SHARED-COMPONENT MODEL WITH APPLICATION TO MAPPING GENDER SPECIFIC PATTERN IN HIV TESTING AND CONDOM USE IN NAMIBIA

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Abstract

The main objective of the study was to examine gender-specific and shared spatial variation in HIV testing and condom use in Namibia for targeted health promotion interventions.

The study used data from the Namibia Demographic and Health Survey (NDHS) carried out between 2006 and 2007. Bayesian hierarchical spatial mapping techniques were applied to generate specific and shared spatial patterns in HIV testing and condom use. Particularly, a number of Bayesian Structured Additive Regression (STAR) models were fitted and followed by joint spatial models through the shared component latent variables approach. Firstly, we modelled HIV testing and condom use in males and females with fixed effects such as educational level, frequency of reading newspapers and magazines, frequency of listening the radio, frequency of watching television, wealth index, times away from home, smoking, alcohol consumption, employment status, age at first sexual intercourse, type of residence and marital status whereas spatial references to the communities were modelled as structured and unstructured spatial effects. Secondly, diffuse priors were assumed for the fixed effects, while conditional autoregressive priors were assigned to the structured spatial effects and exchangeable priors for the unstructured random effects. Simulation techniques through Markov Chain Monte Carlo were applied for model estimation. Common and divergent patterns of HIV testing and condom use emerged. Common areas among men and women on HIV testing and condom use were observed in Khomas, Erongo, Oshikoto, and Oshana, while divergent patterns were estimated in Caprivi, Kavango and Karas regions. Urban influence was also captured in the model. Exposure to media was one of the covariates that were found to have a positive effect on the use of condoms and HIV testing.

The study underscore the usefulness of Bayesian hierarchical mapping model in highlighting areas lagging behind in the uptake of HIV testing and condom use with emphasis on

differences between men and women in the same area. We found that compared with gender-specific modeling approach, the shared component model offered useful additional information when modeling HIV testing and condom use in men and women. The information will be valuable for guiding public health actions that are targeted at the overall reduction of risk-sexual behaviours through HIV testing and the use of condoms.

Acknowledgements and Dedication

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I must acknowledge as well the many friends, colleagues, students and everybody who assisted, advised and supported my research and writing efforts over the year.

Declarations

I, Etuhole Moshili Mwahi, declare hereby 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.

Etuhole Moshili Mwahi Date

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List of Abbreviations

AIC	Akaike Information Criterion
AIDS	Acquired Immune Deficiency Syndrome
BIC	Bayesian Information Criterion
CAR	Conditional Autoregressive
DIC	Deviance Information Criterion
EA	Enumeration Area
GIS	Geographical Information System
GAM	Generalized Additive Model
GAMM	Generalized Additive Mixed Model
GLM	Generalized Linear Model
HIV	Human Immune Virus
ICAR	Improper Conditional Autoregressive
MCMC	Markov Chain Monte Carlo
MRF	Markov Random Field
NDHS	Namibia Demographic and Health Survey
PSU	Primary Sampling Unit
PCAR	Proper Conditional Autoregressive

STAR	Structured Additive Regression
SADC	Southern Africa Development Community
VCM	Varying Coefficient Model

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Chapter 1

Introduction

1.1 Background

According to the UNAIDS on global AIDS epidemic (2010), an estimated 33.3 million people were living with HIV worldwide, with as estimated two million AIDS-related deaths and 2.7 million new HIV infections. Although Sanchez et al. (2009) reported that Sub-Saharan African countries have shown noticeable decrease in HIV prevalence rate from 10% in the late 1990s to 6.1% in 2005, Sub-Saharan Africa remain the worst heavily affected region worldwide, accounting for around two-thirds of the world's population living with HIV and AIDS and with an average HIV prevalence of 5%.

The Southern African Development Community (SADC) countries are the hardest hit within Sub-Saharan African. For example, Swaziland has the worst national adult HIV prevalence within SADC at 25.9%, and Botswana's national adult average is comparably severe at 24.8% (Campbell et al., 2012). Namibia's 2010 National HIV Sentinel Survey (NNHSS) placed Namibia's HIV prevalence at 18.8% among pregnant women, although infection rates vary considerably between Namibia's regions. In Caprivi for example, the HIV prevalence at antenatal clinics is estimated to stand at around 35.6%.

The biggest challenges with HIV/AIDS in Namibia is the high rate of multiple concurrent relationships, transactional sex, cross-generational sex, low and inconsistent condom use, high rate of alcohol abuse, a high rate of mobility and migration and a low rate of male circumcision. These factors are fuelled by poverty, high unemployment rates, unequal gender relations and a persistent legacy of post-apartheid discrimination.

In Namibia, HIV testing is carried out on pregnant women for collection of national statistics. The reliability of this data can, of course, be contested, since it constitutes a limited sample: antenatal clinical testing does not include men at all, and excludes women who do not get pregnant. However, Namibia Demographic and Health Survey (NDHS) provide more reliable statistics. According to 2006/07 NHDS, 54.8% of women reported having been tested for HIV and 34.3% of men reported having been tested for HIV. Men are less likely to go for testing for HIV and other Sexually Transmitted Diseases (STDs), but are more likely to engage in risky sexual behavior (Brooks et al., 2008).

Gender is regarded as one of the social determinants of health. Gender power affects health norms and practices, exposures and vulnerabilities to health problems and the ways in which health systems and research respond (Sen et al., 2007). These gender imbalances have also been observed in HIV/AIDS pandemic (Summers, 2005). Indeed, the imbalances between female and male risks and vulnerabilities have become evident as the differences in the rates of infection have grown. Gender norms and gender dynamics influence people's attitudes to sex, sexuality and risk taking. In some regions girls and women are seen as repositories of male or family honor and the self-respect of communities (Fazio, 2004). Gender inequality and the role of power in sexual relations, especially women's lack of economic empowerment are important factors in the spread of HIV/AIDS. Economic dependency and insecurity are at the core of the gender dynamics of HIV/AIDS. For both married and unmarried women, their limited access to economic assets increases the likelihood of their inability to negotiate safe sexual practices, exchanging sex for money or staying in a relationship that they perceive to be violent or risky.

The fact that many women in Namibia have lower economic and social status than men renders women and girls particularly susceptible to becoming infected by HIV, as well as to

being denied or having delayed access to treatment for HIV and AIDS, and having their workloads increased by caring for someone with AIDS (Campbell et al., 2012). Teenage pregnancy is also one of the major problems in Namibia. In most instances, young women who fall pregnant ends up leaving school early, this worsens their chances of being able to find employment, and can impact on self-esteem, which in turn reduces their ability to negotiate healthy relationships and sexual activities.

1.2 Statement of the problem

Namibia is one of the countries in Africa with a high rate of HIV prevalence. According to the UNAIDS report on the global AIDS epidemic (2010), HIV prevalence stood at 13.1% among adults aged 15-49 in Namibia. HIV/AIDS threatens human welfare, socio-economic advances, productivity and social cohesion. HIV testing and condom use contributes directly to the prevention of HIV transmission. There have been calls to promote HIV testing among the youth in order to discourage high-risk sexual behaviors among them. Within the same programmatic goal the use of condoms has been promoted as an alternative measure of reducing high-risk sexual behaviors (Venkatesh et al., 2001).

The uptake of HIV testing and condom use has shown gender disparities. Females tend to go for HIV testing more than their male counterparts. According to the 2006/07 Namibia Demographic and Health survey (NDHS), 54.8% of women reported having been tested for HIV while 34.3% of men reported having been tested. Substantial geographic variation also exists on the testing. On condom use, 60.0% of women reported condom use at first sexual intercourse while 47.7% of men reported use of condom at first sexual intercourse. These show that disparity exist in HIV testing and condom use at first sexual intercourse between men and women in Namibia. Moreover, preliminary analysis show geographical variability in the use of condom and HIV testing, yet this epidemiological phenomena has not been studied.

Since HIV/AIDS prevention programmes are interested in strengthening their programmes in areas lagging behind, it will be useful to investigate gender-specific geographical differences in HIV testing and condom use.

In order to improve gender imbalances in both the context and the process of health promotion, it is essential to collect and present data disaggregated by gender. The geographical distribution of interventions should show the situation of women and men in the society and economy for a meaningful formulation, monitoring of policies and plans, and inform the public. To the best of our knowledge, analyses of gender-specific geographical patterns in HIV testing and condom use have not been done in Namibia. The purpose of this study is to quantify the main risk factors that influence HIV testing and the use of condoms, and to produce maps of the pattern of HIV test and the use of condoms using Bayesian spatial models.

1.3 Objectives of the study

Given the high HIV prevalence rate in Namibia, it is very essential to look at the spatial patterns of HIV testing and the use of condoms as preventative measures in Namibia. This study aims at highlighting spatial disparities in coverage of HIV testing and condom use between men and women in Namibia.

1.3.1 Main Objective

The main objective of this research is to model and evaluate gender-specific spatial variation in HIV testing and condoms use in Namibia.

1.3.2 Specific Objectives

1. To model gender-specific and shared spatial variation in HIV testing and condom use in Namibia.

2 To compare HIV testing and condom use variations across regions and constituencies by gender in Namibia.

3 To investigate factors that promotes condom use and HIV testing among men and women in Namibia.

4 To evaluate different spatial models applicable for the analysis of area-based health promotions.

1.4 Significance of the Study

This study is significant especially in Namibia given its high HIV prevalence because it will highlight areas lagging behind in uptake of HIV testing and condom use with emphasis on differences between men and women in the same area. The information will be useful for guiding public health actions that are targeted at the overall reduction of risk-sexual behaviors through HIV testing and the use of condoms.

Chapter 2

Literature Review

Spatial epidemiology is the description and analysis of geographic variations in diseases with respect to demographic, environmental, behavioral, socioeconomic, genetic, and infectious risk factors (Elliot et al., 2004). Research in the area of spatial distribution are becoming more common due to the availability of low cost Geographical Information System (GIS), statistical methodology, and availability of high-resolution, geographically referenced health and environmental data. These have created opportunities to investigate environmental and other factors in explaining local geographic variations in diseases.

GIS is a system that is very useful and rapidly increasing in its importance in many fields and disciplines. The existing spatial toolbox built in GIS is largely inadequate prompting the need to create more relevant methods to analyze geographical data. Indeed, there are several statistical software's developed that are capable of coping with the complex nature of the spatial data. Advances in technology now allow not only disease mapping but also the application of spatial statistical methods, such as cluster analysis (Kulldorff et al., 1997; Rosenberg et al., 1999). Apart from GIS, Bayesian approaches have become commonplace in epidemiological, medical and public health applications. A few studies applying joint spatial or shared component models have been carried out in the Southern African region (Manda, 2011). Most of the researches concentrated on infection and prevalence of diseases of which administrative or sample data have been used. None were done on prevention strategies, for example, on condom uses and HIV testing, let alone disaggregated by gender. One of the recent studies that concentrated on diseases prevalence was conducted by Manda et al. (2012). They investigated the ecological association between HIV and syphilis in South Africa using joint spatial modeling for multiple disease outcomes. Manda et al concluded in

their study that there is a huge demand for joint spatial modeling methods for multiple disease outcomes in the epidemiological field, and that their study has demonstrated the feasibility and utility of such a model to an important application in public health. With the introduction of statistical software like WinBUGS, R, BayesX and many more, Bayesian methodologies have seen great advances. This research was developed to examine gender-specific spatial variation in HIV testing and condom use in Namibia through Bayesian approaches.

2.1 Types of Spatial data

2.1.1 Point data

Point processes are discrete events that can be located with more or less precision in space. They are usually assumed to follow a probability distribution and are often described as Poisson processes. Much like time series data, spatial points are not independent and points near each other are like each other, or perhaps even affect each other. Spatial points may be associated with covariates, and analyses might involve assessing the role of covariates in determining intensity, or controlling for covariates effects when assessing interaction between points (DiMaggio, 2012).

We are interested in studying the spatial distribution of these points, testing hypothesis about the observed pattern: if it is random or, on the contrary, if it presents itself in agglomerates or is regularly distributed. Another case is to establish a relationship between the occurrences of events with the characteristics of the individual, incorporating possible environmental factors about which there is no data available (Camara et al., 2009). There are several methods and algorithms that are developed to describe patterns for a collection of points such as: quadrant

count method; Kernel density estimation (K means) and nearest neighbour distance (K function).

2.1.2 Lattice data

These are data associated to population surveys, like census and health statistics, and that are originally referred to individuals situated in specific points space. The geographical space under investigation is comprised of a set of area units, typically made by partitioning the region into fixed areas that are regularly or irregularly defined in space. They aim to provide information on the size, distribution, composition and other social and economic characteristics of the population as well as the housing conditions and household amenities.

If the area units are relatively small in size in relation to the overall size of a study region, values for each unit may be applied to a specific point within the area. Exploratory methods for point data such as Kernel density estimation may be used to explore the process under study. However, for larger units different methods can be used, which include: standardized mortality ratio (SMR), Bayesian smoothing and autocorrelation statistics (Stevenson, 2003).

2.1.3 Continuous data

These are data estimated from a set of field samples that can be regularly or irregularly distributed. Usually, this type of data results from natural resources, which includes phenomena such as rainfall, humidity, air pollution and soil mineral concentrations, variables that may be measured at all possible locations (Stevenson, 2003). While proportional symbol maps are useful for preliminary visualization of data they give no appreciation of spatial continuity. To achieve continuity it is necessary to predict the mean of the variable of interest across the entire area under investigation. This entails the construction of a ‘surface’ representing the attribute of interest and deriving contour plots from this surface for purposes

of interpretation. There are principal methods used for estimating the mean of a variable of interest across space such as tessellation methods, variograms and kernel estimation techniques (Stevenson, 2003).

2.2 Statistical Methods of Spatial data

2.2.1 Cluster Analysis

Studies on spatial cluster could reveal information about underlying geographical process that generates the spatial pattern, which can further aid the comprehension of the underlying geographical process and its relationship with the phenomenon under study (Lu, 2000). Cluster analysis is categorized into two and these are global and local cluster analysis. Global clustering basically assumes that the risk surface is clustered or has areas of like elevated risk. However, they provide little information about where clusters are. Indicators that show local patterns and measure local instabilities are suitable for identifying specific clusters existing in data set. This is called local clustering. However, they simply assume the existence of spatial clustering without actual examination. Discussed below are the different scenarios for clustering.

2.2.1.1 Hot Spot Clustering

According to Lawson (2008), any area or region can be regarded as a cluster. This is due to the assumption of a zero neighborhood criterion. Simply, any area displaying “excess” or “unusual” risk by some criterion is a hot spot.

2.2.1.2 Clusters as Objects or Groupings

Clustering might be considered to be apparent in a data set when a specific form of grouping is apparent. This grouping would usually be predefined. Usually the criterion would also have a neighboring or proximity condition. That is, only neighboring or proximal areas can be

considered to be “in a cluster”. Hence some parametric conditions must be met under this definition (Lawson, 2008).

2.2.1.3 Clusters Defined as Residuals

Assume that y_i is the count of disease within the i th census tract within a study area and that our basic model for the average count $\mu_i = E(y_i)$ is $\log \mu_i = a_i + \varepsilon_i$. Here a_i consist of a linear or non-linear predictor as a function of covariates and could consist of random effects of different kinds. Simply, we assume that a_i is the “smooth” part of the model and ε_i is the rough or residual part. The idea is that if we model a_i to include all relevant non-clustering confounder effects then the residual component must contain residual clustering information. Therefore, if we examine the estimated value of ε_i then this contain information about any clusters unaccounted for in a_i. This does not account for any pure noise that might also be found in ε_i . This implies that an estimate of ε_i could have at least two components: structured and unstructured (Lawson, 2008).

2.2.2 Spatial Autocorrelation

Spatial autocorrelation comes from the statistical concept of correlation, used to measure the relationship between two random variables. The preposition “auto” indicates that the measurement of the correlation is done with the same random variable, measured in different places in space. Spatial cluster is positive spatial autocorrelation when similar values are spatially clustered together. On the other hand, it is negative spatial autocorrelation when similar values are dispersed from each other (Boots et al., 1988). A number of techniques are developed to test for spatial autocorrelation and some of these will be discussed in the following subsections.

