DETERMINANTS IN FAMILY PLANNING SERVICE UTILIZATION AMONG WOMEN OF REPRODUCTIVE AGE IN ETHIOPIA: CLASSICAL AND BAYESIAN APPROACHES

BY

ADUGNA TESFAYE

A Thesis submitted to the Department of Statistics, College of Natural Science and Jimma University as partial fulfillment of the requirements for the degrees of Master of Science (MSc.) in Biostatistics.

February, 2018

Jimma, Ethiopia

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ADUGNA TESFAYE

Advisor: Geremew Muleta.(PhD Fellow)

Co-advisor: Demeke Kifle(MSc.)

February, 2018

Jimma, Ethiopia

Approval Sheet

This is to certify that the thesis titled **" determinants in family planning service utilization in Ethiopia: Classical and Bayesian approaches** “submitted in partial fulfillment of the requirement for the degree of **Master of Science in Statistics (Specialization: Biostatistics)** to the college of natural science Jimma University,and is record of original research carried out by **Adugna Tesfaye, ID.No: RM 1216/09**, under my supervision and no part of the thesis has been submitted for another degree or diploma. The assistance and the help received during the course of this investigation have been duly acknowledged. Therefore, I recommended that it may be accepted as fulfilling the thesis requirement.

Geremew Muleta (PhD Fellow)	----------------------------	-----------------------
Main advisor	Signature	Date
Demeke Kifle (MSc.)	-----------------------------	----------------------
Co-advisor	Signature	Date

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

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Name of chairman	Signature	Date
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Name of Main Advisor	Signature	Date
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Name of Co-advisor	Signature	Date
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Name of internal Examiner	Signature	Date
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Name of External Examiner	Signature	Date

Declaration

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

Adugna Tesfaye	-------------------------	--------------
Name of student	Signature	Date

Jimma University, Jimma Ethiopia

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Acronyms and Abbreviations

A/BIC:	Akaike/ Bayesian Information Criteria
CSA	Central Statistical Agency
CPR	Contraceptive prevalence rate
DFBETS	Difference in Betas
EDHS	Ethiopian Demographic Health Survey
FMOH	Federal Ministry of Health
HEW	Health Extension Workers
ICC	Intra Class Correlation Coefficient
IUD	Intrauterine Contraceptive device
FP	Family planning
HEW	Health Extension Worker
LAM	Lactation amenorrhea method
LRT	Likelihood ratio test
MCAR	Missing completely at random
MCMC	Markov Chain Monte Carlo
MCSE	Monte Carlo standard error
ML	Maximum Likelihood
MOHE	Ministry of Health Ethiopia
OR	Odds Ratio
RH	Reproductive Health
SDM	Standard Days Method
TV	Television
WHO:	World health organization

Abstract

Family planning services enable individuals or couples to determine freely the number and spacing of their children and to select the means by which it is achieved. Population growth in Ethiopia is not in parallel with the development of health services and other basic infrastructures. The objective of this study was to identify the factors that affect utilization of family planning service among reproductive age women's in Ethiopia. Cross-sectional data from Ethiopian Demographic and Health Survey was used for the analysis. Data was collected by the Central Statistical Agency from January 18, 2016 through June 27, 2016 and the sampling technique employed was multistage. A total of 9824 women were considered in this study. Descriptive analysis, single level, multilevel and Bayesian logistic regression were used for data analysis using socio-economic, demographic, and proximate variables and utilization of family planning service as the dependent variable. The results of the study show that, out of a total of 9824 sampled women 35.83 percent used the family planning services while 64.17 percent did not. The single level, multilevel and Bayesian logistic regression analyses revealed that the variables that affect the women's utilization of family planning service in Ethiopia were place of residence, age of a woman, religion of a woman, visited by family planning worker, educational level of women, economic status, knowledge about family planning method, occupation of women, exposure to mass media, husband education level, husband occupation and number of having children. The multilevel logistic regression analysis revealed that there was significant variation with regard to women's utilization of family planning services across the regions under investigation. From the methodological aspect, it was found that random coefficient model is better compared to the other two models in setting the data well. The results obtained by applying Bayesian logistic regression analysis show that the standard errors for the variables incorporated in the model were smaller than the classical logistic regression analysis. This implies that the Bayesian logistic regression model give a better estimation than the classical approach.

Keywords: Bayesian analysis, multilevel analysis, Family planning

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the study

Worldwide population growth rate has declined from its historic peak of 2.1% per year in the late 1960's to 1.13% today. According to United Nations population statistics, the world population Growth rates of the world's most populous countries(in decreasing order) are China, India, United States, Indonesia, Brazil, Pakistan, Nigeria, Bangladesh, Russia and Japan . However, Sub-Saharan Africa still faces the highest fertility and population growth rate at 4.71% in the world. Some countries facing population growth are Eritrea, Ethiopia, Sudan, Chad, Niger, Nigeria, Mali, Senegal, Gambia, Algeria, The Democratic Republic of Cong, Egypt, Colombia, Brazil and Mexico. Ethiopia is one of those countries having high growth rate of population increase, with an estimated at 2.6 %(UNFPA, 2016).

This increase in population has caused many difficulties, especially in developing countries because it has triggered limitation of resources along with a greater economic burden. In addition, the increased population has also resulted high fertility and also increased the chances of health risks for mother and child, leading to poor quality of life, and reduces access to education, food, and employment. In order to overcome the obstacles with increased population growth, family planning can play an imperative role in population dynamics that aids in economic stabilization of the country. Family planning also has a significant role in improving the health of the mother and the child by dropping the number of unintended pregnancies, thus reducing the maternal and child mortality rate. However, it has been reported that the use of family planning is low in underdeveloped countries due to lack of education, resources, and poverty as compared to developed countries like the United States (Bbaale E and Mpuga P, 2011).

Family planning services enable individuals and couples to determine freely the number and spacing of their children and to select the means by which this may be achieved. It involves consideration of the number of children a woman wishes to have, including the choice to have no children, as well as the age at which she wishes to have them (United Nations, 2018).

Family planning is a means of promoting the health of women and families and is part of a strategy to reduce the high levels of maternal, infant, and child mortality. People should be offered the opportunity to determine the number and spacing of their own children. Information about family planning should be made available, and access to family planning services should be actively promoted for all individuals desiring them(Republic, 2011).

Globally, each year, nearly 350,000 women die while another 50 million suffer illness and disability from complications of pregnancy and child birth (Hogan et al., 2008). It has been reported that Ethiopia is one of among six countries that contribute to about 50% of the maternal deaths along with India, Nigeria, Pakistan, Afghanistan and the Democratic Republic of Congo (Hogan et al., 2008). The Ethiopia Demographic Health Surveys of 2000, 2005, 2011 and 2016 gave figures of 871, 673, 676 and 412 per 100,000 live births maternal mortality ratios respectively (CSA, 2000, CSA, 2005, CSA, 2011 and CSA, 2016).

Family planning is the practice to prevent or avoid unwanted birth and control the spacing between child birth to help create a small and planned family. It is the best way to control the rapidly and massively growing population. So, family planning contributes to promote the health and welfare of the family and thus contribute effectively to the social development of a country. The health of mothers is not only affected by nutrition status but also by early marriage, frequent pregnancies, early motherhood, abortion etc. Moreover, the health of a child is also affected by the mother‘s health status (WHO, 2015).

Family planning has a clear effect on the health of women, children, and families worldwide especially those in developing countries (Darrochet al., 2011). It offers women opportunities to plan and space pregnancies in order to achieve personal goals and self-sufficiency. It allows individuals to anticipate and attain their desired number of children and the spacing and timing of their births. Family planning has a direct impact on women‘s health and well-being as well as on the consequence of each pregnancy (WHO, 2015). Globally, contraceptives help to prevent an estimated 2.7 million infant deaths and the loss of 60 million of healthy life in a year (Darroch et al., 2011).

More over Promotion of family planning in countries with high birth rates has the potential to reduce poverty and hunger and avert 32% of all maternal deaths and nearly 10% of childhood deaths (Cleland et al, 2006).It would also contribute substantially to women‘s empowerment, achievement of universal primary schooling, and long-term environmental sustainability. Thus in addition to spacing and limiting the number of children it improves maternal and child health empowers women and enhances economic development (Ferdousi et al., 2010).

In developing countries millions of sexually active women of reproductive age (15-49) want to avoid pregnancy and delay child bearing for at least two years or want to stop pregnancy and limit their family size but have unmet need for Family Planning (Darroch et al., 2011). Which implies even recognizing these benefits of Family Planning Unmet Need for Family Planning remains high in the Least Developed Countries. Over the past 40 years, the emerging economies have experienced very rapid increases in their contraceptive coverage, enabling rather steady fertility declines. By contrast, the least developed countries, mostly located in sub-Saharan Africa, are just beginning to use modern contraceptives (Rwanda and Ethiopia are among the few exceptions). Unmet need for family planning remains high in sub-Saharan Africa. About 25 percent of women who would like to postpone their next birth by two years do not currently use a contraceptive method. This need could be met by improving contraceptive knowledge and the supply of reproductive health services so that women can better plan their families (Jean and John, 2013).

The factors that influence family planning practice are multifaceted and challenging. Several studies evident that most women‘s knowledge and practice of Family Planning is associated with socio-demographic, socio-cultural, socio economic, source of information and family planning factors. For instance, according to different study findings socio-demographic and economic and media exposure related factors were found to contribute on the practice of Family Planning (Mekonnen et al., 2011 Ibnouf et al., 2007, Mostafa et al., 2010).

Family planning helps people have the desired number of children, which as a result improves the health of mothers and contributes to the nation’s social and economic development. In most developing countries, including Ethiopia, it is common practice for women to have too many children, too close to one another. As a consequence, the population size of the country has grown dramatically but economic growth has not kept in parallel with it. Such an unbalanced population size will inevitably have a negative impact on the wellbeing of the nation. Family planning is one of the strategies which is proving to be effective in tackling these problems (Mekonnen et al., 2011 Ibnouf et al., 2007, Mostafa et al., 2010).

At present, family planning service which is free of cost is provided in both governmental and NGO health facilities in Ethiopia, including hospitals, clinics, health centers, and health stations (UN, 2016). But, Ethiopia is among countries with low contraceptive prevalence rate, with only 29% (CSA, 2016). This resulted in high total fertility rate and unwanted pregnancy which intern Affects the maternal and child health status (Hailemariam et al., 2006).

Considering the present lower utilization of Family Planning, It will be a major challenge for Ethiopia. Therefore, the identification of the possible factors that determine the use of Family Planning will have greater input to program managers for designing programs, proper implementation and evaluation of their contribution regarding family planning. To identify these factors the 2016 EDHS data is considered and this study is based on two stage stratified cluster sampling. Here the units at a lower level are individuals i.e. in our case women who are nested within units at the higher level i.e. region. The response variable in this study is the utilization of family planning service which is binary and hence multilevel and Bayesian logistic regression can be used for modeling. Logistic regression is a special case of a generalized linear model, is appropriate for these data since the response variable is binomial. Multilevel models are particularly appropriate for research designs where data for participants are organized at more than one level i.e., nested data (Fidell, Barbara G. Tabachnick, Linda S. 2007). Multilevel consider the variations due to the hierarchy structure in the data. It allows the simultaneous examination of the effects of group level (regional) and individual level variables. Also these analyses will allow the examination of both between the group and within group variability as well as how group level and individual level variables are related to variability at both levels. An alternative approach to obtaining stable logistic regression coefficients is to use Bayesian inference. Bayesian inference is the process of analyzing statistical models with the incorporation of prior knowledge about the model or model parameters. The root of such inference is Bayes' theorem: By Bayes' theorem, the joint posterior distribution of the model parameters is proportional to the product of the likelihood and priors. Monte Carlo methods are often used in Bayesian data analysis to summarize the posterior distribution. The idea is that, even if you cannot compute the posterior distribution analytically, you can generate a random sample from the distribution and use these random values to estimate the posterior distribution or derived statistics such as the posterior mean, median, standard deviation (Gelman et al., 2008).

1.2 Statement of the problem

Family planning is critical in safeguarding individual health rights but also in improving the quality of life for women. The World Health Organization observes that with low contraceptive use coupled with high fertility rates can always contribute to women's and young children's ill health, and yet family planning can avert up to 25–30 per cent of all maternal deaths that occur (WHO, 2015). High fertility rates resulted in high rates of many children, uneven birth spacing, unwanted pregnancies, unplanned deliveries, unsafe abortions and maternal mortalities.

Population growth in Ethiopia is not in parallel with the development of health services and other basic infrastructures. To cope with this alarming population growth and improve maternal and infant survival, there need to be a comparable increment in health care coverage and other infrastructures. Considering the low socioeconomic status of the country, resources are insufficient to expand infrastructures needed for the growing population. Hence, the alternative is regulation of fertility to the extent that the family, community and country can afford. Family planning service technology has the potential to benefit to people at lower cost than any other technology now available for development (Population Reference Bureau, 2002).

It is believed that fertility decline continues if the wider use of family planning continues in all levels and groups of peoples. It is critical for family planning workers to continue to meet the needs of existing family planning users, and also to address barriers for family planning users in the society since, individual interests, behaviors, etc. differ from one unit to another within each level, owing to variability among various socioeconomic and geographical factors such as religion, income, place of residence, education, occupation, mass media access, and so on. That is why their efforts and approaches do not seem to be equally effective, evenly served or acknowledged in some areas. This is an indicator of the effectiveness of the program to vary considerably.

Most family planning studies in the country have been institution-based and are small-scale research, focusing on a handful of communities, usually small-sized rural communities. Their geographic scope limits the applicability of their result on a large scale, particularly considering the complex multi-regional and multi-ethnic setting of Ethiopia. It is necessary to assess the within-group and between-group level variation, and to estimate the true effect of the above-mentioned factors on multilevel determinants of family planning use in order to implement more effective future family planning policies that target particular units at various levels of the hierarchy levels. The factors responsible for the variation are at different hierarchy individual family (cluster), and community (regional levels), embedded in socio-economic, demographic and cultural Society of Ethiopia. Furthermore, several studies in Ethiopia on the utilization of family planning services were not using advanced statistical models. Therefore, this study mainly concentrated on classical and Bayesian approaches to identify significant factors associated with utilizing family planning services. Therefore, this study aims to address the following research questions:

i. Which demographic and socio-economic factors affects utilizations of family planning?

ii.Is there result variation among multilevel and Bayesian logistic regression in identifying determinants of family planning use?

iii.How much of the variation of usage of family planning is accounted for regional level and women level?

1.3. The objective of the study

1.3.1. General objective

The main objective of the study was to investigate factors that affect utilization of family planning services among reproductive age of women in Ethiopia through classical and Bayesian approaches

1.3.2. Specific objectives

The specific objectives are:

1. To identify different demographic and socio- economic determinants of use of Family planning services in Ethiopia.
2. To compare results obtained from classical and Bayesian approach in identifying determinants of the utilization of family planning services in Ethiopia.
3. To analyze the within and between regions variation of family planning utilization among women of the reproductive age group in Ethiopia.

1.4. The significance of the study

It is hoped that the findings from this research could be useful in many ways. Governmental and non-governmental organizations could take intervention measures and set appropriate plans to increase the existing level of awareness and use of family planning by identifying and giving priority for the areas which have low and poor utilizers of family planning. The results could also be helpful for policy making, monitoring and evaluating the activities for the government and different concerned agencies. And it helps individuals to have enough knowledge about the use of family planning service. It is hoped that this study could contribute to the improvement of family planning services in the country through appropriate service delivery approaches and strategies. It is also used to know the difference between Bayesian and classical logistic regression. In addition, it is used for identifying factors that are statistically associated with Family planning service utilization in Ethiopia.

CHAPTER TWO

2 LITERATURE REVIEW

2.1 Overview of family planning

Family planning has been cited as an important indicator for tracking progress on improving maternal health (Eliason et al., 2013 and Cates et al., 2010). Family planning is one of four pillars with antenatal care, safe delivery, and postnatal care that was introduced by the Safe Motherhood Initiative in 1987 to reduce maternal mortality in developing countries, where 99% of all maternal deaths occur (Ahmed et al., 2012).

Contrary to popular belief, family planning does not coincide with abortion. The term "family Planning "covers a wide range of services concerning women, children, and their families. Family planning services can include access to birth control, contraceptives, sexual education, and other health resources. Access to family planning services can provide much needed reproductive resources such as birth control, contraceptives and prevention and treatment for STDS and HIV (Gold,et al., 2009). Family planning clinics are also sources of knowledge for birth spacing and help make known the benefits of spacing births (Gold et al., 2009). Access to family planning resources has led to the reduction of infant and maternal mortality, as well (Gold et al., 2009). The goal of family planning is to reduce unwanted births, teen pregnancy, spread of STDs and HIV, and improve the overall health of mother, child, and, ultimately, the family unit.

Family planning improves health, reduces poverty and empowers women (Bongaarts et al., 2012). Voluntary high-quality family planning programs speed fertility declines, thus improving health and boosting economies. Indeed, they are among the most cost-effective health and development investments available to governments (Bongaarts et al., 2012). The case for family planning has been made, yet more than 200 million women in the developing world who want to avoid pregnancy are not using a modern contraceptive method. The reasons for this are many, including lack of access to information and appropriate health services, traditional gender norms that impede women's ability to adopt contraception, real and perceived concerns about safety and side effects, and cost, among others. Underlying socio-behavioral issues, including risk perception, ambivalence, and social costs, may also play a role in demand and use.

Effective family planning program make the rapid spread voluntary modern family planning method possible in any country such program help people to achieve their personal reproductive goals. Family planning is identified by the world health organization (WHO) as one of the six essential health intervention needed to achieve safe mother hood and by united nation children found (UNCF) as one of seven strategies for child survival (John et al., 2010).

Family planning has a direct impact on women‘s health and well-being as well as on the consequence of each pregnancy (WHO, 2015). In the developing countries millions of women in the reproductive age who don‘t use contraceptives prefer to postpone or limit their birth. This indicates their failure to take necessary decision to prevent and avoid unwanted pregnancy (Malwenna et al., 2012).

2.2 Situation of Family Planning in Ethiopia

Ethiopia like, most countries in Sub-Sahara Africa, is experiencing rapid population growth. Currently the country‘s Population is growing at a rate of 2.89 percent, one of the highest rate in the World and if continues unabated, the population will have doubled in the next 20 years, preventing any gain in the nation development effort (WPR, 2014).

Ethiopia is one among the six countries that contribute to about 50% of the maternal deaths along with India, Nigeria, Pakistan, Afghanistan and the Democratic Republic of Congo (Hogan et al., 2008). The Ethiopia Demographic Health Surveys of 2000, 2005, 2011 and 2016 gave figures of 871,673 , 676 and 412 per 100,000 live births maternal mortality ratios respectively (CSA, 2000, CSA,2005 , CSA, 2011 and CSA 2016).

The modern family planning service in Ethiopia started in 1966 (EMOH, 2011a) but showed little signs of expansion for an extended period of time. However, in the last 20 years, with the adoption of the population policy in 1993 (GOE, 1993 and TGOE, 1993), numerous local and international partners in family planning have come together to assist the government in expanding family planning programs and services. The National Population Office was established to implement and oversee the strategies and actions related to the population policy (EMOH, 2011a).

In 1996, the Ministry of Health released Guidelines for Family Planning Services in Ethiopia to guide health providers and managers, as well as to expand and ensure quality family planning services in the country (MOH, 1996). The ministry designed new outlets for family planning services in the form of community-based distribution, social marketing, and work-based services, in addition to the pre-existing facility-based and outreach family planning services. Work-based

Services are services made available to users at their place of work such as factories, prisons, and Schools (EMOH, 2011a).

Moreover, in the last decade, integration and linkage between family planning services and HIV/AIDS care, along with maternal and other reproductive health services, have been emphasized in guidelines and strategic documents with the aim of enhancing family planning utilization (EMOH, 2011a). Currently, the service has been provided to rural communities at the household level through the Health Extension Programme. Moreover, in the current road map for accelerating the reduction of maternal and newborn morbidity and mortality in Ethiopia, family planning is identified as one of the strategic objectives. The following targets are identified related to family planning: to increase contraceptive prevalence rate to 66%, decrease unmet needs for family planning to 10%, and reduce adolescent pregnancy rate to 5% (EMOH, 2011b).

Though the overall contraceptive prevalence has been progressive with evidences of 2.6%, 8%, 14%, and 29% reported in 1990, 2000, 2005 and 2011 respectively (CSA, 2000 2005 and 2011and Alkema et al., 2013).The practice of family planning differs significantly among regions, urban and rural areas various studies identified different demographic variables to influence women FP practice in Ethiopia. These variables among others include age, number of leaving children and lack to exposure risk of pregnancy (Bandura, 2010).

