BAYESIAN MULTILEVEL MODEL ON MATERNAL MORTALITY IN ETHIOPIA

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A Thesis Submitted to the Department of Statistics, School of Graduate Studies, College of Natural Science, Jimma University as a Partial Fulfillment for the Requirements for the Degree of Masters of Science in Biostatistics

November 2018

Jimma, Ethiopia

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November 2018

Jimma, Ethiopia

Approval Sheet 1

This is to certify that the thesis titled **" Bayesian Multilevel Model of maternal mortality in Ethiopia"** submitted in partial fulfillment of the requirement for the degree of **Master of Science in Biostatistics** to the college of natural science Jimma University, and is record of original research carried out by **Dabala Jabessa Dugasa, ID.No: RM1218/2009**, under my supervision and no part of the thesis has been submitted for another degree or diploma. The assistance and the help received during the course of this investigation have been duly acknowledged. Therefore, I recommended that would be accepted as fulfilling the thesis requirement.

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Main advisor signature Date

Megersa Tadesse (MSc) -- -------------------------

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As the members of the board of examiners of MSc. thesis open defense examination of **Dabala Jabessa Dugasa**, we certify that we have read and evaluated the thesis and examined the candidate. We recommend that the thesis has been accepted as it fulfills the requirements for the degree of Master of Science in Biostatistics.

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Statement of Author

This thesis has been submitted to the department of statistics at Jimma University in partial fulfillment of the requirements for the Master of Science Degree in Biostatistics. I declare that this thesis has not been submitted to any other institution and anywhere for the award of an academic degree, diploma or certificate.

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Place: Jimma University, Jimma, Ethiopia

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ACKNOWLEDGMENTS

First, and foremost glory to Almighty God for giving me full of health, peace, the opportunity to pursue my graduate study at Jimma University and for being with me in all aspects elsewhere.
I would like gratefully and sincerely to thank my thesis advisor, Akalu Banbeta (Ph.D. scholar), for his invaluable comments, suggestions, and patience during the entire time of the study. I would like to express my heartfelt thanks to my co-advisor, Magarsa Tadesse (MSc) for his encouragement, supervision and constructive comments that develop my research abilities and in improving the quality of the Thesis.

My sincere thanks are due to the Central Statistical Agency of Ethiopia for providing the DHS data. My special appreciation and acknowledgment go to Mettu University for offering me the opportunity and financial support during my study at Jimma University.

Finally, I take this opportunity to sincerely express my gratitude to my Beloved family who are the source of pride and encouragement throughout my life. I am thankful to my mother, Bakashe Beyene, my brother Shibiru Jabessa, and to all my sisters and brothers for their encouragement and pray to the success of this work.

LIST OF ABBREVIATION

AIC:	Akaiken Information Criteria
ANC:	Antenatal Care
BIC:	Bayesian Information Criterion
DHS:	Demographic Health Survey
DIC:	Deviance Information Criteria
EA:	Enumeration Area
EM:	Expectation Maximization
EDHS:	Ethiopian Demographic Health Survey
LB:	Live Birth
MCMC:	Markov Chain Monte Carlo
MDG:	Millennium Development Goal
MMR:	Maternal Mortality Ratio
MoH:	Ministry of Health
OLS:	Ordinary List Square
RELR:	Random Effect Logistic Regression
SDG:	Sustainable Development Goal
UN:	United Nation
UNICEF:	United Nations International Children Emergency Fund
WHO:	World Health Organization

ABSTRACT

Introduction: *Maternal mortality is one of the socio-economic problems and widely considered a serious indicator of the quality of a health. As UNICEF report in 2016 the global MMR declined by 44% during the MDG era, which indicate that, the annual reduction of 2.3% between 1990 and 2015. Maternal mortality is significantly affecting the county of low resources especially sub-Saharan country and the distributions of the death are different from county to country and also from region to region. Ethiopia is considered to be one of the top six sub-Saharan countries with severe maternal mortality. The objective of this study was to investigate the effects of the Demographic and Socio-economic determinant factors of maternal mortality in Ethiopia using Bayesian multilevel model.*

Data and Method: *Data from the 2016 Ethiopia Demographic and Health Survey indicated that the sample of women (15-49) was (n=15683) in Ethiopia. However, due to some women were not eligible under some covariates, the sample size with full information of maternal mortality for all covariates was (n=10103). The Bayesian multilevel Logistic regression model was used to explore the major risk factors and regional variations in maternal mortality in Ethiopia. To determine the posterior marginal, the MCMC methods with non-informative priors have been applied. The DIC model selection criteria were used to select the appropriate model.*

Results: *The analysis result revealed that out of the 10103 number of women's considered in the analysis, 145(1.43%) mothers were died due to pregnancy, while 9958 (98.67%) were not.. Using model selection criteria Bayesian multilevel logistic regression of random coefficient model was found to be appropriate. Thus, with this model, Age of mother, marital status, number of living children, wealth index and Educational level are found to be the significant determinants of maternal mortality in Ethiopia. The study indicated that there was within and between regional variations in maternal mortality.*

Conclusions*: The major significant factors affecting maternal mortality are: mother's education level, wealth index, number of children, marital status and age of mothers. It also revealed that there is a contribution of those major factors to maternal mortality variations among regional states. The Bayesian multilevel random coefficient model is the appropriate model.*

Key words: DHS 2016, Ethiopia, Bayesian Multilevel Logistic Regression Analysis, Random Intercept Logistic Regression Model, Maternal Mortality.

CHAPTER ONE

1 Introduction

1.1 Background of the study

Maternal mortality is the death of a woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental or incidental causes (WHO, UNICEF, UNFPA, 2015). Globally, an estimated 287 000 maternal deaths occurred in 2015, a decline of 47% from levels in 1990. Even if the death of maternal mortality throughout the world was decreased it did not filter down to sub-Saharan Africa, for this reason among others, maternal health deserves attention especially sub-Saharan county because pregnancy involves normal, the life-enhancing process of procreation which carries a high risk of death of women reproductive ages (Gelman, 2006).

The overwhelming majority of maternal deaths occurs in low resource countries and arises from the risks attributable to pregnancy and childbirth as well as from the poor performance of health services. Sub-Saharan Africa (56%) and Southern Asia (29%) accounted for 85% of the global burden (245 000 maternal deaths) in 2010. At the country level, two countries account for a third of global maternal deaths: India at 19% (56 000) and Nigeria at 14% (40 000). The global MMR declined by 44% during the MDG era, representing an average annual reduction of 2.3% between 1990 and 2015. In sub-Saharan Africa, one out of every 13 women dies of pregnancy-related causes during their lifetime as with one in 4,085 women in industrialized countries (McAlister, 2006)

Ethiopia is one of the countries with the most serious problems with maternal mortality from the world. Continuing this, a study developed on individual and community level factors associated with institutional delivery in Ethiopia, by multilevel logistic regression and the researcher categorize as individual and community level. From this study, we suggested that there was a variation within and between the community levels (Mekonnen, 2015).

Sustainable Development Goals is a post Millennium Development Goal agenda by experts in the world which will be implemented within the next 15 years until 2030. It has 17 goals and 169 targets, from this the targets 3.1 is to achieve a reduction of global maternal mortality ratio to less than 70 per 100,000 live births (WHO, 2015). In order to achieve the SDG target of 70 per 100 000 live births by 2030, the global annual rate of reduction will need to be at least 7.3%. Maternal mortality is a key factor strongly connected with well-being of population and take as indicator of health development and socioeconomic status. That is why reduction of maternal and child mortality is a worldwide target and one of the most important key indicators of the sustainable development goals (United Nations, 2016).

The classical model is naturally less accurate than the Bayesian approach models since all information in the classical has been obtained from likelihood only where in the Bayesian approach it was the integration of prior information and that of likelihood. Thus, to address the gaps with those previous studies, the hierarchical level of logistic regression with the Bayesian setting was fitted with this study (Ntoimo, 2018).

Ethiopia, a country with more than 90 million people living in a geographically diverse environment (1,104,300 square kilometers of land area ranging from high peaks of 4,550m above sea level to a low depression of 110m below sea level) carries a high burden of maternal ill health and is one of top six countries that contribute to about 50% of maternal mortality; the others being India, Nigeria, Pakistan, Afghanistan and Democratic Republic of Cong. (WHO, et al, 2015). According to the global estimates for “trends in Maternal Mortality”, the MMR for Ethiopia reduced from 43,300 to 13,000 from 1990 to 2013 indicating a reduction by 38% and with 4% contribution to the overall global maternal death (WHO, 2013) The inference is made based on the posterior of the parameter which results from the combination of the information in likelihood and the information from previous studies or personal experience of the researcher known as the prior distribution and in this case posterior distribution has no closed form, then by applying different method of simulation like Markov chain Monte Carlo (MCMC) for any sample size and obtain accurate estimates of parameters (Larget, 1999).

1.2 Statements of the problem

It is clear that women play a principal role in the rearing of children and the management of family affairs, and their loss from maternity-related causes is a significant social and personal tragedy. Understanding the significant variable for maternal mortality is necessary to inform governmental and non-governmental public health police and to design strategies that made reduction of maternal mortality. Particularly in sub-Saharan countries maternal mortality is one of the most serious socioeconomic measurements. Maternal mortality in Ethiopia is also one of the serious socioeconomic problems from the world and the challenging problem that we need to address.

Many demographers and scholars believe and recommend the need to conduct in-depth studies on the various aspects of maternal mortality causes and factors in different demographic, economic and socio-cultural settings. So far, there are no such detailed studies conducted to explore all aspects of maternal mortality in Ethiopia particularly the effects of socio-economic factors, regional variation, and factors that contribute for a regional variation on maternal mortality using Bayesian multilevel logistic regression model.

The classical multilevel logistic regression treats the unknown parameters as fixed constants for a fixed effect and treats as random for random effect without any distribution; while the Bayesian approach treats them as random variables, which means that the parameters can vary according to a probability distribution (prior distribution). This variation can be regarded as purely stochastic for a data-driven model, but it can also be interpreted as beliefs of uncertainty under the Bayesian approach (Kynn, 2005).

Hence, the studies were addressed the following basic research questions:

1. Which variables are significant impacts on maternal mortality from the study variables?
2. Are there the variations of maternal mortality within and between the Regional States of Ethiopia?
3. From the study variables which predictors have variation across regions?

1.3 Objectives of the study

1.3.1 General objectives

The general objective of this study is to identify and explain the effects of the Demographic and Socio-economic factors of maternal mortality in Ethiopia using Bayesian multilevel model.

1.3.2 Specific objectives

1. To identify the significant impact associated with maternal mortality in Ethiopia
2. To examine the extent of the within and between regional variations of maternal mortality in Ethiopia.
3. To determine from the study variables, the variation of predictors across regions.

1.4 The significance of the study

Despite the amount of work published on the topic as well as policies and initiatives being adopted in an effort to reduce maternal deaths, it continues to occur at high rates and solutions to the problem are still not clear and previous study was identify some variable for the cause and risk at specific level like hospital or district however these only present the level of maternal mortality at individual level not at national level. This study is therefore unique as it attempts to combine information on maternal deaths recorded from a facility-based review conducted in 9 regions and two administrative cities of the country. The purpose of this study was identifying the major contributing socio-economic and demographic risk factors that can determine maternal mortality and the factors that cause variations of maternal mortality in regional states of Ethiopia. Understanding the different factors that can determine maternal mortality and variations of maternal mortality provides basic information to policy makers and researchers for further studies on maternal mortality. This research again fills the statistical analysis by adopting an appropriate method which is hierarchical by its nature. In general; this research has a significant role for our country to identify the most serious determinants of maternal mortality using a Bayesian multilevel logistic regression model that will help to take action on those identified determinants. Finally, this study would stimulate further research in the application of the Bayesian multilevel model in the area of maternal health and mortality.

CHAPTER TWO

2 Literature Review

2.1 Global estimates of maternal mortality

The World Health Organization WHO (2005) estimates that 536,000 maternal deaths occur worldwide each year from complications arising from pregnancy, and a high proportion of these deaths occur in sub-Saharan Africa. Developing countries accounted for 99% (533,000) of the deaths. Slightly more than half of the maternal deaths (270,000) occurred in the sub-Saharan Africa region alone, followed by South Asia (188,000). (Hill, 2007)

Most of the studies were based on logistic regression which actually cannot be empowered to answer whether there were geographical variations or not. This study was intended to fill the gap on this regards by considering the random effects under the multilevel model of the Bayesian paradigm. Besides, the other studies were conducted at hospital level with very limited covariates; and based on the classical models that have the relative drawback. Thus, with this study, the authors have addressed all those gaps by fitting different multilevel models (Grzenda, 2015), (Acquah H. D., 2013)

2.2 Demographic, Socio-economic and environmental characteristics of maternal deaths

Different studies indicate that demographic, socio-economic and environmental characteristic variables have been identified to influence for maternal mortality. The following variables are some of them which were applied under this stud regarding with previous different studies.

Age of mother at birth's: Pregnancy is a leading cause of death for young women aged 15 to 19 worldwide, with complications of childbirth and unsafe abortion being the major factors (Guerra-reyes, 2013). Other studies conducted in Rural Tanzania case of Rufiji Health and Demographic Surveillance Site (HDSS**)** suggest as Women 40 years and older experienced a protective effect in that they were 18% less likely to experience a maternal death compared to those less than 20years (Mbaruku, 2013). Under this studies mother's aged between 30-39 years was the highest risk of maternal death (154% more likely to experience maternal death as compared to those women less than 20 years) (Geubbels, 2015), But contradicting this idea the pregnancy-related mortality rate is highest among women in the 30-34 age group (1.10), followed by women in the 40-44 age group (0.78), Therefore this study is proposed to identify which mother's age is most significant for maternal mortality. In another case, early marriage age is dangerous to the health status of women (Asu, 2013).

Place of residence: Unlike urban communities, rural communities are at high risk of having home births, which is similar to findings in other studies; the nature of urban and rural areas explains this discrepancy. Urban areas are accessible to health facilities, with a higher proportion of informed and educated people, and better infrastructure (Bicego, 2002). When a woman experiences a complication during pregnancy, she needs immediate medical care. However, families living in these remote communities have a long journey to these medical centers and cannot bring these mothers to the clinics in time, this show as the majority of maternal mortality occurs in rural communities in developing countries (Dahiru, 2015). Women living in rural areas experience higher maternal mortality than women living in urban (Liu, 2011).

