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Multilevel Analysis of Determinants of Early Marriage Among Women in Ethiopia: Using Bayesian and Classical Approach

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A Thesis Submitted to, College of Science, Bahir Dar University, in Partial Fulfillment of the Requirement for the Degree of Master of Science (MSc) in Biostatistics.

Advisor: Ashenafi Abate (Ass.Prof.)

August, 2020
Bahir Dar

Declaration

This is certify that thesis entitled "Multilevel Analysis of Determinants of Early Marriage among Women in Ethiopia: Using Bayesian and Classical Approach", submitted in the partial fulfillment for the requirements of Degree of Master of Science in Biostatistics of department of statistics, Bahir Dar University, is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been duly acknowledged.

Negash Moges Chekole ____________________ ____________________

Date Signature

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Approval of the thesis for defense

I hereby certify that I have supervised, read, and evaluated this thesis titled "Multilevel Analysis of Determinants of Early Marriage among Women in Ethiopia: Using Bayesian and Classical Approach" by Negash Moges Chekole prepared under my guidance. I recommend the thesis be submitted for oral defense.

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Approval of the thesis for defense result

As members of the board of examiners, we examined this thesis entitled "Multilevel Analysis of Determinants of Early Marriage among Women in Ethiopia: Using Bayesian and Classical Approach" by Negash Moges Chekole. We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of "Master of Science in Biostatistics".

Board of Examiners

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Chair person's name	Signature	Date
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Abstract

Early marriage is still widely exercised in many parts of the world chiefly in Latin America, the Caribbean, Southern Asia and countries of Africa. Ethiopia has one of the highest rates of early marriage in the world and Sub-Saharan Africa, ranking 18th globally. In Ethiopia the national prevalence of early marriage was 58%. Thus, this study was aimed to identify the determinants of early marriage among women in Ethiopia using Bayesian and classical approach. The data were extracted from the 2016 Ethiopia Demographic and Health Survey. The study included a sample from 9479 married women nested within eleven regions with age 15-49 years. The data were collected using two-stage cluster design that includes selections of enumeration area as first stage and selection of households as second stage. A two-stage model comparison was fitted to determine the individual and regional level factors associated with early marriage. Besides, this, the researcher has compared the Bayesian and classical multilevel logistic regression models. This study also revealed that the prevalence of early marriage among the women aged between 15 to 49 years in country was around 58.2%. For this study Bayesian random intercept multilevel model was found to be appropriate model in fitting the data suitably. The study, results revealed that the predictors such as place of residence, religion of woman, educational level of women, husband's education level, respondents work status, wealth index and exposure to mass media and ethnicity were found to be significant predictors for early marriage among women. The Bayesian random intercept model also revealed that there was a significant variation in early marriage across regions of Ethiopia. The results showed that a random effects of religion, women and husband educational level of women is found to be significant in explaining the variation of early marriage across the regions of Ethiopia. As a result special attention require to be committed, in specifically to the regions' access to education for young women to reduce early marriage and educating women through their religious leaders is also good means of raising the age at the first marriage. Especially it is advisable to Muslim religion leaders to delay early marriage of women for their followers by giving basic information regards to marriage and by developing the perception of women.

Key words: *MCMC, Early marriage, Multilevel model*

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Acronym and list of abbreviation

CSA	Central Statistics Agency
EA	Enumeration areas
EDHS	Ethiopian Demographic Health Survey
FMoH	Federal Ministry of Health
ICC	Intra Class Correlation
ICRW	International Center for Research on Women
IWHP	Integrated Women's Health Programme
MCMC	Markov Chain Monte Carlo
MLE	Maximum Likelihood Estimation
NCTP	National Committee on Traditional Practices in Ethiopia
SNNP	Sothern Nations Nationalities and Peoples Region
SPSS	Statistical Package for Social Science
UNDESA	United Nations Department Economic and Social Affairs
UNICEF	United Nations Children's Fund
UNFPA	United Nations Fund for Population Activities
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1. Background

Women are victims of diversified socio-economic and political violations and exclusions. They are severely affected by sexual violence, early marriage and harmful traditional practices such as female genital mutilation and tattooing. Due to these in human and discriminatory practices, women and girls are banned from access to education, health care services, employment and other opportunities and resources. Early Marriage is, one of the ways of violation of human and women's rights (Mengistu, 2017). Early marriage is a formal or informal marriage of women below the age of 18 years when the women is not yet physically and emotionally mature enough to bear a child and take the social responsibility of the wife (Unicef, 2014).

Millions of women are affected by early marriage throughout the world. Of the current global population, UNICEF (2014) estimates that 720 million women were married before the age of 18 and more than one-third of those women, approximately 250 million, were married before the age of 15 (Unicef, 2014). The practice primarily affects women and data indicate that 1 in 3 women currently aged 20-24 in the developing world have married before the age of 18 and an estimated 15 million women under 18 marry each year (Girls Not to Bride, 2016. Early marriage is not isolated to any geographic region or defined by any culture or religion. It takes place in countries as diverse as Bangladesh, Burkina Faso, and Brazil, and Niger, Nicaragua, and Nepal. Although the largest total number of early marriage resides in South Asia, the majority of countries with the highest prevalence rates of early marriage in the world are in sub-Saharan Africa (Parsons et al., 2015).

In developing countries, one in every three women is married before reaching age 18 and one in nine is married under age 15(UNFPA, 2015). The overall 20 to 50 percent of women are married before the age of 18 developing world with highest percentage in West African within sub-Saharan African and south Asia. Approximately 40% of women aged 20-24 worldwide who were married before the age of 18 live in sub-Saharan, thus resulting in early marriage being largely sub-Saharan African phenomena (Petroni et al., 2017).

Sub-Saharan Africa had the highest rates of early marriage in the world and from 20 countries that had the highest rate of early marriage worldwide, 18 were found in the Sub-Saharan region (Koski et al., 2017). Based on demographic and health survey reported that more than half of the women in the region marry before 18 years in many countries in the sub-Saharan region(Efevbera et al., 2019)

Early marriage is very worst in Africa, in sub-Saharan Africa in general and in Ethiopia in particular (Unicef, 2015). In Ethiopia, women tends to marry considerably earlier than man(CSA, 2017). Ethiopia has one of the highest rates of early marriage in the world, ranking 18th globally in 2013 (ICRW, 2015). It is the second most populous country in Africa and is characterized by high population growth of 2.57% annually(UNDESA, 2019). The fertility rate was 4.99 children per woman and most of the population is young people (CIA, word fact book, 2018). In 2016, nearly half (47%) of the total population was under 15 years old (Demographic, 2016). In addition, a large proportion (20%) of the population are aged 15–24 (CIA, word fact book, 2018), of whom 47% are affected by early marriage(Demographic, 2016).

According to a previous study one in six young women in Ethiopia had married by the age of 15 (Erulkar, 2013). Early marriage and harmful traditional practices are the most common socio-cultural events in most rural areas of Ethiopia (Asrese and Abebe, 2014). Ethiopia, from every 10 women who were getting into marriage, about 3 had married before maturity age and the prevalent of early marriage in the rural Ethiopia was higher, especially the communities Christian dominated and Northern part of Ethiopia women was married early compared to other region. This part of the region accounts the 54.6% of the women married early. In addition, the South and South-Western part of the Ethiopia have the prevalence of 50% so far as early marriage is related (Mengistu, 2017).

In general Ethiopia is one of the nations that have highest early marriage proportion. In 2011, the prevalence of early marriage was 41% of Ethiopian women aged 20-24 had been married before they reached 18 (CSA and ICF International, 2012). According to the Ethiopian demography and health survey 2016, also the national prevalence of early marriage was 58%(CSA, 2017).

Early marriage practices of women were a significant social concern globally in recent years due to dangerous health consequences such as increased risk of acquiring sexually transmitted diseases, child malnutrition, teenage pregnancy, miss the opportunity of formal education, dropping out of school, maternal and child morbidity and mortality on young women who marry at early ages (Montazeri et al., 2016).

Women most likely to marry as early are those who live in rural areas, come from poor households, and have little or no education (Loaiza Sr and Wong, 2012). Women who marry at younger ages tend to have a larger age difference with their husbands, as well as lower power and autonomy in their relationships (Lee-Rife et al., 2012) and are potentially at higher risk of domestic violence (Santhya et al., 2010).

Global and national statistics are clearly indicative of the problem in many sub-Saharan African countries especially in Ethiopia. However, they mask within-country geographical variations and given the varying marital cultures and traditions within country, it is probable that the extent of early marriage and union formation will vary in nation communities. The 2016 Ethiopian Demographic and Health Survey data used for this study are based on two stage stratified cluster sampling. The appropriate approach to analyzing early marriage among women from this survey is therefore based on nested sources of variability. Here the units at a lower level are individuals (married women whose age was from 15-49) who are nested within units at a higher level (region). Beside the nested source of variability; the response variable in this study is early marriage among women which is a binary response. Because of this, the multilevel logistic regression analysis considers the variations due to the hierarchy structure for a binary response. Thus, this research was employed multilevel logistic regression analysis for hierarchy structure of data with a Bayesian approach was used.

1.1. Statement of the problem

The WHO report shows, thousands of women have died because of early pregnancy and childbirth and confirmed that around 70,000 early married women aged 15 to 19 die each year due to complication of pregnancy and childbirth (WHO, 2012). Other additional problems of early marriage leads early pregnancy and fertility had mostly been followed by negative consequence such as, obstetric fistula, excessive hemorrhaging, contamination in HIV/AIDS and other sexually transmitted diseases (IWHP., 2015.

In Ethiopia, early marriage has the main health problem and socioeconomic impacts on married women. Some of these consequences include adverse pregnancy outcomes, miss the chance of formal education, lack of opportunity for salary employment and social power inequities, such as sexual violence, imbalanced profit producing opportunity, little money for achieving their regular necessities and gender inequality in and out of their households (Mengistu, 2017).

Several studies have been done in Ethiopia to identify the determinant of early marriage among the women (Bezie and Addisu, 2019). Most studies on early marriage among women in Ethiopia in the country level have been exercised commonly based on the frequentist approach and as far as the researcher reading concern no any other study is conducted with Bayesian perspective. In addition to this, the comparisons of those approaches for the early marriage among the women's have not well performed previously. Although the size of the data obtained from the EDHS was seems large enough to estimate the unknown parameters with the information from likelihood, due to only 95% of the EDHS, eligible women response rate have been covered; the research aimed to consider this data set as non-representative of the target population. Literature supported that for the study with non-representative sample, believe that the prior information has empowered the estimation of the parameters(Alkema et al., 2013). It also still empowers the efficiency of the data even when the size of observation may large enough in representing the target population by giving distribution for the unknown parameters(Rue et al., 2017).

Thus, the researcher motivated to conduct the study on this issues and believed that the study will helps to reduced early marriage in Ethiopia. Based on all the aforementioned studies, this study focuses on identifying the determinants early marriage among women in Ethiopia and try to address the regional variation of early marriage among women. This study tries to come up and give answer to the following main research questions

1. Which predictors have a statistically significant effect in determining the status of early marriage among women in Ethiopia?
2. Does early marriage among women vary across the regional states of Ethiopia?
3. Which predictors that explain the variation of early marriage among women between the region of Ethiopia?
4. Which model is good to fit the early marriage practice of women appropriately?

1.2 Objective of the Study

1.2.1 General Objective

The main purpose of this study was to identify the determinants of early marriage among women and determine variations in early marriage between and within regions of Ethiopia using EDHS 2016.

1.2.2 Specific Objective

- To identify the determinant factors of early marriage among women in Ethiopia.
- To determine the within and between regional variation of early marriage among married women's in the country.
- To identify the factors that explains the variation in early marriage between regions of Ethiopia.
- To fit the Bayesian and classical multilevel logistic regression model.

1.3. Significance of the study

The findings of this study help to planners in the planning, formulation, and implementation of policy concerning about the negative impacts of early marriage and also important to create an awareness about effect of early marriage among women over the country level. Since the study attempts to reveal significant factors of early marriage among women in Ethiopia, governmental and non-governmental organizations will take intervention measures and prepare appropriate plans to undertake the existing early marriage problems.

It is expected that this study will provide relevant recommendations for policymakers and suggest directions for future studies. The study could be used as a means for further studies, analysis and developing appropriate intervention.

The hierarchical level models are very flexible and have the ability to handle the variability in the clustered data. Thus, researchers will gain from this study not to use the traditional models that account the correlated data treated as an independent observation which results to the standard errors of regression coefficients to be underestimated.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Overview of Early Marriage

In 2012, an estimated 33 to 40 percent of women aged 20-24 were married before the age of 18 globally (Nguyen and Wodon, 2012). Early marriage is a widespread challenge, with estimated prevalence exceeding 30 percent or more in 41 countries(Loaiza Sr and Wong, 2012). Half of women affected by early marriage live in South Asia, although the risk is greatest for women living in parts of West Africa (Loaiza Sr and Wong, 2012). Youth populations in countries most affected by early marriage, if current trends continue the number of early married of women annually is estimated to increase from 14.2 million in 2010 to 15.1 million in 2030 (Loaiza Sr and Wong, 2012).

The overall prevalence of early marriage in Africa is higher than the global average and if current trends continue, Africa will become the region with the largest number and global share of early marriages by 2050 and Although early marriage is prevalent across Africa, prevalence is greatest in West and Central Africa where it is estimated that four out of ten women aged 20 to 24 were married before age 18(UNICEF., 2015).

The convention on the elimination of all forms of discrimination against women as the current estimates show that approximately 82 million girls between 10–17 years will be married before they reach 18 years and 331 million girls aged 10–19 in developing countries (excluding China), Although early marriage is predominantly a female problem, a minority of boys may also be forced to marry early and in the least-developed countries the prevalence of early marriage is even higher nearly one in two (UNICEF., 2012). Study done by the world highest rate of early marriage before 18 years age, as follows; Niger (76%), Central Africa Republic (68%), Chad (68%), Bangladesh (65%), Mali (55%), Guniea (52%), South Sudan (52%), Burkinafaso (50%), Malawi (50%) and Mozambique (48%)(UNICEF., 2015). Southern Asian countries in the world accounts the second highest rate in early marriage (ICRW., 2013).

Women aged 10-19, who comprise 24% of the population (CSA and ICF International, 2012) , face numerous challenges. The 2011 Ethiopia Demographic and Health Survey reveals that the average age at marriage is 16.5 years, and over 41% of women aged 20-24 report that they were married before the age of 18 (CSA and ICF International, 2012). As a result of early marriage, Ethiopia has one of the highest adolescent fertility rates in sub-Saharan Africa – 72.4 births for every 1,000 young women aged 15-19 (UNFPA., 2012).

The median age at first marriage among women age 25-49 has increased slightly since 2011, from 16.5 years to 17.1 years. During the same period, the percentage of women marrying before age 18 has declined from 63% to 58%. Eight percent of women married before their 15th birthday in 2011, as compared with 6% in 2016 (CSA., 2016).

2.2. Socio-Economic Factors

The education level of women

The study conducted on the factors associated with age at the first marriage in Uganda. (Agaba et al., 2010) investigated determinants of age at first marriage among women using Cox's proportional hazard model and showed that educational attainment, religion, district of residence (region), occupation and age were strong socio-economic determinants of age at first marriage in Western Uganda. The risk of first marriage was 18 percent lower for the women with primary education and 34 percent lower for women with at least secondary education, all compared with women with no education. The significance level for all education categories were significant and thus risk of getting married reduced as the level of education increased. These results provide empirical evidence that a woman's educational attainment is an important determinant of early marriage.

Furthermore, a study which was conducted in the Nigeria (Adebowale et al., 2012) used Chi-square and Cox proportional hazard models to determine Survival Analysis of Timing of First Marriage among Women of Reproductive age in Nigeria data on Nigeria Demographic and Health Survey, 2008. The finding of the study revealed that women who had primary, secondary and higher education with the respective odds were 18%, 32% and 56%, indicating less likely to marry early than among women those with no education.

Another study which is conducted in decline in child marriage and changes in its effect on reproductive outcomes in Bangladesh using multivariate logistic regression analysis, Women's education showed a significantly negatively relationship with timing of marriage when other socio-demographic covariates kept constant. For instance, women with primary, secondary and higher education, compared to those with no adjust formal education, were respectively odds of practice of early marriage were 28%, 65%, and 94% times lower as compared to the married at very young age (Kamal, 2012).

Similar study conducted on statistical analysis of early marriage among women shows that Women who had no education, primary and secondary were more likely to be married early (OR=4.95, 4.41 and 2.21) respectively compared to women with higher education level controlling for other variables in the model. Lower levels of education are associated with a higher probability of early marriage (Gashaw, 2019).

