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Factors Influencing Women's Intention to Limit Child-bearing in Rural Ethiopia

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This is to certify that the thesis prepared by Reta Lemessa, entitled: *Factors Influencing Women's Intention to Limit Child-bearing in rural Ethiopia* and submitted in partial fulfillment of the requirements for the degree of Master of Science in Statistics complies with the regulations of the University and meets the accepted standards with respect to originally and quality.

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LIST OF ABBREVIATIONS

AGQ	Adaptive Gaussian Quadrature
AIC/BIC	Akaike/Bayesian Information Criterion
ASFR	Age-Specific Fertility Rate
CSA	Central Statistical Agency
EDHS	Ethiopian Demographic and Health Survey
FP	Family Planning
GFR	General Fertility Rate
HIV/ AIDS	Human Immune Deficiency Virus Acquired Immune Deficiency Syndrome
ICC	Intra class Correlation Coefficient
RIGLS	Reweighted Iterative Generalized Least squares
LR	Likelihood Ratio
MCMC	Markov Chain Monte Carlo
MLE	Maximum Likelihood Estimation
MQL	Marginal Quasi Likelihood
OR	Odds-Ratio
PQL	Penalized Quasi Likelihood
SNNP	Southern Nations Nationalities and People
TFR	Total Fertility Rate
WHO	World Health Organization
UN	United Nations

Abstract

The fertility level of Ethiopia, especially in the rural areas, is unacceptably high. This is leading to negative influence on economic and social development. Thus, understanding those factors that influence the fertility intention of women is important for family planning program purposes and population policy. The main objective of this study is to identify factors which influence women's intentions to limit child-bearing in rural Ethiopia. The source of the data was the 2011 Ethiopian Demographic and Health Survey. A weighted sub-sample of 10,864 women was drawn from the DHS women's dataset. The ordinary logistic regression analysis and multilevel logistic regression were applied to examine the association between intention to limit child-bearing and demographic, socio-economic, and cultural characteristics. The ordinary logistic regression analysis revealed that the age of a woman, region of residence, religion, woman's education, knowledge about family planning (FP), current use of any family planning method, marital status of women, visited by FP workers, wealth index, media exposure, number of living children and occupation of women were the most important variables that explained the variability in desire to limit child-bearing. The multilevel logistic regression analysis showed that there were substantial variations in desire to limit child-bearing among eight regions in rural Ethiopia. Accordingly, the random intercept model revealed that there was a significance variation in intention to limit child-bearing across the considered regions. Results of random coefficient for the selected few predictor variables, number of living children was found to be significant in explaining variations in intention to limit child-bearing across the regions. Thus, improving access to family planning services to women who have achieved their fertility goals would be important.

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CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The world population was about 6.8 billion in 2009 and 7 billion in 2012 with 5.6 billion (80 percent) of the world total living in the less developed regions (UN, 2012). The population of the more developed regions remained largely unchanged at 1.2 billion inhabitants. The three least developed countries including Bangladesh, Ethiopia, and the Democratic Republic of the Congo were among the ten most populous countries in the world. Thus, whereas the population of more developed regions was rising at an annual rate of 0.34 percent, that of the developing regions was increasing four times as fast, i.e. 1.37 percent annually, and the least developed countries as a group were experiencing even more rapid population growth, at 2.3 percent per year (UN, 2012).

Ethiopia is the second most populous country in Africa next to Nigeria, with a population size estimated 81 million and a growth rate of 2.6 percent per year (Aynalem Adugna, 2010). Of the total population, more than 84 percent live in rural areas. Uncontrolled fertility has adversely influenced the socio-economic, demographic and environmental development of the country. Poverty, war and famine, associated with low levels of education and health, a weak infrastructure, and low agricultural and industrial production have exacerbated the problem of overpopulation (Ezra, 2001). Like many other African countries, Ethiopia has so far shown little change in fertility. The desire for large family size is one of the factors influencing fertility in Ethiopia. Thus, understanding factors that influence the fertility intentions of women is important for family planning program purposes and population policy.

The desire to limit child-bearing is expected to be a natural progression in the reproductive life course. The proportion of women who intend to limit child-bearing is one of the most important conditions because it bears directly on population growth and designates a segment of the population that may be at risk of having an unwanted birth. Thus the proportion of women of child-bearing age who want no more children is also an important predictor of fertility levels and trends. In the past few years, the proportion of women who desire to limit child-bearing has been rising in Sub-Saharan Africa. Analysis of DHS data from sub-Saharan Africa, between 1990 and

2001 has shown that the proportion of women with the intention to limit child-bearing ranged from a low of less than 10 percent in Niger and Chad to a high of 53 percent in Kenya in sub Saharan Africa (Westoff and Bankole, 2002).

Some women tend to say that they want more children when they have had an unplanned birth or when they think it is the socially desirable answer given their reproductive circumstances. It is also possible that women who want children at high parities genuinely desire larger families. In traditional societies, especially where polygamy is practiced, having many children may be a means to secure one's marriage, or to gain social status or access to family resources (DeRose et al, 2002).

Fertility desires and intentions are central in theoretical and empirical approaches to studying child-bearing behavior. Coale's (1973) seminal formulation of demographic transition theory argues that fertility will decline when child-bearing enters the "calculus of conscious choice" – that is, when having children becomes a subject about which it is possible to have preferences. A common notion in demography is that people decide the number of children they want over their reproductive lives and stop child-bearing whenever that number is achieved (Easterlin and Crimmins, 1985).

