ADDIS ABABA UNIVERSITY
COLLEGE OF NATURAL SCIENCES
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A BAYESIAN ANALYSIS TO DETERMINE FACTORS INFLUENCING THE INTENTION NOT TO USE CONTRACEPTIVES AMONG SEXUALLY ACTIVE WOMEN IN ETHIOPIA

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This manuscript is in Memory of:

My Sister;
W/r Shitaye Sorissa
Lost her life during my study

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Abstract

There are several possible reasons why sexually active women may not intend to use contraception. These include lack of knowledge about contraception, lack of knowledge about where contraceptives can be obtained, difficulty in obtaining contraceptives, high cost of contraceptives, separation from husband, desire for more children, opposition to family planning, health concerns or worries about side effects, presumed infecundity and religious prohibitions. This study aims to identify factors that affect the intention not to use contraceptives among sexually active women in Ethiopia. The data used for this study come from 2005 Ethiopia Demographic and Health Survey (EDHS, 2005). We used Bayesian logistic regression model to model the effects of the covariates included. Inference is fully Bayesian based on Markov chain Monte Carlo techniques. These models allow us to analyze generalized linear effects of categorical covariates within a Bayesian framework for modeling and inference. The variables age of women, number of living children, place of residence, religion, educational level of women, knowledge of any method, ever use of contraceptive methods, heard contraceptive methods through radio and visited a health facility are found statistically significant. It is recommended that educational status and knowledge of a woman should be improved either through formal or through non-formal approaches; contraceptives information should be disseminated through media, and access to health facilities should be improved.

List of Abbreviations

AIDS= Acquired Immune Deficiency Syndrome

CSA= Central Statistical Agency

DHS= Demographic and Health Survey

EDHS=Ethiopian Demographic and Health Survey

ETR= Ethiopian Trend Report

HIV= Human Immunodeficiency Virus

MCMC=Markov Chain Monte Carlo

MH=Metropolis-Hastings

NASA=National Aeronautics and Space Administration

NGO= Non Government Organization

SNNPR= Southern Nation Nationalities and Peoples Region

SPSS=Statistical Package for Social Science

UN= United Nations

UNFPA= United Nation Population Fund

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Currently, the world population is growing by over 80 million people every year. Such a change is unprecedented. In 1800, the world's total population was less than 1 billion. However, it took approximately one century to reach 2 billion. Global population which stood at 2.5 billion in 1950 has risen to 6.9 billion today. According to the UN projections, by 2025 the world would contain over 9 billion people, of which some 6.8 billion would live in developing countries (UNFPA, 1996).

The total population of Africa was 967 million in 2008. In less than three decades the populations are projected to double. The total fertility rate for Africa is 4.9. This high fertility rate is highly contributed by Sub-Saharan Africa since the total fertility rate for sub-Saharan Africa is 5.4 (World Population Data Sheet, 2008).

Studies have shown that modern contraceptive practice is a primary determinant of fertility in developing countries. The fertility declines are largely attributable to the rapid increase in contraceptive use (Bongaarts et al., 1990).

A recent qualitative study conducted in rural Nepal indicated that poor knowledge and misconceptions are important reasons for low use of family planning (Sturley, 1998). On the whole, studies suggest that method-related problems are important reasons for contraceptive discontinuation and not intending to use. However, the relative importance of different method related problems varies from country to country.

Based on a study conducted in India and other developing countries the most commonly cited reasons for contraceptive discontinuation and not intending to use are quality, accessibility, cost of family planning services; side effects (either experienced by a woman herself or by other women she knows); fear of a particular method or health reasons for not using a method; desire for more children; a woman's perception that she is already sterile or in menopause; and resistance to family planning for religious or other reasons. Misconceptions about contraceptive use and a negative perception of the family planning programme are also sometimes mentioned as reasons for discontinuation and not intending to use contraceptives (Mishra et al., 1999).

A study on Contraceptive Intentions and Subsequent Behavior in Rural Bangladesh indicated that the reason for 69 percent of the women not to intend to use contraceptives is the need for more children. The distribution of the reasons differed between the two groups of women. Approximately 70 percent of the women who wanted to have more children did not intend to use contraceptive due to one of three reasons: husband's objection, religious reasons, or the desire for more children. Of the remaining 30 percent, nearly half did not intend to use contraceptive because they were newly married, and due to other reason understandable in a culture in which the in-laws and husband expect the newly married woman to present them with a child (preferably a male) as fast as possible. Among the remaining, women's personal distate for contraception prevented nearly half from intend to use. Among women who did not desire more children, advanced age (denoting sub fecundity or infertility) was the reason posited by 50 percent for not intending to use contraceptive. Twenty percent listed the husband's objection, about 12 percent gave religious reasons, and approximately 10 percent said no for reasons of health. Some 3 percent were dissuaded from future use because of having experienced side effects (Bhatia, 1982).

A study in Nigeria in 1998 showed that 35% of married women of the reproductive age who were not intending to use family planning reported that they were not intending to use contraception because they themselves or someone they knew had encountered a method-related problem or had fears associated with the use of contraception. In the same study, another 31% of the women reported that their husbands were opposed to family planning (Fakeye and Babaniyi, 1989). In examining religious beliefs about contraception among Muslims and beliefs about the possible health hazards of oral contraceptives, El-Islam et al. (1988) found that religious beliefs and beliefs about health risks are mutually reinforcing.

Ethiopia is one of the sub-Saharan countries and the second populous country in Africa with a population of 77,812,236 in 2010 next to Nigeria. In Ethiopia, total fertility rate did not show any marked decline between the mid 1950s and mid 1980s (UN, 1994). Since the late 1980s the fertility rate began to decline from 6.4 children per woman in 1990 (CSA, 1993) to 5.9 births in 2000 (EDHS, 2000), and it further declined to 5.4 in 2005 (EDHS, 2005). The growth rate is 2.6 percent and the projected population in 2025 and 2050 are 107.8 and 144.7 million people, respectively.

In Ethiopia, modern contraception was introduced in 1966 by Family Guidance Association of Ethiopia (FGAE), which is a non-governmental and non-profit organization established to provide information, counseling and clinical services to families who want to space the birth of their children (Antenane, 1997). Before 1980, family planning services were not provided in government health facilities. Until recently, FGAE was the only NGO offering family planning information and services (Assefa et al., 2006). At present, family planning services are provided through government and NGO service outlets, including hospitals, health centers, health posts, and community based distribution and social marketing.

Although contraceptives have been provided for a prolonged time, contraceptive prevalence has not reached a level whereby it will have an impact on fertility. This was mainly attributed to the service delivery system which was carried out through the network of general health facilities that are available mostly in urban or semi-urban communities and the bulk of rural population remained without access to family planning services (Assefa et al., 2006). The recent EDHS conducted in 2005 revealed that contraceptive prevalence was only 14.7 % (47% in urban and 11% in rural areas).

Further demographic projections reveal that women in the reproductive age group (15-49 years) constitute 23.9% of the total population while 42.9% of the population was less than 15 years in 2006. This skewed age structure towards the young indicates the high potential for an accelerated population growth and heavy demand for all types of health services especially for reproductive and maternal health services. Identification of the reason behind not practice contraceptive is one of best options.

Based on EDHS report of 2005 there are several possible reasons why currently married women may not use and may not intend to use contraception in the future. These include lack of knowledge about contraception, lack of knowledge of a source where contraceptives can be obtained, difficulty in obtaining contraceptives, high cost of contraceptives, separation from husband, desire for more children, opposition to family planning, health concerns or worries about side effects and presumed infecundity.

1.2 Statement of the Problem

Contraceptive demand is a reflection of the desires or expectations of women in need of contraception and encompasses actual use and potential/latent need to use contraception. The gap between current contraceptive prevalence and demand remains unfilled (Casterline and Sinding, 2000). While the literature on contraceptive prevalence and unmet need is extensive, rather little is known on how to estimate directly contraceptive demand. The study of unmet need was initially thought to fill this gap but this is not the case. There is therefore a need to have a direct measure of contraceptive demand. To do this, researchers have argued that one needs to understand how intention to use contraception influences future use (Ross and William, 2001).

Not intending to use contraceptives is the immediate cause for not using contraceptives, and the root cause for unwanted pregnancy, unwanted birth, population growth, un-safe abortion, problems on maternal and child health. These factors are significant contributors to poverty, hunger, crime and impediment to development.

This study focuses on the effect of demographic, socio-economic, knowledge, information and practice of contraceptives on not intending to use contraceptives among sexually active women in Ethiopia. The statistical analysis in this thesis is based on modern Bayesian approaches, which allow a flexible framework for realistically complex models. These models allow us to analyze Bayesian logistic regression for modeling and inference.

1.3 Objectives of the Study

The general objective of the study is to identify factors why sexually active (15-49) women are not intending to use contraceptives in Ethiopia.

The Specific Objectives of the Study are:

- To examine factors that affect the intention not to use contraceptives among sexually active women in Ethiopia.
- To examine correlates of the intention not to use contraceptives with explanatory variables.
- To identify factors which affect the intention not to use contraceptives using Bayesian logistic regression.

1.4 Significance of the Study

This study develops behavioral model that is intention to use contraceptives as an alternative to the traditional analysis of factors affecting the use or nonuse of contraception. Realizing the effect of demographic, social, economic, knowledge and other factors on the intention to use contraceptives is one way of predicting human behavior on using contraceptives or not. This attracted the attention of major demographers, researchers and policy makers when they attempted to base their estimates of future fertility and population.

1.5 Limitations of the Study

- Some important predictor variables are not included in the model due to high missing values.
- There is lack of literature about the situation in our country related to the subject under study.
- There are no materials from which Bayesian prior information can be obtained.
- The study focused on behavior /intention (quantitative approach) to use contraceptive methods; qualitative method is not used.

1.6 Definition of Terms

Contraception/family planning-the intentional prevention of conception by artificial or natural means

Fecundity- is the monthly probability of conception.

Unmet need-refers to the contraceptive needs of currently married, fecund and non-pregnant women who intend to limit or space pregnancy but not practicing.

Limiters- refers to currently married, fecund and non pregnant women who do not want any more children.

Spacers- refers to currently married, fecund and non pregnant women who want to delay their next birth at least for two years.

Fertility- the ability to conceive and have children, the ability to become pregnant through normal sexual activity.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 General

According to a study in India in 1992–93 some seven demographic and socioeconomic characteristics have effect on reasons for not intending to use contraception in the future. The response variable (reasons for not intending to use contraception in the future) is grouped into four broad categories: desire for more children, cannot have children, method problem, and opposition to family planning using multivariate analysis. Since wanting more children and intending to use contraception in the future (after having the desired number of children) are compatible, some of the respondents who supplied these answers may have effectively evaded the question on reasons for not intending to use contraception in the future (Mishra et al., 1999).

In Pakistan, Carton and Agha (2009) examined intentions to use family planning in the future using Principal components analysis and Multinomial logistic regression analysis. The authors found that a woman's intentions to use family planning increased by 31% if her husband approved of family planning, and her intentions to use family planning were higher if a family planning facility was less than 30 minutes away. Sirageldin et al. (1975) concluded that while latent demand for family planning existed, cultural and social constraints such as husband's approval prevented this demand from being converted into family planning use. A study by Agha (2010) indicated that the supply of information and services was too weak to catalyze latent demand into the use of family planning and that the program delivery system was seriously inadequate.

Intention to use contraception in the future provides a forecast of potential demand for family planning services and represents a summary indicator of attitudes toward contraception among current nonusers (Indonesia DHS, 2002/03).

Even though intentions to use contraceptives are conceptually very important, few studies have looked at predictors of contraceptive intentions. A rare study re-interviewed married women from the 1992 Moroccan DHS in 1995 and examined the predictive effect of contraceptive use intentions on contraceptive use three years later. Reported contraceptive use intentions in 1992 had strong predictive effect on contraceptive use in 1995, even after controlling for a range of factors. The strength of this effect was second only to that of previous contraceptive use. Moreover, those women who reported intentions to use contraception in 1992 but were not using a method in 1995 had an unmet need for contraception (Curtis et al., 1996).

Although the assumption is often made that women who intend to use contraceptives will use them in the future, few studies have examined whether contraceptive intentions are, in fact, translated into behavior. One reason for the scarcity of studies concerning this issue is the lack of suitable data. Most fertility surveys in developing countries are cross-sectional in design, whereas longitudinal data from individual respondents are required to evaluate the predictive validity of contraceptive intentions. In 1995, the Demographic and Health Surveys (DHS) project conducted a panel survey in Morocco using a subsample of respondents from the 1992 Morocco DHS. This panel survey provides longitudinal data on respondents that allow reported contraceptive behavior during the period 1992-95 to be related to stated contraceptives intentions in 1992 (Curtis et al., 1996).

Based on a study using logistic regression in Ghana (Mutisya, 2007) women who expressed the need for contraception were more likely to use a method than those who did not. This is because intention to practice contraception is an expression of the need to adopt a method at the right and convenient time. Developing intention is therefore a process that leads women to use contraceptives, and women who express the need must have thought about it. Moreover, intention to use contraceptives is an implication for behavioral change towards using contraceptives for women in the reproductive age group. It reflects acceptability of family planning methods to limit or space their family size.

In the study on intention to use contraception, we can estimate unmet needs as well as estimate the demand for contraception, since intention to use and unmet need are known to overlap (Roy et al., 2003). To bridge this gap, and to understand how to fulfill unmet needs, it is salient to have empirical evidence of how contraceptive intention influences future contraceptive use. Thus, the relationship between contraceptive intention and unmet need is an important one, since it determines which family planning programmes needs to target (Mutisya, 2007).

Based on a study in Ghana using multivariate logistic regression, contraceptive use is known to mediate between fertility intention and subsequent fertility behavior, which in turn influence contraceptive intention. Thus, such competing intentions are important in that change of fertility intention can be used to determine contraceptive intention and subsequent use (Mutisya, 2007).

2.2 Demographic Factors

Among the widely studied variables that determine not intending to use contraceptives are demographic variables. These variables among others include age of women and number of living children.

Based on a study conducted in Kenya using logistic regression analysis (Njogu, 1991), it has been observed that women are less likely to use contraceptives at the youngest and oldest ages of the reproductive life span. This pattern is interpreted partly as it may reflect desire for more children among young women, and effects of declining frequency of intercourse, perception of low risk of becoming pregnant or traditional views that favor large families at old ages. A number of studies show that age is an important determinant of contraceptive use.

Based on a study conducted in Ghana on intention to use contraceptives using logistic regression, women aged 27 to 36 years have a higher likelihood of adopting a contraceptive method than those aged 17 to 26 and 37 to 47 (Mutisya, 2007).

Based on knowledge, attitude and practice (KAP) study on contraceptive intentions and subsequent behavior in rural Bangladesh, when family planning services are made available, the initial acceptors are mainly women who have achieved their desired family size, and therefore tend to be relatively older and of higher parity. The percentage of use rises with age; the prevalence of use reached a peak of 31 per 100 married women aged 35 years and over (Bhatia, 1982).

According to the study made in Kenya using logistic regression, the number of living children is one of the factors for not intending to use contraceptive method. Large number of living children encourages couples to space or limit the fertility. That means the likelihood of wanting no more children increases with the actual number of living children. The intention to use contraceptives increase as couples have large family size. Moses and Khasakhala (2006) in their study indicated that couples who have more children are more likely to intend to use contraceptives than those who have fewer children or none at all. A similar study in Mali (Bongaarts et al., 1990) indicated that the intention among non-users to start contraception rose from 7.7 percent for those with no children to 14.7 percent for those with four surviving children.

According to a study conducted in Ghana on intention to use contraceptives using logistic regression, contraceptive use increases with increasing number of living children. Women with more than three living children are twice more likely to adopt a method than those with three or less children (Mutisya, 2007). In rural Bangladesh, the prevalence of use increased consistently with the increase in the number of surviving children, from 3 per 100 childless women up to 34 per 100 mothers of five or more surviving children. The trend was similar when prevalence rates were calculated by number of surviving sons (Bhatia, 1982).

According to the 2005 EDHS report, 18% cited the desire for as many children as possible as the main reason for not intending to use contraceptives. The proportion of women who cited desire for more children has dropped markedly from 42% in 2000 to 18% in 2005, suggesting that women are realizing the disadvantages of large family sizes.

2.3 Socio-economic Factors

Among the widely studied factors that determine not intending to use contraceptives are socio-economic factors. These factors include, among others, region, place of residence, religion, educational level of women and occupation of women.

Not intending to use contraception differs by place of residence. It is suggested that the larger proportion of potential spacers and limiters are residing in rural areas, as there would be poor means of transportation and less access to a range of family planning services than couples in urban areas. Due to this, the contraceptive prevalence rate in rural areas tends to be very low. There is a significant variation in the use of contraception by place of residence. Thus, use of modern family planning is about four times higher in urban than in rural areas (42% versus 11%) (EDHS, 2005). And also the unmet need for contraception among women in rural areas is higher (36%) than in urban areas (17%). Urban women usually have better access than do rural women to contraception, to information about contraception, and to healthcare providers in case they have a problem when using contraception. For these reasons, urban or rural residence is likely to affect intentions to use contraception.

According to a study in India using multivariate logistic regression, contraceptive use and method choice vary by religion. Muslims are less likely to use contraception than are Hindus. If they use contraception, their choice is temporary method than Hindus. Additionally, if they do not use contraception, they are more likely than Hindus to give religious opposition as the reason (Mishra et al., 1999).

The roles of religion and culture as determinants of fertility have been a subject of considerable discussion in fertility literatures. Every social group has a characteristic culture, complex of belief, attitudes, values and social controls. The cultural and religious background of a given community has a powerful effect on health seeking behavior in general, and contraceptive use in particular. The strongest opposition of contraceptive use comes from the Catholic Church, which prohibits utilization of artificial contraception in the 1930s, and followed by Islam (Hailemariam et al., 2000).

A study conducted in Bangladesh using multivariate analysis revealed that the percentage of current users of contraceptive methods among Muslims was significantly lower than their non-Muslim counterparts (30.2% and 36.3%, respectively) (Shahid and Chakroborty, 1993).

In the study conducted among women of reproductive age group in Zimbabwe using logistic regression analysis, modern contraceptive use and fertility regulation have significant association with increased educational attainment, although at low level of education (less than 6 years) there was no clear association between education and use of modern contraception. It was reported among women who have completed primary school (seven years of education) that the powerful effect of education becomes apparent. Women who have completed secondary school and above were about twice as likely to use modern contraceptive methods as women who did not complete primary schooling (World Bank,1995).

The power differentials, conflicting gender roles and lack of economic resources prevent many women from effectively negotiating contraceptive use and safer sex practices with their male partners. Women are either under collective decision-making with their husbands or completely rely on the husbands' decision on issues that affect their reproductive life. Despite this fact, global efforts to control rapid population growth targeted women for family planning. Instead of trying to win men's cooperation, many family planning programs have seen men as obstacles to women's contraception use or portrayed as irresponsible adversaries. This fact is considered as one of the major reasons for failure of African based family planning programs (Shah and Radovanovic, 1998).

2.4 Knowledge, Information and Practice of Contraceptive Methods

Various studies have identified knowledge, information and practice of contraceptives as influential in not intending to use contraceptives. These variables include, among others, knowledge of any contraceptive methods, ever use of contraceptive methods, lessons on contraceptives in the media and exposure to family planning services.

To use contraception, women must not only know about the existence of contraception itself, but also what services are offered, where and when. Studies have shown that the more women find contraception to be available, the more likely they intend to use (Population Info., 1996).

Lack of knowledge is an important cause for not intending to use contraceptives. Couples are considered to have acceptable knowledge of method if they can describe whether they have ever heard of a method that a couple can use to delay or avoid pregnancy, but does not imply respondents knowledge on how it is used, its main side effects, and where it can be obtained. Studies conducted in 13 countries by using DHS data depicted that the most important reasons for non-users is lack of knowledge (Bongaarts and Bruce, 1995).

According to a study using logistic regression by Bongaarts and Bruce (1995), if a couple knows types of contraceptive methods and the source then their intention to use increases. There would be a direct relationship between the availability of the method and the prevalence of its use. A study conducted in 10 countries suggested that contraceptive prevalence declines as distance to family planning facilities lengthens (Bongaarts and Bruce, 1995). On the other hand, it indicates that the level of unmet need rises as distance from the source of contraceptive methods increases.