2.3 Determinants of family planning use

The factors associated with family planning use can be divided into socioeconomic and demographic factors. Demographic factors such as age, marital status, religion and number of living children are also known to be associated with family planning practice. Among the socio-economic factors that may affect Women‘s practice of family planning methods are place of residence, work status/occupation, education level of women, wealth index and region are considered to be important (John et al., 2011).

Visited by family planning worker

The study conducted by (Selamawit Sisay,2015) on determinants of family planning practice among women of reproductive age,15-49 years in Ethiopia by using logistic regression analysis revealed that visited by family planning worker in the last 12 months before the survey, was a significant predictor for women‘s family planning practice.

Women’s and Husbands occupation

A study conducted in Bangladesh on the current situation of utilization of modern family planning methods showed that family planning methods were highly significantly associated with women's occupation. There was also a significant association (p=0.024) with the occupation of father (Women, 2018).

Economic status

Family planning use is lower among poorer than among wealthier women. In Southern Africa, the prevalence rate among the wealthiest group is higher than poorer(Gribble, 2018).

Women's and Husbands Education level

The study conducted on utilization of family planning services and influencing factors among women in Assosa district, West Ethiopia revealed that women's literacy status significantly affected the chance of family planning service utilization: literate women are more likely to use family planning service than illiterate ones(Amentie, Abera and Abdulahi, 2015).The study conducted on Factors influencing the uptake of family planning services in Ghana revealed that the educational level of women's positively associated with usage of family planning services . The study used a logistic regression model to identify factors influencing the uptake of family planning services in Ghana .The study demonstrated that educated women are more likely to use family planning services as compared to their peers who did not receive a formal education (Apanga and Adam, 2015).Also a study conducted using binary logistic regression analysis in assessing and identifying factors that influence the use of family planning in Ambo town, Ethiopia showed that level of education have a significant effect on the use of family planning(Reddy et al., 2015)

Knowledge of Family planning

The study conducted on utilization of family planning services and influencing factors among women in Assosa district, West Ethiopia revealed that women who were knowledgeable on family planning service were more likely to receive family planning service currently than not knowledgeable ones. That is, lack of knowledge on family planning methods accounted for non-user of family planning service. This is due to the fact that women who had knowledge on the important and effect of family planning method could decide easily to use the service (Amentie, Abera and Abdulahi, 2015).

Age of women

A study conducted on binary logistic regression analysis in assessing and identifying factors that influence the use of family planning in Ambo town, Ethiopia showed that age has a significant effect on the use of family planning. From the result of the study it was concluded that at the earlier reproductive age of women has a better of using family planning method than another age category (Reddy et al., 2015).

Media Exposure

Media exposure exerts a considerable influence on family planning service use. women who are exposed to any one of the media, namely, radio, television, or newspapers etc. have higher family planning service use compared to women who had no media exposure at all (Gizaw and Regassa, 2011).Also a study conducted on binary logistic regression analysis in assessing and identifying factors that influence the use of family planning in Ambo town concluded that women's who frequently had the habit to follow media had a good habit of using family planning as compared to others (Reddy et al., 2015).

Number of having children

The total number of children women have and family planning service utilization are strongly related. If women have more children who are living with them, the possibility of using family planning methods for limiting is expected to be high, and if the number of children desired by women is perceived to be not enough, they may use family planning methods for spacing purpose(Gizaw and Regassa, 2011).

Place of residence

A study conducted by (selamawit sisay ,2015) on determinants of family planning practice among women of reproductive age 15-49 years in Ethiopia showed that the proportion of family planning practice among women differed by place of residence. Among the women who resided in urban areas, 75.9 percent practiced family planning. Among rural women, 11.6 percent practiced family planning and 88.4 percent did not practice family planning. Thus the practice of family planning was much higher among women who were residing in urban areas as compared to Women in a rural area.

Religion

A study conducted by(selamawit sisay ,2015) on determinants of family planning practice among women of reproductive age 15-49 years in Ethiopia showed that family planning methods was higher among those women who were followers of Protestant followed by Catholic 17.5 percent. The lowest percentage of family planning practice was observed among women who were followers of the Muslim religion. Out of those women who have knowledge of family planning methods, 14.4 percent practices family planning and the remaining 85.6 percent didn't practice family planning.

A study conducted by (selamawit sisay ,2015) on determinants of family planning practice among women of reproductive age 15-49 years in Ethiopia showed that there is within and between regional variations in family planning practice. The study revealed that woman who lived in Afar and Somali region practice family planning methods less than women who live in other regions of Ethiopia.

CHAPTER THREE

3. METHODOLOGY

3.1 Description of the Study Area

Ethiopia is known as the FDRE (Federal Democratic Republic of Ethiopia), and a landlocked country located in the Horn of Africa. It is the second-most populous nation in Africa next to Nigeria. 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 the capital city of Addis Ababa.

3.2 Source of data

The dataset used in this study has been taken from the EDHS conducted by CSA in 2016. The 2016 EDHS is a nationally representative survey of women aged 15−49 from 16,583 households from 645 clusters in Ethiopia, 202 in urban areas and 443 in the rural areas. The survey utilized a multistage cluster sample based on the 2007 population and housing census sampling frame and was designed to obtain and provide information on the basic indicators of the health and demographic variables of interest. This multistage 2016 EDHS dataset is of hierarchical structure. The hierarchy for this study follows individual women as level-1, and regions as level-2. This means that individuals are nested in regions. From among the 18,008 households, 16,583 women were identified as eligible for the individual interview. Interviews were completed with 15,683 women, yielding a response rate of 95 percent. Thus, the analysis presented in this study on women family planning utilization is based on 9824 women of reproductive age.

3.3 Study Population

The target population in this study is all women within the reproductive age group (15-49) years living in Ethiopia. The unit of analysis is the individual woman.

3.4 Study Design

This is a secondary data analysis and the study design was a cross sectional survey carried out in 2016 using population based representative sample.

3.5 Sample Inclusion and Exclusion Criteria

Women included in this study are Ethiopian women aged 15 years and above but not more than 49 years of age. This is referred to as reproductive age in this study.

3.6 Variable description

The dependent variables of this study is family planning service utilization which is recoded as follows: those women who are currently using any of the methods which are modern (pill, IUD, Injectable, condoms, LAM etc.), traditional (periodic abstinence, withdrawal etc.) and folkloric methods (use of herbs etc.) are coded as 1 and those who do not use any method are coded as 0. The response variable for the i^{th} woman 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} Women y_i was measured as a dichotomous variable.

That is

$$Y_i = \begin{cases} 1 & , if\ the\ i^{th} woman\ uses\ any\ family\ planning\ methods \\ 0 & Otherwise \end{cases}$$

Several variables that are associated with family planning use as suggested in the literature review section 2.3 were included as predictor variables. So the main target for this study is to investigate the effect of the following explanatory variables on family planning service utilization.

Table 3. 1: explanatory variables of the study

No.	**Factors/ variables**	**Categories**
1	Age of a woman	1=15-24 ,2=25-39 and 3=Above 39
2	Place of Residence	0= Urban ,1= Rural
3	Region	1=Tigray ,2=Afar 3=Amahra,4=Oromiya,5=Somali,6=SNNP …11= Addis Ababa
4	Occupation of a woman	0=Not working ,1=Agriculture Employee ,2=Non-Agriculture Employee
5	Religion group of a woman	1=Orthodox ,2=Protestant ,3=Muslim, 4=Others

6	Women‘s education level	0=No education, 1=Primary, 2=Secondary and higher
7	Exposure to any mass media	0=No ,1= Yes
8	Knowledge of FP method	0= Knows no FP method ,1= Knows a FP method
9	Number of having Children	0= No children ,1= small (1-2 children), 2= medium (3-4 children), 3=large(5 and above children)
10	Desire for more children	1=No ,2=Yes,3=Undecided
11	Visited by FP worker during the last 12 Months	0= No ,1= Yes
12	Economic status	1=Poor ,2=Middle ,3=Rich
13	Husband's Occupation	1=Not working ,2=Agriculture Employee ,3=Non-Agriculture Employee
14	Husband's education level	1=No education, 2=Primary, 3=Secondary and higher

3.7 Methods of Analysis

The single level, multilevel and Bayesian logistic regression were used to predict a binary dependent variable from a set of independent variables.

3.7.1 Introduction to the logistic regression model

Regression methods have an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables. It is often the case that the outcome variable is categorical, taking on two or more values. When the outcome variable is binary or dichotomous many distribution functions have been proposed for use. Logistic regression model can be used mainly for two reasons. The first is from a mathematical point of view, it is an extremely flexible and easily used function, and the second it leads itself to meaningful interpretation (Hosmer and Lemeshow, 2011).

Odds and Odds Ratio

Odds are the ratio of the probability of an event will occur divided by the probability of it will not occur. In this study, the event E is that the women i utilizes the family planning service, y_i=1 and given by:

$$odds(E) = \frac{P(E)}{P(not\ E)} = \frac{P(E)}{1-P(E)}$$

Where, $P(E)$ is the probability of family planning service.

Odds always have values greater than zero and if the odds value is larger than one it means that success will occur more likely than failure. Odds ratio, as the name indicates, is the ratio of two Odds and given as follows:

$$\text{Odds ratio} = \frac{p1(E)}{1-P1(E)} \Big/ \frac{P2(E)}{1-P2(E)}$$

Here, p_1 and p_2 refer to the probability of success in group 1 and group 2 respectively. If the odds ratio value is greater than one indicates that the odds of the outcome in group 1 is larger than in group 2. Thus, subjects in group 1 are more likely to have success than subjects in group 2. In binary logistic regression analysis, odds ratio is the exponential of the estimated coefficient β, (exp(β)).

3.7.2 The Multiple Logistic Regression Model

The logistic regression model is a special type of generalized linear model with many interesting properties. Loosely speaking logistic regression analysis does not require strict assumptions about the distribution of the response variable, although, it is clear that the response has a binary outcomes. This means implicitly that the Bernoulli/Binomial distributions are the natural choices. Therefore, the assumption on the distribution of the response is quite evident. Thus, a logistic regression model is appropriate to predict the binary dependent variable. In logistic regression, a single outcome variable y follows a Bernoulli probability function that takes on the value 1 with probability P_i and 0 with probability 1-pi. Then P_i is varies over the observations as an inverse logistic function of a vector x, which includes a constant and k explanatory variable (Efron, 1975). The specific form of the logistic regression model with unknown parameters $\beta o, \beta 1, \ldots, \beta k$ is

$p_i = \mathrm{P(yi = 1|xi)} = \frac{e^{\beta o+\beta 1xi1+\cdots\beta kxik}}{1+e^{\beta 0+\beta 1xi1+\cdots+\beta kxik}}$

At times, it is convenient to change the notation slightly by writing $x_0 = 1$, thus the above model becomes

$$\frac{e^{xi\beta}}{1+e^{xi\beta}} = \frac{1}{1+e^{-xi\beta}} \quad \text{---} (3.1)$$

Where, $X_i = (x_0 = 1, x_1,., x_p)'$ and $\beta = \beta_0,\beta_1,\dots ,\beta_k$.

The logit link function of P_i and X in equation (3.1) are nonlinear. However, it is possible to form linear relationship between the response and explanatory variables by applying the logit transformation, and is given by

$$\text{Logit (pi)}=\log(\frac{Pi}{1-Pi}) \quad \text{---} (3.2)$$

Under the above transformation, we can write the regression model (3.2) as

$$\text{Logit (Pi)} = xi'\beta \quad \text{-------- -- ----}(3.3)$$

3.7.3 Maximum Likelihood (ML) Estimation of the Parameters

The most commonly used method of estimating the parameter of a logistic regression model is the method of maximum likelihood (ML) estimation. The method of maximum likelihood estimation yields to estimate values for the unknown parameters which maximize the probability of obtaining the observed set of data. Suppose we have a sample of n independent observations (y_i, x_i), i= 1, 2, ..., n. Where y_i denotes the value of a dichotomous outcome variable and x_i is the value of the explanatory variables for the i^{th} subject and assume Yi ∼ Bernoulli (1, P_i). To find the ML of $\beta = \beta_0, \beta_1,\dots, \beta_k$ in (3.3), we define the likelihood function as follows

$$L= L(\beta) = \prod_{i=1}^{n}[Pi^{yi}(1-Pi)^{1-yi}]$$

$$= \prod_{i=1}^{n}[\frac{Pi}{1-Pi}]^{yi}(1-Pi)$$

$$= \prod_{i=1}^{n}\frac{e^{yixi'\beta}}{1+e^{xi'\beta}} \quad ------------ (3.4)$$

Taking the natural logarithm of both sides yields the following expression for log-likelihood function:

l = Log L (β)= $\sum_{i=1}^{n} e^{yixi\prime\beta} - \sum_{i=1}^{n} \log\left(1 + e^{xi'\beta}\right)$ $\quad ----------\quad$ (3.5)

It can be verified that the first two partial derivatives of the log-likelihood function exist and are given as follows:

$$\frac{\partial l}{\partial \beta_j} = \sum_{i=1}^{n} (yi - \mu i)xij, where\ \mu i = E(yi) = Pi$$

$$\frac{\partial^2 l}{\partial \beta_j \partial \beta_k} = -\sum_{i=1}^{n} Pi(1 - Pi)x_{ij}x_{ik}.$$

Hence, through the maximization of equation (3.5) or (3.4) we can theoretically estimate the parameter vector β. But the equation is nonlinear in β and the estimates do not have a closed form expression. Therefore, β will be obtained by maximizing (3.5) using a numerical iterative method (Agresti, 1996). Newton Raphson method is used to obtain the MLE.

3.7.4 Goodness-of-fit of the Model

Measures of goodness of fit are statistical tools used to explore the extent to which the fitted response obtained from the postulated model compares with the observed data. Clearly, the fit is good if there is a good agreement between the fitted and the observed data.

Likelihood-Ratio Test

The likelihood ratio test statistic (LRT) is the most common test for assessment of overall goodness of fit of logistic regression model. The likelihood ratio test is used to test the significance of a number of explanatory variables. This is appropriate for a variety of types of statistical models. The likelihood-ratio test is used to test the ratio of the maximized value of the likelihood function for the full model (L_{ful}) over the maximized value of the likelihood function for the reduced model (L_{red}).

The likelihood-ratio test statistic is given by:

$$\mathrm{LRT} = -2(l_{red} - l_{ful}),$$

Where, l_{red} and l_{ful} are the log-likelihood function of the reduced and full model, respectively (Hosmer and Lemeshow, 2011).

Hosmer-Lemeshow Test

The Hosmer-Lemeshow test statistic evaluates the goodness-of-fit of the model by creating 10 equal groups of subjects and then compares the number actually in each group (observed) to the number predicted by the logistic regression model. The test is similar to a $\chi 2$ test statistic and has the advantage of partitioning the observations into groups of approximately equal size, and therefore, there are less likely to be grouped with very low observed and expected frequencies. In this case, the better model fit is indicated by a smaller difference in the observed and predicted classification. The Hosmer-Lemeshow test statistic is given by:

$$\hat{C} = \sum_{k=1}^{g} \frac{(O_k - E_k)^2}{V_k},$$

Where, $E_k = np_k$, $V_k = np_k(1 - p_k)$, g is the number of groups, O_k is observed number of events in the k^{th} group. This test statistic has approximately $\chi 2$ distribution with $(g - 2)$ degrees of freedom (Agresti, 1996).

3.7.5 Statistical tests of individual parameters

Wald test

The Wald test is also an alternative test which is commonly used to test the significance of the individual logistic regression coefficients for each independent variable (that is, to test the null hypothesis in logistic regression analysis that a particular logit (effect) coefficient is zero i.e. $H_0{:}\beta_i = 0$ against $\beta_i \neq 0$. The Wald test statistic is:

$$w = \frac{\widehat{\beta}_i^2}{var(\widehat{\beta}_i)}$$

For large sample size this test statistic has an approximate chi-square distribution with one degree of freedom (Menard, 2002). Furthermore,the likelihood ratio test and score test also used for a significance test of the null hypothesis H_0: $\beta_i = 0$. They all exploit the large sample normality of maximum likelihood estimators. For small to moderate sample sizes, the likelihood-ratio test is usually more reliable than the Wald test (Agresti, 1996).

3.7.6 Model Diagnostic

Before concluding that the model "fits", it is crucial that other measures be examined to see if the fit is supported over the entire set of covariate patterns. This is accomplished through a series of specialized measures falling under the general heading of regression diagnostics. Model diagnostic procedures involve both graphical methods and formal statistical tests. These procedures allow us to explore whether the assumptions of the regression model are valid and decide whether we can trust subsequent inference results.

The difference in betas (DFBETAs): assess the effect of an individual observation on the estimated parameter of the fitted model. A DFBETAS diagnostic is computed for each observation for each parameter estimate. It is the standardized difference in the parameter estimate due to deleting the corresponding observation. The DFBETAs are useful in detecting observations that causes instability in the selected coefficients. The influential observations for the individual regression coefficients are identified by

DFBETAS j(i) ,*j*= 0,1,2,... *p* , where each *DFBETAS j(i)* is the standardized change in $\hat{\beta}_j$ when the i^{th} observation is deleted from the analysis. Thus

BFBETAS j(i)=$\frac{\hat{\beta}_j-\hat{\beta}_{j(i)}}{Si\sqrt{c_{jj}}}$

DFBETASj(i) measures the change in $\hat{\beta}_j$ in multiples of its standard error.

Leverage (hat matrix): an observation with an extreme value on the predictor variable is called a point with high leverage. Leverage is a measure of how far an observation deviates from the mean of that variable. These leverage points can have an effect on the estimate of regression coefficients. It can be calculated by:

$$h_i = \frac{1}{n} + \frac{(x_i - \bar{x})2}{S_{xx}}$$

Where h_i =Leverage value, n= Number of observations and Sxx is a Standard error

Cook's distance (D): measures of how much the residual of all cases would change if a particular case were excluded from the calculation of the regression coefficients. A large Cook's distance indicates that excluding a case from the computation of the regression statistics changes the coefficients substantially (Cook and Weisberg, 1982).

$$Di = \frac{r_i^2 var(yi)}{pVar(yi)} = \frac{r_i^2 hii}{p(1-hii)}$$

Where:- D_i = Cook's distance, r_i^2= Standardized residual, h_{ii} = Leverage and

P= Number of predictors

3.8 Multilevel Logistic Regression Model

The multilevel logistic regression model is appropriate for research designs where data for respondents are organized more than one level i.e, nested data. The units of analysis are individuals at a lower level i.e., women in our case who are nested within aggregate units at a higher level i.e. regions. A multilevel logistic regression model is also referred to as a hierarchical logistic regression model, or as random effects (mixed effects) logistic regression model. The multilevel logistic regression extends from single level logistic regression model by including random effects to the model (Snijders and Bosker, 1999).

Multilevel logistic regression analysis can be employed in the simplest case without explanatory variables, (usually called the empty model) and also with explanatory variables by allowing only the intercept term or both the intercept and slopes (regression coefficients) to vary randomly. In this study, the multilevel logistic regression model taking into account the data to be analyzed in the case of two-levels. We note that extensions to the case of three or higher levels are straight-forward. In this study, women are considered as level-1 and regions is considered as level-2 (Snijders and Bosker, 1999).

3.8.1 A Two-Level Logistic Regression Model

Multilevel analysis is a methodology for the analysis of data with complex patterns of variability, with a focus on nested sources of variability. The best way to analyze multilevel data is an approach that represents within-group as well as between group relations within a single analyze, where 'group' refers to the units at the higher levels of the nesting hierarchy. Very often it makes sense to use probability models to represent the variability within and between groups, in other words, to conceive of the unexplained variation within groups and the unexplained variation between groups as a random variability. For example, a study of women within regions means that not only unexplained variation between women, but also unexplained variation between regions is regarded as random variable. This can be expressed by statistical models called the random coefficient model. Multilevel analysis is an approach to the analysis of such data including the statistical techniques as well as the methodology of how to use two-level logistic regression (Snijders and Bosker, 1999)

Testing heterogeneous proportions

The most commonly used test statistic to check for heterogeneity of proportion between groups (regions) which is a proper application of multilevel analysis is the chi-square test statistic. To test whether there are systematic differences between the groups (regions), the chi-square test can be used and written as:

$$X^2 = \sum_{j=1}^{g} nj \frac{(\bar{y}.j - \hat{p}.)^2}{\hat{p}.(1-\hat{p}.)} \qquad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.6)$$

Where, $\bar{Y}_{.j}$ is group average, obtained as $\bar{Y}_{.j} = \frac{1}{n_j}\sum_{i=1}^{n_j} Y_{ij}$ is the proportion of successes in group j which is an estimate for the group-dependent probability p_j and $\hat{P}.$ is the overall average, i.e.$\hat{P}_{.} = \bar{Y}_{..} = \frac{1}{n}\sum_{j=1}^{g}\sum_{i=1}^{n_j} Y_{ij}$is the overall proportion of successes. The decision is based on chi-square distribution with a g-1 degrees of freedom (Agresti, 1996).