Measuring fertility intentions, and determining the extent to which they predict fertility behavior, is also important for population policy and the implementation of family planning programs. Substantial evidence from more developed countries and growing evidence from less developed countries shows that preferences are associated with child-bearing behavior, even after accounting for other socio demographic characteristics. However, there is little evidence on how fertility desires predict fertility in sub-Saharan African settings, where rapid and radical socioeconomic changes coupled with a massive HIV/AIDS epidemic have placed immense strains on traditional marital and reproductive systems. In addition, the conditions under which preferences are more strongly or weakly associated with behavior are not well understood (Hayford and Agadjanian, 2011).

Differentials in fertility behavior and fertility levels in different areas and among population strata or characteristics have been among the most pervasive findings in demography (Cochrane, 1979). It is essential to identify risk factors associated with high fertility and to provide services to address those who are at risk. To develop effective strategies for fertility control, it is necessary to understand the factors affecting fertility. It is hypothesized that women in vulnerable groups, such as those who got married at an early age, are illiterate, are living in rural areas, are poorest, and have little knowledge of family planning, have high fertility(Beekle and Cabe, 2006).

An estimated 222 million women in developing countries would like to delay or stop child-bearing but are not using any method of contraception. Reasons for this include (WHO, 2012):

- limited choice of methods;
- limited access to contraception, particularly among young people, poorer segments of populations, or unmarried people;
- fear or experience of side-effects;
- cultural or religious opposition;
- poor quality of available services;
- gender-based barriers.

As the desire for more children is an indicator of large family, the intention to limit births is often considered as a precondition for fertility decline (Bongaarts, 1997). The extent to which a given society desires to limit fertility has significant implications for family planning programs. It is often taken as an indicator of the demand for family planning services.

1.2 Current fertility in Ethiopia

The fertility level of Ethiopia especially in the rural areas is unacceptably high. The higher fertility of women, the more the risk associated with each birth. The reproductive role on top of the productive role of women puts them in a poor social and economic status. In developing countries like Ethiopia, pregnancy and child birth is 18 times more likely to end in the woman's death than in developed countries (John Hopkins University, 1999).Apart from the high fertility, there exist large variations in fertility between rural and urban areas, regions and various ethnic and religious groups in Ethiopia. These differentials call for urgent attention among both researchers and policy and decision makers.

Childlessness whether biological or by choice is very low in Ethiopia; less than 2 percent of Ethiopian women who have completed or were close to completing their reproduction period at the time of the survey, reported themselves as childless (Aynalem Adugna, 2010).

The Total Fertility Rate (TFR) for Ethiopia in rural areas exceeds the TFR in urban areas by almost three children per woman (5.5 and 2.6 children per woman, respectively).Also the General Fertility Rate (GFR) shows great difference between urban and rural Ethiopia (in rural areas 184 and in urban areas 89). There are substantial differentials in the TFR among the regions, ranging from 1.5 children per woman in Addis Ababa (below the replacement level of fertility) to 7.1 children per woman in Somali regional state. Fertility levels are higher than the national average in Somali, Oromiya, Benishangul-Gumuz, Affar, and SNNP and lower than the national average in the other six regions. The level of fertility is inversely related to women's educational attainment, decreasing sharply from 5.8 children among women with no education to 1.3 children among women who have more than secondary education. Fertility is also strongly associated with wealth quintiles. Women in the lowest wealth quintile have a TFR of 6.0, more than twice as high as women in the highest wealth quintile, at 2.8 (EDHS, 2011).

Another way to examine fertility trends is to compare current estimates with estimates from earlier surveys. Estimates of the TFR and Age-Specific Fertility Rate (ASFR) are available from the two previous EDHS surveys (2000 and 2005). These estimates offer an opportunity to assess fertility trends over the last decade. These data show that the TFR decreased only slightly from 5.5 children in 2000 to 5.4 children in 2005, and then decreased further to 4.8 children in 2011. Although the level of fertility decreased over time, the age pattern of fertility was similar in all three surveys, with fertility increasing from age 15-19 to age 25-29 and decreasing thereafter (EDHS, 2011).

When we compare the 2000and 2005 EDHS surveys, we observe that the proportion of married women who desire to limit child-bearing had increased for five years for all categories of living children, with an overall increase from 32 percent in 2000 to 42 percent in 2005. Conversely, it was observed that the proportion of currently married women who desire to limit child-bearing has decreased in the past five years for all categories of living children, with an overall decrease from 42 percent in 2005 to 37 percent in 2011.

The overall proportion of currently married women who desire to limit child-bearing is almost the same in urban areas as in rural areas (37.1 and 36.9 percent, respectively). However, when the number of children is held constant, urban women are more likely than rural women to want to limit child-bearing, with the largest difference among women with two living children (41 percent among urban women and 15 percent among rural women).Also, there is a significant regional variation in the desire to limit child-bearing, ranging from 11 percent in the Somali region to 41 percent in the SNNP region. As women's education increases, their reported desire to have no more children decreases. For example, 41 percent of women with no education desire to limit child-bearing compared with 32 percent of women with primary education. Currently married women in the middle wealth quintile are most likely to want to limit child-bearing (40 percent).

1.3 Statement of the Problem

Changes in the demand for children and greater accessibility to contraception are important conditions for fertility transition. The proportion of women who intend to limit child-bearing is one of the most important conditions because it bears directly on population growth and designates a segment of the population that may be at risk of having an unwanted birth. This proportion of women of child-bearing age who want no more children is also an important predictor of fertility levels and trends. In the past few years, the proportion of women who desire to limit child-bearing has been rising in sub-Saharan Africa. According to Bongaart (1997) the desired family size was more than four children in sub-Saharan African countries, where child mortality is high and poverty is rampant. This trend also, appears to continue in the future.