Disseminating information through the mass media increases awareness about new technologies, ideas on specific things and so on. Indeed, broadcast through the radio and television, and printed materials such as newspapers, leaflets may bring change in individual's attitude towards accepting modern life style. In particular, they can serve to disseminate information on family planning. Having information and knowledge about modern contraceptive methods is mandatory to utilize the service. In most developing countries, especially in Sub-Saharan Africa, promoting family planning through radio and television is an important means of raising awareness, improving knowledge, and motivating use of modern contraceptive methods (ETR, 2007). In most countries, regular exposure to mass media has a positive effect on intention to use contraceptive.

A cross sectional study conducted in Kenya, Uganda, Mauritius, Swaziland and Zambia identified that a high proportion of women (74.3%) who belonged to various clubs and associations that discussed health related topics were knowledgeable and contraceptive users, which indicated that information exchanges through discussion in such organization increase their intention for contraceptives (Kaona et al., 1996).

According to the result obtained from the household survey of Uganda conducted in 1995 and 1999, the exposure to BBC message in the media was found to be strongly associated with current use of a modern contraceptive method and with the intention to use a method in the near future among non users (Gupta et al., 2003).

Recently, there is increasing evidence of the role of diffusion of values and ideas on contraception through social networking and interaction. The study conducted in Ghana using longitudinal analysis shows an increase in contraceptive use among women who discuss contraception with their peers, husbands/partners or in their social groupings (Soldan, 2004). Furthermore, it is noted that the effect of social networking seems more pronounced in communities with high fertility rate, where it influences the need to adopt a method among the non-users. Individuals do not make decisions in isolation but through interacting with one another (Behrman et al., 2002). The rationale is that positive social interaction serves as an encouragement and shows tolerance of the intended behavior in the community, which in turn builds confidence among those with intentions. The implication of this is a higher adherence rate to stated intention in that community if contraception is socially acceptable (Bawah, 2002).

According to the study conducted using logistic regression analysis in United States of America, one important factor that stimulates adherence to stated intention is past behavior and experience (Williams et al., 1999). Studies have shown that past contraceptive users are more likely to adopt than those without prior knowledge on use, with one study concluding that women with unmet need lacked prior knowledge of contraception (Curtis et al., 1996). This is because past users are knowledgeable about different types of contraception; know the advantages and disadvantages of contraceptive methods; and are likely to state firm intentions to which the probability of adhering is high. Other studies have supported this finding, indicating that method adoption is likely to ensue when intentions are held with greater conviction (Schoen et al., 1999).

The study on factors influencing contraceptive methods choice in Nepal indicated that there was a significant relationship between contraceptive method choice and family planning worker's visit. Women were more likely to use contraception when they were exposed to family field workers especially for women who use pills and injectables (Rana, 2002).

CHAPTER THREE

3. SOURCE OF DATA AND METHODOLOGY

3.1 Source of Data

This study uses data from the 2005 Ethiopia Demographic and Health Survey (EDHS, 2005). It was conducted under the auspices of the Ministry of Health and implemented by the then Population and Housing Census Commission Office (PHCCO), now merged with the Central Statistical Agency (CSA).

The 2005 EDHS collected information on the population and health situation, covering topics on family planning, fertility levels and determinants, fertility preferences, infant, child, adult and maternal mortality, maternal and child health, nutrition, malaria, women's empowerment, and knowledge of HIV/AIDS. In addition, the EDHS includes population estimates of HIV and anemia prevalence in the country. Key indicators relating to each of the above topics are provided for the nine regional states and two city administrations. In addition, data are also provided by urban and rural residence for the country.

3.2 Sample Design

The 2005 EDHS sample was designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole; urban and rural areas of Ethiopia (each as a separate domain); and 11 geographic areas (9 regions and 2 city administrations). In general, a DHS sample is stratified, clustered and selected in two stages. A representative sample of approximately 14,500 households from 540 clusters was selected. The sample was selected in two stages. In the first stage, 540 clusters (145 urban and 395 rural) were selected from the list of enumeration areas (EA) from the 1994 Population and Housing Census sample frame. As part of the second stage, a complete household listing was carried out in each selected cluster. Then, between 24 and 32 households from each cluster were then systematically selected for participation in the survey.

The survey collected information from 14,070 women age 15-49 years. For this study, the final sample size was reduced to 11,443 after missing cases were excluded.

3.3 Operational Definition of the Variables

3.3.1 The Response variable

The intention to use contraceptives is expressed as the women who were intending to use any contraceptive methods to avoid pregnancies during the time of data collection. Women who were not intending to use contraceptives are categorized as 1 and those who intend to use categorized as 0.

$$Y_i = \begin{cases} 1, & \text{if the } i^{th} \text{ individual is not intending to use contraceptives} \\ 0, & \text{otherwise} \end{cases}$$

3.3.2 The Predictor variables

Demographic variables

- Age of women

It refers to the current age of women in a complete year at the time of the survey. The age of women are classified into three categories: 15 to 24, 25 to 34 and 35 to 49.

- Number of living children

It refers to the total number of living children of the women at the time of the survey. It is categorized into three groups: no children, one or two children and three or more children.

Socio-economic Variables

- Region

Ethiopia is administratively structured in nine regional states, namely, Tigray, Afar, Amhara, Oromia, Somali, Ben-gumuz, SNNPR, Gambela, Harari and two city administrations, that is, Dire Dawa, and Addis Ababa. Therefore, region refers to the region where the women live at the time of conducting the survey.

- Place of residence

It refers to the women's place of residence at the time of the survey as urban or rural area.

- Religion

It refers to the religion the women follow during the time of the survey. It is classified into four main classes: Coptic Orthodox, Muslim, Protestant, and Others.

- Educational level of women

It refers to the highest level of education in completed years that the woman has attended in the formal education. It is categorized into three levels: no education, Primary, and Secondary and above.

- Occupation of women

It refers to the activities in which the women were engaged at the time of conducting the survey. These activities can be categorized into three groups: not working, agricultural work, and others.

Knowledge, Information and Practice of contraceptives

- Knowledge of contraceptive methods

It refers to knowledge of contraceptive method of a woman at the time of the survey. It is categorized into two: knows modern methods or knows no methods.

- Ever use of contraceptive methods

It refers to women who ever used any contraceptive methods at the time of the survey. It is categorized into two: used modern methods and never used.

- Heard about contraceptive methods in the last months

It refers to women who had heard about contraceptive information through radio broadcasting in the last months prior to the interview. It is categorized into two: those who heard and not.

- Visited a health facility in the last 12 months

It refers to women who had visited a health facility in the last twelve months prior to the survey. It is categorized into two: those who visited and not.

Table 3.1 Summarized operational definition and level of measurement of dependent and predictor variables

iables	Variables representation	Operational Definitions	Level	Coding	Scale of measurement
endent Variable					
ntion to use traceptive	Y[]	Women who were intending to use any contraceptive methods	Use later	0	Nominal
			Does not intend to use	1	
dictor Variables					
e of women	X1[]	The current age of women (in complete years) at the time of the survey	35-49	3	Ordinal
			25-34	2	
			15-24	1(ref)	
nber of living dren	X2[]	The total number of living children that the women had	Three or more children	3	Ordinal
			One up to two children	2	
			No children	1(ref)	
ion	X3[]	The region where the women live	Tigray	11	Nominal
			Dire Dawa	10	
			Harari	9	
			Gambela	8	
			SNNPR	7	
			Ben-gumuz	6	
			Somali	5	
			Oromia	4	
			Amhara	3	
			Afar	2	
			Addis Ababa	1(ref)	
ce of residence	X4[]	The place where the women was living	Urban	1	Nominal
			Rural	0(ref)	
igion	X5[]	The religion the women follow	Protestant	3	Nominal
			Muslim	2	
			Coptic Orthodox	1(ref)	
cational level vomen	X6[]	The highest level of education that the women had attended	Secondary and above	3	Ordinal
			Primary	2	
			No education	1(ref)	
upation of nen	X7[]	The activities in which the women were engaged	Others	3	Nominal
			Agriculture	2	
			Not working	1(ref)	
owledge of any hod	X8[]	Women knowledge of contraceptive methods	Knows modern methods	1	Nominal
			Knows no methods	0(ref)	
r use of traceptive hods	X9[]	Women who ever used any contraceptive methods	Used modern methods	1	Nominal
			Never used	0(ref)	
rd through o	X10[]	Heard about contraceptive on radio last month	Yes	1	Nominal
			No	0(ref)	
ited a health lity	X11[]	Visited a health facility in the last 12 months	Yes	1	Nominal
			No	0(ref)	

3.4 Bayesian Methodology

3.4.1 General

Bayesian statistics began with a posthumous publication in 1763 by Thomas Bayes, a nonconformist minister from the small English town of Tunbridge Wells. His work was formalized as Bayes theorem which, when expressed mathematically, is a simple and uncontroversial result in probability theory. However, specific uses of the theorem have been the subject of continued controversy for over a century, giving rise to a steady stream of passionate arguments in a number of disciplines. In recent years, a more balanced and pragmatic perspective has developed, and this more unified attitude is reflected in the Bayesian approach (Spiegelhalter, 2004).

The first thing to note is that, in a Bayesian framework, regardless of whether we have a frequentist hypothesis test problem or one of point estimation or any other standard statistical problem, the Bayesian approach is essentially the same. We start with a suitable prior distribution, combine this with the data to obtain the posterior distribution and finally analyze and draw conclusions based on the posterior distribution (Acad, 2001).

Prior Distribution

This is a probability distribution that represents the prior information associated with the parameter of interest. There are many types of prior distributions and many ways to derive them (Spiegelhalter, 2004). They can be based on information available in the literature, clinical databases, expert opinion or information from any other appropriate source. A prior distribution can also be non-informative, that is representing the state of very little or no relevant prior information (Acad, 2001).

Combining the Prior with the Data

Once a prior distribution has been obtained, it needs to be combined with the data (likelihood) using Bayes theorem to give a posterior distribution. This process is fundamental to the Bayesian approach. Conceptually, the idea involves 'merging' the prior distribution with the likelihood to give a new combined, posterior distribution (Acad, 2001).

Thus, the prior distribution is 'merged' with the likelihood to give a final posterior distribution which is, in a sense, an 'average' of the two distributions. Note, however, that the posterior distribution has a smaller variance (that is, it has a tighter distribution) than either the prior distribution or likelihood. This reflects the greater amount of information present in the posterior distribution since it combines information from both the prior and the likelihood. The power of the Bayesian formulation is that although it can accommodate data, it is possible to define a working model without it (Acad, 2001).

In a Bayesian paradigm the parameters vary according to a probability distribution but it can also be interpreted as belief uncertainty or prior belief about the value of the parameter. If the prior belief or knowledge can be quantified it will be represented by probability distribution. Bayes theorem provides a mechanism for updating these beliefs in the light of data (Lee and Mallick, 2004).

Let the initial probability of the parameter P(θ) be the prior probability. The probability of the parameter given the data, P(θ/X) is the posterior probability; and the probability of the data given the parameter P(X/θ) is called the likelihood function, as it is the likelihood of the parameter given the data. P(X) is the probability of the data X, which is not dependent on the parameter and acts as a normalizing constant. Bayes' Theorem follows directly from the axioms of probability theory, and is used to relate the conditional distributions of two variables as follows (Kynn, 2005).

$$\mathrm{P}(\theta/\mathrm{X}) = \frac{P(X/\theta)\times P(\theta)}{P(X)}$$

Hence the posterior probability for θ given X is equal to the likelihood that the observed value X occurs given the parameter θ, times the prior probability for θ, divided by the likelihood for observing X. Using Bayes' theorem this can be summarized as posterior proportional to prior times likelihood.

Analyzing the Posterior Distribution

Until the modern computing age, the problem with the Bayesian information was the often intractable equation for the posterior (Lindley and Smith, 1972). Prior distributions can be specifically chosen to be compatible with the likelihood function to avoid this problem (called conjugate priors). However the significant advances in computing power, methodology and software over the last few decades, mean that the posterior density function can be directly sampled using simulation techniques (such as Markov Chain Monte Carlo, MCMC). The current difficulty of the Bayesian model is the specification of the prior distribution. A common approach is to use an informative prior, representing little prior knowledge which is not useful when the data is limited or of poor quality. The alternative is to make the prior informative; explicitly stating prior knowledge and assumptions, and allow it to define the model in the absence of data.

Various analyses can now be performed on the posterior distribution. Among these are computing the mean of the posterior distribution and the 95% Bayesian confidence interval (given by: posterior mean ± 1.96 × posterior SD). Note that, unlike in the case of the frequentist confidence interval, the true parameter value has a probability of 0.95 of being contained in the 95% Bayesian confidence interval (Acad, 2001).

3.4.2 Bayesian Logistic Regression Model

There has been much recent interest in Bayesian inference for non linear models like logistic and related models. The increasing popularity of Bayesian methods for these and other model classes is mainly caused by the introduction of Markov Chain Monte Carlo (MCMC) simulation techniques which allow realistic modeling of complex problems.

Logistic regression is the most common approach for modeling binary/dichotomous dependent variable. It is used in many areas of substantive interest in the social and biological sciences to model the conditional expectation (probability) of a binary dependent variable as a function of an observed (or unobserved) vector of covariates (Hosmer and Lemeshow, 1989). In this thesis, since the dependent variable is "intention to use contraceptives or not", logistic regression model is appropriate.

Extending the classical logistic regression assumption, there is no formal requirement for multivariate normality, homoscedasticity, or linearity of the independent variables within each category of the response variable. However, the assumptions that apply to logistic regression model include: meaningful coding, inclusion of all relevant and exclusion of all irrelevant variables in the regression model, low error in the explanatory variables, no outliers and no multicollinearity (Hosmer and Lemeshow, 1989). In this thesis, since all covariates fitted are categorical there were no problems of outliers and multicollinearity.

In the terminology of Logistic Regression Analysis the odds of a success is defined to be the ratio of the probability of a success to the probability of a failure. Hence, if p is the true success probability the odd of success is $\frac{p}{1-p}$.

Let Y be an $n \times 1$ dichotomous outcome random vector with categories 1 (do not intend to use contraceptive) and 0 (intend to use contraceptive). And also, let X be an n × (p+1) matrix of p-predictor variables of Y, that is:

$$X = \begin{bmatrix} 1 & x_{11} & \cdots\cdot & x_{p1} \\ 1 & x_{12} & \cdots & x_{p2} \\ . & \cdots\cdots\cdots & . & . \\ . & \cdots\cdots\cdots & .. & . \\ 1 & x_{1n} & \cdots\cdot & x_{pn} \end{bmatrix}$$

X is called the regression matrix and without the leading column of 1s, is termed as predictor data matrix.

In logistic regression analysis, it is assumed that the explanatory variables are related to the response through a suitable transformation of the probability of success. This transformation is a suitable link function of p_i, and is called the logit-link, which is defined as:

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) \text{--(1)}$$

The transformed variable logit (p_i) is related to the explanatory variables as:

$$\text{logit}(p_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_p x_{pi} = X_i'\beta \text{ -----------------------(2)}$$

where, $\beta = (\beta_0, \beta_1, \ldots, \beta_p)'$ are the model parameters and $X_i = (x_{i0}, x_{i1}, \ldots, x_{ip})'$ is a vector of predictor variables with $x_{i0} = 1, i = 1, \ldots, n$.

The above relation can be given as:

$$Y_i = p(\beta, x_i) + \varepsilon_i \text{ --(3)}$$

$$Y_i = \frac{\exp(X_i'\beta)}{1+\exp(X_i'\beta)} + \varepsilon_i \text{ --(4)}$$

With further rearrangement, we obtain the odds of success

$$\text{Odds } (Y_i = 1) = \frac{p_i}{1-p_i} = e^{X_i'\beta} \text{ --(5)}$$

3.4.2.1 Prior Distribution

The prior distribution is a key aspect of a Bayesian analysis. In each research domain, a lot of experience has been built over the years. If we can extract this prior information and transform it into quantitative information, we could incorporate it into a Bayesian model. Typically, informative prior distribution is created from historical studies, pure expert knowledge (experience) and a combination of both. Even if there is prior knowledge about what we are examining, in some cases we might prefer not to use this and let the data speak for themselves. In this case, we wish to express our prior ignorance into the Bayesian system. This leads to noninformative priors.

An historical prior is constructed from previous experiments or experience. Ibrahim et al. (2001) defined several different classes of priors used in clinical trials. One of these is a clinical prior, which may be formed from the results of previous similar clinical trials.

Expert priors are constructed directly from an expert's knowledge. It requires that the experts quantify their knowledge, which in itself is a task that requires careful thought where it is possible. Furthermore, it is unlikely that any person (expert or not) would be able to quantify her/his knowledge directly in terms of the parameters for the logistic regression equation (Bedrick and Christensen, 1996). Rather, the equation can be decomposed into probabilities, such as the probability of success given certain conditions. From these probabilities the expected mean value of the parameters can be calculated. Additionally, a measure of how sure or unsure the expert is about these probabilities can be used to determine the spread of the prior distribution. Although expert priors have been used for a number of different models and in different disciplines, published research on expert priors for the logistic regression equation is almost nonexistent, in spite of the model's general popularity (Kynn, 2005).

Some prior distributions, called conjugate priors, combine easily with the likelihood. We give the conjugate priors for the most commonly used likelihoods. From a mathematical and computational perspective, it can be convenient if the prior distribution is a member of a family of distributions that is conjugate to the form of the likelihood, in the sense that they 'fit together' to produce a posterior distribution that is in the same family as the prior distribution. In many circumstances likelihoods can be assumed to have an approximately normal shape, and thus in these circumstances it will be convenient to use a normal prior (the conjugate family), provided it approximately summarizes the appropriate external evidence. Modern computing power is, however, reducing the need for conjugacy (Lesaffre, 2007).

When adequate data are not available, it seems logical that prior knowledge is incorporated and the choice of the prior is crucial. However, when we have sufficient data, the effect of the prior we choose will be small compared to the data or the likelihood will dominate the prior. In that case, we can get very similar posteriors despite starting from quite different priors. All that is necessary is that they give reasonable weight over the range that is indicated by the likelihood. The exact shape of the prior does not matter as such. The data are said to "swamp the prior." (Bolstad, 2004). In such cases, the choice of prior distribution is less crucial, since information in the data heavily outweighs information in the prior. Thus, often the prior distributions chosen for analysis are very diffuse with high variances to reflect our desire to express ignorance prior to the analysis about the possible values for the regression parameters. The prior distribution for each regression coefficient $\beta_0, \beta_1, \ldots, \beta_p$ follows a normal distribution with mean 0 and variance of 1000. These prior distributions are assumed to be independent. This prior choice reflects that we have little prior knowledge about the values of the regression coefficients. These diffuse prior distribution choices have historically been standard choices in Bayesian generalized linear regression (DeGroot, 1970) though the choices are sufficiently uninformative enough that the posterior estimates are less sensitive to the prior distribution. Similarly, according to Bolstad (2004), if we really do not have any prior information, we would give all values equal prior probability. Thus,

$$\beta_j \sim N(0,1000) \text{ --(6)}$$

for $j = 0, 1, 2, \ldots\ldots, p$

This could be equivalently written as a multivariate normal distribution with all covariances set to zero and mean zero.

The diffuse prior distribution or highly dispersed Gaussian prior for each parameter β_j with mean 0 and variance 1000 is:

$$f(\beta_j) = \frac{\exp^{-\beta_j^2 / 2\times 1000}}{\sqrt{2\times 1000\times \pi}} \quad \text{for } j = 0, 1, 2, \ldots\ldots, p \text{-------------------------(7)}$$

Since each prior is distributed independently, the joint prior probability distribution for $\beta_0, \beta_1, \ldots, \beta_p$ is:

$$f(\beta_0, \beta_1, \ldots, \beta_p) = \frac{\exp^{-\beta_0^2 / 2\times 1000}}{\sqrt{2\times 1000\times \pi}} \times \frac{\exp^{-\beta_1^2 / 2\times 1000}}{\sqrt{2\times 1000\times \pi}} \times \ldots\ldots\ldots\ldots \times \frac{\exp^{-\beta_p^2 / 2\times 1000}}{\sqrt{2\times 1000\times \pi}}$$

$$= \frac{\exp^{-\sum_{j=0}^{p}\beta_j^2 / 2\times 1000}}{(2\times 1000\times \pi)^{\frac{p+1}{2}}} \quad \text{---(8)}$$

3.4.2.2 Markov Chain Monte Carlo methods

The Bayesian approach applies probability theory to a model derived from substantive knowledge and can, in theory, deal with realistically complex situations; the approach can also be termed 'full probability modeling'. It has to be acknowledged, however, that the computations may be difficult, with the specific problem being to carry out the integrations necessary to obtain the posterior distributions of quantities of interest in situations where nonstandard prior distributions are used in the model. These problems in integration for many years restricted Bayesian applications to rather simple examples. However, there has recently been enormous progress in methods for Bayesian computation, generally exploiting modern computer power to carry out simulations known as Markov chain Monte Carlo (MCMC) methods. The Markov Chain Monte Carlo (MCMC) simulation is to do the integration numerically rather than analytically by sampling from the posterior distribution of interest even when the form of that posterior has no known algebraic form (Spiegelhalter, 2004). This will yield all posterior summary statistics (approximately).

