Third, the data used for the study were collected in 2006/2007, thus the findings might give a different picture on adult mortality and socioeconomic factors from the current situation on the ground. Finally, we assumed single hazard for all regions. Thus, there is a need to have region-specific hazard modelling.

In conclusion, this paper demonstrated the existence of socioeconomic disparities in adult mortality in Namibia. While a huge literature in Europe and USA has documented mortality and socioeconomic status patterns and trends over the past several decades, we actually know less about African countries, particularly for those that have high rates of HIV, like Namibia. This study actually fulfilled this objective. Socioeconomic differentials provide important clues regarding the etiology of a particular disease, and moreover, the magnitude of these relations is of importance. Furthermore, considerable heterogeneity in mortality patterns across

regions and sub-regions (constituencies) has been established. It is hoped that these should permit health planners and policymakers to design and evaluate programs and develop strategies aiming at improving the health and well-being of adults targeted for such hotspots. Adults are the economically active and productive age group for a population, thus if the Namibian Government is to meet its national development goals (NDPs) such as NDP4 or Vision 2030, then reducing adult mortality, taking into consideration socioeconomic factors, should be considered as a major public issue. Compared to those under 15 years, however, mortality is lower and, to some extent, not discounting other findings, this would support the policy argument of focusing on child mortality rather than adult mortality. Arguably, these efforts should be taken together with other interventions concentrating on infant and maternal health for optimal programming.

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References

- Antonovsky, A. 1967. "Social Class, Life Expectancy and Overall Mortality." *Milbank Memorial Fund Quarterly* 45(1): 31–73.
- Banerjee, S. and B.P. Carlin. 2003. "Semiparametric Spatio-temporal Frailty Modeling." *Environmetrics* 14(5): 525–35.
- Bassuk, S.S., L.F. Berkman and B.C. Armick. 2002. "Socioeconomic Status and Mortality among the Elderly: Findings from the Four US Communities." *American Journal of Epidemiology* 155(6): 520–33.
- Becher, H., O. Muller, A. Jahn, A. Gbangou, G. Kynast-Wolf and B. Kouyate. 2004. "Risk Factors of Infant and Child Mortality in Rural Burkina Faso". *Bulletin of the World Health Organization* 82:265-73.
- Belitz, C., A. Brezger, T. Kneib and S. Lang. 2009. *BayesX-software for Bayesian Inference in Structure Additive Regression Models*, version 2.01. Retrieved October 10, 2009. <<http://www.dtst.uni-muechen.de/bayes2.01>>
- Bendavid, E., E. Holmes and J. Bhattacharya. 2012. *HIV Development Assistance and Adult Mortality in Africa*. National Institute of Health. Washington, DC.
- Bradshaw, D. and I.M. Timaeus. 2006. "Chapter 4: Levels and Trends of Adult Mortality." In D. T. Jamison, R. G. Feachem and M. W. Makgoba, eds., *Diseases and Mortality in Sub-Sahara Africa*. Washington, DC: World Bank.
- Box-Steffensmeier, J. and S.B. Jones. 2004. *Event History Modelling: A Guide for Social Scientists*. Cambridge, UK: Cambridge University.
- Davis, M.A., J.M. Neuhaus, D.J. Moritz and M.R. Segal. 1992. "Living Arrangements and Survival among Middle-aged and Older Adults in the NHANES I Epidemiologic Follow-up Study." *American Journal of Public Health* 82(3): 401–6.
- de Walque, D. and D. Filmer. 2013. "Trends and Socio-economic Gradients in Adult Mortality around Developing World." *Population and Development Review* 39(1): 1–29.
- Diez-Roux, A.V. and C. Mair. 2010. "Neighborhoods and Health." *Annals of the New York Academic of Sciences* 1186:125-45.
- Henderson, R., S. Shimakura and D. Gorst. 2002. "Modelling Spatial Variation in Leukemia Survival Data." *Journal of the American Statistical Association* 97 (460): 965–72.
- Hennerfeind, A., A. Brezger and L. Fahrmeir. 2006. "Geoadditive Survival Models." *Journal of the American Statistical Association* 101(475): 1065–75.
- Jamison, D.T., R.G. Feachen, M.W. Makgoba, E.R. Bos, F.K. Baigana, K.J. Hoffman, et al. 2006. *Disease and Mortality in Sub-Sahara Africa* (2nd ed.). Washington, DC: The World Bank.
- Kazembe, L.N., C.C. Appleton and I. Kleinschmidt. 2007. "Spatial Analysis of the Relationship between Early Childhood Mortality and Malaria Endemicity in Malawi." *Geospat Health* 2(1): 41–50.
- Kazembe, L.N. 2013. "A Bayesian Two Part Model Applied to Analyze Risk Factors of Adult Mortality with Application to Data from Namibia." *PLoS One* 8(9): e73500.
- McIntyre, S., A. Ellaway and S. Cummins. 2002. "Place Effects on Health: How Can We Conceptualise, Operationalize and Measure Them?" *Social Science and Medecine* 55(1), 125–39.
- Mackenbach J.P., A.E. Kunst, J.M. Cavelaars, F. Groenhouf, J.J.M. Geurts and the EU Working Group on Socioeconomic Inequalities in Health. 1997. "Socioeconomic Inequalities in Morbidity and Mortality in Western Europe." *The Lancet* 349:1655–59.