Fertility is one of the elements in population dynamics that has significant contribution towards changing population size and structure over time. In some of the least developed countries, high fertility rates hamper development and perpetuate poverty, while in some of the richest countries, low fertility rates and too few people entering the job market are raising concerns about prospects for sustained economic growth and the viability of social security systems (UN, 2012).

Rapid population growth is leading to fresh-water shortages and ground-water depletion, particularly in densely populated countries in the developing world. Steadily increasing population also contributes to pollution of both local and global environments. The poorest regions of the world are set to be worst hit. Countries with limited natural resources and extremely rapid population growth, most of them in sub-Saharan Africa, fare the worst (UN, 2012).

Differences in mortality and morbidity that relate to socioeconomic class constitute an inequity. The poor do not have the same access to life-saving and health-maintaining interventions as the rich, yet they aspire to the same healthy lives as those who are economically better off. However, a difference in fertility between the rich and poor is not an inequity provided the poor have higher fertility because they want to have more children. As high fertility is associated with increased obstetric and medical risks of mothers, in order to reduce fertility and control population growth of the country, the factors that influence fertility should be clearly identified (Zhang, 2007). Fertility affects the well-being of mothers and their children. If proper care and action are not taken, a high fertility rate could disturb the socio-economic development of a nation. In the immediate future, there will be a high pressure on child health and educational provisions. This will lead to overcrowding in these services and consequently less than satisfactory service provision. Children will be in large classes with limited resources hence underachieving. There will be long waiting lists for health services which will result in health problems. Spacing and limiting the number of children improves maternal and child health empowers women and enhances economic development (Samuel Yohannes et al, 2011).

In countries around the world, women who are determined to limit their family size and time their child-bearing will use all available means to do so; if contraception is not a viable option, women will turn to abortion even if it is illegal. Extensive evidence demonstrates, however, that when modern contraceptives are made available to women, their increased use over time replaces previous reliance on abortion and becomes the major factor associated with reduced abortion rates. Policy makers seeking to reduce the incidence of abortion would do well to address its root cause unintended pregnancy by facilitating widespread access to modern contraceptives and by promoting their effective use (Smith, 1993).

The situation in Ethiopia indicates that demographic and developmental factors reinforce each other so that high fertility and rapid population growth exert a negative influence on economic and social development. Low levels of economic and social development provide conditions that favor a high fertility rate and rapid population growth. The rapid population growth does not match with available resource in Ethiopia where the economy has been agrarian based on household subsistence farming (Wubegzier Mekonnen and Alemayehu Worku, 2011).

Generally, high fertility and rapid population growth have an impact on the overall socio economic development of a country and maternal and child health in particular. Maternal and child mortality are two of the major health problems challenging healthcare organizations, especially in developing countries.

Hence this study attempts to identify major socio-economic, demographic, cultural and environmental factors that influence women's intentions to limit child-bearing in rural Ethiopia.

1.4 Objectives of the study

The main objective of this study is to identify factors which influence women's intentions to limit child-bearing in rural Ethiopia.

The specific objectives of the study are:

- To describe the level of women's intentions to limit child-bearing regionally.
- To examine the relationship between selected demographic and socioeconomic variables and limiting child-bearing.
- To investigate the existence of regional differentials in intention to limit child-bearing in rural areas of Ethiopia.
- To suggest measures to address the issue of limiting child-bearing in rural Ethiopia.

1.5 Significance of the study

Ethiopia is one of the developing countries with high growth rate of population, high level of maternal and child mortality. Particularly, in rural areas there are many factors that lead to high risk of fertility.

Hence, the outcome of this study would provide information about factors that influence intentions of women to limit children for governmental and non-governmental organizations and individuals (women and men).

CHAPTER TWO

2. REVIEW OFTHE LITERATURE

The analysis of fertility intentions is of fundamental importance for family planning program purposes and for population policy because it determines the demand for contraception and the potential impact on the rate of reproduction (Bongarts and Potter, 1983). Thus, understanding the factors which influence women's fertility intention is critical for countries like Ethiopia that have to reduce fertility using a sound population policy. The following sections bring to light socio economic and demographic factors that impact child-bearing.

2.1 Determinants of Limiting Child-bearing

The population of the world increases every year because the global birth rate exceeds the death rate. For example, in the early 1990s population size increased at an annual rate of 1.5 percent. Thus, the difference between a birth rate of 2.4 percent and a death rate was 0.9 percent (Bongaarts, 1997). At country level, population growth is also affected by migration, but for the regional aggregates of population used in this study, migration is usually a minor factor, and it will therefore not be discussed in detail.

Previous researches have shown that the fertility intentions of women are influenced by various demographic, socioeconomic and program factors. Using DHS data in Africa, Westoff and Bankole (1995) demonstrated that fertility intentions of women vary with the age of women, number of living children, place of residence, education and exposure to media. Fertility intentions are also shaped by couples' experiences with child mortality and their expectation about child survival conditions as well as their preferences for a single sex, usually a son. Other studies have identified knowledge, approval and use of family planning as important factors influencing fertility intentions (Pullum, 1983; Short and Kiros, 2002). In relation to knowledge and approval of family planning, many have posited that exposure to mass media, particularly those promoting family planning, is important in influencing fertility related behaviors of women (Gupta et al, 2003). Apart from the high fertility, there exist large variations in fertility between rural and urban areas, regions and various ethnic and religious groups in Ethiopia. These differentials call for urgent attention among both researchers and policy and decision makers.