By application of the mean value theorem of calculus, the integral may be approximated. In application of MCMC, if we use the endpoints of the subintervals to approximate the integral, we run the risk that the values at the endpoints do not accurately represent the average value of the function on the subinterval. A point, which is much more likely to be close to the average, would be the midpoint of each subinterval. Using the midpoint in the sum is called the midpoint rule. Appling this technique to the sampled values, where β_k' is the median k^{th} sampled value of the parameter and the points β_k' fully cover the range of integration. Similarly, $P(\beta / Y)$ is the function, the approximation of the integrals should be as follows:

$$\int \beta P(\beta / Y) d\beta \approx \frac{1}{K} \sum \beta_k' \text{ --(9)}$$

The classical Law of Large Numbers applied to the sampled values ensures that when k is large enough the sum approximates the integral to the desired accuracy.

In the past few years, computer algorithms (e.g., the Gibbs Sampler and the Metropolis-Hasting algorithm) have been developed to draw an (approximate) random sample from the posterior distribution, without having to completely evaluate it. We can approximate the posterior distribution to any degree of accuracy we wish by taking a large random sample from it. This removes the disadvantage of Bayesian statistics; it can be done in practice for problems with many parameters, and for distributions from general samples and having general prior distributions.

There is a wealth of theoretical work on ways of sampling from a joint posterior distribution that is known to be proportional to a likelihood times prior, defined as the product of $f(Y|\beta)$ and $f(\beta)$, where the latter expression is of known form. These methods focus on producing a Markov chain, in which the distribution for the next simulated value $\beta^{(j+1)}$ depends only on the current $\beta^{(j)}$. The theory of Markov chains states that, under broad conditions, the samples will eventually converge into an 'equilibrium distribution'. A set of algorithms are available that use the specified form of $f(Y|\beta)$ times $f(\beta)$ to ensure that the equilibrium distribution is exactly the posterior of interest: popular techniques include Gibbs sampling, Metropolis-Hastening algorithm and Slice Sampling (Spiegelhalter, 2004).

The method is called Gibbs sampling since the inventor Geman (1984) first applied the technique to develop image processing tools with the Gibbs distribution. In thermodynamics, the Gibbs distribution determines the equilibrium average (Lesaffre, 2007). The basic idea behind the Gibbs sampling algorithm is to successively sample from the conditional distribution (these are known as full conditional distributions). The Metropolis-Hastings algorithm is different from the Gibbs sampling approach in that it does not need the conditional distributions.

Suppose we need the posterior distribution $P(\theta_1, \theta_2 | y)$ where, θ_1 and θ_2 are the parameters and y is the likelihood. A dependent sample from this distribution can be obtained if we can sample from the conditional posterior distributions $P(\theta_1 | \theta_2, y)$ and $P(\theta_2 | \theta_1, y)$. Moreover a sample from the marginal posterior distributions $P(\theta_1 | y)$, $P(\theta_2 | y)$ will be obtained (Lesaffre, 2007).

The sampling procedure goes as follows:

Sample $\theta_1^{(j+1)}$ from $P(\theta_1 | \theta_2^{(j)}, y)$

Sample $\theta_2^{(j+1)}$ from $P(\theta_2 | \theta_1^{(j)}, y)$ ---(10)

The result gives a series of bivariate vectors $\theta^{(1)}, \theta^{(2)}$ ... called a Markov chain, where $\theta^{(1)}$ and $\theta^{(2)}$ are the realized values of θ_1 and θ_2 respectively, with a joint distribution converging to both $P(\theta_1, \theta_2 | y)$, the target distribution and the equilibrium distribution. The term "equilibrium distribution" appears because it can be shown that when sampling is immediately from $P(\theta_1, \theta_2 | y)$, then the sampling procedure in (10) will yield samples staying in $P(\theta_1, \theta_2 | y)$. Further, the samples $\theta_1^{(k+1)}$, $\theta_1^{(k+2)}$, ... and $\theta_2^{(k+1)}$, $\theta_2^{(k+2)}$,... will ultimately be taken from the correct marginal posterior distributions for a suitably large value of k.

The Gibbs Sampler assumes that sampling from the conditional distributions can be done. This may or may not be an easy task. Another possibility is to use the Metropolis (1953) or the Metropolis-Hastings (1970) (MH) algorithm. The Metropolis-Hastings algorithm is different from the Gibbs sampling approach since it does not need the conditional distributions. Instead, it uses a proposal density to sample from. The proposal density is used as a vehicle to explore the posterior distribution. The better the proposal density the true posterior distribution approximates, the better the exploration will be (Lesaffre, 2007).

Metropolis-Hastings algorithm: This is a powerful algorithm that provides a general approach for producing a correlated sequence of draws from the target density that may be difficult to sample by a classical independence method. To define the algorithm, let $q(\theta,\theta^*)$ denote a source density, which is referred to as the proposal or candidate generating density. This density is interpreted as saying that when a process is at point θ, the density generates a value θ^* from $q(\theta,\theta^*)$. The densities have this property $q(\theta,\theta^*) > 0$ and $q(\theta^*,\theta) > 0$. If it happens that $q(\theta,\theta^*)$ itself satisfies the reversibility condition (11) for all θ and θ^* our search is over but most likely it will not.

$p(\theta)q(\theta,\theta^*) = p(\theta^*)q(\theta^*,\theta)$ ---(11)

where, $p(.)$ is the target distribution.

We might find, for example, that for some θ and θ^*

$p(\theta)q(\theta,\theta^*) > p(\theta^*)q(\theta^*,\theta)$ ---(12)

In this case, speaking somewhat loosely, the process moves from θ to θ^* too often and from θ^* to θ too rarely. A convenient way to correct this condition is to reduce the number of moves from θ to θ^* by introducing a probability $\alpha(\theta, \theta^*) < 1$ that the move is made. We refer to $\alpha(\theta, \theta^*)$ as the probability of a move. If the move is not made, the process again returns θ as a value from the target distribution. Thus transitions from θ to θ^* $(\theta \neq \theta^*)$ are made according to

$T_{MH}(\theta, \theta^*) \equiv q(\theta,\theta^*)\,\alpha(\theta, \theta^*),\ \theta \neq \theta^*$ --(13)

where, $T_{MH}(\theta, \theta^*)$ is the transition kernel of the MH chain and $\alpha(\theta, \theta^*)$ is yet to be determined.

Consider again inequality (12), it tells us that the movement from θ^* to θ is not made often enough. We should therefore define $\alpha(\theta^*, \theta)$ to be as large as possible, and since it is probability, its upper limit is one. But now the probability of a move $\alpha(\theta, \theta^*)$ is determined by requiring that $T_{MH}(\theta, \theta^*)$ satisfies the reversibility condition, then

$$
\begin{aligned}
p(\theta)q(\theta,\theta^*)\,\alpha(\theta, \theta^*) &= p(\theta^*)q(\theta^*,\theta)\,\alpha(\theta^*, \theta) \\
&= p(\theta^*)q(\theta^*,\theta)
\end{aligned}
$$

We now see that $\alpha(\theta, \theta^*) = {p(\theta^*)q(\theta^*,\theta)} \big/ {p(\theta)q(\theta,\theta^*)}$, if $p(\theta^*)q(\theta,\theta^*) > 0$. Of course if the inequality in (12) is reversed, we set $\alpha(\theta, \theta^*) = 1$ and derive $\alpha(\theta^*, \theta)$ as above. The probabilities $\alpha(\theta, \theta^*)$ and $\alpha(\theta^*, \theta)$ are thus introduced to ensure that the two sides of (12) are in balance or, in other words, that $T_{MH}(\theta, \theta^*)$ satisfies reversibility. Thus we have shown that in order for $T_{MH}(\theta, \theta^*)$ to be reversible, the probability of move must be set to

$$\alpha(\theta, \theta^*) = \min\left[\frac{p(\theta^*)q(\theta^*,\theta)}{p(\theta)q(\theta,\theta^*)},1\right], \text{ if } p(\theta^*)q(\theta,\theta^*) > 0$$

$$= 1, \qquad \text{otherwise.}$$

For example, when the chain is at $\theta^{(n)}$, sample for the next location a candidate value θ^* using the proposal density $q(\theta,\theta^*)$ with θ equals to $\theta^{(n)}$. The next value $\theta^{(n+1)}$ will be θ^* (accepted) with probability of $\alpha(\theta, \theta^*)$ or remains in $\theta^{(n)}$ (rejected) with probability of 1- $\alpha(\theta, \theta^*)$. If the proposal value is rejected, then the next sampled value is taken to be the current value (Chib and Greenberg, 1995).

The Metropolis-Hastings algorithm ensures sampling all areas of the posterior distribution in a balanced way and can be viewed as the stochastic version of a stepwise mode-finding algorithm (Lesaffre , 2007).

In instances where it is difficult to find an efficient Metropolis-Hastings proposal distribution, the slice sampling algorithm does not require an explicit specification. It is a general purpose algorithm for single site updating that always produces a new value at each iteration. The slice sampling algorithm draws samples from the region under the density function using a sequence of vertical and horizontal steps. First, it selects a height at random from 0 to the density function $f(x)$. Then, it selects a new x value at random by sampling from the horizontal "slice" of the density above the selected height.

If a density function $f(x)$ is given, then the following steps are used to generate random numbers:

1. Assume an initial value $x(t)$ within the domain of $f(x)$.
2. Draw a real value y uniformly from $(0, f(x(t)))$, thereby defining a horizontal "slice" as $S = \{x: y < f(x)\}$.
3. Find an interval $I = (L, R)$ around $x(t)$ that contains all, or much of the "slice" S.
4. Draw the new point $x(t+1)$ within this interval.

5. Increase $t \rightarrow t+1$ and repeat steps 2 through 4 until you get the desired number of samples.

Slice sampling can generate random numbers from a distribution with an arbitrary form of the density function, provided that an efficient numerical procedure is available to find the interval $I = (L,R)$, which is the "slice" of the density (http://www.mathworks.com).

3.4.2.3 Checking Goodness of Fit of the Model

Once a model has been developed through the various steps indicated in the above section, we now would like to know how effective the model is in describing the outcome variable. This is referred to as goodness-of-fit. The most common ways of checking goodness of fit are: diagnosis for Convergence and Mixing, and Posterior-predictive check.

3.4.2.3.1 Goodness of fit test using Diagnosis for Convergence and Mixing

The Markov chain must be started somewhere, and initial values are selected for the unknown parameters. In theory the choice of initial values will have no influence on the eventual samples from the Markov chain, but in practice convergence will be improved and numerical problems avoided if reasonable initial values can be chosen (Spiegelhalter, 2004).

Convergence diagnostics are widely used to determine how many initial “burn-in” iterations should be discarded from the output of a Markov chain Monte Carlo (MCMC) sampler in the hope that the remaining samples are representative of the target distribution of interest. The best method is choosing the number of burn-in iterations r by applying convergence diagnostics to one or more pilot chains, and then basing estimation and inference on a separate long chain from which the first r iterations have been discarded (Kathryn and Rosenthal, 1998).

Checking whether a Markov chain, possibly with very many dimensions, has converged to its equilibrium distribution is not at all straightforward. Lack of convergence might be diagnosed simply by observing erratic behaviour of the sampled values, but the mere fact that a chain is moving along a steady trajectory does not necessarily mean that it is sampling from the correct posterior distribution: it might be stuck in a particular area due to the choice of initial values. For this reason it has become generally accepted that it is best to run multiple chains from a diverse set of initial values, and formal diagnostics exist to check whether these chains end up, to expected chance variability, coming from the same equilibrium distribution which is then assumed to be the posterior of interest (Spiegelhalter, 2004).

To use summary statistics of the estimated posterior distributions for inference the realized value of the parameters (the MCMC value) should converge. To check this we have to use suitable diagnosis to evaluate mixing and convergence of a sampler. From different methods of checking convergence, Brooks, Gelman and Rubin (BGR) diagnostic, trace and history plots, kernel density plot and autocorrelation are among the common (Lesaffre, 2007).

Brooks, Gelman and Rubin (BGR) diagnostic compares the within-chain and the between-chain variability, and if the ratio (converges approximately to one or if lines for each chain on the BGR are nearly together, this implies that the statistics converge (Lesaffre, 2007).

A trace or time-series plot of the values in the chain or of values derived from them show that if the chain is drifting, perhaps indicating that the burn-in was not long enough, and it will illustrate the speed of mixing, which is how quickly the chain moves across the distribution. Chains that mix slowly will produce long, slow cycles, and they take longer to converge. Mixing can sometimes be improved by reparameterizing the model (Thompson and Palmer, 2006).

The realized values are not independent of each other. The autocorrelation (of lag k) is a popular way to measure this dependence. An autocorrelation plot shows the Pearson correlation of the subsequent values in the chain as a function of the lag. The higher the autocorrelation the slower the (marginal) posterior distribution of the parameter is explored; one says also that the mixing is slower in this case (Thompson and Palmer, 2006).

Once we confirmed that convergence has been achieved, we will need to run the simulation for a further number of iterations to obtain samples that can be used for posterior inference. The more samples you save, the more accurate will be your posterior estimates. One way to assess the accuracy of the posterior estimates is by calculating the Monte Carlo error for each parameter. This is an estimate of the difference between the mean of the sampled values (which we are using as our estimate of the posterior mean for each parameter) and the true posterior mean (http://mathstat.helsinki.fi).

As a rule of thumb, the simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation. The Monte

Carlo error (MC error) and sample standard deviation (SD) are reported in the summary statistics table (http://mathstat.helsinki.fi).

The posterior samples may be summarised either graphically, e.g. by kernel density plots, or numerically, by calculating summary statistics such as the mean, variance and quantiles of the sample (http://mathstat.helsinki.fi).

3.4.2.3.2 Goodness of fit test using Posterior-predictive check

A posterior-predictive model check is another method used to assess model adequacy or the departures of the observed data from the assumed model. This approach was initially proposed by Guttman (1967) and Rubin (1984), and was extended to more general discrepancy functions by Gelman et al. (1996). This approach has three advantages over standard applications of fit statistics. First, an extremely wide range of fit statistics can be defined based on the distribution of predictions under a model; researchers need not be confined to various forms of residual sums of squares. Second, the Bayesian basis for the statistic allows the calculation of p-values, describing the probability that the data arose by chance given the model assumptions. Third, posterior predictive simulation explicitly accounts for the parametric uncertainty that is usually ignored by alternative approaches. In many models, the output from numerical algorithms used to generate samples from the posterior distribution can be used to generate observations from the predictive model, which in turn can be used to compute p-values for the discrepancy function of interest. Posterior-predictive model assessment also facilitates case-diagnostics, which, in many circumstances, are more telling in examining model fit than are global goodness-of-fit statistics.

Model fit statistics can be assessed by comparing the observed $T(y)$ to the posterior predictive distribution $T(y\text{rep})$. A Bayesian p-value can be defined as the probability (proportion) that the measure sampled from the posterior predictive distribution exceeds the observed measure, i.e. $p = \Pr(T(y\text{rep}) \geq T\ (y)|y)$, which can be interpreted as, conditional on the model, the probability of observing data at least as extreme as that actually observed. Small p values reflect the implausibility of the data under the model (and hence the lack of fit of the model to the data) and therefore suggest examining other models (Johannes and Mechelen, 2000). The choice of p value considered small enough to merit rejection of a model is a subjective determination but may be made based on conventional standards (e.g.,$p < .05$,$p < .01$, etc.) (Lynch, 2004).

3.4.2.4 Posterior Inference

The posterior distribution is obtained from prior information and likelihood (data) by using Bayes theorem mentioned above. All inferential conclusions in Bayesians are based on the posterior distribution of the model generated. The inference is performed by sampling from posterior distribution until the convergence to the posterior distribution is achieved (Dezfuli, 2009). The emphasis in the Bayesian is on point and credible interval estimate of the parameters not hypothesis testing. The major problem in the Bayesian approach is that in most cases the full form of the posterior distribution cannot be obtained in closed form, that is, the posterior density may not belong to standard distribution. Such problem cannot be solved easily. In order to solve such problems we use Markov Chain Monte Carlo (MCMC) simulations that are described in 3.4.2.2 in detail.

In this study, the posterior distribution should be as follows:

$$f(\beta_0, \beta_1, ..., \beta_p / Y) = \frac{f(Y / \beta_0, \beta_1, ..., \beta_p) * f(\beta_0, \beta_1, ..., \beta_p)}{\int\int ....\int f(Y / \beta_0, \beta_1 ...., \beta_p) * f(\beta_0, \beta_1, ..., \beta_p) d\beta_0, d\beta_1, ..., d\beta_p}$$

where, $\beta_0, \beta_1, ..., \beta_p$ are the parameters, $f(\beta_0, \beta_1, ..., \beta_p / Y)$ is posterior distribution; $f(Y / \beta_0, \beta_1, ..., \beta_p)$ is the likelihood function and $f(\beta_0, \beta_1, ..., \beta_p)$ is the joint prior distribution. The above posterior distribution can be written as:

$$f(\beta_0, \beta_1, ..., \beta_p / Y) = \frac{\dfrac{\exp^{X_i'\beta}}{1 + \exp^{X_i'\beta}} * \dfrac{\exp^{-\sum_{j=0}^{p} \beta_j^2 / 2*1000}}{(2 * 1000 \; * \pi)^{\frac{p+1}{2}}}}{\int\int ....\int \dfrac{\exp^{X_i'\beta}}{1 + \exp^{X_i'\beta}} * \dfrac{\exp^{-\sum_{j=0}^{p} \beta_j^2 / 2*1000}}{(2 * 1000 \; * \pi)^{\frac{p+1}{2}}} d\beta_0, d\beta_1, ..., d\beta_p}$$

One of the main advantages of Bayesian methods is that it uses prior knowledge, along with the information from the sample. Using Bayes' theorem combines both prior and sample information into the posterior. Frequentist methods only use sample information (Bolstad, 2004).

3.4.2.7 Methods of Data Analysis

In this thesis, all Bayesian computation is accomplished using Bayesian software WinBUGS (3.0.3). This software is free downloadable from *http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml*.. Moreover, SPSS 15 is used in descriptive analysis and data management, especially in cleaning and coding of data.

CHAPTER FOUR

4. ANALYSIS AND RESULT

In this chapter, the first section presents and discusses descriptive results and the second section discusses inferential statistics based on Bayesian logistic regression model. Using inferential statistics, we will examine intention to use contraceptives with: demographic, socio-economic, knowledge, information and practice characteristics.

4.1 Descriptive and Explanatory Analysis of Variables

The results in Table 4.1 and Annex A1 present cross tabulation of dependent variable versus each predictor variables for 11,443 subjects included in this study. Among 11,443 subjects included 5,902 (51.6%) intend to use contraceptives while 5,541 (48.4%) does not intend to use.

i. Demographic factors

Table 4.1 shows that, of women in the age group 15-24, 67.0 % of them intend to use contraceptives. This figure is 54.5% and 25% for women in the age group 25-34 and 35-49, respectively.

We can also see that among women who have no children, 67% of them intend to use contraceptives. On the other hand, of those women who have one-to-two children and three-or-more children about 49% and 39% intend to use contraceptives, respectively.

ii. Socio-economic Variables

As we can see from Annex A1, intention to use contraceptives varies from one region to another. For example, the highest intention to use is in Addis Ababa (67.3%) followed by SNNPR (65.7%). On the other hand, the lowest intention to use was recorded in Somali (4.2%) followed by Afar (8.6%).