Multivariate logistic regression on maternal health care utilization factor studied in India suggested as rural women were less likely to autonomous as compared to their urban counterparts and also rural women with no education were less likely to receive antenatal care from a health professional. Women education has a positive and significant effect on the place of delivery at the time of childbirth (Navaneetham K. &., 2002; Asamoah, 2011).

Place of Delivery: Globally, among 132,352,900 births, it is estimated that 34% of mothers deliver with no skilled attendant; this means there are 45 million births at home without skilled health personnel each year. Skilled attendants assist in more than 99% of births in developed countries compared with 62% in developing countries. Globally, the goal is to have 80% of all births assisted by skilled attendants by 2005, 85% by 2010 and 90% by 2015 (Shah, 2007). In Ethiopia, as the majority of deliveries and maternal deaths occur at home (estimated at around 90% in 2011 (CSA, 2011). Despite the fact that using maternal health care services is essential for further improvement of maternal and child health, little is known about the current magnitude of use of and access to maternal care service. Access to proper medical attention and hygienic conditions during delivery can reduce the risk of complications and infections that may lead to death or serious illness for the mother and/or baby (Melaku, 2014)

Marital status: Marital status is the factors that were found to be associated with increased risk of maternal death. Marital status information showed that women who had ever been married had a protective effect of 62% compared to women who had never been married (Mbaruku, 2013) and additional study in Women who were not living together with their partners had a significantly high risk of maternal mortality as compared to those living together with partners. Additionally, the previous study which was conducted in rural Tanzania suggested by survival model with univariate Cox proportional regression model maternal age and marital status was significantly associated with maternal mortality (Illah, 2010.).

Number of living children: High-fertility setting a woman faces the risk of maternal death multiple times, and her lifetime risk of death will be higher than in a low-fertility setting. Family size is the determinant of maternal mortality in some findings. The number of times a woman had given birth; also tends to increase the risk of dying due to the material cause. This was confirmed by a study conducted in rural Guinea-Bissau, where they found a positive relationship between maternal death and number of living children, especially in the presence of pathogenic factors (Hedegaard, 2002). Another finding conducted in Nigeria said that number of living children is one of the variables that clearly emerged as one of the strong contributors to maternal mortality. Many researchers reported high levels of maternal deaths among having many children. As the researcher found that as the number of child birth increase the probability of maternal death was also increased (Abe E, 2008).

Wealth index: family income was one of the most important determinants of the standard of living, economic and social welfare. As studies developed on the risk factor that determines maternal mortality in the rural Tanzania status of women by linking poverty and maternal deaths have indicated that with increasing poverty, the proportion of women dying of non-maternal causes generally increased, and the proportion dying of maternal causes increased consistently. This is because the social status of women in developing countries limits their access to basic education or economic resources, which in turn affects their ability to make decisions related to their health (Guerra-reyes, 2013).

The study conducted on Determinants of maternal mortality in the Eastern Mediterranean region using the econometric model and the authors suggest that income is one of the significant factors for maternal mortality. Under this investigation, the findings obtained from evaluating the model showed a negative significant relationship between Gross Domestic Products, female literacy rate, skilled birth attendance and maternal mortality (Bayati, 2016)

Source of drinking water: The lack of access to clean water and basic sanitation may contribute to increased maternal and neonatal mortality at different points. One of the point raised here is it may affect the health of the woman and the fetus during the pregnancy. When a pregnant woman drinks polluted water, she is exposed to a host of bacterial, viral, and parasitic infections (Sommer, 2015). In many instances, women contract various diarrheal diseases including dysentery, cholera, or typhoid. These diseases may directly kill a woman or weaken her immune system, which leads to complications during birth (Jamie M. Sommer, 2015). Certain diseases, like Hepatitis, are more commonly transmitted when a community lacks access to basic sanitation facilities. Such waterborne diseases tend to have more severe consequences for pregnant women than for the broader population (Cheng, 2012).

Level of Education of Mother's: Mothers' educational level is an important factor influencing an individual's attitudes and opportunities and a significant determination of maternal mortality. Education for girls is a key to reducing maternal mortality. The risk of maternal death is 2.7 times higher among women with no education, and two times higher among women with one to six years of education than for women with more than 12 years of education (Jat, 2011). According to studies in Nigeria increasing level of education decrease maternal mortality and the studies suggested as illiterate women were associated with very high maternal mortality ratio (Dahiru, 2015).

Another study developed on Multivariate logistic regression on maternal health care utilization factor studied in India suggested as Women whose educational level was secondary/higher had higher odds of institutional delivery when compared to those with no education (OR=3.55 for rural sample and OR=4.28 for total sample). This indicates that education is also a significant factor in maternal mortality (Navaneetham K. &., 2002).

Contraceptive use: It is widely recognized that family planning contributes to reducing maternal mortality by reducing the number of births and, thus, the number of times a woman is exposed to the risk of mortality (Ahmed, 2012). Increases in the use of modern contraceptives have made and can continue to make an important contribution to reducing maternal mortality in the developing world. This show as the reduction in at-risk births brought about by contraceptive use leads to lower levels of the MMR. The use of contraceptives reduces unwanted pregnancies, lower rates of abortion, decreases the rate of baby dumping and reduces the risk of premature deaths. Those are some of the benefits and roles of family planning in improving maternal health (MoHSS, 2009). The same study found that contraceptive use is effective for the primary prevention of maternal mortality in developing countries by about 44%. (Ahmed, 2012).

Regions: Pregnancy-related complication in different continent, countries, and region are different. The World Health Statistics 2013 also showed that the MMR in some high-income countries ranges from 3–5/100,000 live births. As a result, the mean MMRs of countries with low income, lower middle income, upper middle income, and high-income groups were 410, 260, 53, and 14/100,000 live births, respectively. It was also reported that more than 50% of all maternal deaths worldwide occurred in three Asian (India, Pakistan, Afghanistan) and three African (Nigeria, Ethiopia, and the Democratic Republic of Congo) countries. This shows income has one of an impact that accounted for maternal mortality variation with different continent or countries (Berhan, 2014).

Ethiopia is a diverse country and maternal mortality is not evenly distributed throughout the country. Regional disparities in maternal mortalities are associated with factors at the community level that distinguish these regions from each other. The availability of services and social amenities in communities, or the lack of infrastructure, may positively or negatively influence the health of the residents of communities. Some of these factors include differences in community-level development, population density, the prevalence of poverty, and the availability of maternal and child health care services. The study developed on trends in maternal mortality in Ethiopia by using logistic regression shows the odds of being exposed to high-risk pregnancy estimated to be higher among women in Somali and Afar regions compared to those in Addis Ababa. Women in Somali were 37% more likely than those in Addis Ababa to have had high-risk pregnancy; this was nearly 50% higher in Afar. From regional and city two city administrations of Ethiopia, women in Addis Ababa had the lowest exposure to high-risk pregnancy. As this study shows both women’s income and education emerged among the most important predictors of women's exposure to high-risk pregnancy (UNFPA, 2012).

Antenatal Care: Antenatal care (ANC) from a skilled provider is important to monitor pregnancy and reduce morbidity and mortality risks for the mother and child during pregnancy, delivery, and the postnatal period (within 42 days after delivery). Women who used a skilled provider for ANC services and who had four or more ANC visits for their most recent birth in the five years preceding the survey increases greatly with women's education. This indicates that there is a positive association between antenatal care and level of education. The most recent studies about maternal mortality in Nigeria shows antenatal care visit is significantly related to maternal mortality (Omo-Aghoja, 2008). Maternal mortality decreases with an increase in the number of antenatal visits. The researcher applied logistic regression and analysis as the odds of the mother with four or more visits reduce the risk of maternal mortality by 99.7% compared to odds of mothers with no visit. The study indicated that the likelihood of mothers experiencing maternal mortality reduces with the number of visits (Yaya, 2015).

2.3 Why Bayesian Multilevel Logistic Regression Model?

The Bayesian method is particularly effective in the presence of data measurements in contrast to other methods. It's taking into account both the information provided by the observations and knowledge available to the experimenter. The approach is presented as a method of estimating random models and requires the calculation of estimators from a posteriori probability distribution generally very complicated. To solve a variety of "unsolvable" problems in Bayesian inference we used the Markov Chain Monte Carlo approach (Mira, 2005.).

Multilevel models also allow us to study the effect that varies by entity (group) and also estimate group-level averages. The analysis of structure datasets is collected with an inherent multilevel or hierarchical or nested structure. The multilevel model provides a coherent model that simultaneously incorporates both individuals- and group-level models as well as getting the right standard error (Gelman, 2006). If multilevel analyzing data corresponding to individuals nested within groups are correlated, the assumption of independence of observations is violated, resulting in incorrect standard errors and inefficient estimates. Additionally, none independence of observation within a group was accounted; that is why we are interested in Bayesian.

The study conducted to provide knowledge on risk factors for TB in South Africa, using both the classical approach and Bayesian approach; as the authors suggested, the results from Bayesian approach were different from that of classical statistics. The Bayesian models are given preference because the technique is more robust and precise than the traditional (classical) statistics. Bayesian approach is usually criticized based on the prior included in the model which add strengthen the quality of outputs; therefore they concluded that Bayesian methods provide a more precise and powerful result. (Ojo OB, 2017).

The study developed on Malignant Breast Cancer in Nigeria by comparing the classical approach and Bayesian approach to identify the profile of patients living with benign and malignant breast cancer. As the author comparison between Bayesian approach and classical approach results indicated a reduction of standard errors is associated with the coefficients obtained from the Bayesian approach and also the simulation results and application of Bayesian produces precise estimates and more robust compared to the classical (Ogunsakin, 2017).

The Bayesian estimation is flexible and does not require compliance with demanding assumptions as suggested in the maximum likelihood estimation or as in classical techniques which is hard to estimate ranking probabilities and assess the statistical uncertainty of rankings (Acquah H. D., 2013). In Bayesian methods, the inference is made based on the posterior distribution of the parameters, which results from the combination of the information in observed data and the information from previous studies or personal experience of the researcher known as the prior distribution. In case the posterior distribution does not have a closed form, one can apply the Markov Chain Monte Carlo (MCMC) simulation methods for any sample size and obtain accurate estimates of parameters (Browne, 2006). The progress in MCMC methods has made it possible to fit various nonlinear regression models (Acquah H. D., 2013).

CHAPTER THREE

3 Methodology

3.1 Description of the Study Area

Ethiopia is officially known as the Federal Democratic Republic of Ethiopia, is a landlocked country located in the Horn of Africa. It is the second-most populous nation in Africa, with over 102,403,196 populations according to the united nation estimate of 2016 and the tenth largest by area, occupying 1,100,000 km2. Ethiopia is bordered by Eritrea to the North, Djibouti, and Somalia to the East Sudan and South Sudan to the West, and Kenya to the South. Ethiopia has eleven geographic or administrative regions: nine regional states (Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, SNNPR, and Harari) and two city administrations (Addis Ababa and Dire Dawa that are considered as the region) with a capital city of Addis Ababa. Administratively, each of the 11 geographic regions in Ethiopia is divided into zones and each zone is divided into lower administrative units called woredas. Each woreda is then further subdivided into the lowest administrative unit, called a kebele.

3.2 Source of Data

The data used for this study is 2016 Ethiopia Demographic and Health Survey (2016 EDHS). The data was implemented by the Central Statistical Agency (CSA) at the request of the Ministry of Health (MoH) and Data collection took place from January 18, 2016, to June 27, 2016 with national representative of 18,008 households were selected based on a nationally representative sample that provides estimates at the national and regional levels and for urban and rural areas.
The Woman's Questionnaire from 15683 was used to collect information from all women age 15-49 from the selected households. Since the data of EDHS has many missed cases across some variables, after clearing those missing values, a total of the sample of 10103 women between the ages of 15-49 years in Ethiopia was included in this study.

Administratively, Ethiopia is divided into nine geographical regions and two administrative cities. Each region in Ethiopia is divided into zones, and zones, into administrative units called weredas. Each wereda is further subdivided into the lowest administrative unit, called kebele.

During the 2007 census, each kebele was subdivided into census enumeration areas (EAs), which were convenient for the implementation of the census. The 2016 EDHS samples were selected using a stratified, two-stage cluster design and EAs were the sampling units for the first stage. The sample for the 2016 EDHS was designed to provide estimates of key indicators for the country as a whole, for urban and rural areas separately, and for each of the nine regions and the two administrative cities. The 2016 EDHS sample was stratified and selected in two stages. Each region was stratified into urban and rural areas, yielding 21 sampling strata. Samples of EAs were selected independently in each stratum in two stages. Implicit stratification and proportional allocation were achieved at each of the lower administrative levels by sorting the sampling frame within each sampling stratum before sample selection, according to administrative units in different levels, and by using a probability proportional to size selection at the first stage of sampling. For the first stage, the 2016 EDHS sample included 645 EAs (202 EAs in urban areas and 443 EAs in rural areas), were selected with probability proportional to the EA size (based on the 2007 PHC) and with independent selection in each sampling stratum. In the second stage of selection, a fixed number of 28 households per cluster were selected with an equal probability systematic selection from the newly created household listing. All women age 15-49 and all men age 15-59 who were either permanent residents of the selected households or visitors who stayed in the household the night before the survey were eligible to be interviewed (CSA, 2016).

3.3 Variable of study

Depending on the demonstrated related literature reviews the variables included in this study are listed as follows. As discussed in the literature review socio-economic, demographic and environmental characteristics are to be the essential and proximate determinants of maternal mortality at a worldwide and national level as well. In this study, the potential determinant factors expected to be correlated with pregnancy-related death are included as variables. This variable was

Response variable: The response variable in this study is the survival status of mothers at a reproductive age and this variable is dichotomous, coded as 1 if death due to pregnancy has occurred and 0 otherwise,

$$Y_{ij}=\begin{cases} 1 \text{ if the i}^{\text{th}} \text{ women are dying in the } \text{j}^{\text{th}} \text{ region} \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases} \text{------------------------------ (3.1)}$$

with i=1, 2, 3,…, M and j=1, 2, 3, …, N.

Where: M-is the number of women under reproductive age in each region j.
N-is the number of regions.

Let denote the proportion of success (maternal mortality):

$$\mathrm{P}\left(Y_{ij} = 1\right)=\pi_{ij}, P\left(Y_{ij=0}\right)=1 - \pi_{ij} \text{ -------------------------------------- (3.2)}$$

And $Y_i \sim Bernoulli(\pi_i)$

Independent (or Explanatory) variables: Many explanatory variables were used as predictors of maternal mortality. The explanatory variables that included in this study were a place of delivery, Antenatal care, Mother's age at birth, Place of residence, Region, mothers education, Marital status, Wealth index, Contraceptive, number of living children, source of drinking water. Different authors use different variable according to the area of their study, therefore these study was also developed by taking different variables regarding on different study (Omo-Aghoja, 2008), (Ahmed, 2012), (Navaneetham K. &., 2002), (Jamie M. Sommer, 2015), (Bayati, 2016), (Liu, 2011).