Ample research shows that fertility intentions predict behavior. Women who report wanting to stop or postpone child-bearing are more likely to use contraception (and less likely to have a child) than women who want a child. Improving measures of fertility motivations would also likely improve understanding of contraceptive and fertility behavior (Hayford and Agadjanian, 2011).

Better prospects of the household economic situation, personal health, etc. would lead to reluctance to stop child-bearing, all else equal, because as the literature suggests, in sub-Saharan Africa, people want to stop child-bearing when times are hard (Lindstrom and Berhanu, 1999).

Kodziand Johnson (2010) identified determinants of the desire to stop child-bearing among women in southern Ghana using fixed effects of logit regression technique. The study revealed that the desire to stop child-bearing was influenced by aging, the number of children born, spousal fertility preferences, concerns about health and household economic welfare. The study showed some determinants of the desire to stop child-bearing at personal level. At personal level, a woman's reproductive history and her husband's preferences were the key factors that determine her desire to stop child-bearing. Women with a child or two children were not likely to want to limit births. Generally, at high parities women were less likely to say they wanted to limit births on grounds of their general health than at lower parities.

Muhoza at el. (2009) conducted a study in Rwanda on desire to stop child-bearing and having unmet need. The data for the study were drawn from 2005 Rwanda DHS with sample of 4,817 women. The objective of the study was to identify factors associated with the desire to limit family size and to determine the individual and contextual constraints associated with non-use of contraceptives by women who want no more children. More than 50 percent of those who wanted to stop having children had an unmet need for modern contraception. Education and wealth seemed to play roles in reducing unmet need, but the effects were limited. Talking about family planning is a taboo in many Rwandan households; the majority of women have never discussed family planning with their husbands or have done so only once or twice, and many were not sure whether their partner approves of it. This turns out to be the major obstacle in the use of modern contraceptives. Negative attitudes toward family planning and failing structures of provision are the dominant constraints on the use of modern contraceptives. Women's socioeconomic status played a negligible role in their demand for means of family limitation. Salaried women were significantly more likely to have a demand for family limitation than those working in agriculture (OR = 1.4). On the contrary religious affiliation did not influence the demand for family limitation. Also rural women were less likely than urban women to have a demand for family limitation (OR = 0.7). A woman's level of education was not strongly associated with her desire to end child-bearing, but the proportion of women who wanted to limit their family size was higher in urban areas, wealthy households, more educated women (Muhoza at el., 2009).

The concept "unmet need" describes the condition of fecund women of reproductive age who do not want to have a child soon or ever but are not using family planning (Concepcion, 1980). Women with unmet need includes all fecund women who are married or living in union, and thus presumed to be sexually active but are not using any form of family planning (unmet need for limiting births) or want to postpone their next birth for at least two years (unmet need for spacing births). The unmet need measure gives an estimate of the proportion of women who might potentially use contraception. Meeting unmet need requires that policy makers and program managers know the characteristics of women with a demonstrated unmet need for family planning, that is, the reasons that some couples do not use contraceptives even when they do not want children and use that information to reduce the health and development consequences of unintended fertility (USAID, 2005).Women whose pregnancies are unwanted or mistimed and who became pregnant because they were not using contraception as well as those who recently gave birth but are not yet at risk of becoming pregnant because they are pregnant or amenorrhea and their pregnancies were unintended are also considered to have unmet need. Unmet need in Sub-Saharan Africa is almost twice for spacing is as high as for limiting (Westoff and Bankole, 1996).

Some consequences of unmet need (Ashford, 2003, RHSC 2009, Mackenzie and Drahota, 2010, WHO, 2010) can:

- increase maternal and child morbidity and mortality, particularly when births cannot be adequately spaced;

- lead to an increase in unsafe abortions;
- contribute to the incidence of HIV and sexually transmitted infections (STIs) (compromises women's abilities to be productive in their communities and national economies;
- force girls and young women to drop out of school due to unplanned pregnancies;
- exacerbates women's lower social status and gender inequality;
- increase poverty and slows economic growth; and
- contribute to unsustainable population growth.

Yohannes (2008) identified age of women, education, number of living children, knowledge of family planning, use of family planning, experiences of child death and exposure to media as the main factors that influence women's intention to limit child-bearing in Oromia Regional State, Ethiopia. Older women (ages 35-49 years) were two times more likely than younger women (15-24 years) to limit child-bearing (OR= 2.15). There was no significant difference in the level of intention to limit child-bearing between young women (15-24 years) and those in the middle of their reproductive years (25-34 years). Household socio-economic status (Wealth Quintile) was another important variable associated with women's intention to limit child-bearing. The odds of the desire to stop child-bearing increased as wealth increased. Women from households in the richest wealth quintile were two and half times more likely to desire to limit child-bearing than women of the poorest wealth category (OR= 2.56). Wealth may indicate a greater exposure of people to new ideas and commodities, and may thus influence fertility intentions of people. Women with two sons were two times more likely to desire to stop child-bearing (OR 2.34) as compared to women with one son. The desire of women who had two daughters was 42 percent higher than those with one daughter.