2.2.2.1 Moran's I

Moran's I (Moran, 1950) is a global test of autocorrelation. It is based on cross-products of the deviations from the mean and is calculated for n observations on a variable x at locations i and j as:

$$I = \frac{n}{S} \frac{\sum_i \sum_j w_{ij} \left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_i \left(x_i - \bar{x}\right)^2} \tag{2.1}$$

where $\bar{x}$ is the mean of the variable x, w_{ij} are the elements of the weight matrix, and $S = \sum_i \sum_j w_{ij}$ is the sum of the elements of the weight matrix. The expectation of Moran's I statistic is $\frac{-1}{n-1}$, which tends to zero as the sample size increases. A value of Moran's I = 1 indicates perfect positive spatial autocorrelation, whilst a value of I very close to 0 indicates no spatial autocorrelation.

2.2.2.2 Geary's C

Geary's C (Geary, 1954) is based on the deviations in responses of each observation with one another:

$$C = \frac{n}{2S} \frac{\sum_i \sum_j w_{ij} (x_i - x_j)^2}{\sum_i (x_i - \bar{x})^2}. \tag{2.2}$$

Geary's C ranges from 0 to a positive value for high negative autocorrelation. If the value of Geary's C is less than 1, it indicates positive spatial autocorrelation.

2.2.2.3 Local Indicators of Spatial Association (LISA)

The LISA statistics are preferably determined for each area such that their sum for all zones is proportional to the global Moran's I. The LISA statistic for each area is calculated as:

$$I_i = Z_i \sum_{j, j \neq i}^{n} w_{ij} Z_j \tag{2.3}$$

where Z_i and Z_j are the observed values in standardized form, and w_{ij} is a spatial weight matrix in row-standardized form.

2.3 Generalized Linear Models (GLMs)

Generalized Linear Models (GLMs) are generalizations of the classical linear models that assume that the dependent variable is a linear function of a set of independent variables. They are quite common in social sciences and other sciences. In addition to the linear regression part of the classical models, generalized linear models can involve a variety of distributions selected from a simple exponential family

$$f(y_i \mid \theta_i, \phi, w_i) = \exp\left(\frac{y_i \theta_i - b(\theta_i)}{\phi} w_i + c(y_i, \phi, w_i) \right) \tag{2.4}$$

$i = 1, ..., n$ where θ_i is the natural parameter of the exponential family, ϕ is a scale or dispersion parameter common to all observations, w_i is a weight and $b(.)$ and $c(.)$ are functions depending on the specific exponential family.

The expectation $E(y_i \mid u_i) = \mu_i$ is linked to the linear predictor $\eta_i = u_i' \gamma$ through the link function $\eta_i = g(\mu_i)$; where the link function is g and γ is a vector of unknown regression coefficients. In contrast to the classical linear model, the variance of y_i in general also

depends on the linear predictor since $\text{var}(y_i \mid u_i) = \sigma^2(\mu_i) = \frac{\phi v(\mu_i)}{w_i}$ with $v(\mu_i) = b''(\theta_i)$. In most practical situations, GLMs do not account for non-linear effects of the covariates and the spatial structure of the data. To overcome these difficulties, Structured Additive Regression (STAR) models are used.

2.4 Structured Additive Regression (STAR)

While GLMs are being flexible in terms of the supported response distributions, they obey assumptions considering the linearity of the influence of covariates and the independence of the observations (Brezeger et al. 2005). However, in practical regression situations where some effects may be of unknown nonlinear form, observations spatially correlated, observations temporary correlated, heterogeneity among units not sufficiently described by the covariates and interactions between covariates is of complex, nonlinear form, GLMs may be vulnerable to use.

To overcome these difficulties, we replace the strictly linear predictor $\eta_i = u_i'\gamma$ by a semi-parametric additive predictor

$$\eta_i = f_1(v_{i1}) + \ldots + f_p(v_{ip}) + u_i'\gamma \tag{2.5}$$

where i is a generic observation index, v_j are generic covariates of different type and dimension, and f_j are the functions of the covariates.

2.4.1 Generalized Additive Model (GAM)

The predictor of a GAM for observations $i, i = 1, \ldots, N$ is given by

$$\eta_i = f_1(v_{i1}) + \ldots + f_p(v_{ip}) + u_i'\gamma \tag{2.6}$$

where f_k are smooth functions of continuous covariates x_k which can be modelled by P-splines, random walks, or Gaussian stochastic process priors (Hastie et al. 1990).

2.4.2 Generalized Additive Mixed Model (GAMM)

Consider the data for individuals $i = 1,...,N$, observed at time $t \in \{t_1, t_2, ..., t_n\}$. A GAMM extend the GAM model by introducing individual-specific random effects

$$\eta_{it} = f_1(v_{it1}) + ... + f_p(v_{itp}) + b_{1i}w_{it1} + ... + b_{qi}w_{itq} + \mu_{it}'\gamma \tag{2.7}$$

where $\eta_{it}, v_{it1}, ..., v_{itp}, w_{it1}, ..., w_{itq}, u_{it}$ are predictors and covariate values for individual i at time t and $b_i = (b_{1i}, ..., b_{qi})'$ is a vector of random intercepts.

2.4.3 Geo-additive model

Consider the data with additional geographical information for every observation. A geo-additive model for such data is given by

$$\eta_{it} = f_1(v_{it1}) + ... + f_p(v_{itp}) + f_{tm}(t) + f_{sp}(s_{it}) + \mu_{it}'\gamma \tag{2.8}$$

where f_{tm} is a possibly nonlinear, temporary correlated time trend and f_{sp} is a spatially correlated effect of the location where observation s_{it} belongs to. The spatial effect in these models may be modeled using Markov Random Fields (MRFs) (Besag et al. 1991) or two dimensional P-splines (Brezger et al. 2006).

2.4.4 Varying Coefficient Model (VCM)

A VCM proposed by Haustie and Tibshiran (1993) is given by

$$\eta_i = g_1(v_{i1})z_{i1} + ... + g_k(v_{ik})z_{ik} \tag{2.9}$$

where the effect modifiers v_{ij} are continuous covariates or time scales and the interacting variables z_{ij} are either continuous or categorical.

2.5 The Bayesian Hierarchical Modelling

In Bayesian modelling the parameters have distributions. These distributions control the form of the parameters and are specified by the investigator based, usually, on their prior belief concerning their behaviour (Lawson, 2008).

2.5.1 The likelihood Function

Let $\{y_i\}$ $i=1,...,m$ be a random variable with probability density function $f(y_i \mid \theta)$, where $\theta = \{\theta_1,...,\theta_p\}$ is a p length vector of relative risk parameters. Then, the likelihood of $\{y_i\}$ is defined as

$$F(y \mid \theta) = \prod_{i=1}^{m} f(y_i \mid \theta) \tag{2.10}$$

The assumption is made here that the sample values of $y = \{y_1,...,y_m\}'$ given θ are independent, making it possible to take the product of individual contribution of $f(y_i \mid \theta)$ in (2.11) (Lawson, 2008). In the following subsections, we discuss the Binomial and Poisson count likelihoods.

2.5.1.1 Binomial model for count data

In the case where we examine arbitrary small areas, usually a count of disease is observed within each spatial unit. Define this count as y_i and assume that there are m small areas. We also consider that there is a finite population within each small area out of which the count (n_i) of a disease has arisen.

In this situation, we can consider a binomial model for the count data conditional on the observed population in the areas. Hence we can assume that given the probability of a case is p_i, then y_i is distributed independently as $y_i \sim bin(p_i, n_i)$ and that the likelihood is given by $L(y_i \mid p_i, n_i) = \prod_{i=1}^{m} \binom{n_i}{y_i} p_i^{y_i} (1-p_i)^{n_i - y_i}$. (2.11)

The commonest link function for the probability p_i to a linear predictor is a logit link so that $p_i = \frac{\exp(\eta_i)}{1+\exp(\eta_i)}$. The models specification is envisaged within η_i to include spatial and non-spatial components.

2.5.1.2 Poisson model for count data

The most commonly encountered model for small area count data is the Poisson model. This model assume that the disease count y_i have a mean and is independently distributed as $y_i \sim poiss(\mu_i)$.

The likelihood function is given by

$$L(y \mid \mu) = \prod_{i=1}^{m} \mu_i \exp(-\mu_i) / y_i ! \quad (2.12)$$

The expectation is $E(y_i) = \mu_i = \varepsilon_i \theta_i$ where ε_i is the expected rate for the i th area and θ_i is the relative risk for the i th area (Lawson, 2008).

2.5.2 Prior Distributions

Lawson (2008) defined a prior distribution as a distribution assigned to the parameter θ before observing the data $\{y_i\}$. He further stated that prior distributions provide additional

'data' for a problem and they can be used to improve estimation or identification of parameters. Given a single parameter, θ, the prior distribution can be denoted by $g(\theta)$, while for a parameter vector, ϑ, the joint prior distribution is denoted as $g(\vartheta)$. In his book, Lawson considered two types of priors, namely; propriety and non-informative priors. In the next subsections, we consider some properties of these two types of priors.

2.5.2.1 Propriety

A prior distribution is said to be impropriety if its integration of the random variable θ over its range (Ω) is not finite. That is,

$$\int_{\Omega} g(\theta)\, d\theta = \infty \tag{2.13}$$

A prior distribution is improper if its normalizing constant is infinite. While impropriety is a limitation of any prior distribution, it is not necessarily the case that an improper prior will lead to impropriety in the posterior distribution.

2.5.2.2 Informative Priors

An informative prior is a prior that is not dominated by the likelihood function and that has an impact on the posterior distribution. If a prior distribution dominates the likelihood, it is clearly an informative prior.

2.5.2.3 Non-informative Priors

These are priors that do not make strong preferences over values of the variables. They have a relatively flat form yielding close-to-uniform preference for different values of the variables. This tends to mean that in any posterior analysis the prior distributions will have little impact compared to the likelihood of the data (Lawson, 2008).

2.5.2.4 Conjugate Priors

A prior is conjugate for a family of distributions if the prior and the posterior are of the same family. Specifically, for a binomial likelihood with parameter θ, and the beta prior distribution with parameter θ, the posterior distribution of θ is also a beta distribution (Lawson, 2008). For example,

$$y \sim Bin(n, \theta)$$
$$\theta \sim Beta(\alpha, \beta)$$
$$\theta \mid y \sim Beta(y + \alpha, n - y + \beta)$$

Hence, beta prior for θ is a conjugate prior. Conjugate priors are useful as building blocks in more complicated models, even though the full model will not be conjugate.

2.5.2.5 Jeffery's Priors

Jeffrey's prior (Jeffrey, 1961) is a prior that does not change much over the region in which the likelihood is significant and does not assume large values outside that range. It is based on the Fisher information matrix. Jeffrey's prior for a single parameter θ is defined as

$$P(\theta) \propto \sqrt{I(\theta)} \tag{2.14}$$

where $I(\theta) = -E\left[\frac{\partial^2 \ln P(y \mid \theta)}{\partial \theta^2}\right]$ is the fisher information matrix based on the likelihood function $P(y \mid \theta)$. Following equation (2.13), Jeffery's prior distribution for a binomial likelihood with a single parameter θ and sample size n is given by $P(\theta) = \sqrt{\frac{\theta}{\theta(1-\theta)}} = n^{1/2}\theta^{-1/2}(1-\theta)^{-1/2}$.

2.5.3 Priors for spatial data

As discussed in section 2.1, spatial data contain information about the attribute of interest as well as its location in space. The broad principle of regression and modelling also apply to spatial datasets. Markov Random Fields (MRFs) are the dominant approach to analyzing areally-aggregated spatial data, such as disease counts in administrative units (Paciorek, 2012).

Paciorek (2012) argue that the most common form of MRF represents the spatial dependence structure such that areas that share boundaries are considered neighbours, with an area conditionally independent of any non-neighbour areas, a so-called first order neighbourhood structure. A common alternative to this standard nearest neighbour is to extend the neighbourhood structure beyond bordering areas (Song et al. 2008).

2.5.3.1 Spatial Model Structure for Point and Areal data

Let $\mu_i = E(y_i \mid X_i, g)$ be related via a link function, $h(.)$ to a linear predictor:

$$h(\mu_i) = X_i^T \beta + K_i g \tag{2.15}$$

where K_i is the ith row of a mapping matrix. Let $g(.)$ be the unknown latent spatial process represented as a piecewise constant surface on a fine rectangular grid,

$$g \sim N\left(0, (kQ)^{-}\right) \tag{2.16}$$

where Q is an MRF precision matrix and k a precision parameter, recognizing the potential singularity of Q by using the generalized inverse notation (Paciorek, 2008).

Parciorek (2008) indicated that, for point data K_i will be a sparse vector with a single 1 that matches the location of the observations to the grid cell in which it falls. We discuss the potential MRF models in the following sections.

2.5.3.2 Improper Conditional Autoregressive (ICAR) model

This model was developed from the lattice models of Kunsch (1987) and it uses the definition of spatial distribution in terms of differences and allows the use of a singular normal joint distribution. The prior for this model is defined as

$$p(u \mid r) = \frac{1}{r^{m/2}} \exp\left(-\frac{1}{2r} \sum_i \sum_{j \in \delta_i} \left(u_i - u_j \right)^2 \right) \tag{2.17}$$

Where δ_i is a neighbourhood of the i th tract. This neighbourhood is assumed to be defined for the first neighbour only (Rue et al., 2005). Neighbourhoods could consist of first and second neighbours defined by common boundary or by a distance cut-off.

The uncorrelated heterogeneity (v_i) is defined to have a conventional zero-mean Gaussian prior distribution:

$$p(v) = \sigma^{-m/2} \exp\left(-\frac{1}{2\sigma} \sum_{i=1}^{m} {v_i}^2 \right) \tag{2.18}$$

where both r and σ are assumed to have improper inverse exponential hyper priors:

$prior(r, \sigma) = e^{-\varepsilon/2r} e^{-\varepsilon/2\sigma}$, $\sigma, r > 0$ and $t = 0.001$ (Besag et al., 1991).

The full posterior distribution where Poisson likelihood is assumed for the tract counts is given by

$$p(u,v,r,\sigma \mid y_i) = \prod_{i=1}^{m}\left\{\exp\left(-e_i\theta_i\right)\left(e_i\theta_i\right)^{y_i} / y_i!\right\} \times \frac{1}{r^{m/2}} \exp\left(-\frac{1}{2r}\sum_i \sum_{j\in\delta_i}\left(u_i - u_j\right)^2\right) \times \sigma^{-m/2} \exp\left\{-\frac{1}{2\sigma}\sum_{i=1}^{m} v_i^{\,2}\right\} \times prior(r,\sigma)$$

This posterior distribution can be sampled using MCMC algorithms such as the Gibbs or Metropolis-Hastings samplers. The conditional moments of the intrinsic Gaussian formulation are defined as simple functions of the neighbouring values and number of neighbours ($n\delta_i$):

$$E(u_i \mid ...) = \overline{u_i} \text{ and } \operatorname{var}(u_i \mid ...) = r / n\delta_i . \tag{2.19}$$

The conditional distribution is defined as $\left[u_i \mid ...\right] \sim N\left(\overline{u_i}, r / n\delta_i\right)$ where $\overline{u_i} = \sum_{j\in\delta_i} u_j / n\delta_i$, the average over the neighbourhood of the i th region (Lawson, 2008).

2.5.3.3 Proper Conditional Autoregressive (PCAR) models

Define the spatially-referenced vector of interest as $\left\{u_i\right\}$. One specification of the proper CAR formulation yields

$$\left[u_i \mid ...\right] \sim N(\mu_i, r / n\delta_i); \quad \mu_i = t_i + \phi \sum_{j\in\delta_i}\left(u_j - t_j\right) / n\delta_i \tag{2.20}$$

where t_i is the trend $\left(= x_i^{'}\beta\right)$, r is the variance and ϕ must lie on a predefined range which is a function of eigenvalues of a matrix. In detail, the range is the maximum and minimum $\left(\phi_{\min} < \phi < \phi_{\max}\right)$ of $diag\left\{n\delta_i^{1/2}\right\}.C.diag\left\{n\delta_i^{-1/2}\right\}$

where $C_{ij} = c_{ij}$ and $c_{ij} = \frac{1}{n\delta_i}$ if $i \sim j$ or 0 otherwise.