Estimation of between and within-group variance

Consider a population having two-levels, the basic data structure of two-level logistic regression analysis is a collection of N groups (units at level-two i.e. regions) and within group j $(j= 1, 2, \ldots, N)$ a random sample of n_j level-one units (women). The outcome variable is dichotomous and denoted by Y_{ij},($i = 1,2, \ldots, n_j, j = 1,2, \ldots, N$) for level-one unit i in group j. The total sample size is. $M = \sum_{j=1}^{N} n_j$.

Then, the theoretical variance between the groups (regions) dependent probabilities, i.e., the population value of Var (P_j), can be estimated by:

$\hat{\tau} = S^2 between - \frac{S^2 within}{\tilde{n}}$,

$$Where\ \tilde{n} = \frac{1}{N-1}\left(M - \frac{\sum_{j=1}^{N} {n_j}^2}{M}\right) = \bar{n} - \frac{S_{(n_j)}^2}{N\bar{n}}$$

For dichotomous dependent variable, the observed between-groups variance is closely related to the chi-squared test statistic (Snijders and Bosker, 1999). They are given by the formula:

$$S_{between}^2 = \frac{\hat{p}(1-\hat{p})}{\tilde{n}(N-1)}\chi^2$$

Where,χ^2 is as given by equation (3.6), and the within-group variance in the dichotomous case is a function of the group**:**

$$S_{within}^2 = \frac{1}{M-N}\sum njPj(1-Pj)$$

i. The Empty Logistic Regression Model

The empty level-2 model for a dichotomous outcome variable refers to a population of groups (level-two units, i.e. regions) and specifies the probability distribution for dependent probabilities P_j without taking further explanatory variables into account. This model only contains random groups and random variation within groups. It can be expressed with logit link function as follows.

Logit (P_j) = $\beta_0 + u_{0j}$ ………………………………………………………………… (3.7)

Where, β_0 is the average of the outcome variable (intercept) of the transformed probabilities and u_{0j} the random deviation from this average for group j. For the deviations u_{0j} is assumed to be independent random variables with a normal distribution with mean 0 and variance ${\sigma_0}^2$ $i.e.$ u_{0j}~iid(0,${\sigma_0}^2$).

ii.The Random Intercept Logistic Regression Model

In the random intercept logistic regression model, the intercept is the only random effect meaning that the groups differ with respect to the average value of the response variable. It represents the heterogeneity between groups in the overall response.

The logistic random intercept model expresses the log-odds, i.e. the logit of P_{ij}, as a sum of a linear function of the explanatory variables and the random part of the model. That is,

$$\log it(P_{ij}) = \log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_{0j} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + ... + \beta_k x_{kij}$$

Where, the intercept term β_{0j} is assumed to vary randomly and is given by the sum of an average intercept β_0 and dependent deviations u_{0j}. That is:

$\beta_{oj} = \beta_o + U_{oj}$, As a result

$$\log it(P_{ij}) = \log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2ij} + ... + \beta_k x_{kij} + U_{0j} \text{ ……………………...…….. (3.8)}$$

where, β_0 is the log-odds that y = 1 when x = 0 and u = 0,β_k is effect on log-odds of one unit increase in x for individuals in the same group (same value of u), $exp(\beta_k)$ is an odds ratio, comparing odds for individuals spaced 1-unit apart on x but in the same group (regions).u_{0j} is the effect of being in group j on the log-odds that y = 1 also known as a level 2 residual, δ_o^2 is the level 2 (residual) variance, or the between-group variance.

Note that the first part of the left-hand side of (3.8), incorporating the regression coefficients, $\beta_o + \sum_{k=1}^{k} \beta_k x_{kij}$is the fixed part of the model, because the coefficients are fixed. The remaining part,U_{oj}, is called the random part of the model. It is assumed that the residual, U_{oj} are mutually independent and normally distributed with mean zero and variance σ_0^2. Equation (3.8) is considered as a mixed model because it has both fixed effects and random effects (Snijders and Bosker, 1999).

iii. The Random Coefficients Logistic Regression Model

In the random intercept logistic regression model, the intercept is the only random effect meaning that the groups differ with respect to the average value of the dependent variable. But we have assumed that the effects of the explanatory variables are the same for each region. This assumption is considered by allowing the difference between explanatory variables within a region to vary across regions. To allow for this effect, we will need to use a random coefficient for those explanatory variables. So, the random coefficient model represents heterogeneity in the relationship between the response and explanatory variables.

As stated above the response variable in the study, is binary and the statistical model employed is the two-level random coefficient logistic regression model. The model, with k level-1 predictors and p level-2 predictors, can be expressed as:

$$logit(Pij) = \log\left(\frac{Pij}{1-Pij}\right) = \beta_{oj} + \sum_{k=1}^{k} \beta_k \, x_{kij} + \sum_{p=1}^{p} u_{pj} \, x_{pij,}$$

Where, $\beta_{0j} = \beta_0 + u_{0j}$, $u_{0j} \sim iid(0, \sigma_0^2)$ and $u_{pj} \sim iid(0, \sigma_p^2)$.

Now the above equation is written as

$logit(Pij) = \log\left(\frac{Pij}{1-Pij}\right) = \beta_o + \sum_{k=1}^{k} \beta_k \, x_{kij} + u_{oj} + \sum_{p=1}^{p} u_{pj} \, x_{pij}$………………… (3.9)

The first part of the equation (3.9), $\beta_o + \sum_{k=1}^{k} \beta_k \, x_{kij}$, is called the fixed part of the model and the second part $u_{oj} + \sum_{p=1}^{p} u_{pj} \, x_{pij,}$ is called the random part (Snijders and Bosker, 1999).

Intra-class Correlation Coefficient (ICC)

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 in the following equation:

$$ICC = \frac{\delta_{uo}^2}{\delta_{uo}^2 + \delta_e^2}$$

Where, σ_e^2 is a variance of individual (lower) level units.

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 reformulated as:

$$ICC = \frac{\delta_{uo}^2}{\delta_{uo}^2 + 3.29}$$

Parameter Estimation for Multilevel Logistic Regression Model

Parameter estimation for multilevel logistic regression model is not straightforward like the methods for the classical logistic regression model. The most common methods to estimate the parameters in the multilevel logistic regression model are based on the marginal maximum likelihood (Bock and Aitkin, 1981).

3.9 Bayesian Logistic Regression

The use of Bayesian inference has become increasingly popular in the modern statistical analysis, with applications in numerous scientific fields. Bayesian inferences differ from classical inference by considering parameters as a random variable and using the data to update prior knowledge about parameters and functions of those parameters (Congdon, 2005). Thus, prior knowledge about a parameter is an important aspect of the inference process. Bayesian statistics provides a much more complete picture of the uncertainty in the estimation of the unknown parameters (Lee, 2010).

The idea of Bayesian statistics is based on Bayes' theorem. Assume that we observed a random variable y and inferences about other random variable θ, where θ is drawn from some distribution P(θ).The purpose is to generate the posterior distribution of the unknown parameters given both the data and some prior density for the unknown parameters. Bayes' theorem represents how the conditional probability of parameters observed data given parameters relates to the converse conditional probability of parameters given observed data (Gelman, 2004).

$$P(\theta / y) = \frac{P(\theta, y)}{P(y)} = \frac{P(y/\theta)\,P(\theta)}{P(y)} \quad\ldots\ldots(3.10)$$

Where P (y/θ) is the likelihood of y under a model and P (θ) is the prior density, or the density of θ before y is observed. This density expresses accumulated knowledge about θ, or the degree of uncertainty about θ

3.9.1 Bayesian Logistic Regression Parameters

Bayesian logistic regression procedure is adopted to make inference about the parameters of a logistic regression model i.e. a response variable of interest has only two possible outcomes that can be represented by a binary indicator variable taking values 0 and 1. Bayesian inference for the logistic regression model is derived by applying a Markov Chain Monte Carlo (MCMC) algorithm to simulate from the joint posterior distribution of the regression and the link parameters (Congdon, 2005).

3.9.2 Likelihood Function

The classical analysis focuses on the likelihood function P (y/θ) without introducing a prior, whereas Bayesian analysis updates the prior information about θ with the information contained in the data. The joint probability distribution of n independent Bernoulli trials is the product of each Bernoulli densities, where the sum of n independent and identically distributed Bernoulli trials has a binomial distribution. Specifically, let $y_1, \dots, y_n$ be independent Bernoulli trials with success probabilities $p_1, \dots, p_n$ that is (y_i= 1) with probability or (y_i= 0) with probability 1-P_i, for i = 1,2,… , n. Since, the trials are independent, the joint distribution of $y_1, \dots, y_n$ is the product of n Bernoulli probabilities. The probability of success in logistic regression model varies from one subject to another, depending on their covariates (Congdon, 2005). Thus, the likelihood function is illustrated in equation (3.10).

3.9.3 Test of Convergence of the algorithm

The empirical results from a given MCMC analysis are not viewed as reliable until the chain has reached its stationary distribution. To account this, the term convergence of an MCMC algorithm refers to whether the algorithm has reached its equilibrium (target) distribution. If this is true, then the generated sample comes from the correct target distribution. Hence, monitoring the convergence of the algorithm is essential for producing results from the posterior distribution of interest. Among several convergence assessment methods, basically, the most popular approaches used to determine convergence for Markov chains are discussed below.

Autocorrelation: High autocorrelation 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 will tend to explore less space with much time. In analyzing Markov chain autocorrelation, it is helpful to identify lags in the series in order to calculate the long run trends in correlation, and in particular whether they decrease with increasing lags (Merkle and Trisha, 2011).

Time series plots or trace plots*:* Iteration numbers on x-axis and parameter value on y-axis is commonly used to assess convergence (Merkle and Trisha, 2011). If the plot looks like a horizontal band, with no long upward or down ward trends, then we have evidence that the chain has converged. The posterior distribution is obtained by sampling toward the end of this longer iteration sequence when the posterior distribution is stationary, as determined by an examination of trace plots of the iteration history of selected model quantities.

Gelman-Rubin statistic: for a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel chains (Merkle and Trisha, 2011). The model is judged to have converged if the ratio of between to within variability is close to one.

Density plot: This is another technique for identifying convergence and a classic sign of non-convergence is multimodality of the density estimate (Merkle and Trisha, 2011).

3.9.4 Posterior Distribution

The posterior distribution is the conditional probability that is assigned after the relevant evidence is taken into account. The prior information is synthesized with the information in the data to produce the posterior distribution, which expresses what we know about the parameters after observing the data. Therefore, the inference of θ should be characterized by the joint posterior density of the logistic regression model parameters.

The posterior distribution is obtained as the product of the prior distribution of the parameters and the likelihood function. Thus, the posterior distribution is given as follows:

$$P(\theta/y) = P(y/\theta)P(\theta)$$

$$= \prod_{i=1}^{n} \left[\frac{p(xi)}{1-p(xi)}\right]^{yi} (1-p(xi))\, x \prod_{j=1}^{p} \frac{1}{\sqrt{2\pi\delta j^2}}\, e^{\frac{-1}{2}} \left(\frac{\beta j-\mu j}{\delta j}\right)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.12)$$

Where $p(xi) = \frac{e^{xi'\beta}}{1+xi'\beta}$ and $p(\theta/y)$ are the posterior distribution which is the product of the likelihood function of the logistic regression and the normal prior distribution for the parameter θ_j. Conditioning upon the observed data, the posterior distribution is used to make statements about θ, which is still a random variable. For instance, the mean of the posterior distribution can be used as a point estimate of θ. computing the estimate of θ of the posterior distribution may be difficult; to overcome this situation, we need to use non- numerical integration method such as simulation techniques. The most popular and common method of simulation technique is the Markov chain Monte Carlo methods which was used in this study.

3.9.5 Markov Chain Monte Carlo Methods

Bayesian inference is solved by randomly drawing a very large sample from the posterior distribution. The idea of drawing a large sample from the posterior distribution is called Markov Chain Monte Carlo. Using MCMC techniques such as Gibbs sampling or the Metropolis-Hastings algorithm, we can directly sample sequences of values from the posterior distribution of interest, giving up the need for analytic solutions. MCMC methods have transformed Bayesian inference to a practical area of modern Statistics (Gelman, 2009).

3.9.6 Gibbs Sampling

The Gibbs sampler (Gelman, 2009) is a widely used MCMC technique and is a special case of Metropolis-Hastings algorithm where the random value is always accepted. The goal of Gibbs sampling is to find estimates for the parameters of interest in order to determine how well the observable data fits the model of interest. To implement the Gibbs sampler one starts with initial guesses of the β_i values such as $\beta_1^{(0)}$,…, $\beta p^{(0)}$ and then simulates one at a time simultaneously.

Once all of the parameters of interest have been sampled, the nuisance parameters are sampled given the parameters of interest and the observed data.

Gibbs sampling algorithm is especially useful in the binary response models in applications of Bayesian analysis that generates random variables indirectly from univariate distributions without having to calculate the density for which a wide variety of computational tools exist (Gilks et al., 2011). Usually, these conditional distributions have a known form and thus, random numbers are simulated using standard functions in statistical and computing software.

The Gibbs sampling algorithm is defined by sampling the set of full conditional posterior distributions (Gilks et al., 2011) and which is given as follows:

$f_0(\beta_0|\beta_1,\ldots,\beta_p);f_1(\beta_1|\beta_0,\beta_2\ldots,\beta_p);\ldots;f_p(\beta_p|\beta_1,\ldots,\beta_{p-1})$.

Gibbs sampler algorithm will be stated as follows:

1.Specify an initial value:

$$\beta^{(o)} = (\beta_o^{(o)}, \beta_1^{(1)}, \ldots, \beta_p^{(o)})$$

2. Repeat for$j = 0,1,\ldots, M-1$

Generate $\beta_o^{(j+1)}$ from, $f_o(\beta o|\beta 1^{(j)},\beta_2^{(j)},\ldots,\beta_p^{(j)})$

Generate $\beta_1^{(j+1)}$ from, $f_1\,(\beta 1|\beta o^{(j+1)},\beta_2^{(j)},\ldots,\beta_p^{(j)})$

⋮

Generate ${\beta_p}^{(j+1)}$ from,$f_p(\beta_p|\beta o^{(j+1)}, {\beta_1}^{(j+1)}, \ldots, {\beta_{p\_1}}^{(j+1)})$,

3. Return the values $(\beta^{(1)},\beta^{(2)},\ldots,\beta^{(M)})$

3.9.7 Prior distribution

Prior distribution plays an important role and the basis in Bayesian analysis i.e. one of the pre-condition in the Bayesian analysis is the choice of a prior distribution. A logistic regression model using Bayesian statistics require the formulation of a set of prior distributions for any unknown parameters. The probability distribution expresses one's uncertainty about unknown parameters before the data is taken into account. Different types of prior distributions exist, namely informative and non-informative.

Non-informative prior distributions are distributions that have no population basis and play a minimal role in the posterior distribution (Clark et al., 2002 and Mila et al., 2003). It is used when we have very little knowledge or information about the prior distribution. That means the idea behind the use of non-informative prior distributions is to make inferences that are not greatly affected by external information or when external information is not available. On the other hand, informative priors have a stronger influence on the posterior distribution. The influence of the prior distribution on the posterior is related to the sample size of the data and the form of the prior. non-informative priors are employed if either little is known about the coefficient values or if one wishes to ensure that prior information plays a very little role in the analysis.

The most common Bayesian approach to logistic regression model is to impose a univariate Gaussian prior with mean 0 and variance σ^2 =100 on each parameter β_j (i.e. the most common choice of priors in logistic regression parameters is normal distribution and choice for prior mean μ_j is 0 for all the coefficients. Prior variance σ is usually chosen to be large enough to be considered as non-informative, common choices being in the range from σ=10 to σ=100, and is given as follows.

$$\Pr(\beta j) = \frac{1}{\sqrt{2\pi\delta j^2}} e^{\frac{-1}{2}\left(\frac{\beta_{j-}\ \mu_j}{\delta_j}\right)^2} \qquad \text{.........(3.11)}$$

3.10.8 Assessing Accuracy of the Bayesian Logistic Regression

Once we are happy that convergence has been achieved, we need to run the simulation for a further number of iterations to obtain samples that can be used for posterior inference. One way to assess the accuracy of the posterior estimates is by calculating the Monte Carlo standard error for each parameter (Gelman, 1998).

CHAPTER FOUR

4 RESULTS AND DISCUSSIONS.

4.1 Results

The objective of this chapter is to provide analysis of results on socioeconomic, demographic and other proximate determinants of women's family planning utilization. The analysis was done using SPSS version 21, MLwiN 3.06 and STATA version 14.

4.1.1 Descriptive analysis

Of the target population, 9824 women were randomly selected in the study. From the graph below it is observed that majority women's 64.17% don't used family planning service while only 35.83% used family planning services. The descriptive bar graph is given here below.

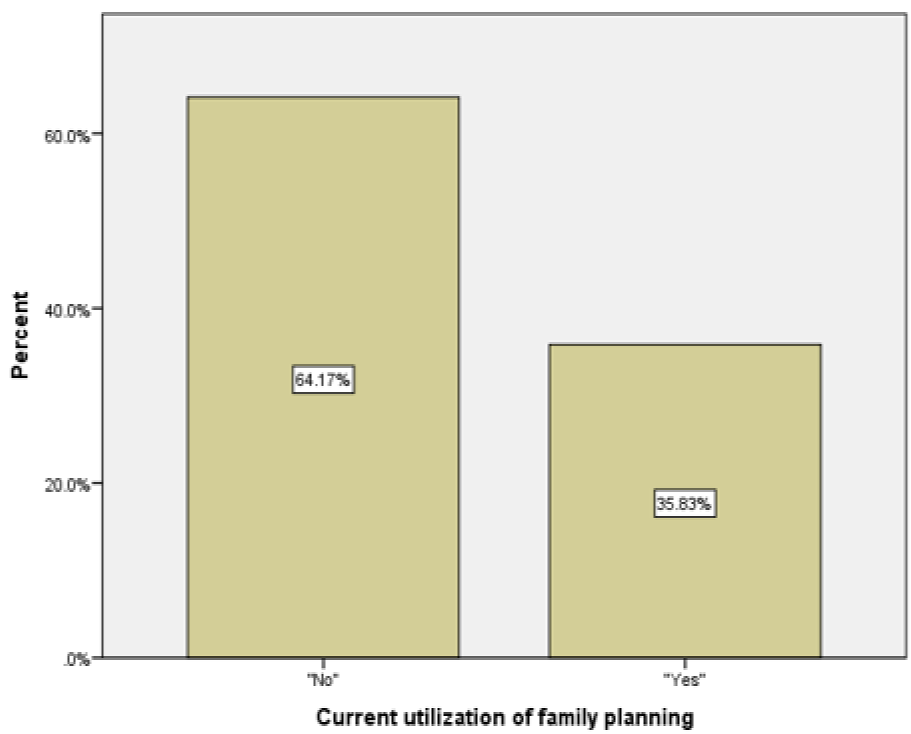


Figure 4.1: Simple Bar chart of the current utilization of family planning in Ethiopia (EDHS, 2016).