Samuel Yohannes et al. (2011) conducted a cross sectional study to determine duration and birth interval among women of child-bearing age in southern Ethiopia. They identified rural women were more likely to have shorter birth intervals than urban women [OR= 2.7 (95% CI: 1.4, 5.1)]. Education was considered to be one of the most important socioeconomic factors having an indirect influence on birth interval length. Among mothers with no education (25.5 percent) and primary education (54.8 percent) the length of birth interval was shorter than 3 years when compared to women with secondary and above education (19.7 percent). The length of birth intervals showed a difference by age of mothers in which younger women had shorter birth intervals than older women.

The two studies by Short and Kiros (2002) in Ethiopia by Mohammed and Ringheim (1997) in Pakistan showed that couple's knowledge, and adopting family planning are correlated with the desire not to have additional children.

A study in Malawi revealed that women's intentions to limit child-bearing varied with their knowledge and use of family planning methods. Women who knew at least one method of family planning were 80 percent more likely to desire to stop child-bearing (OR= 1.80) than women who did not know any method of family planning. Women who were using family planning were 50 percent more likely to desire to limit child-bearing (OR= 1.5) than women who were not using family planning. The desire to limit child-bearing also varied with exposure to mass media. Those women with exposure to at least one of the three media (radio, TV and newspapers) were 19 percent more likely to limit child-bearing as compared to women who had no access to any kind of media. Those with exposure to at least two of the media were 31 percent more likely than those with no access to any of the media.

2.2 Intentions to Using Contraceptives Methods

Fertility and modern contraceptive use are two inter-related yet distinct themes. Fertility deals with the number of live births a woman or couple may have, whereas contraceptive use has been identified as a key determinant of fertility.

A woman is considered to have met her need for contraceptives for spacing births when she is using some family planning method and indicates that she wants to conceive sometime in the future but not within the next two years or is undecided; a woman is considered to have met her need for contraceptives to limit births when she is using some method of family planning and states that she wants to have no more children in the future (Creanga et al., 2011).

Creanga et al. (2011) categorized the use of contraceptives into two depending on the purpose of they used: long-term methods (intrauterine devices, implants and sterilization), usually used to limit child-bearing, and short-term methods (pills, condoms, spermicides, injectables, other modern methods and all traditional methods), better suited for women who want to delay but not forfeit having a child. Univariate and bivariate logistic regression analyses were done to examine the associations of interest and trends in contraceptive use and related wealth-inequity over time in 13 sub-Saharan African countries. They investigated the effect of using a long-term rather than a short-term method of contraception as a function of two key covariates namely, women's reproductive intention (spacing versus limiting child-bearing) and household wealth quintile. The finding revealed that women of reproductive age were more likely to use contraception to space rather than to stop child-bearing; so the use of short-term methods has increased. Wealth-related inequalities declined as short-term contraceptive methods increased. When child-bearing intentions were controlled for, women in the richest wealth quintile appeared to be more likely than women in the poorest wealth quintile to use long-term contraception, which is more expensive than short-term contraception and usually provided at clinics. Thus, accordingly closing this particular gap between the rich and the poor in developing countries will entail addressing women's access to contraceptives and making all methods affordable.

The analysis of DHS from Burkina Faso, Ghana and Kenya for1998–1999 arrived at similar results among women who wanted to delay child-bearing but did not practice contraception. Such women need information on short-term methods and about side effects to reduce fears and allay health concerns. It was suggested to put in place outreach programs to change partner and community norms opposing contraceptive use.

A study by (Speizer, 2006) which included women who wanted to limit child-bearing, did not practice contraception and those who said it would be a big problem if they became pregnant soon. It was found that the majority of these women perceived themselves to be in fecund or sub fecund.

As of the early twenty-first century, less than half of women who said that they would like to stop or postpone child-bearing used contraception in developing countries (Sedgh et al. 2007).

Many women in developing countries used family planning methods to prevent unwanted and unplanned pregnancies. Contraceptive use is seen as pivotal to protecting women's health and rights, impacting upon fertility and population growth, and promoting economic development particularly in much of sub-Saharan Africa. Globally, contraceptives help prevent an estimated 2.7 million infant deaths and the loss of 60 million years of healthy life (Darroch et al., 2008). In less developed countries modern contraceptive methods were used by only 43 percent of women of reproductive age overall, and a wide gap in use is seen between the highest and lowest wealth quintiles (52percent versus 35percent, respectively). This gap between the rich and poor in the use of contraception has persisted despite general global improvements in socioeconomic status and the expansion of family planning services.

Contraceptive use is a proximate factor affecting fertility among countries. At the same time, culture and socio-economic conditions have significant roles in the use of contraceptive methods. By and large, an increase in contraceptive prevalence rates was consistent with an increase in the proportion of woman who needs to avoid pregnancy, which then led to a decrease in fertility (Feyisetan and Casterline, 2000).

The prevalence of use of contraceptive methods increased in Pakistan with the increase in the number of living children as well as education level of the respondents (SajidandWhite,2005; Azhar and Pasha, 2008).

A similar association was also found in rural Tanzania where the number of living children and education were the main factors impacting the use of contraception (Marchantet al., 2004).

The situation was the same in Nepal where the sex preference was an important barrier to the increase of contraceptive use and the decline of fertility in the country (Tizianaet al., 2003).

According to Kwame Boadu (2002) the fertility behavior in Ghana was influenced by a multitude of socio-demographic and economic, and cultural factors. These factors, in turn, affected contraceptive practice in a variety of ways. The outcome of the analysis appeared to support the view that knowledge of and contraceptive adoption were gradually making an impact on fertility behavior in Ghana.