2.5.4 Posterior Distributions

Prior distributions and likelihood provide two source of information about any problem. The prior distribution provides information about the parameter through prior beliefs or assumptions whereas the likelihood provides information via the data. The product of the likelihood and the prior distributions is called the posterior distribution. This distribution describes the behaviour of the parameters after the data are observed and prior assumptions are made (Lawson, 2008).

Let ϑ be a parameter vector and $\{y_i\}$ $i=1,...,m$ a random variable such that $y=\{y_1,...,y_m\}'$. Then the posterior distribution is defined as;

$$p(\vartheta|y)=L(y|\vartheta)g(\vartheta)/C. \tag{2.21}$$

where $C=\int_p L(y|\vartheta)g(\vartheta)d\vartheta$, $g(\vartheta)$ is a joint distribution of ϑ, $L(y|\vartheta)$ is a likelihood function and C is called the normalizing constant.

2.5.4.1 The Binomial example

Let y_i denote the number of HIV testing or condom use cases. We assume that $y_i \sim Bin(p_i, n_i)$. Thus, the likelihood function is given by equation (2.11). Assume that $\text{logit}(p_i)=x_i'\alpha+z_i'\gamma$. In this case, $z_i'\gamma$ is a vector random effect, x_i' is a vector of individual and γ is a unit vector. Suppose a logit link is appropriate for the probability and that a random effect (v_i) at the individual level is to be included. Thus,

$$p_i=\frac{\exp(\alpha_0+v_i)}{1+\exp(\alpha_0+v_i)} \tag{2.22}$$

would represent a basic model with intercept to capture the overall rate and prior distribution for the intercept. The random effects could be assumed to be $\alpha_0 \sim N\left(0, \tau_{\alpha_0}\right)$, and $v_i \sim N\left(0, \tau_v\right)$ (Lawson, 2008). The hyper prior distribution for the variance parameters may follow either a gamma, inverse gamma, or a uniform distribution. For instance, a gamma distribution may be defined as follows,

$y_i \sim Bin(p_i, n_i)$ such that $\text{logit}(p_i) = \alpha_0 + v_i$ and the appropriate priors summarized as

$$\alpha_0 \sim N\left(0, \tau_{\alpha_0}\right)$$
$$v_i \sim N\left(0, \tau_v\right)$$
$$\tau_{\alpha_0} \sim G\left(\psi_1, \psi_2\right)$$
$$\tau_v \sim G\left(\phi_1, \phi_2\right)$$

2.6 Bayesian Markov Chain Monte Carlo (MCMC) Method

Simulation techniques based on Markov chains are very general and flexible. They are widely used to carry out posterior inference in the case where the product of the likelihood and the prior are analytically intractable. Ntzoufras (2011) stated that MCMC methods enable quantitative researchers to use highly complicated models to estimate the corresponding posterior distribution with accuracy. An alternative to MCMC methods is the approximate Bayesian inference by using integrated nested laplace approximation (Rue et al. 2009; Palcious et al. 2012 and Holand et al. 2013). However, in this section we only discuss MCMC methods.

2.6.1 The MCMC algorithm

Ntzoufras (2011) defined a Markov chain as stochastic process $\left\{\theta^{(1)}, \theta^{(2)}, ..., \theta^{T}\right\}$ such that

$$f\left(\theta^{(t+1)} \mid \theta^{(t)},...,\theta^{(1)}\right) = f\left(\theta^{(t+1)} \mid \theta^{(t)}\right) \tag{2.23}$$

That is, the distribution of θ at sequence $t+1$ given all the preceding θ values depends only on the vector $\theta^{(t)}$ of the previous sequence t. When the Markov chain is irreducible, aperiodic, and positive-recurrent, the distribution $\theta^{(t)}$ converges to its equilibrium distribution which is independent of the initial values of the chain $\theta^{(0)}$ (Nummelin, 2004). In order to generate a sample from $f(\theta \mid y)$, we must construct a Markov chain with two properties namely, $f\left(\theta^{(t+1)} \mid \theta^{(t)}\right)$ should be "easy to generate from"; and the equilibrium distribution of the selected Markov chain must be the posterior distribution of interest $f(\theta \mid y)$ (Ntzoufras, 2011).

From this Markov chain, we can then follow a standard approach to Bayesian inference using MCMC as follows:

1. Select an initial value $\theta^{(0)}$.
2. Generate T values until the equilibrium distribution is reached.
3. Monitor the convergence of the algorithm using convergence diagnostics. If convergence diagnostics fail, we then generate more observations.
4. Cut off the first b observations.
5. Consider $\left\{\theta^{(1)}, \theta^{(2)},..., \theta^{T}\right\}$ as the sample for the posterior analysis.
6. Plot the posterior distribution.
7. Finally, obtain summaries of the posterior distribution.

2.6.2 Describing the target distribution using MCMC output

Let $\theta^{(1)},\theta^{(2)},...,\theta^{(t)},...\theta^{(T')}$ be a random sample from the MCMC output. Ntzoufras (2011) indicated that for any function $G(\theta)$ of the parameter of interest θ, we can;

1. Obtain a sample of the desired parameter $G(\theta)$ by simply considering

   $$G\left(\theta^{(1)}\right),G\left(\theta^{(2)}\right),...,G\left(\theta^{(t)}\right),...,G\left(\theta^{(T')}\right)$$

2. Obtain any posterior summary of $G(\theta)$ from the sample using traditional sample estimates. For example, we can estimate the posterior mean by,

   $E\left(G(\theta)\mid y\right)=\overline{G(\theta)}=\frac{1}{T'}\sum_{t=1}^{T'}G\left(\theta^{(t)}\right)$ and the posterior standard deviation by

   $$SD\left(G(\theta)\mid y\right)=\frac{1}{T^1-1}\sum_{t=1}^{T'}\left[G\left(\theta^{(t)}\right)-E\left(G(\theta)\mid y\right)\right]^2$$

3. Calculate and monitor correlations between parameters.

4. Produce plots of the marginal posterior distributions (histogram, density plots, error bars, boxplots, etc.).

2.6.3 Monte Carlo error

The Monte Carlo error measures variability of each estimate due to simulation. It is required that the Monte Carlo error must be low to calculate the parameter of interest with increased precision. There are two most common ways to estimate MC error namely; the batch mean

method and window estimator method. These two methods are discussed in full details by Ntzoufras (2011, pp. 39-40).

In the next subsection, we discuss some of the most common basic MCMC algorithms.

2.6.4 The Metropolis-Hastings algorithm

Metropolis et al. (1953) originally formulated the Metropolis algorithm by introducing the Markov-chain-based simulation methods widely used in the field of science. This algorithm was further generalized by Hastings (1970) to what is now known as Metropolis-Hastings algorithm.

The Metropolis-Hastings alogorithm is summarized below:

Let $p(x)$ be a target distribution from which we wish to generate a sample of size N and $x^{(t)}$ a vector of generated values in t iteration of the algorithm. Then;

1. Set initial values $x^{(0)}$.
2. For $t = 1, ..., N$ repeat the following steps:
    a. Set $x = x^{t-1}$.
    b. Generate new candidate value x' from a proposal distribution $q\left(x \to x'\right) = q\left(x' \mid x\right)$.
    c. Calculate $\alpha = \min\left(1, \frac{p\left(x\right)q\left(x \mid x'\right)}{p\left(x\right)q\left(x' \mid x\right)}\right)$.
    d. Update $x^{(t)} = x'$ with probability α and $x^{(t)} = x = x^{(t-1)}$ with probability $\alpha - 1$.

The Metropolis-Hastings algorithm will converge to its equilibrium distribution regardless of whatever proposal distribution q is selected (Ntzoufras, 2011).

2.6.5 The Gibbs Sampler

This is another MCMC algorithm which according to Ntzoufras (2001) was introduced by Geman and Geman (1984) as an algorithm for simulating samples from the posterior distribution. The algorithm can be summarized by the following steps:

1. Set initial values $\theta^{(0)}$.
2. For $t = 1,...,T$, repeat the following steps:
   a. Set $\theta = \theta^{(t-1)}$.
   b. For $j = 1,...,d$ update θ_j from $\theta_j \sim f(\theta_j \mid \theta_{\setminus j}, y)$.
   c. Set $\theta^{(t)} = \theta$ and save it as the generated set of values at $t+1$ iteration of the algorithm.

Thus, given a particular state of chain $\theta^{(t)}$, we generate the new parameters by

$\theta_1^{(t)}$ from $f\left(\theta_1 \mid \theta_2^{(t-1)}, \theta_3^{(t-1)}, ..., \theta_p^{(t-1)}, y\right)$

$\theta_2^{(t)}$ from $f\left(\theta_2 \mid \theta_1^{(t)}, \theta_3^{(t-1)}, ..., \theta_p^{(t-1)}, y\right)$

$\theta_3^{(t)}$ from $f\left(\theta_3 \mid \theta_1^{(t)}, \theta_2^{(t)}, \theta_4^{(t-1)} ..., \theta_p^{(t-1)}, y\right)$

. . .

. . .

. . .

$\theta_j^{(t)}$ from $f\left(\theta_j \mid \theta_1^{(t)}, \theta_2^{(t)}, ..., \theta_{j-1}^{(t)}, \theta_{j+1}^{(t-1)}, ..., \theta_p^{(t-1)}, y\right)$

. . .

. . .

$\theta_p^{(t)}$ from $f\left(\theta_p \mid \theta_1^{(t)}, \theta_2^{(t)}, ..., \theta_{p-1}^{(t)}, y\right)$.

Generating values from $f(\theta_j \mid \theta_{\setminus j}, y) = f\left(\theta_j \mid \theta_1^{(t)}, ..., \theta_{j-1}^{(t)}, \theta_{j+1}^{(t-1)}, ..., \theta_{p-1}^{(t-1)}, y\right)$ is relatively easy since it is a univariate distribution and can be written as $f\left(\theta_j \mid \theta_{\setminus j}, y\right) \propto f\left(\theta \mid y\right)$, where all variables except θ_j are held constant at their given values (Ntzoufras, 2011).

2.7 Multivariate Spatial model

2.7.1 A Joint Model

Consider counts data observed as $\{y_{li}\}$, $l = 1, 2$ and $i = 1, ..., m$. Suppose the objective of the study is to locally compare the odds of getting outcome 1 or outcome 2. Then it might be important to jointly model each outcome without conditioning. A joint model for the two outcomes with common components will thus be defined as

$$
\begin{aligned}
y_{1i} &\sim Pois\left(\mu_{1i}\right) \\
y_{2i} &\sim Pois\left(\mu_{2i}\right) \\
\mu_{1i} &= e_{1i} \exp\left\{\beta_0 + X_i^{'}\beta_1 + W_{1i}\right\} \\
\mu_{2i} &= e_{2i} \exp\left\{\beta_0 + X_i^{'}\beta_2 + W_{1i}\right\}
\end{aligned}
$$

where $X_i^{'}\beta_1$, $X_i^{'}\beta_2$ is the covariate predictor for outcome 1 and 2 respectively, and W_{1i} is a common component. Separate random effects could thus be assumed which have prior correlation so that

$$\mu_{1i} = e_{1i} \exp\left\{\beta_0 + X_i^{'}\beta_1 + W_{1i}\right\}$$
$$\mu_{2i} = e_{2i} \exp\left\{\beta_0 + X_i^{'}\beta_2 + W_{2i}\right\}$$
$$\begin{pmatrix} W_{1i} \\ W_{2i} \end{pmatrix} \sim N\left(0, \Gamma\right)$$

with a zero vector and Γ is defined as

$$\Gamma = \begin{pmatrix} k_1 & \sqrt{k_1}\sqrt{k_2}\,pw \\ \sqrt{k_1}\sqrt{k_2}\,pw & k_2 \end{pmatrix}$$

where k_1, and k_2 are the prior variances of the two effects and pw is the prior correlation (Lawson, 2008).

2.7.2 Shared Component model

Shared components models highlight common and specific spatial components, allowing the linear predictor to be decomposed into shared and disease-specific spatial variability terms. In the example of Knorr-Held and Best (2001) this takes the form of

$$\mu_{1i} = e_{1i} \exp\left\{\beta_0 + u_{2i} + \delta_{u_{1i}}\right\}$$
$$\mu_{2i} = e_{2i} \exp\left\{\beta_0 + u_{1i} / \delta\right\}$$

Where μ_{2i} is a separate random component for the first disease; μ_{1i} is the shared component and δ is a scaling component with the prior distribution $\log(\delta) \sim N\left(0, \kappa_\delta\right)$ with a small fixed variance of $\kappa_\delta = 0.17$ in Konorr-Held and Best (2001). The joint modelling approach can be easily generalized to more than two outcomes. For more than two outcomes, each

spatial field u_k, is assigned weights $\delta_{k,j}$ to determine the relative contribution of the spatial field to each relative outcome. Held at al. (2005) assumed that the log relative risk for area i and outcome j is conditionally independent with mean u_{ij}, given as an intercept plus a weighted sum of the relevant fields,

$$u_{ij} = \alpha_j + \sum_k \delta_{k,j} u_{ki} \tag{2.24}$$

and unknown precision. For each latent GMRF u_k, they assumed that $\log \delta_{k,1}, ..., \log \delta_{k,nk}$ is a multivariate normal with mean zero and marginal variance $\sigma_k^{\,2}$ for each $l = 1, ..., nk$, but under the restriction that $\sum_{l=1}^{nk} \log \delta_{k,l} = 0$. This model requires the pre-specification of the number of spatial fields and the outcomes relevant for each spatial field (Held et al. 2005).

2.7.3 Proportional intensity model

Another approach which provides for joint analysis is the proportional intensity model, which was introduced by Dabney and Wakefield (2005) and referred to as Proportional Mortality Model (PMM) because mortality count data were considered. Dabney and Wakefield (2005) demonstrated how this model may be used to model two outcomes. Assume $Y_{ki} \sim Poisson(\lambda_{ki}), k = 1, 2, i = 1, 2, ..., n,$ where we begin by assuming $\log \lambda_{ki} = \alpha_{k0} + \alpha_{k1} x_i$, so that there are no random effects, but x_i represents an area level covariate associated with both diseases through the area level relative risks $\exp(\alpha_{11})$ and $\exp(\alpha_{21})$. Similar assumption can also be made for binomial counts. If we define $M_i = Y_{1i} + Y_{2i}$ as the sum of the two outcomes counts in area i, then

$$Y_{1i} \mid M_i = m_i \sim Binomial(m_i, \gamma_i),$$

where

$$\gamma_i = \frac{\exp\{(\alpha_{10} - \alpha_{20}) + (\alpha_{11} - \alpha_{21})x_i\}}{1 + \exp\{(\alpha_{10} - \alpha_{20}) + (\alpha_{11} - \alpha_{21})x_i\}}.$$

Hence, one can model the data with a logistic model of the form $\log it(\gamma_i) = \beta_0 + \beta_1 x_i$, where the parameter β_1 can be interpreted as the difference $\alpha_{11} - \alpha_{21}$. In this way, inference can be made on the difference in log relative risks without knowledge of the population counts from where the sample was drawn.

The proportional intensity model to the problem of mapping two outcomes can be applied by introducing random effects. We first consider the following individual outcome mapping models: $\log \theta_{ki} = \alpha_{k0} + U_{ki} + S_{ki}$, where the U_{ki} values are spatially unstructured, and the S_{ki} values are spatially structured random effects for outcome $k, k = 1, 2$.

We can then consider $Y_{1i} \mid M_i = m_i \sim Binomial(m_i, \gamma_i)$, with

$$\gamma_i = \frac{\exp\{\log(Y_{1i} / Y_{2i}) + (\alpha_{10} - \alpha_{20}) + (U_{1i} - U_{2i}) + (S_{1i} - S_{2i})\}}{1 + \exp\{\log(Y_{1i} / Y_{2i}) + (\alpha_{10} - \alpha_{20}) + (U_{1i} - U_{2i}) + (S_{1i} - S_{2i})\}} \tag{2.25}$$

giving the logistic model $\log it(\gamma_i) = \log \frac{Y_{1i}}{Y_{2i}} + \beta_0 + U_i^* + S_i^*$.