Wealth index

Economic status of the household has been identified as one of the significant factor for women to exercise early marriage in Ethiopia. A study in Ethiopia by using the title statistical analysis of early marriage based on Ethiopian Demographic and Health Survey, 2011 data. For instance, women whose economic status poorest, poorer, middle and richer with respective odds was more likely being married early were 1.19, 1.53, 1.23 and 1.41 than among the richest category (Gashaw, 2019). In agreement with this view, other study was conducted in Bangladesh using multilevel logistic regression analysis the women from the richest, richer, middle and poorer economic status with respective odds were 36%, 31%, 16% and 15% times lower being married early as compared to the poorest category. Lower levels of income household are associated with higher probability of early marriage (Kamal, 2012).

Research shows that the poorest countries have the highest early marriage rates. Early marriage is concentrated in the poorest countries, with the lowest gross domestic product countries tending to have the highest early marriage prevalence rates (ICRW, 2006). National Research Council and Institute of Medicine (2005) reported that women from wealthier households are less likely to marry at younger ages as compared to women from poorer households, because they have more options for education and employment. It is also most common among the poorest households. In a study of women ages 20 to 24 in 49 countries, early marriage was most common among the poorest 20 percent of households in every country. A women from the poorest household in Senegal, for example, is more than four times as likely to marry before age 18 as a women in the richest household (UNICEF., 2005).

Place of residence

In many kinds of literature place of residence found to be a significant association with early marriage among women. Different researcher added the place of residence have been implemented in determinants of early marriage among the women.

A study was conducted in determinants of early marriage among female children in Sinan district; Northwest Ethiopia community-based cross sectional study design was carried out. The result shows that the odds of being married early were 12.2(95% C.I: 5.79, 26.23) times higher among rural residents compared to urban residence (Workineh et al., 2015).

Other study was conducted in Nigeria using the Cox proportional hazard models to determine survival analysis of timing of first marriage among women of reproductive age in Nigeria data on Nigeria Demographic and Health Survey, 2008. The result showed that place of residence was significant variables. Women who reside in rural area (H.R=1.15) times married early than their urban residence area. In this research tells that the urban residence have batter awareness about the impacts of early marriage than the rural residence(Adebowale et al., 2012) .

Moreover the study done on trends in marriage and early childbearing in developing countries reported that higher rates of early marriage in rural areas than in urban areas that is women in rural residences are more likely to marry 1.5 years younger than women in urban areas(Westoff, 2003). Other study shows that the survival time was lengthened for women who are lived in urban area were 1.7% times greater than those who are lived in rural area (Tessema et al., 2015).

Mass media exposure

Mass media is important tools to transmit information in order to create awareness about different harmful tradition practice through different way of mechanism like listening radio, watching TV…etc. The practice of listening different media has positive influence on the early marriage in day to day life. To check the contribution of mass media on early marriage consent behavior, many researchers have been conducted in different time. The study was conducted in Ethiopia on modeling the determinants of time-to-age at first marriage in women using the multivariable Log-logistic-Inverse Gaussian shared frailty model for age at first marriage dataset, EDHS, 2011 shows that the survival time was lengthened for those women who had any access of media were 2.00%

(ϕ: 1.0202, 95% CI: (1.0110, 1.0294)) times higher than those not had any access to media. This indicated that access to mass media is increase the early marriage among women was decrease (Tessema et al., 2015).

Similarly, study shows that the women mass media exposure has statistically associated with early marriage. The study shows that the odds of being married early was increased by 36% for a women who do not exposure to any mass media via radio, TV or newspapers/magazine than women exposed to any mass media (Gashaw, 2019). Others study agree with this result shows the regression coefficient proposes that, with reference to females who have any access to media, the no access women are more likely to be married previous 18 years and which were 1.19 times higher. It is recognized that media make conscious of an individual so respondents who have entrance to mass media they are relatively more watchful about the worse situation of marriage happen at early age (Zahangir and Kamal, 2011).

Religion

In many findings, religion was found to be a significant association with the exercise of early marriage. Consequently, a study done in Bangladesh using multilevel logistic regression has investigated that religion was an important predictor for early marriage practice. In this study Muslim believer women were 79 percent more practice early marriage than those women in Non-Muslim (Zahangir and Kamal, 2011). Another study has investigated the role of religion upon the practice of early marriage and hence the odds of early marriage in Orthodox, Muslim and Protestant were 1.690258, 1.383015 and 1.171983 times higher as compared to others religion respectively (Gashaw, 2019).

Regional variation

Ethiopia is a multi-ethnic and multi-cultural country then the practice of early marriage was not evenly distributed throughout the country. A Study conducted on examines the effect of demographic and socioeconomic variables to determine early marriage among women among the Regional States of Ethiopia. The study used to analysis the 2011 Ethiopian Demographic and Health Survey data source to examine the determinants and cross-regional variations of early marriage among women aged 15 to 49 years in Ethiopia and study revealed that there was a regional variation of early marriage among women across the regions (Gashaw, 2019).

Other study was conducted in Malawi on factors affecting age at first marriage based on 2000 MDHS collected data for 13220 women aged 15-49 whereas the 2004 DHS collected data for 11698 women of the same age range. Total sample for this analysis comprises 10,600 and 9605 ever-married women aged 15-49 years old in 2000 and 2004 data sets respectively. The finding of the result shows that the risk of marriage for women who live in the Central region of Malawi is lowered than that of women who live in the Northern region. The difference in age at marriage is due to concentration of low educational status of women, levels of socioeconomic development may be culturally different lead to differences in marriage timing (Kumchulesi et al., 2011).

Husband's education

In many fields of studies husband's educational status considered as a significant effect on early marriage among women. In line with this, the study was conducted in Ethiopia on modeling the determinants of time-to-age at first marriage in women using the multivariable Log-logistic-Inverse Gaussian shared frailty model for age at first marriage dataset, EDHS, 2011 shows that the survival time of age at first marriage increased with changing from one category to another (primary, secondary and higher) educational level relative to those heads/parents with no education as a reference group and the survival times was lengthened by 3.50%, 4.05% and 4.44% respectively for the group of primary, secondary and higher educational level of heads/parents (Tessema et al., 2015).

Furthermore, the study conducted in Bangladesh using logistic regression analysis by the title of several attributes linked with early marriage of women's shows that the husband's educational attainment was effects on the practice of early marriage in women. Consequently, women married to men who had completed the primary and no education with respective odds of being married early were 50.1%(1.501) and 67.9%(1.679) times higher to marry early than among women married to men who completed the secondary education (Zahangir and Kamal, 2011).

Husband's occupation

This is also another socio-economic factor that contributes to early marriage among women .The study conducted on modeling the Determinants of time-to-age at first marriage in Ethiopian Women: Based on , the result shows that the time rate and 95% Confidence interval of acceleration factors for occupational status of heads/parents for a group of professional, business, laborers and Others were 1.0218(1.0079, 1.0360), 1.0433(1.0306, 1.0581), 1.0441(1.0209, 1.0679) and 1.0538 (1.0297, 1.0785) when compared to occupation of agriculturalists group (as reference category) respectively. In other way the survival time of age at first marriage increased with changing from one category to another (professional, business, laborers, others) occupational status of heads/parents with agriculturalists group as reference groups and the survival times was lengthened by 2.2%, 4.33%, 4.41% and 5.4% respectively for the group of professional, business, laborers and Others occupational status of heads/parents (Tessema et al., 2015).

Women's Occupation

As many studies identified that woman's working status as an important factor in influencing early marriage among women. A study done in Democratic Republic of Congo on determinants of early marriage among young Women using Binary logistics analysis, shows that the odds of being married early were decreased by 25% for a women who had work as compared to the women who had no work (Mpilambo et al., 2017).

Similarly, studies in Bangladesh revealed the implication of women's working status on early marriage. In this study specifies that the respondent's currently working status is also an important determinant factors of early marriage of women. It is observed that marriage takes place before 18 years of age is likely to be were 1.25 times higher among women who currently not working outside the residence than those of working women. After marriage, women who go outdoors for work in most cases the earnings of their partner's is inadequate hence they are almost bound to do any kinds of inferior jobs to fulfill some basic requirements of the family (Zahangir and Kamal, 2011).

2.3. The motivation for multilevel model and Bayesian approach

The multilevel logistic regression analysis considers the variations due to hierarchical structure in the data. It allows the simultaneous examination of the effects of group level and individual level variation-independence of observations within and between groups (Khan and Shaw, 2011). It is a family of statistical models in analyzing data with hierarchical structure. Different names were given to this family of models depending on the area of study, for example, multilevel or hierarchical model.

Multilevel models have an advantage of incorporating effects that vary by group (region in this study). The multilevel model provides a coherent model that simultaneously incorporates both individual- and group-level models as well as getting the right standard error (Gelman and Hill, 2006). Multilevel modeling is a direct way to include indicators for clusters at all levels of a design, without being overwhelmed with the problems of over fitting that arise from applying least squares or maximum likelihood to problems with large numbers of parameters.

Generally ignoring the correlated or nested data can completely be resulted with the wrong estimation which in turn leads to a wrong conclusion (Sainani, 2010). Therefore, the nature of EDHS data is hierarchical in which individuals are nested within regions for which multilevel models are advisable.

Bayesian estimation and inference have a number of advantages in statistical modeling and data analysis. It provides a way of improving estimation in sparse or small datasets by borrowing strength from prior distribution of the parameters in combination with the likelihood (e.g. in stratified sampling)(Richardson and Best, 2003). And allow finite sample inferences without appeal to large sample arguments as in maximum likelihood and other classical methods. It can also assess the probabilities on both nested and non-nested models (unlike classical approaches) and, using modern sampling methods, is readily adapted to complex random effects models that are more difficult to fit using classical methods (Carlin et al., 2001). Bayesian methods may also improve on classical estimators in terms of the precision of estimates. This happens because of specifying the prior that brings extra information or data based on accumulated knowledge, and the posterior estimate is based on the combined sources of information (prior and likelihood) therefore has greater precision(Richardson and Best, 2003). Another advantage of the Bayesian approach is the possibility of improving the precision of the results by introducing external information in terms of the priori distribution((M.L. Call et al., 2006). Finally Bayesian approach is preferred over the usual frequentist technique is that the power of information obtained from the approach is much better as it is the combination of likelihood data and prior information about the distribution of the parameter (Rue et al., 2017).

CHAPTER THREE

3. DATA AND 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 109,000,000 populations (CIA, word fact book, 2019) and the tenth largest by area, occupying 1,126,829 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, Gambella and Harari) and two city administrations (Addis Ababa and Dire Dawa that are considered as a region) with a capital city of Addis Ababa.

3.2. Source of data

The dataset in this study was obtained from the Demographic and Health Survey conducted in Ethiopia in 2016. The 2016 Ethiopia Demographic and Health Survey (EDHS) is the fourth Demographic and Health Survey conducted in Ethiopia. It was implemented by the Central Statistical Agency (CSA) at the request of the Federal Ministry of Health (FMoH). Data collection took place from January 18, 2016, to June 27, 2016. The data provide in-depth information on family planning, fertility, marriage, infant, child, adult and maternal mortality, maternal and child health, gender, nutrition, malaria, knowledge of HIV/AIDS and other sexually transmitted diseases.

3.3. Sample Design

The 2016 EDHS sample was selected by considering two-stage cluster design and census enumeration areas (EAs) are the sampling units for the first stage. A typical two-level stratification involves first stratifying the population by region at the first level and then by urban-rural within each region. The sample included 645EAs (202 in urban areas and 443 in rural areas).In the sampling procedure, households comprised the second stage of sampling. A complete listing of households is carried out in each of the 645 selected enumeration areas by equal probability systematic sampling according to proportional to EA's measure of size from January 18, 2016, to

June 27, 2016. The total number of 18,008 households by incorporating all women age 15-49 and all men age 15-59 in these households are selected for the sample, of which 16,650 households are successfully interviewed. In the interviewed households, 16,583 eligible women are identified for individual interviews, of which 15,683 women are successfully completed.

3.3.1 Study Design

The study design for this study was a cross sectional survey conducted in 2016 using population based representative sample. Variables are collected for several sample units at the same points in time, just the data collected from the respondents directly in a particular time.

3.3.2 Study Population

The study populations was all the married women in the last five years preceding the survey of Ethiopia using the 2016 EDHS data. Therefore, the number of eligible married women data collected by the EDHS 2016 is 9479; and this data has entirely taken for analysis.

3.4. Variables in the Study

3.4.1. The response variable

During the survey all women were asked a series of questions regarding their marital status and whether they had ever lived with a man. All those who reported that they were ever married or ever-lived with a man, were asked to indicate how old they were at the time when they started, for the first time ever, living with a man as a wife, irrespective of the legality or otherwise of their union. The response to this question constitutes the woman's age at first marriage. All the women who indicated that they had never been in a union or lived with a man were considered single and as a result they were not asked the question about the age at first marriage. This is the standard way in which age at first marriage is being measured in the worldwide DHS program (Ikamari, 2005).

The response variable for the i^{th} married women is represented by a random variable Y_i with two possible values coded by 1 and 0. In view of this, the response variable of the i^{th} married women Y_i is measured as a dichotomous variable. For current analysis a given dependent variable can be dichotomized as follows.

$$Y_i = \begin{cases} 1, \text{if age at first marriage is under } 18 \text{ years} \\ 0, \text{if age at first marriage is } 18 \text{ and above years} \end{cases}$$

3.4.2. Explanatory variables

Variables considered in this study were selected based on literature which have been conducted at the global level and Explanatory variables considered in the study were selected based on some previous studies and those that are expected to be potential determinants factors of early marriage among women. As suggested in the literature review, several variables that are associated with early marriage are considered as predictor variables. Therefore, those variables that are reviewed in the literature are listed below

- Women's education level
- Husband's education level
- Husband's occupation
- wealth index
- Respondents work status

Religion

Type of residence

Exposure to Any Mass Media

Table 3.1: Description of Independent Variables and coding

Predictors Variables	Description	Categories
1.Women's Education level	Educational level of married women	(1) None(Ref) (2) Primary (3) Secondary (4) Higher
2.Type of residence	Place of residence for married women	(1) Urban (Ref.) (2) Rural
3. Region	Region of married women	(1) Tigry (2) Afar (3) Amahara (4) Oromia (5) Somali (6) Benshangul-Gumize

		(7) SNNP (8) Gambela (9) Harari (10)Addis abeba (11)Dire Dawa
4.Religion group of a woman	The religion group of the married women	(1) Orthodox(Ref.) (2) Catholic (3) Muslim (4) Protestant (5) Others
5.Husband's education level	The husband education level of married women	(1) None (Ref.) (2) Primary (3) Secondary (4) Higher
6.Wealth index	Wealth index of the household	(1) Poorest(Ref.) (2) Poorer (3) Middle (4) Richer (5) Richest
7.Respondents work status	The working status of the married women	(1) Not working(Ref.) (2) Working
8.Exposure to any media	The exposure to any media of the women	(1) No(Ref.) (2) Yes
9.Husband's occupation	The husband occupation	(1)Agriculturalists(Ref.) (2) Professional (3) Business (4) Laborers (5) Others

3.5. Methods of Data Analysis

At current time there exist two very different approaches to statistics. These are the traditional (classical or frequentist) and the Bayesian approaches. Therefore, for the role of analysis, both Bayesian and classical multilevel logistic regression models were employed by considering the opportunity of EDHS 2016 data.

3.5.1. Multilevel logistic regression

When researchers are focusing on fitting multilevel models, researchers are assuming some structure exists in the data and often this amounts to clustering in the dataset where certain observations are collected from the same level 2 units (regions in this case) and it is believed that such observations should be more similar than observations collected from different level 2 units. With this regard, the multilevel analysis is a methodology for the analysis of data with complex patterns of variability with a target on nested sources of variability.

The multilevel data analysis is an approach that can handle within the group (a region in this case) as well as between groups relations within a single analysis, where group refers to the units at the higher levels of the nesting hierarchy (a region in this study). Mostly, using the probability model can give sense to models to represent the variability within and between groups. In this study not only the unexplained variation of early marriage among women but also unexplained variation between regions is regarded as a random variable. Considering the ability of a random coefficient model in incorporating such variation, it can be used to analyze for such case of variability. The multilevel logistic regression analysis considers the variations due to the hierarchy structure in the data. Hence, the model will help in examining the effects of group level and individual level variation of early marriage among women.

The 2016 EDHS data set used for this study is based on a two stage stratified cluster sampling. The appropriate approach to analyzing married women data from this survey is therefore based on nested sources of variability. Here the units at lower level are individuals (married women aged15−49) who are nested within units at higher level (regions). Due to this nested structure, the odds of women experiencing the outcome of interest are not independent, because women from the same cluster (regions) may share common exposure to community characteristics. The response variable in this study is Age at first marriage which is binary and hence multilevel logistic regression model is a natural choice for modeling. The multilevel logistic regression analysis considers the variations due to hierarchy structure in the data. It allows the simultaneous examination of the effects of group level and individual level variation-dependence of observations within and between groups.