Table 3-1 Covariates/explanatory variables with their coding

No	Variables	Categories
1	Region	1= Tigray 2= Afar 3= Amhara 4= Oromia 5= Somalia 6= Benshangul gumuz 7= SNNP 8= Harari 9= Gambella 10= Addis Ababa

		11= Dire Dawa
2	Place of residence	0= Urban 1= Rural
3	Place of delivery	0= Home 1= Health facilities
4	Age of mother	0= 15-19 1= 20-24 2= 25-29 3= 30-34 4= 35-39 5= 40-44 6= 45-49
5	Educational level	0= Not educated 1= Primary 2= Secondary and above
6	Wealth index	0= Poor 1= Middle 2= Rich
7	Contraceptive	0= Not use 1= Use
8	Source of drinking water	0= Piped 1= Tubewell 2= Surface and other
9	Number of living children	0= No child 1= 1-2 child 2= 3-4 child 3= 5+ child
10	Current marital status	0= Not married 1= Married 2= Separated/living with the partner

		3= widowed/divorced
11	Number of antenatal visits	0= No antenatal visit 1= 1-2 Visit 2= 3-4 Visit 3= 5+ Visit
12	Mother status	0= otherwise 1= Death related to pregnancy

3.4 Method of Data Analysis

The statistical model that used for this data to analysis was the Bayesian multilevel logistic model. The data collection procedure is the hierarchical level or structures that means the levels are nested one another; Thus why the reason for selecting this model. MLwiN 2.02 version software was adopted for the analysis of this study.

3.4.1 Multilevel Logistic Regression Model

The main statistical model of multilevel analysis is the hierarchical generalized linear model, an extension of the generalized linear model that includes nested random coefficients. Multilevel hierarchical modeling explicitly accounts for the clustering of the units of analysis, individuals nested within groups. Such data structures are viewed as a multistage sample from a hierarchical population. Multilevel analysis is a methodology for the analysis of data. The multilevel logistic regression analysis considers the variations due to the hierarchy structure in the data. Hence, the study helps for examination of the effects of group level and individual level variation- of observations.

Multilevel models are statistical models which allow not only independent variable at any level of a hierarchical structure but also at least one random effect above level one group. A multilevel logistic regression model can account for lack of independence across levels of nested data (i.e., individuals nested within regions). For simplicity of presentation two-level models for this study, i.e., models accounting for women-level and regional -level effects.

In this data structure, level-1 is the women level and level-2 is the regional level. Within each level-2 unit, there is n_j in the j^{th} region.

We further simplify the presentation by assuming there is a women-level predictor and regional level factor of maternal mortality. To provide a familiar starting point, we will first consider a two-level model for binary Outcomes with a single explanatory variable. Suppose we have data consisting of women, (level one) grouped into regions (level two). Let Yij be the binary response for maternal mortality among i[th] women in region j and Xij be an explanatory variable at the women level. We define the probability of the response equal to one πij = p(yij = 1).

Where; πij be modeled using a logit link function. The standard assumption is that Yij has a Bernoulli distribution. Then, the two-level models are given by

logit(π_{ij}) = log$\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right]$ = $\beta_{0j} + \sum_{h=1}^{k} \beta_{hj} x_{ijk}$ -- (3.3)

i = 1, 2… n_j, h = 1; 2… k, j = 1, 2… 11

$\beta_{0j} = \beta_0 + U_{oj}, \beta_{1j} = \beta_1 + U_{1j}, \dots, \beta_{kj} = \beta_k + U_{kj}$

logit(π_{ij}) = log$\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right]$ = $\beta_0 + \sum_{h=1}^{k} \beta_{hj} x_{ijk}$ -- (3.4)

X_i= $(X_{1ij}, X_{2ij}, \dots, X_{kij})$ represent the first and the second level covariates, for variable k

$(\beta = \beta_0, \beta_1, \dots, \beta_k)$ are the regression parameter coefficient. $U_{0j}, U_{1j}, \dots, U_{kj}$ is the random effect of the model parameter at level two. With the assumption, U_{hj} follows a normal distribution with mean zero and variance σ_u^2.

Without U_{hj} the above equation can be the single-level logistic regression. That means the 1[st] equation is the single level logistic model and the 2[nd] equation is two levels model. Therefore conditional on U_{0j}, U_{1j}, U_{kj}, the y_{ij} can be assumed to be independently distributed as Bernoulli random variables.

3.4.1.1 Bayesian Multilevel Analysis of Empty Model (Null Model)

The empty two-level model for a dichotomous outcome variable refers to a population of groups (level-two units (regions)) and specifies the probability distribution for group-dependent probabilities p_j in Y_{ij}= p_j+ε_{ij} without taking further explanatory variables into account.

The logit linear predictor is given as:

logit (π_{ij})= $\beta_0 + U_{0j}$ --(3.5)

$\pi_{ij} = \frac{e^{\beta_0+U_{0j}}}{1+e^{\beta_0+U_{0j}}}$, and the deviation U_{0j} are assumed normally distributed with mean zero and σ_0^2

The intra-class correlation coefficient (ICC) measures the proportion of variance in the outcome explained by the grouping structure. ICC can be calculated using an intercept-only model or an empty model. The ICC can be calculated as:

$$ICC=\frac{\sigma_u^2}{\sigma_u^2+\sigma_e^2} \text{ -- } (3.9)$$

Where σ_u^2 is the variance between the group which can be estimated by U_{0j} and σ_e^2 is within-group variance (John, 2009). Denote π_0 the probability corresponding to the average value β_0 as defined by p(π_0) = β_0 for the logit function, the so-called logistic transformation of β_0, is defined as:

$$\pi_0=\text{logit}(\beta_0)=\frac{e^{\beta_0}}{1+e^{\beta_0}} \text{ -- } (3.10)$$

Note that due to the non-linear nature of the logit link function, there is no simple relation between the variance of the deviations U_{0j}. However, there is an approximate formula which is valid when the variances are small and is given by:

$$\text{var}(\pi_j)=\left(\pi_0(1-\pi_0)\right)^2\sigma_u^2 \text{ ---------------------------------}(3.11)$$

Note that an estimate of population variance var(π_j) can be obtained by replacing sample estimates π_0 of and σ_0^2

The resulting approximation can be compared with the nonparametric estimate,

$$\tau^2=S_{between}^2-\frac{S_{within}^2}{n}$$

Hypothesis:

H0: There is no regional variation in maternal mortality in Ethiopia.

H1: There is a regional variation of maternal mortality in Ethiopia

3.4.1.2 Bayesian Multilevel Analysis of Random Intercept Model

In the random intercept logistic regression model, the intercept is the only random effect meaning that the groups (regions) differ with respect to the average value of the response variable. But the relation between explanatory and response variables can differ between groups (regions) in more ways. We assume that there are variables which potentially explain the observed success and failure. These variables are denoted by Xh, h=1, 2... K, with values indicated by Xhij. Since some or all of those variables could be level one variable, the success probability is not necessarily the same for all individual in a given group. The logit of π_{ij} is a sum of the linear function of explanatory variables and given as:

$logit(\pi_{ij)}$= log$\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right]$=$\beta_{0j}$+$\beta_1 X_{1ij}$+…+$\beta_k X_{kij}$=$\beta_{0j} + \sum_{h=1}^{k} \beta_{hij}$ --------------------------- (3.12)

Where the intercept term β_{0j} is assumed to vary randomly and is given by the sum of an average intercept β_0 and group-dependent deviations U_{0j} that is $\beta_{0j} = \beta_0$+U_{0j} as a result.

logit(π_{ij})=β_0+$\sum_{h=1}^{k} \beta_{hj}\, x_{hij}$+$U_{0j}$ --- (3.13)

Where β_0+$\sum_{h=1}^{k} \beta_{hj}\, x_{hij}$is the fixed part of the model and U_{0j} is the random or stochastic part of the model.

3.4.1.3 Bayesian multilevel Analysis of Random Coefficients Model

The multilevel analog, random coefficient logistic regression is based on linear models for the log-odds that include random effects for the groups or other higher level units. The random coefficients build upon the random intercept model by allowing the effects of individual predictors to vary randomly across level 2, that is, level 1 slope coefficients are allowed to take on different values in different aggregate groupings. In the random coefficient model both the intercepts and slopes are allowed to differ across the region. The multilevel random effect coefficients logistic regression model is based on linear models for the log odds that include random effects for groups or other higher levels.

Consider a model with group-specific regression of logit of the success probability logit(π_{ij}) on a single level -one explanatory variable X

$logit(\pi_{ij)}$= log$\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right]$=$\beta_{0j} + \sum_{h=1}^{k} \beta_{hij}$+$U_{0j}$+ $\sum_{h=1}^{k} U_{\boldsymbol{hj}}\, X_{hij}$ --------------------------- (3.14)

The term $\sum_{h=1}^{k} U_{\boldsymbol{hj}}\, X_{hij}$can be regarded as a random interaction between group and the explanatory variables. This model implies that the groups are characterized by two random effects: their intercepts and their slopes. It assumes that for different groups, the pairs of random effects (U_0, U_{hj}, h= 1,2,...,k) are independent and identically distributed. The random intercept variance, Var(U_{0j}) = σ_0^2, the random slope variance, Var(U_{1j}) = σ_1^2 and the covariance between the random effects, Cov(U_{0j}; U_{1j}) = σ_{01}^2 are called variance components (Snijders and Bosker, 1999).

3.4.1.4 Likelihood Function

The key ingredients to a Bayesian analysis are the likelihood function, which reflects information about the parameters contained in the data, and the prior distribution, which quantifies what, is known about the parameters before observing data.

$$Y_{ij}/\pi_{ij} \propto Bernoulli(\pi_{ij})$$

Let us denote the likelihood function us $L\ (Y_{ij}, \pi_{ij})$ and written as follows;

L$\left(\pi_{ij}/Y_{ij}\right)$=$\prod_{ij}\left(Y_{ij}/\pi_{ij}\right)$ and the linear predictor or the logit function is:

$$\text{logit}(\pi_{ij})=\log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right]=\beta_{0j}+\sum_{h=1}^{k}\beta_{hj}\,X_{hij}+U_{0j}+\sum_{h=1}^{k}U_{hj}\,X_{hij} \quad \text{------------------------------ (3.15)}$$

Where, $\pi_{ij}=\frac{e^{\beta_{0j}+\sum_{h=1}^{k}\beta_{hj}\,X_{hij}+U_{0j}+\sum_{h=1}^{k}U_{hj}X_{hij}}}{1+e^{\beta_{0j}+\sum_{h=1}^{k}\beta_{hj}\,X_{hij}+U_{0j}+\sum_{h=1}^{k}U_{hj}X_{hij}}}$ -- 3.16)

3.4.1.5 Prior Distribution

The prior distribution is a probability distribution that represents the prior information associated with the parameters of interest. It is a key aspect of a Bayesian analysis. There are two types of prior distribution: Informative priors and Non-informative priors. Informative prior distributions are created from historical studies, pure expert knowledge (experience) and a combination of both. Even if there is prior knowledge about what we are examining, in some cases we might prefer not to use this and let the data speak for themselves. In this case, we wish to express our prior ignorance into the Bayesian system. This leads to non-informative priors. The prior distribution for the parameter β_0 and σ_0^2will be given as follows:

P(β_0)~ uniform distribution (1)

P (σ_0^2) =Gamma (α, θ) where α and θ are fixed constant parameter

Let us denote the parameters β_0, β_1, …, β_k and Ω_u as prior distribution as follows

$p(\beta_0) \propto 1, p(\beta_1) \propto 1, \ldots$ p(β_k) $\propto 1$ and p(Ω_u)$\propto$ inverse-Wishart (m*S_u, m) distribution. The parameter Ω_u is the variance-covariance matrices and S_u is an estimate for the true value of Ω_u and m is the number of row in the variance-covariance matrix.

The Wishart distribution is the sampling distribution of the matrix of sums of squares and products of normal distributional assumption.

3.4.1.6 The Posterior Distribution

It is obtained by multiplying the prior distribution over all parameters by the full likelihood function. All Bayesian inferential conclusions are based on the posterior distribution of the model generated. Using the prior and likelihood function above the full conditional distribution of posterior parameter β_0, β_1, …, β_k is given by:

$$p\left(\beta_h \mid \Omega_{u,} U_{0j}, y_{ij}\right) \propto \prod_{ij} \pi_{ij}^{y_{ij}} \left(1-\pi_{ij}\right)^{1-y_{ij}} \quad \text{-------------------------------------} \ (3.17)$$

Where h=1, 2, …, k and

$$p\left(\Omega_{u,}/\, \beta_h,\ U_{0j}, y_{ij}\right) \propto\ p\left(\frac{y_{ij}}{\Omega_{u,}} \beta_h, u_{0j}\right) p\left({}^{U_{0j}}\!\big/_{\Omega_{u,}}\right) p\left(\Omega_{u,}\right)$$

Computing the estimate of β of the posterior distribution may be difficult, for this reason, we need to use the non-analytic method such as simulation techniques. The most popular method of simulation technique is Markov Chain Monte Carlo (MCMC) methods.

3.5 Estimation Techniques

3.5.1 Markov Chain Monte Carlo (MCMC) Methods

The use of Markov chain Monte Carlo (MCMC) methods to evaluate integral quantities has exploded over the last fifteen years. The primary distinction made here is between standard Monte Carlo simulation and the Markov chain type of Monte Carlo methods. The initial definition required is that of a more primitive concept that underlies for the second MC which is called Markov chains. MCMC estimation of ranking probabilities and their confidence intervals is straightforward.