The log ratios of expected counts are included as an offset term to account for any differential spatial trends in expected numbers for the two diseases. Here S_i^* can be thought of as the difference $S_{1i} - S_{2i}$, so that the S_i^* values capture similarity and dissimilarity between the spatial random effects of each outcome. A large absolute value of S_i^* indicates that the two outcomes differ significantly in odds in area i in terms of the spatial component, whereas a value closer to zero indicates the two outcomes are similar in this area. Similarly, U_i^* can be thought of as a difference $U_{1i} - U_{2i}$ in the unstructured spatial effects, and a map of these quantities would point out areas in which the effects of unobserved non-spatial covariates are similar or different between the two outcomes. However, in a case of three or more outcomes,

then a multinomial (product multinomial) can apply with $Y_i \mid M_i \sim Multi(M_i, \gamma_i)$ (Manda, 2012).

2.8 Model Selection and Assessments

The foremost goal of model comparison is achieving good balance between two opposing pressures, goodness of fit and complexity. There are different representative measures that help to achieve this balance. Some of these measures are: Akaike Information Criterion (AIC); Bayesian Information Criterion (BIC); and Deviance Information Criterion (DIC). These are discussed in the following subsections.

2.8.1 The Deviance Information Criterion (DIC)

The Deviance Information Criterion (DIC) was introduced as an easily computable and rather universally applicable Bayesian criterion for posterior predictive model comparison (Spiegelhalter et al., 2002). Like many other criteria it compromises between data and model complexity, and it generalizes AIC which appears as a special case under a vague prior. For example, experiences indicating that DIC works well if the sampling distribution belongs to an exponential family but less so if it is a mixture are hard to explain, and hence modifications are hard to justify. This criterion assumes that a better fitted model has $\Delta DIC > 10$. The ΔDIC 4-10 implies a moderate difference and $\Delta DIC < 4$ implies non-distinguishable difference.

2.8.2 The Akaike Information Criterion (AIC)

For maximum likelihood or empirical Bayesian, one can use the Akaike Information Criterion (Cui et al. 2008). The Akaike (1973, 1974) information criterion was developed as estimators of the expected Kullback-Lieber discrepancy between the model generating the data and a fitted candidate model (Cui et al. 2008). The Akaike information is defined

as $AIC = -2\ln f\left(y \mid \theta_k\right) + 2k$ where k is the number of parameters in the model, f is the likelihood function and ln is the natural logarithm. The best model is determined by examining their relative distance to the "truth". The best model is the one with a minimum AIC value. AIC have a number of advantages e.g. valid for both nested and non-nested models, compare models with different error distribution and avoid multiple testing issues. However, AIC cannot be used to compare models of different data sets. For example, if nonlinear regression model g1 is fitted to a data set with n = 140 observations, one cannot validly compare it with model g2 when 7 outliers have been deleted, leaving only n = 133 (Hu, 2007).

2.3.3 The Bayesian Information Criterion (BIC)

Bayesian information criterion (BIC) was introduced by Schwarz (1978) as a competitor to the AIC information criterion (Cavanaugh, 1999). BIC is defined as $BIC = -2\ln f\left(y \mid \theta_k\right) + k\ln n$. BIC was derived to serve as an asymptotic approximation to a transformation of the Bayesian posterior probability of a candidate model. In large-sample settings, the fitted model favoured by BIC ideally corresponds to the candidate model which is a posterior most probable; i.e., the model which is rendered most plausible by the data at hand. The computation of BIC is based on the empirical log-likelihood and does not require the specification of priors. The penalty term of BIC is more stringent than the penalty term of AIC (for n> 8, *k ln n* exceeds 2k). Consequently, BIC tends to favour smaller models than AIC. BIC can be used to compare non-nested models. It can be used to compare models based on different probability distributions. However, when the criterion values are computed, no constants should be discarded from the goodness-of-fit term. In a model selection application, the optimal fitted model is identified by the minimum value of BIC.

Chapter 3

Methods and Applications

3.1 Study setting and design

This study is based on a cross-section design using survey data collected as part of the 2006/07 Namibia Demographic and Health Survey (NDHS). The survey employed a two-stage cluster sampling techniques with the Primary Sampling Units (PSUs) as the first stage and households as the second stage sampling units. The study was conducted to generate reliable estimates at national and regional levels. In 2006/07, Namibia was divided into 13 regions, which were further subdivided into 107 constituencies, and each constituency is sub-divided into Enumeration Areas (EA). Each EA is comprised of about 100 households. All women aged 15-49 and all men aged 15-49 who were permanent residents of the households in the 2006/07 NDHS sample or visitors present in the household on the night before the survey were eligible to be interviewed.

3.2 Sample

A total sample of 10352 women and 4446 men participated in the survey. However, the sample sizes used in this study both for women and men is smaller because the questions on HIV testing and condom use are specific to a particular group. The study used 9804 women and 3915 men as sample sizes.

3.3 Data collection

This study made use of the Namibia Demographic and Health Survey (NDHS) data as secondary data from the Ministry of Health and Social Services. The 2006/07 NHDS data were collected by 28 teams, each consisting of a team supervisor, a field editor, three female

interviewers, one male interviewers and a driver. The assignment of field took into consideration the person's proficiency in the major languages spoken in Namibia. Quality assurance was maintained by national and regional supervisors through close supervision and monitoring during fieldwork. The questionnaires were edited by the field editor in the field and verified by the team supervisor before being transported to the central office. National and regional supervisors ensured quality control through editing of questionnaires and observation of interviewers.

NDHS respondents were asked whether they have ever been tested for HIV and whether they used a condom the first time they had sexual intercourse. The response variable, y_i, for HIV testing takes the value $y_i = 1$ if the *ith* respondent have been tested for HIV and $y_i = 0$ if otherwise. The response variable for condom use was constructed in a similar way.. Consistent condom use is advocated by HIV control programmes to reduce the risk of sexual transmission of HIV among sexually active young adults. Young adults who use condoms at first sex are more likely to sustain condom use later in life. Condom use at first sex serves as an indicator of reduced risk of exposure at the beginning of sexual activity.

3.4 Conceptual Framework

This study made use of the Protection Motivation Theory (PMT) (Rogers, 1983) and the Health Belief Model (HBM) as the conceptual frameworks to guide on variables selection. The Health Belief Model developed in the 1950s by social psychologists Hochbaum, Rosenstock and Kegels working in the U.S. Public Health Services has been adapted to explore a variety of long and short-term health behaviors, including sexual risk behaviors and the transmission of HIV/AIDS (Rosenstock et al, 1994). On the contrary, the PMT is a general theory of persuasive communication, with an emphasis on the cognitive processes

mediating behavioural change (Rogers, 1983). These two theories were all applied in this study to help in identifying the above explanatory variables. Furthermore, to apply spatial models to explain health promotion, we used as a conceptual framework the schematic representation of the contributions of neighbourhood environment to health inequalities proposed by Diez Roux & Mair (2010). In their study of Neighbourhoods and Health, Diez-Roux & Mair (2010) explored the link between neighbourhoods and health interventions, and proposed multilevel and spatial models within the random effects framework. Dummy variables were created and all variables considered in this study were all modeled as binary variables.

3.5 Ethical considerations

The data used in this study is secondary data. The data was obtained under informed consent by Macro International. However, while forbearing that this is secondary data, Macro International granted permission to use the data for research purposes only.

3.6 Statistical Data Analysis

The variables of interest were assessed for any statistical association with the response variables, HIV testing and the use of condom using the chi-square test. The following explanatory variables that showed significant association with HIV testing and condom use at p-value of 0.05 were retained for subsequent analysis: highest educational level, current marital status, wealth index, type of place of residence (rural or urban), age at first sexual intercourse, employment status, times away from home in the last 12 months, frequency of reading newspaper or magazine, frequency of listening to radio, frequency of watching television, smoking and alcohol consumption. Table 3.1 gives an overview of these explanatory variables.

Table 3.1: Description of explanatory variables used in the analysis

Variable	Type	Description
Frequency of reading newspaper		
Not at all (Nles0)	binary	Not at all: 0=No, 1=Yes
Less than once a week (Nles1)	binary	Less than once a week: 0= No, 1= Yes
At least once a week (Natl2)	binary	At least once a week: 0= No, 1= Yes
Almost every day (Nevry3)	binary	Almost every day: 0= No, 1= Yes
Frequency of listening to radio		
Not at all (Rles0)	binary	Not at all: 0= No, 1= Yes
Less than once a week (Rles1)	binary	Less than once a week: 0= No, 1= yes
At least once a week (Ratl2)	binary	At least once a week: 0= No, 1= Yes
Almost every day (Revry3)	binary	Almost every day: 0= No, 1= Yes
Frequency of watching television		
Not at all (Tles0)	binary	Not at all: 0= No, 1= Yes
Less than once a week (Tles1)	binary	Less than once a week: 0= No, 1= yes
At least once a week (Tatl2)	binary	At least once a week: 0= No, 1= Yes
Almost every day (Tevry3)	binary	Almost every day: 0= No, 1= Yes
Times away from home in the past 12 months		
Never away (T0)	binary	Never away: 0= No, 1=Yes
1-4 times (T1to4)	binary	1-4 times: 0= No, 1= Yes
5-9 times (T5to9)	binary	5-9 times: 0= No, 1= Yes
more than ten times (Tmr10)	binary	more than ten times: 0= No, 1= Yes
Smoke Nothing?	binary	1= Yes "Smoke nothing"
Yes	binary	0= No
No		
Ever drank alcohol?		
Yes	binary	1= Yes
No	binary	0= No
Respondent currently working?		

No	binary	0= No
Yes	binary	1= Yes
Age at first sexual intercourse		
Age<15 years	binary	age less than 15: 0= No, 1=Yes
Age 15 to21 years	binary	age 15to19: 0=N0, 1= Yes
Age 22 years or more	binary	age 22 or more: 0= No, 1= Yes
Type of place of residence		
Rural	binary	0= Rural
Urban	binary	1= Urban
Wealth Index		
Poor (Wpoor)	binary	Poor: 0= No, 1= Yes
Middle (Wmind)	binary	Middle: 0= No, 1= Yes
Rich (Wrich)	binary	Rich: 0= No, 1= Yes
Marital status		
Married	binary	1= married
Never Married	binary	0= Never married
Highest Educational level		
No education (Educno)	binary	No education: 0= No, 1= Yes
Primary (Educp)	binary	primary: 0= No, 1= Yes
Secondary (Educs)	binary	secondary: 0= No, 1= Yes
Tertiary (Educh)	binary	tertiary: 0= No, 1= Yes

3.7 Model Building

A number of models were developed to determine the relationship between HIV testing and condom use and the potential risk factors among males and females. The dependent variables HIV testing and condom use are binary, hence we fit the binary logistic regression to investigate the association between the two variables with the independent variables given in Table 3.1. In this study, the logistic regression was of the form

$$\text{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_i + ... + \beta_k x_k \qquad (3.1)$$

where the dependent variable y (HIV testing or condom use) ~ Binomial (1, π) where π is the probability of success. The binary logistic regression was fitted for HIV test and condom use in males and females separately, giving a total of 4 models. The study used the software called BayesX to fit the above models. Taking into consideration that classical Generalized Linear Models (GLMs) make no, or limited use of spatial structure of the data, neither do they consider possible nonlinear effects of the risk factors, we also fitted the Structured Additive Regression Model (STAR) and then followed by joint spatial models through the shared component latent variables approach.

A STAR model replaces the strictly linear predictor in classical models by a more flexible semi-parametric predictor that incorporates non-linear effects and spatial effects (structured and unstructured). On the contrary, joint spatial models enable us to make an assessment on similarities as well as differences between risk factors among males and females sharing common risk profiles with regard to HIV testing and condom use.

The STAR model used in this study was of the form

$$\eta = \gamma_0 + \gamma_1 Nles1 + \gamma_2 Natl2 + \gamma_3 Nevry3 + ... + \gamma_k Educh + f^{str}(const) + f^{unstr}(const) \quad (3.2)$$

where η is the predictor and γ_i are the fixed effects parameter. Spatial effects of the constituency is split up into a spatially correlated part $f^{str}(const)$ and an uncorrelated part $f^{unstr}(const)$ where the correlated part is modelled by a Markov random field prior where the neighbourhood matrix and possible weights associated with the neighbours are obtained from the constituency map. We assumed diffuse priors for fixed effects, exchangeable normal priors for unstructured spatial random effects and conditional autoregressive priors for the structured spatial random effects.

For joint analysis, we considered the proportional intensity model of the form

$$\log it(\gamma_i) = \log \frac{Y_{1i}}{Y_{2i}} + \beta_0 + U_i^* + S_i^* . \qquad (3.3)$$

We assume a binomial model for $Y_{1i} \mid Y_{1i} + Y_{2i} \sim Binomial(Y_{1i} + Y_{2i}, \gamma_i)$ with area level covariates added to the linear predictor.

We modeled HIV testing and condom use in males and females with fixed effects provided in Table 3.1. Simulation techniques through Monte Carlo Markov Chains were applied for model estimation. Structured Additive Regression (STAR) and the joint models were also fitted using BayesX version 2.1. To estimate the models we used the method regress of bayesreg object in BayesX. Convergence was reached at 12000 iterations after a burn-in period of 2000 for each model. These models are summarized in table 3.2 on the next page.

Table 3.2: Models considered to assess factors associated with probability of HIV testing and condom use.

Model	Variable
M	Fixed effects
M0	Structured spatial effects at constituency level
M1	Structured spatial effects at regional level
M2	Spatial effects (structured + unstructured) at constituency level
M3	Spatial effects (structured + unstructured) at regional level
M4	Structured spatial effects at constituency + regional level
M5	Spatial effects (structured + unstructured) at constituency + regional level
M6	Fixed effects + structured spatial effects at constituency level
M7	Fixed effects + structured spatial effects at regional level
M8	Fixed effects + structured spatial effects at constituency + regional level
M9	Fixed effects + spatial effects (structured + unstructured) at constituency level
M10	Fixed effects + spatial effects (structured + unstructured) at regional level
M11	Fixed effects + spatial effects (structured + unstructured) at constituency + regional level
M12	Fixed effects+ spatial effects (structured + unstructured) at constituency level

The first model M in this study was a linear logistic regression model provided by equation (3.1). Considering that model M do not account for spatial effects, and the hierarchical structure of the data, geo-additive models provided by equation (3.2) that simultaneously account for the spatial dependence in the variables were fitted. The next two models M0 and M1 examine only the spatial correlated random effects in the two dependent variables HIV testing and condom use at constituency and regional level respectively. The next two models,

M2 and M3, were fitted by introducing the uncorrelated spatial random effects to model M0 and M1. The fifth model, M4, was fitted by taking into consideration the region and constituency correlated spatial effects simultaneously. Model M5 was an improvement to model M4 and it was fitted by introducing uncorrelated spatial effects. The next models, M6 and M7, account for the effects of spatially structured covariates respectively at constituency and regional level. By making use of the constituency and regional level structured spatial effects simultaneously, model M8, in the similar manner as M6 and M7, accounts for the effects of spatially structured covariates. Models, M9 and M10, consider the effects of covariates on HIV testing and condom use by incorporating both unstructured and structured random effects at constituency and regional level respectively. The last model, M11, is an extension to either model M9 or M10 in a way that it considers both the effects of large area level (regional) together with the effects of small area level (constituency). Model M12 is a joint spatial model of HIV testing and condom use for females given the total counts in each constituency. In summary, model M was a linear logistic regression, models, M0 to M11, were STAR models and M12 was a joint spatial model. We used the Deviance Information Criterion (DIC) to select the best models fitted.

Chapter 4

Results and Summary

4.1 Descriptive summaries

Table 4.1 and 4.2 shows distribution of socio-demographic factors with regard to HIV testing and the use of condom respectively. The distribution shown on the tables reflects the outcomes on gender differences.