Place of residence, whether urban or rural, is one important characteristic that determines access to services and exposure to information pertaining to reproductive health and other aspects of life. Among women in urban area, 47% of them intend to use contraceptives while from women in rural area 63% of them intend to use contraceptives (Table 4.1).

Annex A1 shows that among women who are followers of Muslim and Coptic Orthodox, 60.5% and 59% of them intend to use contraceptives, respectively. On the other hand, of those women who are followers of Protestant, 38.2% of them intend to use contraceptives.

According to the descriptive statistics under Table 4.1, among women who completed secondary and above educational level, 76.6% of them intend to use contraceptives. On the other hand, of those women who completed primary education and have no education about 68.1% and 39.9% of them intend to use contraceptives, respectively.

Under Annex A1, among women who work on agriculture, 51.2% of them intend to use contraceptives, while from those women who are not working 57.4% of them intend to use contraceptives.

Table 4.1 shows that among women who have knowledge of contraceptives, 59.7% of them intend to use contraceptives while of those women who do not know contraceptive methods 14.2% of them intend to use contraceptives.

According to the descriptive statistics under Annex A1, among women who ever used contraceptive methods, 66.4% of them intend to use contraceptives. This figure is 49.9% for women who never used contraceptive methods.

We can see that among women who ever heard about contraceptives on radio a month prior to the survey, 67.3% of them intend to use contraceptives, while from those women who do not heard about contraceptives in radio in the last month prior to the survey 44.2% of them intend to use contraceptives.

Annex A1 shows that among women who visited a health facility during the last 12 month prior to the survey, 60.6% of them intend to use contraceptives. On the other hand, for women who did not visit a health facility during the last 12 month prior to the survey, 48.8% of them intend to use contraceptives.

Table 4.1 Cross tabulation of categorical predictor variables in the study Vs response variable

Predictor variables		**Response variable**		**Total**
		Intend to use	**Does not intend to use**	
Age of women	35-49	797	2406	3203
		24.9%	75.1%	100.0%
	25-34	1815	1514	3329
		54.5%	45.5%	100.0%
	15-24	3290	1621	4911
		67.0%	33.0%	100.0%
Number of living children	Three or more children	1771	2791	4562
		38.8%	61.2%	100.0%
	One up to two children	1284	1346	2630
		48.8%	51.2%	100.0%
	No children	2847	1404	4251
		67.0%	33.0%	100.0%
Place of residence	Urban	3842	4331	8173
		47.0%	53.0%	100.0%
	Rural	2060	1210	3270
		63.0%	37.0%	100.0%
Educational level of women	Secondary and above	1476	451	1927
		76.6%	23.4%	100.0%
	Primary	1616	756	2372
		68.1%	31.9%	100.0%
	No education	2810	4334	7144
		39.9%	60.7%	100.0%
Knowledge of any method	Knows modern methods	5611	3784	9395
		59.7%	40.3%	100.0%
	Knows no methods	291	1757	2048
		14.2%	85.8%	100.0%
Overall dependent		**5902**	**5541**	**11443**
		51.6%	**48.4%**	**100.%**

4.2 Bayesian Logistic Regression Model Results

In this section we analyze the predictors using Bayesian approach by employing Bayesian Logistic Regression Model discussed in the methodology section. Detail WinBUGS code written to estimate the model parameters is provided in Appendix A2.

In this study, the response variable is binary/dichotomous variable and all predictor variables are categorical. Therefore, dummy variables are used in setting up the model in WinBUGS 3.0.3. Since an overall effect is included in the model, the number of dummy variables within each predictor is one fewer than the level of that predictor.

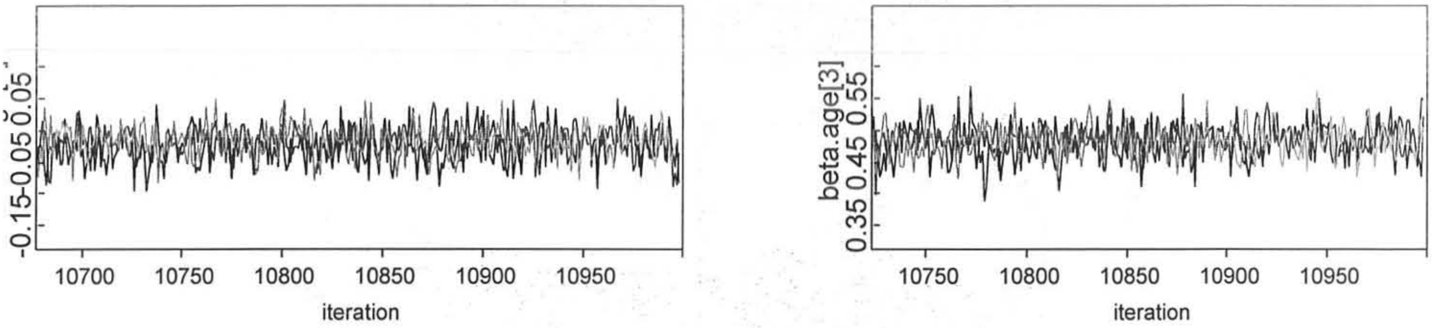
In Ethiopia, (at least to the knowledge of the researcher) research on this topic using Bayesian model has not been done so as to obtain prior information from it. Therefore, the suitable option is to use weak prior information that is normal distribution with large variance $[\beta_j \sim N(0,1000)$ for $j = 0, 1, 2,\ldots\ldots, p]$. Gibbs sampler with three chains were constructed each consisting of 11,000 iterations with initial values mentioned within the model code. The choices of initial values have no influence as far as the samples from Markov chains converge. In this study, as we observed from Diagnosis for Convergence and Mixing, the sample values converge. This implies that the initial values have no influence (Spiegelhalter, 2004).

4.2.1 Goodness of fit results for the model Parameters

4.2.1.1 Goodness of fit results using Diagnosis for Convergence and Mixing

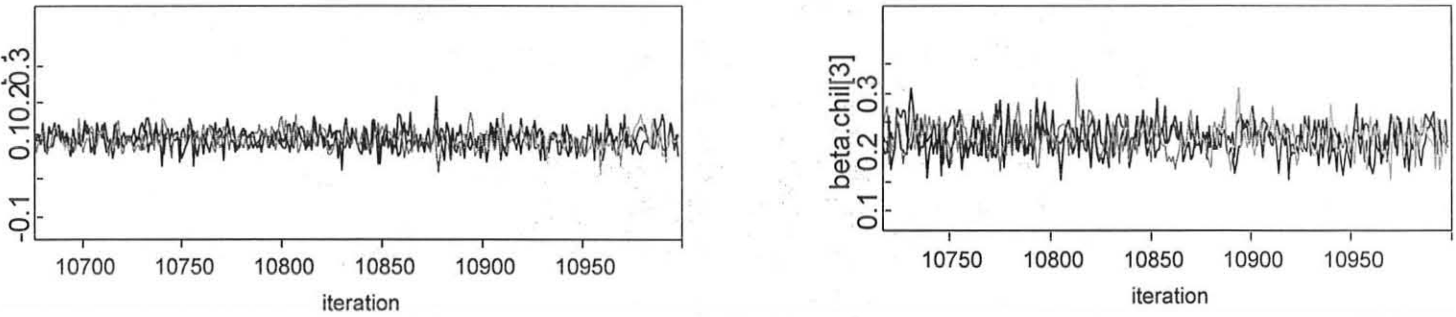
Gibbs sampler with three chains is constructed each consisting of 10,000 iterations. One method of checking convergence is by observing the mixing of the chains in the trace and history plots. From trace and history plots shown in Fig. 4.1, 4.2, Annex B1 and B2, we are reasonably confident that convergence has been achieved for the estimated parameters, since the three chains appear to be overlapping.

Figure 4.1: Trace plot of the regression coefficients used in the model



a) *i*) Trace plot of 25-34 years old

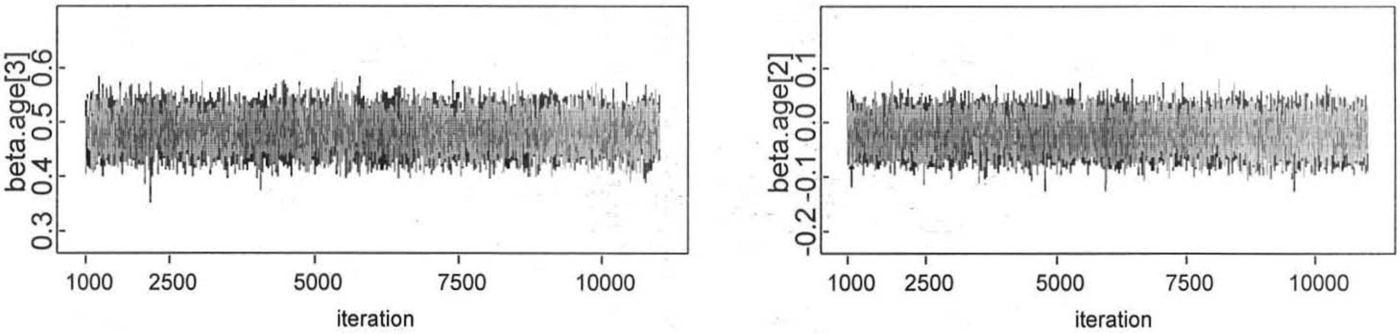
a) *ii*) Trace plot of 35-49 years old



b) *i*) Trace plot of one up to two children

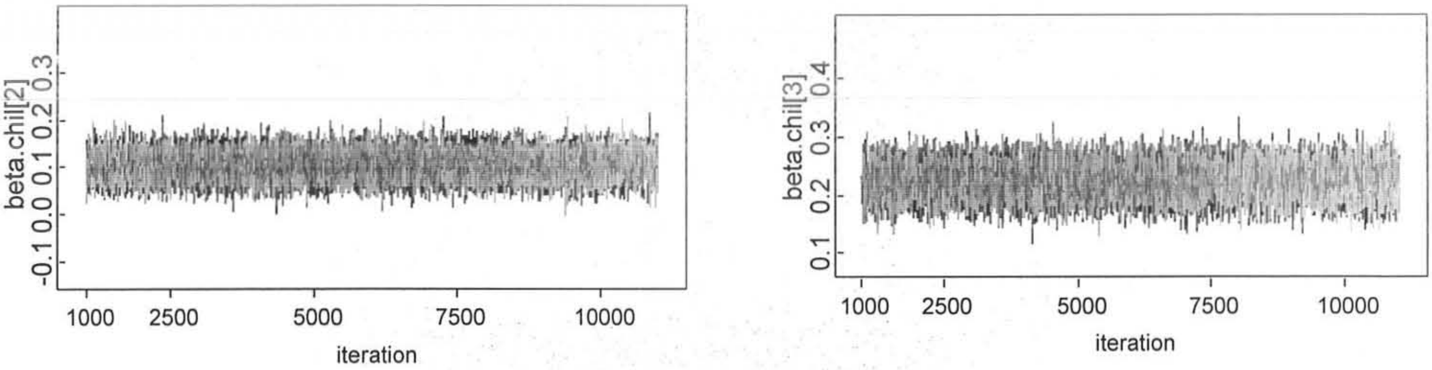
b) *ii*) Trace plot of three or more children

Figure 4.2: History plots of the regression coefficients used in the model



a) *i*) History plot of 25-34 years old

a) *ii*) History plot of 35-49 years old



b) *i*) History plot of one up to two children b) *ii*) History plot of three or more children

The posterior distribution summarizes the current state of knowledge about all the uncertain quantities (including unobservable parameters and latent data). The prior distribution is 'merged' with the likelihood to give a final posterior distribution which is, in a sense, an 'average' of the two distributions. The marginal posterior distribution can be obtained from the joint distribution. We can see in Fig. 4.3 and Annex B3, the smooth, unimodal shape of (approximately normally distributed) posterior marginal distribution for beta parameters.

Figure 4.3: Posterior marginal distribution

a) *i*) Kernel density plot of 25-35 years old a) *ii*) Kernel density plot of 35-49 years old

b) *i*) Kernel density plot of one up to two children b) *ii*) Kernel density plot of 3 or more children

A more convincing evidence for convergence is observed in the Brook, Gelman and Rubin (BGR) diagnostic (Fig 4.4 and Annex B4), which compares the within-chain and the between-chain variability. The figures indicate that between-chain to the within-chain variability is one for each parameter or converge to approximately one indicating the convergence of chains.

Figure 4.4: Plot for Brook, Gelman and Rubin statistic for convergence

a) *i*) BGR diagnostic of 25-34 years old a) *ii*) BGR diagnostic of 35-49 years old

b) *i*) BGR diagnostic of one up to two children b) *ii*) BGR diagnostic of 3 or more children

The realized values during MCMC are not independent of each other. The autocorrelation (of lag k) is a popular way to measure this dependence. An autocorrelation plot shows the Pearson correlation of the subsequent values in the chain as a function of the lag (Lesaffre, 2007).

The higher the autocorrelation, the summary statistics are less precise, and the chain explores the posterior distribution slowly and hence, it will take long before convergence will be claimed. The autocorrelation can often be lowered by transforming the parameters. As can be seen from Fig. 4.5 and Annex B5, the autocorrelation of the parameter estimates is very low and quick drop-off in the autocorrelation function for the parameter estimates implying that the statistics are more precise and the sampler explored the posterior distribution much quicker.

Figure 4.5: Plot of autocorrelation for the regression coefficient used in the model

a) *i*) Autocorrelation of 25-34 years old

a) *ii*) Autocorrelation of 35-49 years old

b) *i*) Autocorrelation of one up to two children

b) *ii*) Autocorrelation of 3 or more children

4.2.1.2 Goodness of fit results using Posterior-predictive check

As mentioned in the methodology section small *p* values reflect the implausibility of the data under the model (and hence the lack of fit of the model to the data) and suggest the need for examining other models (Johannes and Mechelen, 2000). The choice of *p* value considered small enough to merit rejection of a model is a subjective determination but may be made based on conventional standards. For example, if p-value is less than 0 .05 or less than 0 .01, we cannot use the model for inference. As the p-value increases the fit of the model also increases (Lynch, 2004). In this study, the average p-value is 0.781, which indicates that the model fits the data best.

4.2.2 Summary statistics of the estimated posterior distributions

The above diagnostics using trace, history, posterior density plot, Brook, Gelman Rubin(BGR), autocorrelation and posterior predictive check results suggest that the sample value converges. Therefore, we can use the MCMC summary statistics for inferential purpose.

The posterior mean of the parameter θ is obtained from the mean of sampled values of the Monte Carlos (after the burn-in period), hence $\bar{\theta} = \frac{\sum_1^n \theta^{(n)}}{n}$. Similarly, the posterior variance is $\sigma_\theta^2 = \frac{1}{n-1} \sum_1^n (\theta^{(n)} - \bar{\theta})^2$. If the sampled values were independent; then the standard error of the mean would be equal to $\frac{\sigma_\theta}{\sqrt{n}}$. The Bayesian "confidence interval" is called a highest posterior density (HPD) region or credible set. For one parameter the HPD region is sometimes called a credible interval (CI). Suppose θ is a univariate parameter. A 95% HPD interval for θ is the interval such that 95% of the highest area of the posterior density is contained in this interval. If θ is multidimensional, they are called HPD regions.

The standard summary statistics for an MCMC chain for each parameter contain: the mean, which is often taken as the point estimate of the parameter; the standard deviation, which describes the spread of the distribution; the standard error, which is calculated allowing for autocorrelation giving an indication of whether the chain was long enough for the accuracy we require; the median, which is an alternative point estimate for nonsymmetric distributions; the 95% credible intervals, (calculated using the 2.5th and 97.5th percentiles of the posterior samples) which is a central 95% interval calculated from the posterior, similar in spirit to a 95% confidence interval.

Table 4.2: Results of the posterior summary statistics and the precision of the estimates

							95% Credible interval				Precision = $1/(sd)^2$
de	mean	$Exp^{(mean)}$	sd	5%*sd	MC_error	median	val2.5 pc	val97. 5 pc	start	sample	
erall effect	0.054*	1.055	0.026	0.0013	2.38E-04	0.053	0.002	0.104	1001	30000	1505.8
e 15-24[1](ref)	-	-	-	-	-	-	-	-	-	-	-
e 25-34[2]	-0.020	0.980	0.026	0.0013	1.73E-04	-0.020	-0.071	0.031	1001	30000	1512.9
e 35-49[3]	0.483*	1.620	0.026	0.0013	1.66E-04	0.483	0.431	0.534	1001	30000	1468.0
children[1](ref)	-	-	-	-	-	-	-	-	-	-	-
children[2]	0.105*	1.110	0.026	0.0013	1.59E-04	0.105	0.053	0.156	1001	30000	1457.9
3 children[3]	0.224*	1.251	0.026	0.0013	1.80E-04	0.224	0.174	0.275	1001	30000	1519.9
dis Ababa[1](ref)	-	-	-	-	-	-	-	-	-	-	-
ar[2]	0.195*	1.215	0.030	0.0015	1.85E-04	0.195	0.137	0.253	1001	30000	1143.7
hara[3]	0.032	1.033	0.027	0.0014	1.65E-04	0.032	-0.022	0.085	1001	30000	1325.2
omia[4]	-0.156*	0.856	0.027	0.0013	1.58E-04	-0.156	-0.209	-0.103	1001	30000	1383.0
mali[5]	0.169*	1.184	0.030	0.0015	1.69E-04	0.169	0.111	0.227	1001	30000	1122.3
n-gumuz[6]	0.047*	1.048	0.029	0.0015	1.64E-04	0.047	-0.011	0.106	1001	30000	1153.8
NPR[7]	-0.174*	0.841	0.028	0.0014	1.66E-04	-0.174	-0.227	-0.119	1001	30000	1310.9
mbela[8]	0.064*	1.066	0.030	0.0015	1.62E-04	0.064	0.005	0.122	1001	30000	1111.9
rari[9]	-0.012	0.988	0.030	0.0015	1.85E-04	-0.013	-0.071	0.046	1001	30000	1127.6
e Dawa[10]	0.007	1.007	0.030	0.0015	1.70E-04	0.007	-0.051	0.065	1001	30000	1131.4
ray[11]	-0.055	0.946	0.029	0.0014	1.77E-04	-0.055	-0.112	0.001	1001	30000	1206.5
ral[0](ref)	-	-	-	-	-	-	-	-	-	-	-
an[1]	0.116*	1.123	0.025	0.0012	2.03E-04	0.116	0.068	0.164	1001	30000	1641.8
ptic thodox[1](ref)	-	-	-	-	-	-	-	-	-	-	-
slim[2]	-0.066*	0.936	0.027	0.0014	1.73E-04	-0.066	-0.120	-0.013	1001	30000	1328.1
testant[3]	0.246*	1.278	0.025	0.0012	1.70E-04	0.245	0.197	0.294	1001	30000	1635.1
education[1](ref)	-	-	-	-	-	-	-	-	-	-	-
mary[2]	-0.185*	0.831	0.026	0.0013	1.67E-04	-0.185	-0.237	-0.134	1001	30000	1425.1
ndary and ve[3]	-0.210*	0.810	0.028	0.0014	1.75E-04	-0.210	-0.264	-0.157	1001	30000	1321.4
t working[1](ref)	-	-	-	-	-	-	-	-	-	-	-
iculture[2]	-0.025	0.976	0.028	0.0014	1.60E-04	-0.025	-0.079	0.030	1001	30000	1299.5
ers[3]	0.000	1.000	0.027	0.0013	1.66E-04	0.000	-0.052	0.052	1001	30000	1420.8
w no meth.[0](ref)	-	-	-	-	-	-	-	-	-	-	-
w mod. method[1]	-0.409*	0.665	0.025	0.0012	1.96E-04	-0.409	-0.457	-0.360	1001	30000	1622.0
er used con.[0](ref)	-	-	-	-	-	-	-	-	-	-	-
r used cont.[1]	-0.100*	0.905	0.028	0.0014	1.60E-04	-0.100	-0.156	-0.044	1001	30000	1245.1
Heard con.[0](ref)	-	-	-	-	-	-	-	-	-	-	-
rd cont.[1]	-0.207*	0.813	0.026	0.0013	1.55E-04	-0.207	-0.257	-0.157	1001	30000	1527.1
Visited h. f.[0](ref)	-	-	-	-	-	-	-	-	-	-	-
ed health fac.[1]	-0.111*	0.895	0.026	0.0013	1.55E-04	-0.111	-0.162	-0.061	1001	30000	1474.8

Note: * means significant at 95% credible interval

The MC error (SEM) shows how much uncertainty we have about the true posterior mean via the sampled mean. As a rule of thumb, the simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation (http://mathstat.helsinki.fi). In Table 4.2 the Monte Carlo error (MC-error), sample standard deviation (SD), 5% of the SD and the 5% credible intervals for all parameters are reported. It can be seen that for all parameter estimates (Overall effect – visited a health facility) the Monte Carlo error (MC-error) is less than 5% of standard deviation. So we can use this parameter estimate for inferential purpose.