3.5.2 Metropolis-Hastings algorithm

Metropolis–Hastings algorithm is a Markov chain Monte Carlo (MCMC) method for obtaining a sequence of random samples from a probability distribution. The Metropolis–Hastings algorithm works by generating a sequence of sample values. In such a way that, as more and more sample values are produced, the distribution of values more closely approximates the desired distribution p(x). In this thesis the posterior doesn't look like any distribution we know (no Conjugacy) and some (or all) of the full conditionals do not look like any distributions we know (no Gibbs sampling for those whose full conditionals we don't know. Thus why we were interested to use Metropolis–Hastings algorithm

The Metropolis-Hastings Algorithm follows the following steps:

Initialize θ^0

Start b=0

Set B number of iterations: in this study we use 100,000

Iterate as follow

While b<B

do

Set θ=θ^b select a component i

Propose new variable θ_i for component i from proposal distribution q (θ_i/θ^b)

Set θ^{b+1}

Accept i.e. set θ_i^{b+1}=θ_i with the probability α=min (1,$\frac{\pi(\theta)q(\theta_i|\theta^b)}{\pi(\theta^b)q(\theta_i|\theta^b)}$)

Otherwise set θ^{b+1}=θ^b

Set b = b + 1, end while

Once convergence is reached, all simulation values are from the target posterior distribution and a sufficient number will be drawn so that all areas of the posterior will be also explored

3.6 Model selection and comparison

Model selection is to select the best model among several choices based on an evaluation of the performance of the models. A widely used statistic for comparing models in a Bayesian framework is the Deviance Information Criterion. The deviance information criterion (DIC) is a hierarchical modeling generalization of the AIC (Akaike information criterion) and BIC (Bayesian information criterion, also known as the Schwarz criterion). It is particularly useful in

Bayesian model selection problems where the posterior distributions of the models have been obtained by Markov chain Monte Carlo (MCMC) simulation.

Like AIC and BIC it is an asymptotic approximation as the sample size becomes large. It is only valid when the posterior distribution is approximately multivariate normal. The definition of Deviance is different in the frequents, deviance is a 2loglikelihood ratio of the reduced model compared to the full model. In Bayesian, the lowest expected deviance has the highest posterior probability. It is possible to have a negative deviance, likelihoods greater than 1 lead to negative deviance and is appropriate. The advantage of DIC over other criteria, for Bayesian model selection, is that the DIC is easily calculated from the samples generated by a Markov chain Monte Carlo simulation. Assessing goodness of fit involves investigating how close the values are predicted by the model with that of observed values (Bewick et al., 2005).

3.7 Model Diagnostic

Once a model has been developed, we will like to know how effective the model is in describing the outcome. This is referred to as goodness of fit. The most common ways of checking goodness of fit are: diagnosis for convergence and mixing and posterior-predictive check. We have used the following in our study for convergence tests for the variables are:

Time Series Plots: are used to assess convergence (Merkle E., et al., 2005) If the plot looks like a horizontal band, with no long upward or downward trends, then we have evidence that the chain has converged.

Kernel Density Plot: it is the other techniques to check convergence of Bayesian analysis. This plot is like a smoothed histogram. In the case of density plot, if the coefficients of the independent variables are normally distributed implies that the Markov chain has attained its posterior distribution. Instead of counting the estimates into bins of particular widths like a histogram, the effect of each iteration is spread around the estimate via a Kernel function (normal distribution). This means that at each point we get the sum of the Kernel function is parts of each iteration. The simulated parameter value indicated convergence.

Monte Carlo Standard Error: The Monte Carlo Standard Error (MCSE) is an indication of how much error is in the estimate due to the fact that MCMC is used. As the number of iterations increases the MCSE goes to zero if it converges. However, it is adjusted due to the autocorrelation in the chain. This plot shows the standard error or precision of the posterior estimate of the mean against the number of iterations. This graph allows us to calculate how long to run the chain to achieve a mean estimate with a particular desired MCSE. The standard error can be conceived here as for how much random noise in the estimate is due to the MCMC procedure. This standard error is based on the degree of correlation in the sample and is projected forward to show how precision will increase with a longer simulation run.

The Effective Sample Size: Effective sample size is a measure of efficiency that provides an estimate of the equivalent number of independent observations that are contained in the chain; this will, of course, be directly related to the degree of autocorrelation or dependence in the sequence for that parameter. After we have run a given number of simulations and they are behaving N number of independent observations. This number of independent observation show as for whether this is enough or not to give a good quality estimate.

CHAPTER FOUR

4 Results and Discussions

4.1 Descriptive summary

Basic descriptive information that summarizes the association between predictors and response variable is presented in Table 4.1. The result shows the row percentage and count of Mothers status of aged from15-49 years with respect to the categorical covariates. From the region of Ethiopia, Afar was the highest number of maternal mortality, age between 40-44 and home-delivered women were also the highest maternal mortality. No antenatal visit and urban resident women were the highest frequency of maternal mortality. No educational attainment and poor wealth index women were also more affected women.

Since the data of EDHS has many missed or not illegible cases across some variables, after clearing those missing values, a total of the sample of 10103 women between the ages of 15-49 years in Ethiopia was included in the study. The response variable considered in this study was the maternal mortality (Death are related to pregnancy or otherwise). From table 4.1, the results of 2016 EDHS data the proportion of the death status of the mother with related to pregnancy was varied from one region to the other region in Ethiopia. The highest percentage of maternal mortality was observed in Afar (2.93%) followed by Somalia (2.72%) while the lowest percentage of maternal death was recorded in Addis Ababa (0.46%) and followed by Dire Dawa (0.67%) in 2016. Hence, there appears to be some variation of maternal mortality among the region of Ethiopia.

Regarding with the age of mother's maternal mortality rate are 2.11%, 2.03%, 1.71%, 1.24%, 1.18%, 1.13%, 0.76% for mother's whose age are 40-44, 35-39,30-34 25-29, 15-45-49 and 20-24 respectively. This show as 40-44 year and 35-39 was the highest percentage of maternal mortality. Based on place of delivery the percentage of maternal mortality those who deliver at home was 2.01% and 0.59% those who deliver at health facilities. Likewise according to the number of antenatal visits the percent of maternal mortality was 2.04%, 1.70%, 1.12% and 0.79% for those, 1-2 visit, no visit at all, 3-4 visit and more than 4 number of visit respectively. The proportion of maternal mortality was differing by place of residence. The highest percent of maternal death has occurred in the rural part of the country (1.69%) which was high with relative to the urban (0.85%).

Considering mothers educational attainment, maternal death rates are 1.87%, 0.94% and 0.57% for mothers of no education, primary education, secondary and above, respectively. This indicates that maternal mortality was highest for mothers of no education and lowest for secondary and above. The number of mothers death related to pregnancy also varies according to wealth index. A higher percentage of the death of mother related to pregnancy was observed in poor wealth index (2.02%) as opposed to the lowest percentage of the death of mother related to pregnancy was observed in rich wealth index (0.57%). About 2.72% died those who are not married and (0.71%) of women were the lowest percent those who are no longer living together or separated. Accordingly, a higher proportion of maternal mortality was observed mother who did not use a contraceptive method (1.57%) compare to mother who uses (1.02%). The proportion of maternal mortality also differs from the source of drinking water they use. The highest proportion of maternal mortality was observed for mother whose source of drinking water was surface water (1.98%) followed by tube well water (1.51) and the lowest proportion of maternal mortality was the mother whose source of drinking water was piped water (0.84%).

Table 4.1 also reveals that the proportion maternal mortality varies by the number of children in the household. The highest percentage of maternal mortality was observed the whose number of children in a house was 3-4 (1.77%) followed by mother those who have more than five number of children (1.71%) as opposed to the lowest percentage of maternal mortality which was recorded who has no child at all (0.57%)

Table 4-1 the description of the socioeconomic, demographic and environmental factor of maternal mortality in the regional state of Ethiopia

Variables	Number of Mothers	No death (%)
Place of delivery		
Home	6021	121(2.01%)
Health facilities	4082	24(0.59%)

No of antenatal		
No antennal visit	3467	59(1.70%)
1_2 visit	2007	41(2.04%)
3_4 visit	2597	29(1.12%)
>=5 visit	2032	16(0.78%)
Place of residence		
Urban	3044	26(0.85%)
Rural	7059	119(1.69%)
Educational attainment		
No education	5922	111(1.87%)
Primary	2770	26(0.94%)
Secondary and above	1411	8(0.57%)
Wealth index		
Poor	4753	96(2.02%)
Medium	1822	29(1.59%)
Rich	3528	20(0.57%)
Contraceptive		
Not using	7557	119(1.57%)
Use	2546	26(1.02%)

Pearson chi-square test was applied to know predictors having a strong association with the response variable and. For each predictor, a test of association was carried out using the Pearson at 5% level of significance. The bivariate association between maternal mortality and predictors indicates that mother's status related to pregnancy was strongly associated with place of delivery, age of mother, region, number of antenatal visit, place of residence, wealth index, marital status, contraception, educational attainment, source drinking water and number of child are found significant at 5% level of significance indicating that, association with maternal mortality

Test of Heterogeneity: Before analyzing the data using Bayesian multilevel analysis, there is a need to check for the heterogeneity of maternal mortality aged between 15-49 years with regard to regions. Hence x^2 test statistic was applied to assess the heterogeneity in the proportion of maternal mortality between regions in Ethiopia. The result obtained by cross tabulation in (Appendix Table 4.1) was x^2= 38.702, df=10, p=0.000 α= 0.05, hence we have enough evidence to reject the null hypothesis and conclude that there is heterogeneity of maternal mortality among regions of Ethiopia.

4.2 Bayesian Multilevel Logistic Regression Analysis

Bayesian multilevel logistic analysis procedure was used to make inference about the parameters of a multilevel logistic model. 15000 burn-in terms discarded and the Metropolis hasting algorithm was implemented with 100000 iterations. The researcher use non-informative uniform prior distribution with scale parameter (0, 1) for the fixed effect and gamma distribution with a scale of 0.001 and shape 0.001 (Acquah H. D., 2013). In the multilevel analysis, a two-level structure is used with regions as the second-level units and women as the first level units. This is basically with the expectation that there would be a difference in maternal mortality among regions. Under this section we revealed three Bayesian multilevel model; empty model, intercept model and coefficient model to identify the appropriate model which fit our data. The nesting structure is women within regions with a total of 10103, 2016 EDHS.

4.2.1 Bayesian Multilevel Logistic Regression Analysis of the Empty Model

The simplest important specification of the hierarchical linear model is a model in which only the intercept varies between level two units and no explanatory variables are entered in the model. The empty model contains no explanatory variables and it can be considered as a parametric version of assessing heterogeneity of maternal mortality among regions. The variance of the random factor is significant which indicates that there are regional differences in maternal mortality. From table 4.2 below, both data showed that there is a significant variation among the region. The regional variation of maternal mortality is 3.966(1.811) which is significant.

Table 4-2 Bayesian Multilevel Logistic Regression of Empty Model

Model	Coefficient	SD	MCSE	95%CI
Fixed intercept (*βoj*)	-5.257	0.359	0.0046	(-6.048, -4.545)
Random intercept var(*Uoj*)=σ_{u0}^2	3.966	1.811	0.0252	(0.997, 8.012)

From the results presented in Table 4.2 above show that the overall mean of maternal mortality is estimated that β_0 = -5.257 found to be significant, suggest that evidence of regional effects on maternal mortality. Coming to regional variation tests; Here the null hypothesis tested is σ_{u0}^2 = 0. i.e., there is no regional variation in maternal mortality in Ethiopia. Based on the above result data the values are significant at 95% credible interval which means that the interval is greater than zero, therefore, the null hypothesis has to be rejected indicating strong evidence that the between region variance is greater than zero. The variance of the random factor is significant which indicates that there are regional differences in maternal mortality and thus, Bayesian multilevel analysis can be considered as an appropriate approach for further analysis.

4.2.2 Bayesian Multilevel Logistic Regression Random Intercept Model

From the result of Bayesian Multilevel Random intercept model listed on (Appendix Table 4.3), we have seen that the random part is the intercept only having many covariates. The random intercept model is where the intercept is allowed to vary across regions after controlling for covariates of pregnancy-related mortality. The results from the random intercept model showed that the random intercept β_{0j} is significant implying that the average pregnancy-related death is differing from region to region. The result shows that the variance of the random effect is significant which indicates that there are regional differences in maternal mortality in the given data set. The Bayesian multilevel logistic regression analysis result displayed in (Appendix Table 4.3) also estimates the variance of random effect at the regional level $var(u_{0j}) = \sigma_u^2$ =4.07 since the 95% credible interval was greater than zero under the interval, which indicates that there is a significant regional variation. This confirmed the significance of the regional difference of maternal mortality in Ethiopia.

4.2.3 Bayesian Multilevel Logistic Regression Random Coefficient Model

It is possible to generalize the model so that the effect of level-1 covariates is different in each region. This can be done by adding random coefficients in front of some of the individual-level covariates of the model. In the random intercept model, we allowed the intercept only to vary across regions by fixing explanatory covariates. From the output of the random coefficient Bayesian multilevel model presented in Table 4.4 below, we interpret the results as follows. Place of delivery is one of the predictor variables under this study and also it was a significant association with maternal mortality. The odds of maternal death in health facilities was 58% (OR=0.42) times less likely than the odds of maternal death in a home. Regarding too number of antenatal visit the odds of maternal mortality for 1-2 number of antenatal visit was 1.42 more likely than that of no antenatal visits assuming all other factor constant, contradicting to this the odds of maternal death those who visit 3-4 and more than 5 number of antenatal visit was 0.81 and 0.64 less likely than the odds of no antenatal visit by assuming other variable constant respectively. Another finding of this study indicates that the age of individual women is significantly associated with maternal mortality with 95% credible interval. Particularly, the odds of maternal mortality with age of mothers between 20-24 years was 1.17 times more likely to be dead than the odds of maternal mortality aged between 15-19 years and the odds of maternal death aged between 25-29 years were 1.98 times more likely to be dead than the odds of mothers age between 15-19 years. Continuously women aged between 30-34 years, 35-39 years, 40-44 years and 45-49 years were 3.02, 3.63, 3.80, 1.70 times more likely to be dead than aged between 15-19 years respectively. This implies that women age between 15-19 year were less likely to be death pregnancy-related than the other aged and women age between 40-44 were more likely to be death related to pregnancy as compared to the age of women.

Educational attainment has a significant contribution to maternal mortality. The odds of pregnancy-related death of women for primary education was about 45% (OR=0.55) less likely than the odds of pregnancy-related death of women who have no education (illiterate) and the odds of maternal mortality for secondary and above education were about 66% (OR=0.34) less likely than the odds of maternal mortality for who has no education by assuming another factor constant. From this, we conclude that the illiterate mother has a high chance of pregnancy-related death as compared to the others. Another finding show as marital status has a significant contribution to maternal mortality. The odds of maternal death for married women was 0.056 times (OR=0.056) less likely than the odds of not married women and maternal mortality of Divorced/widowed and also separated/no longer living together women was statistically different from not married women (reference category).