- Magadi, M. and M. Desta. 2011. "A Multilevel Analysis of the Determinants and Cross National Variations of HIV Seropositivity in Sub-Saharan Africa: Evidence from the DHS." *Health and Place* 17(5):1067–83.
- Marmot, M. G., M. Shipley and G. Rose. 1984. "Inequalities in Death: Specific Explanations of a General Pattern?" *Lancet* 323(8384): 1003–6.
- Mathers, C.D., D. Ma Fat, M. Inoue, C. Rao, and A.D. Lopez. 2005. "Counting the Dead and What They Died From: An Assessment of the Global Status of Cause of Death Data." *Bulletin of the World Health Organization*, 83(3): 171–77.
- Ministry of Health and Social Services (MoHSS) [Namibia] and Macro International Inc. 2008. *Namibia Demographic and Health Surveys 2006/07*. Windhoek, Namibia and Calverton, MD: MoHSS and Macro.
- Murray, C.J.L., J.K. Rajaratnam, J. Marcus, T. Laakso and A.D. Lopez. 2010. "What can we Conclude from Death Registration? Improved Methods for Evaluating Completeness." *PLoS Medicine* 7(4): p. e1000262.
- Nikoi, C.A. 2009. *The Association between Socio-Economic Status and Adult Mortality in Rural Kwazulu-Natal, South Africa*. Johannesburg, South Africa: Wits University.
- Obermeyer, Z., J.K. Raja, C.H. Park, E. Gakidou, M.C. Hogan, A.D. Lopez and C.J.L. Murray. 2010. "Measuring Adult Musing Sibling Survival: A New Analytical Method and New Results for 44 Countries, 1974-2006." *PLoS Medicine* 7(4): p. e1000260.
- Preston, S.H and N. G. Bennett. 1983. "A census-based method for estimating adult Mortality." *Population Studies*, 37: 91-104.
- R Development Core Team. 2011. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Rajaratnam, J.K., J.R. Marcus, A. Revin-Rector, A.N. Chalupka, H. Wang, L. Dweyer, et al. 2010. "Worldwide Mortality in Men and Women Aged 15-59 Years from 1970 to 2010: A Systematic Analysis." *Lancet* 375(9727): 1704-20.
- Rogers, G.R., A.R. Hummer and M.P. Krueger. 2005. "Adult Mortality." In Poston, D.L., M. Micklin (Editors). *Handbook of Population*. New York: Springer, (pp. 283–309).
- Ross, C.E. and J. Mirowsky. 2001. "Neighborhood Disadvantage, Disorder, and Health." *Journal of Health and Social Behavior* 42: 258–76.
- Sammy, K. 2009. *Socio-Economic Status and Elderly Adult Mortality in Rural Ghana: Evidence from the Navrongo DSS*. Master's thesis. Retrieved December 14, 2013. <<http://wiredspace.wits.ac.za/jspui/bitstream/10539/7548/1/Sammypdf.pdf>>.
- Sartorius, B., K. Kahn, M.N. Collin, K. Sartorius and S.M. Tollman. 2013. "Dying in their Prime: Determinants and Space-time Risk of Adult Mortality in Rural South Africa." *Geospatial Health* 7(2): 237–47.
- Spiegelhalter, D.J., N.G. Best, B.P. Carlin and A. Van der Linde. 2002. "Bayesian Measures of Model Complexity and Fit." *Journal of the Royal Statistical Society: Series B* 64(4): 583–639. Revised.
- Sudore, R., K. Yaffer, S. Sattlerfield, T. Harris, K. Mehta, E. Simonsick, et al. 2006. "Limited Literacy and Mortality in the Elderly." *Journal of General Internal Medicine* 21(8): 806-12.
- Zhi, H. and Y. Xie. 2007. "Socioeconomic Differentials in Mortality among the Oldest in China." *Research on Aging* 29(2): 125–43.