Table 4.1: Distribution of HIV testing by socio-demographic factors among males and females

Variable	% Females HIV tested	Total # of females	P-value	% Males HIV tested	Total # of males	P-value
Frequency of reading newspaper						
Not at all	25.7	3496		18.3	2665	
Less than once a week	54.5	1884	0.000	33.2	792	0.000
At least once a week	55.8	3118		36.1	1143	
Almost every day	68.6	1306		51.7	730	
Frequency of listening to radio						
Not at all	41.2	1191		10.2	334	
Less than once a week	50.1	736	0.000	22.0	315	0.000
At least once a week	51.3	1924		29.1	653	
Almost every day	57.2	5953		36.3	2613	
Frequency of watching television						
Not at all	41.3	5088		18.3	1582	
Less than once a week	53.1	757		29.9	485	

At least once a week	53.7	906	0.000	32.0	573	0.000
Almost every day	61.4	3053		36.3	1275	
Times away from home in the past 12 months						
Never away	51.3	4800		29.4	2053	
One to four times	55.4	3851		34.2	1224	
Five to nine times	63.3	599	0.000	43.7	272	0.002
More than ten times	67.2	554		51.8	366	
Smoke Nothing						
No	51.8	7751	0.254	18.3	1012	0.003
Yes	54.6	8947		31.1	2903	
Ever drank alcohol						
No	62.3	6467	0.001	53.1	1407	0.000
Yes	58.1	3337		35.5	2508	
Respondent currently working						
No	52.4	5601	0.000	19.3	1458	0.000
Yes	65.9	4203		35.5	2457	
Age at first sexual intercourse						
Less than 15 yrs	48.8	2118		22.9	1135	
Between 15 to 21 yrs	63.1	6027	0.000	37.4	2511	0.000
More than 21 yrs	65.0	1659		46.1	269	
Type of residence						
Rural	48.3	5399	0.000	33.7	2242	0.000
Urban	61.0	4405		43.9	1673	
Wealth Index						
Poor	45.6	3350		19.3	1196	
Middle	52.9	2223	0.000	29.0	1082	0.000
Rich	62.1	4231		46.3	1637	

Marital Status						
Married	64.3	4256		45.5	1408	
Never Married	47.5	5548	0.000	29.8	2507	
Highest Educational level						
No education	10.3	776		18.1	406	
Primary	50.2	2616	0.000	24.7	1189	0.000
Secondary	55.7	5854		35.5	2088	
Tertiary	80.5	558		69.0	232	

Table 4.2: Distribution of condom use by socio-demographic factors among males and females

Variable	% Females used condom	Total # of females	P-value	% Males used condom	Total # of males	P-value
Frequency of reading newspaper						
Not at all	56.4	3496		43.4	1250	
Less than once a week	63.2	1884	0.000	51.0	792	0.000
At least once a week	67.0	3118		55.8	1143	
Almost every day	76.9	1306		63.1	730	
Frequency of listening to radio						
Not at all	40.7	1191		28.8	334	
Less than once a week	51.9	736	0.000	37.5	315	0.000
At least once a week	57.1	1924		48.1	653	
Almost every day	63.3	5953		55.5	2613	
Frequency of watching television						
Not at all	51.3	5088		48.6	1582	
Less than once a week	60.9	757	0.000	53.6	485	0.000
At least once a week	67.6	906		51.1	573	

Almost every day	70.3	3053		62.9	1275	
Times away from home in the past 12 months						
Never away	54.3	4800		61.2	2053	
One to four times	63.4	3851	0.061	50.1	1224	0.312
Five to nine times	53.2	599		51.5	272	
More than ten times	56.8	554		57.4	366	
Smoke Nothing						
No	40.2	857	0.009	33.4	1012	0.016
Yes	59.8	8947		49.3	2903	
Ever drank alcohol						
No	68.4	6467	0.017	56.3	1407	0.176
Yes	62.5	3337		52.6	2508	
Respondent currently working						
No	64.8	5601	0.592	55.2	1458	0.421
Yes	58.3	4203		49.8	2457	
Age at first sexual intercourse						
Less than 15 yrs	55.3	2118		52.9	1135	
Between 15 to 21 yrs	62.7	6027	0.000	59.2	2511	0.003
More than 21 yrs	51.8	1659		66.7	269	
Type of residence						
Urban	64.4	4405	0.000	56.2	1673	0.005
Rural	54.1	5399		44.9	2242	
Wealth Index						
Poor	41.4	3350		52.9	1135	
Middle	56.3	2223	0.000	53.2	1082	0.000
Rich	71.0	4231		60.6	1637	

Marital Status						
Married	40.8	4256	0.000	50.5	2507	0.904
Never married	73.4	5548		48.5	1408	
Highest Educational level						
No education	28.2	776	0.000	19.7	406	0.000
Primary	41.6	2616		45.2	1189	
Secondary	66.6	5854		54.6	2088	
Tertiary	79.7	558		60.0	232	

From Table 4.1, it can be observed that HIV testing was highly associated with exposure to media, wealth index, type of residence (rural or urban) and highest educational level. Smoking status was significantly related to HIV testing among the male while it was not significant among women. Overall, it was found that most women tend to go for HIV tests than their male counterparts regardless of the socio-demographic factors considered. Table 4.2 showed that, respondents from urban areas have an increased probability of condom use at first sexual intercourse. In addition, there is a strong positive relationship between level of education, wealth status and the use of condom at first sexual intercourse.

4.2 Multivariate models results

Under this section, we present results of fitting models to the NDHS 2006/07 data.

4.2.1 Results of the models comparison

In Table 4.3 and Table 4.4, model M was a logistic regression and it was included to assess the difference in the DIC values in relation to the best model fitted among geo-additive models (M0-M11) that takes into consideration the spatial dependence in the variables. Model M12 was a joint model, also a different model from models M0 to M11, refer to the

discussion under Table 3.2. In the following summary Table 4.3 and Table 4.4, we present samples of deviance, the effective number of parameters (pD) and the Deviance Information Criteria (DIC) proposed by Spiegelhalter et al. (2002).

Table 4.3: HIV testing model comparison using DIC values

	Females				Males			
Model	**Deviance**	**pD**	**DIC**	**∆DIC**	**Deviance**	**pD**	**DIC**	**∆DIC**
M	11600.98	25.75	11652.48	-	4187.34	24.81	4236.96	-
M0	12991.94	50.48	13092.90	1561.41	4627.91	40.38	4708.67	491.99
M1	13120.22	11.78	13143.78	1612.29	4724.11	11.76	4747.64	530.96
M2	12979.49	55.43	13090.36	1558.87	4620.86	44.14	4709.13	492.45
M3	13119.91	11.82	13143.55	1612.06	4724.03	11.80	4747.63	530.95
M4	12996.55	48.92	13094.40	1562.91	4630.74	40.00	4710.75	494.07
M5	12979.80	55.56	13090.93	1559.44	4625.37	43.18	4711.72	495.04
M6	11433.01	56.25	11545.50	14.01	4149.61	36.91	4223.43	6.75
M7	11496.54	35.29	11567.11	35.62	4151.15	33.74	4218.63	1.95
M8	11432.87	56.02	11544.91	13.42	4145.42	38.48	4222.38	5.7
M9	11395.35	69.59	11534.53	3.04	4141.39	41.44	**4216.68**	0.00
M10	11495.96	34.59	11565.14	33.65	4149.55	33.56	4224.27	7.59
M11	11391.50	69.99	**11531.49**	0.00	4136.61	41.30	4219.21	2.53
M12	1131.25	47.66	11502.39	-	4173.67	37.65	4207.63	-

From Table 4.3, Model, M8, indicates that considering fixed effects with the combined spatial effects of regions and constituencies explained the chance of getting tested for HIV better than considering the effects of regions or constituencies separately. Model M8 is even

much more improved if we consider unstructured effects as indicated by model M9 (DIC value of 11534.53). Looking at the difference in DIC values of the other models relative to model M11, it can be concluded that model M9 can be weakly differentiated as it has the DIC difference value of 3 to 7 from the best model. With regards to males, the situation is more or less the same as for females when it comes to models comparison from model M0 to M5. The best model that explains the chance of getting HIV tested among males was model M9 (DIC value of 4216.68). In model M9, we considered the fixed effects together with the structured and unstructured spatial effects at constituency level. By comparing the models, we observe that there is no much difference between the best model (M9) and models M6, M7, M8 and M11. Overall, there is no clear explanation why the best model among females is not the same best model in males' thus further investigations may be required.

Table 4.4: Condom use models comparison using DIC values

	Females				Males			
Model	**Deviance**	**pD**	**DIC**	**∆DIC**	**Deviance**	**pD**	**DIC**	**∆DIC**
M	3135.44	25.80	3187.04	-	1366.61	24.70	1416.01	-
M0	3325.78	35.31	3396.40	238.14	1380.62	36.52	1453.66	130.67
M1	3398.80	10.67	3420.14	261.88	1446.57	10.72	1468.00	145.01
M2	3315.70	40.92	3397.55	239.29	1377.19	37.82	1452.84	129.85
M3	3397.93	11.58	3421.09	262.83	1445.70	11.35	1468.40	145.41
M4	3328.23	35.09	3398.41	240.15	1383.35	35.63	1454.62	131.63
M5	3318.68	39.35	3397.38	239.12	1385.17	34.31	1453.79	130.8
M6	3074.54	44.52	3163.58	5.32	1265.99	50.03	1366.05	43.06
M7	3095.29	34.08	3163.45	5.19	1303.06	34.81	**1322.99**	0.00
M8	3082.64	40.70	3164.04	5.78	1275.24	47.35	1369.94	46.95
M9	3055.28	54.33	3163.93	5.67	1262.22	53.61	1369.45	46.46
M10	3092.95	34.27	3161.49	3.23	1302.54	35.41	1373.35	50.36
M11	3068.88	44.69	**3158.26**	0.00	1269.35	50.25	1369.86	46.87
M12	2993.78	55.27	3127.39	-	1285.52	43.78	1313.68	-

On condom use, the best model fitted among females remained the same as for HIV testing (M11 with DIC value of 3158.26). For males, the best model that explains the chance of using a condom at first sexual intercourse was model M7 which considered the fixed effects and the structured spatial effects of regions. Among females, models M6, M7, M8, M9 and M10 can be weakly differentiated as indicated by the DIC differences from the best model.

4.2.2 Covariates results (fixed effects)

From the best models fitted from table 4.3 and 4.5, the summaries of the socio-demographic factors considered in this study to explain their influences on the use of condom and HIV testing were produced. The table below presents these results.

Table 4.5: Fixed effects summaries of the best STAR models fitted as described in Table 4.3 and 4.4.

	Females		Males	
	HIV	**Condom**	**HIV**	**Condom**
Covariates	**OR (95% C.I)**	**OR (95% C.I)**	**OR (95% C.I)**	**OR (95% C.I)**
Marital Status				
Never married	1.00 -	1.00 -	1.00 -	1.00 -
Married	1.71 (1.54, 1.88)	0.54 (0.44, 0.67)	1.86 (1.56, 2.21)	0.86 (0.48, 1.47)
Respondent currently working?				
No	1.00 -	1.00 -	1.00 -	1.00 -
Yes	1.42 (1.30, 1.57)	0.75 (0.64, 0.88)	1.65 (1.38, 1.99)	0.87 (0.62, 1.15)
Ever drank alcohol?				
No	1.00 -	1.00 -	1.00 -	1.00 -
Yes	0.95 (0.86, 1.06)	1.01 (0.83, 1.21)	1.12 (0.96, 1.31)	0.86 (0.60, 1.13)
Frequency of reading newspapers				
Not at all (Nles0)	1.00 -	1.00 -	1.00 -	1.00 -
Less than once a week (Nles1)	1.17 (1.01, 1.34)	1.32 (1.00, 1.67)	1.37 (1.04, 1.82)	1.42 (0.91, 2.34)
At least once a week (Natl2)	1.17 (1.03, 1.32)	1.39 (1.08, 1.75)	1.33 (1.01, 1.68)	1.29 (0.83, 2.06)
Almost every day (Nevry3)	1.35 (1.12, 1.64)	1.90 (1.34, 2.67)	1.62 (1.18, 2.18)	1.24 (0.78, 2.16)
Frequency of listening to radio				
Not at all (Rles0)	1.00 -	1.00 -	1.00 -	1.00 -
Less than once a week (Rles1)	1.05 (0.84, 1.31)	0.80 (0.54, 1.17)	1.14 (0.73, 1.72)	0.89 (0.48, 1.77)
At least once a week (Ratl2)	1.09 (0.91, 1.26)	0.92 (0.69, 1.22)	1.37 (0.94, 1.98)	1.49 (0.85, 2.83)
Almost every day (Revry3)	1.15 (0.98, 1.37)	1.00 (0.75, 1.37)	1.43 (1.06, 1.92)	1.36 (0.82, 2.42)
Frequency of watching television				
Not at all (Tles0)	1.00 -	1.00 -	1.00 -	1.00 -
Less than once a week (Tles1)	0.81 (0.68, 0.93)	1.09 (0.84, 1.45)	0.93 (0.74, 1.17)	1.82 (1.29, 2.76)
At least once a week (Tatl2)	0.82 (0.70, 0.97)	1.51 (1.07, 2.04)	0.93 (0.73, 1.20)	1.27 (0.87, 1.76)
Almost every day (Tevry3)	0.90 (0.78, 1.05)	1.24 (0.92, 1.66)	1.03 (0.82, 1.30)	2.43 (1.62, 3.83)
Times away from home in past 12 months				
Never away (T0)	1.00 -	1.00 -	1.00 -	1.00 -
One to four times (T1to4)	1.05 (0.95, 1.15)	1.21 (0.99, 1.44)	1.12 (0.93,1.34)	0.89 (0.68, 1.22)
Five to nine times (T5to9)	1.20 (1.01, 1.47)	0.94 (0.68, 1.39)	1.30 (0.92, 1.73)	0.68 (0.36, 1.15)
More than 10 times (Tmr10)	1.29 (1.09, 1.63)	1.18 (0.72, 1.79)	1.48 (1.14, 1.88)	1.15 (0.65, 2.08)
Smoke nothing?				
No	1.00 -	1.00 -	1.00 -	1.00 -
Yes smoke nothing (Snyes)	1.32 (1.12, 1.57)	1.66 (1.16, 2.45)	0.84 (0.69, 0.99)	0.67 (0.46, 0.95)

Age at first sexual intercourse				
Less than 15 years (A<15)	1.00 -	1.00 -	1.00 -	1.00 -
Between 15 years to 21 years	5.31 (4.72, 5.99)	2.08 (1.61, 2.73)	1.87 (1.55, 2.30)	4.18 (3.06, 5.77)
More than 22 years	5.09 (4.30, 6.00)	1.71 (1.03, 2.72)	2.17 (1.55, 2.87)	4.78(1.50,14.34)
Type of place of residence				
Rural	1.00 -	1.00 -	1.00 -	1.00 -
Urban	1.24 (1.08, 1.45)	0.77 (0.63, 1.00)	1.29 (1.08, 1.54)	0.81 (0.55, 1.27)
Wealth index				
Poor (Wpoor)	1.00 -	1.00 -	1.00 -	1.00 -
Middle (Wmind)	1.02 (0.88, 1.16)	1.26 (0.98, 1.66)	1.52 (1.17, 1.93)	1.25 (0.93, 1.97)
Rich (Wrich)	1.03 (0.86, 1.22)	1.58 (1.17, 2.14)	2.00 (1.49, 2.62)	1.60 (0.81, 2.02)
Highest educational level				
No education (Educno)	1.00 -	1.00 -	1.00 -	1.00 -
Primary (Educp)	1.62 (1.35, 1.92)	1.68 (1.07, 2.61)	1.51 (1.05, 2.10)	1.65 (0.89, 2.76)
Secondary (Educs)	2.07 (1.71, 2.52)	2.97 (1.99, 4.61)	1.92 (1.37, 2.90)	2.40 (0.94, 2.86)
Tertiary (Educh)	4.18 (3.17, 5.55)	4.54 (2.12, 9.18)	4.78 (2.96, 8.01)	1.00 (0.69, 6.26)

Table 4.5 provide estimates of odd ratios (OR) and 95% confidence interval (CI). It can be observed that respondents who read newspapers almost every day are more likely to have been tested for HIV compared to those who read the newspapers occasionally both in females and males with OR=1.35 (1.12, 1.64) and OR=1.62 (1.18, 2.18) respectively. The probability of HIV testing is very high among females who had their first sexual intercourse at the age of 15 to 21 with OR=5.31 (4.72, 5.99) relative to those that had their first sexual intercourse at a younger age. However, among males the odds of HIV testing is high among those who had their first sexual intercourse at the age of 22 or more. Women and men who live in urban areas are more likely to have been tested for HIV than their rural counterparts with OR=1.24 (1.08, 1.45) and OR=1.29 (1.08, 1.54). Unsurprisingly, women and men with higher educational level have a high chance of having been tested for HIV relative to those with no education respectively with OR=4.18 (3.17, 5.55) and OR=4.78 (2.96, 8.01).