A number of living children was another significant factor in maternal mortality. The odds pregnancy-related death of women who have 1-2 number of child were 3.38 more likely died than women of no child, the odds of pregnancy-related death of women having 3-4 number of child were 6.85 more likely died than that of no child at all and have more than 4 children, maternal mortality was 5.14 more likely died than that of no child-women. From this, we conclude that having more children was the most significant contribution to maternal mortality in Ethiopia.

The study also reveals that place of residence was another variable but it was not significant contribution on maternal mortality and the odds of pregnancy-related death for women who reside rural place were 95% (OR=1.95) more likely than who live in urban. This means that women who live in the rural area of the country were high maternal mortality as compared to the urban area of the country. Contraception was also another variable which was considered under this stud. The odds of maternal mortality who use contraceptive method were 4% (OR=0.96) less likely than that of not use and contraception was not a significant contribution to maternal mortality according to this study.

Another finding from the above table show as a source of drinking water was not a significant contribution to maternal death. The odds of pregnancy-related death of women those whose source of drinking from the surface water was 53% (OR=1.53) more likely than piped water and the odds of pregnancy-related death those whose source of drinking from tubewell water was 0.86 less likely than that of the pipe. Another wealth index was also significant for pregnancy-related death as we observed from the analysis. The odds of pregnancy-related death for rich women were 1.30% (OR=0.013) less likely than that of poor women. But the wealth index for the middle category was not significant and the odds of pregnancy-related death for the middle category were 0.71 less likely than the odds of pregnancy-related death for poor wealth index category. This study indicates that family income had a significant association with maternal mortality.

From the table 4.4 the sample obtained from posterior distribution, summary statistics of all parameters for posterior distribution are present and the predictor variables like; place of delivery, Age of mother, educational attainment, Marital status, wealth index and number of living children were found to be significant determinants of maternal mortality at 95% credible interval (Since the credible intervals of these variables does not contain zero (at least one category). This shows significant variables are more determining of maternal mortality.

The Bayesian multilevel logistic regression analysis result displayed in Table 4.4 below, also estimates the variance of random effect at the regional level, var(U_{0j}). Thus, the value of var(u_{0j})= 4.085 indicate there was significant variation (which means the 95% credible intervals is greater than zero). This confirmed the significance of the regional difference in maternal mortality in the regional state of Ethiopia. The researcher tried to identify to see the level of variation; that the intra-region correlation coefficient ICC is estimated as $\rho = \frac{4.085}{4.085+3.29}$ =0.5538. This means that about 55.38% of the total variability in maternal mortality is due to differences across regions, with the remaining unexplained 44.62% attributable to individual differences.

This model contains a random slope for wealth index and the number of living children; which means that it allows the effect of the coefficient of this variable to vary from region to region. This model is more appropriate than the previous model for the variables being used since from wealth index category rich has fixed coefficient -1.296 (0.308), which suggests that this is the strong predictor and from wealth index category rich women were significantly less likely than poor women. It is necessary to see that the effect of wealth index on maternal mortality varies from region to region in Ethiopia which implies that there is a considerable variation in the effects of wealth index and the number of living children. The region wise intercept (U_{0j}) and slope (wealth index=U_{20j}) vary significantly, that is, there is a significant variation in the effects of these explanatory variables across the regions. The negative sign for the covariance between intercepts and slopes implies that regions with higher intercepts tend to have on average lower slopes on the corresponding predictors. The covariance between the intercept and random slope of wealth index were -9.225 This implies that the pregnancy-related death whose their family are rich was less than those whose their mother are poor by a larger factor at regions.

Another concept under this study the researcher revealed that the variance of the random slopes. The values of var($u_{0j\,20}$)=31.193 with credible interval of (95% CI: 6.551, 70.06) and σ_{13}^2 = 4.168 with (95% CI: 0.644, 12.69) the interval was greater than zero. This indicates that the random slope of wealth index and the number of living children in the region is significant.

This means that the wealth index and the number of living children factor for maternal mortality vary from region to region.

Table 4-4 Bayesian Estimates for Random coefficient model

Fixed effect	Categories	Estimates	SD	MC error	95% CI
Intercept		-4.955	0.880	0.0979	(-6.757, -3.407)
P.delivery	Home(ref)				
	H.facilities	-0.864	0.286	0.001	(-1.423, -0.306)
No Ante.visit	No visit(ref)				
	1-2 visit	0.352	0.253	0.0009	(-0.148, 0.851)
	3-4 visit	-0.210	0.273	0.0009	(-0.759, 0.311)
	5+ visit	-0.46	0.344	0.0012	(-1.142, 0.192)
No children	No child(ref)				
	1-2 child	1.219	0.717	0.0075	(-0.106, 2.654)
	3-4 child	1.925	0.738	0.0091	(0.537, 3.426)
	5+ child	1.628	0.749	0.0416	(0.174, 3.060)
P residence	Urban(ref)				
	Rural	0.666	0.447	0.0037	(-0.192, 1.598)
E attainment	No educ (ref)				
	Primary educ	-0.589	0.267	0.0009	(-1.115, -0.076)
	Sec.and above	-1.069	0.465	0.0016	(-2.040, -0.167)
Wealth index	Poor(ref)				
	Middle	-0.342	0.270	0.001	(-0.894, 0.189)
	Rich	-1.296	0.308	0.0011	(-1.927, -0.721)
Contraceptive	Not use(ref)				
	Use	-0.049	0.274	0.0038	(-0.581, 0.469)
Random	σ_{u0}^2	4.085	1.222	0.051	(1.659, 3.885)
effect	$\sigma_{u\,20}^2$	31.193	17.983	1.074	(6.551, 70.06)
	σ_{13}^2	4.168	3.073	0.138	(0.644, 12.69)

(ref - is reference category

4.3 Model Comparison

From the result of Table 4.6 below, the DIC diagnostics of random intercept Bayesian multilevel logistic regression model is reduced by 101.33 from the Bayesian multilevel logistic regression of an empty model. This show as adding covariate variables to the model indicates how the variable is determined maternal mortality. Thus; Bayesian multilevel logistic regression for random intercept was the better model as compared to Bayesian multilevel for an empty model. The DIC diagnostics of Bayesian multilevel logistic regression of random coefficient model is reduced by 50.01 from Bayesian multilevel for random intercept so, this Bayesian multilevel random coefficient model is a great improvement suggesting that this model is the appropriate model than a Bayesian multilevel empty model and Bayesian multilevel for intercept model to determine the maternal mortality factors.

Therefore, this Bayesian deviance information criterion showed that Bayesian multilevel random coefficient model is the most significant model and best fit the data. The average deviance from the complete set of iterations ($\widehat{D}$) also decreased from an empty model to random intercept and from random intercept to the random coefficient model. D ($\hat{\theta}$) shows that the deviance at the expected value of the unknown parameters and it also shows the decreasing trend from an empty model to random intercept and from random intercept to the random coefficient model.

Table 4-3 DIC values for model comparison

Bayesian Deviance Information Criterion (DIC) for model comparison				
Model	$\widehat{D}$	D($\hat{\theta}$)	Pd	DIC
Null model	1222.06	1061.04	161.02	1383.09
Random intercept	1110.73	939.70	171.03	1281.76
Random coefficient	1047.24	862.73	184.51	1231.75

($\widehat{D}$): The average deviance from the complete set of iterations

D ($\hat{\theta}$): The deviance at the expected value of the unknown parameters

pD: The Estimated degrees of freedom consumed in the fit, ie Dbar- D(thetaBar)

DIC: Fit + Complexity; Dbar + PD

4.4 Assessing Accuracy of Bayesian Model

The posterior summary estimates by the MCMC algorithm (metropolis hasting algorithm), like posterior mean, standard deviation, and Monte Carlo error and credible interval were estimated using MLwIN software. To assess the accuracy of Bayesian multilevel analysis, we can use the Monte Carlo error for each parameter. If the MC error value is less than 5% of its posterior standard deviation, then the posterior density is estimated with accuracy. In this study, MC error for each significant variable is less than 5% of its standard deviation. This indicates that the convergence and accuracy of posterior estimates are attained and the model is appropriate to estimate posterior statistics. Based on the Bayesian approach the significant variables that determine maternal mortality was a place of delivery, an age of the mother, number of living children, educational attainment, wealth index, and marital status.

4.5 Assessment of Model Convergence

There are a lot of commonly used methods to assess the convergence of MCMC output, but in this study only some of them are used., we have seen that time series plots (iteration number on x-axis and parameter value on y-axis) we have seen that the plot looks like a horizontal band with no long upward or downward trends. So, we have evidence that the chain has converged at 100,000 iterations. From the plot again, we have seen the kernel graph which another technique for is checking model convergence.

There is another recommended technique for identifying model convergence. The plots of all statistically significant covariates indicated that none of the coefficients have bimodal density and hence the simulated parameter values have converged. The ACF measures how correlated the values in the chain are with their close neighbors. The lag is the distance between the two chains to be compared. High autocorrelation indicates slow mixing within a chain and usually slow convergence to the posterior distribution. So, the plots displayed in Figure 4-1 below indicate low autocorrelation and efficient sampling as we have seen it. The PACF measures discrepancies from such a process and so should normally have values 0 after lag 1 which shows again convergence. The Monte Carlo Standard Error (MCSE) is an indication of how much error is in the estimate due to the fact that MCMC is used. As the number of iteration increased the

MCSE was decreased as we have seen from the graph. The following figures were some parts of Convergence for some parameter.

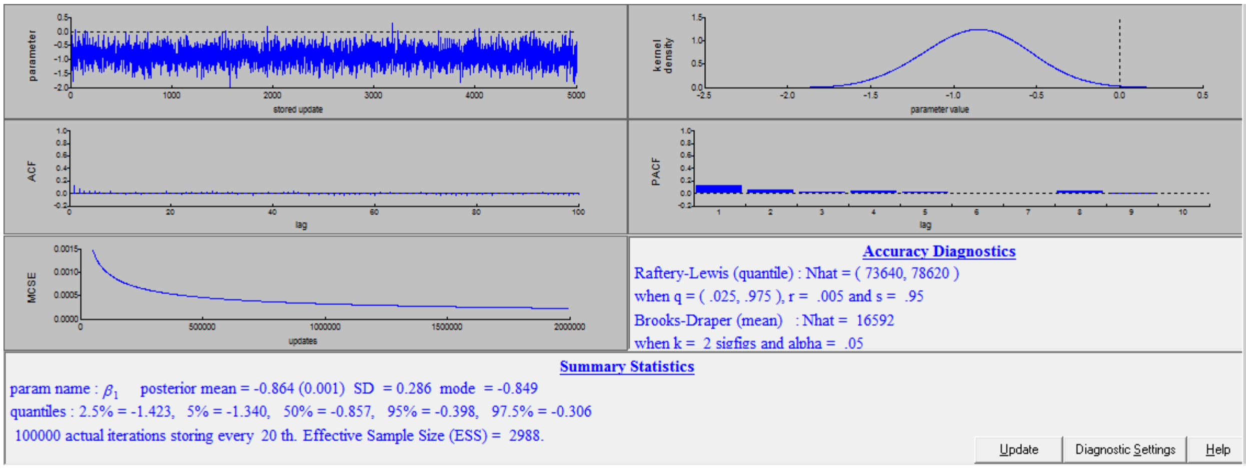

Figure 4-1 convergences for $\boldsymbol{\beta_1}$

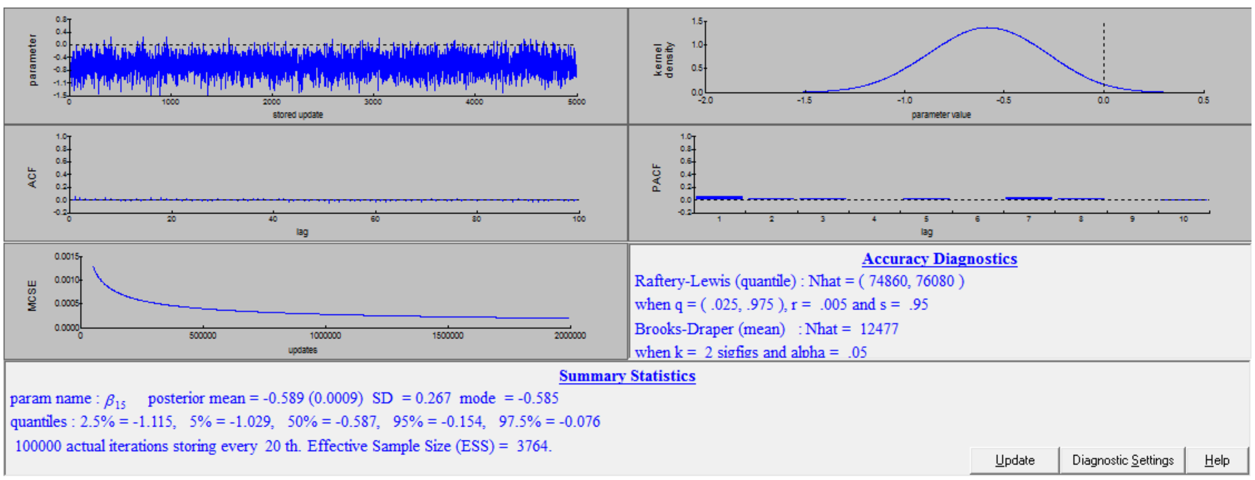

Figure 4-2 convergences for $\boldsymbol{\beta_{15}}$

4.6 Discussion

These studies were attempted to identify some socio-economic and demographic determinants of maternal mortality in Ethiopia using 2016 EDHS data. Accordingly, the descriptive method and Bayesian Multilevel logistic regression were used in the analyses. The variables, having the significant association with maternal mortality (based on Chi-square test of association) place of delivery, Antenatal care, Mother's age at birth, Place of residence, Region, mothers education, Marital status, Wealth index, Contraceptive, number of living children, a source of drinking water. The Bayesian multilevel logistic regression empty model, the Bayesian multilevel logistic regression random intercept model, and Bayesian multilevel logistic regression random coefficient model were used in this study. From the result of the model adequacy Bayesian multilevel logistic random coefficient model is the best-fitted model (Spiegelhalter DJ, 2002).

