CLASSICAL AND BAYESIAN REGRESSION ANALYSIS OF CORRELATES OF MODERN CONTRACEPTIVE METHODS USAGE AND PREFERENCE

BY

HABTAMU KIROS G/SELASSIE

HARAMAYA UNIVERSITY

COLLEGE OF COMPUTING AND INFORMATICS,

DEPARTMENT OF STATISTICS, HARAMAYA, ETHIOPIA

List of Abbreviations

AIDS	Acquired Immune Deficiency Syndrome
CPR	Contraceptive Prevalence Rate
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
FP	Family Planning
IUD	Intra Uterine Devices
LAM	Lactational Amenorrhoea Method
MCMC	Markov Chain Monte Carlo
MDGs	Millennium Development Goals
MLE	Maximum Likelihood Estimation
SNNPR	Southern Nations Nationalities People Region
SPSS	Statistical Package for Social Science
STI	Sexually Transmitted Infection
TFR	Total Fertility Rate
UNDP	United Nations Development Program
UNFPA	United Nations Population Fund
UNICEF	United Nations Children’s Fund
USAID	United Stated Agency for International Development
WHO	World Health Organization
Win BUGS	Windows for Bayesian inference Using Gibbs Sampling

Table of Contents

Title

Page

Abstract

Despite widespread adoption of family planning in the developing world contraceptive use is still very low in sub-Saharan Africa including Ethiopia and in other regions. The general objective of this study was identifying the socioeconomic factors of modern contraceptive methods usage and preference among married women of reproductive ages (15-49 years old) in Hawassa city. From a total 990 sampled married women about 57.9% (573) were modern contraception methods users. Out of these 573 modern contraceptive users, 426(74.3%) were long term methods users, like injectables, implant and intrauterine devices. The Bayesian logistic regression analysis results revealed that age of the respondent, number of children, education level, occupation, monthly income, family planning field workers visit, frequency of following radio program, source of information, experience on modern contraceptive use and husband's encouragement had statistically significant impact on modern contraceptive usage. In the classical logistic regression analysis, age of the respondent, religion, number of children, education level, desire for more child, experience on modern contraceptive use, frequency of watching television, availability of service in near place and service provider, were found statistically significant predictors of modern contraception methods preference among married women of reproductive age in the city.

Key words: *Bayesian, Logistic regression, modern contraceptive, family planning, married women*

1. INTRODUCTION

1.1 Background

The population of any society depends primarily on its territory or physical environment for sustenance. Most of its food and other needs largely derive directly or indirectly from the environment, which consists essentially of land and its derivatives. Unfortunately, while populations of nations increase overtime, the various land masses on which these populations depend for sustenance are relatively fixed. Herein lays the general concern about population size and growth rate. However, the key to understanding over population is not population density, but the number of people in an area relative to its resources and the capacity of the environment to sustain human activities.

A rapid population growth is a burden on the resources of many developing countries. Unregulated fertility, which contributes to such situations, compromises the economic development and political stability of these countries. Therefore, many countries consider limiting population growth as an important component of their overall developmental goal to improve living standards and the quality of life of the people. This strategy is now enhanced by the availability of effective modern contraceptive methods since the 1960s.

Many international institutions and organizations such as the World Health Organization (WHO), World Bank (WB), United Nations Population Fund (UNFPA) and United Nations Children’s Fund (UNICEF) have strongly advocated family planning as a means to space children and limit family size and should be one of the essential primary health care services provided.

Despite widespread adoption of family planning in the developing world, contraceptive use is still very low in much of sub-Saharan Africa and in other regions where women are very poor, uneducated and have limited access to quality family planning services. Women are defined as having an unmet need for family planning if they say they prefer to avoid pregnancy but are not currently using a contraceptive method. Sub-Saharan Africa has the highest level of unmet need-about one-fifth of women there do not want to become pregnant, yet use no contraceptive method.

About 80 million unintended pregnancies are estimated to occur worldwide annually in developing countries of which more than one-third of all pregnancies are considered unintended and about 19% will end up in abortion, which are most often unsafe accounting for 13% of all maternal death globally (Guttmacher institute , 2007, Marston, 2004).

The Millennium Development Goals, adopted by the United Nations in 2000, require member countries to achieve a set of goals, of which Goal 5 is to improve maternal healthy, reducing three quarters of the ratio of women dying in childbirth by 2015. In all these programs, modern contraception plays a central role in the strategies to achieve the goals set. The use of these methods has grown more than the use of traditional methods, such as periodic abstinence (rhythm), withdrawal and others traditional methods. Modern contraceptive methods are generally more effective in preventing pregnancy than are traditional methods (Trussell, 1987). The increased use of effective family planning methods is the primary cause of the dramatic fertility declines observed in many developing countries (Abernethy, 2002).

Family planning in Ethiopia

In Ethiopia family planning was initiated four decades back. However, even after four decades, family planning use is among the lowest in Africa (8%) and unmet need for family planning is very high (34%) (Amaha, H. and Fikre, E. 2006).

Ethiopia is a typical example of a high fertility country (World Bank 2007). Its current total fertility rate is estimated about 5.4 which is the predicted number of children a woman will have over her reproductive age. During the period 1990 to 2005 Ethiopia's total fertility rate declined by about one child and the use of contraceptives tripled from 5 percent to 15 percent, with most of the increase coming from modern methods, especially pill and injectables (Central Statistical Authority Ethiopia, 2006).

Contraceptive use has become more common in developing countries and much of this increase has been in the form of modern methods of fertility control (UNFPA, 2000). These methods include female and male sterilization, the pill, the IUD, injectables, implants, condoms, diaphragm/foam/jelly and lactational amenorrhea method.

All modern methods which provide a wide range of protection from durations of as short as days to permanent protection such as voluntary surgical sterilization, intrauterine device, pills, injectables, condoms and other barrier methods are available in Ethiopia. However, according to 2005 Demographic and Health Survey (DHS), about 15 percent of married women use some method of contraception and that the majority of them rely on a modern method, where injectables account for about 10 percent and oral contraceptives 3 percent.

1.2 Statement of the Problem

The benefits of contraceptive use are dramatic and far-reaching. These include decreasing fertility rate, preventing unintended pregnancies, reducing the number of abortions, and reducing the incidence of deaths and illnesses related to complications of pregnancy and childbirth. Despite the overall high knowledge of women about modern contraceptive methods, contraceptive use is relatively low in Ethiopia. According to the data from DHS 2005, awareness of women in reproductive ages of at least one modern contraceptive method is as high as 88 percent, whereas for currently married accounts it is 87 percent. The current use of modern contraceptives is only 14 percent among married women which are totally dominated by short term methods such as pill but long term methods such as injectables intrauterine device (IUD) and implants accounted for less than 1 percent and only 0.3 and 0.2 percent of women gave unavailability and high price, respectively as the reason for not using contraception (DHS, 2005).

Most studies of contraceptive use focus on prevalence and the economic correlates of the methods that are accepted by individual women. How ever, contraceptive use is the consequence of contraceptive acceptance, method preference, continuation, switching and failure. When fertility preferences decline and contraceptive prevalence increases, contraceptive use becomes a more established behavior and therefore prevalence rate is no longer a sufficient marker of program success (Hammerslough, 1991; Jejeebhoy 1991; Wang and Diamond, 1995). Therefore, barriers to the use of modern contraceptive methods and factors influencing women’s contraceptive method preference need further study.

1.3 Objective

General Objective

The main objective of this study has been to identify factors influencing modern contraceptive methods usage and preference among married women of reproductive age (15-49 years) in Hawassa city, using classical and Bayesian regression analyses.

Specific objectives:

- To identify the influences of demographic and socioeconomic variables on modern contraception method usage among married women of reproductive age.

- To explore the factors that can influence long term modern contraceptive methods usage among married women of reproductive age.

- To describe the prevalence of modern contraceptives usage among married women of reproductive age.

- To determine whether government family program has an influence on modern contraceptive usage among married women of reproductive ages.

- To provide information for the concerned governmental and non governmental organizations.

1.4 Significance of the Study

Modern contraception methods have intension of saving the lives of millions of women in the globe and to have children who are healthy and can achieve greater levels of education.

By helping women and couples plan their families and have healthy babies, improved reproductive health care including increased access to contraceptive services would contribute directly to attaining three Millennium Development Goals (MDGs): reducing child mortality, improving maternal health and promoting women's empowerment and equality.

Modern contraceptive methods have various benefits including, preventing unintended pregnancies, reducing the number of abortions, and reducing the incidence of deaths and illnesses related to complications of pregnancy and childbirth. However, in Ethiopia the overall contraception prevalence rate among women of childbearing age (15 to 49 years) is 15% and modern contraceptive methods was totally dominated by the use of shorter-term methods such as pills and injectables.

The underlying causes of low contraceptive use and method preference need further investigation. Therefore, this study focuses on socioeconomic and demographic factors that can influence modern contraceptive use and methods preference among married women. Thus, investigating, evaluating and appropriately addressing those underlying factors would better equip the government family planning program with the knowledge and would lead to achievement of better results on promoting modern contraceptive usage and controlling population growth in the country.

2. LITERATURE REVIEW

2.1 Definition of Contraception

Contraception is the deliberate use of a technique or device to prevent a conception or pregnancy. Those who intend to prevent conception or pregnancy and want no more children or wish to postpone a birth are subject to the decision to practice contraception. Contraception can be accomplished by either modern methods or traditional methods. Modern methods include short term methods such as male condom, daily pills, Lactational Amenorrhea, female condom, vaginal methods (diaphragm, foam, and jelly) and long term methods such as intra uterine device (IUD), injectables, implant(or Norplant) and permanent methods such as male and female sterilization.

2.2 Contraceptive Method Preference

The importance of exploring influencing factors on women's contraception decision making, use of temporary methods or long term methods, preference for specific type of contraceptives or nonuse has been found as critical in many studies and essential for family planning programs and policy makers (Entwisle 1996, Bulatao 1989, Perjaranonda, 1986). Both governments and family planning programs need to consider these underlying causes and essential elements in order to successfully design, implement and evaluate programs, which could bring long lasting change and increase women's satisfaction with reproductive health.

2.3 Factors Affecting Contraceptive Usage and Method Preference

Contraceptive method preference has many determinants. There is a vast difference between a situation wherein individuals have perfect freedom to choose from among a variety of family planning methods and one wherein a particular family planning program or government policy dictates the particular method to be used by couples (Bulatao, 1989). Considering direct relations between contraceptive choice of women and family planning programs, different aspects determining choice has been analyzed in the present literature.

Health Center and Family Planning Outlets

Health center and family planning outlets are found to be very influential on women's contraception decision making, including preferences for particular choices (Entwisle, 1996). Entwisle's study in rural Thailand using multinomial logistic regression model found pill use as a preference of women accessing sub-district health centers, who were encouraging its use. The finding is based on historical specialization of health centers and does not have a potential of replication, unless other service provision centers also specialized in pill promotion. The value of this finding is in demonstrating the effect of accessing service providing centers on women's contraceptive method choice.

Social networks

Social networks have been found to be influential on women's method choice by sharing information about success and failure of each other with certain methods, thus creating perceptions about those methods (Entwisle, 1996, Kohler 1997) has examined the influence of social networks. According to him, women are uncertain about the merits of modern contraception and estimate the different qualities of available methods based on imprecise information from network partners. Women contraceptive choices are determined by this estimate and by private knowledge about own personal characteristics. This process of social learning leads to path-dependent adoption of fertility control within, and diversity in contraceptive practices across villages or social strata (Kohler, 1997). It may also partly explain the difference of contraceptive method preferences between villages found in the study by Entwisle in rural Thailand.

Availability and Accessibility of Contraceptives

Availability and accessibility of contraceptive methods are determining factors of contraceptive use and method selection of women in many studies (Ross, 2002, Ozalp, 1999). This relation is mainly based on the basic understanding, where women simply cannot choose and use a method, which is not available or accessible. In addition, different studies show that the role of availability, where in many cases there is a wide range availability of methods, their accessibility to women and uninterruptible supply have a determining role in increased use of modern contraceptives (Mannan, 2002, Ross 2002).

Previous Experience of Contraceptive Use

A study in Nigeria using binary logistic regression model found that women who had ever practiced contraception were more likely than those who had not to be aware of contraceptive methods (Aziken, 2003). Similarly increase in women knowledge on contraceptives due to past use was found by Little (2001) in the United Kingdom. Both studies highlighted contribution of previous experience on contraceptive methods to the knowledge. Contribution has been found at least on knowledge related to the particular method practiced before. Another study in Finland found that women knowledge on certain contraceptive methods increased due to the past use of them. IUD was found as a method on which those women, who practiced it before had greater knowledge (Sihvo, 1998). Practicing contraception improves women's knowledge especially on proper use or on required using procedures.

Socio-demographic Factors

Studies and surveys in many countries revealed that women's modern contraceptive use and method choice are influenced by a variety of socio-demographic and behavioral factors such as age, education, occupation, work status, number of living children, desire for additional children, knowledge of contraceptive methods, exposure to mass media and others (Mannan 2002, Raine, 2003, Trussell, 1999).

Women's Age

Women are less likely to practice contraception when their fecundity is low, that is at the extremes of maternal age and as age and parity increase, the women would switch to more effective methods of contraception (Klein, 2001). In support to this argument, a study in Thailand by Entwisle and Rindfuss (1996), adopting binary logistic regression model found that the relationship between age and contraceptive use took an inverted U-shape; that is the proportion of women using modern methods varied with age, reaching peak among those in their 30s and declining thereafter. The need for contraceptive methods was considerably reduced with increasing age and, therefore proportions using different methods were likely to decline.

Similarly the report of fertility and family planning surveys in different countries indicated that current use of contraceptives was mostly common among women aged 30 - 39 years, and least common among youngest women, gradually increasing to a peak number during the mid to late childbearing years, then dropping off among the women of older age (Dang, 1995). Women's preference toward contraceptive method type changes with their age (Apter, 2004; Mannan, 2002, Godley, 2001, Ozalp, 1999). It is related to the changes in lifestyle, behavior, surrounding factors and reflects the changed needs and requirements.

Women in their early reproductive ages can be expected to have more non-permanent sexual relations than those of older ages. Young women have biologically higher fecundity compared to their older counterparts. However, nowadays the global trend is towards later marriage and later childbearing, which can be achieved through effective contraception. Taking into account the possibility of nonpermanent sexual relationships, young women's contraception needs include prevention of both STIs and pregnancies. The main options for adolescents are condoms, backed up by emergency contraception, and oral contraceptives in a longer, mutually monogamous relationship (Apter, 2004). For the group of women in their middle reproductive ages, who can be assumed to be predominantly married or in a steady relationships, any available method might be suitable (Toirov, 2004).

.

However, different studies reveal that preference of married women in middle reproductive ages is largely in favor of temporary and long term methods (Ozalp, 1999, Godley 2001). As age and duration of marriage increase, along with all temporary and long term methods, couples are more likely to use sterilization. This is possibly because, with increase in age or marital duration, women are more likely to reach their desired fertility and prefer permanent methods to prevent pregnancy (Mannan, 2002).

Religion

Women’s contraceptive behavior is influenced by their beliefs and religion. Historically, religious norms have been against contraception of any type. Different contraceptive methods are not accepted by the leading religions, Christianity, Islam and Buddhism. This still continues and not all religious leaders are supportive of contraceptive methods (Toirov, 2004).

However, experience from Iran, an Islamic country that has incorporated religious teaching into family planning practice, shows that religion can be a positive force in contraceptive use. As a result, the Iranian family planning program has been very successful in reducing the fertility rate from 5.6 to 2.0 during the period 1985-2000 (Fahimi, 2002). Contradictory to Iranian experience, a study in India applying binary logistic regression model indicated that Muslims and the Hindu scheduled casts show significantly lower contraceptive use than Hindu other castes (Bhende, 1991).

The same study also revealed that Muslims seem to prefer non-permanent and natural methods, especially the condom with significantly lower use of both male and female sterilization. It has been concluded that the lower use of female sterilization among Muslims might be due to their larger family size objectives.

Education

As the major influencing factor in different aspects of social and behavioral science, knowledge and education are the key determinants of contraceptive method choice (Bulatao 1989, Hampton, 2001). Information on women's education serves as an explanatory variable for understanding differences in fertility, knowledge and effective practice of the contraceptive method, knowledge of side effects and receptivity to the "new technologies" (Pejaranonda, 1986). Even the literacy level by itself, excluding knowledge on particular contraceptives, has been found to have a big influence on women's method choice: a multinomial logistic model found that the odds of method use among illiterate women were 34 percent lower compared to those among women with a secondary or higher education (Dang, 1995).

Past studies document the relationship of female education to the decline in fertility (Abernethy, 2002). According to Abernethy's study, education can influence women’s reproduction in several ways: by increasing knowledge of fertility, increasing socioeconomic status, and changing attitudes about fertility control. Education may also affect the distribution of authority within households, whereby women may increase their authority with husbands, affect fertility and use of family planning (Bulatao, 1989).

Women's Occupation

Female employment is another key factor influencing contraceptive choice (Choe, 1995, Gage, 1995). Women who work outside the home, and particularly those who earn cash incomes, are presumed to have greater control over household decisions, increased awareness of the world outside the home, and subsequently more control over reproductive decisions (Gage, 1995; Choe, 1995). Employment outside the home also provides alternative satisfactions for women, which may compete with her childbearing and childrearing.

Although the nature of the relationship between female employment status and contraceptive behavior is confirmed in developed countries, there are studies that have found little or no association in less developed countries. Some studies using binary logistic models have found a strong positive relationship between current economic activity and contraceptive use (Shapiro, 1994; Gage, 1995); others report contradictory findings revealing weak or no association between work status and use of contraception (Lloyd, 1991). These inconsistencies might be attributed to the fact that even work outside the home does not always conflict with childbearing in a developing country context. It might be due to the problems in the measurement of women‘s work in many of these countries. Therefore, only when working outside the home conflicts with childbearing, it is expected that workingwomen will be contraceptive innovators.

Number of Living Children

The number of living children can influence also contraceptive use. A comparative study in Indonesia by Samijo, Weller and Sly (1991), among 20 provinces showed that the proportion of never users tended to decrease as the number of children increased. Similarly, according to a study in Uganda, contraceptive use was found to increase with parity. By applying a binary logistic model, Gupta et al. (2003) found that women with one to three children were nearly three times more likely to use contraception based on their motivation to limit family size.

The report from Ethiopia Demographic and Health Survey 2005 showed that there was association between contraceptive practices and number of living children. The contraceptive use constitutes about 12 percent among women with no children and 17 percent among women with one or two children. A similar finding was found in a study in Turkey by Uyger and Eskaya (2001), using binary logistic model. There was a significant association between contraceptive use and number of living children the more children they had the more they used contraception.

Desire for more children

A longitudinal study in central India indicated that one third of women did not use contraception because they desired to have another child and two-third of those with no children or only one child reported that they would use contraception after they had enough children (Roy et al., 2003). This finding showed that women would not practice any method if they still desire for additional children in the near future. Another study in peninsular Malaysia (Davenzo, 1989) using a binary logistic regression model also revealed that women who did not desire additional children were much more likely to use contraception than women who had reached their family size goal.

Husband's approval of family planning

Most countries in the world, especially, developing countries still have male dominated cultures. The husband has an influence over his wife in terms of income, decision making in the family and outside as well. In Nigeria, although the husbands did approve and have a positive attitude towards family planning, it was interesting to note that they were more willing to support their wives in using contraception than they were to use themselves (Oni and McCarthy, 1991). Similarly, in the studies done in Sudan and Indonesia, the most common reason that a woman gave for non-use of contraception was their husband's disapproval (Joesoef et al., 1988; Khalif, 1988). Similarly, in Jimma town of Ethiopia, using a binary logistic regression model, it has been seen that husband's approval of family planning is highly associated with contraceptive use (Amaha Haile and Fikre Enqueselassie, 2006).