On condom use, males with secondary as their highest educational level are more likely to have used a condom at their first sexual intercourse compared with those with no education with OR=2.40 (0.94, 2.86). Similarly, females with higher education have an increased chance of using a condom at their first sexual intercourse OR=4.54 (2.12, 9.18). The results

reflect that males and females who are poor are at risk of not using a condom at their first sexual intercourse. It can also be observed that exposure to media increases the chance of condom use at first sexual intercourse. Unsurprisingly, married men are at the lower chance of using a condom at their first sexual intercourse OR=0.86 (0.48, 1.47). There appear to be no significant difference between males and females that drink alcohol on condom use relative to those that do not drink.

4.2.3 Spatial effects

All smoothed geographical effects estimates are interpreted using maps that are developed using fully Bayesian approach. Under this section, for all total spatial geographical effects maps presented, the darker color indicates regions with high odds of HIV testing or condom use whereas the lighter color indicates regions with low odds. For probability maps, black denotes areas with strictly lower uptake; white denotes areas with strictly high uptake and grey shows areas of no significance difference.

Figure 4.1 indicates that there is a significance difference in the uptake of HIV testing between males and females. Females are more likely to go for HIV testing than males in the northern parts of the country. This divergent pattern between males and females was observed in Oshikoto, Kavango and Omusati regions. The rest of the regions have common spatial pattern among men and women with Ohangwena and Caprivi having the lowest common uptake of HIV testing in men and women.

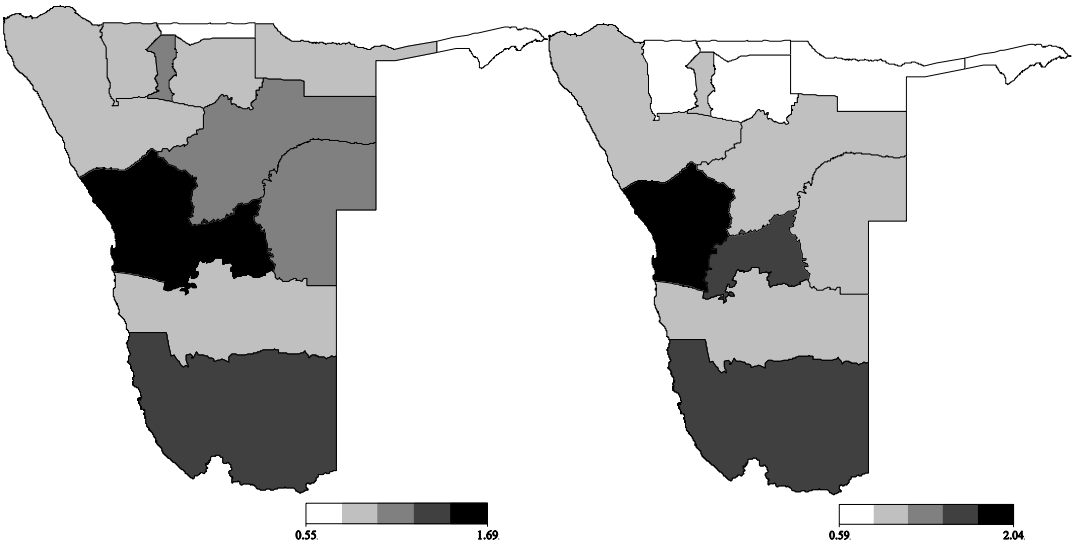

Figure 4.1: Total (structured and unstructured) spatial geographical effects of HIV testing at regional level in males (right) and female (left) model M1.

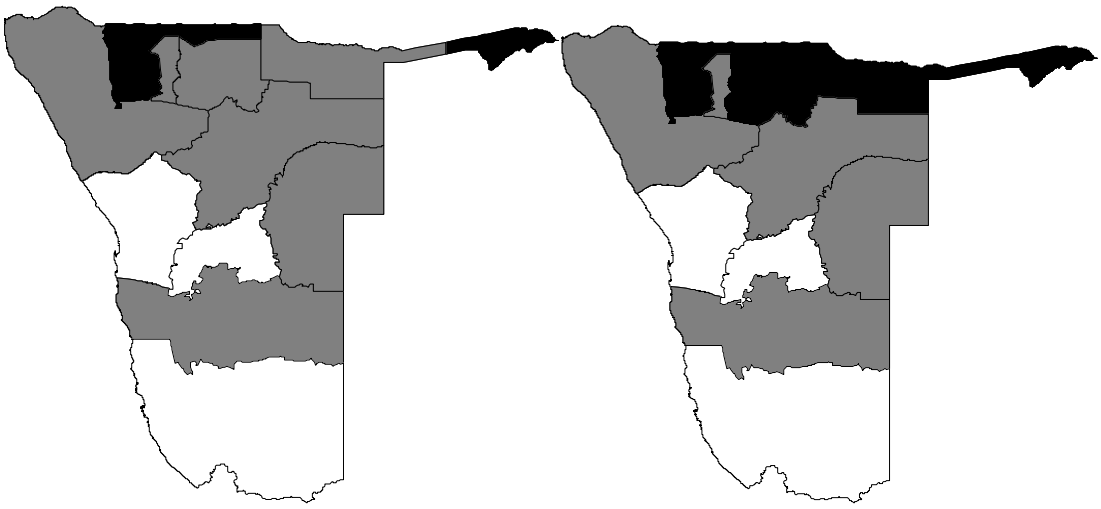

Figure 4.2: Probability maps of total (structured and unstructured) spatial geographical effects of HIV testing at regional level in males (right) and female (left) at nominal level of 95%.

Probability maps helps to identify whether the observed spatial effects are significant. The above figure show clear evidence of significant spatial effects of HIV testing, with higher HIV uptake occurring in Karas, Khomas and Erongo both in men and women. A lower

uptake occurred at Northern parts (Omusati, Ohangwena, and Oshikoto) and Northern-east parts (Kavango and Caprivi) in men. In Women, a lower uptake was observed only in three regions (Caprivi, Omusati and Ohangwena).

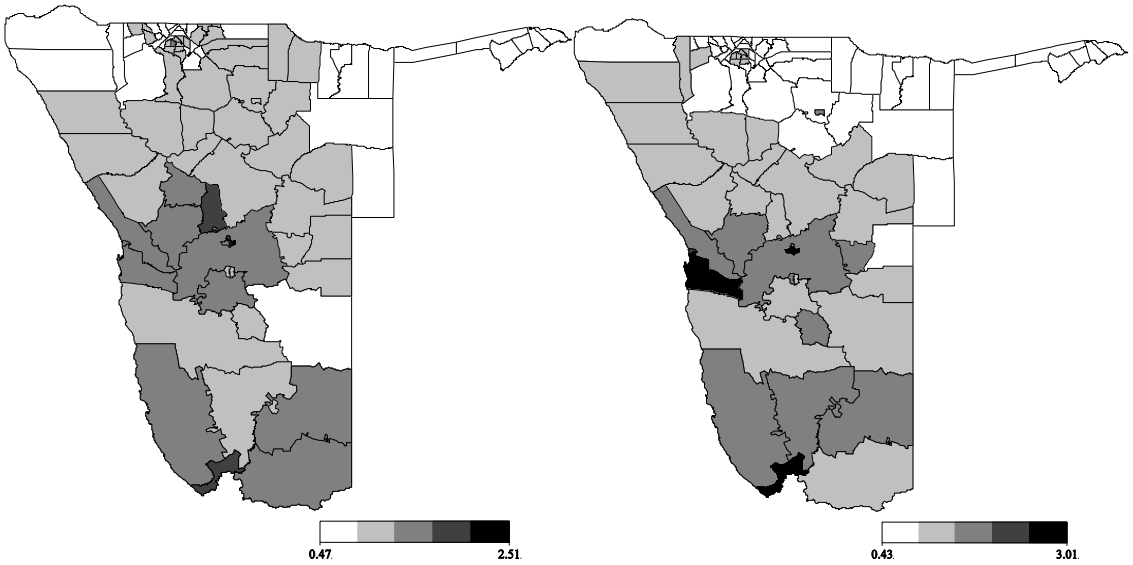

Figure 4.3: Total (structured and unstructured) spatial geographical effects of HIV testing at constituency level in males (right) and female (left) model M0.

Figure 4.3 reflects the same spatial pattern as in Figure 4.1 at constituency level. However, at small area level a clear spatial pattern of HIV testing is observed. For instance, in Kunene region there are two constituencies with a low uptake of HIV testing in females namely; Epupa and Opuwo. In Erongo region, Walvis Bay rural has a very high probability of HIV testing in men as compared to women.

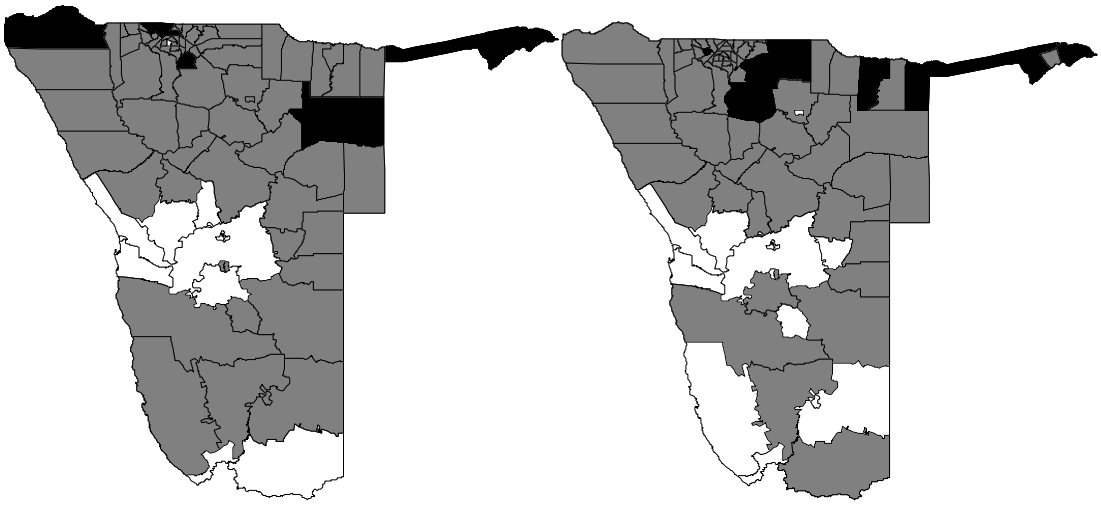

Figure 4.4: Probability maps of total (structured and unstructured) spatial geographical effects of HIV testing at constituency level in males (right) and female (left) at nominal level of 95%.

The figure above shows high significant uptake of HIV testing at the central and southern parts of the country both in men and women. Caprivi remained with a low uptake both in men and women as in Figure 4.2.

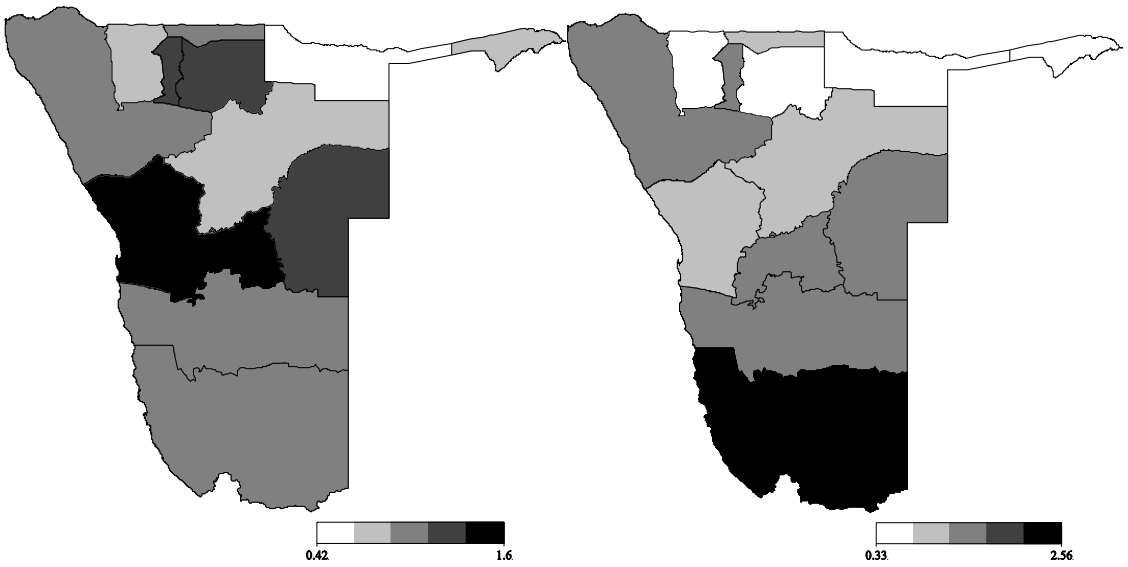

Figure 4.5: Total (structured and unstructured) spatial geographical effects of condom use at regional level in males (right) and female (left) model M1.

Figure 4.5 shows that the use of condom at first sexual intercourse is very high in Karas region among men and very high in Erongo and Khomas among women. Kavango region is the problematic region with regard to condom use among females. Low probability of condom use at first sexual intercourse among males was observed in Caprivi, Kavango, Oshikoto and Omusati.

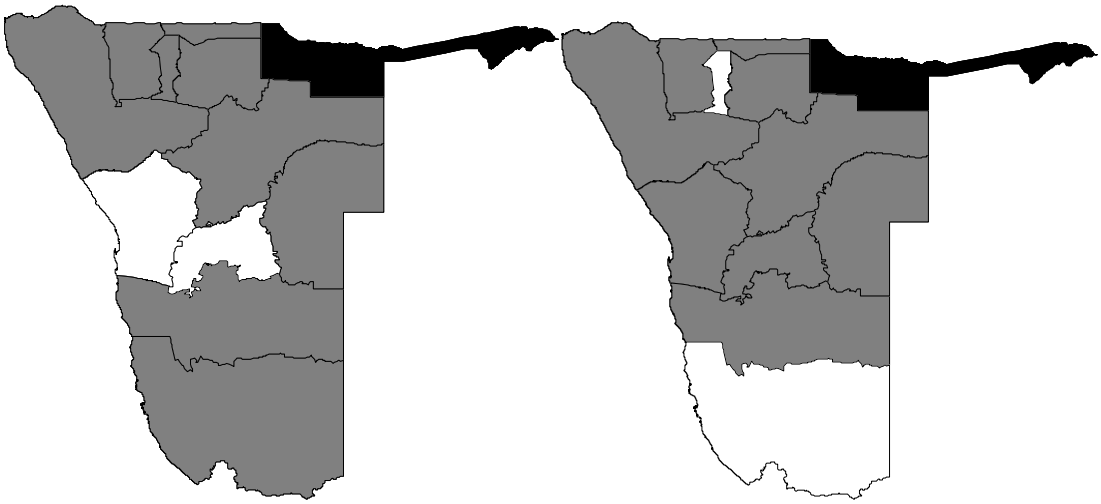

Figure 4.6: Probability maps of total (structured and unstructured) spatial geographical effects of condom use at regional level in males (right) and female (left) at nominal level of 95%.