For simplicity of presentation two-level models have been considered for this study, models accounting for married women-level and regional-level effects. In this data structure, level-1 is the married women level and level-2 is the regions level. Within each level-2 unit, there is in the j^{th} region. The researcher further simplifies the presentation by assuming there are married women-level determinants and regional level factors regarding early marriage among women.

To provide a familiar starting point, the researcher has considered a two-level model for binary Outcomes with a single explanatory variable. Suppose researchers have data consisting of women, (level one) grouped into regions (level two). Let Y_{ij} be the binary response for early marriage among i^{th} women in j^{th} region and X_{ij} be an explanatory variable at the women level. Researcher defined the probability of the response equal to one π_{ij} = p (Y_{ij} =1); where π_{ij} be modeled using a logit link function. The standard assumption is that Y_{ij} has a Bernoulli distribution. Then, the two-level models are given by:

$$logit(\pi_{ij}) = \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_{oj} + \sum_{h=1}^{k} \beta_{hj} X_{hij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

Where i=1, 2, 3… n_j , h=1, 2, 3……k j=1, 2, 3…..11, $\beta_{oj}=\beta_o+U_{oj}$,

$\beta_{1j}=\beta_1+U_{1j}$,….. $\beta_{jk}=\beta_k+U_k$

$$logit(\pi_{ij}) = \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_o + \sum_{h=1}^{k} \beta_{hj} X_{hij} + U_{oj} + \sum_{h=1}^{k} U_{hj} X_{hij} \ldots\ldots\ldots\ldots [2]$$

X_{hij}=(X_{1ij}, X_{2ij}……..X_{kij}) denote the first and the second level covariate for variable K.

β=($\beta_o, \beta_{1,} \ldots\ldots\ldots\ldots\ldots.. \beta_k$) Denote regression coefficients parameters.

$U_{oj}, U_{1j}, U_{2j} \ldots\ldots U_{kj}$ are the random effect of the model parameters at level two with the assumption, U_{hj} follows a normal distribution with mean zero and variance $\delta^2{}_u$. Without U_{oj} and

U_{hj} the above equation can simply be the single-level logistic regression. Therefore, conditional on U_{oj}, U_{1j}, U_{2j}……..,U_{kj} the Y_{ij} can be assumed to be independently distributed as Bernoulli random variables(Snijders and Bosker, 1999).

3.5.2. Multilevel Analysis of Empty Model

The empty two-level model for a binary response variable refers to a population of groups (level two units) and specifies the probability distribution for group dependent probabilities π_{ij} without taking further explanatory variables into account. Therefore, the group dependent π_{ij} can be characterized as Y_{ij}=π_{ij} +e_{ij}. Here, the logit transformed model, $logit(\pi_{ij})$ can have the normal distribution. Consequently, the empty model can possibly be expressed in the form of the following formula:

$$logit(\pi_{ij}) = \beta_o + U_{oj} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [3]$$

In the equation above, β_o indicates the population average of the transformed probability and U_{oj} is the random deviation from this average for region j. The residual term that is associated with the group dependent deviation, U_{oj} has a unique effect of regions j on the response variable; and it is assumed to be normally and independently distributed with mean zero and variance, $\delta_o{}^2$ that is U_{oj}~N(0, $\delta_o{}^2$). In this situation, the level 2 residual can possibly capture the variation across region means. In this model, the amount of variance regarding early marriage among women that is attributable within group characteristics (here, married women) and between-group difference (region) can be investigated. Equation (3) does not include a separate parameter for the level one variance (Snijders and Bosker, 1999). The reason is the level one residual variance of binary outcome variable follows directly the success probability indicated as follow:

$$var(e_{ij}) = \pi_{ij}(1- \pi_{ij}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [4]$$

Where e_{ij} is a married woman dependent residual. In this case, the likelihood function is given as:

$$l(\pi_{ij}=Y_{ij})=\prod \pi_{ij}{}^{Y_{ij}} (1-\pi_{ij})^{1-Y_{ij}}$$

3.5.3. 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. Researcher assumed that there are variables which potentially explain the observed success and failure. These variables are denoted by X_h , h=1, 2... K with their values indicated by X_{hij}. 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 linear function of explanatory variables and given as;

$$logit(\pi_{ij}) = \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_{oj}+\beta_{1j}X_{1ij}+\beta_{2j}X_{2ij}+\ldots\ldots +\beta_{kj}X_{kij} = \beta_{oj} + \sum_{h=1}^{k}\beta_{hj}X_{hij} \ldots\ldots\ldots \text{[5]}$$

Where the intercept term β_{oj} is assumed to vary randomly and is given by the sum of an average intercept β_o and group-dependent deviations that U_{oj} is $\beta_{oj} = \beta_o + U_{oj}$ as a result:

$$logit(\pi_{ij}) = \beta_o + \sum_{h=1}^{k}\beta_{hj}X_{hij} + U_{oj} \ldots\ldots \text{[6]}$$

Where, $\beta_o + \sum_{h=1}^{k}\beta_{hj}X_{hij}$ is the fixed part of the model and U_{oj} is the random effect part of the model. From the above equation π_{ij} is given as:-

$$\pi_{ij} = \frac{\exp(\beta_o + \sum_{h=1}^{k}\beta_{hj}X_{hij} + U_{oj})}{1 + \exp(\beta_o + \sum_{h=1}^{k}\beta_{hj}X_{hij} + U_{oj})}$$

Thus, a unit difference between the X_h values of two individuals in the same group is associated with a difference of β_h in their log-odds, or equivalently, a ratio of $\exp(\beta_h)$ in their odds (Snijders and Bosker, 1999).

Equation (6) does not include a level-one residual because it is an equation for the probability π_{ij} rather than for the outcome Y_{ij}.

3.5.4. Multilevel Analysis of Random Coefficient Model

Since the logistic regression model can be changed to linear using the logit link function, similarly in the multilevel analog, random coefficient logistic regression is based on linear models for the logit link function that include random effects for the groups or other higher level units. Consider explanatory variables which are potential explanations for the observed outcomes. The researcher can denote these variables by X_1,X_2……………,X_k. The values of X_h(h=1,2,3,...,k) are can also be assigned in the usual way by X_{hij}, since some or all of these variables could be level one variables, the success probability is not necessarily the same for all individuals in a given group(regions). Therefore, the success probability depends on the individual as well as the group, and is denoted by π_{ij} . Now consider a model with group specific regression of logit of the success probability $\text{logit}(\pi_{ij})$ on single level one explanatory variable X.

$$\text{logit}(\pi_{ij}) = \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_{oj} + U_{oj} + \sum_{h=1}^{k} \beta_{hj} X_{hij} + \sum_{h=1}^{k} U_{hj} X_{hij} \ldots\ldots\ldots\ldots\ldots\ldots [7]$$

The expression $\sum_{h=1}^{k} U_{hj} X_{hij}$ can be considered 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_{oj} , U_{hj} h= 1, 2... k, j=1, 2…11) are independent and identically distributed. The random intercept variance, $\text{var}(U_{oj}) = \delta_o{}^2$, the random slope variance,$\text{var}(U_{1j}) = \delta_1{}^2$ and the covariance between the random effects, $\text{cov}(U_{oj}, U_{1j}) = \delta_{01}$ are called variance components (Snijders and Bosker, 1999).

3.5.5. Likelihood Function

The maximum likelihood (ML) method is a general estimation procedure, which produces estimates for the population parameters that maximize the probability of observing the data that are actually observed. The joint distribution of n independent Bernoulli trials is the product of each Bernoulli densities, where the sum of independent and identically distributed Bernoulli trials has a Binomial distribution. Specifically, let Y_{1j} ,Y_{2j}, Y_{3j}…………… Y_{ij} be independent Bernoulli trials with success probabilities π_{1j}, π_{2j} , π_{3j}. ……... π_{ij} that is Y_{ij}=1 (women exercise early marriage) with probability π_{ij} and Y_{ij}= 0 (women don't exercise early marriage) do with failure probability 1- π_{ij} , for i= 1, 2,…,n and j=1,2,…11.

Since, the trials are independent, the joint distribution of Y_{1j} , Y_{2j} , Y_{3j} . …… … Y_{ij} is the product of n Bernoulli probabilities. The probability of success in logistic regression varies from one subject to another, depending on their covariates. Thus, the likelihood function is illustrated below as product of n Bernoulli trials:

$L(\pi_{ij} / Y_{ij})$ $=\prod \pi_{ij}{}^{Y_{ij}} (1-\pi_{ij})^{1-Y_{ij}}$…………………………………….. [8]

Where, π_{ij} represents the probability of the event for subject ij who has covariate vector X_{ij} , Y_{ij}=1 indicates the exercise (early marriage) and Y_{ij}= 0 is don't exercise (early marriage) of the event for the given subject. The probability of success in logistic regression can be defined as:

$$\pi_{ij}=\frac{\exp(\beta_o + U_{oj} + \sum_{h=1}^{k} \beta_{hj} X_{hij} + \sum_{h=1}^{k} U_{hj} X_{hij})}{1+\exp(\beta_o + U_{oj} + \sum_{h=1}^{k} \beta_{hj} X_{hij} + \sum_{h=1}^{k} U_{hj} X_{hij})}$$

3.6. Bayesian Approach of 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. In a Bayesian formulation the uncertainty about the value of each parameter can be represented by a probability distribution, if prior knowledge can be quantified, (Kynn, 2005).

Bayesian approach provides a very different approach to the problem of unknown model parameters in that the uncertainty about the unknown parameters is quantifiable using probability distributions, so that the unknown parameters are considered as random variables. The basic concepts and procedures that should be considered in analysis of Bayesian inference are the likelihood function of the data, a prior distribution over all unknown parameters, and the posterior distribution over all parameters. Bayesian inference for multilevel logistic regression model is derived applying a Markov Chain Monte Carlo algorithm to simulate from the joint posterior distribution of the regression and the link parameters (Kynn, 2005).

3.6.1. The 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. The prior distribution and likelihood can be easily combined to form the posterior distribution, which represents total knowledge about the parameters after the data have been observed. Statistical inferences are usually based on maximum likelihood estimation (MLE). MLE chooses the parameters that maximize the likelihood of the data, and is intuitively appealing. In MLE, parameters are assumed to be unknown but fixed and are estimated with some confidence. In Bayesian statistics, the uncertainty about the unknown parameters is quantified using probability. So that, the unknown parameters are regarded as random variables in addition to this individual subjects in the group are assumed independent from each other, the likelihood function over a data set of n subjects in the J=11 regions are then:

$$L(y / \beta_i , \delta_u 2)=\prod_{i=1}^{n} \prod_{j=1}^{11}[(\frac{e^{\beta_o + \beta_{1j}X_{1ij}+\beta_{2j}X_{2ij}+\cdots+ \beta_{kj}X_{kij}+ U_{oj}}}{1+e^{\beta_o + \beta_{1j}X_{1ij}+\beta_{2j}X_{2ij}+\cdots+ \beta_{kj}X_{kij}+ U_{oj}}})]^{y_{ij}} \quad (1 - \frac{e^{\beta_o + \beta_{1j}X_{1ij}+\beta_{2j}X_{2ij}+\cdots+ \beta_{kj}X_{kij}+ U_{oj}}}{1+e^{\beta_o + \beta_{1j}X_{1ij}+\beta_{2j}X_{2ij}+\cdots+ \beta_{kj}X_{kij}+ U_{oj}}})^{1-y_{ij}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots [9]$$

3.6.2. 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. One of the pre-conditions in any Bayesian analysis is the choice of a prior. The main idea here is that when the data have sufficient information, even a bad prior still not greatly affect the posterior. If the posterior is highly dependent on the prior, then the data (likelihood function) may not contain sufficient information. However, if the posterior is relatively stable over a choice of priors, then the data indeed contain significant information. In general, any prior distributions can be used depending on the available prior information.

Assigning prior can include informative prior distributions if something is known about the likely values of the unknown parameters or non-informative priors if there is no information about the parameters to be estimated. A non-informative prior distribution that is used to express complete ignorance of the value of before the data is collected. They are non-informative in the sense that no value is favored over any other and are also described as diffuse or at prior due to this reason and their shape. In this study the researcher uses normal distribution prior for the fixed effect (β) and Inverse gamma prior for random effect ($\delta_u 2$). To fit the model the prior for fixed effect and random effects have been taken none informatively. Also, non-informative priors were recommended for fixed effect and random effect parameters in multilevel models (Gelman and Hill, 2006).

3.6.3. Prior Distribution for Empty Model Parameters

The distributional formula for the theoretical prior assignment can be formulated separately. Thus, the prior distribution for the empty model of the parameters β and $\delta_o 2$ have the form:

$$P(\beta_o) \sim f(\beta_o) = \frac{1}{\sqrt{2\pi\delta_o 2}} \exp\left\{\frac{-1}{2}\left(\frac{\beta_o - \mu_o}{\sigma_o}\right)^2\right\}$$

P ($\delta_o 2$) ~ gamma (α, β) Where α and β are fixed constant parameters for which different values were given in the analysis.

3.6.4. Posterior Distribution for Empty Model Parameters

The posterior distribution can be obtained as the product of the prior distribution of the parameters and the likelihood function. Therefore, the Posterior distribution for the random parameter of empty model $p(\beta_o, \delta_u 2/y_{ij})$ can be represented as follows:

The full conditional distribution for parameter β_o is:

$$f(\beta_o|\text{data}) = \prod_{i=1}^{n}\left[\left(\frac{e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}{1+e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}\right)^{y_{ij}} \left(1 - \frac{e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}{1+e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}\right)^{1-y_{ij}}\right] \times$$

$$\frac{1}{\sqrt{2\pi\delta_o 2}} \exp\left\{\frac{-1}{2}\left(\frac{\beta_o - \mu_o}{\sigma_o}\right)^2\right\}$$

For the variance parameter of $\delta_u 2$, since there were gamma prior and Bernoulli likelihood function, the full conditional distribution of posterior for the parameter is the multiplication of the Bernoulli likelihood and the gamma prior distribution is given as:

$p(\delta_u 2 \;/\; \beta_o, y_{ij}) \sim \prod_j (\frac{\exp(\beta_o + \mathrm{U_{oj}})}{1+\exp(\beta_o + \mathrm{U_{oj}})})^{y_{ij}} \; (\frac{1}{1+\exp(\beta_o + \mathrm{U_{oj}})})^{1-y_{ij}} \times gamma(\alpha, \beta)$............ [10]

The prior probability distribution and posterior probability distribution conducted for the random intercept model parameters are the same as the prior and posterior distribution assigned for the empty model.

3.6.5. Prior Distribution for random coefficient model parameters

The prior distribution for the parameters for $\beta_o \; \beta_1 \;\; \beta_2$ ..... β_k , Ω_{u} has been denoted as follow:

$$\mathrm{f}(\beta_j|\mathrm{data}) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\delta_j 2}} \; \exp\left\{\frac{-1}{2}(\frac{\beta_j - \mu_j}{\sigma_j})^2\right\}$$

$\mathrm{p}(\Omega_{\mathrm{u}}) \propto$ inverse – wishart ($\mathrm{s_u}$, v) denotes the inverse Wishart distribution with scale matrix and degrees of freedom ν. The parameter Ω_{u} is the variance covariance matrices. Equivalently, information about a variance-covariance matrix is represented by means of a Wishart (${s_u}^{-1}$, ν) distribution placed on the precision matrix ${\Omega_u}^{-1}$:(Gelman et al., 1996).

$$p({\Omega_u}^{-1}) \propto \mathrm{Wishart}({s_u}^{-1}, \mathrm{v})$$

The Wishart distribution is the multivariate extension of the gamma distribution; although most statisticians use the Wishart distribution in the special case of integer degrees of freedom, in which case it simplifies to a multivariate generalization of the χ^2 distribution. As the χ^2 distribution describes the sums of squares of n draws from a univariate normal distribution, the Wishart distribution represents the sums of squares (and cross-products) of n draws from a multivariate normal distribution.