The study included eleven variables that were categorized under socioeconomic, demographic and environmental proximate variables. In this analysis, women were as level one nested within the different region of Ethiopia and region were level two. In order to explain the regional difference in maternal mortality and to identify which model is the best model to fit the data, we applied three different Bayesian multilevel models for the response variables. By considering the appropriate model which fit our data we identify the significant variable. From the descriptive statistics the probability of maternal mortality for Afar and Somali was high as compared to the other region and also the number of maternal mortality for urban women is less likely than that of rural, place of delivery in health facilities was less than that of home. Coming to the inference parts the analysis of the final model indicated that one of the significant factors of maternal mortality in this study was the place of delivery. The odds of maternal death in health facilities was 58% (OR=0.42) times less likely than the odds of maternal death in a home. This show as the women who delivered at home has died more than those who deliver at health facilities the result for the place of delivery being significant is also consistent with the previous study by (Navaneetham K. &., 2002).

Another finding was showed that wealth index was an important determinant of maternal mortality. This indicates as income is one of the significant factors for maternal mortality. The maternal mortality from the low-income family has more likely died than that of from high income or rich family the result for household wealth index being significant is also consistent with the previous study by (Bayati, 2016).

Age of mother is another determinant of maternal mortality in Ethiopia. Age of mother which was categorized under 30-34, 35-39 and 40-44 years has more likely died than the other age category and maternal mortality for aged between 45-49 year was less likely than the others age category these results are consistent with the previous study by (Mbaruku, 2013).

The study also indicates that the number of living children were one of the other significantly associated with pregnancy-related death. As we observed from the above table 4.5 as the number of children increases the chance of pregnancy-related death also high. Specifically from these study women who have between 3-4 and more than 4 numbers of children was the high probability of maternal mortality. Another message we have understood from these study was the level of education of women also significantly associated with pregnancy-related death. The study showed that educational attainment was an important determinant for pregnancy-related death and had negative effects (Jat, 2011).

Moreover, marital status was another significant factor for pregnancy-related death. Under this, we observed that married women, no longer living together/separated and widowed/divorced women was another important determinant for pregnancy-related death and had significant effects as compared to not married women. As this study showed that, pregnancy-related death for not married women is less likely than the other marital status category (Illah, 2010.).

From the result of the Bayesian Multilevel empty model, we conclude that between regions (regional level) variation of maternal Mortality was existed. This indicates that the Region of individuals has significant effects on Maternal Mortality. Moreover, the Bayesian multilevel intercept model also indicated that there were regional variations of maternal mortality (Mbaruku, 2013).

The analysis based on Bayesian multilevel logistic regression provided estimates for variances of the random effects and interclass correlations. The estimates for each level were different, suggesting that the variance components of maternal mortality were different at individual and regional levels. This means that the sources of variations are individuals and regions. The result of Bayesian multilevel logistic regression model comparison indicates that the random coefficient Bayesian multilevel logistic regression model best fits the model than the null model and random intercept model of the Bayesian multilevel logistic regression model. therefore the researcher suggests that Bayesian multilevel logistic regression for random coefficient were the best fit of the data and the interpretation was depend on random coefficients.

CHAPTER FIVE

5 Conclusions and Recommendations

5.1 Conclusions

The purpose of this study was identifing some socio-economic, demographic and environmental proximate variables as determinants of maternal mortality in the country and the gap from classical by checking the level of variation within and between region. And also we have seen that the convergence of covariance. From those determinant factors wealth index, place of delivery, educational attainment of the mother, number of living children, marital status and age of mother were the significant variables as a determinant of maternal mortality in 2016 data.

The study revealed that maternal mortality is significantly associated with geographical regions. The majority of maternal mortality was found in the Afar and Somalia. The analysis indicated that there was the regional variation of maternal mortality, which is mothers living in Afar, Somalia, Oromia, Amhara, Benishangul-Gumuz, Gambella, Harari, SNNPR, Dire Dawa and Tigray regions were different from each other and they were more likely to die pregnancy-related compared to those residing in Addis Ababa.

The probability of maternal mortality for mothers who deliver at health facilities was less than those who deliver at home. Mother with secondary and above educational level, being died due to pregnancy-related is less than that having a mother with no education. Moreover, it is found that having more children is a high probability of maternal mortality as compared to having a small number of children or no children at all. Specifically, the study revealed that maternal mortality is less likely for mother whose wealth index was rich and middle as compared to poor wealth index. The predictors, marital status are another significantly associated with pregnancy-related death and as this analysis, the probability of maternal mortality was less for married women as compared to not married and also the probability of maternal mortality was less for widowed/divorced as compared to not married.

From the methodological aspect, it was found that Bayesian multilevel random coefficient model is better compared to empty (null) model and random intercept model in fitting the data and in explaining the variations of pregnancy-related mortality across regional levels of Ethiopia. In addition from the empty model and random intercept model, the overall variance of the constant term was found to be statistically significant, implying the existence of a difference in pregnancy-related mortality in Ethiopia. The regional variations were high for the Bayesian multilevel empty model than the Bayesian multilevel for random intercept and lower for Bayesian multilevel for a random coefficient model to explaining the regional variation of 2016.

5.2 Recommendation

The findings of this study have some important policy implications and the identification of factors those are significantly associated with a maternal mortality. Additionally, the study showed as there was the regional variation of maternal mortality in the regional state of Ethiopia, Thus, regional states have to take remedial measures on public health policy and design strategies to improve facility toward the major factors that affecting maternal mortality. This knowledge now needs to be converted into the development of adequate interventions that aim to decrease maternal mortality. Depending on the above important findings, the researcher suggests the following recommendations for researchers and policymakers:

1. Although the variation across the regions has been addressed with this study, the distribution for the prevalence of maternal mortality and the issue of identifying the hot-spot-area is not covered here. Therefore, the researchers are recommended to extend this study with the application of spatial models.
2. The data of this study was basically secondary which have the problem of missing data and the expected potential variables were also not availed. Thus, researchers should have to conduct the study on separate regions with the same models of this study.
3. This study was limited to identifying the socio-demographic factors. However, there are other major causes of maternal mortality. Hence, we recommended researchers so that to study the significance of those causes by considering only maternal mortality using the Poisson model and its extension.
4. The government and other concerned bodies should have to take attention to control the significant factors that lead to maternal mortality like mothers' educational level have to upgrade, Mothers have to be encouraged to reduce home delivery and attitude toward having the small number of children has to be raised

5. The government should take the implementation of interventions such as training, equipping institutions, in addition to the monitoring and supervision that took place at the district level.

Limitation of the study

The following are some of the limitations of the study

The data is obtained from the Ethiopian demographic health survey (EDHS) of 2016) and the information gathered by this survey have not full information. Especially due to some women were not eligible under some covariates, the sample size with full information of maternal mortality for all covariates and missing value of the different variable is one of the problems and the information has not directly taken, therefore there is no full information about maternal mortality. There are many risk factors for affecting the maternal mortality that is studied by different foreign researchers, but in Ethiopia, some important factors that may affect maternal mortality are not gathered. For instance, the main expected predictor of maternal mortality like the distance of household from the health center, types of food or nutritional status during pregnancy specifically were not included

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APPENDIX

Table 6 Descriptive statistics of table 4.1

Variable	mother's status							
	Death		Otherwise					
	N	Percent %	N	Percent	Total	DF	Chi-sqr	p-value
Region					10103	10	38.70	0.000
Tigray	10	0.98%%	1013	99.02%	1023			
Afar	24	2.93%	795	97.07%	819			
Amhara	14	1.19%	1160	98.81%	1174			
Oromia	17	1.31%	1277	98.69%	1294			
Somalia	27	2.72%	967	97.28%	994			
Benshangul	14	1.89%	726	98.11%	740			
SNNP	12	1.05%	1130	98.95%	1142			
Gambela	11	1.58%	686	98.42%	697			
Harari	7	1.16%	592	98.84%	602			
A.A	4	0.46%	866	99.54%	870			
D.daw	5	0.67%	743	99.33%	748			
Age of mother					10103	6	15.89	0.014
15-19	10	1.18%	839	98.82%	849			
20-24	15	0.76%	1952	99.24%	1967			
25-29	29	1.24%	2317	98.76%	2346			
30-34	31	1.71%	1782	98.29%	1813			
35-39	39	2.03%	1880	97.97%	1919			

40-44 45-49	16 5	2.11% 1.13%	744 444	97.89% 98.87%	760 449			
Place of delivery					**10103**	**1**	**34.76**	**0.000**
Home Health facilities	121 24	2.01% 0.59%	5900 4058	97.99% 99.41%	6021 4082			
No of antenatal					**10103**	**3**	**14.87**	**0.002**
No antennal visit 1_2 visit 3_4 visit >=5 visit	59 41 29 16	1.70% 2.04% 1.12% 0.78%	3408 1966 2568 2016	98.30% 97.96% 98.88% 99.22%	3467 2007 2597 2032			
Place residence					10103	**1**	10.40	**0.001**
Urban Rural	26 119	0.85% 1.69%	3018 6940	99.15% 98.31%	3044 7059			
Educational attainment					10103	**2**	20.42	**0.000**
No education Primary Secondary and above	111 26 8	1.87% 0.94% 0.57%	5811 2744 1403	98.13% 99.06% 99.43%	5922 2770 1411			
Wealth index					10103	**2**	30.60	**0.000**
Poor Medium Rich	96 29 20	2.02% 1.59% 0.57%	4657 1793 2508	97.98% 98.41% 99.43%	4753 1822 3528			
Marital status					10103	**3**	10.74	**0.020**

Not married	19	2.72%	679	97.28%	698			
Married	111	1.32%	8300	98.68%	8411			
separated	2	0.71%	2780	99.29%	280			
Widow/divorced	13	1.82%	701	98.18%	714			
No of children					10103	**3**	11.97	**0.007**
No child	4	0.57%	692	99.43%	696			
1_2 child	31	1.00%	3060	99.00%	3091			
3_4 child	60	1.77%	3323	98.23%	3383			
>=5 child	50	1.71%	2883	98.29%	2933			
Contraceptive					10103	**1**	4.12	**0.042**
Not using	119	1.57%	7438	98.43%	7557			
Use	26	1.02%	2520	98.98%	2546			
Source of drinking water					10103	**2**	17.25	**0.000**
Piped water	32	0.84%	3755	99.16%	3787			
Tube well water	39	1.51%	2537	98.49%	2576			
Surface water	74	1.98%	3666	98.02%	3740			

Table 4.2: Bayesian Multilevel Logistic Regression of empty model

Model	Coefficient	Exp(β)	SD	MCSE	95%CI	
Fixed intercept (βoj)	-5.257	0.0052	0.359	0.0046	-6.048	-4.454
Random intercept var(Uoj)=σ_{u0}^2	3.966		1.811	0.0252	0.997	8.012

Table 4.3: Bayesian Multilevel Logistic Regression of Random Intercept

Fixed effect variables	$\hat{\beta}$	SD	Exp($\hat{\beta}$)	MC error	95% CI
Home(ref)	1.00				
Health facilities	-0.907	0.279	0.403	0.0009	(-1.467, -0.374)
Number of antennal visit					
No visit(ref)	1.00				
1-2 visit	0.343	0.248	1.41	0.0008	(-0.159, 0.815)
3-4 visit	-0.210	0.268	0.81	0.0009	(-0.745, 0.305)
5+ visit	-0.387	0.334	0.68	0.0011	(-1.022, 0.249)
Age of mother					
15-19(ref)	1.00				
20-24	0.129	0.513	1.14	0.0029	(-0.843, 1.165)
25-29	0.668	0.494	1.95	0.0034	(-0.251, 1.692)
30-34	1.040	0.501	2.83	0.0035	(0.127, 2.075)
35-39	1.228	0.478	3.41	0.0034	(0.335, 2.206)
40-44	1.276	0.542	3.58	0.0032	(0.233, 2.366)
45-49	0.547	0.688	1.73	0.0031	(-0.844, 1.845)
Number of children					
No child(ref)	1.00				
1-2 child	1.059	0.686	2.88	0.0079	(-0.171, 2.449)
3-4 child	1.777	0.694	5.91	0.0079	(0.478, 3.219)
5+ child	1.448	0.703	4.25	0.0078	(0.160, 2.906)
Place of residence					
Urban(ref)	1.00				
Rural	0.512	0.423	1.67	0.0031	(-0.314, 1.328)
Educational attainment					
No education(ref)	1.00				
Primary education	-0.560	0.258	0.57	0.0009	(-1.066, -0.063)
Secondary and above	-0.980	0.449	0.38	0.0015	(-1.891, -0.118)

Source of drinking					
Piped water(ref) Tube well water Surface water	1.00 -0.196 0.411	 0.355 0.310	 0.82 1.51	 0.0017 0.0015	 (-0.863, 0.503) (-0.180, 1.030)
Wealth index					
Poor(ref) Middle Rich	1.00 -0.245 -1.296	 0.263 0.308	 0.78 0.27	 0.0009 0.0011	 (-0.776, 0.258) (-1.927, -0.721)
Marital status					
Not married(ref) Married No long living together/separated Widowed/divorced	1.00 -2.665 -3.280 -2.202	 0.404 0.940 .497	 0.07 0.037 0.11	 0.0029 0.0033 0.0025	 (-3.474, -1.880) (-5.320, -1.635) (-3.195, -1.246)
Contraceptive					
Not use(ref) Use	1.00 -0.057	 0.268	 0.94	 0.0009	 (-0.600, 0.460)
Constant (β_{0j})	-4.899	0.866	0.0074	0.0142	-6.735, -3.297)
Random effect					
$\hat{\sigma}_u^2 = var(u_{0j})$	4.221	1.487		0.0158	(1.821, 7.623)

Table 4.4 Bayesian Multilevel Logistic Regression of Random Coefficient

Fixed effect variables	$\hat{\beta}$	SD	Exp($\hat{\beta}$)	MC error	95% CI
Intercept	-4.955	0.880	0.010	0.0979	-(6.757, -3.407)
Place of delivery					
Home(ref) Health facilities	1.00 -0.864	 0.286	 0.421	 0.001	 (-1.423, -0.306)
Number of antennal visit					