Wealth Status

Economic status showed a strong positive relationship with contraception practices in Kinshasa, Zaire. The finding showed that proportion of women who ever used and current use were rising steadily as their economic status increased (Shapiro, 1994). Another study in Indonesian by using binary logistic regression model revealed that socioeconomic index of women had significant effect on contraceptive use. High status and moderately poor women were more likely to use contraception compare to extremely poor women (Schoemaker, 2005).

Mass Media

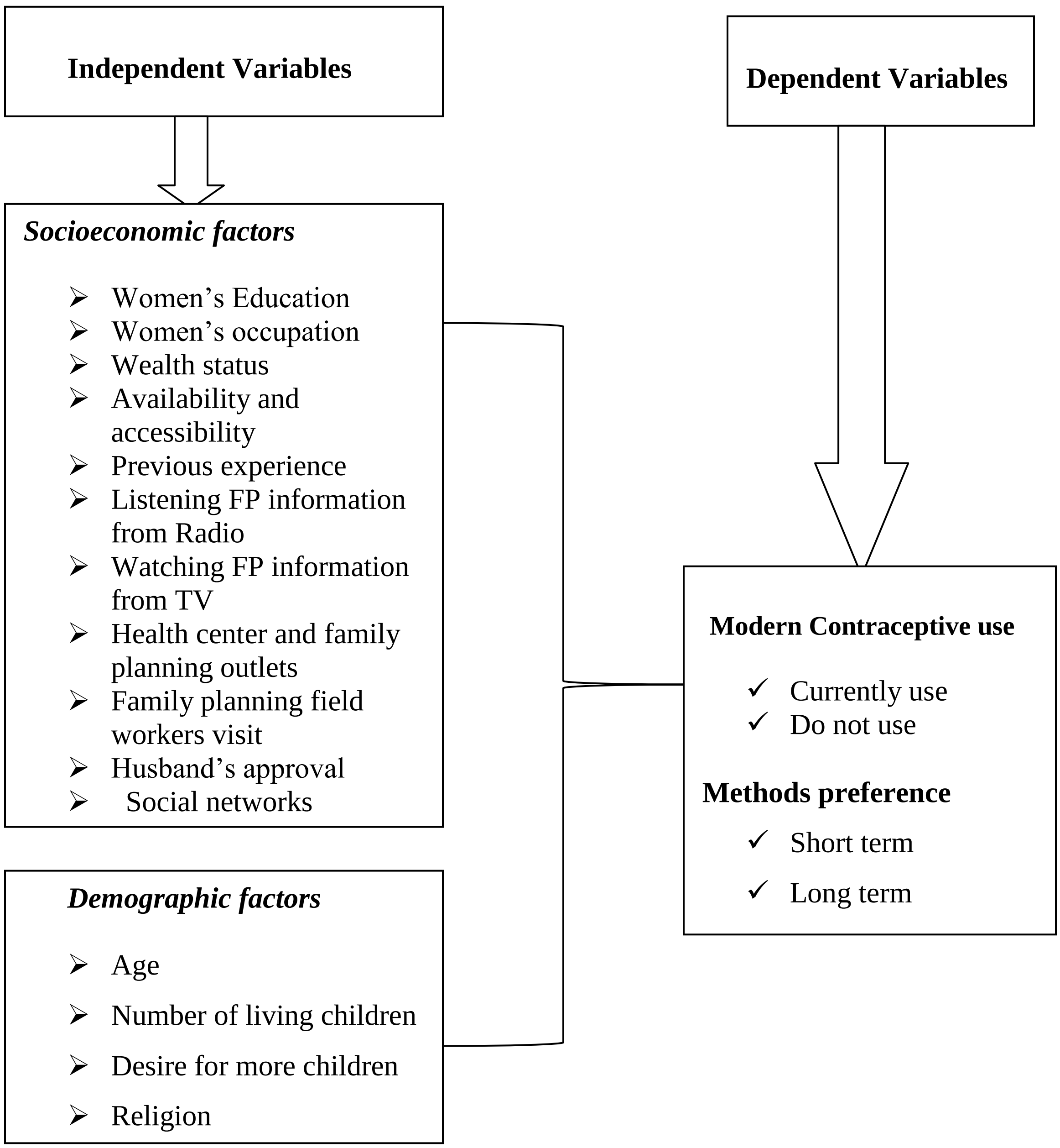
Data from the Bangladesh demographic and health survey 1993-94 which was analyzed by applying binary logistic regression model indicated that exposure to family planning information message through both radio and television had a significant effect on current contraceptive use (Shapiro, 1994). The impact of exposure to mass media was found to have significant association with contraceptive use in another survey in Kenya (Westoff, 1995). The prevalence of currently use contraception of women who never heard any messages of family planning from television or radio were only 14 percent compared to 50 percent of those who were exposed to both types of media. A study on mass media promotion in three cities of Nigeria indicated that television played an important role in increasing the new users of family planning among the three cities (Piotrow et al., 1990).

Family Planning Field Worker's Visit

A study on factors influencing contraceptive method choice in Nepal using multinomial logistic regression model 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 visited by family planning workers, especially, for women who use pill and injectables (Rana, 2002). Another study on the impact of out reach on the continuity of contraceptive use in rural Bangladesh showed that women who were contacted by family planning field workers were predominant to use contraception. More over, the outreach activities could reduce the discontinuation rate by 65 percent if women received home's visit at least once in three months period (Hossain & Phillip, 1990).

2.4 Conceptual Framework

It is possible to observe the two main determinants of modern contraceptive use and method choice among married women from the above literature review. Generally, these are socioeconomic and demographic factors. Therefore, based on this the following conceptual framework was formed.



3. METHODOLOGY

3.1 Description of Study Area and Population

This study has been carried out in Hawassa which is the capital of Southern Nations, Nationalities and Peoples' Regional State, and one of the regions of Ethiopia. The city is located in Sidama Zone 275km south west of Addis Ababa. Geographically, it lies between 07°05' latitude North and 38°29' longitude East, with altitude of 1697m above sea level (Berhanu, 1999 E.C). Administrative wise, the city is divided into 7 sub-cities. These are, Addis Ketema, Bahil-Adarash, Hayikdar, Mahal Ketema, Menaharia, Misrak and Tabor sub-city. According to the 2007 Population and Housing Census report, the city has a total population of 259,803 out of which 48.5 % are females.

High fertility has also been reported in Southern Nations Nationalities and Peoples Region (SNNPR) where Hawassa city is located. According to the Ethiopian DHS 2005, TFR was 5.6 in the region and it was among the highest in the country (CSA, 2006). Unlike most urban areas of the country especially, in the last 10 years, the city is under rapid development and urbanization accompanied by high level of migration and fast population increase with population growth rate of 4.8% and doubling time of 14 years (Hawassa City Finance and Economic Development Office, 2006).

The study population for the problem under consideration was married women of reproductive age (15-49 years old) in Hawassa city.

3.2 Sampling Design and Procedures

Sampling is a process that selects a part of a population, where selection is designed in such a way that it be representative for the whole population. Usually, the purpose is to estimate one or more characteristics about the population based on information contained in the sample. Married women of reproductive age (15 – 49 years old) were the target population in the study. In order to describe the target population adequately in relation to the problem under investigation and to make statistically valid inferences for the population using sample data, the study should incorporate the appropriate sample design and valid data collection technique. Stratified sampling was employed for this study as sampling design, with households as the sampling units. Stratified sampling involves selecting samples independently within strata, which are non-overlapping subgroups of the study population. More over, stratification controls the distribution of the sample size in the strata. It is commonly used in practice to meet a variety of survey objectives such as, to ensure adequate sample sizes for subgroups of interest, including small subgroups, to improve the precision of overall estimates. However, to improve precision, units within strata should be as homogeneous as possible for the characteristics of interest.

The sampling frame (or the list of the group of the households) was stratified administrative wise in seven sub-cities (or strata). Thus, the whole procedure is described as stratified random sampling. Households within strata were selected by using random number method.

3.3 Data and Study Design

This study was cross sectional study. The data collection took place from May 2, 2011 to May 19, 2011, by engaging eight trained data collectors across the seven sub-cities in Hawassa city. The data were obtained through face-to-face interviews from married women of reproductive age (15 – 49 years old) by administering a structured questionnaire. The questionnaire was designed to capture both qualitative and quantitative information related to socioeconomic and demographic variables.

Inclusion and Exclusion Criteria

Female residents of Hawassa city, between the ages of 15 and 49 years, who were married and living with their husband were included in this study. How ever, pregnant women, and women with a chronic physical or mental illness were ineligible. Hence, they were excluded from this study.

3.4 Sample Size Determination

One of the crucial moments of any study is determining the appropriate and adequate sample size. Because by using inadequate or small sample size, the research will lack the precision to provide reliable answers to the questions that are under investigation. On the other hand, using too large sample has its own problem in terms of cost and time. Therefore, in order to overcome such difficulties attention should be paid on the major factors that can influence the sample size determination technique to get sufficient sample size. These factors are the sampling design, level of precision, level of confidence and degree of variability (Cochran, 1977). Stratified sampling was adopted as sampling design in this study. Sample size determination procedure should match the sampling design used in the study. Therefore, the sample size determination procedure in this study follows stratified random sampling techniques. The sample size determination formula used in this study is given below which was taken from Cochran (1977):

$$n = \frac{\sum_{i=1}^{K} \frac{N_i^{\,2} p(1-p)}{w_i}}{\frac{N^2 d^2}{(Z_{\alpha/2})^2} + Np(1-p)}$$

where, n is the total sample size needed, N is the total population size (total households), $Z_{\alpha/2}$ is the inverse of the standard normal cumulative distribution that correspond to the level of significance, p is the probability of being modern contraceptive user in the i^{th} stratum, d is the level of precision, K is the total number of strata (number of sub cities), N_i is population size of the i^{th} stratum, and $W_i = N_i /N$ (the estimated proportion of N_i to N). A study conducted by Samson and Mulugeta (2009) in Hawassa city indicated that the prevalence of contraceptive use was 41%. Hence, in this study the probability of being contraceptive user in the i^{th} stratum was p=0.41 with 3% level of precision (That is, d= 0.03). The level of confidence was 95% for this study, which indicates the specific probability that the sample contains the parameter being estimated. The degree of variability in the characteristics being measured equals p (1-p) and has a direct relationship with the sample size. In other words, the more the degree of variability of the distribution of attributes in the population, the larger the sample size is required to obtain a given level of precision. The less variable population, the smaller the sample size is required. In this study, out of 24178 total households about 990 households were sampled. The over all sample size (or n) required for this study was allocated proportionally among K strata (or sub-cities), by taking awareness as the base for the stratification. Thus, based on proportional allocation scheme the following samples were taken from each sub city, from Addis Ketema =71, Bahil-Adarash = 76, Hayikdar = 67, Mahal Ketema = 51, Menaharia =174, Misrak = 55, Tabor = 496.

3.5 Variables in the Study

Dependent Variables

The dependent variables used in this study were modern contraceptive usage and method preference. These two variables are dichotomous measuring different characteristics of the target population on modern contraception. The first dependent variable measures current modern contraceptive usage status of a woman, by classifying as non-user and user. The second variable measures method preference among currently modern users, by categorizing as short term and long term method users. All the dependent variables mentioned above, their first categories were coded as 0 and the second categories as 1.

Independent Variables

The independent variables included in the study were factors that are expected to influence modern contraceptive usage and method preference among married women of reproductive ages (15-49 years old). The variables with their categories and scale of measurement are given below.

Table 3.1: List of Dependent Variables with their Codes and Description

Independent Variables	**Categories**	**Scale of Measurement**
Age of the respondent	1 =15-24 2 =25 - 34 3 =35 – 44 4 = 45 – 49	Ordinal
Religion of the respondent	1 = Coptic 2 =Muslim 3 =Protestant 4 =Other	Nominal
Number of children	1 =No child 2 =1 - 2 children 3 =3 - 4 children 4 = >= 5 children	Ordinal
Desire for more child	1 =Yes 2 =No	Nominal
Education level	1 =Illiterate 2 =Primary 3 =Secondary 4 =College/University diploma or higher	Ordinal
Husband's education level	1 =Illiterate 2 =Primary 3 =Secondary 4 =College/University diploma or higher	Ordinal
Occupation	1 =House wife 2 =Government employee 3 =Day laborer 4 =Own business 5 =Private organization	Nominal
Monthly income	1 =None 2 =100-400 3 =400-700 4 =700-1000 5 = >= 1000	Ordinal
Husband's Occupation	1 =None 2 =Government employee 3 =Day laborer 4 =Own business 5 =Private organization	Nominal
Husband's monthly income	1 =None 2 =100-400 3 =400-700 4 =700-1000 5 = >= 1000	Ordinal

Family planning field workers visit	1 =Yes 2 =No	Nominal
Frequency of following radio program	1 =Almost every day 2 =Occasionally 3 =At least once a week 4 =Not at all	Ordinal
Frequency of watching television	1 =Almost every day 2 =Occasionally 3 =At least once a week 4 =Not at all	Ordinal
Source of information	1 =Media 2 =Health center 3 =Friends 4 =Family planning field workers	Nominal
Number of known method types	1 =1-3 2 = >=4	Ordinal
Experience on modern Contraceptive Use	1 =Yes 2 =No	Nominal
Husband's encouragement	1 =Yes 2 =No	Nominal
Availability of service in near place	1 =Yes 2 =No	Nominal
Service provider	1 =Hospital 2 =Health center 3 =Clinic 4 =Family planning service provider	Nominal

3.6 Statistical Methods of Analysis

The dependent variables considered in the study are dichotomous. Thus, to examine the net effect of the predictors on the response variables, that is modern contraceptive usage (non-user = 0, user =1) and method preference (short-term = 0, long-term = 1), Bayesian and classical logistic regression analysis methods were used.

3.6.1 Bayesian Logistic Regression

Bayesian logistic regression procedure was adopted to make inference about the parameters of a logistic regression model. The purpose of this method is generating the posterior distribution of the unknown parameters given both the data and some prior density for the unknown parameters. Bayesian Statistics provides much more complete picture of the uncertainty in the estimation of the unknown parameters, especially after the confounding effects of nuisance parameters are removed (Lee, 1997 and Draper, 2000, Tanner 1996). The idea on Bayesian statistics is based on Baye's theorem. Assume that we observe a random variable Y and wish to make inferences about another random Variable β, where β is drawn from some distribution p (β).

The posterior probability distribution function of β conditional on y can be written as:

$$P(\beta \mid y) = \frac{P(y \mid \beta)P(\beta)}{P(y)} \quad \text{.......... ....}(1)$$

where, $P(y) = \int \ldots \int P(y \mid \beta)P(\beta)\, d\beta$ is a normalizing constant

$$\beta = (\beta^{(1),}\ \beta^{(2)} \ldots \beta^{(p)})$$

3.6.1.1 Bayesian Inference for Logistic Regression Parameters

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

Likelihood Function

The likelihood function used in Bayesian approach is equivalent to that of the classical inference. The joint distribution of n independent Bernoulli trials is the product of each Bernoulli densities, where the sum of independent and identically distributed Bernoulli trials has a Binomial distribution. Specifically, let $y_1, y_2, \ldots y_n$ be independent Bernoulli trials with success probabilities $P_1, P_2, P_3, \ldots, Pn$, that is $y_i = 1$ with probability P_i or $y_i=0$ with probability 1- P_i, for i= 1,2,…,n. Since, the trials are independent, the joint distribution of $y_1, \ldots, y_n$ is the product of n Bernoulli probabilities. The probability of success in logistic regression varies from one subject to another, depending on their covariates. Thus, the likelihood function is illustrated below as product of n Bernoulli trials:

$$L(\beta \mid y) = \prod_{i=1}^{n} \left[P_i^{y_i} (1 - P_i)^{(1-y_i)} \right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where, P_i represents the probability of the event for subject i who has covariate vector X_i, $y_i = 1$ indicates the presence and $y_i=0$ the absence of the event for the given subject. The probability of success in logistic regression can be defined as:

$$P_i = \frac{e^{(\beta_0 + \beta_1 x_1 + \ldots \beta_p x_p)}}{1 + e^{\beta_o + \beta_1 x_1 + \ldots . + \beta_p x_p}}$$

Due to the underlying assumption that each of the subjects are independent of each other, the likelihood function over data set of subjects is written as:

$$L(\beta \mid y) = \prod_{i=1}^{n} \left(\frac{e^{\beta_o + \beta_1 x_1 + \ldots . \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + \ldots .. \beta_p x_p}} \right)^{y_i} \left(1 - \frac{e^{\beta_o + \beta_1 x_1 + \ldots . + \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + \ldots .. \beta_p x_p}} \right)^{(1 - y_i)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Prior Distribution

One of the pre conditions in any Bayesian analysis is the choice of a prior. The main idea here is that when the data have sufficient information, even a bad prior will still not greatly influence the posterior. If the posterior is highly dependent on the prior, then the data (likelihood function) may not contain sufficient information. However, if the posterior is relatively stable over a choice of priors, then the data indeed contain significant information. In general, any prior distributions can be used depending on the available prior information. The choice can include informative prior distributions if something is known about the likely values of the unknown parameters $\beta_0, \beta_{1, \ldots}\ \beta_p$ or non-informative priors.

Here, the most common priors for logistic regression parameters will be used, which are of the form: $\beta_j \sim N(\mu_j, \sigma_j^{\ 2})$. This implies the normal distribution with mean μ_j and with variance σ^2_j. Mathematically:

$$P(\beta_j) = \frac{1}{\sqrt{2\pi\sigma_j^{\ 2}}} \exp\left\{ \frac{-1}{2}\left(\frac{\beta_j - \mu_j}{\sigma_j^{\ 2}} \right)^2 \right\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The most common choice for prior mean μ_j is 0 for all the coefficients. Prior variance σ is usually chosen to be large enough to be considered as non-informative, common choices being in the range from σ=10 to σ=100.

Posterior Distribution

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

$$P(\beta \mid y) = \prod_{i=1}^{n} \left[\left(\frac{e^{\beta_o + \beta_1 x_1 + \ldots + \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + \ldots + \beta_p x_p}} \right)^{y_i} \left(1 - \frac{e^{\beta_o + \beta_1 x_1 + \ldots + \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + \ldots + \beta_p x_p}} \right)^{(1-y_i)} \right] X \prod_{j=0}^{p} \frac{1}{\sqrt{2\pi\sigma_j^{\ 2}}} \exp\left\{ \frac{-1}{2}\left(\frac{\beta_j - \mu_j}{\sigma_j} \right)^2 \right\} \ldots (5)$$

Conditioning upon the observed data, the posterior distribution is used to make statements about β, which is still a random variable. Computing the estimate of coefficients of the posterior distribution may be mathematically intractable; to overcome this situation, we need to use non numerical integration method such as simulation techniques. The most popular and common method of simulation technique is the Marcov Chain Monte Carlo (MCMC) methods and that was applied in this study.

3.6.1.2 Assessment of Bayesian Logistic Regression Model

Markov Chain Monte Carlo (MCMC) Methods

The main challenge toward applying the Bayesian approaches is that, the posterior distribution often requires the integration of high dimensional functions. MCMC methods attempt to simulate direct draws from some complex distribution of interest. Also, it is used to generate an irreducible Markov chain with stationary probabilities ∏=p (β|y). A popular way of simulating from a general posterior distribution is by using MCMC methods. Markov chain Monte Carlo techniques enabled quantitative researchers to use highly complicated models and estimate the corresponding posterior distributions with accuracy.