Table 4. 1 results of the descriptive analysis of socio-economic, demographic factors and other variables

Current Utilization of family planning service						
Variables	Categories	Not using	Percent (%)	Using	Percent (%)	Total
Age	15-24	1455	63.1%	850	36.9%	2305
	25-39	3753	61.9%	2307	38.1%	6060
	Above 39	1351	72.7%	506	27.3%	1857
Region	Tigray	417	63.6%	238	36.4%	656
	Afar	84	88.4%	11	11.6%	95
	Amhara	1274	52.7%	1141	47.3%	2416
	Oromia	2848	71.4%	1138	28.6%	3987
	Somali	318	98.5%	4	1.5%	323
	Benishangul	81	71.5%	32	28.5%	113
	SNNPR	1305	60.2%	865	39.8%	2171
	Gambela	19	65.2%	10	34.8%	294
	Harari	17	70.5%	7	29.5%	24
	Addis Adaba	157	44.3%	197	55.7%	355
	Dire Dawa	35	69.7%	15	30.3%	50
Place of residence	Urban	798	48.2%	859	51.8%	1658
	Rural	5761	67.3%	2804	32.7%	8566
Religion	Orthodox	2265	54.7%	1874	45.3%	4140
	Protestant	1325	57.8%	967	42.2%	2293
	Muslim	2769	78.3%	766	21.7%	3536
	Other	199	78.3%	55	21.7%	254
Economic status	Poor	2997	74.5%	1027	25.5%	4025
	Middle	1292	62.8%	764	37.2%	2056
	Rich	2270	54.8%	1871	45.2%	4141
Number of living children	No children	655	70.2%	278	29.8%	933
	Small	1783	56.8%	1356	43.2%	3139
	Medium	1686	61.2%	1068	38.8%	2754
	Large	2436	71.7%	960	28.3%	3396
Knowledge of any FP method	Not knows	919	79%	244	21%	1164
	Knows	5641	62.3%	3419	37.7%	9060
Visited by family FP workers	No	4788	66.7%	2394	33.3%	7183
	Yes	1771	58.3%	1268	41.7%	3040
Highest educational	No education	4303	68.8%	1948	31.2%	6251
	Primary	1756	60.5%	1144	39.5%	2900

level of women's	Secondary and higher	501	46.7%	571	53.3%	1072
Exposure to mass media	No	4989	67.6%	2393	32.4%	73824
	Yes	1571	55.3%	1270	44.7%	2841
Desire for more children	No	2455	62.7%	1462	37.3%	3918
	Yes	3715	64.3%	2059	35.7%	5774
	Undecided	389	73.3%	142	26.7%	531
Women's occupation	Not Working	3629	68.7%	1651	31.1%	5281
	Working Agri employee	2792	60.1%	1851	39.9%	4644
	Non agri employee	138	46.3%	160	53.7%	298
Husbands occupation	Not working	620	77.1%	184	22.9%	805
	Agri employee	5579	63.6%	3189	36.4%	8769
	Non agri employee	348	54.6%	289	45.4%	637
Husband education level	No education	3284	70.1%	1400	29.9%	4684
	Primary	2326	61.7%	1445	38.3%	3772
	Secondary and higher	943	53.4%	822	46.6%	1766

The highest percentage 38.1% of using family planning for women was observed in the age group 25-39 and 36.9% using family planning was observed in the age group 15-24 and the lowest percentage 27.3% of using family planning was observed in the age group above 39.

The proportion of family planning use among women differed by place of residence. Among the women who resided in urban areas, 51.8 % used family planning. Among rural women, 32.7 % used family planning and 67.3 % did not use family planning. Thus the use of family planning was higher among women who were residing in urban areas as compared to women‘s in rural area.

Moreover, women who lived in different regions had the different status of family planning use. The highest proportion 55.7% of women who use family planning was observed in Addis Ababa followed by Amhara 47.3% and the least proportion 1.5% of women‘s who use family planning was observed in Somali region, followed by Afar region 11.6%. There appeared to be some region wise variation in the proportion of women‘s family planning use.

The percentage of women who use family planning methods was higher among those women who were followers of orthodox 45.3% followed by protestant 42.2 %. The lowest percentage

21.7 % of family planning use was observed among women who were followers of Muslim Religion and other religions like Catholic and traditional 21.7%.

The status of using a family planning among women from poor households was 25.5%, 37.2% for women in the medium household and 45.2% for rich women.

With regard to the number of living children, the highest percentage 43.2% of family planning use were those women who had a small number of children(1-2 children) followed by those women who had a medium number(3-4) of living children 38.8% and women who had no children number of living children 29.8% . Moreover, the least proportion 28.3% of women‘s family planning use were women who had a large number of living children.

It is believed that exposure to any kind of family planning methods through mass media like radio, television and newspapers and magazines enhance the use of family planning. Women who were exposed to any kind of mass media, 44.7% used family planning and 55.3% did not use family planning .Out of those women who were not exposed to any mass media, only 32.4% used family planning.
The proportion of women who used family planning methods was 41.7 % among the women who had been visited by a family planning worker during the last 12 months before the survey and 33.3 % among those who had not been visited during the last 12 months before the survey. Out of the women who had a desire for more children, 35.7 % used family planning while 37.3 % of those women who had no desire for more children used family planning.

Results of descriptive statistics also showed that 53.7 % of women who were non-agricultural employee used family planning and 39.9 % of women who were agricultural employee used family planning, while 31.1 % of women who were not working used family planning. The table also shows that the proportion of women using family planning was 53.3 % among women who had secondary and higher education. The proportion of women who used family planning was 39.5 % among women who had primary education and the least percent 31.2% was observed among women with no education.

The percentage of using family planning method of women’s husband’s occupation show that 45.4% of women whose husbands had non-agricultural employee used family planning and

36.4% of women whose husbands had agricultural employee used family planning, while 22.9 % of women whose husbands had not working used family planning.

The table also shows that the proportion of women whose husband's education level using family planning was 46.6% among women whose husbands had secondary and higher education. The proportion of women who used family planning was 38.3 % among women whose husbands had primary education and the least 29.9 % was women whose husbands who had no education.

Table 4. 2: Cross-tabulation of Family planning utilization with predictor variables

Variable	Category	Utilization of Family planning		Total	Chi-sqr	Df	P-value
		No	**Yes**				
		Count (%)	**Count (%)**				
Age	15-24	1455(63.1%)	850(36.9%)	2305	73.6	2	0.000
	25-39	3753(61.9%)	2307(38.1%)	6060			
	Above 39	1351(72.7%)	506(27.3%)	1857			
Region	Tigray	417(63.6%)	238(36.4%)	656	499.03	10	0.000
	Afar	845(88.4%)	111(11.6%)	956			
	Amhara	1274(52.7%)	1141(47.3%)	2416			
	Oromia	2848(71.4%)	1138(28.6%)	3987			
	Somali	318(98.5%)	4(1.5%)	323			
	Benishangul	81(71.5%)	32(28.5%)	805			
	SNNPR	1305(60.2%)	865(39.8%)	2171			
	Gambella	19(65.2%)	10(34.8%)	29			
	Harari	17(70.5%)	7(29.5%)	24			
	Addis Ababa	157(44.3%)	197(55.7%)	355			
	Dire Dawa	35(69.7%)	15(30.3%)	50			
Place of residence	Urban	798(48.2%)	859(51.8%)	1658	220.7	1	0.000
	Rural	5761(67.3%)	2804(32.7%)	8566			
Highest education level	No educat.	4303(68.8%)	1948(31.2%)	6251	217.8	2	.000
	Primary	1756(60.5%)	1144(39.5%)	2900			
	Secondary and higher	501(46.7%)	571(53.3%)	1072			
Religion	Orthodox	2265(54.7%)	1874(45.3%)	4140	531.4	3	.000
	Protestant	1325(57.8%)	967(42.2%)	2293			
	Muslin	2769(78.3%)	766(21.7%)	3635			
	Other	199(78.3%)	55(21.7%)	254			

Economic status	Poor	2997(74.5%)	1027(25.5%)	4025	344.6	2	.000
	Middle	1292(62.8%)	764(37.2%)	2056			
	Rich	2270(54.8%)	1871(45.2%)	4141			
Number of having children	No children	655(70.2%)	278(29.8%)	933	183.4	3	0.000
	Small	1783(56.8%)	1356(43.2%)	3139			
	Medium	1686(61.2%)	1068(38.8%)	2754			
	Large	2436(71.7%)	960(28.3%)	3396			
Knowledge of FP	No	919(79.0%)	244(21.0%)	1164	125.2	1	0.000
	Yes	5641(62.3%)	3419(37.7%)	9060			
Visit by fieldworker in last 12 months	No	4788(66.7%)	2394(27.9%)	7183	65.1	1	0.000
	Yes	1771(58.3%)	1268(36.1%)	3040			
Exposure to mass media	No	4989(67.6%)	2393(32.4%)	7382	134.6	1	0.000
	Yes	1571(55.3%)	1270(44.7%)	2841			
Desire for more children	No	2455(62.7%)	1462(37.3%)	3918	23.8	2	0.000
	Yes	3715(64.3%)	2059(35.7%)	5774			
	Undecided	389(73.3%)	142(26.7%)	531			
Women's Occupation	Not working	3629(68.7%)	1651(31.3%)	5281	121.7	2	0.000
	Agri employee	2792(60.1%)	1851(39.9%)	4611			
	Non agri employee	138(46.3%)	160(53.7%)	298			
Husband's education level	No education	3282(70.1%)	1400(29.9%)	4682	168.5	2	0.000
	Primary	2323(61.7%)	1445(38.3%)	3768			
	Secondary and higher	943(53.5%)	818(46.5%)	1762			
Husband's Occupation	Not working	620(77.1%)	184(13.4%)	805	84.2	2	0.000
	Agri employee	5579(63.6%)	3189(36.4%)	8769			
	Non agri employee	348(54.6%)	289(45.9%)	637			

The chi-square test was carried out to determine the association between the dependent variable (utilization of family planning service) and the independent variables (age, economic status, religion, visited by fieldworker in last 12 months, women's occupation, region, education level, Knowledge of family planning, place of residence, exposure to mass media, desire for more children, number of living children, husband education, husband occupation). The result revealed that all independent variables had a statistically significant association with family planning service utilization at 0.05 level of significance.

The chi-square test does not give any information about the strength of the relationship between the variables. Hence, we should identify statistically significant predictor variables and determine the direction of relationship with the dependent and independent variables using classical and Bayesian logistic regression. The first step in performing a multilevel analysis is testing the heterogeneity of proportions between groups (regions). Chi-square test statistic was applied to assess heterogeneity in the proportion of individuals among regions. The test yield $\chi 2$ (10) = 499.03 with p=0.000<0.05, where 10 is the degrees of freedom. Thus, there is an evidence of heterogeneity of individuals among regions.

Chi-square statistic does not give any information about the strength of the relationship and only conveys the existence or nonexistence of the relationships between the variables investigated. Hence, we should identify statistically significant predictor variables and determine the direction of relationship with the dependent and independent variables using logistic regression.

4.2. A logistic regression model

4.2.1 Model adequacy checking

Hosmer and Lemeshow Test

Assessing the overall significance of a statistical model is essential in order to get valuable information from the data that we have collected for the research. To achieve these objectives, Hosmer-Lemeshow test and likelihood ratio test were considered.

Table 4. 3 Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	11.451	8	.177

The Hosmer-Lemeshow test is a test of assessing goodness of fit of the model. Well-fitting models show non-significance of the Hosmer-Lemeshow goodness-of-fit test, indicating model prediction is not significantly different from observed values. The Hosmer-Lemeshow statistic is used to test the hypothesis:

Ho: the model is a good fit

Ha: the model is not a good fit.

As displayed in table 4.3, we do not reject the null hypothesis at 5% level of significance. This shows that there is no sufficient evidence to reject the null hypothesis. It indicating that the model is a good fit.

Likelihood-Ratio Test

The most common assessment of overall model fit in logistic regression is the likelihood ratio test, which is the chi-square difference between the null model with the constant only and the model containing a set of predictors. Under model summary in table 4.4, we see that -2Log Likelihood statistics is 9781.769. These statistics show us how much improvement is needed before predictors provide the best possible prediction of the response variable, the smaller the statistics the better the model. The statistics for only intercept model is -2LLo=2262.397+9781.769=12044.166.The inclusion of the parameters reduced the -2LogLikelihood statistics by 12044.166 9781.769=2262.397, which is reflected chi-square for the omnibus test.The result (X^2 =2262.397, d.f=34, p-value =0.000), shows that the model is adequate, meaning that at least one of the predictors is significantly related to the dependent variable. That is, the null hypothesis is that there is no difference between the model with only a constant and the model with independent variables was rejected.

Table 4.4 Model summary of the logistic regression model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9781.769a	.206	.291

Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	2262.397	34	.000*
Step 1 Block	2262.397	34	.000*
Model	2262.397	34	.000*

A logistic regression model was used to analyze the relationships between the women's utilization of family planning in Ethiopia and each of the independent variables which are incorporated in the model. As can be seen in table 4.5, all the independent variables incorporated in the logistic regression model had a statistically significant effect on utilization of family planning services.

Table 4. 5: Results of logistic regression

Variables	Coef	Std.Err.	Z	P>|z|	OR	95% Conf. Interval OR	
						Lower	Upper
Intercept	-2.257039	.210055	-10.74	0.000*	.1046599	.0693396	.1579717
Age							
15-24(Ref)							
25-39	-.3569086	.0732022	-4.88	0.000*	.6998364	.6062988	.8078047
Above 39	-1.091642	.10545	-10.35	0.000*	.3356649	.27299	.4127292
Region							
Tigray (ref)							
Afar	-.8872258	.1640215	-5.41	0.000*	.4117966	.2985846	.5679343
Amhara	.7414239	.0994393	7.46	0.000*	2.098922	1.727243	2.550582
Oromia	.069011	.108764	0.63	0.526	1.071448	.8657471	1.326023
Somali	-2.362609	.2687694	-8.79	0.000*	.0941742	.0556103	.159481
Benishangul	.0578846	.1173072	0.49	0.622	1.059593	.8419511	1.333494
SNNPR	.5316319	.114067	4.66	0.000*	1.701707	1.360789	2.128035
Gambela	-.1047866	.1317766	-0.80	0.427	.9005166	.6955419	1.165897
Harari	-.3457635	.1368599	-2.53	0.012*	.7076798	.5411796	.9254058
Addis Ababa	.0559015	.1250858	0.45	0.655	1.057493	.8275695	1.351297
Dire Dawa	-.249796	.1383782	-1.81	0.071	.7789597	.593919	1.021651
Residence							
Urban(Ref)							
Rural	-.4471162	.0858538	-5.21	0.000*	.6394696	.5404319	.7566566
Religion							
Orthodox(Ref)							
Protestant	-.2297413	.0836499	-2.75	0.006*	.7947392	.6745617	.936327
Muslim	-.5782247	.0712476	-8.12	0.000*	.5608932	.4877914	.6449503
Other	-.6999736	.2080166	-3.36	0.001 *	.4965984	.3303249	.7465681
Economic status							
Poor (Ref)							
Middle	.5265686	.0766324	6.87	0.000*	1.693113	1.456989	1.967503
Rich	.7340098	.071239	10.30	0.000*	2.083418	1.811914	2.395605
Number of living children							
No (Ref)							
Small	.931157	.0919327	10.13	0.000*	2.537443	2.119059	3.038433
Medium	.8831568	.1092018	8.09	0.000*	2.418522	1.952528	2.995732
Large	.7495105	.1214473	6.17	0.000*	2.115964	1.667755	2.68463
Visited by FP worker in the last 12 months							
No (Ref)							
Yes	.065341	.0542591	1.20	0.001*	1.067523	1.029595	1.187306
Women’s education level							
No(Ref)							
Primary	.1997182	.0657709	3.04	0.002*	1.221059	1.073377	1.389059
Sec and highe	.2533315	.0998671	2.54	0.011*	1.28831	1.059286	1.56685
Exposure to mass media							
No(ref)							
Yes	.281753	.0635125	4.44	0.000*	1.325451	1.170313	1.501155

Desire more children							
No(Ref)							
Yes	-.3832686	.061896	-6.19	0.000*	.6816298	.6037576	.769546
Undecided	-.4774147	.1352809	-3.53	0.000*	.6203852	.4758939	.8087472
Women's occupation							
Not working(ref)							
Agri employee	.1867197	.052849	3.53	0.000*	1.205289	1.086691	1.336831
Non Agri Employee	.1581509	.1358062	1.16	0.244	1.171343	.8976058	1.52856
Knowledge of Family Planning							
No(Ref)							
Yes	.6301761	.0990978	6.36	0.000*	1.877941	1.546428	2.280522
Husband education							
No(ref)							
Primary	.2389561	.0644486	3.71	0.000*	1.269923	1.119228	1.440907
Second. and high	-.0356695	.0888056	-0.40	0.688	.9649592	.810807	1.148419
Husband occupation							
Not working(ref)							
Agri employee	.541461	.1074768	5.04	0.000*	1.718516	1.392096	2.121475
non Agri Emp	.5027705	.1357592	3.70	0.000*	1.653295	1.267045	2.157292

'*'indicates significance for $p<0.05$:

A negative sign in column labelled "Coefficient" indicates an inverse relationship of an explanatory variable with the log odds of the dependent variable. In contrast,a positive coefficient indicates a positive relationship to the log odds of the dependent variable. To interpret the regression coefficient in the logistic model we used the odds ratio. The odds ratio indicates the effect of each explanatory variable directly on the odds of using family planning rather than on log (odds). Estimates of odds ratio greater than 1.0 indicate that women's status of family planning use is greater than that for the reference category. Estimates of less than 1.0 indicate that women's status of family planning use is less than that for the reference category of each variable. So, the final model presented in table 4.5 is interpreted in terms of odds ratio as follows.

The model revealed that women in the age group of 25-39 were 0.699 times less likely to use family planning compared to the women in the age group of 15-24 while women in the age group above 39 were 0.335 times less likely to use family planning as compared to women in the age group of 15-24 controlling for other variables in the model. Women who resided in the rural areas were 36.1 percent less likely to use family planning compared with those from the urban areas controlling for other variables in the model.

Women who resided in the Amhara region are 2.098 times more likely to use family planning when compared with those residing in Tigray controlling for other variables in the model. Women who lived in SNNPR region were times more likely to use family planning compared to women in Tigray controlling for other variables in the model. Conversely, women who lived in Somali were 90.6 percent less likely to use family planning compared to women in Tigray and women who lived in Afar region were 58.9% less likely to use family planning compared to women who lived in Tigray controlling for other variables in the model.

Women who were followers of Protestant religion were 0.795 times less likely to use family planning compared to those women who were followers of Orthodox religion controlling for other variables in the model. Women who were followers of Muslim religion were 0.561 times less likely to use family planning compared to those Women who were followers of Orthodox religion controlling for other variables in the model. Women who were followers of other religion (Catholic and traditional) were 0.496 times less likely to use family planning compared to those Women who were followers of Orthodox religion controlling for other variables in the model.

Women who live in medium economic status were about 1.693 times more likely to use family planning than that of women who live in poor households and women who had rich wealth were about 2.083 times more likely to use family planning compared to women who were poor controlling for other variables in the model.

Women who had small children (1-2 children) were 2.537 times more likely to use family planning to women who had no children controlling for other variables in the model. Women who had medium were 2.418 times more likely to use family planning to women who had no children controlling for other variables in the model. Women who had large children (5+) were 2.115 times more likely to use family planning to women who had no children controlling for other variables in the model. Women who had primary education were 1.221 times more likely to use family planning compared to women who had no education controlling for other variables in the model and women who had secondary and higher were 1.288 times more likely to use family planning compared to women who had no education controlling for other variables in the model .Women who are agricultural employee were 1.205 times more likely to use family planning as compared to women who are not working controlling for other variables in the model.

Women who were exposed to mass media messages via radio, television, newspapers or magazine were 1.325 times more likely to use family planning compared to those women who were not exposed to mass media messages via radio, television, newspapers or magazine controlling for other variables in the model.

Women who were visited by a family planning worker during the last 12 months were 1.067 times more likely to use family planning than those who were not visited during the last 12 months before the survey controlling for other variables in the model. Similarly those women who had knowledge about family planning methods were 1.877 times more likely to use family planning compared to women who had no knowledge about family planning methods controlling for other variables in the model.

Women's whose husbands occupation are non-agricultural employee were 1.653 times more likely to use family planning as compared to women's whose husbands occupation are not working controlling for other variables in the model and women whose husbands occupation are Agricultural employee were 1.718 times more likely to use family planning as compared to women's whose husbands are not working controlling for other variables in the model.

Women's whose husbands education level had primary education were 1.269 times more likely to use family planning compared to women's whose husbands education level had no education controlling for other variables in the model.

According to table 4.5 as mentioned above region, place of residence, age of a women, religion of a women, educational level of women, economic status, knowledge about family planning method, occupation of women, husband occupation, husband education level, desire more children, exposure to mass media and number of having children of women were found to be significant predictors for women's family planning use.