Based on the 95% credible intervals that do not include zero, the overall effect and the variables: age of women 35-49, number of living children (one or two children and three or more children), region (Afar, Oromia, Somali, SNNPR and Gambela), place of residence, religion (Muslim and Protestant), educational level (primary, and secondary and above), knowledge of any method, ever use of contraceptive methods, heard about contraceptive methods through radio and visited a health facility are found statistically significant. On the other hand, the variables age of women 25-34, region (Amhara, Ben-gumuz, Harari, Dire Dawa and Tigray), and occupation of women (Agricultural and Non-agricultural) are not statistically significant.

CHAPTER FIVE

5. DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.1 Discussion

This study examines whether certain demographic, socio-economic, knowledge and information practice influence the intention of not to use contraceptive methods. Descriptive analysis was used to compare the percentage of not intending to use contraceptive among the selected factors. Factors that influence not intending to use contraceptives were examined using Bayesian logistic regression model.

Since all variables that enter the model were categorical, their odds must be interpreted relative to the reference category rather than as a simple increase or decrease in odds. A negative coefficient for categorical variables implies that the likelihood of not intending to use contraceptives is higher for the reference category, while a positive coefficient implies that the likelihood of not intending to use contraceptives is lower for the reference category.

Age group of women 35-49 is an important determinant of not intending to use contraceptives. Inferential analysis reveals that women in the age group 35-49 are about 1.62 times more likely not to intend to use contraceptives as compared to those in the age group 15-24. Probably women in 35-49 age group perceive that they already have low risk of pregnancy due to less frequent sexual activity or lower fecundity. It is similar with the finding in Thailand (Leoprapai and Thongthai, 1989) and Vietnam (Dang, 1995).

Number of living children is an important determinant of not intending to use contraceptives. The study result reveals that women who have one or two children and three or more children are about 1.11 and 1.25 times more likely not to intend to use contraceptives as compared to those who do not have children, respectively. This shows unexpected result.

The region in which women reside is an important determinant of not intending to use contraceptives. Inferential analysis result reveals that women who reside in Afar, Somali and Gambella are about 1.22, 1.18 and 1.07 times more likely not to intend to use contraceptives as compared to those who reside in Addis Ababa, respectively. This might be due to the fact that the majority of the people who reside in these regions are pastoralists. In this community, children are considered as asset. Therefore, they may not intend to use contraceptives. On the other hand, women who reside in Addis Ababa are 1.17 times more likely not to intend to use contraceptives as compared to those who reside in Oromia. Likewise, women who reside in Addis Ababa are 1.19 times more likely not to intend to use contraceptives as compared to those who reside in SNNP regions.

Place of residence is an important determinant of not intending to use contraceptives. The result of inferential analysis reveals that women who reside in urban area are about 1.12 times more likely not to intend to use contraceptives as compared to those who reside in rural area. The result is unexpected, the reason might be that urban women have access to contraceptive services and are already users of contraceptives than rural women. Therefore, since more women that reside in rural are not using contraceptives, they may intend to use contraceptives.

Religion of women is an important determinant of not intending to use contraceptives. The study result reveals that women who are followers of Coptic Orthodox are 1.07 times more likely not to intend to use contraceptives as compared to those who follow Muslim. On the other hand, women who follow Protestant are about 1.28 times more likely not to intend to use contraceptives as compared to those who are Coptic Orthodox.

Educational level of women is an important determinant of not intending to use contraceptives. Inferential analysis result reveals that women who do not have education are 1.20 and 1.23 times more likely not to intend to use contraceptives as compared to those who completed primary education, and secondary and above education, respectively. Better-educated women were more likely to practice contraception and to use modern methods (Shapiro and Tambashe, 1994). Women with better education probably appreciate better health and economic status advantages of small family sizes and they are more likely to protect themselves from unwanted pregnancy. This is similar to the finding from previous studies in Zaire (Shapiro and Tambashe, 1994) and in Iran (Tehrani et al., 2001).

No knowledge of contraceptive methods is an important determinant of not intending to use contraceptives. The result of inferential analysis reveals that women who know no method are 1.50 times more likely not to intend to use contraceptives as compared to those who have knowledge of contraceptive methods. This might be due to the reason that women who know about contraceptives have more intention to use contraceptives than those who do not.

Ever use of contraceptive methods was found to be an important determinant of not intending to use contraceptives. The study result reveals that women who never used modern contraceptive methods are 1.11 times more likely not to intend to use contraceptives as compared to those who ever used modern contraceptive methods.

Contraceptive information through radio is also an important determinant of the intention to use contraceptives. The result of inferential analysis reveals that women who have not heard contraceptive messages on radio are 1.23 times more likely not to intend to use contraceptives as compared to those who heard contraceptive on radio a month prior to the survey. A study on mass media promotion in three cities of Nigeria shows that using Information and Education (IE) material to promote family planning through Television and Radio can be an important means to improve knowledge and initiate women to practice any modern contraceptive method (Oyedokun, 2007).

Access to a health facility is another important determinant of the intention to use contraceptives. The study reveals that women who did not visit a health facility in last 12 months prior to the survey are 1.12 times more likely not to intend to use contraceptives as compared to those who visited a health facility in last 12 months. This finding is in line with a study on the impact of outreach activity on the continuity of contraceptive use in rural Bangladesh, which reveals that women contacted by family planning field workers predominantly use contraception and could reduce discontinuation rate by 65% (Hossain and Phillip, 1996).

5.2 Conclusion

The major objective of this study was to explore the factors affecting the intention not to use contraceptives among sexually active women in Ethiopia. Three major categories of explanatory variables were considered. These are demographic variables (age of women and number of living children), socio-economic variables (region, place of residence, religion, education level of women and occupation of women) and knowledge, information and practice of contraceptives (knowledge of any method, ever use of contraceptive methods, heard contraceptive through radio and visited a health facility). Bayesian logistic regression is used for inferential analysis of these variables.

Results of Bayesian logistic regression analysis show that most of the variables considered in the study have significant effects on not intending to use contraceptive methods. The study results revealed that of the demographic factors, women's age and number of living children have a significant effect on the intention of not to use contraceptives.

The region in which women reside had a statistically significant effect on not intending to use contraceptives. The analysis result revealed that women who reside in Oromia and SNNPR are more likely to intend to use contraceptives than women who reside in Addis Ababa, while women who reside in Addis Ababa are more likely to intend to use contraceptives than women in Afar, Amhara, Somali, Ben-gumuz and Gambela regions. Likewise, place of residence also has a statistically significant effect on the intention to use contraceptives.

The religion women follow has a statistically significant effect on not intending to use contraceptives. The study result revealed that women who follow Muslim are more likely to intend to use contraceptives than women who follow Coptic Orthodox, while women who follow Coptic Orthodox are more likely to intend to use contraceptives than women who follow Protestant.

Women's education also had a positive effect on intention to use contraceptive. Women with primary, secondary and higher education probably appreciated better health and economic status advantages of small family sizes and they were more likely to protect themselves from unwanted pregnancy. So, their intention to use is higher than those with no education. The result of the study revealed that women who have knowledge of contraceptive methods, who ever used contraceptive methods, who heard about contraceptive methods on radio, and who have visited a health facility recently are more likely to intend to use contraceptives.

5.3 Recommendations

The findings reveal that women who had better education have more intention to use contraceptives than those who had no education. Therefore, family planning program should pay attention to women with no education to change their intention and provide contraceptive services and improve access to education. Similarly, women who have knowledge of contraceptive methods have more intention to use contraceptives than those who do not. Therefore, knowledge relating to contraceptives should be provided to the community. It is better to design and implement behavioral change communication (BCC) approach in addition to formal education.

The findings revealed that intention to use contraceptives vary in different religions in Ethiopia. Due to this, programs that focus on religious leaders should be designed and implemented. By using the position, authority and the social status of religious leaders in the community, it is possible to make contraceptive knowledge accessible.

Women who ever used contraceptive method have more intention to use contraceptives than those who never used. Therefore, programs that target non-users of contraceptives have to be designed and implemented.

Women who heard about contraceptive methods have more intention to use contraceptives. Therefore, we have to advocate for administrators to design and implement programs which focus on contraceptives to be disseminated through media.

Women who visited a health facility have more intention to use contraceptives than those who do not. Therefore, the current government programs that focus on health facilities construction should be encouraged and improved to increase the contact and discussion between the community and health workers.

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ANNEXES

Annex A1: Cross tabulation of categorical predictor variables in the study Vs response variable

Predictor variables		**Response variable**		**Total**
		Intend to use	**Does not intend**	
Region	Addis Ababa	947	460	1407
		67.3%	32.7%	100.0%
	Dire Dawa	317	282	599
		52.9%	47.1%	100.0%
	Harari	358	268	626
		57.2%	42.8%	100.0%
	Gambela	199	355	554
		35.9%	64.1%	100.0%
	SNNPR	1132	591	1723
		65.7%	34.3%	100.0%
	Ben-gumuz	254	415	669
		38.0%	62.0%	100.0%
	Somali	24	551	575
		4.2%	95.8%	100.0%
	Oromia	1206	729	1935
		62.3%	37.7%	100.0%
	Amhara	796	853	1649
		48.3%	51.7%	100.0%
	Afar	59	631	690
		8.6%	91.4%	100.0%
	Tigray	610	406	1016
		60.0%	40.0%	100.0%
Religion	Protestant	1609	2603	4212
		38.2%	61.8%	100.0%
	Muslim	1137	741	1878
		60.5%	39.5%	100.0%
	Coptic Orthodox	3156	2197	5353
		59.0%	41.0%	100.0%
Occupation of women	Others	3794	3809	7603
		49.9%	50.1%	100.0%
	Agriculture	784	748	1532
		51.2%	48.8%	100.0%
	Not working	1324	984	2308
		57.4%	42.6%	100.0%
Ever use of contraceptive methods	Used modern methods	783	396	1179
		66.4%	33.6%	100.0%
	Never used	5119	5145	10264
		49.9%	50.1%	100.0%
Heard through radio	Yes	2452	1190	3642
		67.3%	32.7%	100.0%
	No	3450	4351	7801
		44.2%	55.8%	100.0%
Visited a health facility	Yes	1614	1049	2663
		60.6%	39.4%	100.0%
	No	4288	4492	8780
		48.8%	51.2%	100.0%
Overall dependent		**5902**	**5541**	**11443**
		51.6%	**48.4%**	**100.%**

Annex A2: The code, prior distribution, and initial guess values used to analyze the model in WinBUGS 3.0.3 are as follows:

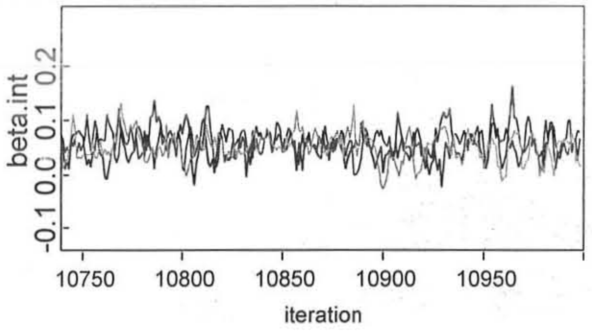
```
model
        {
                for( i in 1 : N ) {
                        Y[i] ~ dbern(p[i]);
logit(p[i])<- beta.int + beta.age[x1[i]]+ beta.chil[x2[i]] + beta.region[x3[i]] + beta.plr*x4[i] +
beta.relgion[x5[i]] + beta.edu[x6[i]] + beta.occ[x7[i]] + beta.knl*x8[i] + beta.evu*x9[i] +
beta.heard*x10[i] + beta.visit*x11[i]
                                Y.rep[i]~dbern(p[i])
                                Pvalue[i]<-step(Y.rep[i]-Y[i]);
   }
        beta.int ~ dnorm ( 0, 1000 )
        beta.age[1]<-0; # corner-point constraint
        for(k in 2:3) {
        beta.age[k] ~ dnorm ( 0, 1000 )
        }
        beta.chil[1]<-0; # corner-point constraint
        for(l in 2:3) {
        beta.chil[l] ~ dnorm ( 0, 1000 )
        }
        beta.region[1]<-0; # corner-point constraint
        for(m in 2:11) {
        beta.region[m] ~ dnorm ( 0, 1000 )
        }
        beta.plr ~ dnorm ( 0, 1000 )
        beta.relgion[1]<-0; # corner-point constraint
        for(n in 2:3) {
        beta.relgion[n]~ dnorm ( 0, 1000 )
        }
        beta.edu[1]<-0; # corner-point constraint
        for(q in 2:3) {
        beta.edu[q]~ dnorm ( 0, 1000 )
        }
        beta.occ[1]<-0; # corner-point constraint
        for(r in 2:3) {
        beta.occ[r]~ dnorm ( 0, 1000 )
        }
        beta.knl ~ dnorm ( 0, 1000 )
        beta.evu ~ dnorm ( 0, 1000 )
        beta.heard~ dnorm ( 0, 1000 )
        beta.visit~ dnorm ( 0, 1000 )
        }
list(N=11443)
Data
```

Inits1 list(beta.int = 0.7, beta.age = c(NA,0.01,0.02), beta.chil= c(NA,0.1,0.05), beta.region= c(NA,0.03,0.07, 0.09, 0.1, 0.02, 0.09, 0.3, 0.08, 0.09, 0.05), beta.plr=0.8, beta.relgion= c(NA,0.1,0.09), beta.edu = c(NA,0.07,0.02), beta.occ=c(NA,0.8, 1), beta.knl=0.4, beta.evu=1, beta.heard=0.2,beta.visit=1)

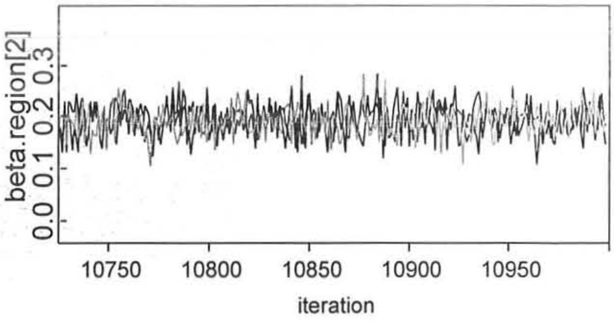
Inits2 list(beta.int = 1, beta.age = c(NA,0.9,0.7), beta.chil= c(NA,0.08,0.5), beta.region= c(NA,0.009,0.8, 0.6, 0.02, 0.4, 0.9, 0.07, 0.6, 0.7, 0.09), beta.plr=0.05, beta.relgion= c(NA,0.05,0.1), beta.edu = c(NA,0.7,0.9), beta.occ=c(NA,0.4, 0.08), beta.knl=0.08, beta.evu=0.5, beta.heard=0.9,beta.visit=0.7)

Inits3 list(beta.int = 0.09, beta.age = c(NA,1,0.009), beta.chil= c(NA,0.04,0.5), beta.region= c(NA,0.8,0.1, 0.06, 0.07, 0.2, 0.2, 0.05, 0.1, 0.3, 0.1), beta.plr=0.6, beta.relgion= c(NA,0.7,0.1), beta.edu = c(NA,0.03,0.9), beta.occ=c(NA,0.9, 0.3), beta.knl=0.7, beta.evu=0.5, beta.heard=1,beta.visit=0.6)

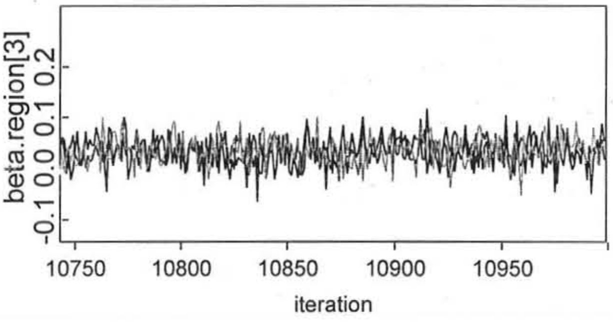
Annex B1: Trace plot of the regression coefficients used in the model