3.6.6. Posterior Distribution for random coefficient model parameters

The posterior distribution is obtained as the product of the prior distribution of the parameters and the likelihood function. Therefore, using the above prior and likelihood functions the full conditional posterior distribution for the parameters $\beta_o \; \beta_1 \;\; \beta_2$ ..... β_k is given by:

$$\mathrm{f}(\beta_j|\mathrm{data}) = \prod_{i=1}^{n}[(\frac{e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}{1+e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}})^{y_{ij}} \quad (1 - \frac{e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}{1+e^{\beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}})^{1-y_{ij}} \;\;)] \times$$

$$\frac{1}{\sqrt{2\pi\delta_j 2}} \exp\left\{\frac{-1}{2}\left(\frac{\beta_j - \mu_j}{\sigma_j}\right)^2\right\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[11]}$$

Where h = 1, 2... K

And the full conditional distribution of the variance-covariance parameter Ω_u has been given as:

$$p(\Omega_u/\beta_h, u_{oj}, y_{ij}) \propto p(y_{ij}/\beta_h, u_{oj}\Omega_u)p(u_{oj}/\Omega_u)p(\Omega_u) \ldots\ldots\ldots\ldots\ldots\ldots \text{[12]}$$

3.6.7. Settings of scalar values for prior distributions' parameters

In this study, non-informative priors have being used which express the ignorance of the value of the parameters. In case of no available prior knowledge, the researcher has used a normal distribution with mean 0 and precision=0.0001 for fixed parameters. In addition, gamma distribution with parameter α=0.01 and β=0.01 for single variance (random intercept) was used. Finally, in the random coefficient model, the prior for random effects is an inverse-Wishart distribution with scalar values:-

$p(\Omega_u)$= inverse- Wishart$\left(s_u = \begin{bmatrix} 10000 & 1 & 1 & 1 \\ 1 & 10000 & 1 & 1 \\ 1 & 1 & 10000 & 1 \\ 1 & 1 & 1 & 10000 \end{bmatrix}, n_u = 4\right)$ is used as the starting value for variance-covariance prior; where nu is the degree of freedom for wishart distribution in the MCMCglmm package. Its value is equal to or greater than the number of rows of the scale matrix given. The scalar values used for fixed effect parameters and single variance in this study are similar with a study of modeling under-five mortality among hospitalized Pneumonia patients in Hawassa city, Ethiopia a crossed-classified multilevel analysis (Tessema, 2018). But the variance-covariance scalar values are taken from related example in MCMCglmm package (Matrix, 2017).

The other fundamental reason for applying multilevel analysis is the existence of intra-class (intra-regional) correlation arising from similarity of early marriage for women in the same region compared to those of different regions. 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 empty model. The ICC can be calculated as:

$$ICC = \frac{\delta_u 2}{\delta_u 2 + \delta_e 2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[13]}$$

Where, $\delta_u 2$ the between group variance which can be estimated from U_{oj} and $\delta_e 2$ is within group variance. Where $\delta_e 2$ is variance of individual (lower) level units and since the logistic distribution for the level one residual variance implies a variance of $\pi^2/_3 \approx 3.29$ (Snijders and Bosker, 1999) and this formula can be rewrite as ICC = $\frac{\delta_u 2}{\delta_u 2+3.29}$

The probability corresponding to the average value β_o , denoted by π_o, is defined by $f(\pi_o) = \beta_o$
For the logit function, the so-called logistic transformation of β_o, is defined by(Snijders and Bosker, 1999) .

$\pi_o = logit(\beta_o) = \frac{\exp(\ \beta_o)}{1+\exp(\ \beta_o)}$.. [14]

Note that due to the non-linear nature of the logit link function, there is no a simple relation between the variance of probabilities and the variance of the deviations U_{oj} (Snijders and Bosker, 1999). However, an approximate variance of the probability given by:

$var(\pi_{ij}) = (\pi_o(1-\pi_o))^2 \delta_u 2$ .... [15]

Note that an estimate of population variance $var(\pi_{ij})$ can be obtained by replacing sample estimates of π_o and $\delta_o 2$. The resulting approximation can be compared with the non-parametric estimate $\hat{\tau}^2 = S^2$between - $\frac{S^2\text{within}}{\hat{n}}$. Chi-square test can be used to test if the variance of population is equal to as specified value. The test is one-sided test.

Hypothesis:

H_O : There is no regional variation of early marriage among women in Ethiopia.

H_1 : There is regional variation of early marriage among women in Ethiopia.

3.7. Heterogeneity Proportion

The basic data structure of the two-level regression is a collection of N groups (units at two levels or regions), within group j, =1, 2…… N random sample of n_j level-one units (individual or number of women exercising early marriage living in the regions j) and Consider the outcome variable that is early marriage practice, Y_{ij} (i = 1, 2,......n_j ; j = 1, 2… N) And denoted by for level-one unit i nested in level-two group j. And the total sample size can be given as M=$\sum_{j=1}^{N} n_j$. The idea is that if there is no inclusion of explanatory variables, the probability of success (early marriage among women in this study) is assumed to be constant in each group (Snijders and Bosker, 1999). Let the probability of being married early among women in region j be denoted by π_j. The dichotomous outcome variable for the married women i in region j, Y_{ij} can be expressed as the sum of the probability in region j, π_j (the average proportion of levels in region j $E(Y_{ij})$ =π_j) and some individual dependent residual which could be given as:

$$Y_{ij}=\pi_j+\epsilon_{ij}$$

Here the residual term is assumed to follow mean zero and variance $var(\epsilon_{ij})$ = π_j (1-π_j)

Since the outcome variable has been coded as 0 and 1, the region sample average is the proportion of success in group j which could be given as follow:

$$\hat{\pi}=\frac{1}{n_j}\sum_{i}^{n_j} Y_{ij}$$

Where, $\hat{\pi}$-is regarded as an estimate for group dependent probability π_j. In addition, the overall sample average is the overall proportion of successes, π and which is given as follow:

$$\pi=\frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{n_j} Y_{ij}$$

3.7.1. Test of heterogeneity proportion

Testing heterogeneity of proportions between groups is the first logical step for the proper application of multilevel analysis. Here researcher has presented two commonly used test statistics that could be used to check for heterogeneity (Snijders and Bosker, 1999). To test whether there are indications of a systematic difference between the groups the well-known Chi-Square test for contingency table has been used. Following this, the Chi-Square test statistic has been given as follow:

$\chi^2 = \sum_{i=1}^{N} n_j \frac{(\widehat{\pi_j}-\hat{\pi})}{\hat{\pi}(1-\hat{\pi})} \sim \chi^2$(N-1)... [16]

Where $\hat{\pi}=\frac{1}{n_j}\sum_{i}^{n_j} Y_{ij}$ the proportion of women who are married early in region j,

$\pi=\frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{n_j} Y_{ij}$

The overall proportion of women who married early with M= $\sum_{j=1}^{N} n_j$

This is can be tested a chi-square distribution with N− 1 degrees of freedom. This chi-squared distribution is an approximation valid if the expected number of success $(n_j\pi_j)$ and of failures $(n_j(1-\pi_j))$ in each group all are at least one while 80 percent of them are at least 5 (Agresti, 1990). This condition will not always be satisfied, and the chi-square test then may seriously lead to wrong conclusions.

3.8. Estimation Method for Bayesian multilevel logistic regression model parameters

3.8.1. Markov Chain Monte Carlo (MCMC) Methods

3.8.1.1. Metropolis-Hastings algorithm

A popular way of simulating from a general posterior distribution is by using MCMC methods. Therefore, in this study metropolis-hasting algorithm is used to estimate the fixed and the random effects parameters for early marriage among the women. The Metropolis-Hastings algorithm is a general term for a family of Markov chain simulation methods that are useful for drawing samples from Bayesian posterior distributions. It is an adaptation of a random walk that uses an acceptance/rejection rule to converge to the specified target distribution. The acceptance ratio for Metropolis-Hastings algorithm could be the ratio of the current sampled value to the previous sampled for parameters and the acceptance ratio should fall between 0.25 and 0.4 for a true posterior estimate (Gelman et al., 1996). Metropolis-Hastings algorithm correctly applied for non-Gaussian data and if the posterior distribution doesn't follows some known distribution (no conjugate distribution).The algorithm proceeds as follow:

Step1: Draw a starting point β^o for which P (β^o/y)>0, from a starting distribution P_o (β^o).

Step2: For t = 1, 2...

a) Sample a proposal (β^*) from a jumping distribution (or proposal distribution) at time t, J_t (β^* / β^{t-1})
b) Then calculate the ratio of the density by:

$$\gamma = \frac{p(\beta^* / y)}{p(\beta^{t-1} / y)}$$

3.9. Estimation method for classical multilevel logistic regression

One aim of this study was intending to compare the result get from Bayesian multilevel logistic regression and classical multilevel logistic regression based on the corresponding model parameter's standard error. Therefore, for a better discussion of the objective stated above, an estimation method for the classical multilevel logistic regression has been considered. Parameter estimation for multilevel logistic model is not straightforward like the methods for logistic regression. In this regard, among a number of estimation method available, the most common methods for estimating the parameters of classical multilevel logistic models are Marginal Quasi Likelihood and Penalized Quasi Likelihood (Goldstein H. a., 1996). This two estimation method (MQL and PQL) are based on Taylor series expansion to achieve the approximation. After applying these quasi likelihood methods, the model parameters are being then estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) (Goldstein H., 2003). The researcher applied the Penalized Quasi likelihood estimation method for the classical multilevel model.

3.9.1 Tests for Convergence

Generally, it is unclear how many times we must run an algorithm to obtain samples from the correct target distributions. Several diagnostic tests have been developed to monitor the convergence of the algorithm. To examine the convergence of MCMC, considering a different method would be useful for detecting poorly sampled Markov Chains. Among several ways of a test of convergence, the most popular and straight forward convergence assessment methods have be used for this study .The following four methods are more potential considered for this study.

1) **Trace plots**: Iteration numbers on x-axis and parameter value on the y-axis are commonly used to assess convergence. If the plot looks like a horizontal band, with no long upward or downward trends, then researcher as evidence that the chain has converged (Merkle et al., 2005).
2) **Autocorrelation**: High correlation between the parameters of a chain tends to give slow convergence, whereas high autocorrelation within a single parameter chain leads to slow mixing and possibly individual non-convergence to the limiting distribution because the chain tends to explore less space in finite time. That is, low or high values indicate fast or slow convergence, respectively. In analyzing Markov chain autocorrelation, it is helpful to identify lags in the series in order to calculate the longer- run trends in correlation, and in particular whether they decrease with increasing lags. (Merkle et al., 2005).
3) **Density plot**:-This is also another method or technique which can be taken for checking convergence in the Bayesian analysis. The idea is that the Markov chain has attained its

posterior distribution when the Density plots of the independent variables' coefficients are normally distributed(Merkle et al., 2005).

4) **Effective sample size**:-A related concept to the MCMC convergence would be the inefficiency factor which is useful to measure the efficiency of the MCMC sampling algorithm. It is given as:-

   Inefficiency factor =1+2$\sum_{i=1}^{\infty} \rho(K)$ where, $\rho(K)$ is the sample autocorrelation at lag k calculated from the sample draws. A large value of inefficiency factor indicates that we need large MCMC iteration. The effective sample size, the number of MCMC output divided by the inefficiency factor. Let the output of MCMC denoted by L, then it can be given:-

   Effective sample size = $\frac{1}{1+2\sum_{i=1}^{\infty} \rho(K)}$ If the value of effective sample size for each parameter is low (<200), MCMC simulation chain is not fully mixed or the posterior estimate would not be converged (Okuto, 2013).

3.10. Model Selection and Comparison

The deviance information criterion is a measure of model comparison and adequacy; it assumes that we can use the posterior mean as good estimate of central location for explaining the posterior distribution. In this study, the researcher has compared the Bayesian multilevel model with the classical multilevel model. The Bayesian and the classical multilevel were compared based on standard error and also, the researcher has compared the Bayesian multilevel model using Deviance Information Criterion. That is, Bayesian multilevel model that are empty, intercept and random coefficient model are compared. DIC over other criteria in the case of Bayesian model selection is that the DIC is easily calculated from the samples generated by a Markov chain Monte Carlo simulation. Hence, the Deviance Information Criterion is the most widely used statistic for comparing models in a Bayesian framework.

The deviance information criterion (DIC) is hierarchical modeling generalization of the (AIC). It is particularly useful in Bayesian model selection problems where the posterior distribution of the models have been obtained by Markov Chain Monte Carlo (MCMC) simulation. DIC is an asymptotic approximation as the sample size become large like AIC. Here define the deviance as D (θ) = 2 log (p(y | θ)) + C, where y could be the data, θ could be the unknown parameters of the model and p(y | θ) could be the likelihood function. C is a constant that could cancel out in all calculations that compare different models and which therefore does not need to be known. The mean $\overline{D} = E[D(\theta\ )]$ could be taken as a measure of how well the model fits the data; the larger this is, the worse the fit. The effective number of parameters of the model could be computed as PD= $\overline{D}$ - ($D(\bar{\theta})$). Therefore, the deviance information criteria formula can be given as: - DIC = PD+$\overline{D}$ =2$\overline{D}$ - $D(\bar{\theta})$. The idea is that models with smaller DIC should be preferred than models with larger DIC.

3.11. Software

In order to fit the model to the data, the parameters of the model have to be estimated. In fact, the model fitting process could be facilitated by the commonly available statistical software. For this study, all calculation for methodology discussed here were carried out with R software program version 3.5.3. Here for this study a Bayesian inference is computed with MCMCglmm package was applied. This is the most important package for Bayesian multilevel model that formulated under R program which can compute the Bayesian inference quickly. Likewise, the classical multilevel model has also been computed using the package glmmPQL which is developed under an R program that capable to compute using penalized quasi likelihood estimation method

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Statistical Data Analysis

The result were presented in two sections. In the first section, to investigate the predictor variables associated with dependent variables. In the second section, identify the determinants factors of early marriage among women using multilevel logistic regression model with Bayesian approach was employed with the help of R software with MCMCglmm package.

4.2. Bivariate Analysis for Categorical Predictor Variables

This study was carried out to identify determinants of the early marriage among women through analyzing the demographic and economic factors which were considered in similar studies conducted previously and using the data obtained from Ethiopia Demographic Health Surveys of 2016. In this study both descriptive and inferential analysis have been investigated for the purpose of identifying the determinants of the early marriage among women. Accordingly, the study used 9479 married women from EDHS 2016 and the results are presented in two main parts. The first part of the result is the bivariate analysis (cross tabulation), with which the association between each predictor variables and early marriage among women was investigated.

In order to determine the association between early marriage among women and individual predictor variables, the Pearson chi-square test was carried out. The frequency distributions of all independent variables with their respective categories are presented in Table 4.1 below. The result obtained in the Table 4.1 below clearly indicated that all of the explanatory variables such as place of resident, husband's education level, women's occupation, wealth index, women's education level, religion, mass media exposure, husband's occupation and ethnicity have significant association with early marriage among women at 5% level of significant.

In similar manner, the result obtained in table 4.1 below also indicated that out of 9479 married women considered in the analysis 5519(58.2%) of marriages occurred early (under the age of 18) while, 3960(41.8%) of these married women occurred 18 years and above when the time of the survey.

The percentage of early marriage differed by place of residence. Percentage of early marriage is higher among women who lived in rural residence was (63.8%) whereas women who lived in urban residence was (41.4%). The early marriage among married women was varies according to their husband educational level. The highest percentage of early marriage occurred at husband education level those women whose husbands have no education (70.8%) as contradicted to the lowest percentage of early marriage which was recorded from women whose husband education level which have higher educational level (28.7%). In similarly manner, also reveals that early marriage among the women varies by their educational status of women's. The proportion of women who married earlier decreased with increasing educational level of respondents which were 68.6%, 51.2%, 34.1% and 19.3% for no education, primary, secondary and higher education respectively.

Table 4.1 also, shows that the proportion of early marriage among women varies in terms of religion categories: Orthodox, Catholic, Protestant, Muslim, and other were 53.0%, 52.5%, 55.0 %, 63.9% and 57.9% respectively and the highest percentage of women who married earlier was occurred those woman who follow Muslim (63.9%) and as opposed to this the lowest percentage occurred those women who follow Catholic (52.5%).

The result below also shows that the women who were included in the study regarding to husband occupation of married women's which is categorized as agriculturalist, laborer, business, professional and others in exercise of early marriage were 65.9%, 51.6%, 56.3%, 39.1% and 41.0% respectively and highest percentage of early marriage was recorded for those women whose husband occupation was agriculturalist (65.9%). However, the lowest percentage of early marriage was occurred those women whose husband occupation was professional (39.1%).