From the above table the estimated model is given by:

$$\text{Logit}(\hat{P}) = \beta_0 + \sum_{i=1}^{11} \beta_{1\,i}\, reg + \sum_{j=1}^{3} \beta_{2\,j}\; age + \sum_{k=1}^{2} \beta_{3\,k}\; resi + \sum_{l=1}^{4} \beta_{4l}\, reli +$$

$$\sum_{m=1}^{3} \beta_{5\,m}\, edule + \sum_{n=1}^{3} \beta_{6n}\, ecosta + \sum_{o=1}^{2} \beta_{7\,o} know + \sum_{p=1}^{2} \beta_{8\,p}\; visited +$$

$\sum_{q=1}^{3}\beta_{9\,q}\, woccup + \sum_{r=1}^{3}\beta_{10\,r}\, hoccp + \sum_{s=1}^{3}\beta_{11\,s}\, hedule + \sum_{t=1}^{2}\beta_{12\,t} Exp +$
$\sum_{u=1}^{4}\beta_{13\,u}\, numchld + \sum_{v=1}^{3}\beta_{14\,v}\, desmorechl$

4.2.2 Model diagnostics:

The adequacy of the fitted model was checked for the possible presence of outliers and influential values. The diagnostic test results for detection of outliers and influential values are presented in Appendix A.The DFBETAs for model parameters including the constant term and Cook's influence statistic were both less than unity. DFBETAs less than unity imply no specific impact of an observation on the coefficient of a particular predictor variable, while Cook's distance less than unity showed that an observation had no overall impact on the estimated vector of regression coefficients β. A value of the leverage statistic less than one shows that no subject has a substantially large impact on the predicted values of the model. Thus, from the above goodness of fit tests and diagnostic checking, we can say that our model is adequate (See Appendix A).

The logistic regression analysis doesn't consider the variations due to hierarchy structure in the data. It doesn't allow the simultaneous examination of the effects of group level individual level variables on individual level outcomes while accounting for the non-independence of observations within groups. Due to this we consider multilevel logistic regression to examine both between groups and within group variability as well as how group level and individual level variables are related to variability at both levels (Goldestein and Rasbash, 1996).

4.3 Multilevel logistic regression analyses.

4.3.1 Random Intercept Only model

This is the type of model that incorporates only the grand mean and random intercept (regional effect) without covariate (predictors). The model is given as:

$$logit(P_j) = \beta_o + U_{oj}$$

$$U_{0j} \sim IID\ (0, \delta_u^2)$$

The Intercept β_o also known as the grand mean is shared by all regions while the random effect U_{oj} also known as level two residual is specific to region j. It shows how the mean of women's family planning use in a particular region deviates from the grand mean.

Table 4. 3 Result of Parameter Estimate of Random Intercept-Only Model

Fixed part	Coef.	Std.Err.	Z	P>|z|	95% C.I. for est.	
					Lower	Upper
β_o = Intercept	-1.071968	.3347431	-3.20	0.001	-1.728053	-0.4158838
Random effect	Estimate	Std. Err.	95% C. I.			
Between-region variance($\hat{\delta}_u^2$)	1.221534	.5366513			0.5163582	2.88975
ICC ($\hat{\rho}$)	0. 27					

LR test vs. logistic model: chibar2 (01) = 1141.10 P-value = 0.000

Table 4.3 shows the output of the estimates of fixed effects and random effects. From the table we can see that the estimate of the fixed part of the model is -1.071968 with z-value of -3.2 and p- value of 0.001 which implies that the estimated average log odds of family planning use are significantly different from zero among reproductive age of women across regions of the country. The intercept informs us β_o=-1.072 that the average probability of family planning use is $\frac{\exp(-1.071968)}{1+\exp(-1.071968)}$=0.255 which means the chance of family planning use is 25.5% on average without accounting for other sources of variation. The table also contains the variance estimate of random effects at the regional level,$\hat{\delta}_u^2$=1.22 with a confidence interval of (0.52 ,2.29) which implies that the between region variance of family planning use is 1.22 and reveals that there is a significant difference in family planning use among women across regions. At the bottom of the table there is the result of the hypothesis H_0:$\delta^2{}_u$=0 is provided showing that there is no cross-regional variation in family planning use. For this hypothesis, we see that the value of the test statistic is 1141.1 with p=0.000.Therefore, the null hypothesis is rejected and there is evidence of heterogeneity or cross-regional variation in family planning use. We can now write the model for the j^{th} region as $logit(P_j)$=-1.07 +U_{0j}.The empty model with random effect also helps to calculate the between region variations by the help of intra –class correlation coefficient (ICC) which is the measure of the correlation between two individuals who are in the same higher level unit (region). ICC for this model is calculated by using $ICC = \frac{\delta_{uo}^2}{\delta_{uo}^2 + 3.29}$ .A low ICC indicates relatively small between region variations. From the table we have between regions variance of 1.22 and level one variance of intra class correlation coefficient is 0.27. The ICC for this model implied that 27% of the variation in family planning use can be explained by grouping the women in regions .The remaining (100-27%=73%) of the variation in family planning use is explained by individual level(within region-differences).

4.3.2 Random Intercept Model

In a random intercept multilevel logistic regression model, we allowed the probability of family planning use to vary across regions, but we assumed that the effects of the explanatory variables are the same for each region. That is, the random intercept varies across regions, but women level explanatory variables are fixed across regions.

Table 4. 4 : Results of Parameter Estimate of Random Intercept Model

Variables		Coef	Std.Err.	Z	P>|z|	OR	95% Conf.Interval OR	
							Lower	Upper
	Intercept	-2.469796	.2998641	-8.24	0.000*	.0846021	.0470042	.1522741
Age	15-24(Ref)							
	25-39	-.3538736	.0731623	-4.84	0.000*	.7019637	.6081893	.8101967
	>39	-1.089225	.1054271	-10.33	0.000*	.336477	.2736627	.4137092
Residence	Urban(Ref)							
	Rural	-.4380418	. 0856648	-5.11	0.000*	.6452988	.5455604	.7632713
Religion	Orthodox(Ref)							
	Protestant	-.2308586	.0834648	-2.77	0.006*	.7938517	.6740529	.9349422
	Muslim	-.5925815	.0715557	-8.28	0.000*	.5528981	.480548	.6361411
	Other	-.7015897	.2080772	-3.37	0.001*	.4957965	.3297523	.745451
economic status	Poor (Ref)							
	Middle	.5308053	.0767053	6.92	0.000*	1.700301	1.462966	1.976139
	Rich	.7369979	.0713037	10.34	0.000*	2.089653	1.817106	2.403079
Number of having children	No (Ref)							
	Small	.9305999	.0919102	10.13	0.000*	2.53603	2.117972	3.036606
	Medium	.8812253	.109159	8.o7	0.000*	2.413856	1.948924	2.9897
	Large	.7452413	.1214006	6.14	0.000*	2.10695	1.660802	2.672948
visited by the field worker	No (Ref)							
	Yes	.0668791	.054252	1.23	0.000*	1.069166	1.0113153	1.189117
Knowledge of FP	No (ref)							
	Yes	.6353529	.0990584	6.41	0.000*	1.887688	1.554575	2.292181
The education level of respondent	No(Ref)							
	Primary	.2024018	.0657687	3.08	0.002*	1.22434	1.076266	1.392786
	Secon.and higher	.2562673	.0998141	2.57	0.010*	1.292098	1.062511	1.571294
Exposure to media	No(ref)							
	Yes	.2817647	.0635049	4.44	0.000*	1.325467	1.170344	1.501151
Desire more children	No(Ref)							
	Yes	-.3876183	.0619261	-6.26	0.000*	.6786713	.6011017	.766251
	Undecided	-.4799364	.1353265	-3.55	0.000*	.6188228	.4746529	.8067824
Women's	Not working(ref)							

occupation	Agri employee	.1886877	.0528501	3.57	0.000*	1.207664	1.08883	1.339467
	Non Agri Emplo	.1573451	.1356719	1.16	0.248	1.1704	.8971188	1.526927
Husband education	No(ref)							
	Primary	.2402686	.0644431	3.73	0.000*	1.271591	1.12071	1.442784
	Secondary and hi	-.0362093	. 0887649	-0.41	0.683	1.317438	.810434	1.147708
Husband occup.	Not working(ref)							
	Agri employee	.5438221	. .1074267	5.06	0.000*	1.722578	1.395524	2.126281
	non Agri Emplo	.502428	.1356413	3.70	0.000*	1.652729	1.266904	2.156055
Estimation of Random effect								
		Estimate	Standard error		wald approximate 95% CI			
Between –region variance($\hat{\delta}_u^2$)		.5547306	.2541581				.2259911	1.361673
ICC($\hat{\rho}$)		0.144						

LR test vs. logistic model: chibar2 (01) = 281.34 P-value = 0.000

Note '* 'indicates significance for $p < 0.05$.

Table 4.4 contains estimates of the random intercept and associated odds ratios. Values of the Wald test statistic used for testing for the significance of individual predictors are given with the corresponding p-values in the table. The Wald test of overall goodness of fit gives wald chi-square=281.34 with p =0.000. This indicates that all explanatory variables are significant. From the table we see that the inclusion of level one covariates decreased regional variations from. 1.22 (level-two variance without covariates) to 0.55, it indicates that there is a significant variation between regions in the utilization of family planning use. The results displayed in table 4.4. showed that intraregional correlation coefficient (ICC) is estimated as $\hat{\rho}$ =0.144,meaning that 14.4 % of the total variability in the utilization of family planning service among reproductive age women(15-49 years) is attributable to the regional level, with the remaining unexplained 85.6% being due to individual differences. From the random part variance component of the random intercept model σ_u^2 was found to be significant, which implies that region difference contributes to the variation of utilization of family planning service among women from the random intercept model. The deviance of the random intercept model, 9841.768 is reduced to 9687.6 when we include covariates for the same random intercept which implies that the random intercept model is better than the empty model. The BIC and AIC values in table 4.9 also ensure this as the smaller the values of AIC and BIC the better the model.

Moreover, the values of chi-square =281.34 and p=0.000 lead to the rejection of the null hypothesis that the random effect is zero. From this, we can conclude that the random effect at the regional level is significantly different from zero. From table 4.4 we see that all categories of the age of woman 25-39 and above 39 are significant for family planning use as compared to the reference category (15-24). In addition number of living children (small, medium and large) are significant factors for family planning use as compared to their reference categories. Additionally Women‘s educational level (primary and secondary and higher),knowledge about family planning, economic status(medium and rich), exposure to mass media, religion (Protestant ,Muslim and others) ,women occupation,(agricultural employee), place of residence, visited by family planning worker, husband occupation and husband education (only primary) significantly affects family planning use compared to their reference categories.

4.3.3 Random coefficient multilevel logistic regression model

Table 4. 5 : Results of random coefficient multilevel logistic regression model

Variables		Coef	Std.Err.	Z	P>|z|	OR	95% Conf.Interval OR	
							Lower	Upper
	Intercept	-2.623441	.3430577	-7.65	0.000*	.072552	0.03	0.14
Age	15-24(Ref)							
	25-39	-.3711351	.0742997	-5.00	0.000 *	.6899508	0.59	0.79
	>39	-1.119341	.1061211	-10.55	0.000*	.3264948	0.26	0.40
Residence	Urban(Ref)							
	Rural	-.1993522	.088099	-2.26	0.024*	.819261	0.68	0 .97
Religion	Orthodox(Ref)							
	Protestant	-.2623873	.1815716	-1.94	0.053	.769213	0.58	1.00
	Muslim	.7044432	.2256265	-3.12	0.002*	.4943838	0.31	0.76
	Other	-.9479625	.3935219	-2.21	0.016*	.387529	0.17	0.83
economic status	Poor (Ref)							
	Middle	..706971	.161074	4.39	0.000 *	2.02784	1.47	2.78
	Rich	1.13428	.2919621	3.89	0.000 *	3.10893	1.75	5.50
Number of having children	No (Ref)							
	Small	.9532606	.0922758	10.33	0.000 *	2.59415	2.16	3.10
	Medium	.9272776	.1099357	8.43	0.000 *	2.52761	2.03	3.13
	Large	.8142657	.1224859	6.65	0.000 *	2.25751	1.77	2.87
Visited by field worker	No (Ref)							
	Yes	.0732884	.0543967	1.35	0.000*	1.07604	1.03	1.19
Knowledge of FP	No (ref)							
	Yes	.5643297	.1007425	5.60	0.000*	1.75826	1.44	2.14
Education level of respondent	No(Ref)							
	Primary	.1981217	.0664638	2.98	0.003*	1.21911	1.07	1.38
	Sec.and higher	.2760345	.1004889	2.75	0.006*	1.31789	1.08	1.60
Exposure to media	No(ref)							
	Yes	.2492757	.063784	3.91	0.000 *	1.28309	1.13	1.45
Desire more children	No(Ref)							
	Yes	-.3657892	.0623723	-5.86	0.000 *	.693649	0.61	0.78
	Undecided	-.4596072	.1358283	-3.38	0.001*	.631531	0.48	0.82
women’s occupation	Not working(ref)							
	Agri employee	.1849205	.0532977	3.47	0.001*	1.20312	1.08	1.33
	Non Agri Emplo	.157701	.13501	1.17	0.243	1.17081	0.89	1.52

Husband education Level	No(ref)							
	Primary	.2324916	.0648437	3.59	0.000 *	1.26174	1.11	1.43
	Sec and higher	.0096686	.0895217	0.11	0.914	1.00971	0.84	1.20
Husband occupations	Not working(ref)							
	Agri employee	.5101966	.1085836	4.70	0.000 *	1.66561	1.34	2.06
	non Agri Emp	.4846465	.1368941	3.54	0.000*	1.62360	1.24	2.12
Estimation of Random effect								
Unstructured		Estimate	Standard error		wald approximate 95% CI			
var(religion)		.1182362	.0634944		.041271		.3387323	
var(Ecstatus)		.191605	.099266		.0694096		.5289251	
var(_cons)		1.218758	.702283		.3939407		3.770544	
cov(religion,Ecstatus)		-.0890767	.064016		-.2145457		.0363923	
cov(religion,_cons)		.1478048	.1579404		-.1617528		.4573624	
cov(Ecstatus,_cons)		-.4634912	.2564797		-.9661821		.0391997	
ICC($\hat{\rho}$)		0.317						

LR test vs. logistic model: chi2(6) = 431.85 p-value = 0.000

Table 4.5 showed the value of Var(religion) and Var (Economic status) are the estimated variance of religion and economic status respectively. These estimated variances indicated that there is a significant variation in the effect of religion and economic status across regions in Ethiopia.

The estimate of the fixed intercept is -2.623 and the log-odds of the probability of family planning use when all level one covariates are zero in region j is given by $-2.623 + \hat{U}_j$ where $\hat{U}_j$is a random intercept with variance of 1.218 indicated in the table as var (cons) which is the between-region variance and standard error 0.702. In the absence of level-one covariates, the status of each region on family planning use as compared to the average family planning use measured with log odds depends on the sign of the random intercept,$\hat{U}_j$. When $\hat{U}_j$ is positive the log odds of family planning use is higher than the average and when $\hat{U}_j$ is negative the log odds of family planning use is less than the average. The individual region slopes of religion and economic status vary with variance 0.1182 and 0.1916 respectively

Table 4. 6 Results of Model comparison

	Empty model	Random Intercept	Random Coefficient
Log likely hood(LL)	-5454.784	-4920.884	-4843.8
-2LL=deviance	10,909.568	9,841.768	9687.6
P-value	0.000	0.000	0.000
AIC value	10913.57	9895.769	9749.599

BIC value	10927.95	10089.94	9972.541

We compare the three multilevel logistic regression models (nested models) considered. To do so, deviance, AIC, and BIC were used. The deviance of the empty model with random intercept (deviance = 10,909.568) and random intercept (deviance =9,841.768) indicate that the random intercept model is better than the empty model with random intercept. In addition to this the AIC value of the empty model with random intercept (AIC = 10913.57) is larger than that for the random intercept model (AIC =9895.769), which implies that random intercept model is better than the empty model with a random intercept in predicting family planning use across regions. The deviance of a random intercept (deviance = 9841.768) and random coefficient model (deviance = 9687.6) show that the random coefficient model is better than the random intercept model. The AIC value of the random coefficient model (AIC= 9749.599) is smaller than the random intercept model (AIC =9895.769) implying that random coefficient model is better compared to the random intercept model in describing family planning service utilization.

4.4 Bayesian Logistic Regression Analysis

In addition to the classical approach, the Bayesian logistic regression analysis was considered to make an inference. The Bayesian method gives estimates of parameters by sampling from their posterior distributions using the MCMC method. Hence, we used the Gibbs sampler algorithm to estimate the parameters by approximate the properties of the marginal posterior distributions for each parameter Stata and MLwiN software were used. We run a simulation with 50,000 iterations, discarding the first 5,000 iterations as burn in. In this study, three different initial values were implemented and we assumed that the regression parameters follow a normal distribution.

The results of the Bayesian logistic regression revealed that all independent variables were found to have a significant effect on utilization of family planning service. Before we proceed to the results of the estimated parameter or examine the model, we should make sure that the sample was truly representative of the stationary or posterior distribution. In order to do this, various schemes of diagnosis were applied to check the convergence of the Markov chains to the target distribution.

4.4.1 Assessment of Model Convergence

There are several methods to check for convergence. These are Time series plot, Autocorrelation Plot, Density plot, Gelman–Rubin Statistics and comparing the MCSE to its posterior standard errors (Ioannis, 2009 and Gelman, 2005).

4.4.2 Assessing the Accuracy of the Bayesian Logistic Regression

One way to assess the accuracy of the posterior estimates is by calculating the Monte Carlo Standard Error (MCSE) for each parameter (Gelman, 1998). This is an estimate of the difference between the mean of the sampled values (which we are using as the estimate of the posterior mean for each parameter) and the true posterior mean. As a rule of thumb, to have accurate posterior estimates the simulation should be run until the Monte Carlo error for each parameter of interest is less than 5% of the parameter's standard deviation. As shown in the table below MCSE for each significant independent variable was less than 5% of its posterior standard error. This implied that convergence and accuracy of posterior estimates has been attained and the model was appropriate to estimate the posterior statistics

Table 4. 7: Results of comparison of MCSE with 5% S.d.

Variables	Categories	Node	MCSE	5% S.d.
	Intercept	beta[1]	.001933	0.003548315
Age	15-24(ref)	-	-	-
	25-39	Beta[2]	0.001062	0.00208062
	Above 39	Beta[3]	0.002184	0.00255907
Residence	Urban(ref)	-	-	-
	Rural	Beta[4]	0.001176	0.001955315
Education level of Women	Not education(ref)	-	-	-
	Primary	Beta [5]	0.001083	0.002946775
	Secondary and higher	Beta[6]	0 .001005	0.003471385
Religion	Orthodox(ref)	-	-	-
	protestant	Beta[7]	0.001392	0.00194891
	Muslim	Beta[8]	0.001714	0.0020396
	other	Beta[9]	0.003756	0.004013085
Economic status	Poor (ref)	-	-	-
	Middle	Beta[10]	0.002386	0.003237035
	Rich	Beta[11]	0 .001213	0.002145565
No living children	No children(ref)	-	-	-
	Small	Beta[12]	0.001351	0.003209625
	Medium	Beta[13]	0.00143	0.002891225

Knowledge of	Large	Beta[14]	0.0016189	0.0030655
	No (ref)	-	-	-
	Yes	Beta[15]	0.001448	0.003386295
Woman Occupation	Not working (ref)	-	-	-
	Non agri employee	Beta[16]	0.001391	0.00215442
	Agri employee	Beta[17]	0.001702	0.00357979
Visited	No (ref)	-	-	-
	Yes	Beta[18]	0.00104	0.00242073
Exposure to media	No (ref)	-	-	-
	Yes	Beta[19]	0.002347	0.00246975
Desire more children	No (ref)	-	-	-
	Yes	Beta[20]	0.001393	0.001783775
	Undecided	Beta[21]	0.002033	0.004059505
Husband education level	No education(ref)	-	-	-
	Primary	Beta[22]	0.001478	0.003060465
	Secondary and higher	Beta[23]	0.00253	0.002745415

Table 4. 8: Posterior summaries of parameters in Bayesian Logistic Regression Model

Variables		Mean	Std.Dev	MCSE	Median	95% Cred.I. for est.	
						Lower	Upper
	Intercept	-2.607511	.0709663	.001933	-2.60	-2.73	-2.47
Age	15-24(Ref)	-	-	-	-	-	-
	25-39	-.2439529	.0416124	.001062	-0.24	-0.32	-0.15
	Above 39	-.9776226	.0511814	.002184	-0.97	-1.07	-0.88
Residence	Urban(Ref)	-	-	-	-	-	-
	Rural	-.132867	.0391063	.001176	-0.13	-0.20	-0.05
Religion	Orthodox(Ref)	-	-	-	-	-	-
	Protestant	-.2822343	.0389782	.001392	-0.28	-0.35	-0.20
	Muslim	-1.07343	.040792	.001714	-1.07	-1.14	-0.98
	Other	-.6808226	.0802617	.003756	-0.68	-0.85	-0.53
economic status	Poor (Ref)	-	-	-	-	-	-
	Middle	.6871856	.0480864	.002386	0.68	0.59	0.77
	Rich	.9163059	.0429113	.001213	0.91	.83	.99
No living children	No (Ref)	-	-	-	-	-	-
	Small	.8843956	.0641925	.001351	0.88	0.75	1.01
	Medium	.7853501	.0578245	.00143	0.79	0.65	0.88
	Large	.5921161	.06131	.0016189	0.60	0.47	0.69
	No (Ref)	-	-	-	-	-	-

Visited	Yes	.0717742	.0484146	.00104	0.073	0.02	0.15
Education level	No(Ref)	-	-	-	-	-	-
	Primary	.2087262	.0589355	.001083	0.20	0.09	0.33
	Secondary and above	.2985551	.0694277	.001005	0.29	0.16	0.43
Exposure Media	No(ref)	-	-	-	-	-	-
	Yes	.2036496	.049395	.002347	0.20	0.10	0.29
Desire more children	No(Ref)	-	-	-	-	-	-
	Yes	-.4790036	.0356755	.001393	-0.47	-0.55	-0.41
	Undecided	-.5045159	.0811901	.002033	-0.48	-.66	-0.36
Women's Occupation	Not working(ref)	-	-	-	-	-	-
	Agri employee	.2291154	.0430884	.001391	0.22	0.14	0.31
	Non Agri Employee	.1034623	.0715958	.001702	0.10	-0.04	0.23
Husband education level	No(ref)	-	-	-	-	-	-
	Primary	.238278	.0612093	.001478	0.23	0.11	0.34
	Secondary and above	-.1491905	.0549083	.00253	-0.14	-0.25	-0.04
Husband occupation	Not working(ref)	-	-	-	-	-	-
	Agri employee	.7333913	.0499788	.001002	.73	.63	.83
	Non Agri Employee	.6953545	.0698297	.002608	.69	.56	.82

Ref = reference category

The table above shows that the estimated posterior quantities of interest such as posterior means, MCSE, together with the estimated certainty or precision of these parameters in terms of posterior standard deviations, credible intervals, or highest posterior density intervals using the samples from the posterior distribution obtained by MCMC.