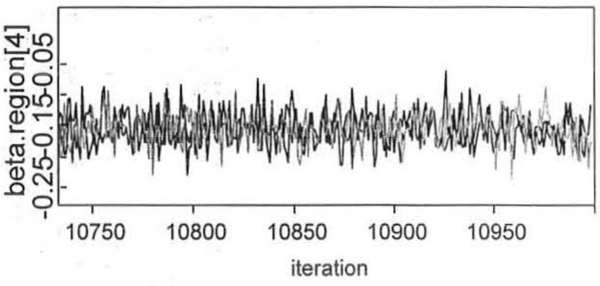
c) Trace plot of overall effect



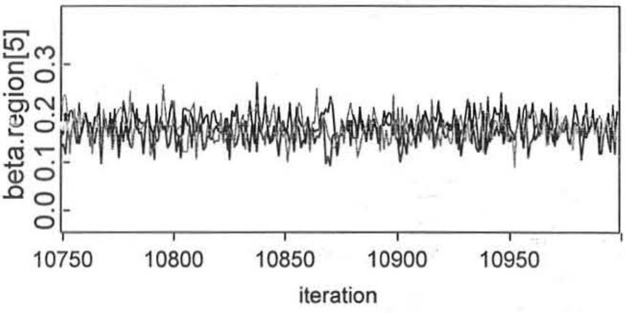
d) *i*) Trace plot of Afar Region



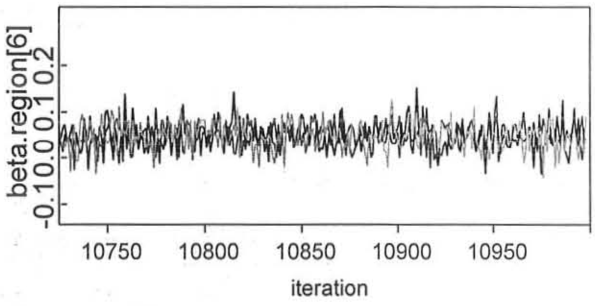
d) *ii*) Trace plot of Amhara Region



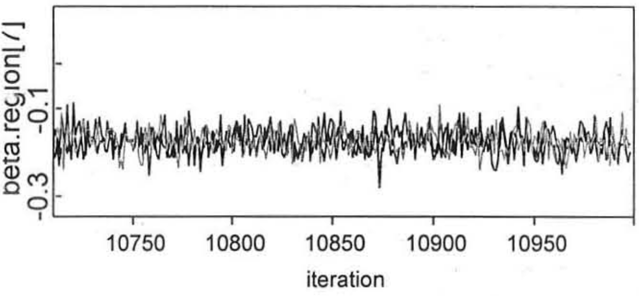
d) *iii*) Trace plot of Oromia Region



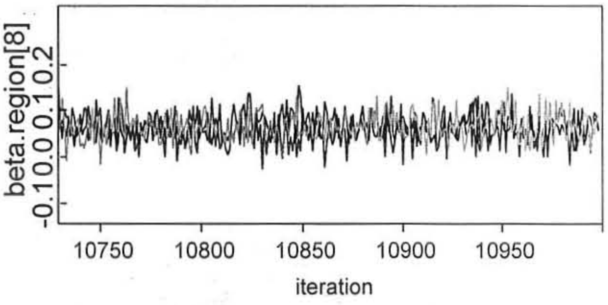
d) *iv*)Trace plot of Somali Region



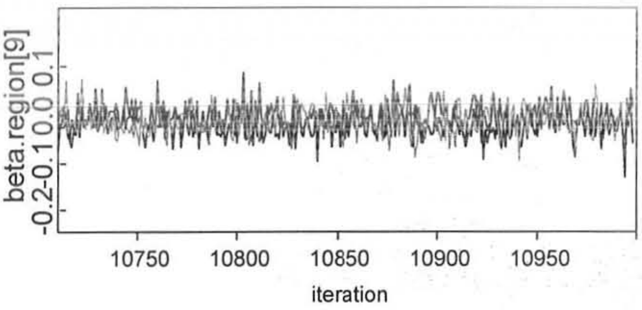
d) *v*) Trace plot of Ben-gumuz Region



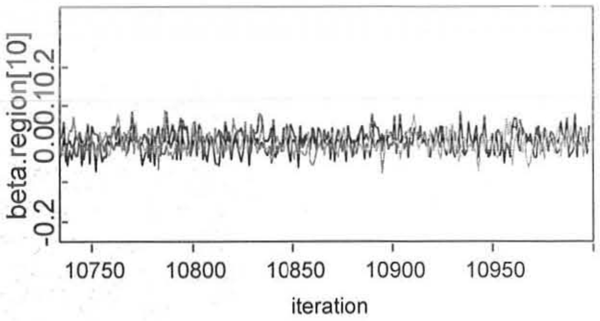
d) *vi*)Trace plot of SNNP Region



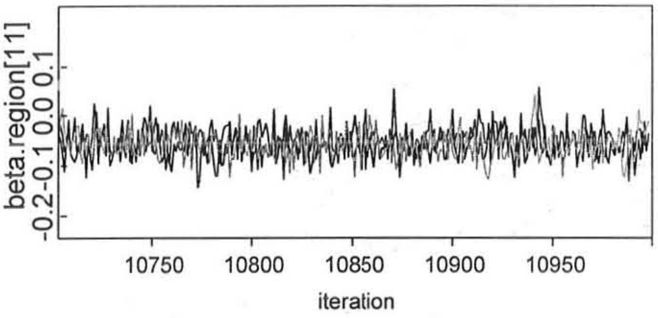
d) *vii*) Trace plot of Gambela Region



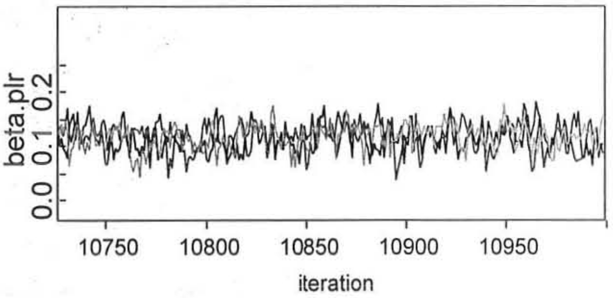
d) *viii*) Trace plot of Harari Region



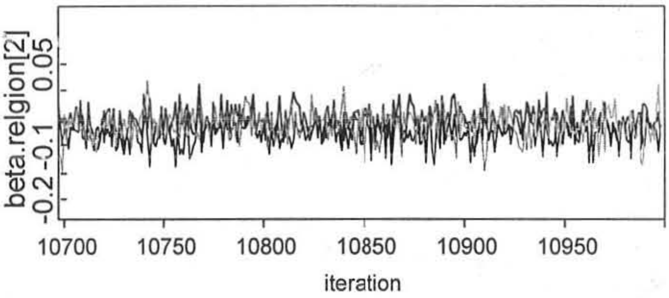
d) *ix*) Trace plot of Dire Dawa City



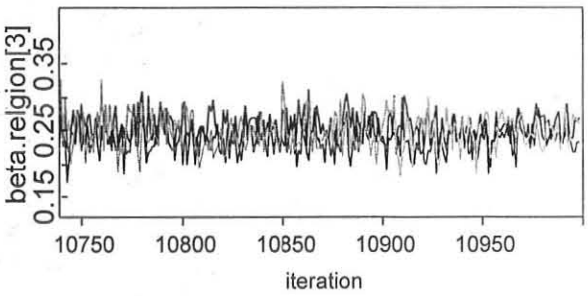
d) *x*) Trace plot of Tigray Region



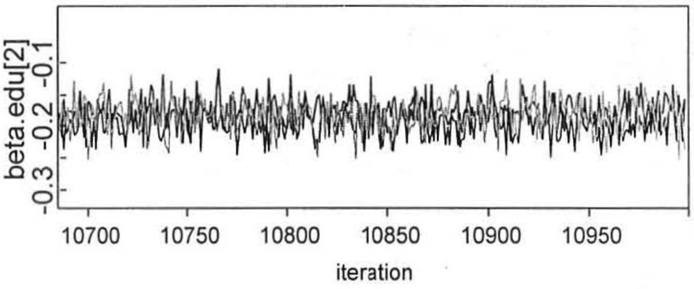
e) Trace plot of Place of residence



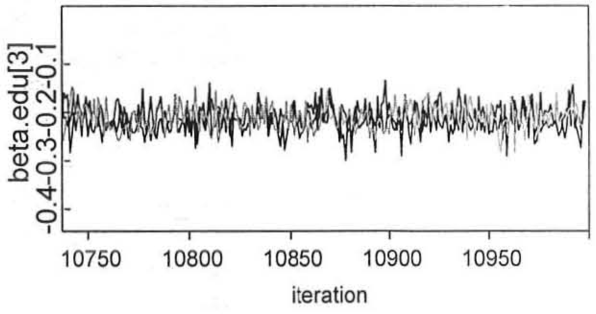
f) *i*) Trace plot of Muslim followers



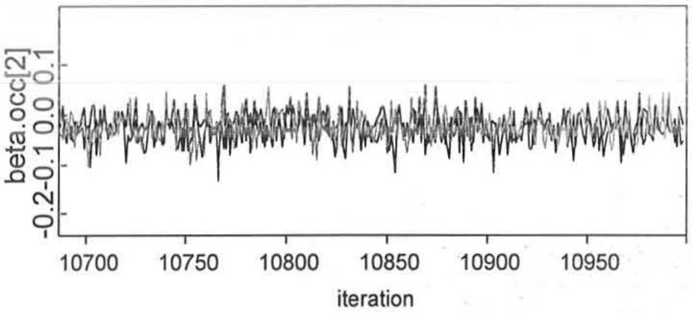
f) *ii*) Trace plot of Protestant followers



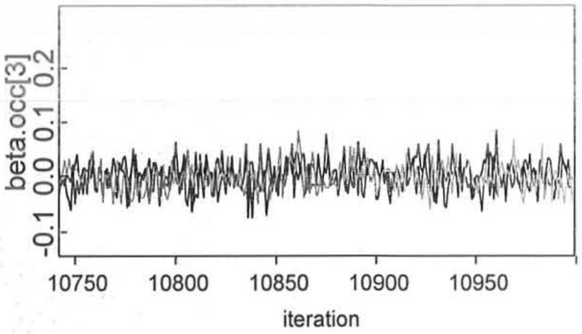
g) *i*) Trace plot of Primary education



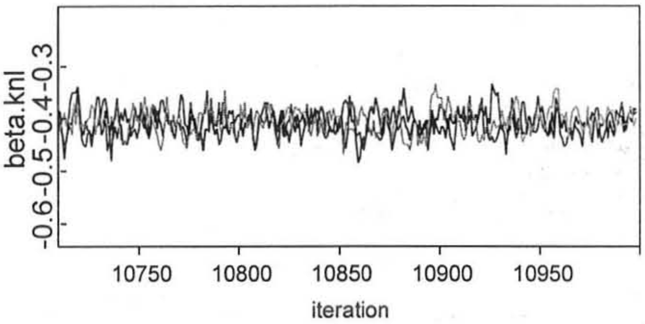
g) *ii*) Trace plot of Secondary and above education



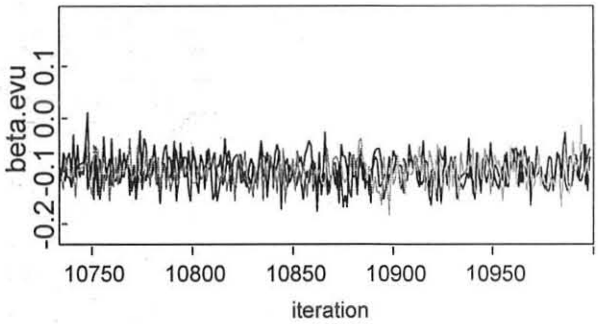
h) *i*) Trace plot of Agricultural workers



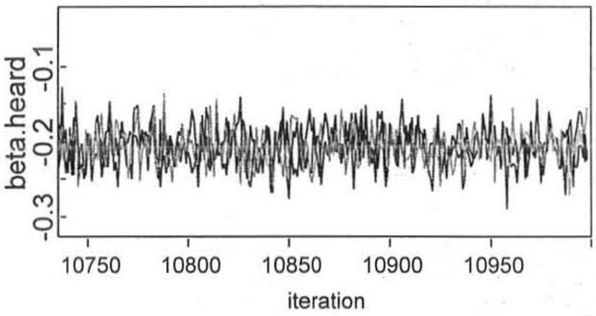
h) *ii*) Trace plot of Non-agricultural workers



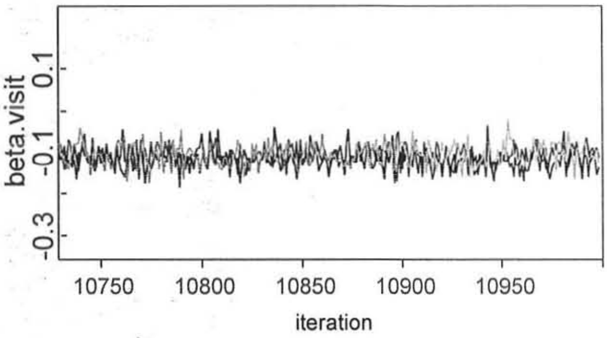
i) Trace plot of knowledge of any methods



j) Trace plot of ever use of cont. methods

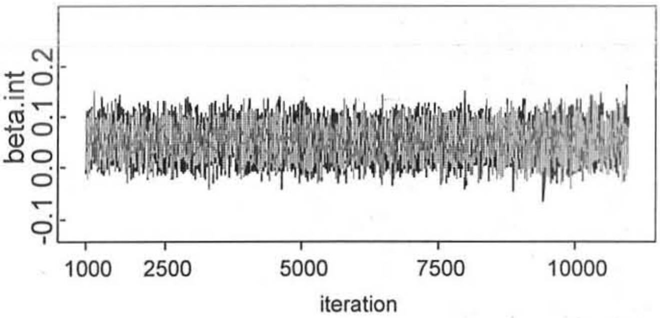


k) Trace plot of heard through radio

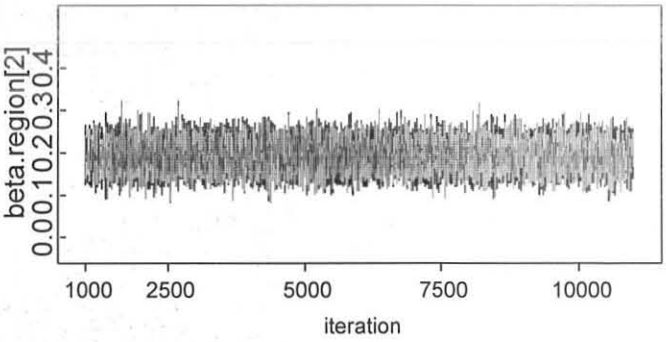


l) Trace plot of visited a health facility

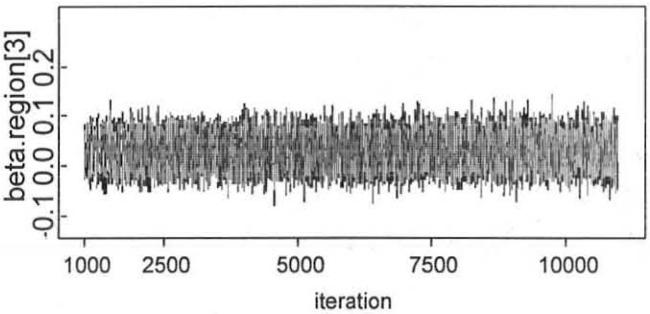
Annex B2: History plots of the regression coefficients used in the model



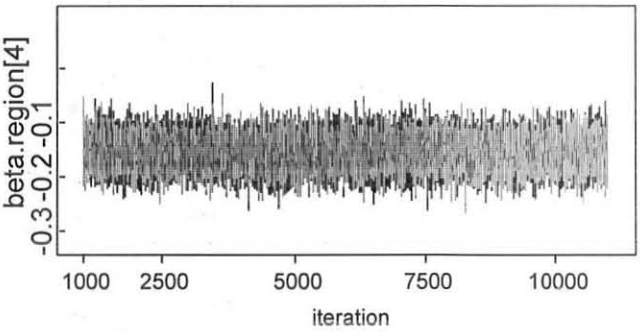
c) History plot of overall effect



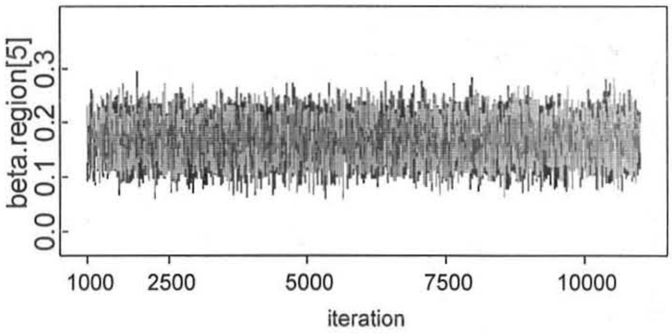
d) *i*) History plot of Afar Region



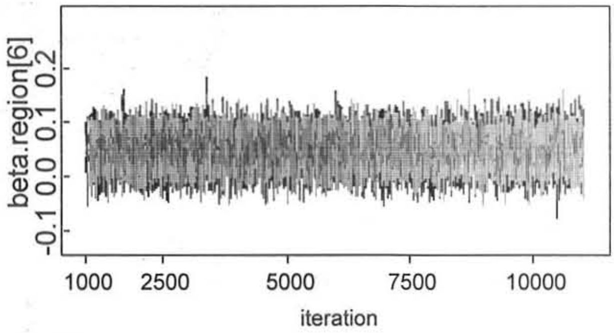
d) *ii*)History plot of Amhara Region



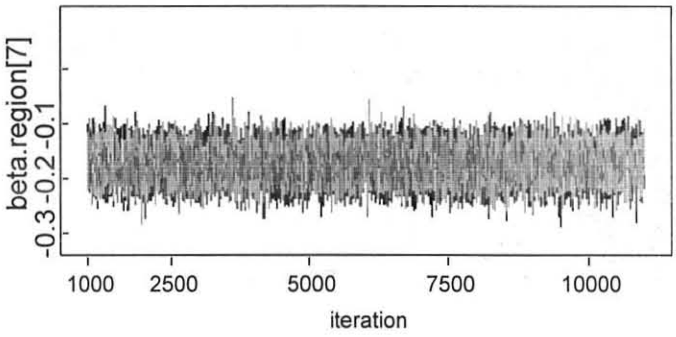
d) *iii*) History plot of Oromia Region



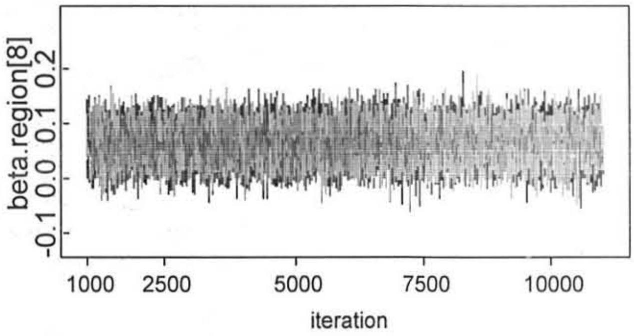
d) *iv*)History plot of Somali Region



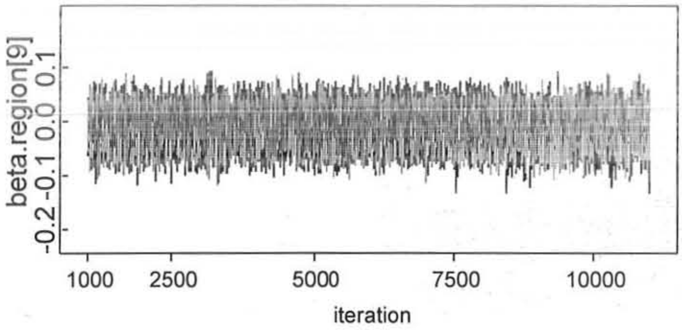
d) *v*) History plot of Ben-gumuz Region



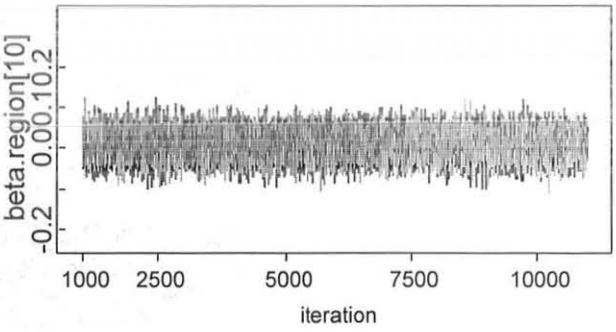
d) *vi*) History plot of SNNP Region



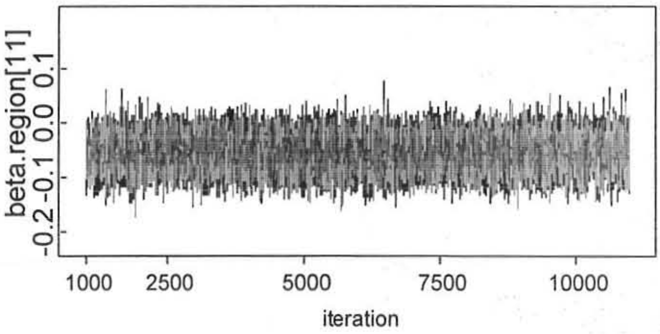
d) *vii*) History plot of Gambela Region



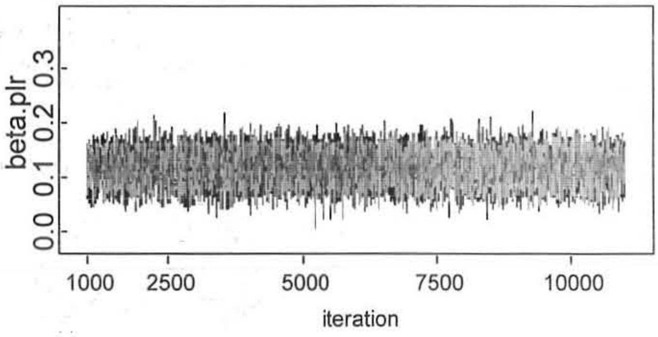
d) *viii*) History plot of Harari Region



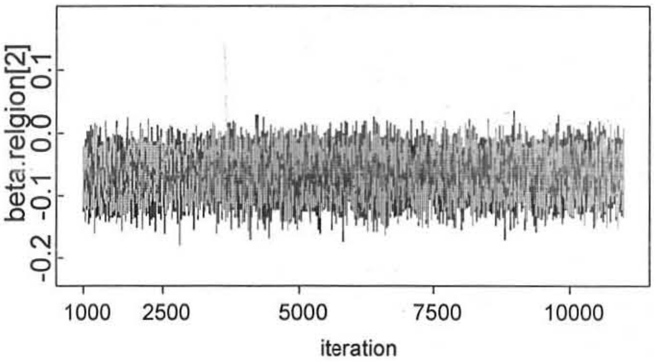
d) *ix*) History plot of Dire Dawa city



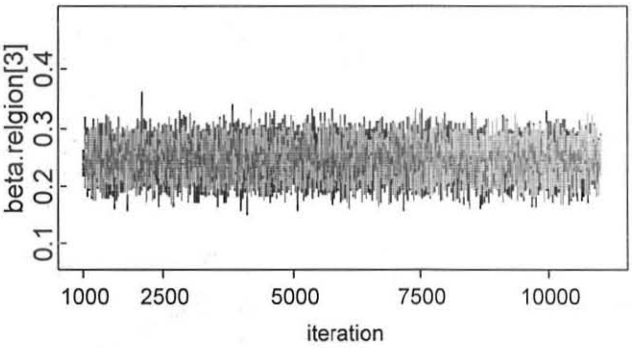
d) *x*) History plot of Tigray Region



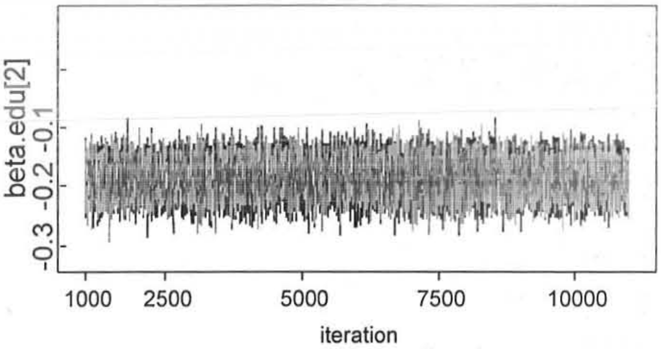
e) History plot of place of residence

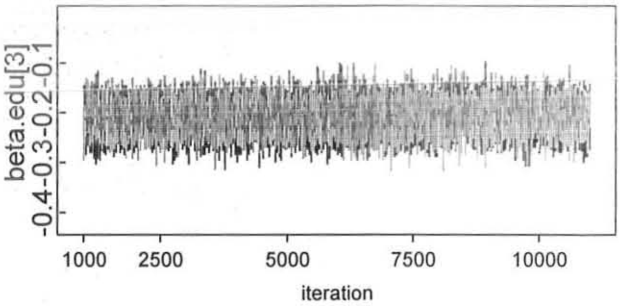


f) *i*) History plot of Muslim followers



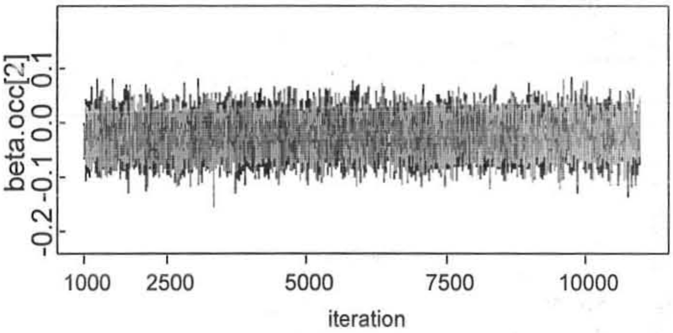
f) *ii*) History plot of Protestant followers