On the other hand, with regard to economic status, the percentage of early marriage practice in terms of family wealth index categories: poorest, poorer, middle, richer and richest were 76.6%, 70.8%, 57.6%, 51.7% and (32.5%) respectively. Similarly, the percentage of early marriage was occurred higher in respondent's non-working women (63.7%) whereas the working women (46.6%). Furthermore, With regard to exposure to mass media, the highest proportion of early marriage was observed for women who have no any exposure to mass media (75.0%) and lower percentage of early marriage which was recorded for women who have any exposure to mass media (39.1

Table 4.1 Cross tabulation of early marriage among women and its determinants

Variables name	Category	Age at the first marriage		Total	Pearson chi-square (p-value)
		(Yes)	(No)		
		Count (%)	Count (%)		
Type of place of residence	Urban	971(41.4)	1374(58.6)	2345	362.241(0.001)
	Rural	4548(63.8)	2586(36.2)	7134	
Husband education	No education	3106(70.8)	1284(29.2)	4390	411.620(0.001)
	Primary	1660(55.8)	1313(44.2)	2973	
	Secondary	478(41.3)	679(58.7)	1157	
	Higher	275(28.7)	684(71.3)	959	
Religion	Orthodox	1794(53.0)	1593(47.0)	3387	102.514(0.001)
	Catholic	31(52.5)	28(47.5)	59	
	Protestant	951(55.0)	779(45.0)	1730	
	Muslim	2673(63.9)	1509(36.1)	4182	
	Other	70(57.9)	51(42.1)	121	
Women education	No education	3812(68.6)	1741(31.4)	5553	637.239(0.001)
	Primary	1326(51.2)	1262(48.8)	2588	
	Secondary	283(34.1)	546(65.9)	829	
	Higher	98(19.3)	411(80.7)	509	
Wealth index	Poorest	2098(74.6)	716(25.4)	2814	470.285(0.001)
	Poorer	1173(70.8)	484(29.2)	1657	
	Middle	853(57.6)	627(42.4)	1480	
	Richer	668(51.7)	623(48.3)	1291	
	Richest	727(32.5)	1510(67.5)	2237	
Respondents work status	Not working	4101(63.7)	2335(36.3)	6436	248.989(0.001)
	Working	1418(46.6)	1625(53.4)	3043	
Mass media exposure	No	3783(75.0)	1259(25.0)	5042	1250.806(0.001)
	Yes	1736(39.1)	2701(60.9)	4437	
	Agriculturalist	3001(65.9)	1552(34.1)	4553	295.116(0.001)

Husband occupation	Laborer	851(51.6)	798(48.6)	1649	
	Business	1236(56.3)	958(43.1)	2194	
	Professional	263(39.1)	410(60.9)	673	
	Other	168(41.0)	242 (59.0)	410	
		5519(58.2)	3960(41.8)	9479	

4.3. Results of Bayesian Approach of Multilevel Logistic Regression Analysis

In the Bayesian multilevel analysis, a two-level structure is used with regions as the second-level units and individual married women as the first level units. This is basically the analysis of region wise variation of early marriage among the women were nested in regions with a total of 9479 women included in this study.

4.4. Test of Heterogeneity Proportions of Early Marriage among Women between the Regional States of Ethiopia

The hierarchical data structure was used in this study. Units at one level are nested within units at the next higher level. Here, the lower level (level-1) units are the individual married women, and the higher level (level-2) units are the regions that constitute the groups into which the married women are clustered or nested. The nesting structure in married women within regions that resulted in a set of 11 regions with a total of 9479 women.

The two-level structure is used with the region as the second-level unit and the married women as level one unit. This is based on the idea that there may be differences in being married early among women between regions that are not captured by the explanatory variables and hence may be regarded as unexplained variability within the set of all regions (Snijders, 1999). Before proceed to multilevel analysis, one has to test the heterogeneity of early marriage among women across eleven regional states of Ethiopia from which essential clues would be obtained for incorporating the random effects. Therefore, the Pearson chi-square for the proportion of early marriage across the region has been investigated in the table below.

4.4.1. Test of Heterogeneity

Table 4.2, the Pearson Chi-square ($\chi^2 cal$) =456.78 which is greater than 18.307 at 10 degree of freedom with P-value = 2.2e-16 which is less than level of significance, implying that strong evidence of heterogeneity with respect to the early marriage among women across regional states of Ethiopia.

Table 4.2 Chi-Square Tests of Heterogeneity of Early Marriage among Women between Regional States of Ethiopia.

Chi-square			
Statistics	Value	Df	P-value
Pearson Chi-square	456.78	10	0.000
N of Valid Cases 9479	----------------------	-------------------------	-------------------------

4.5. Bayesian Multilevel Logistic Regression Model Comparisons

We compare the three Bayesian multilevel models (nested models) considered. Here the comparisons of Bayesian multilevel models such as multilevel empty model, random intercept model, and random coefficient model were conducted based on Deviance information criterion. DIC is an asymptotic approximation as the sample size become large like AIC and it is particularly useful in Bayesian model selection problems where the posterior distribution of the models have been obtained by Markov Chain Monte Carlo (MCMC) simulation. Therefore, as it is shown in Table 4.3 below the Bayesian random intercept model is appropriately fitting the variations of early marriage among women in regional states of Ethiopia for 2016 EDHS data sets as compared to empty and random slope model. Hence, the DIC for Bayesian random intercept model was smaller and preferable in predicting early marriage across the region than the Bayesian empty and Bayesian random slope model.

Table 4.3 Bayesian multilevel model comparisons

Model comparison statistics	Empty model	Random intercept model	Random coefficient model
DIC	12160.89	10306.60	10309.82

Then the three Bayesian multilevel model have been considered as follows. First, a Bayesian multilevel empty model with random effect and no covariates was examined for the over all probability of early marriage. Second, a Bayesian multilevel model for random effect and a fixed slope covariate was examined for early marriage. Finally, a Bayesian multilevel random coefficient model with random effect for early marriage was analyzed.

4.6. Bayesian Multilevel Empty Model

The overall log odds of posterior mean of early marriage among women was estimated to be 0.450423 and the between-region variance of women early marriage practice was estimated as ${\delta_u}^2$=0.6313 which was found to be significant because the credible interval of the respective parameters does not include zero, indicating the variations of being married early among women within regional states of Ethiopia was greater than zero. The variance of the random factor is significant which indicates that there are regional differences in early marriage among women across the region. Hence, we conclude that the regional differences contributed to the variation of early marriage among women in Ethiopia

Table 4.4 Bayesian estimates for parameters of the empty model.

Early marriage among women	Post.mean	S.d	Stand.error	2.5%	50%	97.5%
Intercept(β_o)						
	0.450423	0.225679	0.009213	0.01385	0.45885	0.88591
Random part (U_{oj})						
(${\delta_u}^2$)	0.6313	0.3092	0.01263	0.251	0.5558	1.412

Note: **Post.mean** is posterior mean

4.6.1. Intra Class Correlation

In order to get an idea of how much of variation in early marriage was attributable to the region level factors, it is useful to see the intra-region correlation coefficient. Here researcher can usually interpret for empty model with random effect to calculate the between region variations ${\delta_u}^2$ between cluster by considering the ICC which goes from 0 indicates perfect independence of residuals or the observations do not depend on cluster membership and 1 indicates perfect interdependence of residuals or the observations only vary between clusters (Sommet, 2017). It is usually expressed as:-

$$ICC=\frac{\delta_u 2}{\delta_u 2+\delta_e 2}$$

Where $\delta_u{}^2$ is the variance of the between cluster and $\delta_e{}^2$ the variance of the residual. But, in the context of logistic regression, there is no direct estimation or calculation of the residuals on the first level. Therefore, $\delta_e{}^2$ is the logistic distribution variance which always can be given the value $\frac{\pi^2}{3}$which was 3.29, the intra region correlation coefficient for this study was estimated by $\hat{\rho}=\frac{0.6313}{0.6313+3.29}$=0.161. This indicated that about 16.1% of the total variability in early marriage among women can explained by grouping the women in regions due to the fact that differences across regions and the remaining unexplained 83.9% attributable to individual level, that is within region differences, which strongly suggests the usefulness of the model specification of hierarchical structure and thus, Bayesian multilevel analysis can be considered as an appropriate approach for further analysis.

4.7. Bayesian Multilevel Intercept Model

In this Bayesian intercept model, the intercept is allowed to vary across the region after incorporating independent variables of early marriage among the women. This means that, the intercept (β_o) is shared by all regions, while the random effect u_{oj} is specific to region j and the random effect is assumed to be a normal distribution with variance $\delta_u{}^2$. That is, the random intercept varies across regions, but women level explanatory variables are fixed across regions. Therefore, the Bayesian random intercept model analysis for early among women was compared with an empty model based on their respective deviance information criteria. With this context the deviance information criteria for the intercept model was 10306.6 which is smaller than the empty model (12160.89).This indicates that the model with all predictors variables including the Bayesian random intercept model was found to be better than the Bayesian empty model in predicting early marriage among women in Ethiopia because the DIC for the intercept model is smaller than the empty model DIC.

The results from the Bayesian random intercept model in Table 4.5 showed that the random intercept (β_o) is significant implying that the average proportion of early marriage among women differs from region to region. In other ways, the overall posterior mean of being married early among women was estimated to be 2.44324 which is increased by 2.00 as compared to an empty model (Table: 4.4). Consequently, indicating that many variables that are included in this model have an impacts on being married early among women.

According to the result of the Bayesian random intercept with fixed slope model, the fixed part showed that, religion (Protestant and Muslim), women's education level, husband's education level, place of resident, exposure to any media, respondents work status and wealth index were found to be significant, indicating that strong effects on being married early among women and also giving early marriage among women varies in all regions with respect to the corresponding reference categories (Table 4.5). However, the impacts of husband's occupation of women found to be insignificance, suggesting that there is no enough evidence for the effects of being married early among women in Ethiopia.

The model revealed that the likelihood of early marriage, women living in rural areas have an OR: 3.35 times higher the odds of being married early as compared with women living in urban areas. This is may be due to the fact that the rural residence have less awareness about the negative impacts of early marriage than the urban residence.

Women's educational level and husband's educational level are also significant factors associated with early marriage. For instance, the odds of being married early for women had primary educational were 28.7% (OR: 0.713) times lower as compared to the women had no education level. The odds of being married early for women had secondary educational were 49.89% (OR: 0.5011) times less as compared to the women had no education level. The odds of being married early for women had higher educational were 72.1% (OR: 0.279) times lower than women had no education level. Similarly, the odds of being married early for women whose husband's educational level had primary, secondary and higher educational level were 19.0% (OR: 0.81) 34.4% (OR: 0.66) and 51.7% (OR: 0.483) times lower as compared for a women whose husband's educational level had no education.

The odds of being married early for women in protestant religion were 36.53% times higher as compared to those women in orthodox religion. Similarly, the odds of being married early for women in Muslim religion were 71.5% times higher than women in orthodox religion. However, the odds of being married early for married women in Catholic and other religions was not significantly different from the religion of women in orthodox.

Household wealth index also showed a statistical significant association with early marriage practice of women. The odds of being married early for those women whose wealth index were 20.9%, 51.5%, 59.9% and 80.7% times lower for women from poorer, middle, richer and richest families than those from poorest families respectively. The odds of being married early for women who have work were 50.8% (OR: 0.492) times lower than for women haven't work. In a similar manner, the odds of being married early for women who were exposed to any mass media messages via Radio, TV were 0.752 (OR: 0.248) times lower as compared to those women who were non-exposed to mass media messages via radio, TV.

Table 4.5 Bayesian estimates for parameters of random intercept model.

Fixed Effects							
Covariates	Categories	Post.mean	S.d	Stand.error	2.5%	50%	97.5%
	Intercept	2.44324	0.20311	0.006423	2.04580	2.44255	2.83588
Type of place of residence	Urban(Ref)	-----------	----------	-------------	----------	----------	----------
	Rural	1.20962	0.10935	0.004119	0.99388	1.20937	1.42528
Women educational level	No.edu(ref)	-----------	----------	------------	----------	----------	----------
	Primary	-0.33887	0.07053	0.002465	-0.47263	-0.34111	-0.20141
	Secondary	-0.69103	0.11921	0.004122	-0.93387	-0.68561	-0.45253
	Higher	-1.30962	0.16437	0.005715	-1.63754	-1.30729	-0.99092
Religion	Othro(ref)	-----------	----------	------------	----------	----------	----------
	Catholic	-0.10428	0.36502	0.012187	-0.79073	-0.10543	0.60894
	Protestant	0.30942	0.10928	0.003777	0.09053	0.30828	0.52226
	Muslim	0.53966	0.08936	0.003085	0.36912	0.54069	0.71360
	Other	-0.40406	0.25340	0.008913	-0.91325	-0.40560	0.10435

Wealth index	Poorest(ref)	-----------	----------	------------	----------	----------	----------
	Poorer	-0.23473	0.09708	0.003119	-0.42901	-0.23808	-0.04166
	Middle	-0.72284	0.09844	0.003416	-0.91967	-0.72532	-0.54415
	Richer	-0.91280	0.10184	0.003415	-1.12094	-0.91340	-0.70258
	Richest	-1.64462	0.11619	0.004134	-1.87809	-1.64282	-1.42304
Women occupation	No(ref)	-----------	----------	------------	----------	----------	----------
	Working	-0.70828	0.06240	0.002234	-0.82528	-0.70786	-0.58674
Husband occupation	Agric(ref)	-----------	----------	-------------	----------	----------	----------
	Laborer	-0.13750	0.08307	0.002738	-0.29689	-0.13424	0.01884
	Business	-0.08754	0.07586	0.002872	-0.23801	-0.08521	0.05441
	Professional	0.03447	0.13383	0.004451	-0.23516	0.03446	0.29529
	Other	0.16593	0.15599	0.004933	-0.12944	0.17209	0.46390
Husband educational level	No.(ref)	-----------	----------	------------	----------	----------	----------
	Primary	-0.21353	0.07214	0.002576	-0.35029	-0.21107	-0.07585
	Secondary	-0.42231	0.11042	0.003947	-0.63115	-0.42484	-0.20827
	Higher	-0.72725	0.13028	0.004504	-0.97475	-0.73321	-0.44998
Mass media exposure	No(ref)	-----------	----------	------------	----------	----------	----------
	Yes	-1.39515	0.06476	0.002062	-1.51611	-1.39374	-1.27104
Random Effect							
(δ_u^2)		0.2899	0.1684	0.004953	0.1057	0.2446	0.7228

Note: δ_u^2 regions variance, DIC (deviance information criteria)

The random part of Bayesian random intercept and fixed slope model shows that the intercept variance of the random effect is 0.2899 whereas the variance of the intercept for the Bayesian empty multilevel model is 0.6313. The variance of random effect of the Bayesian intercept and fixed slope model is lower as compared to random effect of the intercept of Bayesian empty model. The decreasing of the random effects of the intercept variance is due to the adding of fixed predictor variables. That is, taking into account the fixed predictor variables can provide additional predictive measure on early marriage in each region. Hence, the distribution of fixed predictor's variables is somewhat different across region of the country. The significance of the random effect for intercept variance indicates that strong evidence of variations across regions on early marriage among women since the credible interval is not containing zero (see Table4.5). This implies that there is gain regional effect.

4.8. Bayesian Multilevel Random Coefficient Model

It is possible to generalize the model so that the effect of lower level predictors is different in each region. This can be done by adding random coefficients in front of some of the individual-level predictors of the model. So far, we have allowed in the above model the researcher seen impact on of early marriage to vary across regions, assuming that the effects of the explanatory variables are the same for each region. However, in this model contain a random slope for religion of women, women's education level, husband's education level and wealth index of families on early marriage might vary from region to region. Therefore, in the Bayesian random coefficient model, we need to introduce a random coefficient of: religion, women's, husband's education level and wealth index of families to vary randomly across regions. But the Bayesian multilevel random coefficient model has not been selected based on deviance information criteria and its result has been presented in Table 4.6 below.

Table 4.6.Bayesian estimates for parameters of random coefficient model.