Here, the 95 percent credible intervals determine which components of estimates are relevant to the model. All selected predictors are significant because their respective 95 percent credible intervals do not contain zero at least for one category. Since we used the Bayesian approach with non-informative priors, the inferences from Bayesian and classical are numerically similar. For example, 95% confidence intervals were very similar to the 95% credible intervals.

Bayesian credible intervals are directly interpreted as the probability that the parameter is in the credible interval, given the data and any prior information. Classical confidence intervals cannot be interpreted in this way if the confidence interval procedure were to be used repeatedly, then 95% of all intervals will contain the true value.

4.5 Discussions

This study is an attempt to identify some determinants of women‘s family planning use based on Ethiopian Demographic and Health Survey, 2016 data. First, the appropriate data handling method was performed and the data was weighted .Accordingly, descriptive analysis, logistic regression, multilevel logistic regression, and Bayesian logistic regression were used. Based on the findings of previous results, this study made a few comparative discussions as follows.

At first, the study included fourteen predictor variables that were categorized under socioeconomic, demographic and health-related characteristics. The descriptive analysis of the study revealed that only 35.83 percent of the sample women were using family planning methods and 64.17 percent did not use family planning.

This study attempted to determine the socio-economic, demographic and health-related factors of utilization of family planning services among women's in Ethiopia. The results of the study showed that, out of a sample of 9824 women's considered, 35.83% used the family planning service while 64.17% never used family planning services.

The chi-square test was carried out to determine the association between utilization of family planning service and individual independent variables. As a result, region, place of residence, age of a woman, religion of a woman, educational level of women, economic status, visited by family planning worker in the last 12 months before the survey, occupation of women, exposure to mass media, number of having children of women, husband education level and husband occupation were significantly associated with the utilization of family planning services.

Both classical and Bayesian logistic regression were employed to analyze factors that affect the utilization of family planning services. The classical logistic regression analyses revealed that women in the age group of 25-39 were less likely to use family planning compared to the age group of 15-24 and Women in the age group above 39 were less likely to use family planning as compared to women in the age group of 15-24. This result is in line with the findings Reddy et al., 2015, who had conducted research works using Binary Logistic Regression Analysis in Assessing and Identifying Factors that Influence the use of family planning in Ambo town, Ethiopia. In this analysis, younger women were more likely to use family planning than older women.

Place of residence is a significant factor contributing to use family planning. Women who resided in the rural areas were less likely to use family planning as compared with those from the urban areas. Studies elsewhere revealed a similar pattern of relationship between residence and family planning use (selamawit, 2015).Furthermore, the study also revealed there is a significant association with exposure to mass media and family planning use. Women who were exposed to mass media messages via radio, TV and newspapers or magazine were more likely to use family planning compared to those women who were not exposed to mass media messages via radio, TV and newspapers or magazine. This result is in line with the results obtained by (Gizaw and Regassa, 2011) and (Reddy et al., 2015).Regarding the regional variations in family planning use, the study revealed that woman who lived in Afar and Somali use family planning service less than women who live in other regions of Ethiopia.

The results of this study also showed that women‘s economic status is an important factor associated with family planning. women who lived in medium economic status were more likely to use family planning than those women who were poor and the odds of family planning use for women who had rich wealth was 3.109 times higher compared to women who were poor. Similarly a study conducted by (Gribble, 2018) found that the use of family planning is higher for the wealthier women as compared to the poorer women.

This study also revealed a statistically significant association between family planning use and women‘s education level. Women who had primary education were more likely to use family planning compared to women who had no education and women who had secondary and above education were also more likely to use family planning compared to women who had no education. This result was in line with the results obtained by (Apanga and Adam, 2015).

Another important factor that significantly affects family planning use is knowledge of family planning method. The study revealed that women who had no knowledge of family planning methods were less likely to use family planning compared to women who had knowledge about family planning methods. This result was similar to the results obtained by (Amentie,Abera and Abdulahi ,2015).

The study also found that women who were visited by a family planning worker during the last 12 months were more likely to use family planning than those women who were not visited during the last 12 months before the survey. This result was similar to the results obtained by (selamawit, 2015).

As far as the religion is concerned, a significant association has been observed between religion and family planning use in the study. Women who were followers of Muslim religion were less likely to use family planning compared to those women who were followers of Orthodox religion and women who were followers of other religion (Catholic and traditional) were less likely to use family planning compared to those women who were followers of Orthodox religion .

The study also revealed that family planning use and a number of having children are significantly associated. Women who had small children (1-2 children) were more likely to use family planning compared to women who had no children and women who had medium children (3-4 children) were more likely to use family planning compared to women who had no children and Women who had large children (5 and above children) were more likely to use family planning compared to women who had no children.

This study has found that the occupation of women is significantly associated with the use of family planning .Women who are agricultural employed were more likely to use family planning as compared to women who are not working.

This study has found that women's husband occupation is significantly associated with the use of family planning. Women's husband's occupation who are agricultural employed were more likely to use family planning as compared to women who are not working and women's husband's occupation who are non-agricultural employed were more likely to use family planning as compared to women who are not working.

This study also revealed a statistically significant association between family planning use and women‘s husband's education level. Women whose husbands had primary education were more likely to use family planning compared to women's husbands who had no education and who had secondary and above education were also more likely to use family planning compared to women's husbands who had no education.

Multilevel logistic regression model allows for comparison of variations between regions. Before the analysis of data using multilevel, heterogeneity of the status of utilizing family planning services with regard to regions was checked first using chi-square test and it was statistically significant. In multilevel logistic regression models with fixed effects of the explanatory variables had a similar interpretation as that of the logistic regression model as discussed above whereas the random parts of the intercept and the coefficients provided additional information. Results obtained based on the empty model the overall variance of the constant term suggest that women’s status of utilizing the family planning differed across regions. In addition to the null model, two other models, one with a random intercept model and another with the random coefficient model were used. The overall variance constant term in both models was found to be statistically significant implying that utilization of family planning services differs across regions.The random coefficient model showed that the random effects of economic status and religion services vary across regions in explaining the utilization of family planning services.

In addition to logistic regression and multilevel logistic regression analysis, Bayesian logistic regression was carried out to see the effect of predictor variables on the utilization of family planning services among women’s. The Bayesian logistic regression analysis also revealed that all independent variables (those we have seen in logistic and multilevel logistic regression analysis) are statistically significant. Using Bayesian, MCSE for each significant predictor was found to be less than 5% of its posterior standard error. This implies convergence and accuracy of posterior estimates of the Bayesian were attained. The estimate of the parameters in Bayesian logistic regression is numerically similar to the estimates obtained in classical logistic regression.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 CONCLUSIONS

The study revealed that exposure to media encourages women's to use family planning service utilization. It is also indicated that the higher income women's and their family had, the better was their utilization of family planning service.

The single level logistic regression analysis revealed that the independent variables that affect the women's utilization of family planning in Ethiopia were region, place of residence, age of a woman, religion of a woman, educational level of women, economic status, visited by family planning worker in the last 12 months before the survey, occupation of women, exposure to mass media, number of having children, husband education level and husband occupation were significant predictors for women's family planning use.

The multilevel logistic regression analysis revealed that there was significant variation with regard to women's utilization of Family Planning across the regions.

The results obtained from Bayesian logistic regression analysis showed that all selected predictors were significant. Compared to classical approaches, lower standard errors of the estimated coefficients in the Bayesian approach for the logistic regression model. Thus the Bayesian logistic regression model gives a better estimation than the classical approach.

5.2 RECOMMENDATIONS

Based on the findings of the study, we forward the following recommendations:

1. Concerned bodies in Ethiopia should focus on creating awareness towards women's utilization of family planning services.
2. There is need a for the National Government to ensure adequate provision of educational services to both male and female children to ensure attainment of higher education levels as it has been shown that couples with higher education have higher utilizations of Family Planning services.
3. The National Government should ensure an adequate number of health extension workers in health facilities to ensure that women are adequately counseled.

4. Finally, further investigations should be conducted on the basis of classical and Bayesian logistic regression.
5. Further studies should be conducted by taking three level logistic regression into account to assess the effect of utilization of Family planning service.

Limitation of the study

The data used here being secondary may have a number of constraints on the outcome of the study but the major constraints of this study was important variables such as fear of side effects, access to family planning service, quality of service delivered etc. are not included in the analysis of this study because of missing values and non-responses.

The data used in this study are from the EDHS 2016.Thus; the results may not necessarily reflect the current situation of Ethiopia.

REFERENCES:

1. Acquah, H. D. (2013) 'Bayesian Logistic Regression Modelling via Markov Chain Monte Carlo Algorithm'.
2. Agresti, A. (1996). An Introduction to Categorical Data Analysis. John Wiley and Sons, Inc., New York.
3. Ahmed, S., Li, Q., Liu, L., & Tsui, A. O. (2012). Maternal deaths averted by contraceptive use:an analysis of 172 countries. The Lancet, 380, 111-125. http://dx.doi.org/10.1016/S0140-6736(12)60478-4
4. Alkema L, Kantorova V, Menozzi C, Biddlecom A: National, regional, and global rates and trends in contraceptive prevalence and unmet need for family planning between 1990 and 2015: a systematic and comprehensive analysis. Lancet 2013, 381(9878):1642-1652.
5. Amentie, M., Abera, M. and Abdulahi, M. (2015) 'Utilization of Family Planning Services and Influencing Factors Among Women of Child Bearing Age in Assosa District , Benishangul Gumuz Regional State , West Ethiopia'.
6. Apanga, P. A. and Adam, M. A. (2015) 'Factors influencing the uptake of family planning services in the Talensi district, Ghana', *Pan African Medical Journal*, .
7. Bbaale E, Mpuga P (2011) Female Education, Contraceptive Use, and Fertility: Evidence from Uganda. Consilience: J Sustainable Dev 6: 20-47.
8. 'Bayesian Logistic Regression Model for Siting Biomass-using' (2004) *Gelman, A., Carlin, J., Stern, H., and Rubin, D. (2004). Bayesian Data Analysis. Chapman & Hall, London.*
9. Bongaarts, J. and S. W. Sinding (2009). "A Response to Critics of Family Planning Programs" International Perspectives on Sexual and Reproductive Health Volume 35, Number 1, March 2009.
10. Breslow N. and Clayton D. (1993). Approximate inference in generalized linear mixed models. Journal of American Statistical Association: 88, 9-25.
11. Brooks S. and Gelman A.(1998). General Methods for Monitoring Convergence of Iterative Simulations. American Statistical Association, Volume 7, Number 4, 434-455.
12. Central Statistical Agency [Ethiopia], and ICF International: Ethiopia Demographic and Health Survey 2011. Addis Ababa, Ethiopia and Calverton, Maryland, USA: Central Statistical Agency and ICF International; 2012.

13. Clark, T., Hall, G. and Griffiths, R. (2002). Bayesian Logistic Regression Using a Perfect Phylogeny. Department of Epidemiology and Public Health Imperial College. London, UK.
14. Congdon P. (2005). Bayesian models for categorical data/Peter Congdon. Wiley series in probability and statistics: ISBN 0-470-09237-8 (cloth: alk. paper).
15. Darroch JE, Singh S, Nadeau J: In Brief (No.5) New York. In contraception: an investment in lives, health and development. New York: Guttmacher Institute and UNFPA; 2011.
16. Debebe, S., Limenih, M. A. and Biadgo, B. (2017) 'Modern contraceptive methods utilization and associated factors among reproductive-aged women in rural Dembia District, northwest Ethiopia: Community based cross-sectional study'.
17. Efron,B.(1975). The efficiency of logistic regression compared to normal discriminant analysis. Jornal of American Statistical Association, .
18. Eliason S, Baiden F, Quansah-Asare G, Graham-Hayfron Y, Bonsu D, Phillips J, AwusaboAsare K. Factors influencing the intention of women in rural Ghana to adopt postpartum family planning. Reprod Health [Online]. 2013. Available from: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3724747/
19. Ethiopia Demographic and Health Survey (EDHS), Addis Ababa, Ethiopia, 2016.
20. Ferdousi SK, et al: Unmet need of family Planning among rural women in Bangladesh. J Dhaka MedColl 2010, 19(1):11-15.
21. Fidell, Barbara G. Tabachnick, Linda S. (2007). Using multivariate statistics (5th ed.). Boston ; Montreal: Pearson/A & B. ISBN 0-205-45938-2.
22. Gelman, A. (2005). Alternative Methods for Monitoring Convergence of Markov Chain Monte Carlo Iterative Simulations. Journal of Computational and Graphical Statistics.
23. Gelman, A.; Jakulin, A.; Pittau, M.G. and Su, Y.S. 2008. "A weekly informative default prior distribution for logistic and other regression models." The Annals of Applied Statistics, Vol. 2, Issue 4, 1360-1383
24. Geman, S. and Geman, D. (2009). Stochastic Relaxation, Gibbs Distribution and the Bayesian Restoration of Images. IEEE Transactions on Pattern Analysis and Machine Intelligence.
25. Gilks, W., Richardson, S. and Spiegelhalter, J. (2011). Markov Chain Monte Carlo in Practice. Chapman and Hall, London, UK.

26. Gizaw, A. and Regassa, N. (2011) 'Family planning service utilization in mojo town, Ethiopia: a population-based study.', *Journal of Geography and Regional Planning* .
27. Goldstein H. and Rasbash J. (1996). Improved approximations for multilevel models with binary responses. Journal of the Royal Statistical Society.
28. Goldstein H. (2003). Multilevel Statistical Models. 3rd Edition London: Arnold; New York: Oxford University Press Inc.
29. Goldstein, H. (1991). Nonlinear multilevel models with an application to discrete response data. Biometrika.
30. Gribble, J. (2018) 'Family Planning in West Africa', (March 2008) .
31. Hailemariam A, Mekbib T, Fantahun M: Family Planning in Ethiopia. In Epidemiology and Ecology of Health and Disease in Ethiopia. Edited by Berhane Y, Hailemariam D, Kloos H. Addis Ababa: Shama Books; 2006:267-285.
32. Hosmer, D. and Lemeshow, S. (2011). Applied Logistic Regression (5th Edition). New York: John Wiley and Sons.
33. Huang, X. (2010) 'Bayesian Logistic Regression Model for Siting Biomass-using Facilities'.
34. Khan, H. R., and Shaw, J. E. H. (2011) 'Multilevel Logistic Regression Analysis Applied to Binary Contraceptive Prevalence Data'.
35. Kishore, H. I. K. (2014) 'A Study to evaluate the factors influencing on Family planning practices among urban married women in Bangalore .
36. Jean-Pierre Guengant and John F.(2013). ―African Demography‖ Centennial Group for Emerging Market Forum, Washington, DC
37. John boscoasiimwe, Patricia nduggaand Johnmushom(2011). ―Socio-demographic factors associated with contraceptive use among young women in comparison with older women in Uganda‖ School of Statistics and Planning, Makerere University, Kampala, Uganda. John G Cleland , Robert P Ndugwa&Eliya M Zulu (2010).‖ Family planning in sub-Saharan
38. Lee, P. (2010). Bayesian Statistics: An Introduction, 2nd edition, Arnold, London.2016.pdf.
39. Malwenna LI, Jayawardana PL, Balasuriya A: Effectiveness of a community based health educational intervention in reducing unmet for modern methods of family planning

among ever married reproductive age women in the Kalutara district Siri Lanka.

40. Mekonnen W, Worku A: Determinants of low family planning use and high unmet need in butajira district. South central Ethiopia. Reprod Health 2011, 8:37. PubMed Abstract | BioMed Central Full Text | PubMed Central Full Text
41. Menard, S. (2002). Applied Logistic Regression, 2nd Edition: Quantitative Applications in the Social Sciences, Sage publications.
42. Merkle, E., Sheu, C. and Trisha, G. (2011). Simulation-Based Bayesian Inference using WinBUGS. WinBUGS Tutorial Outline: http://www.bu.cam.uk/winbugs/cont.shml.
43. Population Reference Bureau (2002) Women of Our World. Washington, DC. PRB, USA
44. United Nations, (2017) 'Family Planning report '.
45. United Nations, (2018) 'Family planning report',
46. Republic, F. D. (2011) 'national guideline for family planning Federal Democratic Republic of Ethiopia',
47. Rhonda S., Lori A., Jay G., and Donna C., PRB, (2009) 4th edition. *Family Planning Saves Lives* Washington DC, USA.
48. Snijders, T. A. B. and R.J. Bosker (1999). An Introduction to Basic and Advanced Multilevel Modeling: Department of Statistics, University of Poone, P. 7. and Appendix: (2015) 'application of multilevel models on', (June).
49. Snijders, T. and Bosker, R. (1999). Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling. London/Thousand Oaks/ New Delhi: Sage Publications Statistical Association.
50. Tanner, M.A. (2011). Tools for Statistical Inference: Methods for the Exploration of Posterior Distributions and Likelihood Functions, New York: Springer-Verlag.
51. UNFPA (2016) The world population estimation: The world population report, Geneva, Switzerland.
52. Women, M. O. J. (2018) 'Current Situation of Utilization of Modern Family Planning Methods in Dhaka City'.