Sohail (2010) conducted a cross sectional study in Pakistan, in which 4,064 males and females were interviewed about intentions to use contraceptives. The objective of the study was to identify a range of psychosocial factors that influence males and females intentions to use family planning methods. The study used multinomial logistic regression to identify the factors. The result of the study indicated that, compared to men age 45 and older, the intention to use condoms as well as other modern methods was higher than among those under age 45. Men with six or more children were less likely to use condom than men with three or fewer children (OR= .47). Men with four or five children were more likely to use a modern method other than a condom than men with three or fewer children (OR= 1.63). Women with secondary level of education (OR= 3.02) or matriculate education (OR= 3.00) had higher intentions to use modern methods. The desire to limit child-bearing was associated with higher intentions to use condoms (OR= 2.54) and higher intentions to use any other modern methods other than condoms (OR= 7.78).

Hayford and Agadjanian (2011) conducted a study on contraceptive use and fertility intentions in rural southern Mozambique. The objective of the study was to measure motivation to limit fertility based on data obtained from 14 villages selected with probability proportional to size of survey in rural area. The sample consisted of 1,680 women. It was found that, women in poor economic status preferred to use modern methods of family planning to stop or postpone child-bearing than women who gave other reasons. The results suggested that economic pressure was a strong motivation to prevent additional children than more purely normative reasons such as reaching an adequate family size (OR= 1.67). There was no difference in contraceptive use between women who reported they did not want to have more children and women who wanted to limit child-bearing for spacing reasons. Women who had attained a high level of education were more likely to use family planning than women with less education, and household wealth was also positively associated with use of contraception. However, parity was not associated with contraceptive use among those who wanted to limit child-bearing.

In developing countries the desire to have more children, fear of side effects among contraceptive users and religious prohibitions were some of the reasons reported for the low utilization of family planning methods. More couples used contraceptive methods for birth spacing than for stopping child-bearing and the family planning decision making role was mostly influenced by both couples (Bankole andSingh,1998).

The Ethiopian Demographic and Health Survey of 2005 revealed that knowledge of contraception had remained consistently high in Ethiopia until 2005; 88percent of currently married women said they have heard of at least one method of contraception (CSA and Macro, 2006). As of 2011, 29 percent of married Ethiopian women of child-bearing age used any method of family planning; this was a dramatic increase from 2005 when only 15 percent of married women of child-bearing age were using any form of contraception. According to EDHS 2011 married women in urban areas were twice as likely as their rural counterparts to use any contraceptive method (53 and 23 percent, respectively), to use any modern method (50 and 23 percent, respectively), and to use any traditional method (3 and 1 percent, respectively).

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The world population was about 6.8 billion in 2009 and 7 billion in 2012 with 5.6 billion (80 percent) of the world total living in the less developed regions (UN, 2012). The population of the more developed regions remained largely unchanged at 1.2 billion inhabitants. The three least developed countries including Bangladesh, Ethiopia, and the Democratic Republic of the Congo were among the ten most populous countries in the world. Thus, whereas the population of more developed regions was rising at an annual rate of 0.34 percent, that of the developing regions was increasing four times as fast, i.e. 1.37 percent annually, and the least developed countries as a group were experiencing even more rapid population growth, at 2.3 percent per year (UN, 2012).

Ethiopia is the second most populous country in Africa next to Nigeria, with a population size estimated 81 million and a growth rate of 2.6 percent per year (Aynalem Adugna, 2010). Of the total population, more than 84 percent live in rural areas. Uncontrolled fertility has adversely influenced the socio-economic, demographic and environmental development of the country. Poverty, war and famine, associated with low levels of education and health, a weak infrastructure, and low agricultural and industrial production have exacerbated the problem of overpopulation (Ezra, 2001). Like many other African countries, Ethiopia has so far shown little change in fertility. The desire for large family size is one of the factors influencing fertility in Ethiopia. Thus, understanding factors that influence the fertility intentions of women is important for family planning program purposes and population policy.

The desire to limit child-bearing is expected to be a natural progression in the reproductive life course. The proportion of women who intend to limit child-bearing is one of the most important conditions because it bears directly on population growth and designates a segment of the population that may be at risk of having an unwanted birth. Thus the proportion of women of child-bearing age who want no more children is also an important predictor of fertility levels and trends. In the past few years, the proportion of women who desire to limit child-bearing has been rising in Sub-Saharan Africa. Analysis of DHS data from sub-Saharan Africa, between 1990 and

2001 has shown that the proportion of women with the intention to limit child-bearing ranged from a low of less than 10 percent in Niger and Chad to a high of 53 percent in Kenya in sub Saharan Africa (Westoff and Bankole, 2002).

Some women tend to say that they want more children when they have had an unplanned birth or when they think it is the socially desirable answer given their reproductive circumstances. It is also possible that women who want children at high parities genuinely desire larger families. In traditional societies, especially where polygamy is practiced, having many children may be a means to secure one's marriage, or to gain social status or access to family resources (DeRose et al, 2002).

Fertility desires and intentions are central in theoretical and empirical approaches to studying child-bearing behavior. Coale's (1973) seminal formulation of demographic transition theory argues that fertility will decline when child-bearing enters the "calculus of conscious choice" – that is, when having children becomes a subject about which it is possible to have preferences. A common notion in demography is that people decide the number of children they want over their reproductive lives and stop child-bearing whenever that number is achieved (Easterlin and Crimmins, 1985).