Fixed Effects							
Covariates	Categories	Mean	SD	SE	2.5%	50%	97.5%
	Intercept	1.59344	0.8241	0.02406	-0.0238	1.62767	3.00077
Type of place of residence	Urban(Ref)	----------	----------	---------	---------	---------	----------
	Rural	1.18775	0.1102	0.00380	0.96539	1.18675	1.40196
Women education level	No.edu(ref)	………..	………..	……….	……….	……….	………..
	Primary	-0.32776	0.07042	0.00235	-0.4615	-0.3300	-0.2003
	Secondary	-0.68102	0.11810	0.00410	-0.9227	-0.6745	-0.4414
	Higher	-1.20851	0.15326	0.00561	-1.5264	-1.3061	-0.9808
Religion	Orto.(ref)	………..	………..	……….	……….	……….	………..
	Catholic	-0.10317	035401	0.01107	-0.7806	-0.1043	0.60783
	Protestant	0.30832	0.10817	0.00366	0.30717	0.30817	0.51116

	Muslim	0.52855	0.08825	0.00307	0.35801	0.53058	0.70250
	Others	-0.40305	0.24230	0.00880	-0.9021	-0.4035	0.10324
Wealth index	Poorest	----------	----------	---------	----------	----------	----------
	Poorer	-0.22724	0.09738	0.00349	-0.4259	-0.2268	-0.0456
	Middle	-0.71153	0.09934	0.00313	-0.9063	-0.7129	-0.5204
	Richer	-0.90556	0.10047	0.00360	-1.1091	-0.9037	-0.7104
	Richest	-1.64926	0.11325	0.00386	-1.8723	-1.6530	-1.4300
Women occupation	No(ref)	----------	----------	---------	----------	----------	----------
	Working	-0.70288	0.06081	0.00201	-0.8218	-0.7062	-0.5809
Husband occupation	Agric(ref)	----------	----------	---------	----------	----------	----------
	Laborer	-0.15316	0.08386	0.00293	-0.3181	-0.1523	0.00649
	Business	-0.09683	0.07882	0.00261	-0.2564	-0.0983	0.05893
	Professional	0.01806	0.12961	0.00459	-0.2431	0.01957	0.27357
	Other	0.14194	0.15077	0.00502	-0.1569	0.14517	0.43985
Husband educational level	No.edu(ref)	………..	……….	………	……….	……….	………..
	Primary	-0.20242	0.07103	0.00246	-0.3401	-0.2005	-0.0747
	Secondary	-0.41121	0.10031	0.00383	-0.6200	-0.4137	-0.2071
	Higher	-0.71614	0.13017	0.00440	-0.9636	-0.7221	-0.4388
Ethnicity	Amhara(ref)	----------	----------	---------	----------	----------	----------
	Oromo	-0.49735	0.12346	0.00409	-0.7443	-0.4989	-0.2615
	Tigrie	-0.08345	0.22983	0.00780	-0.5232	-0.0897	0.36543
	Affar	-0.57048	0.25778	0.00857	-1.0890	-0.5617	-0.0832
	Somalie	-1.13562	0.25998	0.00954	-1.6215	-1.1434	-0.6264
	Others	-0.61883	0.12301	0.00370	-0.8504	-0.6243	-0.3826
Mass media exposure	Yes	-1.39435	0.06197	0.00209	-1.5206	-1.3941	-1.2751
Random Effects							
$\mathrm{Var}(\delta_o{}^2)$		0.1775	0.1237	0.00556	0.04491	0.1452	0.4686
$\mathrm{Var}(\delta_1{}^2)$		0.4632	1.8850	0.08153	0.02876	0.1957	2.0454
$\mathrm{Var}(\delta_2{}^2)$		1.2637	3.3332	0.22488	0.10385	0.5724	8.2983

$\mathrm{Var}(\delta_3{}^2)$		0.7229	2.7683	0.23454	0.02572	0.1900	5.0457
$\mathrm{Var}(\delta_4{}^2)$		2.1787	5.9917	0.99941	0.16959	0.6860	15.927

Table 4.6 above shows that the value of $var(\delta_o{}^2)$,$var(\delta_1{}^2)$,$var(\delta_2{}^2)$, $var(\delta_3{}^2)$ and $var(\delta_4{}^2)$, are the estimated variance of intercept, slope of religion, slope of women's, husband's education level and wealth index respectively.

These estimated variances, intercept and slope of religion of women's are significant since the credible interval is greater than zero this suggesting that intercept and slope of religion of women's vary significantly. So, there is a significant variation in the effect religion of women's across regions in Ethiopia.

These estimated variances, intercept and slope of women's and husband's educational level are also significant since the credible interval is greater than zero this suggesting that intercept and slope of women's and husband's educational level vary significantly. So, there is a significant variation in the effect women's and husbands' educational level across regions in Ethiopia.

These estimated variances, intercept and slope of wealth index of families are significant since the credible interval is greater than zero this suggesting that intercept and slope of wealth index of families vary significantly. So, there is a significant variation in the effect wealth index of families across regions in Ethiopia.

Further this model implies that there exist considerable differences in early marriage practice of women among regions and a model with a random coefficient is more appropriate to explain the regional variation than a model with fixed effect.

4.9. Model Comparison of Bayesian and Classical Multilevel Logistic Regressions

Model comparison for Bayesian multilevel and classical multilevel approaches were identified more significant predictor variables, numerical value different in standard error. The most important comparison method was using the standard error of both approaches. In this section, the researcher has compared the random intercept model which was selected in the Bayesian analysis with the classical random intercept model based on the parameters' numerical value of standard error. Considering the standard errors of the estimated coefficients for comparison of both approaches of Bayesian and classical is a very important method and hence the model with the smaller standard error is the appropriate model for fitting the data. Accordingly, the estimated coefficients and standard errors of both approaches have been presented in Table 4.7 below. But the full classical random intercept model is presented in Appendix A. Therefore, the result in the Table 4.7 indicated that all estimated coefficients' standard errors in Bayesian random intercept model are smaller than the classical random intercept model. So, based on the standard error value Bayesian random intercept model give is a better fit than classical random intercept model.

Table 4.7 Model comparison of Bayesian random intercept and classical random intercept model

Covariates	Category estimated value	Bayesian random intercept model		Classical random intercept model	
		Post.mean	$S.E_B$	β	$S.E_C$
Intercept		2.44324	0.006423	2.0861366	0.1305921
Residence	Rural	1.20962	0.004119	1.0106973	0.0924480
Women educational level	Primary	-0.33887	0.002465	-0.285968	0.0607552
	Secondary	-0.69103	0.004122	-0.579962	0.1022876
	Higher	-1.30962	0.005715	-1.100878	0.1452641
Religion	Catholic	-0.10428	0.012187	-0.095574	0.2945087
	Protestant	0.30942	0.003777	0.2643249	0.0920961
	Muslim	0.53966	0.003085	0.4483744	0.0778922
	Others	-0.40406	0.008913	-0.353561	0.2180038
Wealth index	Poorer	-0.23473	0.003119	-0.195951	0.0814627
	Middle	-0.72284	0.003416	-0.608664	0.0820863
	Richer	-0.91280	0.003415	-0.764689	0.0854155
	Richest	-1.64462	0.004134	-1.394462	0.0981545
Women oc.	Working	-0.70828	0.002234	-0.593682	0.0515745
Husband occupation	Laborers	-0.13750	0.002738	-0.125332	0.0717948
	Business	-0.08754	0.002872	-0.082617	0.0651874
	Professional	0.03447	0.004451	0.0214511	0.1119125
	Others	0.16593	0.004933	0.1220437	0.1289319

Husband educational level	Primary	-0.21353	0.002576	-0.180885	0.0611324
	Secondary	-0.42231	0.003947	-0.363323	0.0893995
	Higher	-0.72725	0.004504	-0.597432	0.1142595
Mass media	Yes	-1.39515	0.002062	-1.178305	0.0534609
Ethnicity	Oromo	-0.49633	0.004064	-0.441585	0.1030830
	Tigrie	-0.09322	0.007478	-0.070729	0.1826131
	Affar	-0.58454	0.008671	-0.496848	0.2091835
	Somalie	-1.03983	0.008938	-1.024974	0.1931521
	Others	-0.62011	0.004547	-0.523264	0.1039389
Random effects	$\mathrm{Var}({\delta_u}^2)$	0.2899		0.2574	

Note: S.E$_B$ is standard error for Bayesian intercept model: **S.E$_C$** is standard error for classical intercept model.

For estimation of random effects in Bayesian multilevel random intercept model gives better fit than the classical multilevel random intercept models. In this estimation of random effect there is a wide difference between the estimation of classical approach and Bayesian approaches (that is 0.2574 and 0.2899 respectively), and the Bayesian multilevel random intercept model is more appropriate in explaining the variation of early marriage among the women across the region of Ethiopia than the classical multilevel random intercept.

4.10. Checking Convergence

Bayesian method gives estimates of parameters by sampling them from their posterior distributions through an MCMC method. In the convergence of an MCMC algorithm would be an important issue for the correct estimation of the posterior distribution of interest. The convergence cannot always be diagnosed as clearly as in optimization methods which are assumed to be the problem of MCMC methods. For this reason both the length of the burn in period and the size of the MCMC output that was used for the posterior analysis could be specified by the user. The next most important problem is a specification of the thinning interval, that is, the numbers of iterations researcher needs to discard until two successive observations become independent.

With this regard, Metropolis-Hasting algorithm was implemented with 60000 iterations, 10000 burn-in terms discarded, and 50 thinning intervals to make observations independent or low autocorrelation. However, in order to be sure that the sample was truly representative of the stationary or posterior distribution, various schemes of diagnosis were applied to check the convergence of the Markov chains to the target distribution. There are many commonly used methods to assess the convergence of MCMC output, but in this study only some of them are used. Therefore, different methods such as trace plot, autocorrelation, and density plot for supervising convergence have been show below.

Trace plots: In Bayesian analysis trace plot is one of methods of assessing the convergence of the Markov chain to its posterior distribution and the graph which could be plotted the iterations versus the generated values. In this graph convergence can be attained if all values are within a zone without strong periodicities up and down periods. If the plot looks like a horizontal band, with no long upward or downward trends, then we have evidence that the chain has converged. Therefore, the trace plots in the figure1below are all straight line which did not show up and down periods. Moreover, the density plots in figure1 are nearly similar with the normal plot. This shows that all posterior estimates were converged. The four independently generated chains demonstrated good chain mixture, an indication of convergence. Not all trace and density plots are presented here; the remaining plots can be found in appendices (see Appendix C).

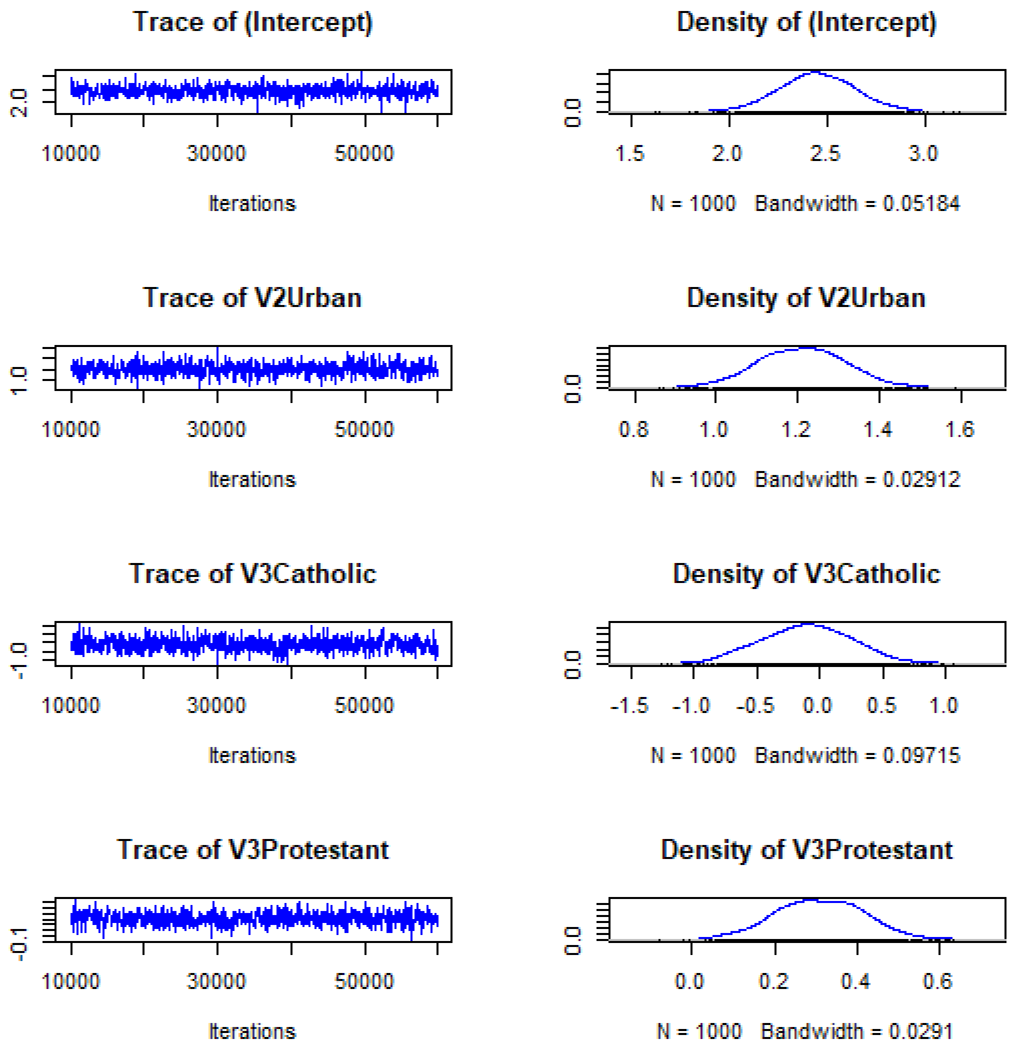

Figure 1: Trace and density plot for convergence check.

Autocorrelation: High autocorrelation within a single parameter chain leads to slow mixing and possibly individual non-convergence to the limiting distribution because the chain will tend to explore less space in finite time. That is, low or high values indicate fast or slow convergence, respectively. Here the requirement is that the chain should not display high autocorrelation. It is observed when there are trends in the data. Autocorrelation means that a next value can be potentially influenced by the previous value. In case of strong autocorrelations, the model estimates posterior means or modes are assumed to be unreliable or not correct. The acceptance autocorrelation according to the rule of thumb is the value less than 0.1(Natalia, 2015). Also, the convergence of posterior estimate has been checked using an effective sample size that is all the effective sample sizes of the estimates are greater than 200. Now, one can be reasonably confident that convergence has been achieved. It has been presented in Table 4.9 (see Appendix B).

4.11. Assessing the Accuracy of the Bayesian Model Estimate

In order to evaluate the accuracy of the Bayesian model estimate, the Monte Carlo standard error was compared with the standard deviation. In addition to the above graphical methods of checking convergence of the chain to its posterior distribution, the Monte Carlo standard error of the posterior mean which is an estimate of the difference between the estimate of the posterior mean for each parameter and the true posterior mean is another way of assessing the accuracy of the posterior estimates. The model that is considered to be accurate if the Monte Carlo standard error is less than 5% times its standard deviation. Thus, with this study, the Monte Carlo standard error of all covariates for the Bayesian random intercept model was less than 5% times of its standard deviation. Therefore, subsequently the convergence and accuracy criteria were reached, then it is potential to say that the posterior estimate of the Bayesian random intercept model was correct. It has been presented in Table 4.10 (see Appendix C).

4.12. Discussions of the Results

The main aim of the study was to identify determinant predictors that are associated with early marriage among women based on the 2016 data of Ethiopian Demographic Health Survey. The study was considered region as random effect of early marriages among women in Ethiopia. Based on the appropriate model comparison tool that was used Bayesian random intercept model found better in fitting the data according to their deviance information criteria was small.

The prevalence of early marriage in Ethiopia was 58.2%. Based on the Chi-square test of association, all the predictor variables included in the analysis, have significant association with early marriage practice of women.

The model that is selected in the Bayesian frame work has been compared with the classical model based on their respective standard error. As result the Bayesian model found to be better than the classical model because the standard errors of independent variables in this model were smaller than the classical model. The results obtained from the Bayesian model have been discussed as follow.

The Bayesian random intercept model predictors such as place of resident, husband education level, work status of women, wealth index, women education level, religion and mass media exposure were found to be significant variables for the exercise of early marriage among women.

The Bayesian random intercept has also shown that the random effect is significantly different from zero, indicating that the practice of early marriage among women varies from region to region. This may suggest differences in lifestyle, culture and ethnic tradition were between different regions. Because of these potential cultural and socioeconomic, reason early marriage exhibits a significant variation among regions of Ethiopia. This study agree with the previous studies on the this case (Gashaw, 2019).

Women who had primary, secondary and higher were less likely to be married early compared to none educated women. The higher educational attainment of the women have, more knowledge gets and understand, including all information about the effect of marriage in early. This finding of the study supported by previous studies (Gashaw, 2019). Women with primary, secondary and higher education, were less probable to be married early compared to those with no education. Lower risk of becoming married early among educated women may be due to looking time for schooling and which may be attributed to the delay the marriage at early caused by advancement in education. The results of study was supported by the previous studies (Kamal, 2012).

The result of this study showed that husband's education level was another important factor for getting marriage early in women. Consequently, women married to men who had completed the primary, secondary and higher were lower risk of marry early than among women married to men who have no education. While husband's education is not so marked like women's education, it also plays an important role in case of early marriage of women(Tessema et al., 2015): (Zahangir and Kamal, 2011).

The women who lived in rural area is higher probability to get marriage early than women who lived in urban. This result of this study similar to the previous findings (Workineh et al., 2015): (Tessema et al., 2015). This is due to, urbanization provides more facilities along with practical life compared to rural and respondents of urban women's address are more aware at every section of life. Hence urban women's inhabitants are less entrance to marry at early age than their rural counterparts.