As a result, MCMC methods have greatly contributed to the development and propagation of Bayesian theory. In quantitative sciences, the problem of evaluation of integrals of the type given below is often necessary.

$$H = \int_x g(x)dx$$

where $g(x)$ is high-dimensional density function and difficult to approximate the integral numerically.

One of the solutions is based on generating random samples and then obtaining the integral shown above by its statistical unbiased estimate, the sample mean. Hence let us assume that the density function *f(x)* of a random variable enables us to easily generate random values. This can be expressed as

$$\mathrm{H} = \int_x \left[\frac{g(x)}{f(x)} \right] f(x)dx = \int_x g^*(x) f(x)dx,$$

where $g^*(x) = g(x)/f(x)$. Hence the integral *H* can be efficiently estimated by:

1. Generating $x^{(1)}, x^{(2)}, ..., x^{(T)}$ from the target distribution with probability density function (p.d.f.) *f(x).*

2. Calculating the sample mean $\hat{\mathrm{H}} = \frac{1}{T} \sum_{t=1}^{T} \left[\frac{g(x^{(t)})}{f(x^{(t)})} \right]$ Ritter and Tanner (1992).

The idea was known from the early days of the electronic computers and was originally adopted by the research team of Metropolis in Los Alamos (Anderson, 1986; Metropolis and Ulam, 1949). The main advantage of this approach is its simplicity. Even if integrals are tractable, nowadays it is much easier to generate samples than calculate high-dimensional integrals. The method described above is directly applicable to many problems in Bayesian inference. Hence for every function of the parameter of interest *P (*ß|y*),* we can calculate the posterior mean and variance by:

1. Generating a sample $\beta^{(1)}, \beta^{(2)}, ..., \beta^{(T)}$ from the posterior distribution P (ß|y).
2. Calculating the sample mean of *P(*ß|y*)* by simply calculating the quantity

$$\hat{\mathrm{H}} = \frac{1}{T} \sum_{t=1}^{T} P(\beta^{(t)} \mid y)$$

Simulation can also be used to estimate and visualize the posterior distribution of *P (*β|y*)* itself. The main problem in the above mentioned procedure is how to generate random samples from the posterior density P (ß|y).

The Gibbs Sampling Algorithm

The Gibbs sampler was introduced in the context of image processing by Geman and Geman (1984), which is a special case of Metropolis-Hastings sampling wherein the random value is always accepted (i.e. α = 1) where α = 1 is acceptance probability of the proposal density $q\left(\beta^{'} \mid \beta^{(t)}\right)$. The goal of Gibbs sampling is to find estimates for the parameters of interest in order to determine how well the observable data fits the model of interest. This sampling procedure requires an initial starting point for the parameters. Then, one at a time, a value for each parameter of interest is sampled given values for the other parameters and data. Once all of the parameters of interest have been sampled, the nuisance parameters are sampled given the parameters of interest and the observed data.

Although Gibbs sampling is a special case of Metropolis-Hasting algorithm, it is usually cited as a separate simulation technique because of its popularity and convenience. One advantage of the Gibbs sampler is that, in each step, random values must be generated from univariate distributions for which a wide variety of computational tools exist (Gilks, 1996). Usually, these conditional distributions have a known form and thus, random numbers can be easily simulated using standard functions in statistical and computing software.

Here, we used the Gibbs sampler implementing by Win BUGS or R to solve approximate properties of the marginal posterior distributions for each parameter. Gibbs sampler algorithm is one attractive method for constructing MCMC algorithms and very widely applicable to a broad class of Bayesian problems and has sparked a major increase in the applications of Bayesian analysis. Gibbs sampling is always moving to new values and does not require specification of proposal distributions. On the other hand, it can be ineffective when the parameter space is complicated or the parameters are highly correlated. Suppose that we partition the parameter vectors of the interest into the p-components, β'= (β_1, β_2, β_3 … βp). The Gibbs sampler algorithm will be implemented by sampling in turn from the P-conditional posterior distributions defined below:

$$\Pi(\beta_1 \mid \beta_2, \beta_3, ..., \beta_p), \Pi(\beta_2 \mid \beta_1, \beta_3, ..., \beta_p), \Pi(\beta_3 \mid \beta_1, \beta_2, \beta_4, ..., \beta_p), ..., \Pi(\beta_p \mid \beta_1, \beta_2, ..., \beta_{p-1}) \ldots\ldots (6)$$

Gibbs sampler Algorithm will be stated as follows:

1. Start with an initial value β^o satisfying, $\beta^0 = (\beta_1{}^o, \beta_2{}^o, ..., \beta_p{}^o)$

2. Repeat for i= 1, 2... n

Generate $\beta_1{}^{(i+1)}$ from $\Pi\left(\beta_1 \mid \beta_2{}^{(i)}, \beta_3{}^{(i)}, \ldots, \beta_p{}^{(i)}\right)$

Generate $\beta_2{}^{(i+1)}$ from $\Pi\left(\beta_2 \mid \beta_1{}^{(i)}, \beta_3{}^{(i)}, \ldots, \beta_p{}^{(i)}\right)$

.

.

.

Generate $\beta_p{}^{(i+1)}$ from $\Pi\left(\beta_p \mid \beta_1{}^{(i+1)}, \beta_2{}^{(i+1)}, \ldots, \beta_{p-1}{}^{(i+1)}\right)$

3. Return the values $\left\{\beta^{(1)}, \beta^{(2)}, ..., \beta^{(n)}\right\}$

Convergence of the Algorithm

The empirical results from a given MCMC analysis are not deemed reliable until the chain has reached its stationary distribution. On account of this, the term convergence of an MCMC algorithm refers to whether the algorithm has reached its equilibrium (target) distribution. If this is true, then the generated sample comes from the correct target distribution. Hence, monitoring the convergence of the algorithm is essential for producing results from the posterior distribution of interest. Convergence diagnosis was adopted to answer the question of how to determine whether the sample has reached its stationary distribution (Albert, 2008).

Tests for Convergence

Generally, it is unclear how many times we must run an algorithm to obtain samples from the correct target distributions. Several diagnostic tests have been developed to monitor the convergence of the algorithm. There are basically three approaches to determining convergence for Markov chains: assessing the theoretical and mathematical properties of particular Markov chain, diagnosing summary statistics from in- progress models, and avoiding the issue altogether with perfect sampling, which uses the idea of "coupling from the past" to produce a sample from the exact stationary distribution (Prop and Wilson, 2005). Here we provide details on the second approach.

The second convergence assessment methodology involves monitoring the performance of the chain as part of the estimation process and making an often subjective determination about when to stop the chain. Among several ways, the most popular and straight forward convergence assessment methods are discussed here.

I. Autocorrelation: High correlation between the parameters of a chain tends to give slow convergence, where as high autocorrelation within a single parameter chain leads to slow mixing and possibly individual non convergence to the limiting distribution because the chain will tend to explore less space in finite time. That is, low or high values indicate fast or slow convergence, respectively. In analyzing Markov chain autocorrelation, it is helpful to identify lags in the series in order to calculate the longer- run trends in correlation, and in particular whether they decrease with increasing lags. Diagnostically, though, it is not necessary to look beyond 30 to 50 lags (Merkle et al., 2005 and Gill, 2004).

II. Time series plots: Iteration numbers on x-axis and parameter value on y-axis are commonly used to assess convergence (Merkle et al., 2005, and Gill, 2004).If the plot looks like a horizontal band, with no long upward or down ward trends, then we have evidence that the chain has converged.

III. Gelman-Rubin statistic: for a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel chains (Merkle et al., 2005, and Gill, 2004). The model is judged to have converged if the ratio of between to within variability is close to one.

IV. Density plot: This is another technique for identifying convergence and a classic sign of non convergence is multimodality of the density estimate (Merkle et al., 2005 and Gill, 2004). A poor choice of starting values and/or proposal distribution can greatly increase the required burn-in time (trending section).

3.6.2 Classical Logistic Regression Model

Regression analysis is one of the most useful and most frequently used statistical methods (Efron and Tibsirani, 1993). The aim of regression methods is to describe the relationship between a response variable and one or more explanatory variables. Among the different regression models, logistic regression plays a particular role. The linear regression model is, under certain conditions, a valuable tool for quantifying the effects of several explanatory variables on one dependent continuous variable. For situations where the dependent variable is qualitative, however, other methods have been developed. One of these is the binary logistic regression model, where the dependent or response variable is dichotomous (binary), such as presence or absence of an attribute (success or failure).

Like ordinary regression, logistic regression provides coefficients which measure each independent variable's partial contribution to variations in the dependent variable. How ever, the objective here (in logistic regression) is to predict correctly the category of outcome for individual cases using the most parsimonious model. To achieve this goal, a model is created that includes all predictor variables that are useful in predicting the response variable. There are two main uses of logistic regression analysis. The first is predicting group membership, and the second is providing knowledge of the relationships and strengths among the variables.

Logistic regression is more relaxed and flexible in its assumptions. That means, logistic regression does not make any assumptions of linearity, normality and homogeneity of variance for the residuals (Tabachnick and Fidell, 1996).

3.6.2.1 Assumptions of Logistic Regression

- Logistic regression does not assume a linear relationship between the dependent and independent variables.
- In logistic regression analysis the dependent variable must be categorical.
- In logistic regression analysis the independent variables need not be interval, nor linearly related, nor of equal variance within each group.
- In logistic regression analysis the categories must be mutually exclusive and exhaustive. That is, a case can only be in one group and every case must be a member of one of the groups.
- Larger samples are needed than for linear regression because maximum likelihood coefficients are large sample estimates. A minimum of 50 cases per predictor is recommended.
- Linearity: in the logit regression equation, the predictor variables should have a linear relationship with the logit form of the dependent variable.

3.6.2.2 Model Description

The model for binary logistic regression analysis assumes that the dependent or outcome variable Y is dichotomous. Value of the out come variable Y_i ($i=1,2\ldots,n$) follows a Bernoulli distribution, that is, Y_i takes either the value 1 with probability of success P_i , and the value 0 with probability of failure(1- P_i), where P_i represents the conditional probability of $Y_i = 1$ given the explanatory variables, that is $P_i = P(Y_i = 1|X)$ and $X = (X_1, X_2, \ldots X_p)$. Logistic Regression analysis does not model the out come variable Y directly, but rather the probabilities associated with the values of Y. The logistic model is defined as follows. Let Y_{nx1} be a dichotomous outcome random variable with categories 1(Long term method user) and 0 (Short term method user). Let X denotes nx(p+1) matrix of p covariates with a column of 1s, where

$$\boldsymbol{X} = \begin{bmatrix} 1 & X_{11} & X_{12} & . & . & . & X_{1p} \\ 1 & X_{21} & X_{22} & . & . & . & X_{2p} \\ . & . & . & .. & . & . & . \\ 1 & X_{n1} & X_{n2} & .. & . & . & X_{np} \end{bmatrix}$$

Then, the conditional probability that a woman is long term method user given a vector of p explanatory variables is denoted by P_i=P (Y_i =1| X), where P_i has the form:

$$P_i = \frac{e^{(\beta_0 + \beta_1 x_{i1} + ... \beta_p x_{ip})}}{1 + e^{\beta_o + \beta_1 x_{i1} + ... + \beta_p x_{ip}}} = \frac{e^{X_i^T \beta}}{1 + e^{X_i^T \beta}} = \frac{1}{1 + e^{-X_i^T \beta}} \text{..................}(7)$$

where,

P_i = the probability that the i^{th} woman is long term method user.

Y_i = the observed method preference status of the i^{th} woman

β is (p+1) x 1 vector of unknown parameters.

The response variable in equation or model (7) is not a linear function of the explanatory variables. However, it is possible to form linear relationship between the response and explanatory variables applying the logarithmic transformation. Thus, the transformed form of model (7) is given below.

$$\log it(P_i) = \log\left(\frac{P_i}{1-P_i}\right) = \beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} \ldots\ldots\ldots\ldots\ldots (8)$$

3.6.2.3 Parameter Estimation for Logistic Regression

The maximum likelihood and non-iterative weighted least squares are the two most computing estimation methods used in fitting logistic regression model (Hosmer – Lemeshow, 1989; Greene, 1991; Collet, 1991). When the assumption of normality of the predictors does not hold, the non- iterative weighted least squares method is less efficient (Kariya and Kurata, 2004; Wolberg, 2005). Instead, the maximum likelihood estimation method is appropriate for estimating the logistic model parameters due to its less restrictive nature of the underlying assumptions (Hosmer – Lemeshow, 1989).

Consider the logistic regression model, $P_i = \frac{e^{X_i^T \beta}}{1+e^{X_i^T \beta}}$. Since observed values of Y say, Y_i's (i=1, 2, 3…., n) are independently distributed as binomial with parameter P_i, the maximum likelihood function of Y is given by:

$$L(\beta, Y) = \prod_{i=1}^{n} \left\{P(y_i \mid X_{i1}, X_{i2}, \ldots, X_{ip})\right\} = \prod_{i=1}^{n} \left[\frac{e^{X_i^T \beta}}{1+e^{X_i^T \beta}}\right]^{y_i} \left[\frac{1}{1+e^{X_i^T \beta}}\right]^{(1-y_i)} \ldots\ldots\ldots (9)$$

where, $\beta^T = (\beta_0, \beta_1, \beta_2, \beta_3 \ldots \beta_p)$.

The aim of the likelihood function is to get an estimator $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_p)$ of β which maximize our ability to predict the probability of Y based on what we know about X.

Since the likelihood equations are non- linear in their parameters, the Newton-Raphson iterative maximum likelihood estimation method expresses $\hat{\beta}_v$ as the initial estimate of β. Then the first step of Newton-Raphson can be expressed as:

$$\hat{\beta}_{v+1} = \hat{\beta}_v + (X^T \hat{U}_v X)^{-1} X^T (y - \hat{\pi}_v)$$

where $\hat{U} = diag\left[\pi_i (1 - \hat{\pi}_i)\right]$ is a diagonal matrix with its diagonal elements $\hat{\pi}_i (1 - \hat{\pi}_i)$.

$\hat{\pi}_v$ is the initial estimate of π, $E(y) = \pi$ and v = 0, 1, 2…

The iteration will continue until there is essentially no change between the elements of β from one iteration to the next, that is, until $\hat{\beta}_{v+1}$ is sufficiently close to $\hat{\beta}_v$. At that point, the maximum likelihood estimates are said to have converged (Collet, 1991, Greene, 1991).

3.6.2.4 Model Adequacy Checking

Before interpreting the results of a model, assessing how well a model matches the data or testing of goodness of fitting of the model is necessary. In case of logistic regression, in which a binary response variable is fitted with several dependent variables, the aim is to summarize the ability of the model to identify and categorizing different subjects in their respective groups (Bewick and Jonathan, 2005).

Various steps are involved in assessing lack-of-fit of the model. First, the importance of individual explanatory variable was assessed by carrying out statistical tests on significance of the coefficients. The overall goodness of fit of the model will then be tested. The Pearson's Chi-square, the likelihood ratio tests (LRT), Hosmer and Lemeshow

Test and the Wald tests are the most commonly used measures of goodness of fit for categorical data (Hosmer and Lemeshow, 2000).

The Wald Statistic

The Wald test is a technique of testing the significance of particular explanatory variables in a statistical model. In logistic regression we have a binary response variable and one or more explanatory variables. For each explanatory variable in the model there will be an associated parameter. The Wald test, described by Polit (1996) and Agresti (1990), is one of a number of ways of testing whether the parameter associated with an explanatory variable is zero. If for a particular explanatory variable the Wald test is significant, then we would conclude that the parameter associated with this variable is not zero, thus the variable should be included in the model. If the Wald test is not significant then this explanatory variable can be omitted from the model. To check the significance of a single parameter, the Wald statistic is just the square of the t-statistic and gives exactly equivalent results (Altman, 1991). Wald χ2 statistic is given by:

$$Z^2 = \left[\frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \right]^2 \quad \text{...(10)}$$

Each Wald statistic is compared with a χ2 distribution with 1 degree of freedom. Wald statistics are easy to calculate but their reliability is questionable, particularly for small samples. For data that produce large estimates of the coefficient, the standard error is often inflated, resulting in a lower Wald statistic, and therefore the explanatory variable may be incorrectly assumed to be unimportant in the model (Bewick et al, 2005).

Likelihood-Ratio Test

The likelihood ratio test statistic (G^2) is the most common test for assessment of overall model fit in logistic regression. The likelihood ratio test is used to test the significance of a number of explanatory variables. This is appropriate for a variety of types of statistical models. The likelihood ratio test is better, particularly if the sample size is small or the parameters are large (Agresti, 2007). The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likelihood function for the null model (L_0). The likelihood-ratio test statistic is given by:

$$G^2 = -2\log(\frac{L_o}{L_1}) = -2\left[\log(L_o) - \log(L_1)\right] = -2(L_o - L_1) \text{......... ....(11)}$$

Then, the value is compared with a χ2 distribution with 1 degree of freedom.

Goodness of Fit of the Model

The goodness of fit of a model measures how well the model describes the response variable. Assessing goodness of fit involves identifying how close values are predicted by the model with that of observed values (Bewick et al., 2005). The comparison of observed to predicted values using the likelihood function is based on the statistic called deviance, which is defined as:

$$D = -2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{\hat{\pi}_i}{y_i}\right) + (1-y_i)\ln\left(\frac{1-\hat{\pi}_i}{1-y_i}\right)\right] \text{..(12)}$$

The larger the difference (or deviance) of the observed values from the expected values, the poorer the fit of the model. However, instead of using the deviance to assess the overall fit of a model, another statistic is usually used that compares the fit of the null model with the full model. Usually, we compare the deviance (***D***) with just the intercept (constant-only model) to the deviance when the new predictor or predictors have been added (the model with *p* number of predictors). The equation is given below:

x^2 = D (model without the variable) - D (model with the variable)

The goodness-of-fit x^2 process evaluates predictors that are eliminated from the full model, or predictors that are added to a smaller model. In general, as predictors are added or deleted, log-likelihood decreases or increases. The aim in comparing models is whether the log-likelihood decreases or increases significantly with the addition or deletion of predictor(s).

R^2 Statistic

In logistic regression the R^2 value does not measure the fitness of the model as ordinary regression or does not explain the total variation accounted by the independent variables on the dependent variable.

The R^2 statistic in logistic regression is used to measure how well are the independent variables in predicting the two categories in the dependent variable (Bewick and Jonathan, 2005). Hence, direct comparison of logistic R-squared measures with R^2 from OLS regression is impossible. In logistic regression, there are measures such as Cox and Snell's, Nagelkerke's, and McFadden's R-squared, which are thought as an approximation to R^2 in OLS.

The Hosmer - Lemeshow Test Statistic

The Hosmer - Lemeshow test is a commonly used test for assessing the goodness of fit of a model and allows for any number of explanatory variables which may be continuous or categorical. The test is similar to a $\chi 2$ goodness of fit test and has the advantage of partitioning the observations into groups of approximately equal size, and therefore there are less likely to be groups with very low observed and expected frequencies. In this case, better model fit is indicated by a smaller difference in the observed and predicted classification (Bewick and Jonathan, 2005).