Measuring fertility intentions, and determining the extent to which they predict fertility behavior, is also important for population policy and the implementation of family planning programs. Substantial evidence from more developed countries and growing evidence from less developed countries shows that preferences are associated with child-bearing behavior, even after accounting for other socio demographic characteristics. However, there is little evidence on how fertility desires predict fertility in sub-Saharan African settings, where rapid and radical socioeconomic changes coupled with a massive HIV/AIDS epidemic have placed immense strains on traditional marital and reproductive systems. In addition, the conditions under which preferences are more strongly or weakly associated with behavior are not well understood (Hayford and Agadjanian, 2011).

Differentials in fertility behavior and fertility levels in different areas and among population strata or characteristics have been among the most pervasive findings in demography (Cochrane, 1979). It is essential to identify risk factors associated with high fertility and to provide services to address those who are at risk. To develop effective strategies for fertility control, it is necessary to understand the factors affecting fertility. It is hypothesized that women in vulnerable groups, such as those who got married at an early age, are illiterate, are living in rural areas, are poorest, and have little knowledge of family planning, have high fertility(Beekle and Cabe, 2006).

An estimated 222 million women in developing countries would like to delay or stop child-bearing but are not using any method of contraception. Reasons for this include (WHO, 2012):

- limited choice of methods;
- limited access to contraception, particularly among young people, poorer segments of populations, or unmarried people;
- fear or experience of side-effects;
- cultural or religious opposition;
- poor quality of available services;
- gender-based barriers.

As the desire for more children is an indicator of large family, the intention to limit births is often considered as a precondition for fertility decline (Bongaarts, 1997). The extent to which a given society desires to limit fertility has significant implications for family planning programs. It is often taken as an indicator of the demand for family planning services.

1.2 Current fertility in Ethiopia

The fertility level of Ethiopia especially in the rural areas is unacceptably high. The higher fertility of women, the more the risk associated with each birth. The reproductive role on top of the productive role of women puts them in a poor social and economic status. In developing countries like Ethiopia, pregnancy and child birth is 18 times more likely to end in the woman's death than in developed countries (John Hopkins University, 1999).Apart from the high fertility, there exist large variations in fertility between rural and urban areas, regions and various ethnic and religious groups in Ethiopia. These differentials call for urgent attention among both researchers and policy and decision makers.

Childlessness whether biological or by choice is very low in Ethiopia; less than 2 percent of Ethiopian women who have completed or were close to completing their reproduction period at the time of the survey, reported themselves as childless (Aynalem Adugna, 2010).

The Total Fertility Rate (TFR) for Ethiopia in rural areas exceeds the TFR in urban areas by almost three children per woman (5.5 and 2.6 children per woman, respectively).Also the General Fertility Rate (GFR) shows great difference between urban and rural Ethiopia (in rural areas 184 and in urban areas 89). There are substantial differentials in the TFR among the regions, ranging from 1.5 children per woman in Addis Ababa (below the replacement level of fertility) to 7.1 children per woman in Somali regional state. Fertility levels are higher than the national average in Somali, Oromiya, Benishangul-Gumuz, Affar, and SNNP and lower than the national average in the other six regions. The level of fertility is inversely related to women's educational attainment, decreasing sharply from 5.8 children among women with no education to 1.3 children among women who have more than secondary education. Fertility is also strongly associated with wealth quintiles. Women in the lowest wealth quintile have a TFR of 6.0, more than twice as high as women in the highest wealth quintile, at 2.8 (EDHS, 2011).

Another way to examine fertility trends is to compare current estimates with estimates from earlier surveys. Estimates of the TFR and Age-Specific Fertility Rate (ASFR) are available from the two previous EDHS surveys (2000 and 2005). These estimates offer an opportunity to assess fertility trends over the last decade. These data show that the TFR decreased only slightly from 5.5 children in 2000 to 5.4 children in 2005, and then decreased further to 4.8 children in 2011. Although the level of fertility decreased over time, the age pattern of fertility was similar in all three surveys, with fertility increasing from age 15-19 to age 25-29 and decreasing thereafter (EDHS, 2011).

When we compare the 2000and 2005 EDHS surveys, we observe that the proportion of married women who desire to limit child-bearing had increased for five years for all categories of living children, with an overall increase from 32 percent in 2000 to 42 percent in 2005. Conversely, it was observed that the proportion of currently married women who desire to limit child-bearing has decreased in the past five years for all categories of living children, with an overall decrease from 42 percent in 2005 to 37 percent in 2011.

The overall proportion of currently married women who desire to limit child-bearing is almost the same in urban areas as in rural areas (37.1 and 36.9 percent, respectively). However, when the number of children is held constant, urban women are more likely than rural women to want to limit child-bearing, with the largest difference among women with two living children (41 percent among urban women and 15 percent among rural women).Also, there is a significant regional variation in the desire to limit child-bearing, ranging from 11 percent in the Somali region to 41 percent in the SNNP region. As women's education increases, their reported desire to have no more children decreases. For example, 41 percent of women with no education desire to limit child-bearing compared with 32 percent of women with primary education. Currently married women in the middle wealth quintile are most likely to want to limit child-bearing (40 percent).

1.3 Statement of the Problem

Changes in the demand for children and greater accessibility to contraception are important conditions for fertility transition. The proportion of women who intend to limit child-bearing is one of the most important conditions because it bears directly on population growth and designates a segment of the population that may be at risk of having an unwanted birth. This proportion of women of child-bearing age who want no more children is also an important predictor of fertility levels and trends. In the past few years, the proportion of women who desire to limit child-bearing has been rising in sub-Saharan Africa. According to Bongaart (1997) the desired family size was more than four children in sub-Saharan African countries, where child mortality is high and poverty is rampant. This trend also, appears to continue in the future.