In the same manner, religion of women was also found one of the determinants factor of early marriage. Married women who were followers of protestant religion were higher probability to exercise early marriage than those who were followers of religions of orthodox women. Similarly Muslim married women were higher probability to get marriage early compared to those religions of Orthodox women. This is due that doing this because their religion or the sharaih allowed for doing it and stopping such exercise means ignoring the religious norms. This result also seems to agree with the finding of a study done in Bangladesh (Zahangir and Kamal, 2011).

The result of the study also shown that wealth index of household has one of the most important significantly factor affecting the women get to marriage early. According to the finding of the study, as compared with women residing in poorest economic status (wealth index), the odds of being married early in poorer, middle, richer and richest wealth index were lower risk respectively. This finding of this study was in line with other studies(Kamal, 2012). This could be due to early marriage as a way to improve the economic status of the family, reasoning that poverty push families to marry the daughters at a young age and for some families the desire to get money paid to the women's family by the men's family is an incentive to marry the daughters at the early age in Ethiopia.

The finding of the study has also shown mass media is one of the most important determinant factors that influence early marriage. The result indicated that women who were exposure to any mass media via radio and TV have less probability to get early marriage compared to non-exposure to any mass media. This mass media is important tools to get information in order to create awareness about conscious of an individual, so respondents who have entrance to mass media they are relatively more watchful about the worse situation of marriage happen at early age (Tessema et al., 2015): (Zahangir and Kamal, 2011).

The result of this study has also shown that woman's working status as an important factor in influencing early marriage women. Consequently, the odds of being marriage early for a women who had work have less likely than the women who had no work. The result of this finding agree with the previous study(Mpilambo et al., 2017).

Bayesian procedure was considered in this study to make inference about the parameters of a multilevel logistic regression model. Bayesian method gives estimates of parameters by sampling them from their posterior distributions through an MCMC method. In this Bayesian analysis, the posterior inference was implemented with a Metropolis-Hasting algorithm with 60000 iterations, 10,000 samples as burn in and 50 thinning interval to make the sequence sampling independent or low autocorrelation with MCMCglmm packages in R software. In order to be sure that the sample was truly representative of the stationary or posterior distribution, various schemes of diagnosis were applied to check the convergence of the Markov chains to the target distributions such as trace plot, density plot, autocorrelation, and effective sample size. With these four methods the convergence of the posterior estimate was correctly achieved.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This study was generally intended to identify determinant of early marriage among women using 2016 EDHS. To address the objectives of the study, both Bayesian and classical multilevel logistic regression has been fitted. Using the standard model comparison technique that the smaller the standard error the better the model is, the Bayesian model was appropriately fitted the data well.

The study also revealed that socio-economic and demographic variables have significant effect on early marriage among women in Ethiopia. The results of Bayesian intercept model shows that place of residence, religion, educational level of women, husband's education level, respondents work status, wealth index and exposure to mass media were important determinants of early marriage in Ethiopia. In another way, the variance of the random component of the intercept term was found to be significant implying that the practice of early marriage among women are varies across regional states. Based on the intra-class correlation, variation of within women's early marriage practice were higher than that of the between region variation.

Particular, the study shows that those women and husband's education levels that have higher level of education was lower risk of early marriage as compared lower level of education. Considering Place of residence, women from rural area are at a higher risk of early marriage as compared to those from urban area. The result also indicated that women who have exposure to any mass media via radio, TV or newspapers/magazine have less likely to be married earlier compared to non-exposure to any mass media. Moreover, According to our findings, as compared with women residing in richest economic status of households (wealth index), the odds of being married early in poorest households were highly significant. The women who had a work are less risk of marrying early as compared to a women who had no work.

5.2. Recommendations

Based on the finding of the study, the following recommendation are forwarded. Subsequently, regions have significant effect on the practice of early marriage in women's, to improve early marriage practice towards the major factors and leading to reducing variations of early marriage among regional states established on the coming points:-

- ❖ As there is variation in the status of early marriage in regional states of Ethiopia, it is advocate that regions have to take policies and programs that cover the problem taking into account in setting of the region.
- ❖ It is also essential to proceed improving women access to education in the country, as this is important ways for enhancing the women's age at first marriage.
- ❖ Increasing the access to mass media can play an effective role in reducing early marriage among women and awareness need to follow the regulation of legal age marriage because it is the most determinants of health of women and child borne.
- ❖ Subsequently, there are variations in being married early across regions in terms of religion, religious leaders is important role in reducing early marriage in Ethiopia. Especially it is advisable to Muslim religion leaders to delay early marriage of women for their followers by giving basic information regards to marriage and by developing the perception of women.
- ❖ Advanced studies should be conducted to identify other factors that affect and bring to early marriage of women variations among regions.
- ❖ In this study, only the overall variation of early marriage among the women between regions was identified. Merely identifying which region is highly exercising early marriage and which is might important to the government in terms of taking the action. Therefore, future studies should incorporate spatial modeling to identify hotspot areas.

5.3. Limitation of the Study

This study has some limitations.

- Lack of literature in our country related to the subject under the study.
- In this study married women who are living with their husbands' were considered. Yet, the findings cannot be generalized to the all women of Ethiopia.
- In addition, the 2016 EDHS data cannot entirely represent the census (the whole population) because the response rate of the survey was 94.6%. Thus, there might still be some variation in the observed response.
- The data used in this study was the 2016 EDHS. Thus, the results may not necessarily reflect the current situation of Ethiopia in 2020.

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APPENDICES

Appendix A: Table 4.8 .Classical random intercept model

Fixed effects							
	Value	Std.error	DF	t-value	95% confidence		P-value
(Intercept	2.0861366	0.1305921	9442	15.974441	1.830512	2.34176	0.0000
Urban(ref)	-------------	------------	-------	------------	-----------	----------	---------
Rural	1.0106973	0.0924480	9442	10.932597	0.829737	1.19165	0.0000
No(ref)	------------	-------------	-------	------------	-----------	----------	---------
Primary	-0.285968	0.0607552	9442	-4.706882	-0.40489	-0.16704	0.0000
Secondary	-0.579962	0.1022876	9442	-5.669911	-0.78018	-0.37974	0.0000
Higher	-1.100878	0.1452641	9442	-7.578458	-1.38522	-0.81653	0.0000
Ortho(ref)	------------	-------------	-------	------------	-----------	----------	---------
Catholic	-0.095574	0.2945087	9442	-0.324522	-0.67205	0.48090	0.7455
Protestant	0.2643249	0.0920961	9442	2.870097	0.084053	0.44459	0.0041
Muslim	0.4483744	0.0778922	9442	5.756341	0.295906	0.60084	0.0000
Others	-0.353561	0.2180038	9442	-1.621812	-0.78028	0.07316	0.1049
Poorest	------------	------------	-------	------------	----------	----------	---------
Poorer	-0.195951	0.0814627	9442	-2.405409	-0.35540	-0.03649	0.0162
Middle	-0.608664	0.0820863	9442	-7.414925	-0.76934	-0.44798	0.0000
Richer	-0.764689	0.0854155	9442	-8.952570	-0.93188	-0.59749	0.0000
Richest	-1.394462	0.0981545	9442	-14.20680	-1.58659	-1.20233	0.0000
Agr.(ref)	-------------	-------------	-------	------------	-----------	----------	---------
Laborers	-0.125332	0.0717948	9442	-1.745703	-0.26586	0.01520	0.0809
Business	-0.082617	0.0651874	9442	-1.267375	-0.21021	0.04498	0.2051
Professional	0.0214511	0.1119125	9442	0.191677	-0.19760	0.24051	0.8480
Others	0.1220437	0.1289319	9442	0.946575	-0.13033	0.37441	0.3439
No.work(ref)	- -----------	-------------	------	------------	-----------	----------	--------
Working	-0.593682	0.0515745	9442	-11.51115	-0.69463	-0.49272	0.0000
No(ref)	-------------	------------	-------	------------	-----------	----------	---------

Yes	-1.178305	0.0534609	9442	-22.04050	-1.28295	-1.07366	0.0000
No(ref)	-------------	------------	-------	------------	-----------	----------	---------
Primary	-0.180885	0.0611324	9442	-2.958908	-0.30054	-0.06122	0.0031
Secondary	-0.363323	0.0893995	9442	-4.064045	-0.53831	-0.18833	0.0000
Higher	-0.597432	0.1142595	9442	-5.228731	-0.82108	-0.37377	0.0000
Random effects							
$\mathrm{var}({\delta_u}^2)$	0.2574529	-------------	-------	------------	0.148175	0.44732	---------

Appendix B: Table 4.9. Autocorrelation of the variables and the effective sample size

Covariates	Categories	Lag 0	Lag 50	Effective sample size
	Intercept	-0.043564437	0.001645443	1000.0
Type of place of residence	Rural	0.009208638	0.009208638	704.9
Women educational level	Primary	-0.03247256	-0.00335076	818.5
	Secondary	0.024027520	-0.009054481	836.6
	Higher	0.0174196965	0.0006086464	827.3
Religion	Catholic	-0.043564437	0.03745055	897.1
	Protestant	-0.01488322	0.04239351	837.0
	Muslim	0.02310416	0.01581052	839.2
	Others	0.041438704	-0.010756930	808.3
Wealth index	Poorer	-0.007165064	-0.015527159	968.6
	Middle	-0.0060801833	0.0554131033	830.3
	Richer	-0.03230616	-0.03028228	889.3
	Richest	0.02949596	-0.01536182	790.1
Women working status	Working	0.007532526	-0.010960301	780.2
Husband education	Primary	-0.023735947	0.028105969	784.0
	Secondary	-0.044968250	-0.031303426	782.5
	Higher	-0.078956775	0.023510041	836.6

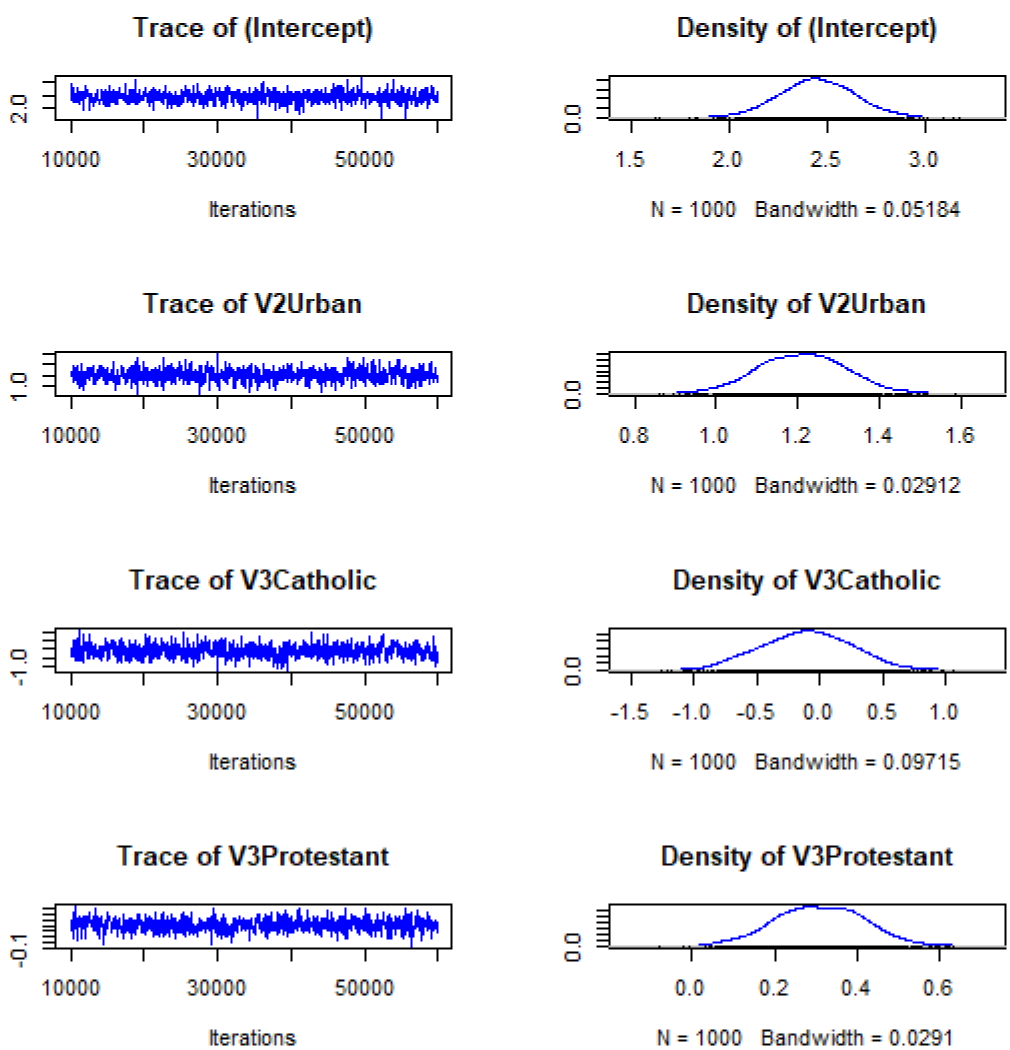
Mass media exposure	Yes	0.059993215	-0.005423704	986.0
Husband occupation	Laborers	-0.04457715	-0.01075753	920.5
	Business	-0.011993221	0.003197661	697.5
	Professional	0.030862558	-0.030330299	904.0
	Others	-0.005791933	0.023556999	1000.0
Regional variance	$\delta_u{}^2$	1.000000	-0.034530986	1156.0

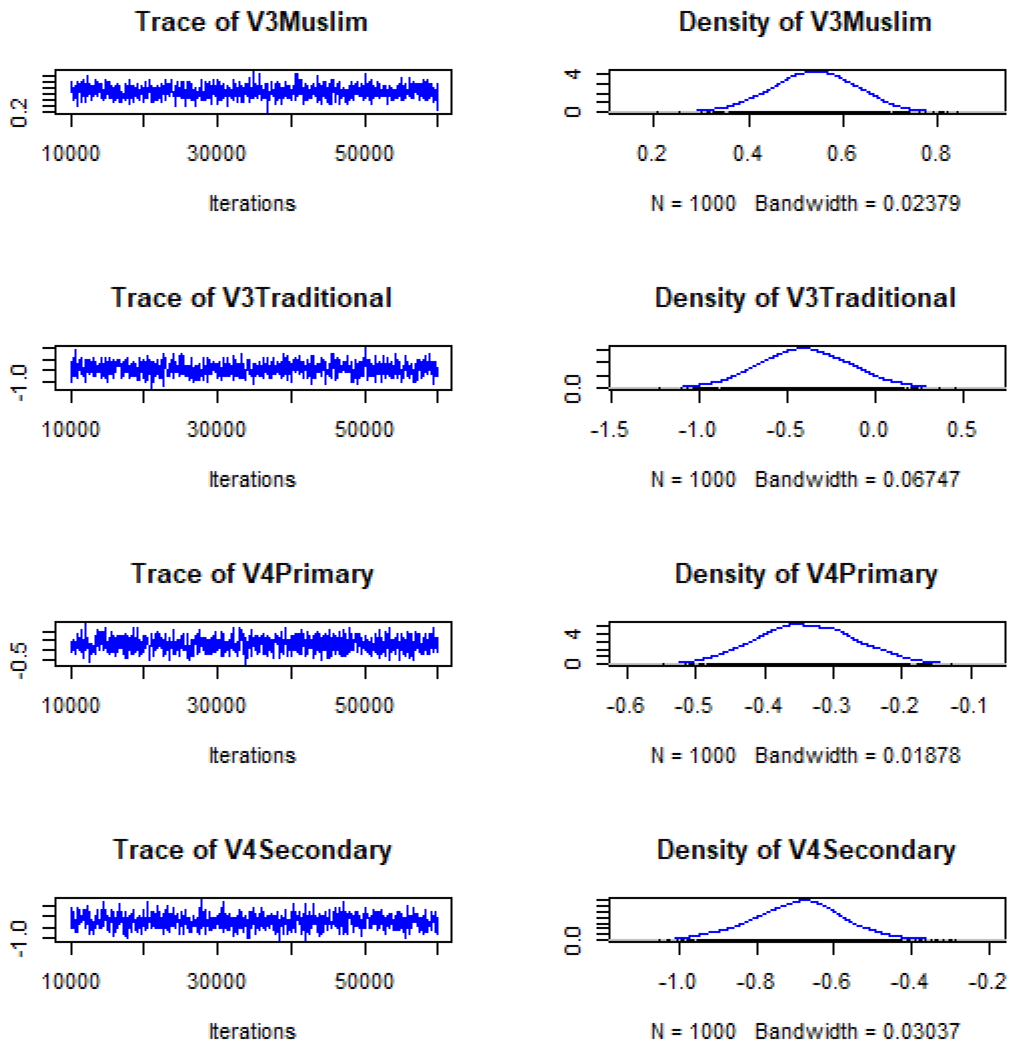
Appendix C: Table 4.10. Comparison of MC error with 5% of Sd.