No visit(ref)	1.00				
1-2 visit	0.353	0.253	1.42	0.0009	(-0.148, 0.851)
3-4 visit	-0.210	0.273	0.81	0.0009	(-0.759, 0.311)
5+ visit	-0.446	0.344	0.64	0.0012	(-1.142, 0.192)
Age of mother					
15-19(ref)	1.00				
20-24	0.156	0.520	1.17	0.003	(-0.874, 1.214)
25-29	0.684	0.506	1.98	0.0035	(-0.273, 1.696)
30-34	1.107	0.507	3.02	0.0035	(0.165, 2.119)
35-39	1.289	0.487	3.63	0.0035	(0.359, 2.280)
40-44	1.336	0.556	3.80	0.0034	(0.250, 2.463)
45-49	0.528	0.702	1.70	0.0032	(-0.924, 1.842)
Number of children					
No child(ref)	1.00				
1-2 child	1.219	0.717	3.38	0.0075	(-0.106, 2.654)
3-4 child	1.925	0.738	6.85	0.0091	(0.537, 3.426)
5+ child	1.638	0.749	5.14	0.0091	(0.246, 3.156)
Place of residence					
Urban(ref)	1.00				
Rural	0.666	0.447	1.95	0.0037	(-0.192, 1.598)
Educational attainment					
No education(ref)	1.00				
Primary education	-0.589	0.267	0.55	0.0009	(-1.115, -0.076)
Secondary and above	-1.069	0.465	0.34	0.0016	-(2.040, -0.167)
Source of D. water					
Piped water(ref)	1.00				
Tube well water	-0.152	0.360	0.86	0.0018	(-0.866, 0.567)
Surface water	0.429	0.320	1.53	0.0017	-(0.182, 1.072)
Wealth index					

Poor(ref) Middle Rich	1.00 -0.342 -4.316	 0.270 2.049	 0.71 0.013	 0.001 0.051	 (-0.894, 0.189) -9.772, -1.082
Marital status					
Not married(ref) Married No long living together/separated Widowed/divorced	1.00 -2.877 -3.572 -2.420	 0.442 1.052 .543	 0.056 0.028 0.088	 0.0035 0.0041 0.003	 (-3.736, -2.031) (-5.882, -1.763) (-3.531, -1.394)
Contraceptive					
Not use(ref) Use	1.00 -0.043	 0.270	 0.96	 0.0038	 (-0.581, 0.469)
Random effect					
$\hat{\sigma}_u^2 = var(U_{0j})$ Var(U_{20j}) Cov(U_{0j}, U_{20j})	3.829 30.991 -9.225	1.284 17.458 4.814		0.0158 1.074	(1.821, 7.623) (6.551, 70.06)

Output for Bayesian Multilevel Logistic Regression of empty model

$$\text{Response}_{ij} \sim \text{Binomial}(\text{denom}_{ij}, \pi_{ij})$$

$$\text{logit}(\pi_{ij}) = \beta_{0j}\text{cons}$$

$$\beta_{0j} = -5.257(0.388) + u_{0j}$$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} 3.966(1.811) \end{bmatrix}$$

$$\text{var}(\text{Response}_{ij}|\pi_{ij}) = \pi_{ij}(1 - \pi_{ij})/\text{denom}_{ij}$$

PRIOR SPECIFICATIONS

$p(\beta_0)\ \alpha\ \ 1$

$p(1/\sigma^2_{u0}) \sim \text{Gamma}(0.001,0.001)$

Deviance(MCMC) = 1222.063(10103 of 10103 cases in use)

Output for Bayesian Multilevel Logistic Regression of random intercept model

$\text{Response}_{ij} \sim \text{Binomial}(\text{denom}_{ij}, \pi_{ij})$

$\text{logit}(\pi_{ij}) = \beta_{0j}\text{cons} + -0.907(0.279)\text{health facilities}_{ij} + 0.343(0.248)\text{1-2 visit}_{ij} + -0.210(0.268)\text{3-4 visit}_{ij} + -0.387(0.334)\text{5+ visit}_{ij} + 0.129(0.513)\text{20-24}_{ij} + 0.668(0.494)\text{25-29}_{ij} + 1.040(0.501)\text{30-34}_{ij} + 1.228(0.478)\text{35-39}_{ij} + 1.276(0.542)\text{40-44}_{ij} + 0.547(0.688)\text{45-49}_{ij} + 1.059(0.686)\text{1-2 child}_{ij} + 1.777(0.694)\text{3-4 child}_{ij} + 1.448(0.703)\text{5+ child}_{ij} + 0.512(0.423)\text{rural}_{ij} + -0.560(0.258)\text{primary education}_{ij} + -0.980(0.449)\text{secondary and above}_{ij} + -0.196(0.355)\text{tube}_{ij} + 0.411(0.310)\text{surface}_{ij} + -0.245(0.263)\text{middle}_{ij} + -1.296(0.308)\text{rich}_{ij} + -2.665(0.404)\text{married}_{ij} + -3.280(0.940)\text{no longer living/separeted}_{ij} + -2.202(0.497)\text{widowed/divorced}_{ij} + -0.057(0.268)\text{use}_{ij}$

$\beta_{0j} = -4.899(0.866) + u_{0j}$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0, \Omega_u) : \Omega_u = \begin{bmatrix} 4.221(1.487) \end{bmatrix}$$

$\text{var}(\text{Response}_{ij}|\pi_{ij}) = \pi_{ij}(1 - \pi_{ij})/\text{denom}_{ij}$

PRIOR SPECIFICATIONS

$p(\beta_0) \alpha \ 1$

$p(\beta_1) \alpha \ 1$

$p(\beta_2) \alpha \ 1$

$p(\beta_3) \alpha \ 1$

$p(\beta_4) \alpha \ 1$

$p(\beta_5) \alpha \ 1$

$p(\beta_6) \alpha \ 1$

$p(\beta_7) \alpha \ 1$

$p(\beta_8) \alpha \ 1$

$p(\beta_9) \alpha \ 1$

$p(\beta_{10}) \alpha \ 1$

$p(\beta_{11}) \alpha \ 1$

$p(\beta_{12}) \alpha \ 1$

$p(\beta_{13}) \alpha \ 1$

$p(\beta_{14}) \alpha \ 1$

$p(\beta_{15}) \alpha \ 1$

$p(\beta_{16}) \alpha \ 1$

$p(\beta_{17}) \alpha \ 1$

$p(\beta_{18}) \alpha \ 1$

$p(\beta_{19}) \alpha \ 1$

$p(\beta_{20}) \alpha \ 1$

$p(\beta_{21}) \alpha \ 1$

$p(\beta_{22}) \alpha \ 1$

$p(\beta_{23}) \alpha \ 1$

$p(\beta_{24}) \alpha \ 1$

$p(1/\sigma^2_{u0}) \sim \text{Gamma}(0.001,0.001)$

Deviance(MCMC) = 1110.728(10103 of 10103 cases in use)

Output for Bayesian multilevel for random coefficient Analysis Result

$\text{Response}_{ij} \sim \text{Binomial}(\text{cons}_{ij}, \pi_{ij})$

$\text{logit}(\pi_{ij}) = \beta_{0j}\text{cons} + -0.864(0.286)\text{health facilities}_{ij} + 0.352(0.253)\text{1-2 visit}_{ij} + -0.210(0.273)\text{3-4 visit}_{ij} + -0.446(0.344)\text{5+ visit}_{ij} +$
$0.156(0.520)\text{20-24}_{ij} + 0.684(0.506)\text{25-29}_{ij} + 1.107(0.507)\text{30-34}_{ij} + 1.289(0.487)\text{35-39}_{ij} + 1.336(0.556)\text{40-44}_{ij} +$
$0.528(0.702)\text{45-49}_{ij} + 1.219(0.717)\text{1-2 child}_{ij} + 1.925(0.738)\text{3-4 child}_{ij} + 1.638(0.749)\text{5+ child}_{ij} + 0.666(0.447)\text{rural}_{ij} +$
$-0.589(0.267)\text{primary education}_{ij} + -1.069(0.465)\text{secondary and above}_{ij} + -0.152(0.360)\text{tube}_{ij} + 0.429(0.320)\text{surface}_{ij} +$
$-0.342(0.270)\text{middle}_{ij} + \beta_{20j}\text{rich}_{ij} + -2.877(0.442)\text{married}_{ij} + -3.572(1.052)\text{no longer living/separeted}_{ij} +$
$-2.420(0.543)\text{widowed/divorced}_{ij} + -0.049(0.274)\text{use}_{ij}$

$\beta_{0j} = -5.116(0.845) + u_{0j}$

$\beta_{20j} = -4.316(2.161) + u_{20j}$

$$\begin{bmatrix} u_{0j} \\ u_{20j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} 4.085(1.222) & \\ -9.160(4.754) & 31.193(17.983) \end{bmatrix}$$

$\text{var}(\text{Response}_{ij}|\pi_{ij}) = \pi_{ij}(1 - \pi_{ij})/\text{cons}_{ij}$