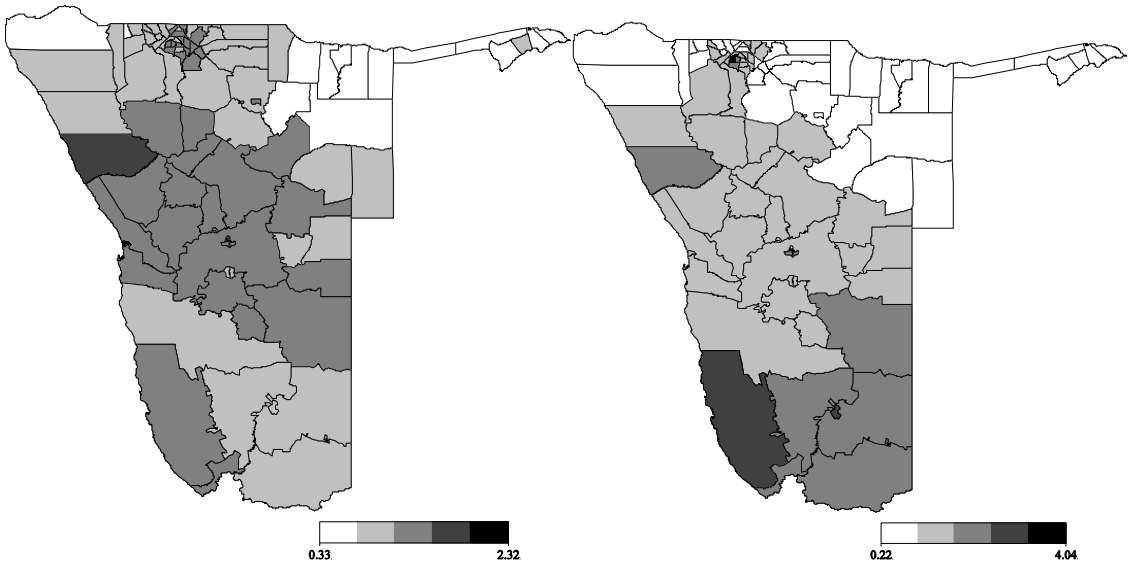

Figure 4.7: Total (structured and unstructured) spatial geographical effects of condom use at constituency level in males (right) and female (left) model M1.

As depicted in the map, high rate of condom use was observed in Kunene among females at Khorixas constituency. Males are more likely to have used a condom at first sexual intercourse in Luderitz as compared to females.

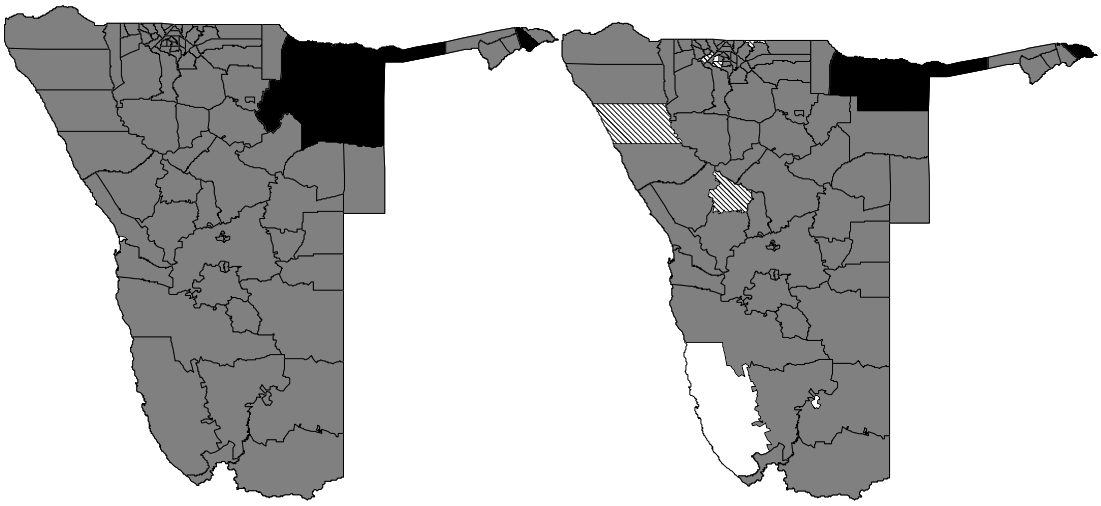

Figure 4.8: Probability maps of total (structured and unstructured) spatial geographical effects of condom use at constituency level in males (right) and female (left) at nominal level of 95%.

4.2.4 Spatial effects with fixed effects results

The following figures in this section compare geographical effects of HIV testing and condom use in males and females both at regional and constituency level accounting for other significant covariates (educational level, type of residence, exposure to media, wealth index, etc.), refer to Table 4.5.

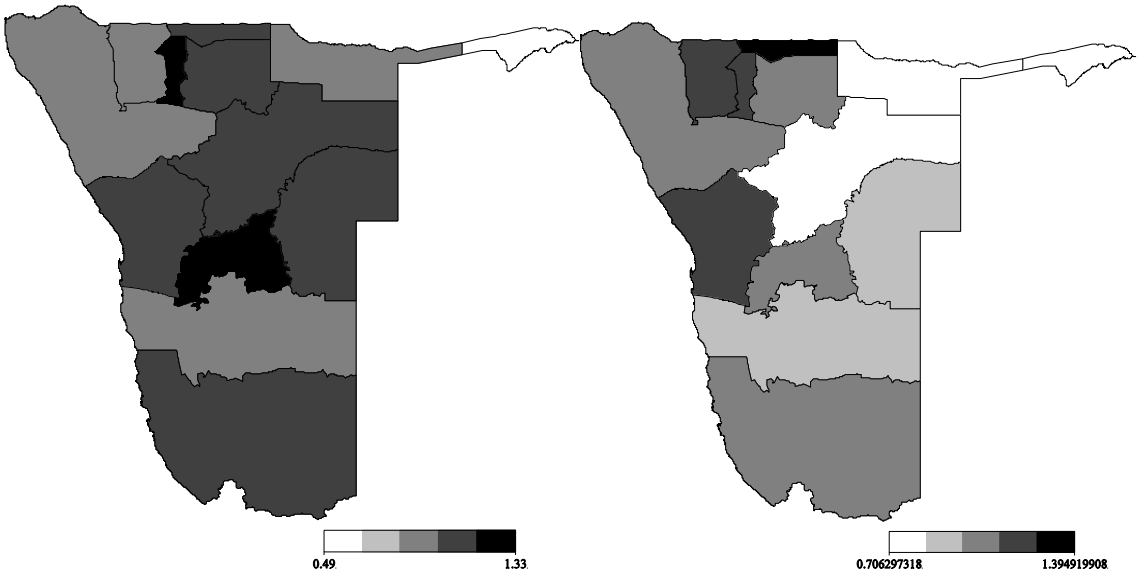

Figure 4.9: Total (structured and unstructured) spatial effects with other significant covariates geographical pattern of HIV testing at regional level in males (right) and female (left) model M7.

Figure 4.9 and 4.10 reflects that with the inclusion of fixed effects, we observe a high uptake of HIV testing among females in Khomas and Oshana region. Caprivi remained with a common low uptake of HIV testing in men and women. In addition to Caprivi, Kavango and Otjozondjupa indicated a very low uptake of HIV testing in males relative to females.

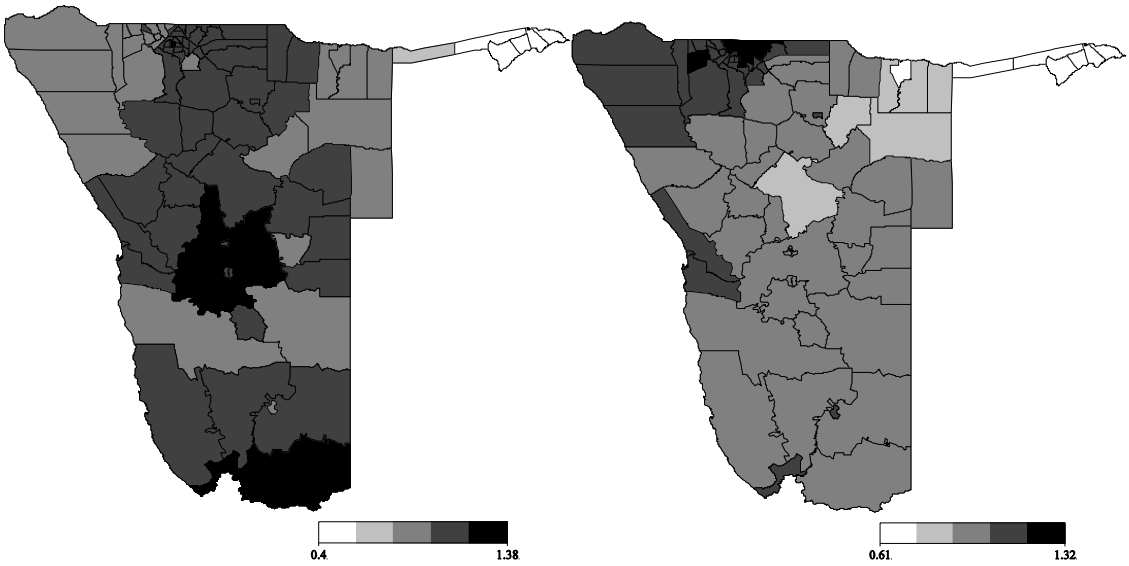

Figure 4.10: Total (structured and unstructured) spatial effects with other significant covariates geographical pattern of HIV testing at constituency level in males (right) and female (left) model M9.

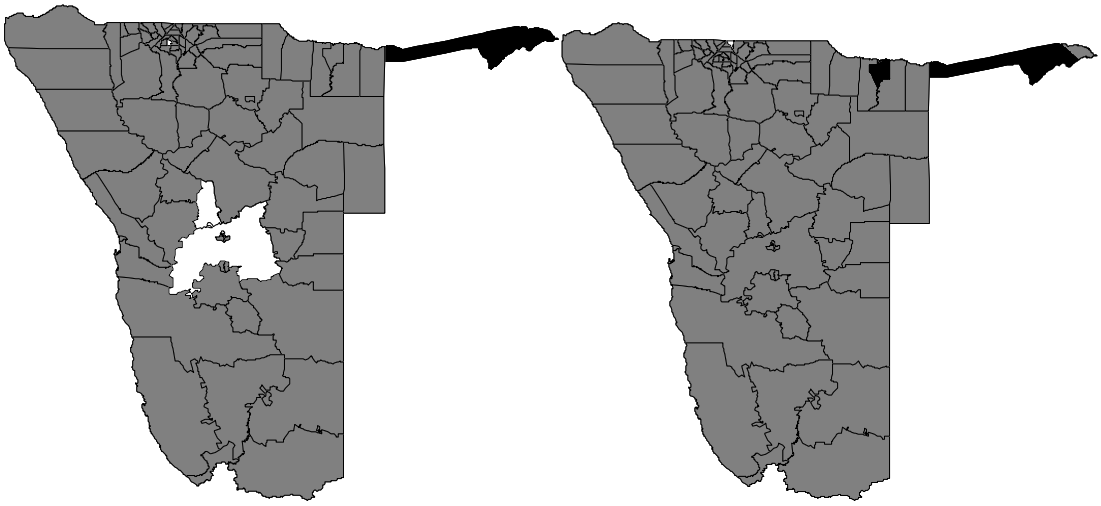

Figure 4.11: Probability maps of total (structured and unstructured) spatial effects with other significant covariates geographical pattern of HIV testing at constituency level in males (right) and female (left) at nominal level of 95%.

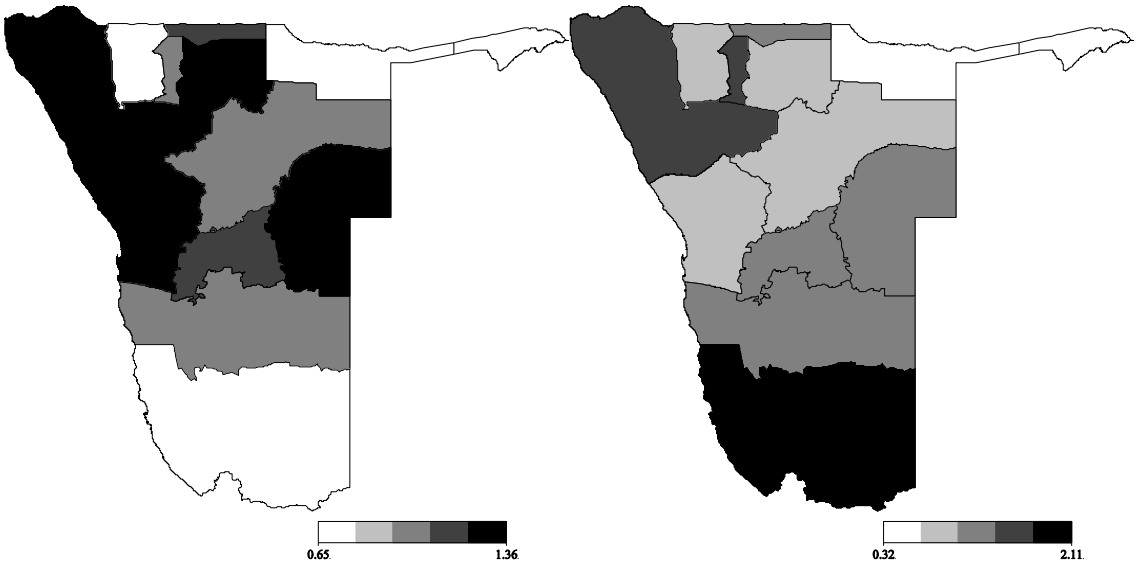

Figure 4.12: Total (structured and unstructured) spatial effects with other significant covariates geographical pattern of condom use at regional level in males (right) and female (left) model M7.

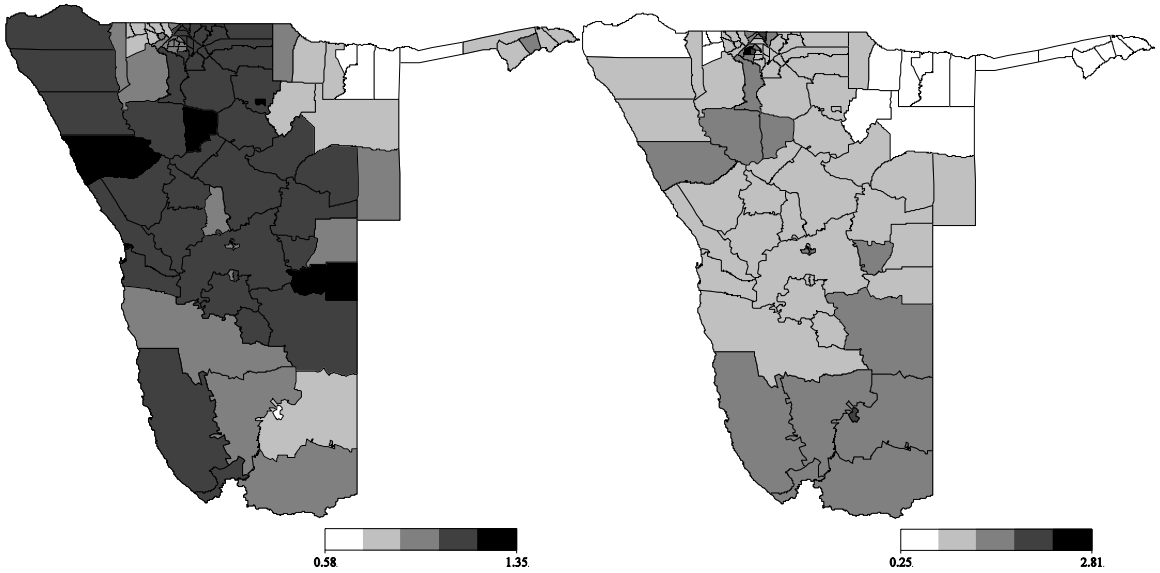

Figure 4.13: Total (structured and unstructured) spatial effects with other significant covariates geographical pattern of condom use at constituency level in males (right) and female (left) model M9.

Figure 4.12 and 4.13 reflects that females were more likely to have used a condom at fist sexual intercourse relative to males in Caprivi region and the most central parts of the country. Moderate pattern was observed in the central parts of the country among males. In Figure 4.12, Karas region has a very low pattern of condom use, however in Figure 4.13 what is very surprising is that most of the constituency in Karas have either a high or moderate condom use pattern except Keetmanshoop rural which have very low pattern.