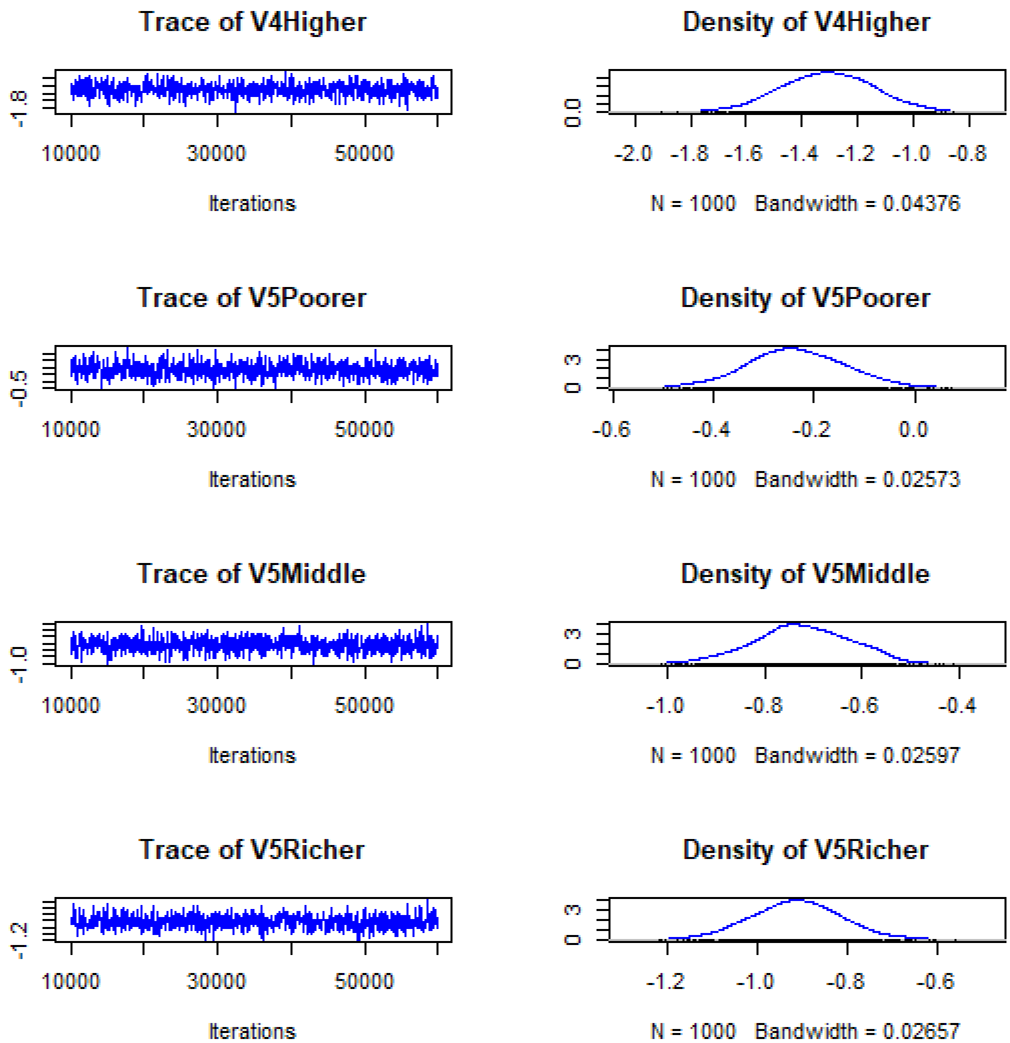
Covariates	Categories	5% of Sd.	MC error
	Intercept	0.01016	0.006423
Place of residence	Rural	0.005467	0.004119
Women education level	Primary	0.003527	0.002465
	Secondary	0.0059601	0.004122
	Higher	0.008218	0.005715
Religion	Catholic	0.018251	0.012187
	Protestant	0.005464	0.003777
	Muslim	0.004468	0.003085
	Others	0.01267	0.008913
Wealth index	Poorer	0.004854	0.003119
	Middle	0.004922	0.003416
	Richer	0.005092	0.003415
	Richest	0.005809	0.004134
Women occupation	Working	0.00312	0.002234
Husband occupation	Laborer	0.004153	0.002738
	Business	0.003793	0.002872
	Professional	0.006691	0.004451
	Others	0.007799	0.004933
Husband educational level	Primary	0.003607	0.002576
	Secondary	0.005521	0.003947

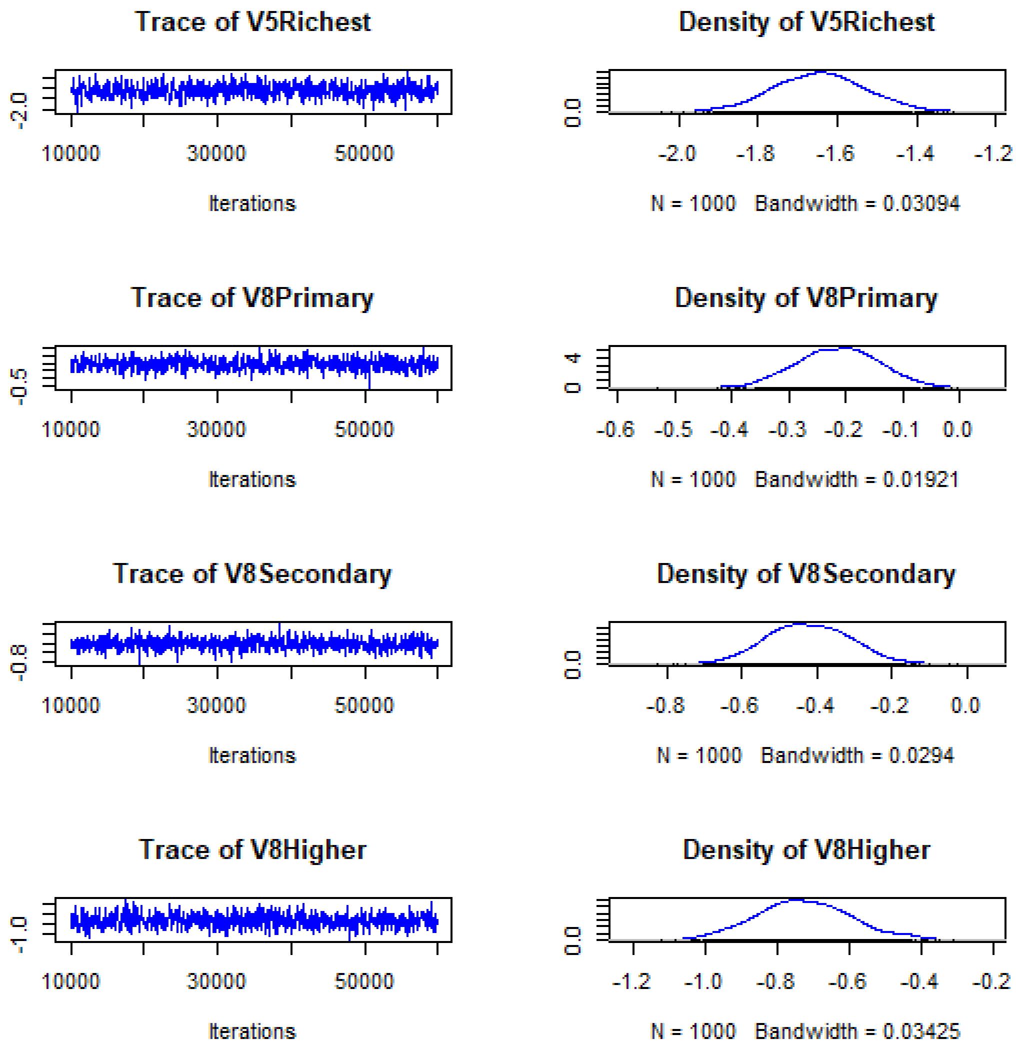
	Higher	0.006514	0.004504
Mass media exposure	Yes	0.003238	0.002062

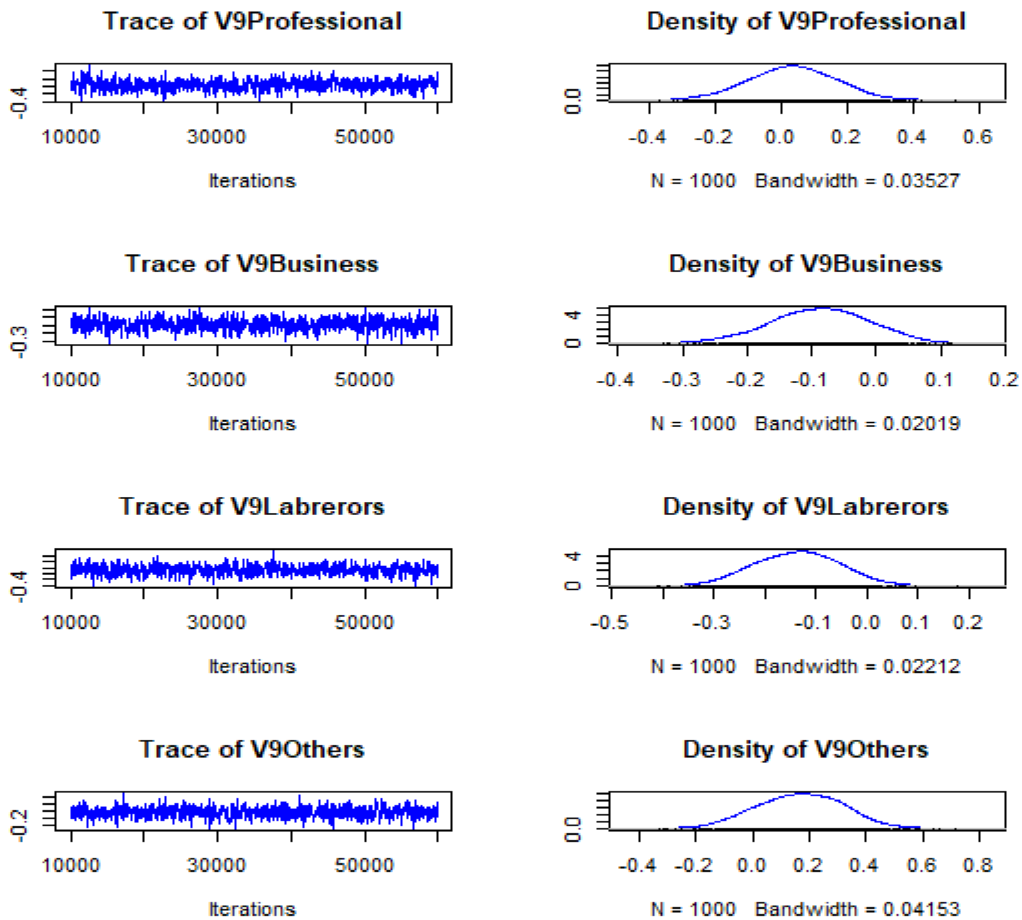
Appendix C: Figure 1 .trace and density plot for the convergence check.



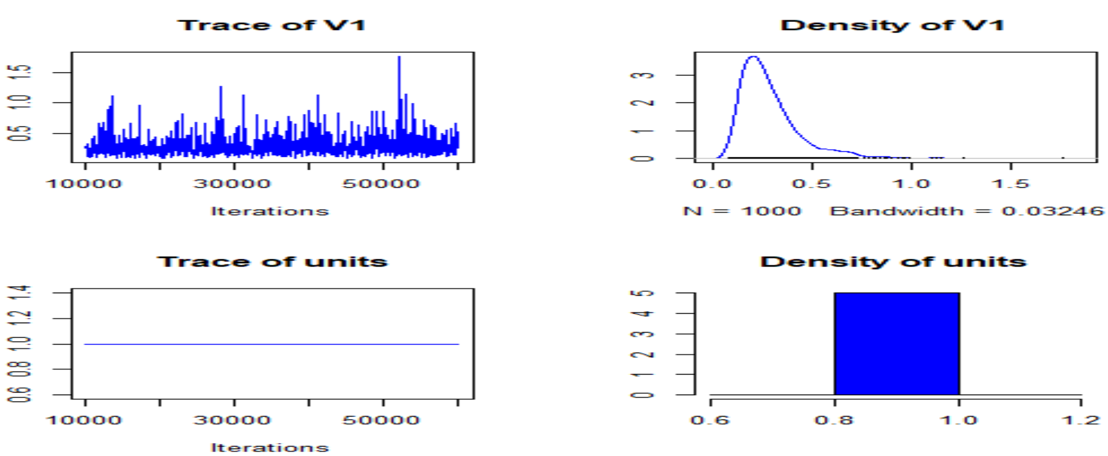

Trace of V3Muslim
0.2
10000
30000
50000
Iterations
Density of V3Muslim
0
4
0.2
0.4
0.6
0.8
N = 1000 Bandwidth = 0.02379
Trace of V3Traditional
-1.0
10000
30000
50000
Iterations
Density of V3Traditional
0.0
-1.5
-1.0
-0.5
0.0
0.5
N = 1000 Bandwidth = 0.06747
Trace of V4Primary
-0.5
10000
30000
50000
Iterations
Density of V4Primary
0
4
-0.6
-0.5
-0.4
-0.3
-0.2
-0.1
N = 1000 Bandwidth = 0.01878
Trace of V4Secondary
-1.0
10000
30000
50000
Iterations
Density of V4Secondary
0.0
-1.0
-0.8
-0.6
-0.4
-0.2
N = 1000 Bandwidth = 0.03037


Trace of V4Higher
-1.8
10000
30000
50000
Iterations
Density of V4Higher
0.0
-2.0
-1.8
-1.6
-1.4
-1.2
-1.0
-0.8
N = 1000   Bandwidth = 0.04376
Trace of V5Poorer
-0.5
10000
30000
50000
Iterations
Density of V5Poorer
0
3
-0.6
-0.4
-0.2
0.0
N = 1000   Bandwidth = 0.02573
Trace of V5Middle
-1.0
10000
30000
50000
Iterations
Density of V5Middle
0
3
-1.0
-0.8
-0.6
-0.4
N = 1000   Bandwidth = 0.02597
Trace of V5Richer
-1.2
10000
30000
50000
Iterations
Density of V5Richer
0
3
-1.2
-1.0
-0.8
-0.6
N = 1000   Bandwidth = 0.02657


Trace of V5Richest
Density of V5Richest
-2.0
10000 30000 50000
Iterations
0.0
-2.0 -1.8 -1.6 -1.4 -1.2
N = 1000 Bandwidth = 0.03094
Trace of V8Primary
Density of V8Primary
-0.5
10000 30000 50000
Iterations
0 4
-0.6 -0.5 -0.4 -0.3 -0.2 -0.1 0.0
N = 1000 Bandwidth = 0.01921
Trace of V8Secondary
Density of V8Secondary
-0.8
10000 30000 50000
Iterations
0.0
-0.8 -0.6 -0.4 -0.2 0.0
N = 1000 Bandwidth = 0.0294
Trace of V8Higher
Density of V8Higher
-1.0
10000 30000 50000
Iterations
0.0
-1.2 -1.0 -0.8 -0.6 -0.4 -0.2
N = 1000 Bandwidth = 0.03425



Trace of V9Professional
-0.4
10000 30000 50000
Iterations
Density of V9Professional
0.0
-0.4 -0.2 0.0 0.2 0.4 0.6
N = 1000 Bandwidth = 0.03527
Trace of V9Business
-0.3
10000 30000 50000
Iterations
Density of V9Business
0 4
-0.4 -0.3 -0.2 -0.1 0.0 0.1 0.2
N = 1000 Bandwidth = 0.02019
Trace of V9Labrerors
-0.4
10000 30000 50000
Iterations
Density of V9Labrerors
0 4
-0.5 -0.3 -0.1 0.0 0.1 0.2
N = 1000 Bandwidth = 0.02212
Trace of V9Others
-0.2
10000 30000 50000
Iterations
Density of V9Others
0.0
-0.4 -0.2 0.0 0.2 0.4 0.6 0.8
N = 1000 Bandwidth = 0.04153



Trace of V1
0.5 1.0 1.5
10000 30000 50000
Iterations
Density of V1
0 1 2 3
0.0 0.5 1.0 1.5
N = 1000 Bandwidth = 0.03246
Trace of units
0.6 0.8 1.0 1.2 1.4
10000 30000 50000
Iterations
Density of units
0 1 2 3 4 5
0.6 0.8 1.0 1.2