3.6.2.5 Detecting Outliers and Influential Observations

Outliers are observed values that are considerably large or smaller than the rest of the observations. Outliers may occur due to measurement errors, following wrong experimental procedure or presence huge of natural variability. In order to detect such observations, the standardized residuals are used. A large standardized residual or Pearson residuals that lie outside the range ($|d_i|>3$) indicates an outlier (Montgomery, Peak and Vinning, 2001). The calculation is done based on the formula given below.

$$d_i = \frac{e_i}{\sqrt{MS_{\mathrm{Res}}}} \quad i=1, 2\ldots n$$

where, e_i is the residual of the i^{th} observation and MS_{Res} is mean square residual.

The most useful and significant method of perturbing the data is deleting the cases from the data one at a time. Then examine the effects or influence of each individual case by comparing the full data analysis to the analysis obtained with a case removed. Thus, observations whose removal causes considerable changes in the logistic regression model are called influential.

Leverage statistic *(h)*, assesses how far away from the mean value are values of the independent variable farther away, the observation the more leverage and influences the logistic regression model. The leverage statistic varies from 0 (no influence on the model) to 1 (completely determines the model). That is, $0 < h < 1$.

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

Cook's distance (*D*) is one of the diagnostic statistics that examine the influence of observations on the logistic regression model fit and calculates the difference in the deviance statistic when a particular observation is removed. Cook's distance depends on the standardized residual of an observation and its leverage, as shown on the formula below.

$$D_i = \frac{Z_i h_i}{(1 - h_i)^2}$$

where Z_i is the standardized residual and h_i is the leverage.

Thus, if the largest D_i is substantially less than one, deletion of a case will not change the estimates of the parameters by much.

DFBETA statistic is another method which enables to investigate the difference in the regression coefficient when a particular observation is removed. A rule of thumb is that cases with DFBETA greater than one may be considered as influential (Belsley and Kuh, 2005).

4. RESULTS AND DISCUSSION

The results were presented in three main parts. In part one frequency distribution and other summary measures are given. The second part of the results is bivariate analyses, where the association between the dependent variables and individual independent variables was investigated. The final part of this chapter is the classical and Bayesian logistic regression analysis, where the net effect of the explanatory variables is identified.

4.1 Univariate Analysis

The information or the data used for the study were obtained from 990 married women of reproductive age (15-49 years) in Hawassa city. The result in table 4.1 shows, out of 990 married women of reproductive ages included in the study, about 57.9% (573) were using one of the modern contraception methods, while 42.1 %(417) were not using any modern contraception methods. Among 573 modern contraceptive users, 147(25.7%) were short term methods user. That is, 138 were pill users, 6 were Lactational Amenorrea users and 3 were Condom. The rest 426(74.3%) were long term users. Namely, 350 were Injectables users, 61 were Implant users, and 15 were Intrauterine Devices users.

Table 4.1: Characteristics of 990 married women of reproductive age (15-49 years old) on modern contraceptive usage and method preference (Hawassa city)

Characteristics		Count	Percentage (%)
Modern contraceptive usage	User	573	57.9
	Non user	417	42.1
Short term methods user	Pill	138	93.9
	Lactational Amenorrea	6	4.1
	Condom	3	2
Long term methods user	Injectables	350	82.2
	Implant	61	14.3
	Intrauterine Devices	15	3.5

In order to determine the association between modern contraceptive usage and method preference among married women of reproductive ages, and individual explanatory variables, the chi-square test was carried out. Furthermore, the frequency distributions of all independent variables with respective categories are given in table 4.2.

The results illustrated in table 4.2 indicate that most of the relationships between modern contraceptive usage and the explanatory variables were statistically significant. The independent variables age, religion, number of children, education level, husband's education level, occupation, monthly income, husband's monthly income, family planning field workers visit, frequency of following radio program, source of information, number of known method types, experience on modern contraceptive use, and husband's encouragement had statistically significant association with modern contraceptive usage at 0.05 significant level. How ever, the associations with desire for additional child, husband's occupation, frequency of watching television and availability of service were found statistically non-significant.

	None	13 (52)	12 (48)	25 (2.5)	2.899

Table 4.2: Association within each explanatory variable with respect to modern contraceptive usage for a sample of 990 married women of reproductive age (Hawassa city, 2011)

Variable	Category	Current Contraceptive Use		Total (%)	Chi-square (p-value)
		User	Non User		
		Count (%)	Count (%)	Count (%)	
Age of the respondent	15-24	223 (70.4)	94 (29.6)	317 (32)	60.428 (0.000)
	25 – 34	297 (57.9)	216 (42.1)	513 (51.8)	
	35 – 44	53 (33.1)	107 (66.9)	160 (16.2)	
Religion of the respondent	Orthodox	297 (56.9)	225 (43.1)	522 (52.7)	11.222 (0.011)
	Muslim	37 (46.3)	43 (53.7)	80 (8.1)	
	Protestant	220 (63.4)	127 (36.6)	347 (35.1)	
	Other	19 (46.3)	22 (53.7)	41 (4.1)	
Number of children	No child	44 (40)	66 (60)	110 (11.1)	59.988 (0.000)
	1 – 2 children	350 (67)	172 (33)	522 (52.7)	
	3 – 4 children	147 (57)	111 (43)	258 (26.1)	
	>= 5 children	32 (32)	68 (68)	100 (10.1)	
Desire for additional child	Yes	371 (57.6)	273 (42.4)	644 (65.1)	0.055 (0.814)
	No	202 (58.4)	144 (41.6)	346 (34.9)	
Education level	Illiterate	56 (47.9)	61 (52.1)	117 (11.8)	46.234 (0.000)
	Primary	250 (67)	123 (33)	373 (37.7)	
	Secondary	188 (62.3)	114 (37.7)	302 (30.5)	
	College/university diploma or higher	79 (39.9)	119 (60.1)	198 (20)	
Husband's education level	Illiterate	12 (35.3)	22 (64.7)	34 (3.4)	39.896 (0.000)
	Primary	153 (68.3)	71 (64.7)	224 (22.6)	
	Secondary	189 (66.3)	96 (33.7)	285 (28.8)	
	College/university diploma or higher	219 (49)	228 (51)	447 (45.2)	
Occupation	House wife	333 (58.6)	235 (41.4)	568 (57.4)	15.160 (0.004)
	Government employee	59(44.4)	74 (55.6)	133 (13.4)	
	Day laborer	19 (51.4)	18 (48.6)	37 (3.7)	
	Owen business	124 (63.6)	71 (36.4)	195 (19.7)	
	Private organization	38 (66.7)	19 (33.3)	57 (5.8)	
Monthly income	None	295 (57.6)	217 (42.4)	512 (51.7)	84.127 (0.000)
	100-400	76 (62.3)	46 (37.7)	122 (12.3)	
	400-700	90 (72.6)	34 (27.4)	124 (12.5)	
	700-1000	82 (75.9)	26 (24.1)	108 (10.9)	
	>=1000	30 (24.2)	94 (75.8)	124 (12.5)	

	Government employee	214 (55)	175 (45)	389 (39.3)	
	Day laborer	80 (59.7)	54 (40.3)	134 (13.5)	
	Owen business	167 (59.6)	113 (40.4)	280 (28.3)	
	Private organization	99 (61.1)	63 (38.9)	162 (16.4)	
Husband's monthly income	100-400	75 (69.4)	33 (30.6)	108 (10.9)	39.224 (0.000)
	400-700	113 (58.6)	80 (41.4)	193 (19.5)	
	700-1000	139 (73.2)	51 (26.8)	190 (19.2)	
	>=1000	246 (49.3)	253 (50.7)	499 (50.4)	
Family planning field workers visit	Yes	354 (65.9)	183 (34.1)	537 (54.2)	31.141 (0.000)
	No	219 (48.3)	234 (51.7)	453 (45.8)	
Frequency of following radio program	Almost every day	167 (55.7)	133 (44.3)	300 (30.3)	8.363 (0.039)
	Occasionally	288 (56.1)	225 (43.9)	513 (51.8)	
	At least once a week	54 (72)	21 (28)	75 (7.6)	
	Not at all	64 (62.7)	38(37.3)	102 (10.3)	
Frequency of watching television	Almost every day	280 (57.7)	205(42.3)	485 (49)	4.085 (0.252)
	Occasionally	206 (55.4)	166(44.6)	372 (37.6)	
	At least once a week	22 (66.7)	11 (33.3)	33 (3.3)	
	Not at all	65 (65)	35(35)	100 (10.1)	
Source of information	Media	211 (54.9)	173 (45.1)	384 (38.8)	72.897 (0.000)
	Health center	234 (74.5)	80 (25.5)	314 (31.7)	
	Friends	55 (58.5)	39 (41.5)	94 (9.5)	
	Family planning field workers	73 (36.9)	125(63.1)	198 (20)	
Number of known method types	1-3	240 (53)	213 (43)	453 (45.8)	8.220 (0.004)
	>=4	333 (62)	204 (38)	537 (54.2)	
Experience on modern Contraceptive Use	Yes	512(72.4)	195(27.6)	707(71.4)	214.472 (0.000)
	No	61(21.6)	222(78.4)	283(28.6)	
Husband's encouragement	Yes	516 (70.2)	219 (29.8)	735 (74.2)	177.810 (0.000)
	No	57 (22.4)	198 (77.6)	255 (25.8)	
Availability of Service in near place	Yes	424 (57.8)	309 (42.2)	733 (74)	0.001 (0.971)
	No	149 (58)	108 (42)	257 (26)	

As shown in Table 4.2 above, about 57.9% of the respondents were currently using one of the modern contraception methods. Modern contraceptive usage with respect to the age categories 15-24 years, 25-34 years, and 35- 44 years were 70.4%,57.9% and 33.1 %, respectively. This suggests that as age of a woman increases modern contraceptive usage declines. Concerning the number of children, women with no child, 1-2 children, 3 - 4 children and greater or equal to 5 children were using modern contraception methods with proportions 40 %, 67 % , 57 % and 32 %, respectively.

Modern contraceptive usage among married women according to education level reveals that 47.9% of Illiterates, 67% of Primary level, 62.3% of Secondary level and 39.9 % of College/University diploma or higher level women were practicing modern contraception. Percentages of modern contraceptive usage in terms of monthly income categories: None, 100-400, 400-700, 700-1000 and >= 1000 Birr were 57.6%, 62.3%, 72.6%, 75.9% and 24.2%, respectively.

The proportion of modern contractive usage was higher (65.9%) among women visited by Family planning field workers than women who were not visited. Similarly, the proportion of modern contraceptive usage among women within categories of Sources of information: Media, Health center, Friends and Family planning field workers were 54.9%, 74.5%, 58.5% and 36.9%, respectively.

Regarding husband’s encouragement, modern contraceptive usage was higher for women that had their husbands’ encouragement. The proportions of modern contraceptive usage were 70% and 22.4% among women who were encouraged by their husbands’ and who were not, respectively.

	None	8(61.5)	5(38.5)	13(2.3)	17.134

Table 4.3: Association within each explanatory variable with respect to method preference for a sample of 573 married women who were modern contraceptive users currently (Hawassa city, 2011)

Variable	Category	Method preference		Total (%)	Chi-square (p-value)
		Short term	Long term		
		Count (%)	Count (%)	Count (%)	
Age of the respondent	15-24	45(20.2)	178(79.8)	223(39)	6.435 (0.04)
	25 - 34	89(30)	208(70)	297(51.8)	
	35 - 44	13(24.5)	40(75.5)	53(9.2)	
Religion of the respondent	Orthodox	87(29.3)	210(70.7)	297(51.8)	14.715 (0.002)
	Muslim	16(43.2)	21(56.8)	37(6.5)	
	Protestant	40(18.2)	180(81.8)	220(38.4)	
	Other	4(21.1)	15(78.9)	19(3.3)	
Number of children	No child	8(18.2)	36(81.8)	44(7.7)	10.112 (0.018)
	1 - 2 children	80(22.9)	270(77.1)	350(61.1)	
	3 - 4 children	45(30.6)	102(69.4)	147(25.7)	
	>= 5 children	14(43.8)	18(56.2)	32(5.6)	
Desire for more child	Yes	107(28.8)	264(71.2)	371(64.7)	5.603 (0.018)
	No	40(19.8)	162(80.2)	202(35.3)	
Education level	Illiterate	19(33.9)	37(66.1)	56(9.8)	7.084 (0.069)
	Primary	69(27.6)	181(72.4)	250(43.6)	
	Secondary	47(25)	141(75)	188(32.8)	
	College/university diploma or higher	12(15.2)	67(84.8)	79(13.8)	
Husband's education level	Illiterate	3(25)	9(75)	12(2.1)	9.276 (0.026)
	Primary	26(17)	127(83)	153(26.7)	
	Secondary	59(31.2)	130(68.8)	189(33)	
	College/university diploma or higher	59(27)	160(73)	219(38.2)	
Occupation	House wife	95(28.5)	238(71.5)	333(58.1)	9.174 (0.057)
	Government employee	9(15.3)	50(84.7)	59(10.3)	
	Day laborer	1(5.3)	18(94.7)	19(3.3)	
	Owen business	31(25)	93(75)	124(21.6)	
	Private organization	11(28.9)	27(71.1)	38(6.6)	
Monthly income	None	79(26.8)	216(73.2)	295(51.5)	15.134 (0.004)
	100-400	8(10.5)	68(89.5)	76(13.3)	
	400-700	26(28.9)	64(71.1)	90(15.7)	
	700-1000	29(35.4)	53(64..6)	82(14.3)	
	>=1000	5(16.7)	25(83.3)	30(5.2)	

	Government employee	54(25.2)	160(74.8)	214(37.3)	
	Day laborer	11(13.8)	69(86.2)	80(14)	
	Owen business	51(30.5)	116(69.5)	167(29.1)	
	Private organization	23(23.2)	76(76.8)	99(17.3)	
Husband's monthly income	100-400	14(18.7)	61(81.3)	75(13.1)	7.963 (0.047)
	400-700	21(18.6)	92(81.4)	113(19.7)	
	700-1000	37(26.6)	102(73.4)	139(24.3)	
	>=1000	75(30.5)	171(69.5)	246(42.9)	
Family planning field workers visit	Yes	90(25.4)	264(74.6)	354(61.8)	0.026 (0.872)
	No	57(26)	162(74)	219(38.2)	
Frequency of following radio program	Almost every day	39(23.4)	128(76.6)	167(29.1)	2.475 (0.480)
	Occasionally	82(28.5)	206(71.5)	288(50.3)	
	At least once a week	12(22.2)	42(77.8)	54(9.4)	
	Not at all	14(21.9)	50(78.1)	64(11.2)	
Frequency of watching television	Almost every day	73(26.1)	207(73.9)	280(48.9)	10.844 (0.013)
	Occasionally	73(26.1)	207(73.9)	280(48.9)	
	At least once a week	4(18.2)	18(81.8)	22(3.8)	
	Not at all	7(10.8)	58(89.2)	65(11.3)	
Source of Information	Media	49(23.2)	162(76.8)	211(36.8)	7.840 (0.049)
	Health center	53(22.6)	181(77.4)	234(40.8)	
	Friends	19(34.5)	36(65.5)	55(9.6)	
	Family planning field workers	26(35.6)	47(64.4)	73(12.7)	
Number of known method types	1-3	56(23.3)	184(76.7)	240(41.9)	1.167 (0.280)
	>=4	91(27.3)	242(72.7)	333(58.1)	
Experience on modern Contraceptive Use	Yes	129(25.2)	383(74.8)	512(89.4)	0.532 (0.466)
	No	18(29.5)	43(70.5)	18(3.1)	
Husband's encouragement	Yes	129(25)	387(75)	516(90.1)	1.165 (0.280)
	No	18(31.6)	39(68.4)	57(9.9)	
Availability of Service in near place	Yes	118(27.8)	306(72.2)	424(74)	4.047 (0.044)
	No	29(19.5)	120(80.5)	149(26)	
Service provider	Hospital	5(35.7)	9(64.3)	14(2.4)	16.652 (0.001)
	Health center	58(19)	248(81)	306(53.4)	
	Clinic	16(40)	24(60)	40(7)	
	Family planning service provider	68(31.9)	145(68.1)	213(37.2)	

The association between the response variable (method preference) and the predictor variables was examined using chi-square test as reported in table 4.3. From a total of 573 modern contraceptive users, 426(74.3%) were long term modern contraceptive methods users.

Long term modern contraceptive usage with respect to the age categories 15-24 years, 25-34 years, and 35- 44 years were 79.8%, 70% and75.5 %, respectively. Regarding the number of children, the percentage of women with no children, 1-2 , 3 - 4 and >=5 children that were currently using long term modern contraception methods were 81.8 %, 77.1% , 69.4 % and 56.2 %, respectively. This implies that long term modern contraceptive usage among women becomes lower as the numbers of children increases.

The proportions of long term modern contraceptive usage based on women's monthly income categories, None, 100-400, 400-700, 700-1000 and >= 1000 Birr were 73.2%, 89.5%, 71.1% ,64.6% and 83.3, respectively. The percentages of long term modern contraception method usage with regard to availability of service nearby, 72.2% were getting the service in nearby location and 80.5% were not. This implies that those who were not getting the service nearby had better chance to use long term modern contraception method.

Moreover, the percentages of modern contraceptive usage according to the service provider: Hospital, Health center, Clinic, and Family planning service provider were 64.3%, 81%, 60% and 68.1%, respectively. This result shows that, long term modern contraceptive usage was higher among women who were getting service from health centers.

4.2 Bayesian Logistic Regression Analysis for Modern Contraceptive Usage

In addition to the classical approach, the Bayesian procedure was considered in this study to make inference about the parameters of a logistic regression model. Bayesian method gives estimates of parameters by sampling them from their posterior distributions through an MCMC method. This approach was employed to model modern contraceptive usage among married women of reproductive ages. Gibbs sampler algorithm with three different initial values was implemented in this study and 10000 MCMC samples were considered for burn-in after 20000 iterations. However, in order to be sure that the sample was truly representative of the stationary or posterior distribution, various schemes of diagnosis were applied to check the convergence of the Markov chains to the target distribution.

4.2.1 Assessing Accuracy of Bayesian Logistic Regression Model

Before proceeding to examine the results of the model, it is essential to do some diagnostics to assess whether the Markov chain has converged to its stationary or posterior distribution. There are several different methods to check for convergence. These are Time series plot, Autocorrelation Plot, Density plot, Gelman –Rubin Statistics and comparing the MC error to its posterior standard errors (Ioannis, 2009 and Gelman, 2005). Discussion on plots of three different independent variables is included in this section and the rest are given on appendix B.

Time series plot: In Bayesian analysis time series plot is one of methods of assessing the convergence of the Markov chain to its posterior distribution. When convergence is achieved the three chains will mix together. In figure 4.1 the values on the Y- axis indicate estimates of parameters and values on the X- axis show the number of iterations. At this stage one can say that convergence is achieved since, the three chains with different colors are overlapped one on the another.