APPENDIXES

Appendix A: Result of Diagnostic Tests for Outliers and Influential Value for Standard Logistic regression analysis of women's family planning service utilization

	N	Minimum	Maximum	Mean	Std. Deviation
Analog of Cook's influence statistics	9824	.00000	.07971	.0035806	.00525727
Leverage value	9824	.00014	.01627	.0035660	.00196820
DFBETA for constant	9824	-.02856	.04086	.0000000	.00312771
DFBETA for age(1)	9824	-.00664	.00496	.0000001	.00106222
DFBETA for age(2)	9824	-.00499	.00301	.0000001	.00079586
DFBETA for region(1)	9824	-.01032	.00824	-.0000001	.00139542
DFBETA for region(2)	9824	-.01162	.01733	.0000003	.00160553
DFBETA for region(3)	9824	-.01079	.00772	.0000000	.00135072
DFBETA for region(4)	9824	-.01100	.00691	.0000000	.00126254
DFBETA for region(5)	9824	-.01238	.06008	.0000001	.00268766
DFBETA for region(6)	9824	-.01078	.00857	.0000000	.00137387
DFBETA for region(7)	9824	-.01085	.00766	.0000000	.00135798
DFBETA for region(8)	9824	-.01009	.00985	.0000000	.00145594
DFBETA for region(9)	9824	-.00956	.00946	.0000000	.00135954
DFBETA for region(10)	9824	-.00815	.00802	-.0000001	.00129638
DFBETA for residence(1)	9824	-.00535	.00545	.0000000	.00087834

DFBETA for religion(1)	9824	-.03659	.02436	-.0000001	.00203880
DFBETA for religion(2)	9824	-.03532	.02283	-.0000001	.00202163
DFBETA for religion(3)	9824	-.03659	.02316	-.0000001	.00203969
DFBETA for Ecstatus(1)	9824	-.00359	.00347	.0000000	.00074135
DFBETA for Ecstatus(2)	9824	-.00359	.00414	.0000000	.00082394
DFBETA fornolivingchld(1)	9824	-.00471	.01236	-.0000001	.00118911
DFBETA for nolivingchld(2)	9824	-.00363	.00495	.0000000	.00083427
DFBETA for nolivingchld(3)	9824	-.00301	.00382	.0000000	.00072682
DFBETA for knowledgeofFP(1)	9824	-.00539	.00862	.0000000	.00099058
DFBETA for visited(1)	9824	-.00233	.00175	.0000000	.00055811
DFBETA for edulevel(1)	9824	-.00620	.00596	.0000000	.00101579
DFBETA for edulevel(2)	9824	-.00567	.00460	.0000000	.00088702
DFBETA for Expmedia(1)	9824	-.00409	.00258	.0000000	.00065764
DFBETAfor desmorechld(1)	9824	-.01583	.01259	.0000000	.00140070
DFBETA for desmorechld(2)	9824	-.01615	.01345	.0000000	.00137513
DFBETA for woccup(1)	9824	-.01335	.01166	.0000000	.00138537
DFBETA for woccup(2)	9824	-.01272	.01209	.0000000	.00137857
DFBETA for hedulevel(1)	9824	-.00687	.00448	.0000000	.00090473
DFBETA for hedulevel(2)	9824	-.00467	.00450	.0000000	.00079055
DFBETA for hoccup(1)	**9824**	**-.00867**	**.01348**	**.0000000**	**.00139382**
DFBETA for hoccup(2)	**9824**	**-.00775**	**.00641**	**.0000000**	**.00094235**

Valid N (listwise)	**9824**				

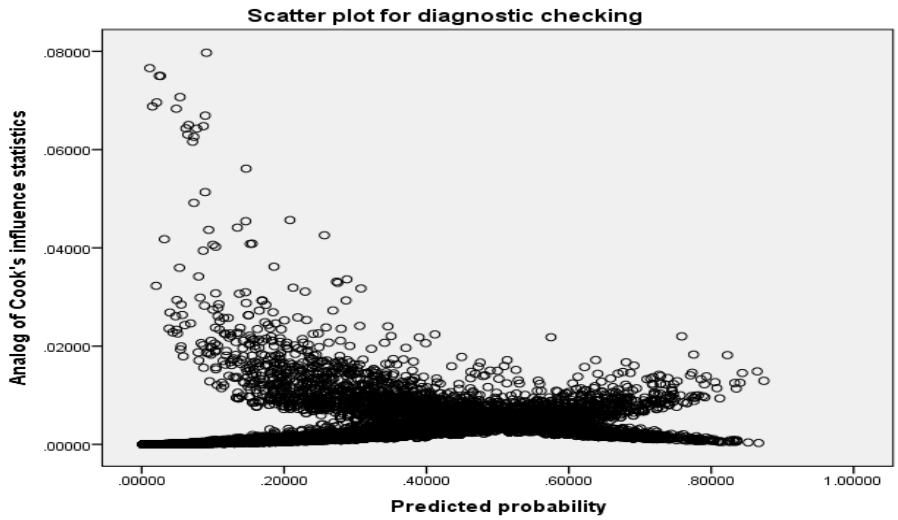


Figure 4. 2: Scatter Plots for Diagnostic Checking for cook's influence statistics

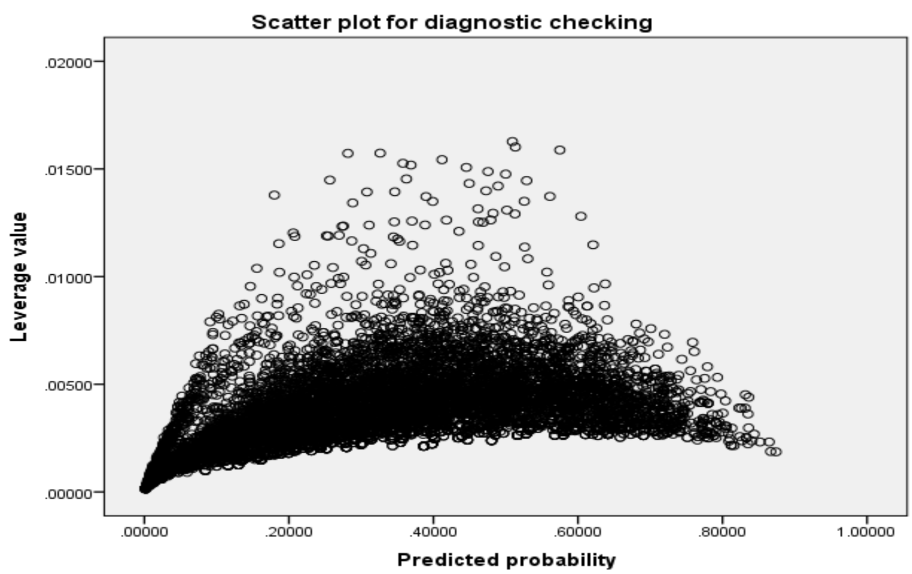


Figure 4. 3: Scatter Plots for Diagnostic Checking for leverage value

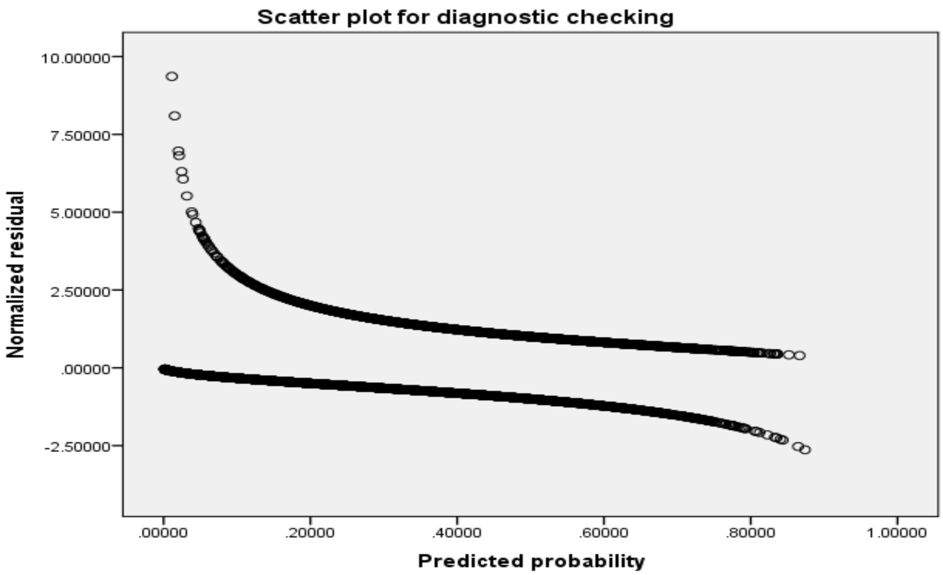


Figure 4. 4: Scatter Plots for Diagnostic Checking of leverage value

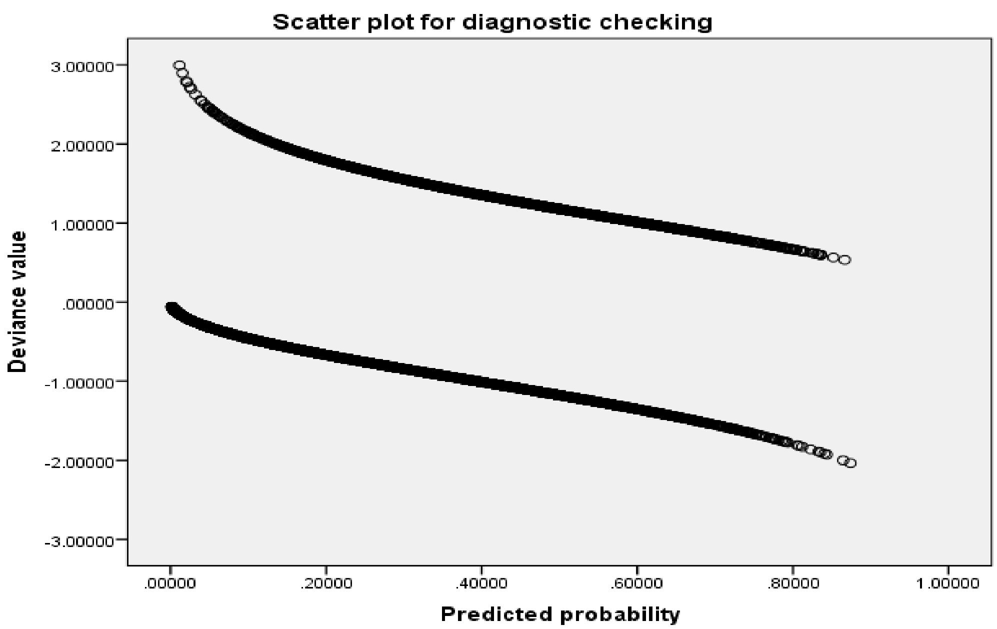
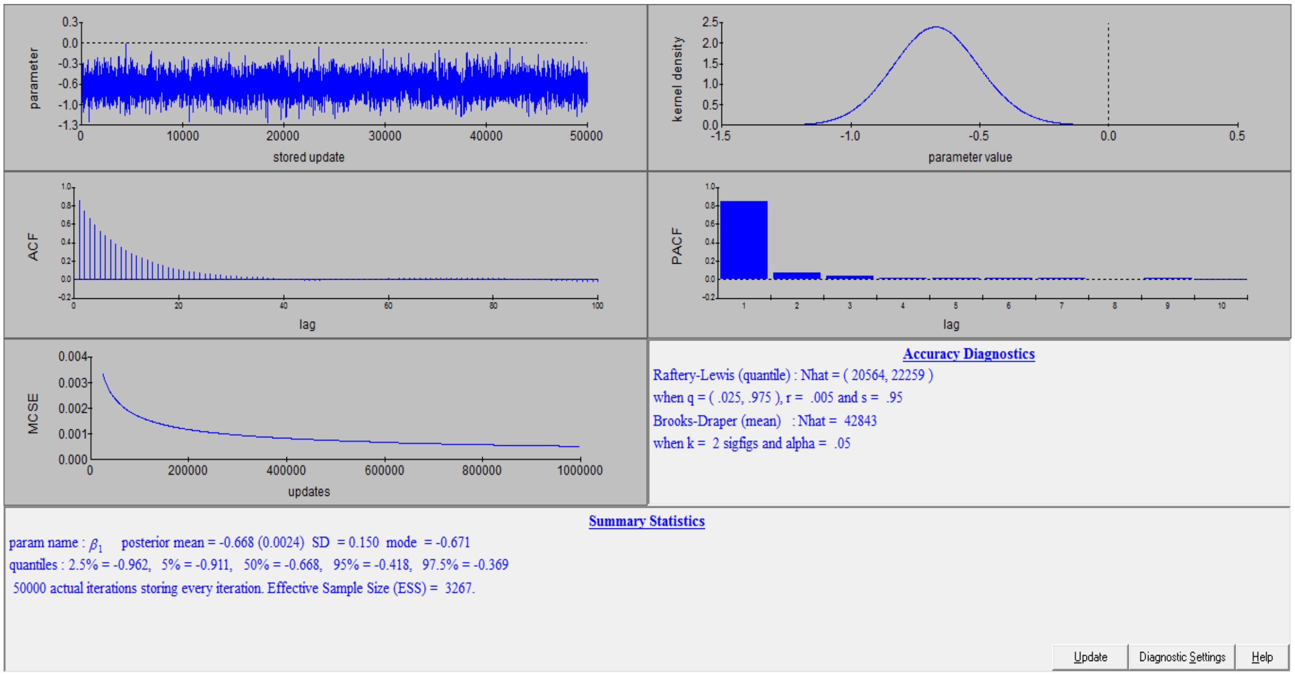
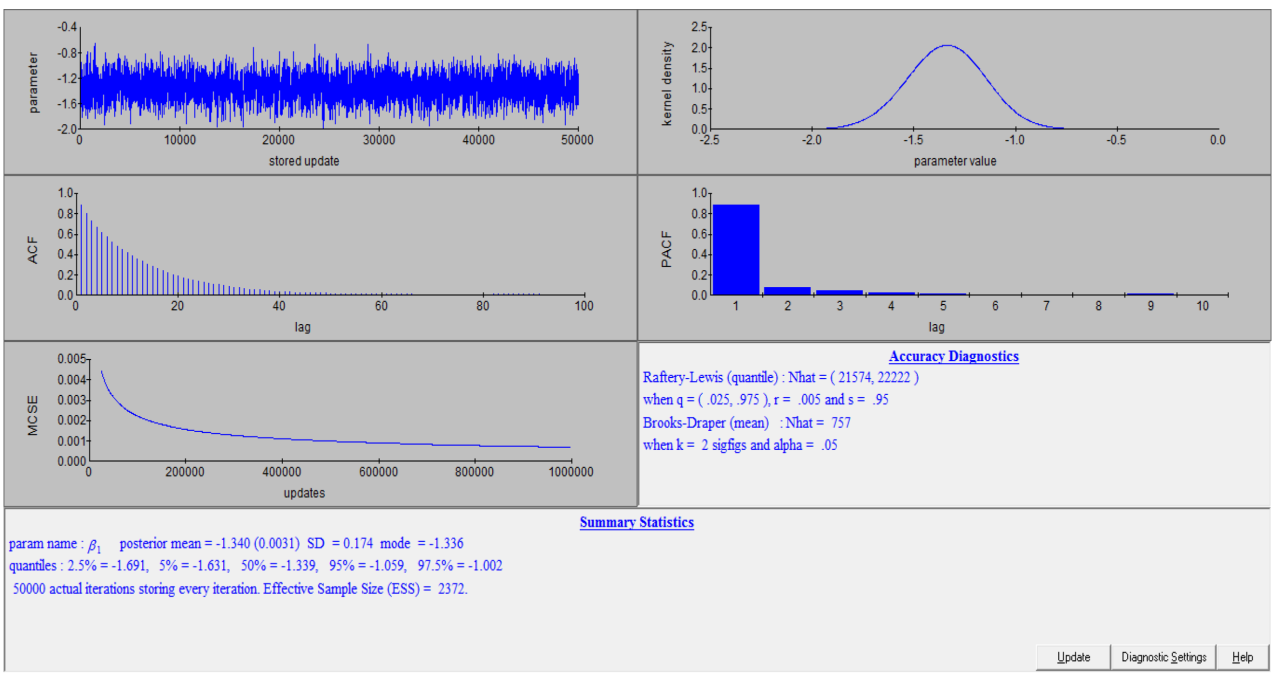


Figure 4. 5: Scatter Plots for Diagnostic Checking for Deviance value

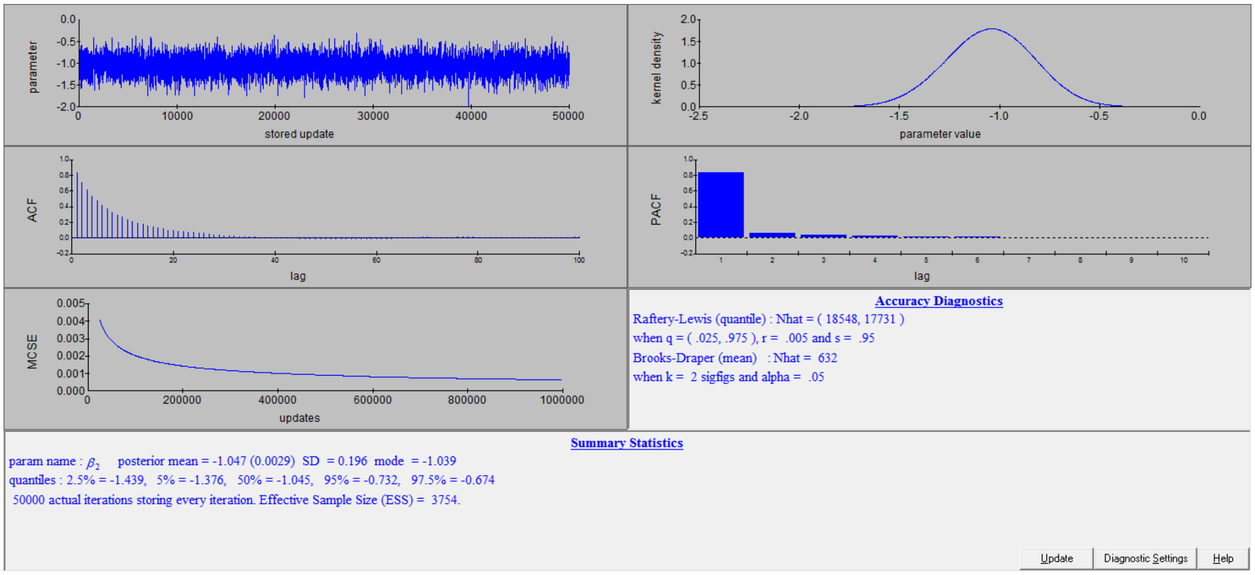
APPENDIX B: Assessment of model convergence



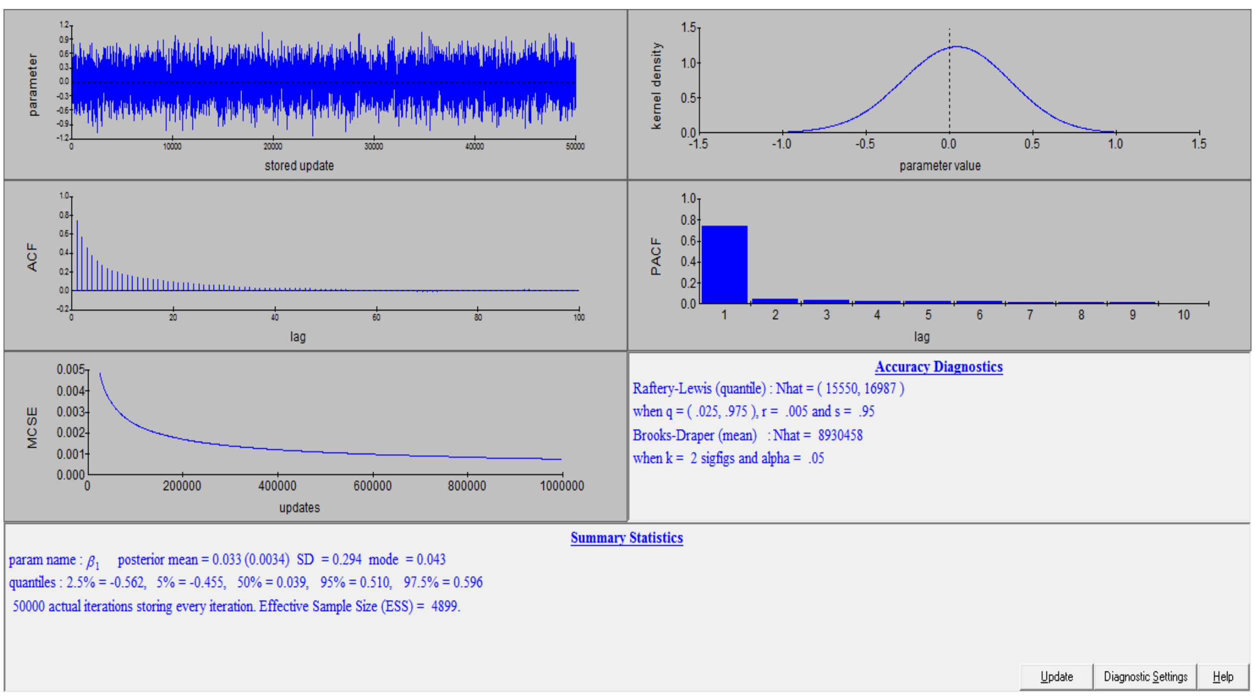
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for the coefficient of age