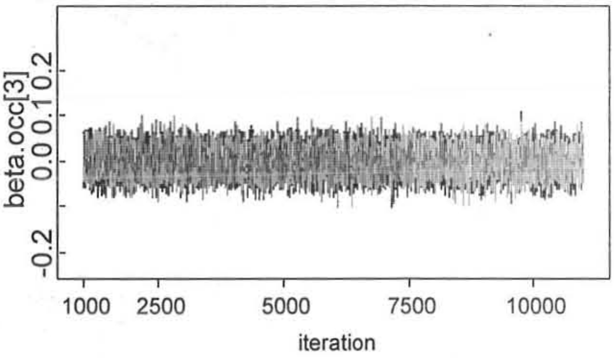




g) *i*) History plot of Primary education

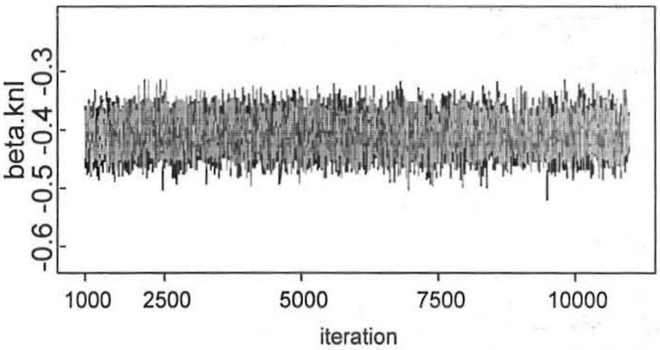
g) *ii*) History plot of Secondary and above



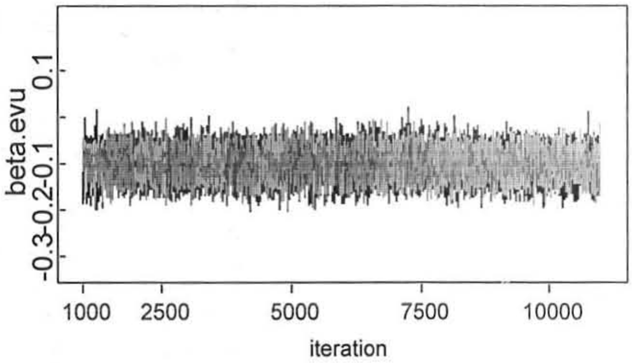


h) *i*) History plot of Agricultural workers

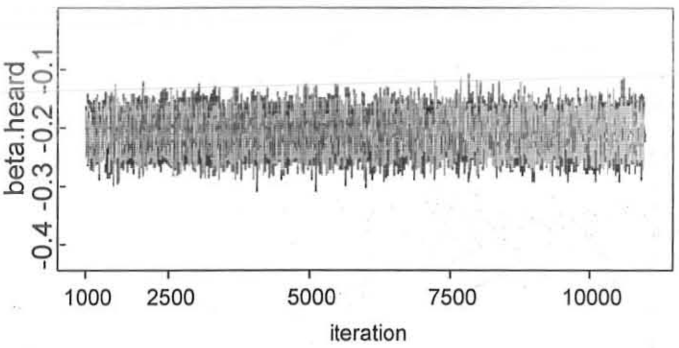
h) *ii*) History plot of Non-agricultural workers



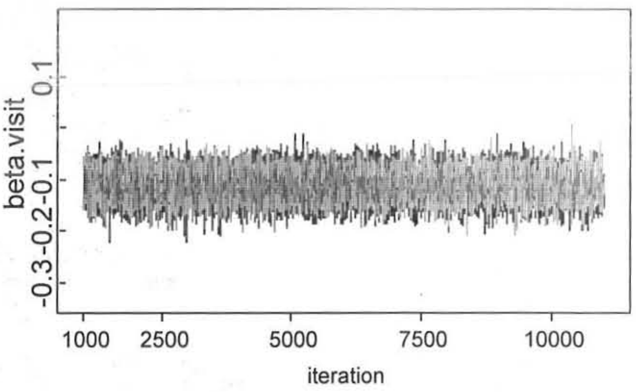
i) History plot of knowledge of contraceptive



j) History plot of ever use of contraceptive

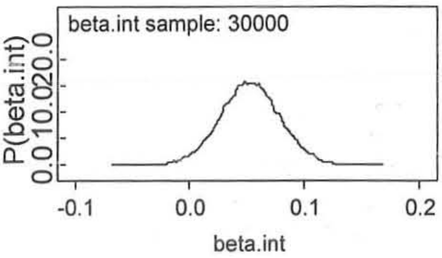


k) History plot of heard contraceptive through radio

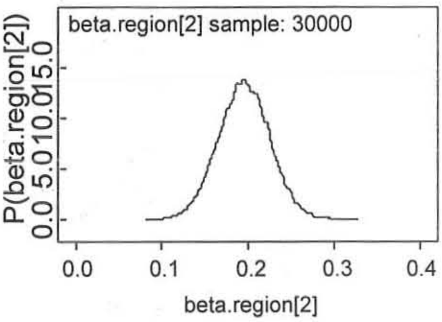


l) History plot of visited health facility

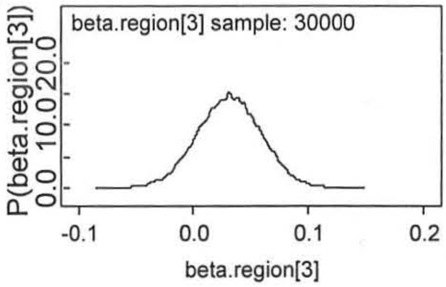
Annex B3: Posterior marginal distribution of each parameter estimate

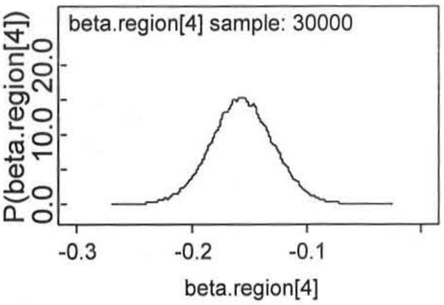


c) Posterior density of overall effect



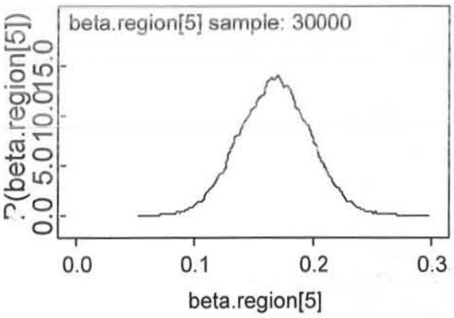
d) *i*) Posterior density of Afar Region



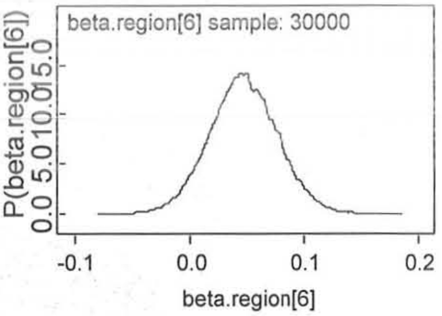


d) *ii*) Posterior density of Amhara Region

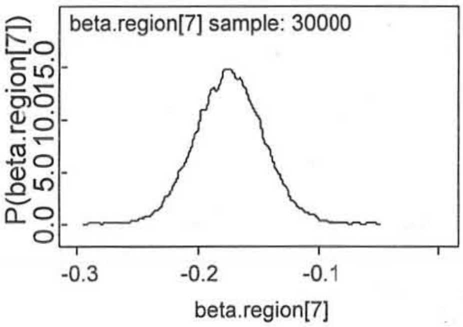
d) *iii*) Posterior density of Oromia Region



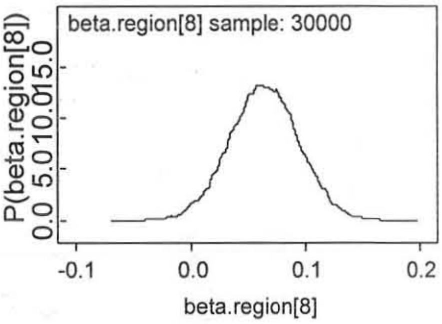
d) *iv*) Posterior density of Somali Region



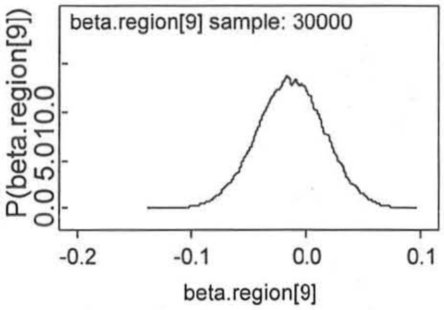
d) *v*) Posterior density of Ben-gumuz Region



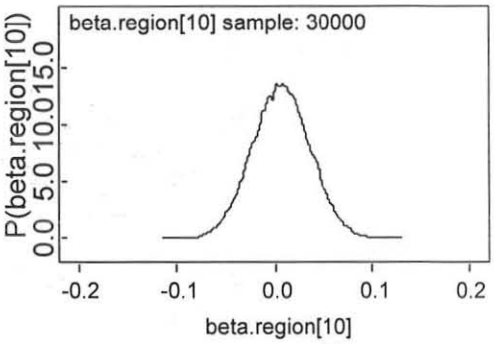
d) *vi*) Posterior density of SNNPR Region



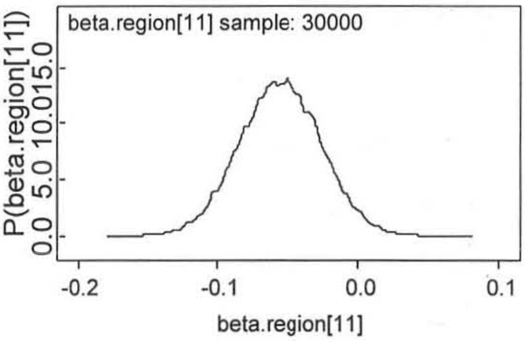
d) *vii*) Posterior density of Gambela Region



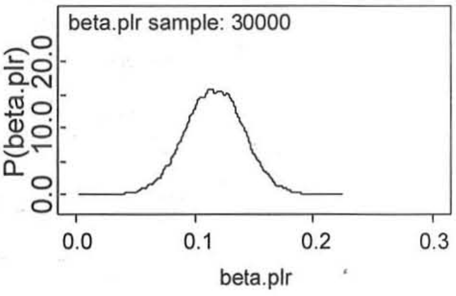
d) *viii*) Posterior density of Harari Region



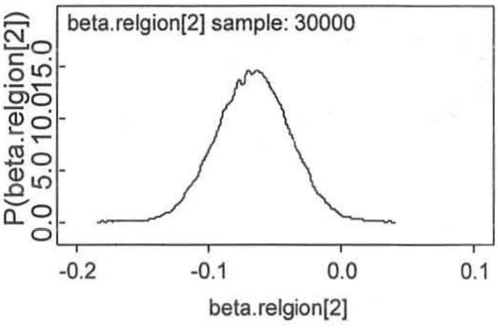
d) *ix*) Posterior density of Dire Dawa City



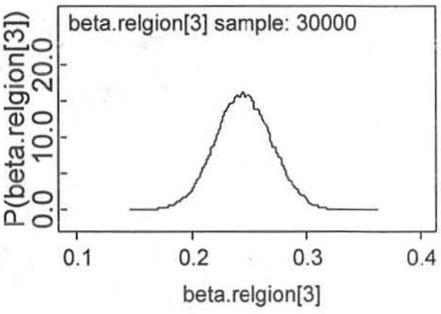
d) x) Posterior density of Tigray Region



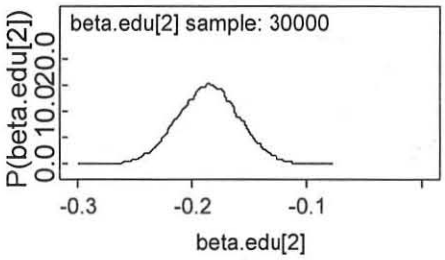
d) Posterior density of place of residence



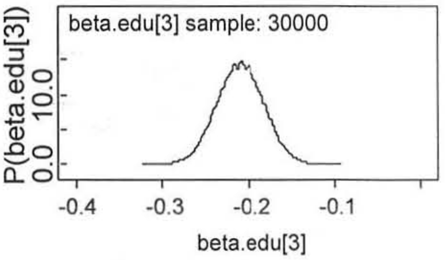
f) i) Posterior density plot of Muslim followers



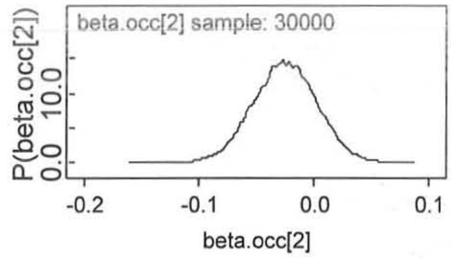
f) ii) Posterior density followers of Protestant followers



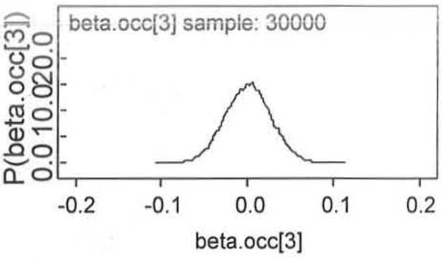
g) i) Posterior density plot of Primary



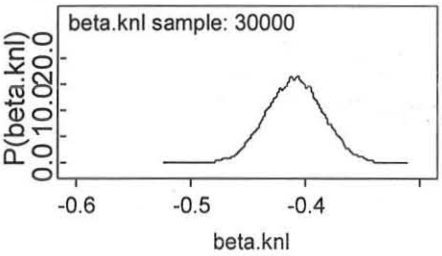
g) ii)Posterior density plot of Secondary and above



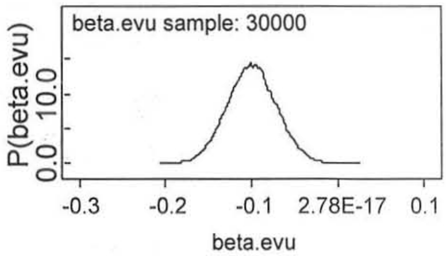
h) *i*) Posterior density plot of Agricultural Workers



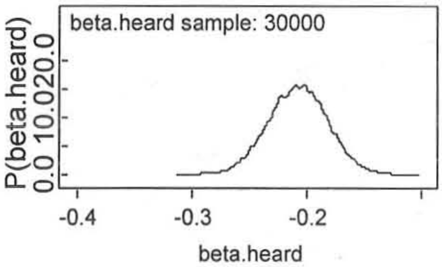
h) *ii*) Posterior density plot of Non-agricultural Workers



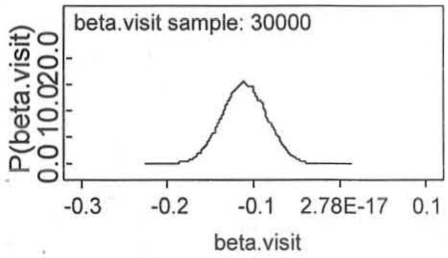
i) Posterior density plot of knowledge of contraceptive



j) Posterior density plot of ever use of contraceptive

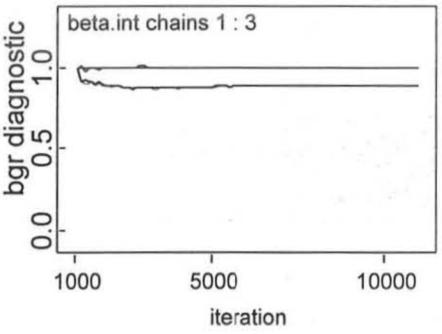


k) Posterior density plot of heard through radio

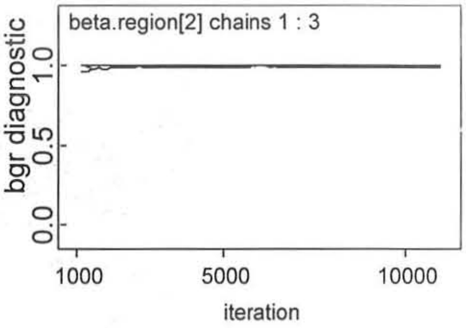


l) Posterior density plot of visited health facility

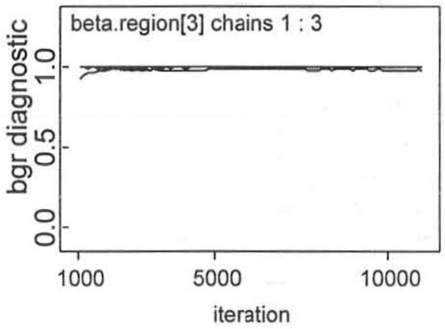
Annex B4: Plot for Brook, Gelman and Rubin (BGR) statistic for convergence