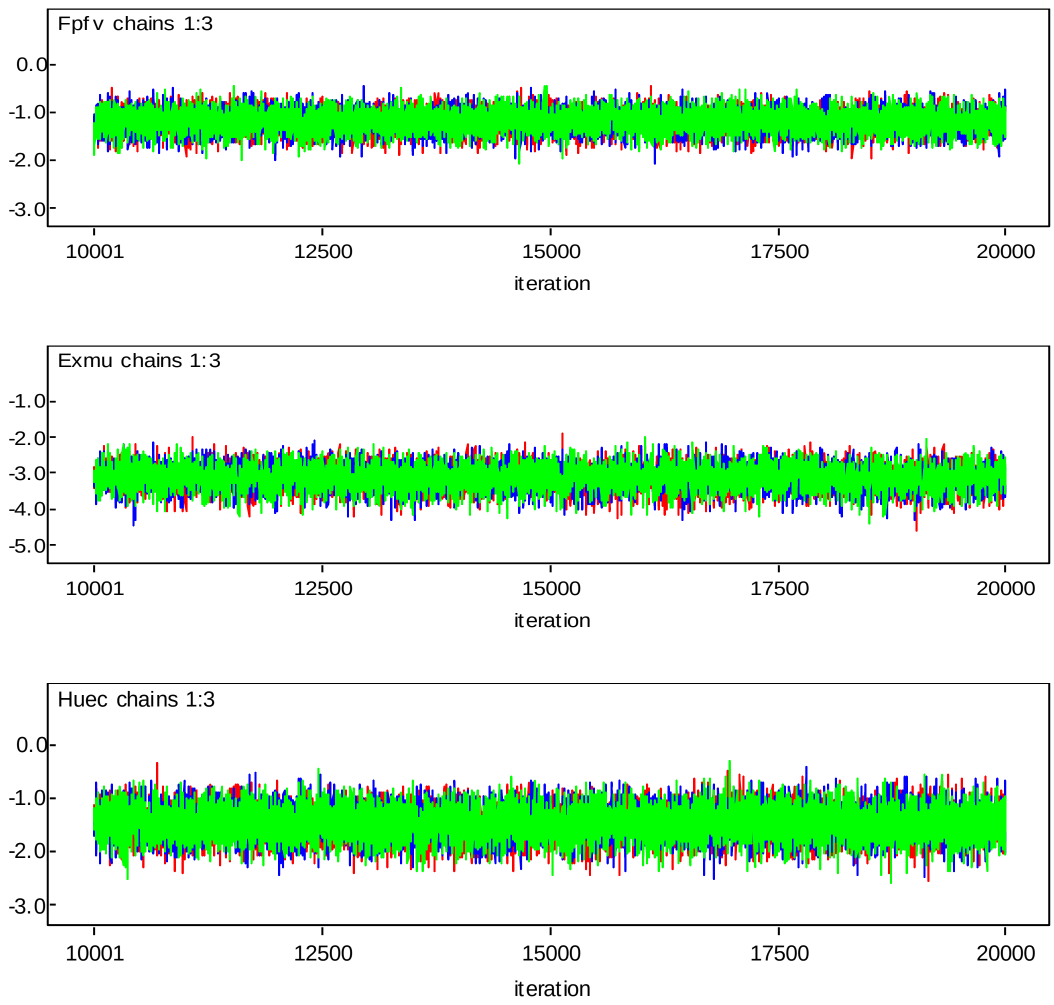


Figure 4.1: Time Series Plots for Convergence of Coefficients for Family planning field workers visit (Fpfv), Experience on modern Contraceptive Usage (Exmu) and Husband's encouragement(Huec)

Gelman –Rubin Statistics: Another method to verify convergence of the Markov chain is to look at the Gelman-Rubin statistic. To perform the test, it is necessary to run two or more chains in parallel, with different initial values. This test compares the variances within and between the chains. In the plots of the Gelman-Rubin statistic in Figure 4.2, the lower two lines represent the within and between chain variations, respectively and the upper line is the ratio of the between and within chain variations. The lower two lines are stable and the upper line converges to 1, which imply that the chain has converged to its target distribution (Brooks and Gelman, 1998).

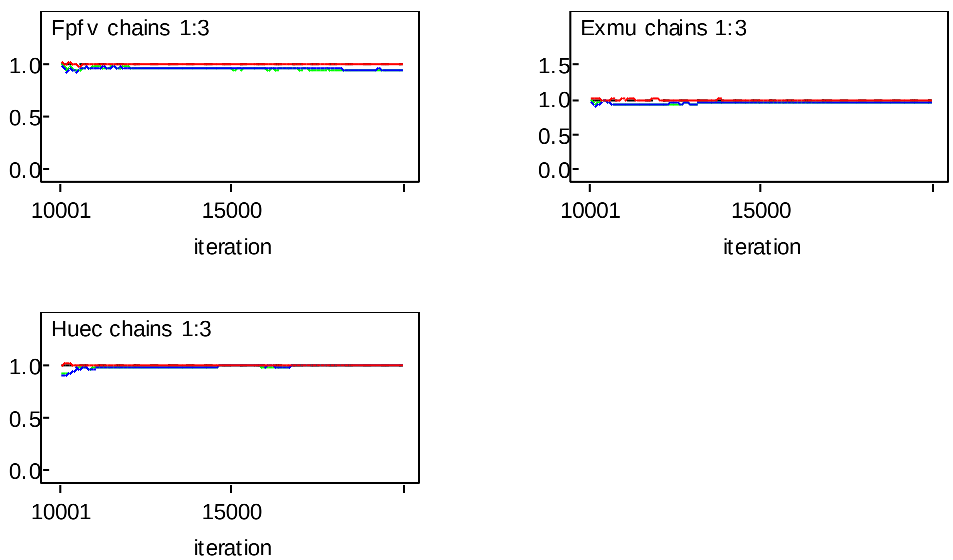


Figure 4.2: Gelman-Rubin Statistics for Convergence of Coefficients for Family planning field workers visit (Fpfv), Experience on modern Contraceptive Usage (Exmu) and Husband's encouragement (Huec)

Autocorrelation Plot: It is one of the convergence test plots in Bayesian analysis. High autocorrelation within a single parameter chain leads to slow mixing and possibly individual non convergence to the limiting distribution because the chain will tend to explore less space in finite time. That is, low or high values indicate fast or slow convergence, respectively. In analyzing Markov chain autocorrelation, it is necessary to identify lags in the series in order to calculate the longer- run trends in correlation, and in particular whether they decrease with increasing lags. Shown in figure 4.3, the autocorrelations for all parameters become smaller after a lag equal to 50 and the three independent chains were overlapped with each other. Now, one can be reasonably confident that convergence has been achieved.

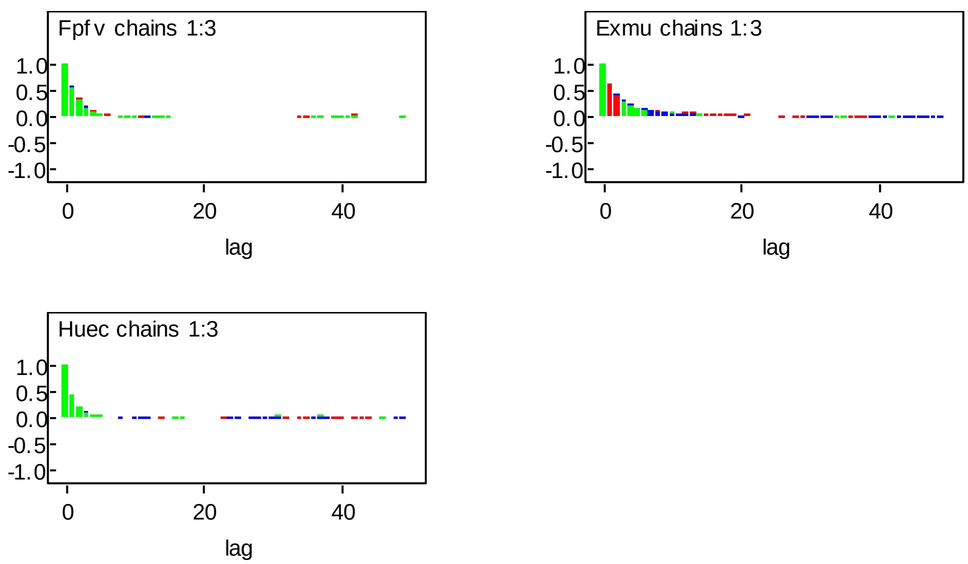


Figure 4.3: Autocorrelation Plots for Convergence of Coefficients of Family planning field workers visit (Fpfv), Experience on modern Contraceptive Usage (Exmu) and Husband's encouragement (Huec)

Density plot: This is one of the graphical methods to assess whether the Markov chain has converged to its stationary distribution. The plots on figure 4.4 show that the coefficients for most of the independent variables were normally distributed. Thus, this indicates that the Markov chain has attained its posterior distribution.

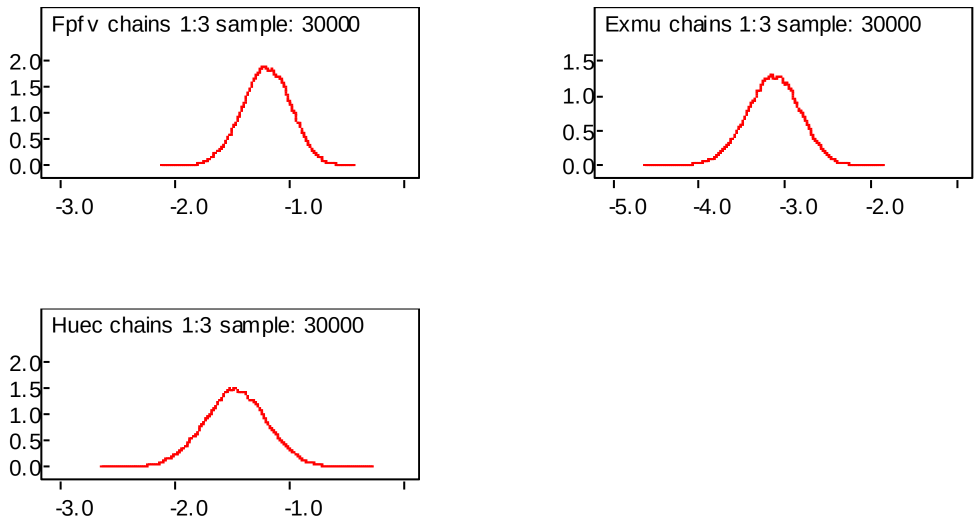


Figure 4.4: Density plots for Convergence of Coefficients of Family planning field workers visit (Fpfv), Experience on modern Contraceptive Usage (Exmu) and Husband's encouragement (Huec)

However, in addition to the above graphical methods of checking convergence of the chain to its posterior distribution, the Monte Carlo standard error of the posterior mean (which is an estimate of the difference between the estimate of the posterior mean for each parameter and the true posterior mean) is another way of assessing the accuracy of the posterior estimates. The simulation should be run until the Monte Carlo error for each parameter of interest is less than 5% the sample standard deviation. The Monte Carlo error (MC error), odds ratio (Exp ($\hat{\beta}$)), sample standard deviation (SD) and 95% confidence intervals for the estimates are reported in table 4.4. Among those predictor variables considered in the model , Age, Number of Children, Education Level, Occupation, Monthly Income, Family Planning Field Workers Visit, Frequency of Following Radio Program, Source of Information, Experience on modern Contraceptive Usage and Husband's Encouragement were significant predictors.

The odds ratio (Exp ($\hat{\beta}$)) is a measure of association, which quantifies the relationship between the predictors and dichotomous response variables. If odds ratio is greater 1, then the odds of success increase (being modern contraceptive user); if the odds ratio is less than 1, any increment in the predictor variables reduces the odds of success.

As presented in table 4.4, the relationship between modern contraceptive usage and the age of the respondent was found statistically significant. The study revealed that being modern contraceptive user for women in age group 25-34 and 35-44 were 0.171 and 0.166 times less likely than who were in age group 15-24, respectively. This implies that as the age of woman increases the probability of being modern contraceptive user decreases.

Number of children was also a statistically significant predictor. Women with number of children between 1-2 and 3-4 children were 18.011 and 11.681 times more likely to use modern contraception method than those with out children.

Table 4.4: Posterior parameter estimates for Bayesian Logistic Regression model (Hawassa city, 2011)

Node	Categories	Mean($\hat{\beta}$)	Exp($\hat{\beta}$)	*S.E* ($\hat{\beta}$)	MC Error	95% CI ($\hat{\beta}$)	
						Lower	Upper
Age	15-24 (Ref)						
	25 – 34	-1.764*	0.171	0.3071	0.00549	-2.378	-1.178
	35 – 44	-1.795*	0.166	0.3833	0.00684	-2.548	-1.053
Number of Child	No child(Ref)						
	1 – 2 children	2.891*	18.01	0.3767	0.00891	2.158	3.644
	3 – 4 children	2.458*	11.68	0.4159	0.00935	1.649	3.286
	>= 5 children	0.1671	1.182	0.479	0.00943	-0.7703	1.118
Education Level	Illiterate(Ref)						
	Primary	0.8927*	2.442	0.3801	0.00963	0.1403	1.641
	Secondary	-0.0972	0.907	0.411	0.01088	-0.8985	0.7097
	College/Univ. dip. or higher	0.4749	1.608	0.4979	0.01246	-0.4962	1.466
Occupation	House wife(Ref)						
	Government Employee	-1.034	0.356	0.5734	0.01377	-2.162	0.0901
	Day laborer	-1.125	0.325	0.7291	0.01504	-2.531	0.3029
	Own business	0.4704	1.601	0.5396	0.01313	-0.5871	1.531
	Private organization	1.368*	3.927	0.6735	0.01263	0.07598	2.724
Monthly Income	None(Ref)						
	100-400	-0.9718	0.378	0.5957	0.01421	-2.139	0.1957
	400-700	0.1149	1.122	0.5818	0.01362	-1.024	1.27
	700-1000	0.6233	1.865	0.4802	0.00865	-0.3053	1.573
	>= 1000	-1.842*	0.159	0.6054	0.01356	-3.049	-0.6541
Field Workers Visit	Yes (Ref)						
	No	-1.2*	0.301	0.2113	0.00236	-1.624	-0.7933
Frequency of Following Radio Program	Almost every day(Ref)						
	Occasionally	0.4479	1.56	0.4445	0.0052	-0.41	1.334
	At least once a week	-1.102	0.33	0.2677	0.0044	-2.132	-0.141
	Not at all	-1.326*	0.26	0.4279	0.0060	-2.506	-0.219
Source of Information	Media (Ref)						
	Health center	0.4907	1.633	0.2656	0.00364	-0.0276	1.013
	Friends	0.06939	1.072	0.3839	0.00446	-0.6777	0.8364
	Family planning field workers	-1.255*	0.285	0.3059	0.00417	-1.863	-0.6607
Experience on modern Contraceptive Usage	Yes (Ref)						
	No	-3.14*	0.043	0.3117	0.00419	-3.77	-2.548
Husband's encouragement	Yes (Ref)						
	No	-1.469*	0.23	0.2728	0.00261	-2.009	-0.9387

Ref = Reference category, * = significant at 5% level of significance

Regarding women's education level, the study indicated that women with primary education level were found more probable to use modern contraception. The odds of being modern contraceptive users for women with primary education level were 2.442 times higher than illiterates. In addition, women's occupation was one of the predictors that had statistically significant relationship with modern contraception usage. Women who were working in private organization were 3.927 times more likely to use modern contraceptive than house wives.

The relationship between modern contraceptive usage and monthly income of women was statistically significant. Women earning >= 1000 birr monthly were 0.159 times less likely to use modern contraception than women with out monthly income. This suggests that, as women's monthly income gets higher, the chance to be modern contraception user becomes lower. Family Planning Field Workers Visit was among those statistically significant variables. The result reveals that women visited by family Planning Field Workers were more probable to use modern contraceptive. Being modern contraceptive user for women who were not visited by family planning field workers was 0.301 times less likely than those who were visited.

Frequency of following radio program was also statically significant predictor in this study. The chance of being modern contraceptive user decrease as the frequency of following radio program decreases. The odds of being modern contraceptive user for women following radio program at least once in a week and not at all decrease by a factor of 0.332 and 0.266 as compared to those who follow radio program almost every day, respectively.

The study suggests that women who get information about modern contraception method from family planning field worker were less probable. The odds of being modern contraceptive user for those who got the information from family planning field workers decrease by an amount of 0.285 as compared to the reference category (media). More over, experience on modern contraceptive usage had also significant effect on current modern contraceptive usage. The odds of modern contraceptive usage for women that had no experience on modern contraceptive usage decrease by a factor of 0.043 as compared to those who had.

The effect of husband's encouragement was statistically significant on modern contraceptive usage. As the study indicates women who had husbands' support were more likely to use modern contraception methods. The odds of being modern contraceptive users for women who were not encouraged by their husbands' decreased by an amount of 0.23 as compared to those who were encouraged.

4.3 Discussion on Modern Contraceptive Usage

One of the main purposes of this study was identifying the Socio-Economic and Demographic factors related to modern contraceptive usage among married women of reproductive ages (15-49 years old) in Hawassa city. The study revealed that, out of 990 currently married women of reproductive ages 57.9 %(572) were modern contraceptive users.

In the Univariate analysis, where the association between the dependent variable and each predictor was tested, modern contraceptive usage among currently married women of reproductive ages (15-49 years old) had statistically significant relationship with most of the proposed socioeconomic and demographic factors.

The Bayesian logistic regression analysis result revealed that the age of the respondent had statistically significant effect on modern contraceptive usage among married women of reproductive ages. The finding indicated that modern contraceptive usage was lower for women in age group 25-34 and 35-44. That is, as the age of married women increases the chance of being modern contraceptive user decreases. This result is consistent with earlier studies by Klein (2001), Leiprapai, Thongthai (1989) and Dang (1995) which indicated that women at higher ages categories were less likely to use modern contraception. Adanu et al. (2009) found that younger women of prime reproductive age were significantly more likely to use modern methods than older women.

Number of children had significant impact on modern contraceptive usage among currently married women. Women with 1-2 and 3-4 children were more likely to use modern contraceptive methods than women with out child. This result is in agreement with a study by Gupta, et al. (2003) which found that women would practice contraception after their desired family size; Samijo et al. (1991) and Irja Nelago (2007) concluded that women with at least two or more living children were likely to be more interested in limiting child birth as compared to child less women.

In addition, women's education level was found statistically significant predictor. The odds of being modern contraceptive user were higher for women with primary education level than uneducated women. This finding was in agreement with studies by Islam and

Mahmud (1995), which revealed that the practice of modern methods was more prevalent among women with primary education. It is possible that the higher educated women are more informed about various modern methods and their side effects, which influence them to use traditional methods.

This study indicated that women's occupation was a significant factor on modern contraceptive usage among currently married women. The result revealed that women engaged in private organizahtion were more likely to use modern contraception method than who were not working (house wives). This finding is similar to many studies such as Shiparo and Tambashe (1994), Shrestha(2000), Govindasamy and Malhotra(1996). More over, the monthly income of women had significant effect on modern contraceptive usage. This study indicated that women with higher monthly incomes were less likely to use modern contraception methods than who were with out monthly incomes. This result is not consistent with Ali et al. (2004), Fikree et al. (2001) and Khan, (1997) who concluded the bargaining power and higher autonomy of economically active women resulted into higher likelihood of contraceptive use among them.

Family Planning Field Workers Visit had significant impact on modern contraceptive usage among married women. In this study women who were not visited by family planning field workers were less likely to use modern contraceptive than those who were visited. This finding is in line with earlier studies by Islam and Muhmud (1995), Rana (2002) which indicated that women who were visited by family planning workers were more likely to use contraception than those who were never visited.

The frequency of following radio program was an important predictor on modern contraceptive usage among married women. This finding indicated that women who follow radio program had better chance to use modern contraceptive methods. This result was in harmony with Kabir and Islam (2000). Concerning source of information, women who were getting information about modern contraceptive method from family planning field workers were less probable to practice modern contraception methods than those who get from mass media. This result is consistent with earlier studies by Mason (1996) and Kabir and Islam (2000), which indicated that women exposed to mass media family planning messages are more likely to use contraception.

Experience on modern contraceptive usage had statistically significant effect on the current modern contraceptive usage among married women. Those who had no experience about modern contraceptive practice were less likely to use modern contraception methods. This finding was similar to earlier studies by Hogan et al. (1999), Degraff (1991) , Little (2001) and Farrukh Toirov (2004), which found that women who had never previously practiced contraception were less likely to currently use contraception compared to women who had used some methods before.