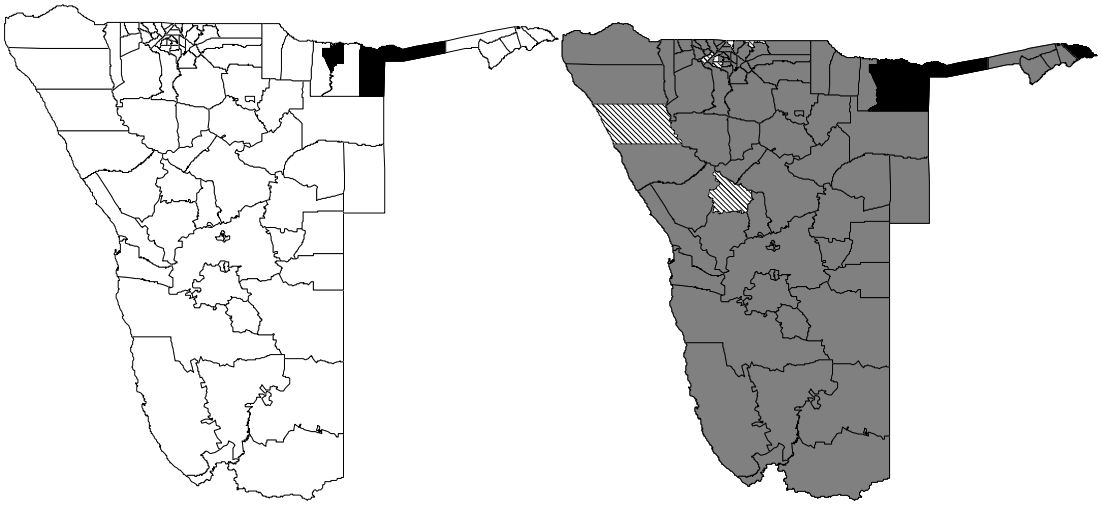

Figure 4.14: Probability maps of total (structured and unstructured) spatial effects with other significant covariates geographical pattern of condom use at constituency level in males (right) and female (left) at nominal level of 95%.

Figure 4.14, shows a high uptake of condom use at first sexual intercourse almost in the whole country among women except in some parts of Kavango region. Among men, there is no significant difference throughout the country except in Kavango and Caprivi where we observe a slightly low uptake.

4.3 Joint Model results

Joint spatial models of HIV testing and condom use for females given the total between men and women in each constituency were fitted to assess common pattern between men and women refer to equation (3.3). The shared spatial (only) component distribution in Figure 4.15 has a larger effect on HIV testing in the Northern to North-Eastern corridor of the country. The shared component distribution also reflects a low-moderate effect on condom use in the Southern parts of the country and a larger effect in the North-Eastern parts. The fixed effects are not shown in this section because the estimates are similar to what has been presented in Table 4.5.

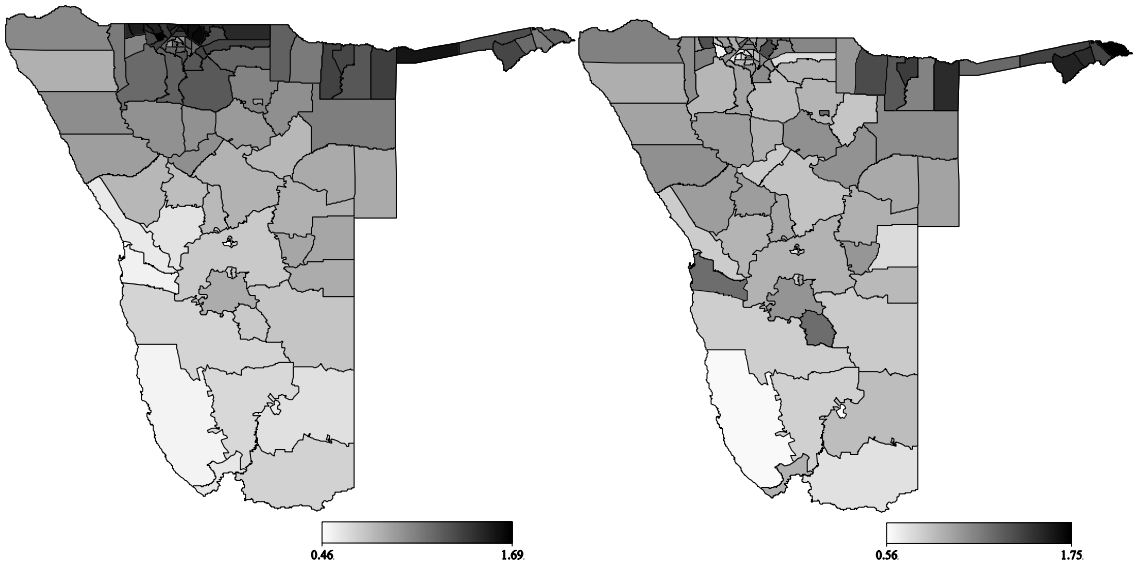

Figure 4.15: Shared structured and unstructured spatial geographical pattern of HIV testing (left) and condom use (right) at constituency level model M1

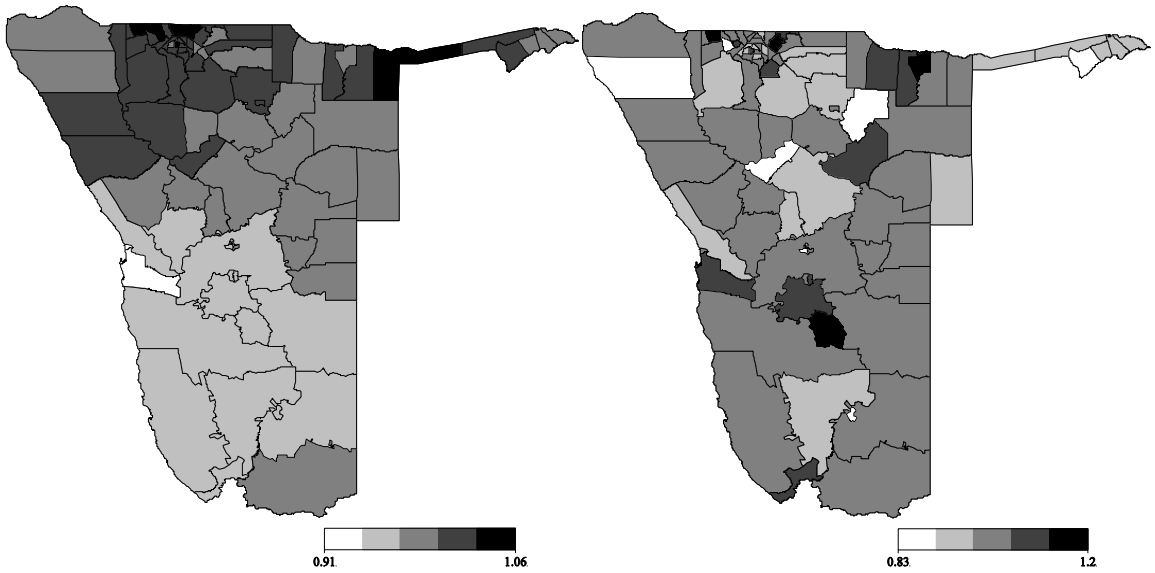

Figure 4.16: Shared structured and unstructured spatial effects with other significant covariates geographical pattern of HIV testing (left) and condom use (right) at constituency level model M12.

After adding other factors in the model (education, urban setting, exposure to media, wealth index, etc.) in figure 4.16, for females as compared to males, the shared component distribution indicated a very low common effect on HIV testing in Walvis Bay rural. The Northern and central parts of the country reflected a larger common effect on HIV testing whereas in the Southern part, only Karasburg had a moderate shared effect on HIV testing relative to the rest with low effects. On condom use, the shared component distribution has a very low effect in six constituencies (Keetmanshop urban, Otjiwarongo, Grootfontein, Opuwo, Linyati and Etayi) relative to the rest of the constituencies in the country.

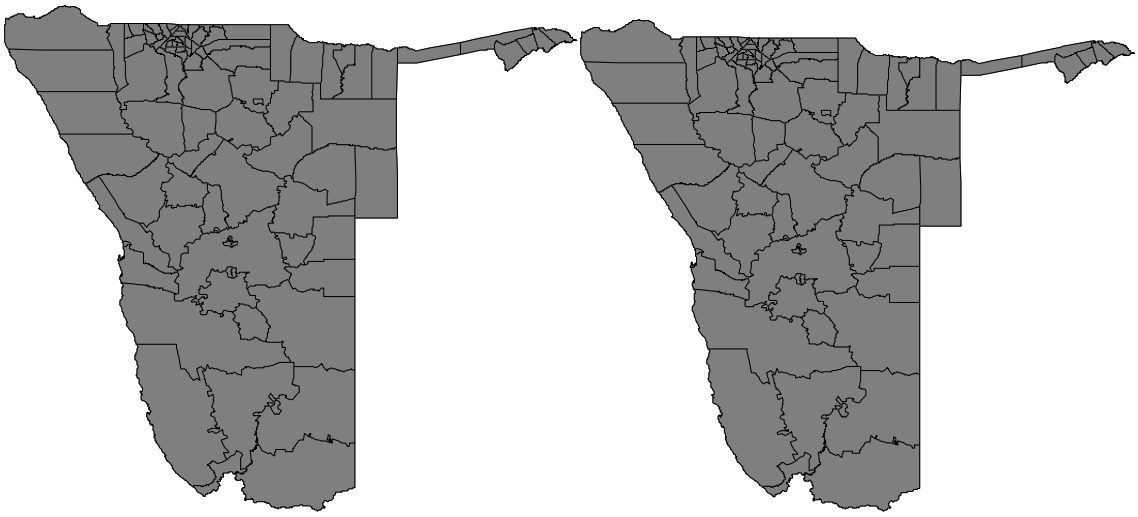

Figure 4.17: Probability maps for shared components models in HIV testing (left) and condom use (right) at nominal level of 95%.

Figure 4.17 shows that there is no significant difference between men and women with regard to HIV testing and condom use in the country. However, this figure may be misleading due to the decreased sample size used in the proportional intensity model.

Chapter 5

Discussion, Conclusion and Recommendations

5.1 Discussion

The uptake of HIV testing and condom use in Namibia has shown gender disparities. Analysis of gender-specific geographical patterns in HIV testing and condom use has not been done in Namibia. This study evaluates the difference between men and women in the same area on the uptake of HIV testing and condom use, in particular estimating specific and shared variation in uptake. The major concern is in the areas where the difference is high.

The study demonstrates the use of STAR and joint modeling approach to develop a multivariate explanatory model for HIV testing and condom use as a tool towards programmatic approaches to combat the spread of AIDS. Logistic regression models were used to help understand the factors associated with the probability of HIV testing and condom use, building on the existing methodological contributions by Gemperli et al. 2004, Kazembe et al. 2010 and Kneib 2005. This study also utilizes a spatial model for joint analysis of HIV testing and condom use in men and women to highlight shared and gender-specific distribution surfaces. The shared terms can be interpreted as surrogate or observable covariate of a latent variable (Kazembe et al. 2009). In joint analysis, the latent components have a direct interpretation in terms of related risk factors which are either shared by either gender or specific to one of the gender. Joint modeling not only achieves a considerable improvement in terms of DIC (Table 4.3 and Table 4.4) but also a gain in precision of the relative risk estimates; this provides strong evidence that a joint modeling approach is a valuable extension of individual analyses (Held et al. 2005). Held et al. 2005 stated that the components in joint analysis are assumed to be independent, and we cannot allow for the

possibility of any interaction between the true, but unobserved covariates. Many risk factors, diseases, utilization patterns or health outcomes might share similar geographical patterns. If so, like it would be the case of gender disparity studies, joint modeling may lead to improved inference by reducing the number of alternative explanations for the observed variability (Best et al. 2005).

The results clearly showed that STAR models quantify HIV testing and the use of condom outcomes effectively as compared to the GLMs. It was also observed that analysis the data at large area-level (region) leads to poor estimation of the health outcome as compared to when it is done at small area-level (constituency). Our results suggest that there are significant differences in the spatial pattern of HIV testing in men and women. Some areas in the central-western and southern parts of the country, were associated with high probability of HIV testing both in men and women, whereas that of the north-eastern part were associated with a low probability of HIV testing when structured and unstructured spatial effects were only considered. Although there is low HIV testing uptake in the north-eastern parts, results indicate a difference between men and women in most parts, with women more likely to have been tested for HIV (Figure 4.3). The high uptake of HIV testing in females may imply that they have better knowledge or they are responsible with their lives and they are more willing to reduce risky sexual behaviors.

On condom use, when considering the structured and unstructured spatial effect only, the study observed that most females in the central and central-western parts of the country were associated with high probability of condom use at their first sexual intercourse as compared to males. However, males in the southern parts of the country were more likely to have used a condom at their first sexual intercourse relative to females (Figure 4.6).

After controlling for other significant covariates, high probability of HIV testing was observed in the central parts of the country in women and in the central-western parts in men. For women, HIV testing was nearly uniform countrywide except in Caprivi region. Low HIV testing uptake was observed in Caprivi, Kavango and Otjozondjupa. It is important to mention that Caprivi has a very low HIV testing uptake both in men and women. This region borders with two countries (Botswana and Zambia) and this may be the reason why it is different from the rest of the regions due to social factors, cultural interaction and other environmental factors.

On the contrary, after controlling for other significant covariates, (provided in Table 4.5), the study observed that females were less likely to have used a condom at fist sexual intercourse relative to males. Moderate pattern was observed in the central parts of the country among males. As shown in Figure 4.12, Karas region has a very low pattern of condom use, however in Figure 4.13 it was very surprising that most of the constituencies in Karas have either a high or moderate condom use pattern except Keetmanshoop rural which has very low pattern.

In this study, joint analysis was only done at small area-level (constituency) and our results indicated a very low common effect on HIV testing in Walvis Bay rural. More revealing pattern were seen when the joint (shared) component model was considered. The Northern and central parts of the country reflected a larger common effect on HIV testing whereas in the Southern parts only Karasburg had a moderate shared effect on HIV testing relative to the rest with low effects. On condom use, the shared component distribution has a very low effect in six constituencies (Keetmanshop urban, Otjiwarongo, Grootfontein, Opuwo, Linyati and Etayi) relative to the rest of the constituencies in the country.

Other than explaining spatial variation, this study also estimated the effect of individual level covariates. Reading newspapers frequently, listening to the radio and watching television

almost every day, number of times away from home, employment status, age at first sexual intercourse, type of place of residence, wealth index, marital status and highest educational level were all found to be associated with HIV testing and condom use in men and women. Some of these findings are similar to what has been reported elsewhere in literature (Leta et al. 2012; Mutale et al. 2010 and Adedimeji et al. 2008).

Men and women who read newspapers, watch television and listen to radio almost every day had a very high chance of being tested for HIV or to have used a condom at their first sexual intercourse. This is likely to be due to the fact that awareness programmes and other related issues on HIV testing and the use of condom are being advertized through the media. The results further indicate that men and women who live in urban areas were more likely to have used condom at their sexual intercourse and also to have been tested for HIV. This is unsurprisingly due to the availability of health services, access to information and improved standard of living in urban areas.

HIV testing and the use of condom is very high among men and women from the highest socio-economic status, as quantified through the wealth index. This is also the same among men and women with higher education. Men and women with higher education are more likely to be from the highest socio-economic status, have access to information and likely to be employed hence it is not surprising that they tend to get tested for HIV more than those with no education at all.

This study had a number of limitations due to the data and the methods used. This study used the 2006/07 Namibia Demographic and Health Survey (NDHS) data. This national survey was not conducted of recent; hence the situation may have changed in the past years.

5.2 Conclusion and recommendations

The study underscore the usefulness of Bayesian semi-parametric regression model and shared component models by highlighting areas lagging behind in the uptake of HIV testing and condom use with emphasis on differences between men and women in the same area. The maps generated increase visibility regarding differentials in HIV testing and condom use as well as risky sexual behaviors in men and women. It was observed that when the analysis is done at large area-level, it may lead to poor estimation of the outcomes. Joint analysis provide more convincing evidence for any real clustering in the underlying risk surface than would be available from the analysis of a single gender. We found that compared with gender-specific modeling approach, the shared component model offered useful additional information when modeling HIV testing and condom use in men and women. The information will be valuable for guiding public health actions that are targeted at the overall reduction of risk-sexual behaviors through HIV testing and the use of condoms. In particular, preventative efforts should be sought to address men and women in Caprivi and Kavango region as well as those in the rural areas.

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