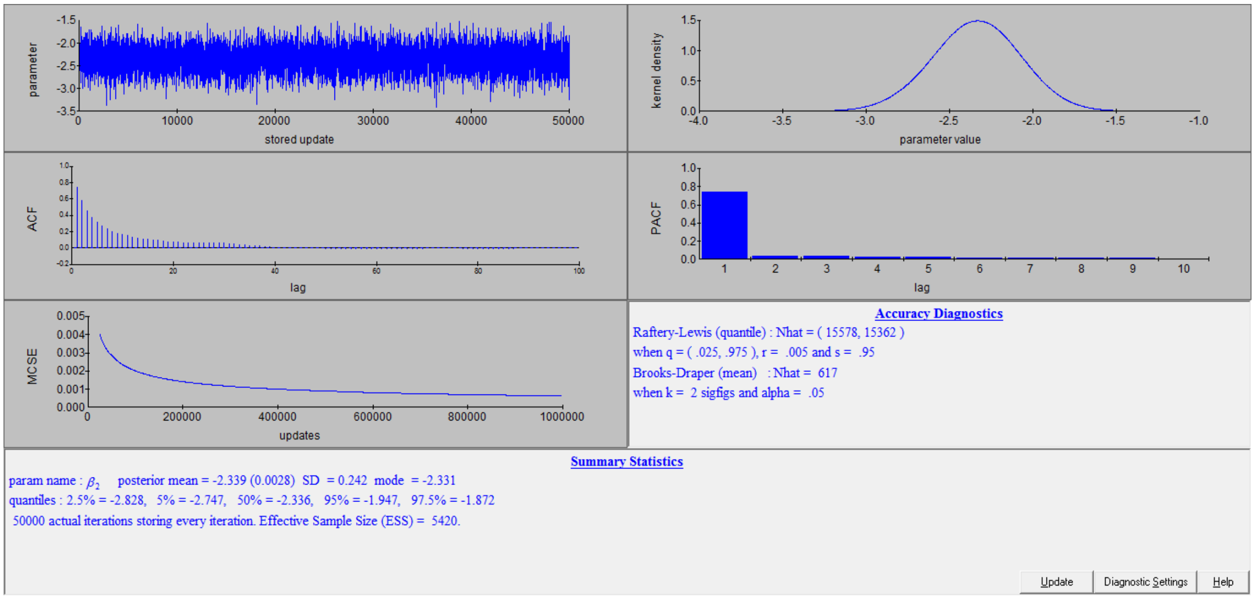
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for the coefficient residence



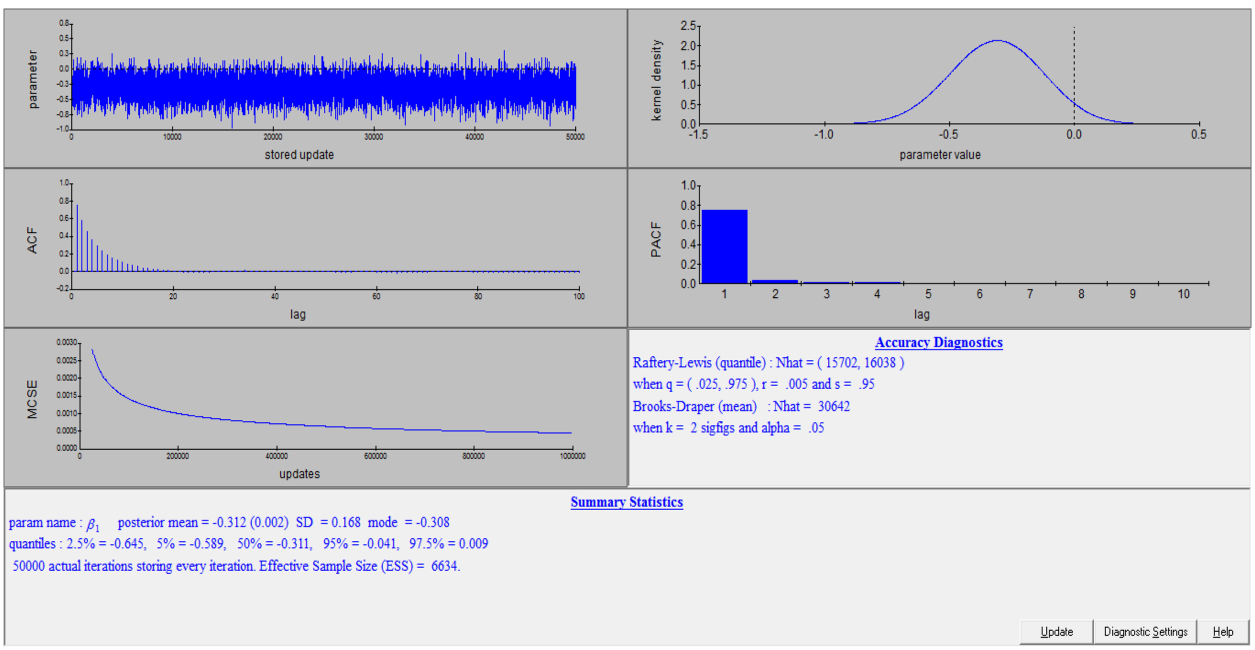
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for the coefficient of religion



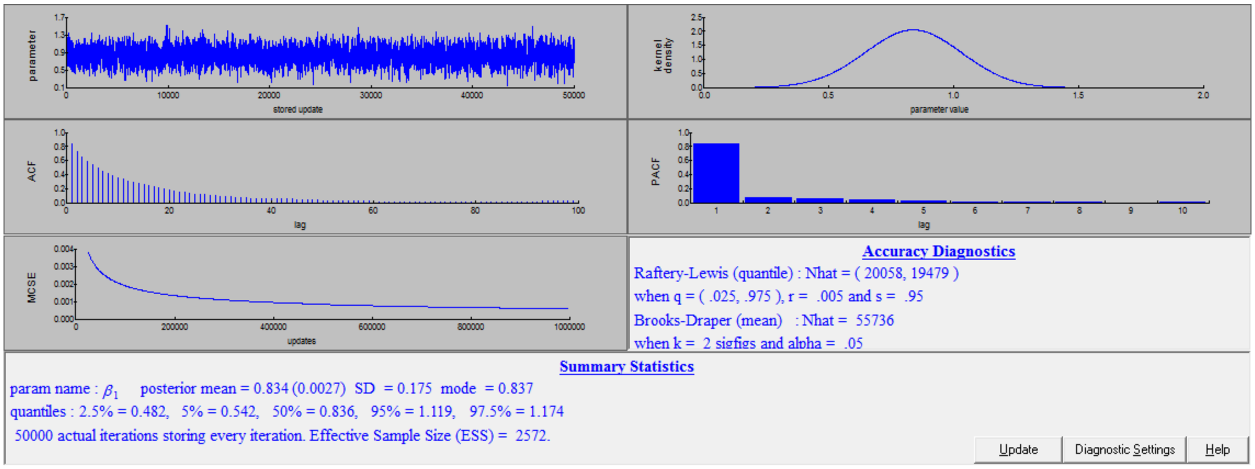
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for the coefficient of economic status



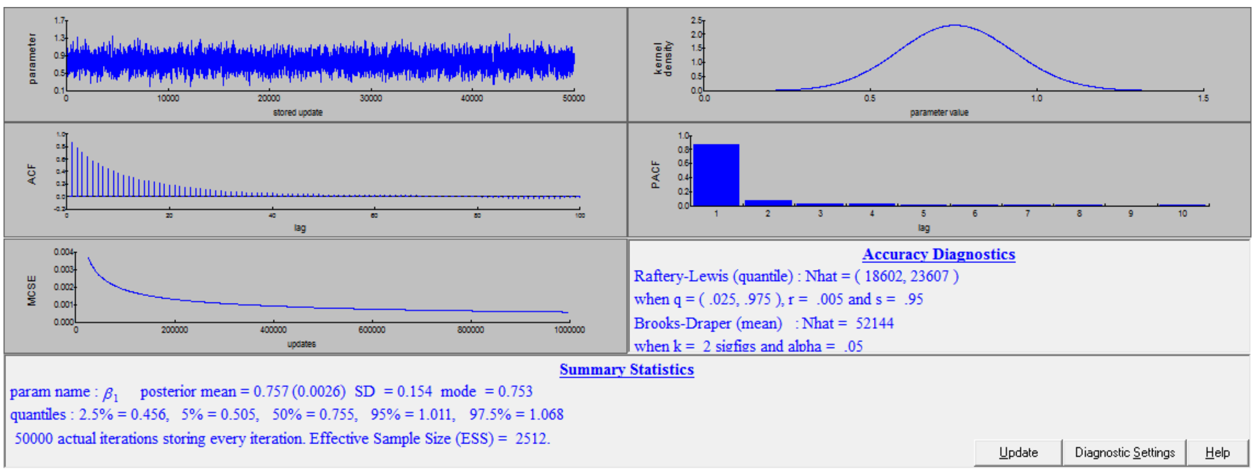
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for the coefficient of no living children



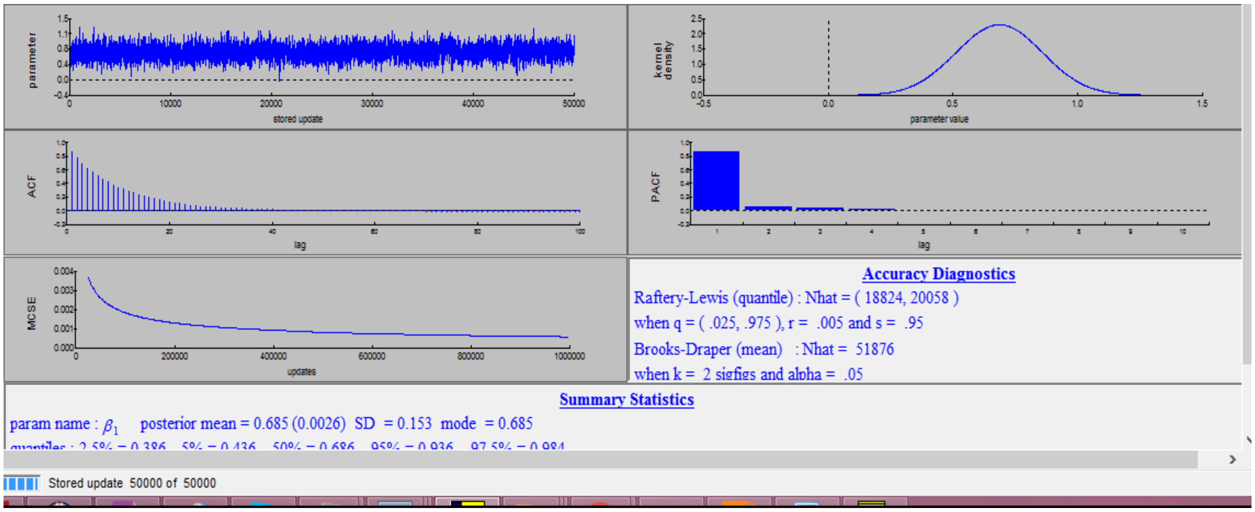
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of Visited by family planning worker



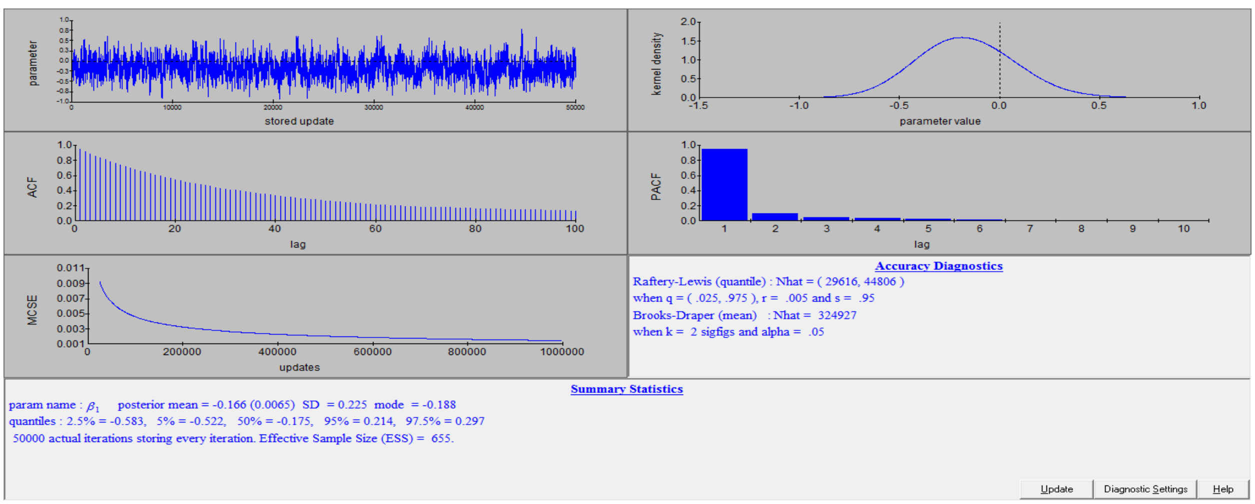
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of education level



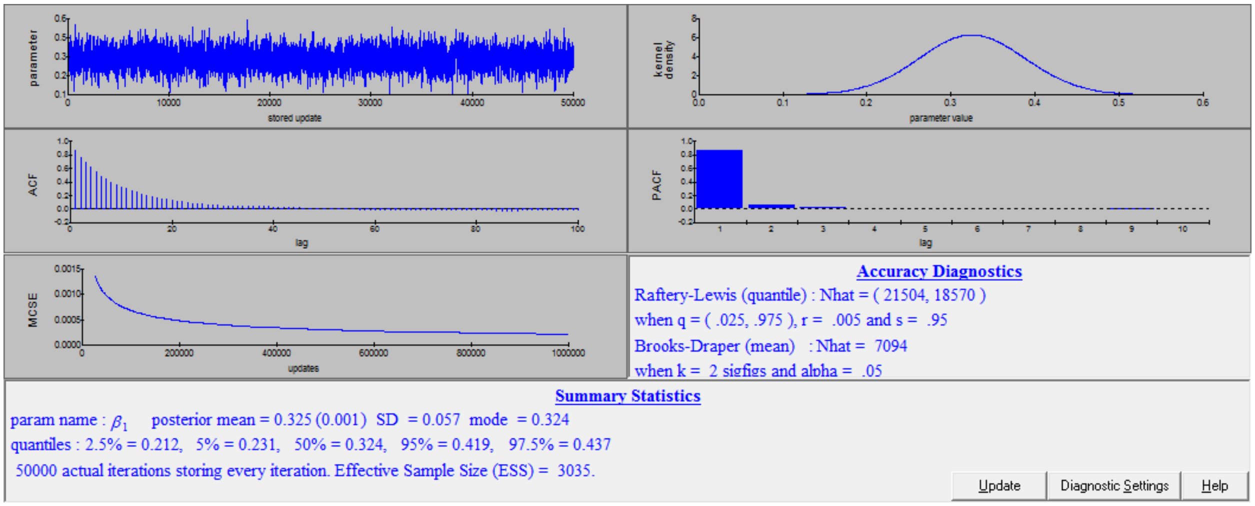
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of desire more children



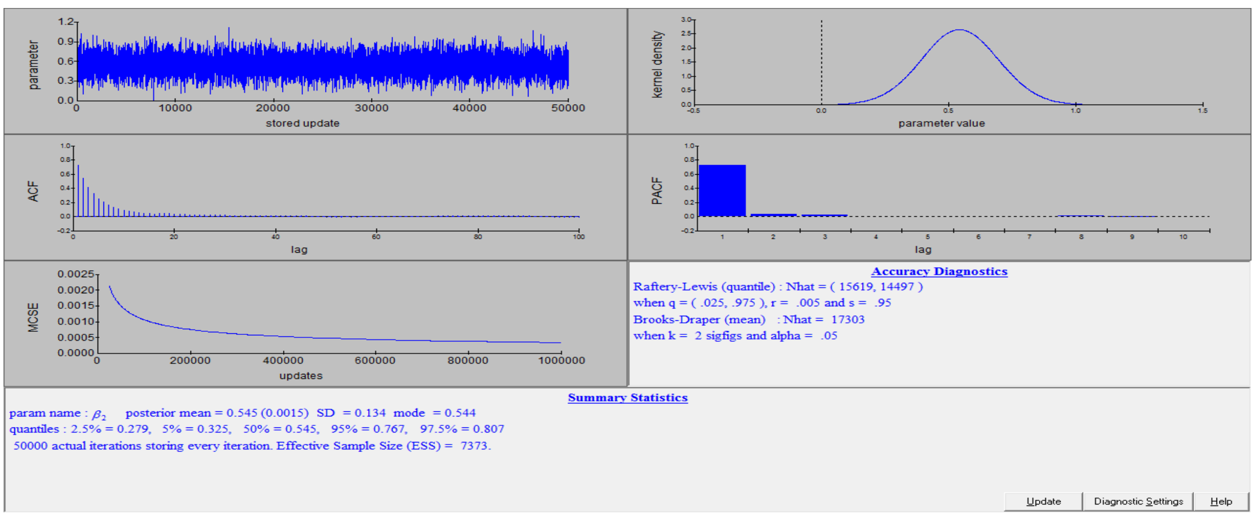
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of exposure to media



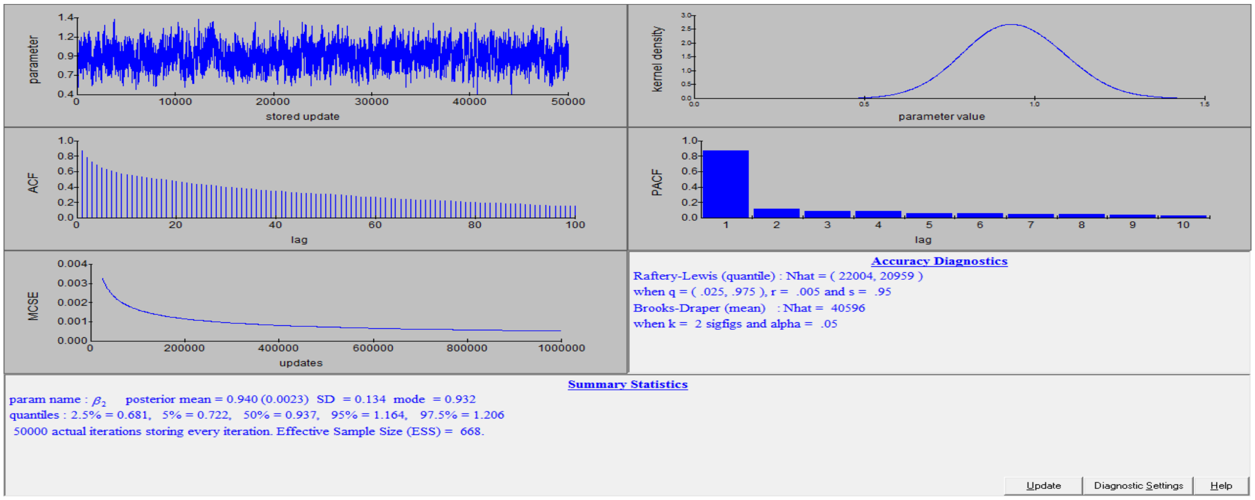
Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of husband education level



Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of woman occupation



Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of woman occupation



Convergence of trace plots, Gelman Rubin statistics, density plot and autocorrelation plot for coefficient of husband occupation

STATA COMMANDS

Stata commands of logistic regression.

logit fpuse i.age i.region i.residence i.edulevel i.religion i.Ecstatus i.nolivingchld i.knowledgeofFP i.desmorechld i.woccup i.visited i.Expmedia i.hedulevel i.hoccup,or

Stata commands of Empty multilevel logistic regression

xtmelogit fpuse || region:,cov(unstr)var

estimates stats it tells as AIC and BIC for empty multilevel logistic regression model

stata commands of random intercept multilevel logistic regression model

xtmelogit fpuse i.age i.residence i.edulevel i.religion i.Ecstatus i.nolivingchld i.knowledgeofFP

i.desmorechld i.woccup i.visited i.Expmedia i.hedulevel i.hoccup ,or women|| region:,cov(unstr)var

estimates stats it tells as AIC and BIC for random intercept multilevel logistic regression model

stata commands of random coeffient multilevel logistic regression model

xtmelogit fpuse i.age i. residence i.religion i. Ecstatus i. nolivingchld i. knowledgeofFP i. visited

i.edulevel i.Expmedia i.desmorechld i.woccup i.hedulevel i.hoccup,or|| reg: religion

Ecstatus,cov(unstr)var

estimates stats it tells as AIC and BIC for random coefficent multilevel logistic regression model

stata commands of bayesian logistic regression model

bayesmh fpuse i.age i.residence i.edulevel i.religion i.Ecstatus i.nolivingchld i.knowledgeofFP i.woccup

i.visited i.Expmedia i.desmorechld i.hedulevel i.hoccup,likelihood(logit) prior({fpuse:}, normal(0,100))