In addition, husband's encouragement was one of the significant predictors of modern contraceptive usage. Women who had no husbands' support to use modern contraception were less likely to practice modern contraception methods. This result is in line with previous studies by Lasee and Becker (1997), Isiugo- Abanihe (1994), Joesoef et al. (1988) and Khalif (1988), where women were less likely to use contraception due to their husband's disapproval.

4.4 Classical Logistic Regression Analysis for Method Preference

The binomial logistic regression was employed to test the relationship between modern contraceptive method choice and the predictor variables. As discussed earlier, among nineteen predictor variables only twelve variables had statistically significant association with method preference. However, in the multiple logistic regression analysis where the net effects of all predictor variables were explored, only nine predictor variables had statically significant influence on method preference. These were age, religion, number of children, desire for more children, education level, frequency of watching television, experience on modern Contraceptive usage, availability of service in near place and service provider.

4.4.1 Model Adequacy Checking

Assessing the overall significance of a model is essential before dealing with the fitted model directly. The Chi square test is used to assess significance of the fitted model, which measures the improvement in fit that the independent variables made compared to the null model or model with the constant only.

To test the significance of the final model over null model, the difference between –2 log likelihood for the best-fitted model and –2 log likelihood for the null model (with constant only) was computed, which has a chi square distribution with degrees of freedom equal to the number of independent variables. As shown in table 4.5, the Model chi-square was equal to 141.348 with 9 degree of freedom and p-value < 0.001. Thus, the final model fits the data well, indicating that the predictor variables do have a significant effect.

Table 4.5: Summary Statistics of the Likelihood Ratio Test

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	Df	Sig.
Null model (Intercept only)	652.545	141.348	9	0.000
Final model	511.197			

Even though there is no direct analogous statistic in logistic regression to the coefficient of determination (R^2), the Model Summary in table 4.6 provides some approximations. For this study, Cox and Snell's R-Square was 21.9%, which indicated about 21.9% of variation on modern contraceptive method preference was explained by the model. While the Nagelkerke R^2 value was 0.322 which indicated that about 32.2% of variation in the dependent variable was explained by the predictor variables.

Table 4.6: Model Summary of Cox & Snell R^2 and Nagelkerke R^2

Model Summary		
-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
511.197	0.219	0.322

The Hosmer and Lemeshow test is an alternative to model chi square that divides subjects into 10 ordered groups of subjects and then compares the observed number or the number actually in the each group to the number predicted by the logistic regression model. The 10 ordered groups were created based on their estimated probability; those with estimated probability below 0.1 form one group, and so on, up to those with probability 0.9 to 1. Each of these categories is further divided into two groups based on the actual observed outcome variable like short term and long term in our case. The expected frequencies for each of the cells are obtained from the model.

The Hosmer-Lemeshow statistic that is given in Table 4.8 has significance of 0.479, which is statistically insignificant and the model has a good fit. That is, there is no difference between the observed number and the number predicted by the logistic regression model.

Table 4.8: Hosmer - Lemeshow Test

Chi-square	Df	Sig.
7.550	8	0.479

In addition to the above methods of assessing goodness of fit, it is possible to look at the proportion of cases we have managed to classify correctly. To do so, we need to look at the classification table (Table 4.9) which tells us the number of cases that have been correctly predicted. In the classification table, the columns are the two predicted values of the dependent variable, while the rows are the two observed or actual values of the dependent variable. In this study, out of 573 modern contraceptive users 42.2 % of short term method users and 93.9% of long term method users were correctly classified. Overall, 80.6% cases were correctly predicted.

Table 4.9: Classification Table

Observed		Predicted		
		Method type used		Percentage Correct
		Short term	Long term	
Method type used	Short term	62	85	42.2
	Long term	26	400	93.9
Overall Percentage				80.6

Binary logistic regression was adopted to explore the net effect of socio-economic and demographic factors on method preference among modern contraceptive users. All the variables involved in the analysis were categorical. Thus, to interpret the results of the analysis, the first category of the variables was taken as reference category in this study. In the analysis nine predictor variables were statistically significant, where at least one of their categories have an influence on method preference.

As illustrated in table 4.10, Age, Religion, Number of Children, Desire for more children, Education level, Frequency of watching television, Experience on modern Contraceptive Usage, Availability of service nearly and Service provider were found statistically significant predictors.

Married women whose age is between 35 – 44 were 0.301 times less likely to use long term modern contraception method than those in age group 15-24. Regarding women's religion, followers of other than protestant and Muslim religions were 4.949 times more likely to use long term methods than women's following Coptic religion. Women whose number of children is between 1-2, 3-4 and >= 5 were 24, 8.529 and 4.82 time more likely to use long term modern contraception methods than women without children, respectively. This implies that long term methods usage decreases as the number of children increases. Moreover, women who had no desire for additional children were 0.459 times less likely to use long term methods than their counter part.

In addition, women's education level was one of the predictors that had statistically significant relationship with method preference. Women with primary, secondary and

College/University diploma or higher education level were 0.205,0.255 and 0.738 times less likely to use long term modern contraception methods than the reference category(or illiterate), respectively. This reveals that, as women's education level increases long term modern contraceptive usage increases among married women. More over, the frequency of watching television was statistically significant in predicting the categories of the response variable, where women who were following television program occasionally, at least once a week were 0.129 and 0.122 times less likely to use long term method than those who were watching almost every day, respectively.

The relationship between long term contraceptive usage and experience on modern contraception methods was statistically significant, where women who had no experience on modern contraceptive usage were 2.95 times more likely to use long term contraception methods than those who had experience. Regarding the availability of service, women who do not get the service nearly were 0.218 times less likely to use long term modern contraception method than those who get the service nearby. On the other hand, the service provider was one of the influential predictors of modern contraception method preference; women who get the service from family planning service provider were 2.008 times more likely to use long term methods than those who get the service from Hospitals.

Table 4.10: Predictors in the Final Logistic Regression Model (Hawassa city, 2011)

Predictors	Categories	$\hat{\beta}$	$S.E(\hat{\beta})$	Wald	Df	p-value	Exp($\hat{\beta}$)	95% C.I for Exp($\hat{\beta}$)	
								Lower	Upper
Age	15-24 (Ref)			8.195	2	0.017			
	25 – 34	-0.541	0.554	0.954	1	0.329	0.582	0.197	1.723
	35 – 44	-1.201	0.516	5.424	1	0.020*	0.301	0.109	0.827
Religion	Coptic (Ref)			11.962	3	0.008			
	Muslim	0.915	0.791	1.336	1	0.248	2.496	0.529	11.78
	Protest	0.028	0.921	0.001	1	0.975	1.029	0.169	6.251
	Other	1.599	0.797	4.025	1	0.045*	4.949	1.037	23.61
Number of Children	No chi(Ref)			15.132	3	0.002			
	1 – 2 child	3.178	0.905	12.321	1	0.000*	24.01	4.070	141.6
	3 – 4 child	2.143	0.606	12.509	1	0.000*	8.529	2.600	27.97
	>= 5 child	1.574	0.588	7.152	1	0.007*	4.825	1.522	15.29
Desire More child	Yes (Ref)								
	No	-0.778	0.338	5.291	1	0.021*	0.459	0.237	0.891
Education level	Illiterate(Ref)			13.032	3	0.005			
	Prim	-1.583	0.742	4.547	1	0.033*	0.205	0.048	0.880
	Second	-1.365	0.559	5.956	1	0.015*	0.255	0.085	0.764
	Col/UniDiHig	-0.304	0.521	0.341	1	0.559	0.738	0.266	2.047
Frequency of watching television	AlmEvD(Ref)			11.781	3	0.008			
	Occasionally	-2.047	0.626	10.703	1	0.001*	0.129	0.038	0.440
	At least once a week	-2.104	0.628	11.225	1	0.001*	0.122	0.036	0.418
	Not at all	-1.478	0.882	2.808	1	0.094	0.228	0.040	1.285
Experience on modern contracept	Yes(Ref)								
	No	1.082	0.471	5.267	1	0.022*	2.950	1.171	7.433
Availability Service in Near by	Yes(Ref)								
	No	-0.793	0.373	4.514	1	0.034*	0.452	0.218	0.940
Service Provider	Hospital(Ref)			13.617	3	0.003			
	Health center	-1.377	0.971	2.010	1	0.156	0.252	0.038	1.693
	Clinic	-0.591	0.559	1.118	1	0.290	0.554	0.185	1.656
	Family Planning Service prov	0.697	0.289	5.800	1	0.016*	2.008	1.139	3.539
Constant		0.014	1.472	0.000	1	0.992	1.014		

Ref = Reference category, * = p-valve < 5% level of significance

4.4.2 Diagnostics for Binomial Logistic Regression Model

Outliers and Influential Observations

The presence of outlier and influential observation were checked, where the minimum and maximum values of the cook's distance were 0 and 0.80727, respectively. The DFBETA statistics for detection of influential values on logistic regression coefficients are presented in the appendix 8. Similarly, the standardized residuals obtained from the model were within the interval -3 and 3, which indicate that no outliers were detected at level of significance at α=0.05.The cook's distance and DFBETA statistics were less than unity which implies that, an observation had no overall impact on the estimated vector of parameters and no specific impact of an observation on the coefficient of a particular predictor variable, respectively.

4.5 Discussion on Methods Preference

This study also identified the major determinants of method choice among modern contraceptive user women. From a total of 572 modern contraceptive users, 426(74.3%) were long term methods users; 350 were injectables users; 61 were implant users; and 15 were intrauterine devices users.

In the Univariate analysis, most of the Socio-Economic and Demographic factors had statistically significant association with method preference. This finding was also similar to studies by Mannan (2002), Raine (2003), Trussell (1999), Apter 2004, Mannan(2002) and Godley (2001).

The classical logistic regression analysis result also indicated that the age of the respondent was statistically significant factor on method preference of modern contraceptive user. Women in age category 35- 44 years old were less probable to practice long term methods. This result was unlike the study by Iwu et al. (2009) who showed that older women were significantly more likely to use a long-term method than younger women.

Religion was another factor that had statistically significant impact on method preference of married women. The result revealed that followers of other religions were more likely to use long term methods. How ever, this result was inconsistent with study by Iwu et al. (2009). Regarding number of children, it was a significant factor of method preference of modern contraceptive user women. The odds of using long term methods decreases as the number of children increases. This result is similar with Rana (2002), but it was unlike the study by Iwu et al. (2009), which indicated that the odds of long-term method use were slightly higher among women with three children or more than those with two children or less.

Desire for additional children was associated with method preference of modern contraceptive user. This study indicated that, women who had no desire for additional child were less likely to practice long term modern contraception methods. This finding is consistent with studies by Toirov (2004), Douthwaite and Ward (2005), and Schoemake (2005). In addition, women's education level was among the statistically significant predictors of method preference. The result suggested that as the level of education increases the chance of using long term methods decreases. This result is in agreement with studies by Berhanu (1997), Mahmood and Ringheim (1996) and Toirov (2004).

Frequency of watching television program had a statistically significant association with method preference of married women. The study indicated that the odds of using long term methods decreases as the frequency of watching television decreases. The finding is in line with earlier studies by Piotrow et al. (1990) and Barkat et al. (1997). On the other hand, experience on modern contraceptive usage was statistically significant factor on method preference. Women who had no experience about modern contraceptive usage were more likely to use long term methods. This result is similar to studies by Sihvo (1998) and Aziken(2003).

Similarly, availability of service nearby had a significant impact on method preference of modern contraceptive user women. This study found that, those who were not getting the service near by were less likely to use long term methods. This finding is similar to previous studies by Ross (2002),Ozalp (1999) and WHO (1998).

The service provider also had a significant association with method preference of modern contraceptive user women. Women who were serviced by family planning service providers were more likely to practice long term modern contraceptive method. This result is in harmony with studies by Entwisle (1996) and Lhamu (2004).

5 Conclusions and Recommendations

5.1 Conclusions

The main purpose of this study was identifying the determinant factors of modern contraceptive usage and method preference among married women of reproductive ages (15- 49 years old) in Hawassa city. In order to meet the objectives of the study, the Bayesian and classical logistic regression approaches were adopted.

A total of 990 married women of reproductive age were considered in the study, of which about 57.9% were modern contraception methods users. While among 573 modern contraceptive users, 74.3% were long term methods users. Modern contraceptive usage and method preference of married women of reproductive ages were found to be significantly associated with most of the predictor variables included in the study.

The Bayesian logistic regression analysis revealed that women aged between 15 - 24, with number of children 1-2 and 3-4, with primary education level , who were private organization workers, who had no monthly income , who were visited by family planning field workers, who were following radio program almost every day, who had husbands' support , who had experience on modern contraceptive usage and those who were getting information about modern contraceptive methods from media were more likely to practice modern contraceptive methods than their counter parts.

In addition, the classical logistic regression analysis also identified the determinants of modern contraception methods preference (short-term, long-term) among married women of reproductive ages (15- 49 years old).

The study revealed that women in the age group 15- 24, who had one or more children, who had a desire for additional children, who were illiterates, who were watching television programs almost every day, who had no experience on modern contraceptive usage, who were served by family planning service providers and who were getting the service nearby, were more probable to be long term modern contraception methods users.

5.2 Recommendations

To expand utilization and acceptance of a wider range of modern contraception methods among married women of reproductive ages, awareness creation, promotion and other programs on family planning should focus on developing the awareness of older married women of reproductive age.

Promoting all available types of modern contraception methods, including explanations about the benefits of limited family size and spaced child birth through television and radio should be given due emphasis.

Enhancing levels of education, creating employment opportunities for women, and encouraging males to support their wives and participate in family planning are successful means of progressing family planning acceptance and increasing the prevalence of modern contraceptive usage.

Developing the knowledge and communication skill of family planning field workers will be essential to communicate smoothly and discuss important topics with married women in the communities.

Other influential predictors of modern contraceptive usage and method preference were availability of service nearby and service provider. All governmental and non governmental organization engaged in family planning programs have to bring in place different strategies that make the existing family planning services available, affordable and accessible for all women of reproductive age.

5.3 Limitations of the Study

Modern contraception method practice not only concerns married women of reproductive ages. However, in this study married women of reproductive ages and living with their husbands' were considered. Hence, the findings cannot be generalized to the whole women of reproductive ages in Hawassa city.

6. References

Adanu, RMK., Seffah, JD., Hill, AG., Darko, R., Duda, RB. and Anarfi, JK. (2009). ContraceptiveUse by Women in Accra, Ghana: Results from the 2003 Accra Women's Health Survey. *Afr J Reprod Health 2009; 13(1):123-133.*

Agresti, A. (2002). *Categorical Data Analysis.* John Wiley & Sons, Inc.

Ali A. Al-Subaihi (2003***).*** Sample size determination. Influencing factors and calculation strategies for survey research Saudi Med J 2003; Vol. 24 (4): 323-330.

Ali, S., Rozi, S. and Mahmood, MA. (2004). Prevalence and factors associated with practice of modern contraceptive method among currently married women in district Naushahro `Feroze. J Pak Med Ass 54: 461-465.

Amaha, H. and Fikre, E. (2006). Influence of women's autonomy on couple's contraception use in Jimma town. *[Ethiop.J.Health Dev.*,20(3):145-151]

Anderson, D. (2007). Markov Chain Monte Carlo Methods in Bayesian Computation, New York: Springer-Verlag

Apter D., Cacciatore R. (2004). "Adolescent contraception". International Congress Series 1266 81– 89

Barkat, A., Rahman, M. and Bose, ML. (1997). Family Planning choice behavior in urban slums of Bangladesh: An econometric approach. *Asia-Pacific Population Journal 12(1): 17 32.*

Belsley, D. and Kuh, E. (2005). Regression Diagnostics: Identifying Influential Data and Sources of Collinearity, Wiley: New York, NY.

Bhende, A. A., Choe, M. K., (1991). "Determinants of Contraceptive Method Choice in an Industrial City of India". Asia-Pacific Population Journal, Vol. 6, No.3, p. 41-66.

Brooks, S.P., Roberts, G.O. (1998). Convergence Assessment Techniques for Markov Chain Monte Carlo. Statist. Comput. 8, 319–335.

Brooks, S. and Gelman, A. (2005). Alternative Methods for Monitoring Convergence of Markov Chain Monte Carlo Iterative Simulations. Journal of Computational and Graphical Statistics. 7, 434-455.

Casella, G. and George, E. (1992). Explaining the Gibbs Sampler. The American Statistician, 46, 167–174.

Chacko, Elizabeth. (2001). Women's use of contraception in rural India: a village level study._7, 3, (September) 2001,: 197-208.

Cochran, W.G. (1977). Sampling Techniques. 3rd Edition. John Wiley & Sons Inc., New York.

Collet, D. (2003). Modeling Binary Data. 2nd Edition. Chapman and Hall/CRC, London.

Commune, J. (2009). Determinants of Hospital Stay among Malaria Patients at a Tertiary Care Hospital in Goa.

Cook, R. D. (1979). Influential Observations in Linear Regression. Journal of the American Statistical Association, 74(365), 169–174.

Cowles, MK., Carlin, BP. (1996). Markov Chain Monte Carlo Convergence Diagnostics: A Comparative Review. Journal of the American Statistical Association,91,883.

Dang, A. (1995). Differential in contraceptive use and method choice in Vietnam. International Family planning perspectives,21(1):2-5

Douthwaite, Megan and Patrick Ward. (2005). Increasing contraceptive use in rural Pakistan: an evaluation of the Lady Health Worker Programme. *Health Policy and Planning* 20, (2): 117-23.

Entwisle, B., and Rindfuss, R. R. (1996). "Community and Contraceptive Choice in Rural Thailand: A Case Study of Nang Rong". Demography, Vol 33, No.1 1-11.

Ethiopia Demographic and Health Survey (2005). Central Statistical Authority, Addis Ababa, Ethiopia, 2006, 41-91

Farrukh, T. (2004). Effects of contraception knowledge and childbearing motivation on the contraceptive method choice of married women in Tajikistan

Fikree, FF., Khan, A., Kadir, MM., Sajan, F., Rahbar, MH.(2001). What Influences Contraceptive Use among Young Women in Urban Squatter Settlements of Karachi, Pakistan? International Family Planning Perspectives, 27:130-136.

Gage A. J. (1995). “Women’s Socioeconomic Position and Contraceptive Behavior in Togo”. Studies in Family Planning, Vol.26, No.5, 264-277

Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. (2005). Bayesian Data Analysis, Second Edition. London: CRC Press.

Geweke, J. (1992). Evaluating the Accuracy of Sampling-Based Approaches to Calculating Posterior Moments. In Bayesian Statistics 4, J.M, Bernardo, J.O. Berger, A.P. Dawid, and A. Smith. (eds.). Oxford: Clarendon Press.

Govindasamy, P. and Malhotra, A. (1996). Women’s Position and Family Planning in Egypt. *Studies in Family Planning*. 27(6): 328-340.

Gupta, N. (2003). Associations of Mass Media Exposure with Family Planning Attitudes and Practice in Uganda. Studies in Family Planning, 34(1): 19 - 31

Hawassa Town Finance and Economic Development Office, Hawassa Town Socio-Demographic Indicators, Hawassa, Ethiopia. 2006.

Health and Health Related Indicators, Federal Democratic Republic of Ethiopia, Ministry of Health, Addis Ababa, Ethiopia, (2003/4).