PRIOR SPECIFICATIONS

$p(\beta_0)\ \alpha\ 1$

$p(\beta_1)\ \alpha\ 1$

$p(\beta_2)\ \alpha\ 1$

$p(\beta_3)\ \alpha\ 1$

$p(\beta_4)\ \alpha\ 1$

$p(\beta_5)\ \alpha\ 1$

$p(\beta_6)\ \alpha\ 1$

$p(\beta_7)\ \alpha\ 1$

$p(\beta_8)\ \alpha\ 1$

$p(\beta_9)\ \alpha\ 1$

$p(\beta_{10})\ \alpha\ 1$

$p(\beta_{11})\ \alpha\ 1$

$p(\beta_{12})\ \alpha\ 1$

$p(\beta_{13})\ \alpha\ 1$

$p(\beta_{14})\ \alpha\ 1$

$p(\beta_{15})\ \alpha\ 1$

$p(\beta_{16})\ \alpha\ 1$

$p(\beta_{17})\ \alpha\ 1$

$p(\beta_{18})\ \alpha\ 1$

$p(\beta_{19})\ \alpha\ 1$

$p(\beta_{20})\ \alpha\ 1$

$p(\beta_{21})\ \alpha\ 1$

$p(\beta_{22})\ \alpha\ 1$

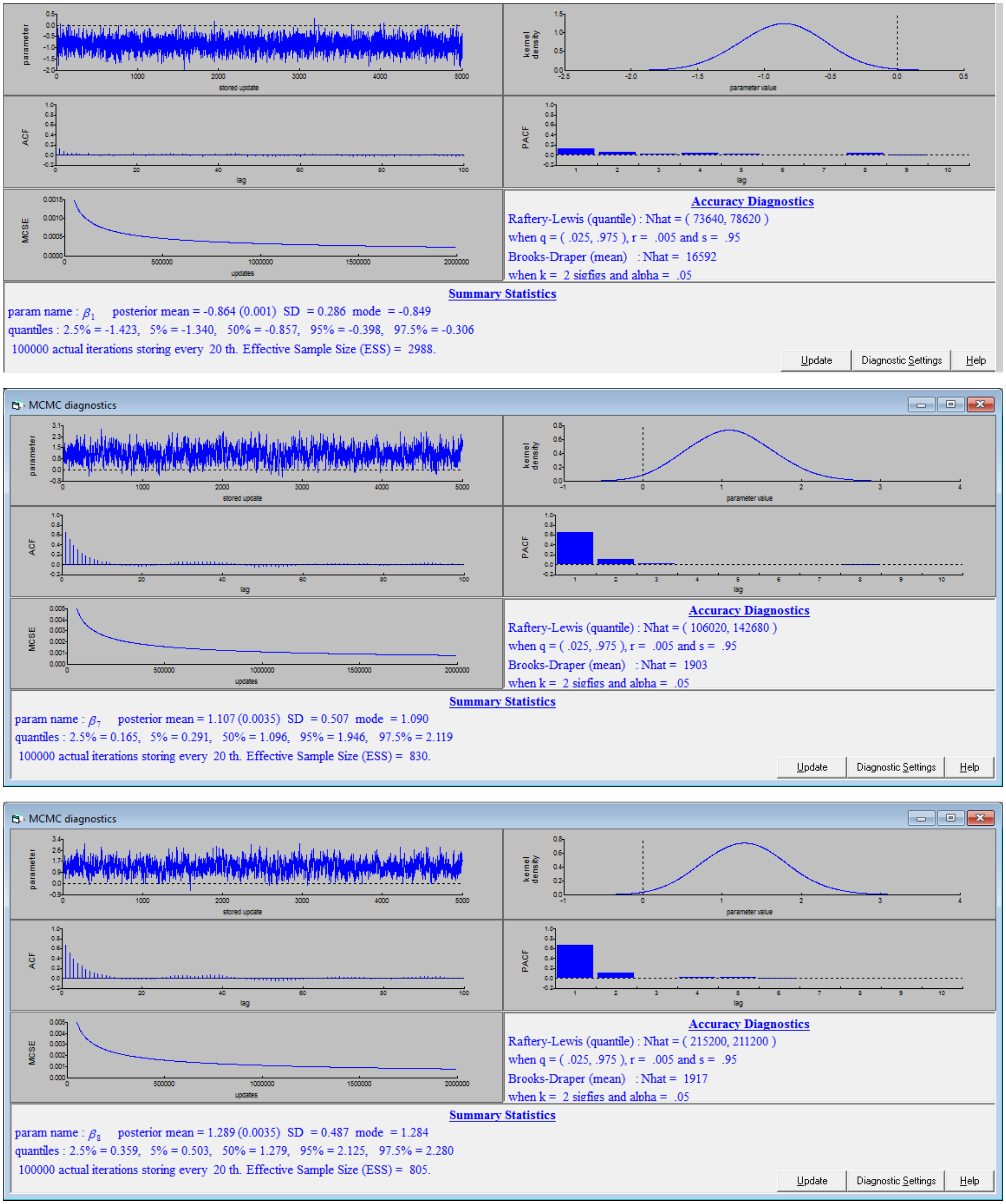
$p(\beta_{23})\ \alpha\ 1$

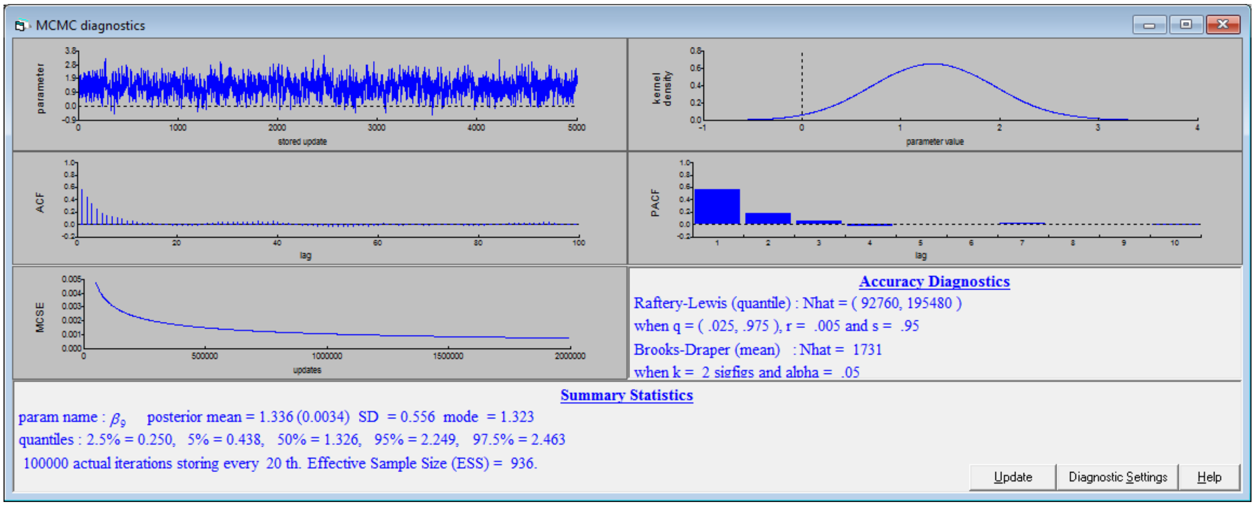
$p(\beta_{24})\ \alpha\ 1$

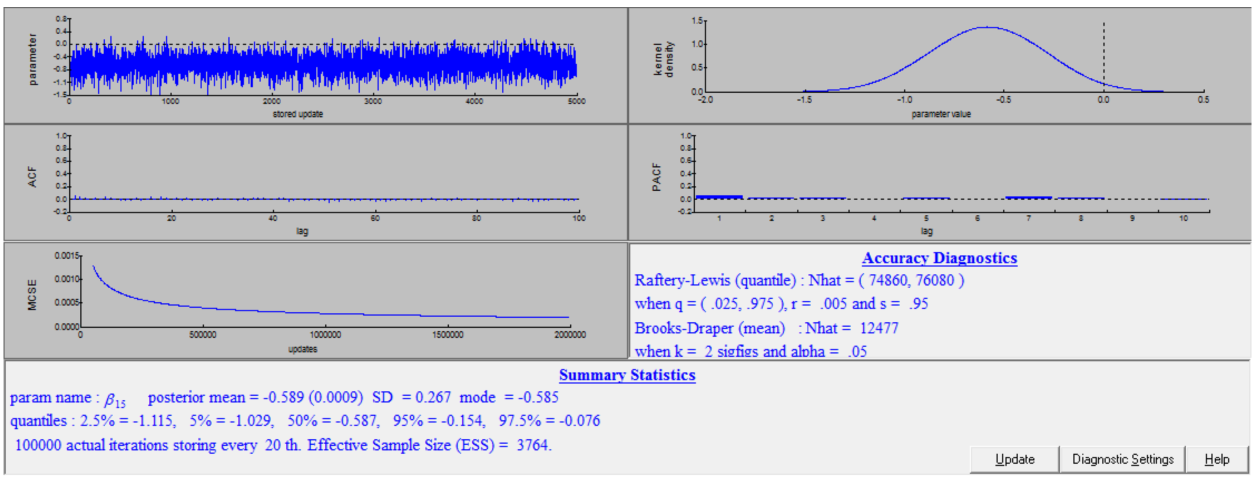
$$p(\Omega_u) \sim \text{inverse Wishart}_2[\ 2{*}S_u, 2],\ \ S_u = \begin{bmatrix} 1.113 & \\ -1.870 & 4.649 \end{bmatrix}$$

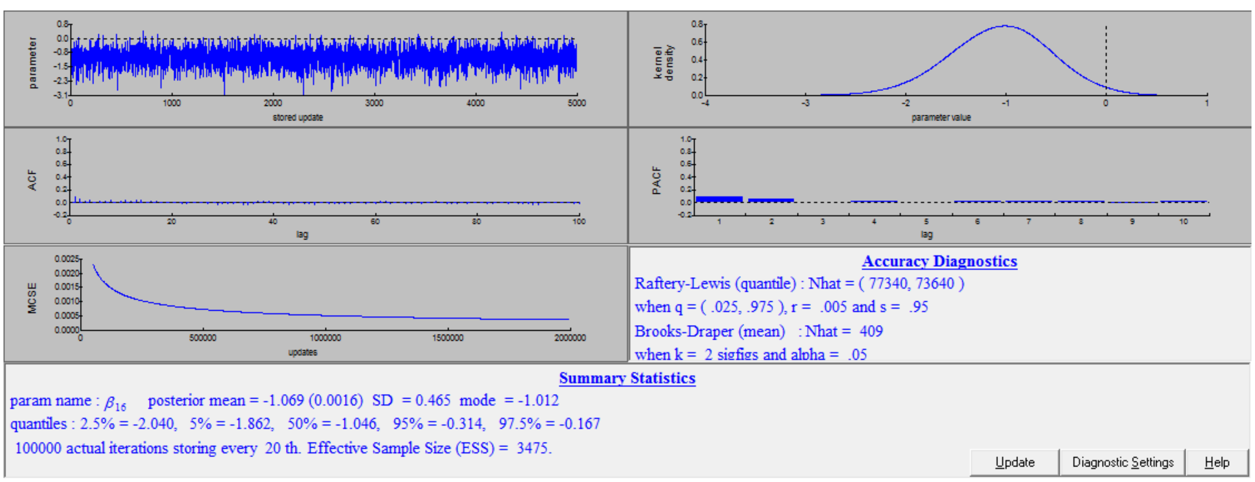
Deviance(MCMC) = 1047.238(10103 of 10103 cases in use)

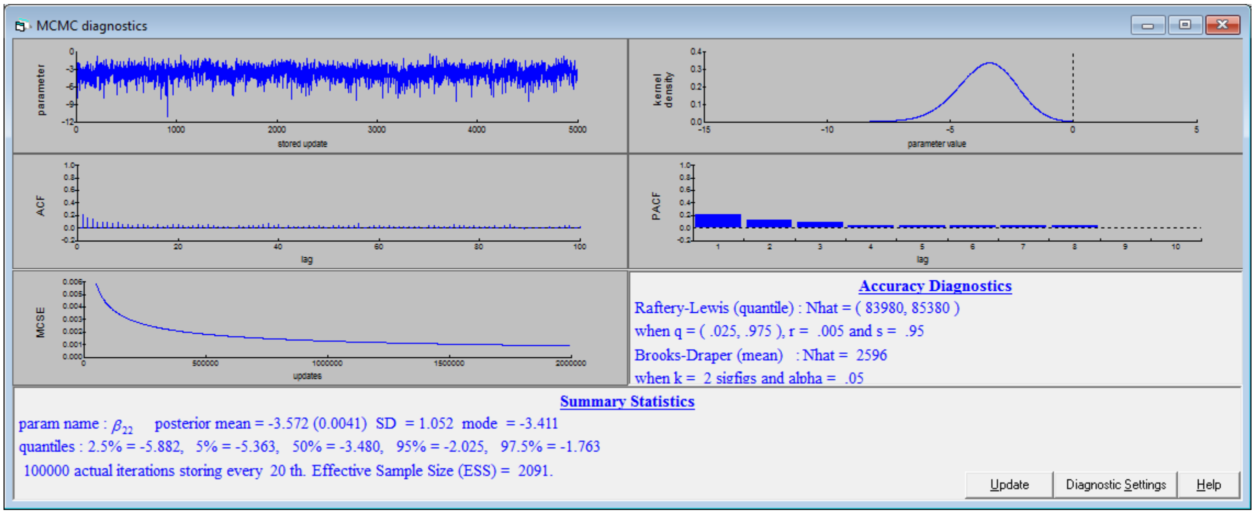
Figure 4.1 Diagnostics of Convergence for parameters significant in Bayesian multilevel Model

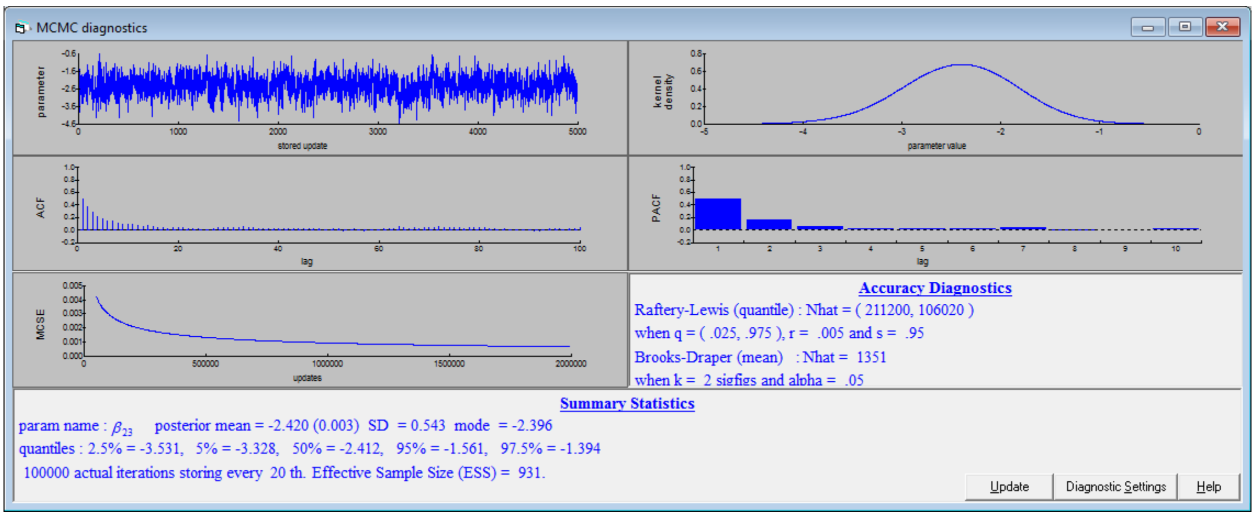


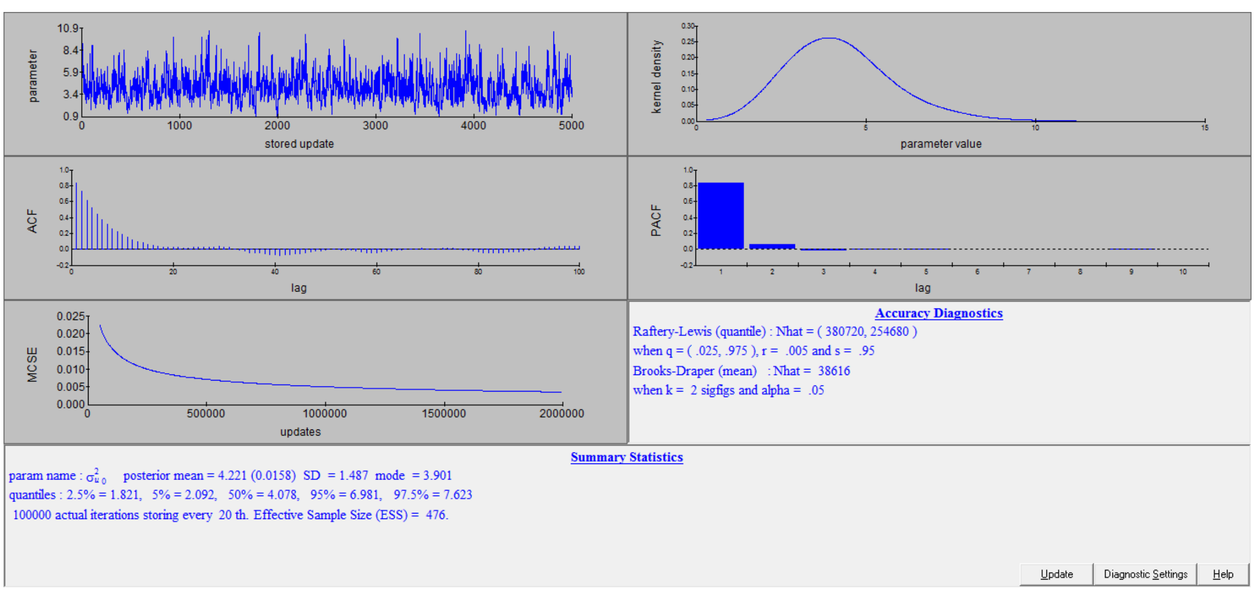

MCMC diagnostics
parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (92760, 195480)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 1731
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : β_9 posterior mean = 1.336 (0.0034) SD = 0.556 mode = 1.323
quantiles : 2.5% = 0.250, 5% = 0.438, 50% = 1.326, 95% = 2.249, 97.5% = 2.463
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 936.
Update
Diagnostic Settings
Help


parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (74860, 76080)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 12477
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : β_{15} posterior mean = -0.589 (0.0009) SD = 0.267 mode = -0.585
quantiles : 2.5% = -1.115, 5% = -1.029, 50% = -0.587, 95% = -0.154, 97.5% = -0.076
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 3764.
Update
Diagnostic Settings
Help


parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (77340, 73640)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 409
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : β_{16} posterior mean = -1.069 (0.0016) SD = 0.465 mode = -1.012
quantiles : 2.5% = -2.040, 5% = -1.862, 50% = -1.046, 95% = -0.314, 97.5% = -0.167
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 3475.
Update
Diagnostic Settings
Help


MCMC diagnostics
parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (83980, 85380)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 2596
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : β_{22} posterior mean = -3.572 (0.0041) SD = 1.052 mode = -3.411
quantiles : 2.5% = -5.882, 5% = -5.363, 50% = -3.480, 95% = -2.025, 97.5% = -1.763
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 2091.
Update
Diagnostic Settings
Help


MCMC diagnostics
parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (211200, 106020)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 1351
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : β_{23} posterior mean = -2.420 (0.003) SD = 0.543 mode = -2.396
quantiles : 2.5% = -3.531, 5% = -3.328, 50% = -2.412, 95% = -1.561, 97.5% = -1.394
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 931.
Update
Diagnostic Settings
Help


parameter
stored update
kernel density
parameter value
ACF
lag
PACF
lag
MCSE
updates
Accuracy Diagnostics
Raftery-Lewis (quantile) : Nhat = (380720, 254680)
when q = (.025, .975), r = .005 and s = .95
Brooks-Draper (mean) : Nhat = 38616
when k = 2 sigfigs and alpha = .05
Summary Statistics
param name : σ^2_{u0} posterior mean = 4.221 (0.0158) SD = 1.487 mode = 3.901
quantiles : 2.5% = 1.821, 5% = 2.092, 50% = 4.078, 95% = 6.981, 97.5% = 7.623
100000 actual iterations storing every 20 th. Effective Sample Size (ESS) = 476.
Update
Diagnostic Settings
Help