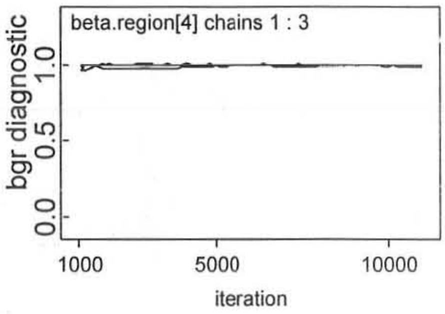
C) BGR plot for overall effect



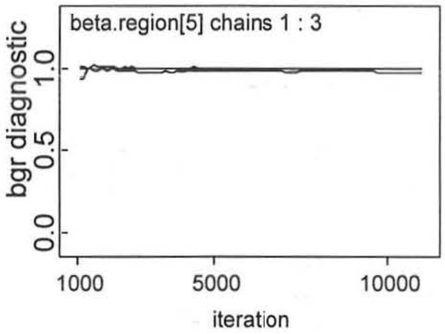
d) *i*) BGR plot of Afar Region



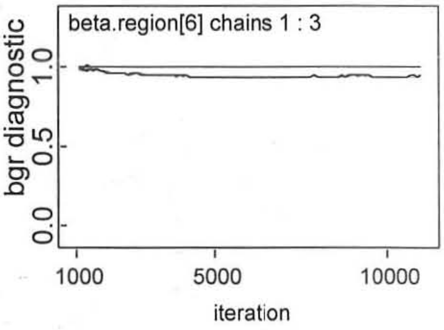
d) *ii*) BGR plot of Amhara Region



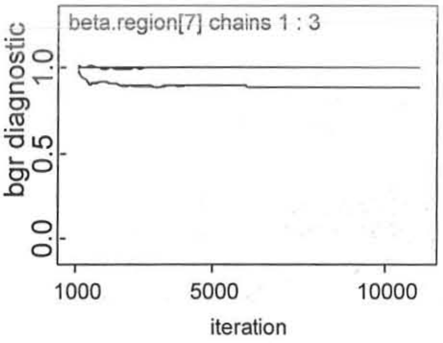
d) *iii*) BGR plot of Oromia Region

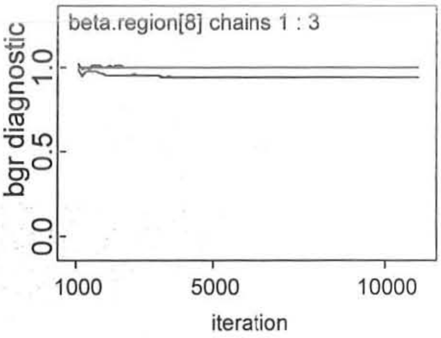


d) *vi*) BGR plot of Somali Region



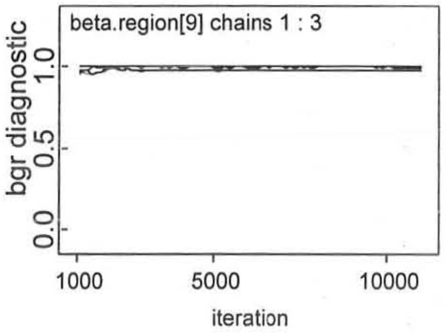
d) *v*) BGR plot of Ben-gumuz

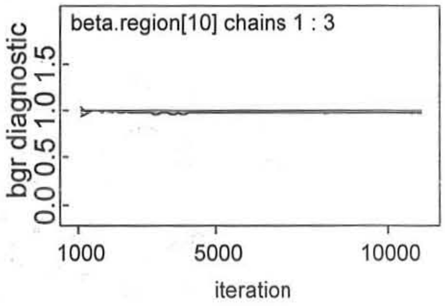




d) *vi*) BGR plot of SNNP Region

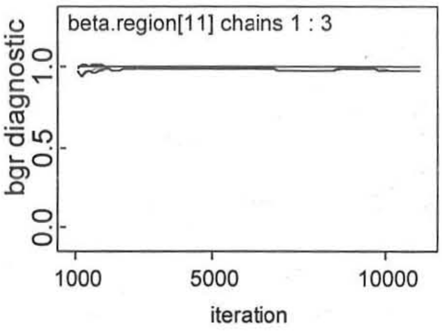
d) *vii*) BGR plot of Gambela Region

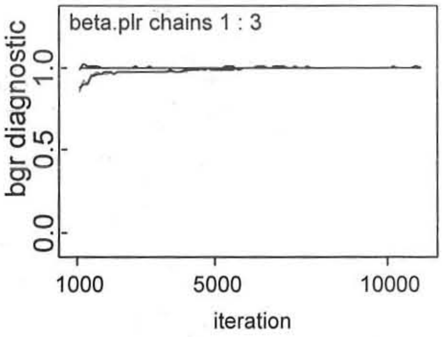




d) *viii*) BGR plot of Harari Region

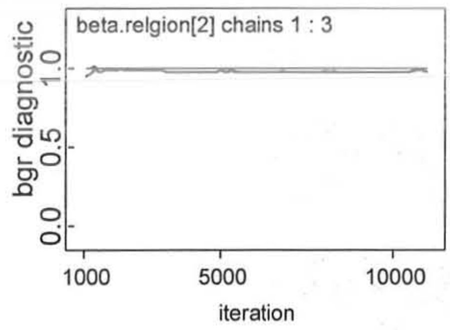
d) *ix*) BGR plot of Dire Dawa city

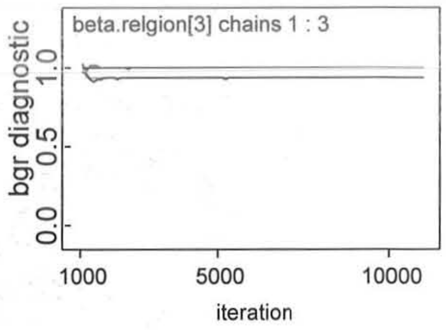




d) *x*) BGR plot of Tigray Region

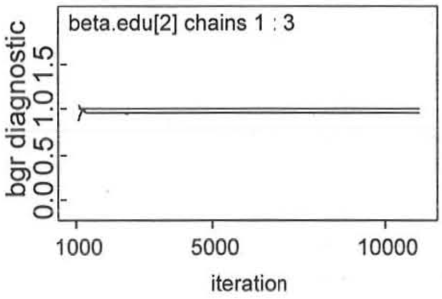
e) BGR plot of place of residence

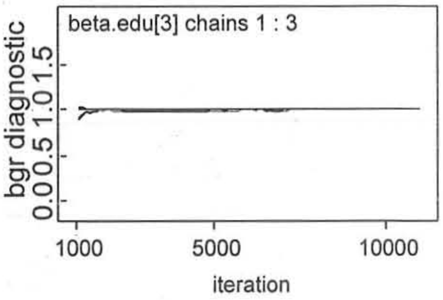




f) *i*) BGR plot of Muslim followers

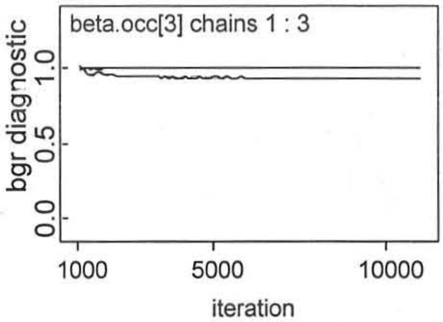
f) *ii*) BGR plot of Protestant followers

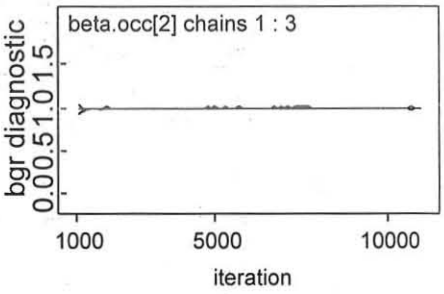




g) *i*) BGR plot of primary education

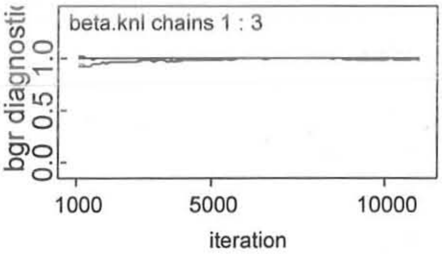
g) *ii*) BGR plot of secondary and above education

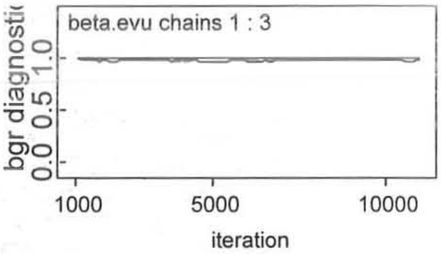




h) *i*) BGR plot of Agricultural workers

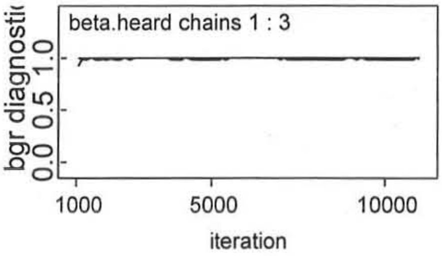
h) *ii*) BGR plot of Non-agricultural workers



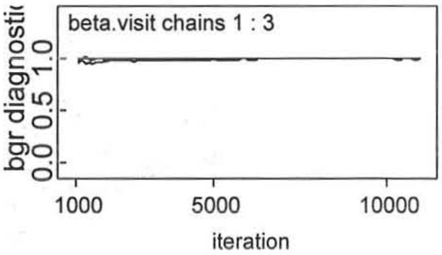


i) BGR plot of knowledge of contraceptive method

j) BGR plot of ever use of contraceptive method

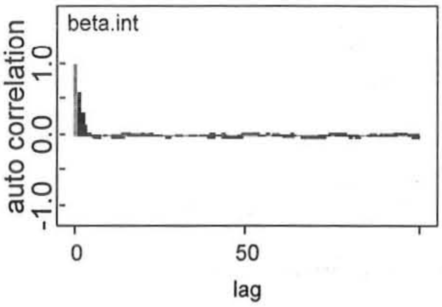


k) BGR plot of heard through radio

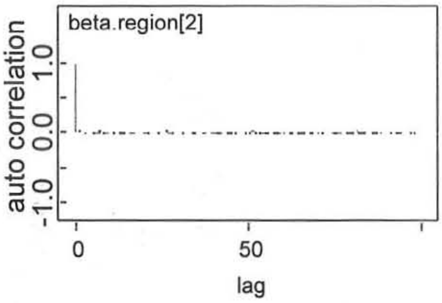


l) BGR plot of visited health facility

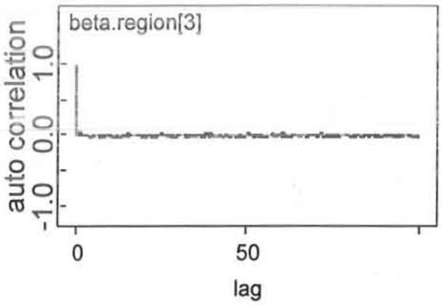
Annex B5: Plot for autocorrelation for the samples

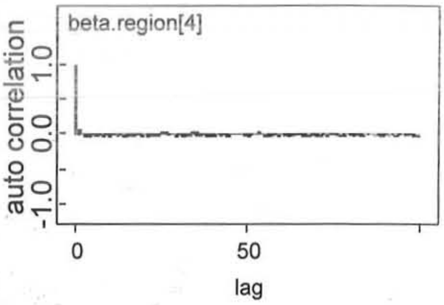


c) Autocorrelation plot of overall effect

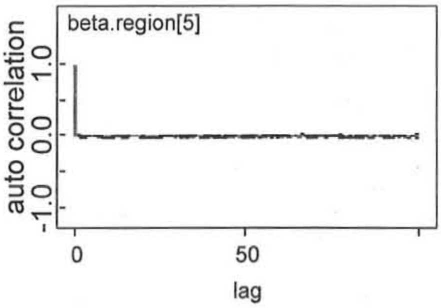


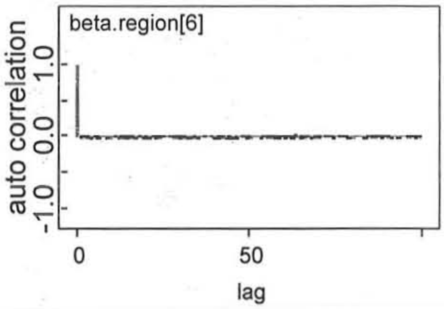
d) *i*) Autocorrelation plot of Afar Region



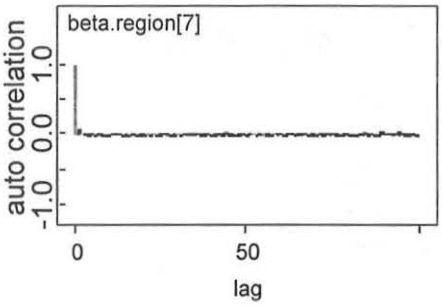


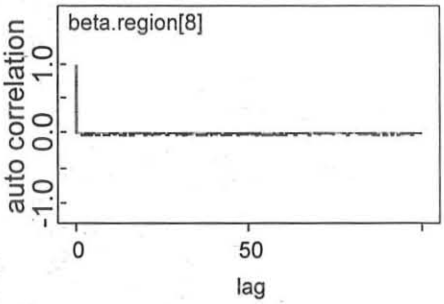
d) *ii*) Autocorrelation plot of Amhara Region d) *iii*) Autocorrelation plot of Oromia Region



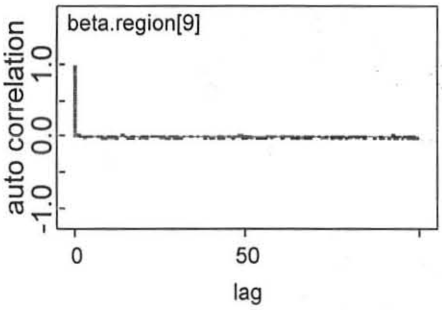


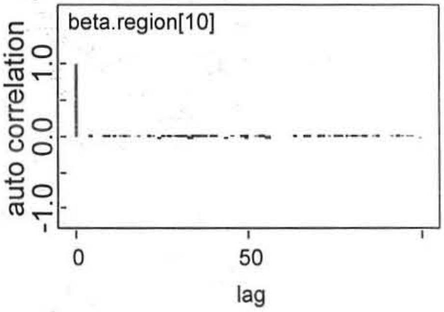
d) *iv*) Autocorrelation plot of Somali Region d) *v*) Autocorrelation plot of Ben-gumuz



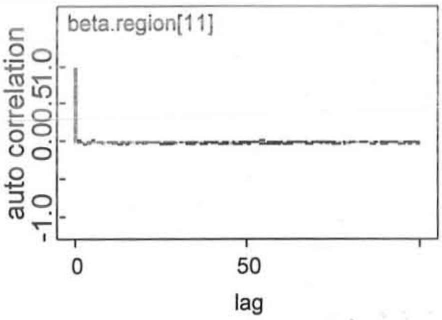


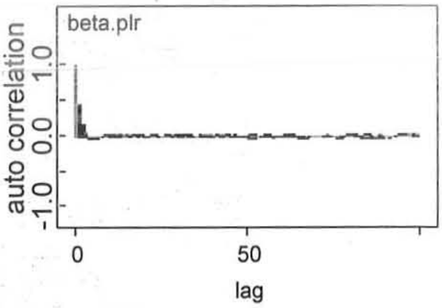
d) *vi*) Autocorrelation plot of SNNP Region d) *vii*) Autocorrelation plot of Gambela Region





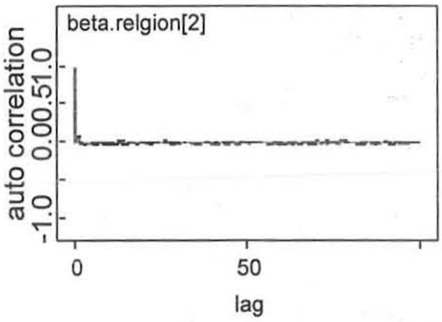
d) *viii*) Autocorrelation plot of Harari Region d) *ix*) Autocorrelation plot of Dire Dawa city

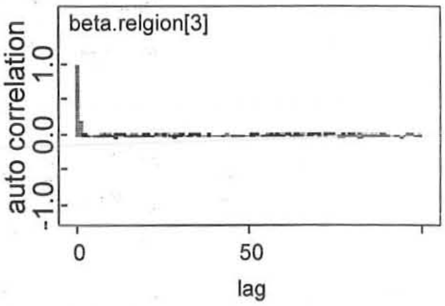




d) *x*) Autocorrelation plot of Tigray Region

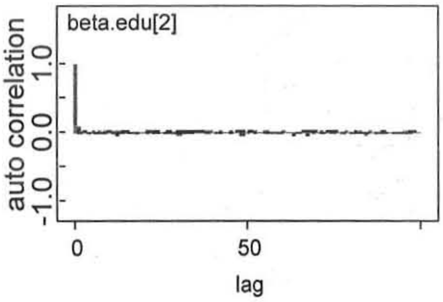
e) Autocorrelation plot of place of residence

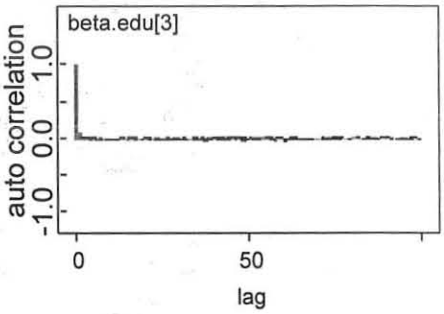




f) *i*) Autocorrelation plot of Muslim followers

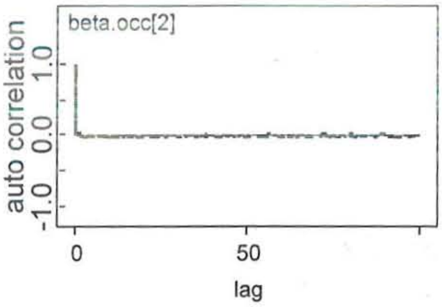
f) *ii*) Autocorrelation plot of Protestant followers



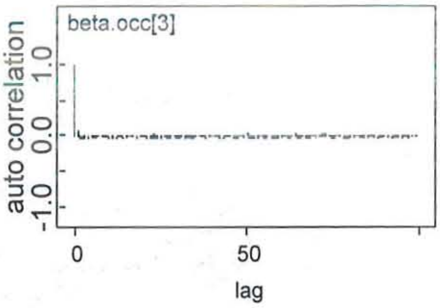


g) *i*) Autocorrelation plot of primary education

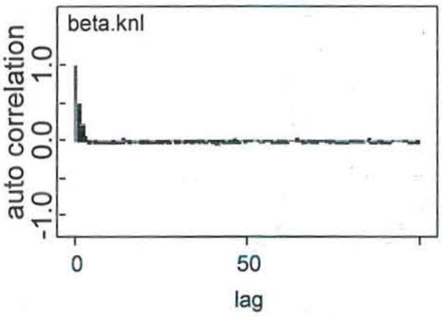
g) *ii*) Autocorrelation plot of secondary and above education



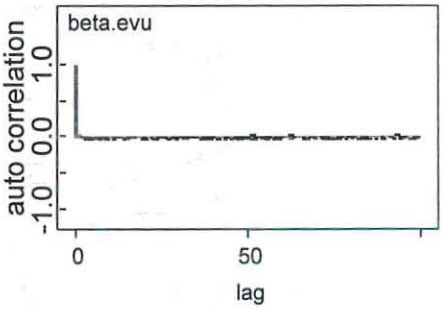
h) *i*) Autocorrelation plot of Agriculture workers



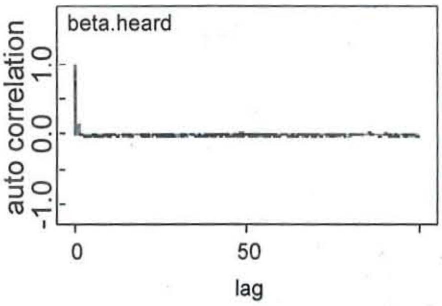
h) *ii*) Autocorrelation plot of Non-agriculture workers



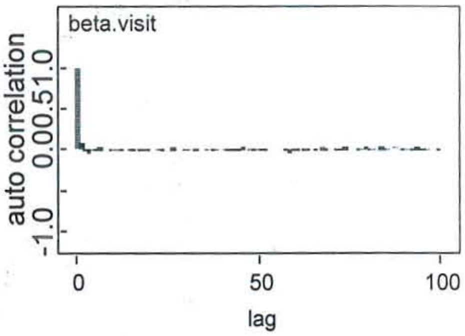
i) Autocorrelation plot of knowledge of contraceptives



j) Autocorrelation plot of ever use of contraceptive



k) Autocorrelation for Heard through radio



l) Autocorrelation plot of visited health facility

DECLARATION

I THE UNDERSIGNED, DECLARE THAT THIS THESIS IS MY ORIGINAL WORK IN PARTIAL FULFILLMENT FOR THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN STATISTICS IN THE UNIVERSITY OF ADDIS ABABA. ALL THE SOURCES OF THE MATERIALS USED FOR THIS THESIS AND ALL PEOPLE AND INSTITUTIONS WHO GAVE SUPPORT FOR THIS WORK ARE FULLY ACKNOWLEDGED. IT HAS NOT BEEN SUBMITTED BEFORE FOR ANY DEGREE OR EXAMINATION AT THIS OR ANY OTHER UNIVERSITY.

NAME: MULUNEH SORISSA

SIGNITURE ____________________

PLACE OF SUBMISSION -DEPARTMENT OF STATISTICS,

COLLEGE OF NATURAL SCIENCES ADDIS ABABA UNIVERSITY

DATE OF SUBMISSION March|28|2021

THIS THESIS WORK HAS BEEN SUBMITTED FOR EXAMINATION WITH MY

APPROVAL AS A UNIVERSITY ADVISOR.

DR. EMMANUEL G/YOHANNES 28/03/2011