Hogan, D.P., Berhanu, B. and Hailermariam, A. (1999). Household Organization, Women’s Autonomy and Contraceptive Behavior in Southern Ethiopia. *Studies in Family Planning* 30(4): 302-314.

Hosmer, D. and Lemeshow, S. (2000). Applied Logistic Regression (2nd Edition). New York: John Wiley and Sons.

Hosmer, D., Cessie, S. and Lemeshow, S. (1997). A Comparison of Goodness-of-fit Tests for The Logistic Regression Model, Department of Biostatistics and Epidemiology, University of Massachusetts, Arnold House.

Irja, N. (2007). Contraceptive use among young women in Namibia: Determinants and policy implication DPhil thesis sociology (Demography)

Islam, M. and Muhmud, M. (1995). Contraception among adolescents in Bangladesh *Asian-pacific population Journal. United Nation : 10 (1) : 21-38.*

Jim, A. (2009).Bayesian Computation with R. second Edition.

Joesoef, M.R, Baughman, A.L and Utomo, B. (1988). Husband's Approval of Contraceptive Use in Metropolitan Indonesia: Program Implications. *Studies in Family Planning.* 19:162-168.

Kabir, M. and Islam, A. (2000). The Impact of Mass Media Family Planning Programmes on Current Use of Contraception in Urban Bangladesh. *Journal of Biosocial Science.* 32:411-419.

Khan, HTA. (1997). A hierarchical model of contraceptive use in urban and rural Bangladesh.Contraception 55: 91-96.

Lasee, A. and Becker, S. (1997). Husband-wife Communication about Family Planning and Contraceptive Use in Kenya. *International Family Planning Perspectives*. 23(1):15-20,33.

Mannan, H. R. (2002). "Factors in contraceptive method choice in Bangladesh: Goals, Competence, Evaluation and Access". Contraception**,** 65, 357–364.

McCullagh, P. and Nelder, J. A. (2001). Generalized Linear Models. 3rd Edition. Chapman and Hall, New York, USA.

Menard, S. (2008). Applied Logistic Regression Analysis, 3rd Edition. Thousand Oaks, CA: Sage Publications.

Merkle, E., Sheu, C. and Trisha, G. (2005). Simulation-Based Bayesian Inference Using WinBUGS.

Metropolis, N. and Ulam, S. (2001). Markov Chain Monte Carlo Concepts Related to Sampling Algorithms. Markov Chain Monte Carlo in Practice: Journal of the American Statistical Association, 44.

Mostafa, K. (2009). Contraceptive use and method use in urban slum of Bangladesh.

Muhwava, W. (2003). "Patterns of Contraceptive Use at the Edge of Fertility Transition in Zimbabwe". African Population Studies, Vol. 18, No. 1, 19-33

National Statistics (2006). Omnibus Survey Report No. 30 *Contraception and Sexual Health 2005/06.* London: National Statistics.

Orji.E, O. and Onwudiegwu,U. (2002). Prevalence and determinants of contraceptive practice in defined Nigerian population. Journal, of obstetrics and gynecology. 22, 5,540-543

Oyedokun, A.O (2007). Determinants of contraceptive usage. Lesson from women in Osun state, Nigeria Journal of humanities & social science. Volume 1.Issue 2.

Ozalp, S. and Yalcin, O. (1999). "Factors affecting the contraceptive choice in a developing country". *International Journal of Gynecology & Obstetrics,* 65, 53 57

Population Reference Bureau (2002). World population Data sheet. Washington, DC, USA

Prop, J.G. and Wilson, D.B. (2005). Exact Sampling with Coupled Marcov Chains and Applications to Statistical Mechanics. Random Structures and Algorithms.

Rana, S.B. (2002). Factors influencing contraceptive Method Choice in Nepal. Thesis submitted to IPSR, Mahidol University, Thailand.

Ria, R., Iwu, U. and Peter, M. (2009). Contraceptive Use Pattern among Married Women in Indonesia. Paper presented at the International Conference on Family Planning: Research and Best Practices, November 15-18, 2009, Kampala, Uganda.

Ritter, C. and Tanner, M.A. (1992). "Facilitating the Gibbs Sampler: The Gibbs Stopper and the Griddy Gibbs sampler." *Journal of the American Statistical Association*, 87, 861-868.

Ross, J. (2002). "Contraceptive Method Choice in Developing Countries". International Family Planning Perspectives**,** Volume 28, Number 1, 32-40

Samson Gebremedhin and Mulugeta Betre (2009). Level and Differentials of Fertility in Hawassa Town, Southern Ethiopia; Original research article. African journal of reproductive health Vol 13 No 1

Schoemaker, J. (2005). Contraceptive use among the poor in Indonesia. *International Family Planning Perspectives* 31 (3): 106-14.

Shah, N.M., Shah, M.A. and Radovanovic, Z. (1998). Patterns of Desired Fertility and Contraceptive Use in Kuwait. *International Family Planning Perspective* 24(3):133-138.

Shiparo, D. and Tambashe, B.O.(1998) The Impact of Women's Employment and Education on Contraceptive Use and Abortion in Kinshasa, Zaire. *Studies in Family Planning*. 25(2): 96-110.

Shrestha, D. (2000). Determinants of Current Contraceptive Use among Nepalese Women: An Analysis of NFH Survey 1991. *Nepal Population and Development Journal.* Ministry of Population and Environment, Nepal.

Singh, S. (2010).The estimated incidence of induced abortion in Ethiopia,2008, International Perspectives on Sexual and Reproductive Health, 36(1):16–25.

Siugo-Abanihe, U.C.(1994). Reproductive Motivation and Family Size Preferences among Nigerian Men. *Studies in Family Planning*. 25(3): 149-161.

Uyger, D. and Eskaya, S. (2001). Contraceptive use and method choice in Turkey. International journal of Gynecology and Obstetrics. 75(1): 87 – 98

Walsh (2004).Markov chain Monte Carlo and Gibbs sampling lecture note for EEB 581,version 26 April 2004

World Health Organization. (1998). World Health Day1998: Improve access to Maternal Health services. World Population Data Sheet (2003), Population Reference Bureau.

7 Appendices

Appendix A: Tables

Table A1: Categorical Variables Coding

Categorical Variables Coding						
Explanatory Variables	Categories	Frequency	Parameter coding			
			1	2	3	4
Occupation	house wife	333	1.000	.000	.000	.000
	government employee	59	.000	1.000	.000	.000
	day laborer	19	.000	0.000	1.000	.000
	Owen business	124	.000	0.000	.000	1.000
	private organization	38	.000	0.000	.000	.000
Monthly income	none	295	1.000	0.000	.000	.000
	100-400	76	.000	1.000	.000	.000
	400-700	90	.000	0.000	1.000	.000
	700-1000	82	.000	0.000	.000	1.000
	>= 1000	30	.000	0.000	.000	.000
Husband's Occupation	none	13	1.000	0.000	.000	.000
	government employee	214	.000	1.000	.000	.000
	day laborer	80	.000	0.000	1.000	.000
	owen business	167	.000	0.000	.000	1.000
	private organization	99	.000	0.000	.000	.000
Service provider	hospital	14	1.000	0.000	.000	
	health center	306	.000	1.000	.000	
	clinic	40	.000	.000	1.000	
	family planning service provider	213	.000	.000	.000	
Religion of the respondent	coptic	297	1.000	.000	.000	
	muslim	37	.000	1.000	.000	
	protestant	220	.000	.000	1.000	
	Other	19	.000	.000	.000	
Number of children	No child	44	1.000	.000	.000	
	1 - 2 children	350	.000	1.000	.000	
	3 - 4 children	147	.000	.000	1.000	
	>= 5 children	32	.000	.000	.000	

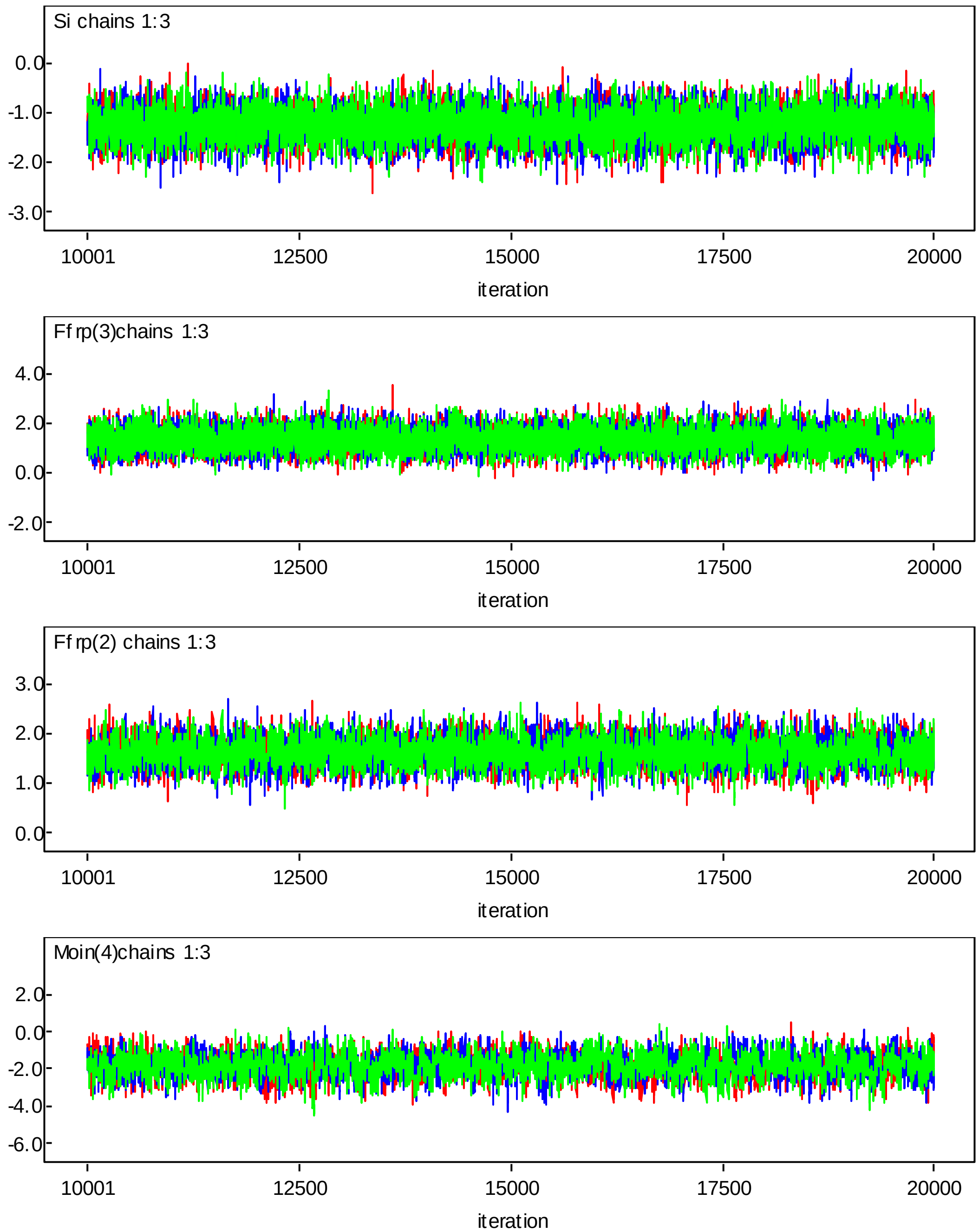
Education level	Illiterate	56	1.000	.000	.000	
	Primary	250	.000	1.000	.000	
	Secondary	188	.000	.000	1.000	
	college/university diploma or higher	79	.000	.000	.000	
Husband's education level	Illiterate	12	1.000	.000	.000	
	Primary	153	.000	1.000	.000	
	Secondary	189	.000	.000	1.000	
	college/university diploma or higher	219	.000	.000	.000	
Husband's monthly income	100-400	75	1.000	.000	.000	
	400-700	113	.000	1.000	.000	
	700-1000	139	.000	.000	1.000	
	>=1000	246	.000	.000	.000	
Frequency of following radio program	almost every day	167	1.000	.000	.000	
	Occasionally	288	.000	1.000	.000	
	at least once a week	54	.000	.000	1.000	
	Not at all	64	.000	.000	.000	
Frequency of watching television	almost every day	280	1.000	.000	.000	
	Occasionally	206	.000	1.000	.000	
	at least once a week	22	.000	.000	1.000	
	Not at all	65	.000	.000	.000	
Source of information	Media	211	1.000	.000	.000	
	Health center	234	.000	1.000	.000	
	Friends	55	.000	.000	1.000	
	family planning field workers	73	.000	.000	.000	
Age of the respondent	15-24	223	1.000	.000		
	25 – 34	297	.000	1.000		
	35 – 44	53	.000	.000		
Availability of service in near place	Yes	424	1.000			
	No	149	.000			
Husband's encouragement	Yes	516	1.000			
	No	57	.000			
Desire for more child	Yes	371	1.000			
	No	202	.000			
Family planning field workers visit	Yes	354	1.000			
	No	219	.000			
Number of known method types	1-3	240	1.000			
	>=4	333	.000			
Experience on modern Contraceptive Use	Yes	512	1.000			
	No	61	.000			

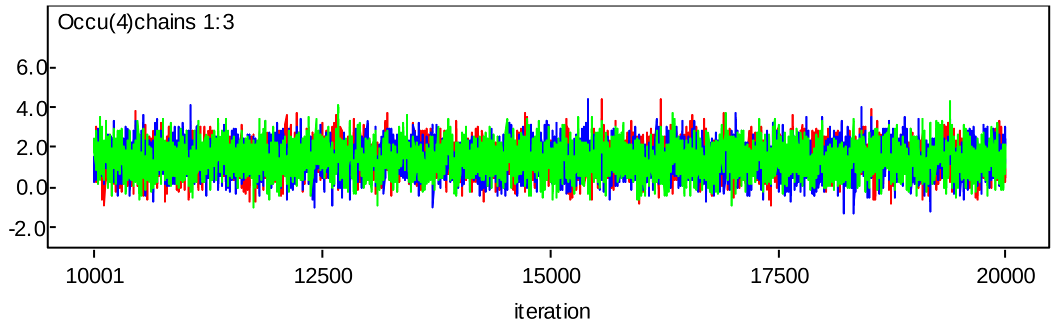
Table A2: Results of Diagnostic Tests for Influential Values

Tests for influential cases	N	Minimum	Maximum
Analog of Cook's influence statistics	573	0.00000	0.80727
DFBETA for constant	573	-0.38271	0.32818
DFBETA for age(1)	573	-0.10172	0.1479
DFBETA for age(2)	573	-0.10948	0.1502
DFBETA for religion(1)	573	-0.18795	0.24451
DFBETA for religion(2)	573	-0.16609	0.21607
DFBETA for religion(3)	573	-0.17705	0.23034
DFBETA for numchildn(1)	573	-0.34593	0.16411
DFBETA for numchildn(2)	573	-0.03292	0.01313
DFBETA for numchildn(3)	573	-0.03524	0.04977
DFBETA for desmochid(1)	573	-0.07807	0.00811
DFBETA for edulevel(1)	573	-0.14942	0.29259
DFBETA for edulevel(2)	573	-0.00123	0.24793
DFBETA for edulevel(3)	573	-0.05458	0.20181
DFBETA for freqwatchtv(1)	573	-0.10371	0.20603
DFBETA for freqwatchtv(2)	573	-0.09663	0.21727
DFBETA for freqwatchtv(3)	573	-0.06021	0.2931
DFBETA for exmoconuse(1)	573	-0.15255	0.11206
DFBETA for avaisernea(1)	573	-0.06775	0.14665
DFBETA for servipro(1)	573	-0.433376	0.32217
DFBETA for servipro(2)	573	-0.01602	0.00058
DFBETA for servipro(3)	573	-0.03493	0.00244

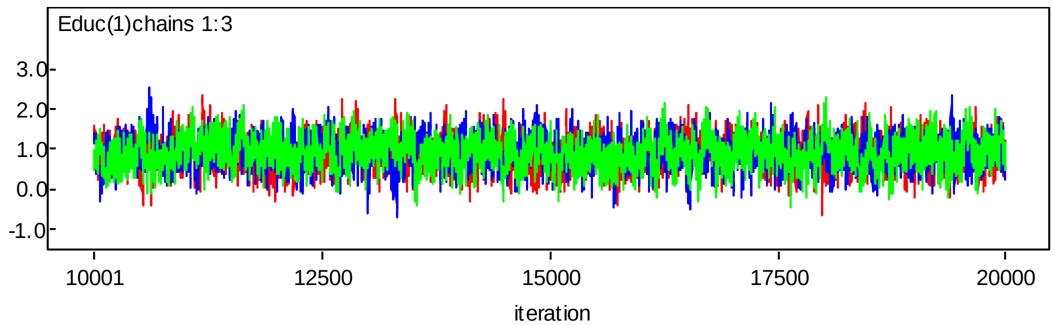
Appendix B: Figures

Figure B1: Time Series Plots of the Simulations of Posterior Distribution of the Model Parameters.

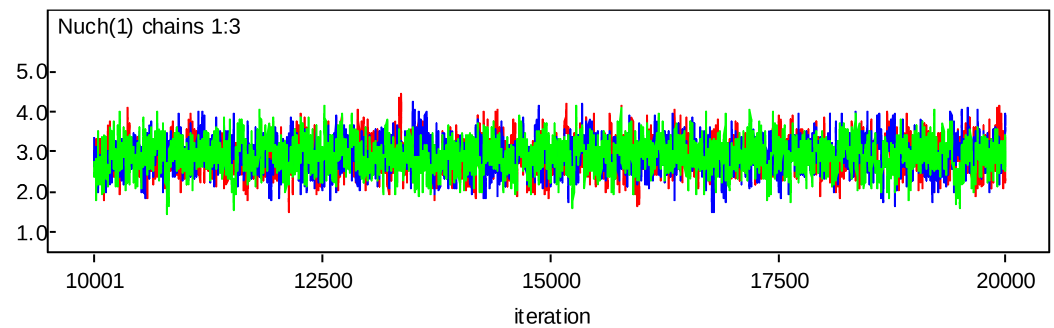




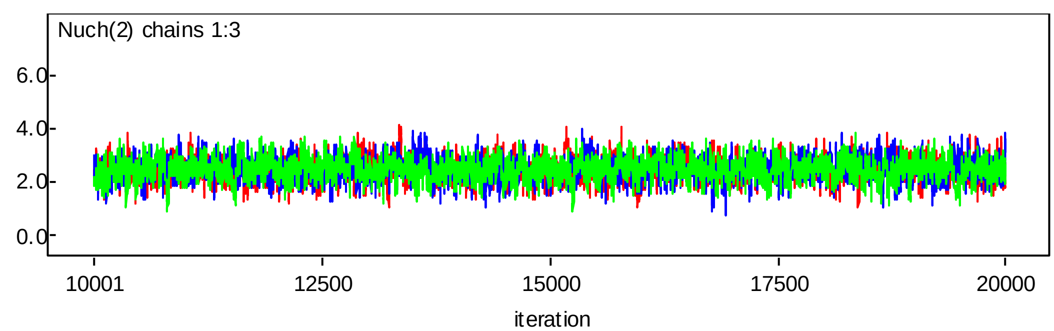
Occu(4)chains 1:3
6.0
4.0
2.0
0.0
-2.0
10001
12500
15000
17500
20000
iteration



Educ(1)chains 1:3
3.0
2.0
1.0
0.0
-1.0
10001
12500
15000
17500
20000
iteration



Nuch(1) chains 1:3
5.0
4.0
3.0
2.0
1.0
10001
12500
15000
17500
20000
iteration



Nuch(2) chains 1:3
6.0
4.0
2.0
0.0
10001
12500
15000
17500
20000
iteration

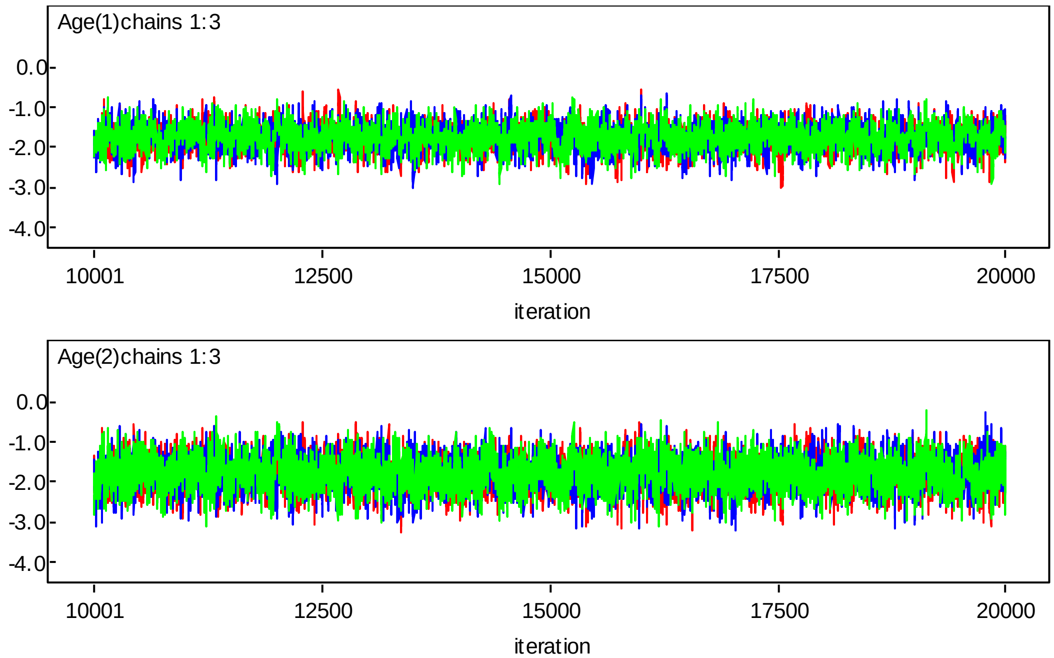
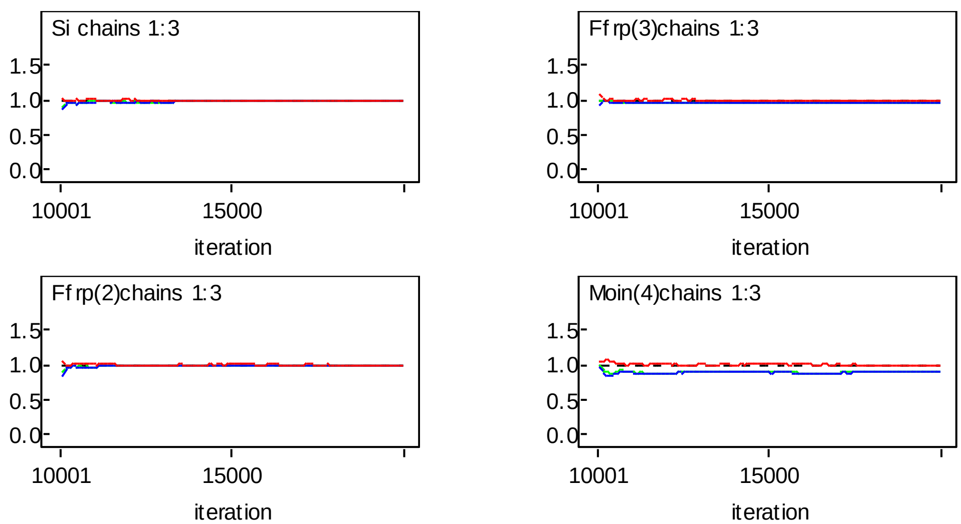


Figure B2: Gelman-Rubin Statistic Plots for the Simulations of Posterior Distribution of the Model Parameters.



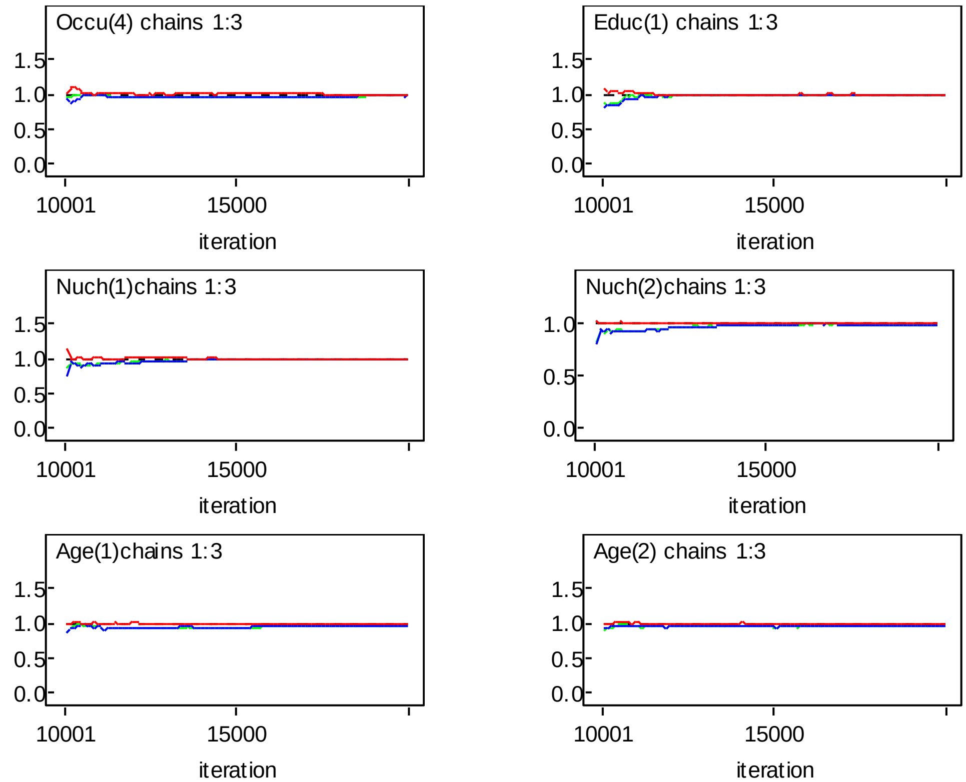
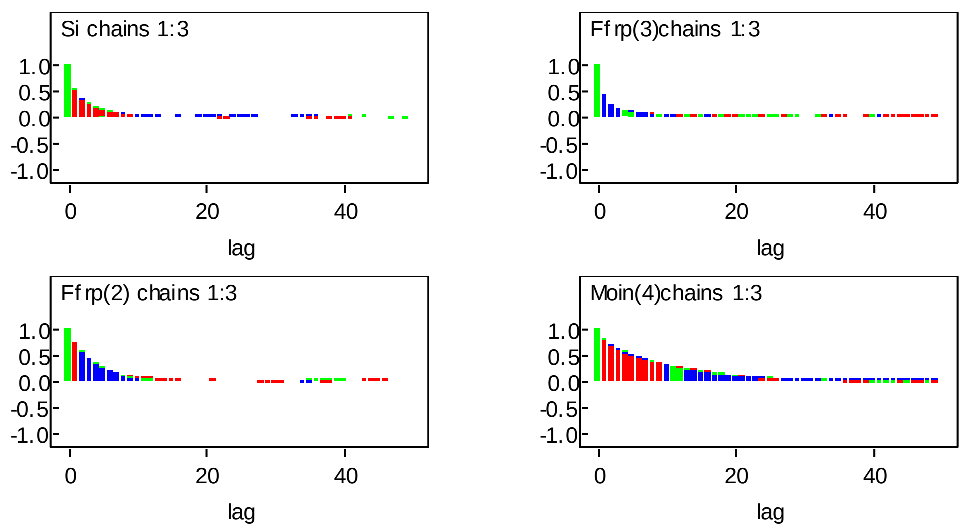


Figure B3: Autocorrelation Plots of the Simulations of Posterior Distribution of the Model Parameters.



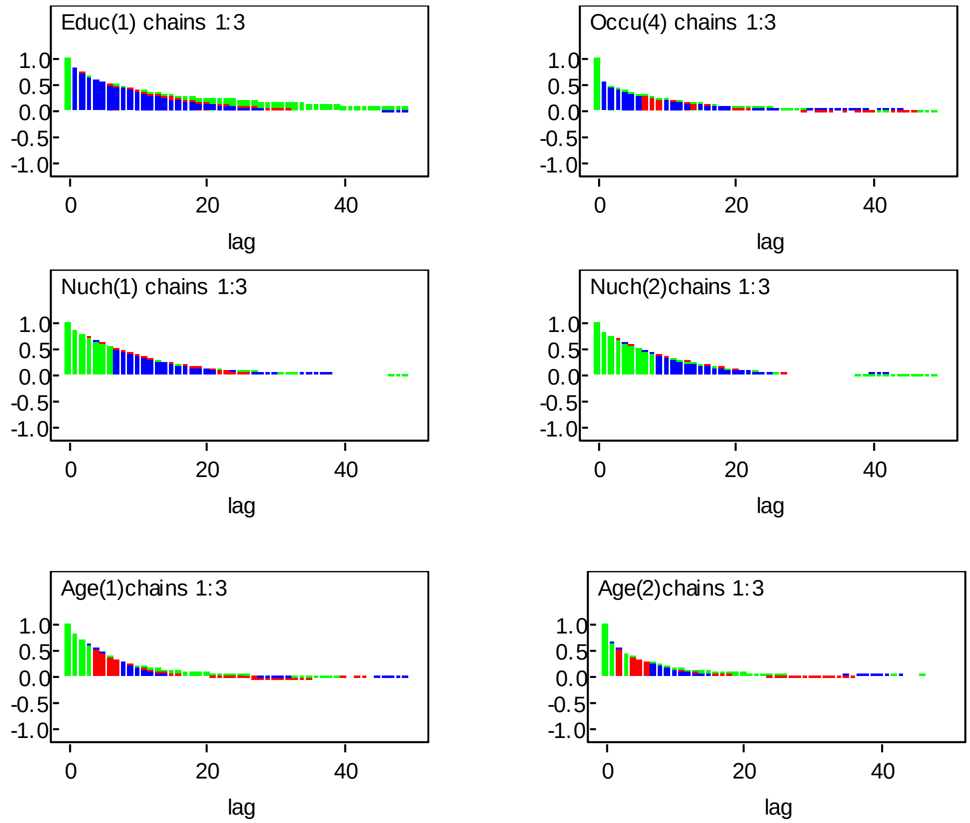
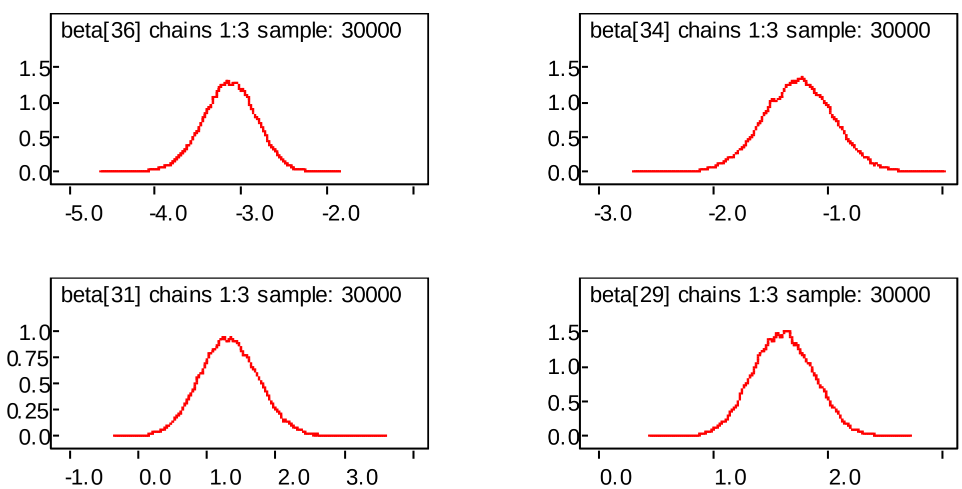
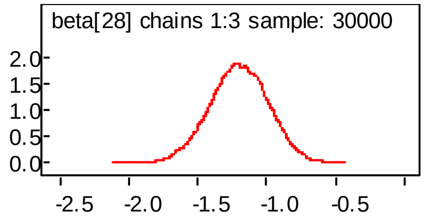
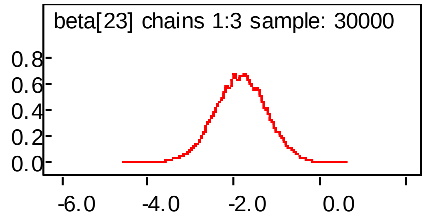
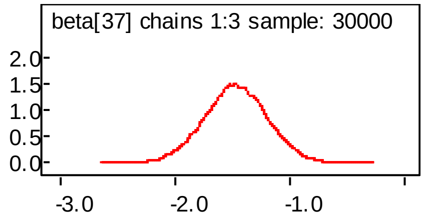


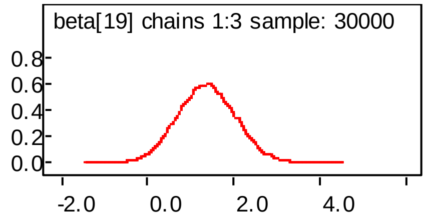
Figure B4: Density Plots for the Simulations of Posterior Distribution of the Model Parameters.

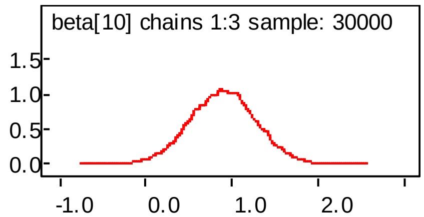


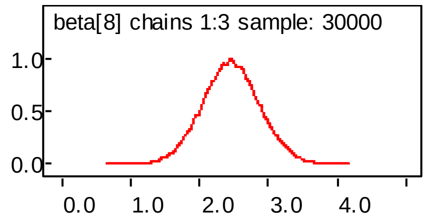

beta[28] chains 1:3 sample: 30000
2.0
1.5
1.0
0.5
0.0
-2.5
-2.0
-1.5
-1.0
-0.5

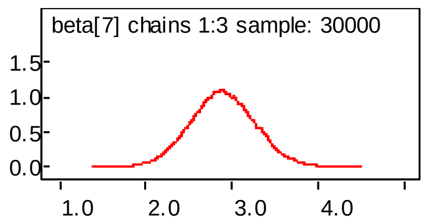

beta[23] chains 1:3 sample: 30000
0.8
0.6
0.4
0.2
0.0
-6.0
-4.0
-2.0
0.0

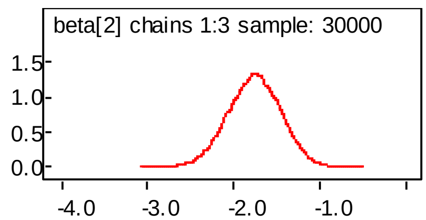

beta[37] chains 1:3 sample: 30000
2.0
1.5
1.0
0.5
0.0
-3.0
-2.0
-1.0

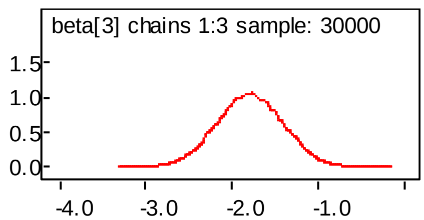

beta[19] chains 1:3 sample: 30000
0.8
0.6
0.4
0.2
0.0
-2.0
0.0
2.0
4.0


beta[10] chains 1:3 sample: 30000
1.5
1.0
0.5
0.0
-1.0
0.0
1.0
2.0


beta[8] chains 1:3 sample: 30000
1.0
0.5
0.0
0.0
1.0
2.0
3.0
4.0


beta[7] chains 1:3 sample: 30000
1.5
1.0
0.5
0.0
1.0
2.0
3.0
4.0


beta[2] chains 1:3 sample: 30000
1.5
1.0
0.5
0.0
-4.0
-3.0
-2.0
-1.0


beta[3] chains 1:3 sample: 30000
1.5
1.0
0.5
0.0
-4.0
-3.0
-2.0
-1.0

Appendix C: Questionnaire

Questionnaire

A. Demographic Information

1. Age 15 – 24 ☐ 25 – 34 ☐ 35 – 44 ☐ 45 – 49 ☐

2. What is your religion? Muslim ☐ Orthodox ☐ Protestant ☐ Other ☐

3. How many sons and daughters do you have?

Sons ____ Daughters______

4. Do you have a desire to have any more child? Yes ☐ No ☐

B. Socio-Economic Information

1. What is the highest education level that you attended?

None ☐ Primary school ☐ Secondary school ☐

College/ University Diploma or Higher ☐

2. What is the highest education level that your husband attended?

None ☐ Primary school ☐ Secondary school ☐

College/ University Diploma or Higher ☐

3. What is your occupation?

Housewife ☐ Government employee ☐ Day laborer ☐

Own business ☐ Private Organization worker ☐ Other ☐

4. How much is your monthly income in Birr?

None ☐ 100 – 400 ☐ 400 – 700 ☐ 700 - 1000 ☐

1000 ≥ ☐

5. What is your husband's occupation?

None ☐ Government employee ☐ Day laborer ☐ Own business ☐
Private Organization worker ☐ Other ☐

6. How much is your husband's monthly income in Birr?

None ☐ 100 – 400 ☐ 400 – 700 ☐ 700 – 1000 ☐

1000 ≥ ☐

7. Have you ever been visited by family planning field workers at home in past 12 months? Yes ☐ No ☐

8. How often do you listen to the radio? Almost every day ☐ Occasionally ☐

At least once a week ☐ Not at all ☐

9. How often do you watch television? Almost every day ☐ Occasionally ☐

At least once a week ☐ Not at all ☐

10. Have you ever heard about any modern contraceptive method?

Yes ☐ No ☐

If your response is yes, from where did you hear?

Media ☐ Health institutions ☐ Friends ☐

Family planning field workers ☐ Other ☐

11. Which of the following modern contraceptive methods do you know?

Pill ☐
Injectables ☐
Implants ☐
Condom ☐
Intrauterine Devices ☐
Diaphragm /foam/jelly ☐

Lactational Amenorrhea ☐

Female sterilization ☐

12. Have you ever used or tried any modern method to delay or avoid getting pregnant?

Yes ☐ No ☐

If your response is yes, which method you were using?

Pill ☐ Injectables ☐ Implants ☐ Lactational Amenorrhea ☐

Intrauterine Devices ☐ Diaphragm /foam/jelly ☐ Condom ☐

Female sterilization ☐

13. Are you currently using any modern method to delay or avoid getting pregnant?

Yes ☐ No ☐

Which method you are using?

Pill ☐ Injectables ☐ Implants ☐ Female sterilization ☐

Condom ☐ Intrauterine Devices ☐ Diaphragm /foam/jelly ☐

Lactational Amenorrhea ☐

14. Do you always get the method you want?

Yes ☐ No ☐

If No, specify the reason ______________________________

15. Does your husband encourage you to use any modern contraceptive methods?

Yes ☐ No ☐

16. Is there family planning service providing center near by your home?

Yes ☐ No ☐

17. From where did you obtain this method?

Family planning service provider ☐ Hospital ☐ Health center ☐

Clinic ☐

Thank you for your participation