Fertility is one of the elements in population dynamics that has significant contribution towards changing population size and structure over time. In some of the least developed countries, high fertility rates hamper development and perpetuate poverty, while in some of the richest countries, low fertility rates and too few people entering the job market are raising concerns about prospects for sustained economic growth and the viability of social security systems (UN, 2012).

Rapid population growth is leading to fresh-water shortages and ground-water depletion, particularly in densely populated countries in the developing world. Steadily increasing population also contributes to pollution of both local and global environments. The poorest regions of the world are set to be worst hit. Countries with limited natural resources and extremely rapid population growth, most of them in sub-Saharan Africa, fare the worst (UN, 2012).

Differences in mortality and morbidity that relate to socioeconomic class constitute an inequity. The poor do not have the same access to life-saving and health-maintaining interventions as the rich, yet they aspire to the same healthy lives as those who are economically better off. However, a difference in fertility between the rich and poor is not an inequity provided the poor have higher fertility because they want to have more children. As high fertility is associated with increased obstetric and medical risks of mothers, in order to reduce fertility and control population growth of the country, the factors that influence fertility should be clearly identified (Zhang, 2007). Fertility affects the well-being of mothers and their children. If proper care and action are not taken, a high fertility rate could disturb the socio-economic development of a nation. In the immediate future, there will be a high pressure on child health and educational provisions. This will lead to overcrowding in these services and consequently less than satisfactory service provision. Children will be in large classes with limited resources hence underachieving. There will be long waiting lists for health services which will result in health problems. Spacing and limiting the number of children improves maternal and child health empowers women and enhances economic development (Samuel Yohannes et al, 2011).

In countries around the world, women who are determined to limit their family size and time their child-bearing will use all available means to do so; if contraception is not a viable option, women will turn to abortion even if it is illegal. Extensive evidence demonstrates, however, that when modern contraceptives are made available to women, their increased use over time replaces previous reliance on abortion and becomes the major factor associated with reduced abortion rates. Policy makers seeking to reduce the incidence of abortion would do well to address its root cause unintended pregnancy by facilitating widespread access to modern contraceptives and by promoting their effective use (Smith, 1993).

The situation in Ethiopia indicates that demographic and developmental factors reinforce each other so that high fertility and rapid population growth exert a negative influence on economic and social development. Low levels of economic and social development provide conditions that favor a high fertility rate and rapid population growth. The rapid population growth does not match with available resource in Ethiopia where the economy has been agrarian based on household subsistence farming (Wubegzier Mekonnen and Alemayehu Worku, 2011).

Generally, high fertility and rapid population growth have an impact on the overall socio economic development of a country and maternal and child health in particular. Maternal and child mortality are two of the major health problems challenging healthcare organizations, especially in developing countries.

Hence this study attempts to identify major socio-economic, demographic, cultural and environmental factors that influence women's intentions to limit child-bearing in rural Ethiopia.

1.4 Objectives of the study

The main objective of this study is to identify factors which influence women's intentions to limit child-bearing in rural Ethiopia.

The specific objectives of the study are:

- To describe the level of women's intentions to limit child-bearing regionally.
- To examine the relationship between selected demographic and socioeconomic variables and limiting child-bearing.
- To investigate the existence of regional differentials in intention to limit child-bearing in rural areas of Ethiopia.
- To suggest measures to address the issue of limiting child-bearing in rural Ethiopia.

1.5 Significance of the study

Ethiopia is one of the developing countries with high growth rate of population, high level of maternal and child mortality. Particularly, in rural areas there are many factors that lead to high risk of fertility.

Hence, the outcome of this study would provide information about factors that influence intentions of women to limit children for governmental and non-governmental organizations and individuals (women and men).

CHAPTER TWO

2. REVIEW OFTHE LITERATURE

The analysis of fertility intentions is of fundamental importance for family planning program purposes and for population policy because it determines the demand for contraception and the potential impact on the rate of reproduction (Bongarts and Potter, 1983). Thus, understanding the factors which influence women's fertility intention is critical for countries like Ethiopia that have to reduce fertility using a sound population policy. The following sections bring to light socio economic and demographic factors that impact child-bearing.

2.1 Determinants of Limiting Child-bearing

The population of the world increases every year because the global birth rate exceeds the death rate. For example, in the early 1990s population size increased at an annual rate of 1.5 percent. Thus, the difference between a birth rate of 2.4 percent and a death rate was 0.9 percent (Bongaarts, 1997). At country level, population growth is also affected by migration, but for the regional aggregates of population used in this study, migration is usually a minor factor, and it will therefore not be discussed in detail.

Previous researches have shown that the fertility intentions of women are influenced by various demographic, socioeconomic and program factors. Using DHS data in Africa, Westoff and Bankole (1995) demonstrated that fertility intentions of women vary with the age of women, number of living children, place of residence, education and exposure to media. Fertility intentions are also shaped by couples' experiences with child mortality and their expectation about child survival conditions as well as their preferences for a single sex, usually a son. Other studies have identified knowledge, approval and use of family planning as important factors influencing fertility intentions (Pullum, 1983; Short and Kiros, 2002). In relation to knowledge and approval of family planning, many have posited that exposure to mass media, particularly those promoting family planning, is important in influencing fertility related behaviors of women (Gupta et al, 2003). Apart from the high fertility, there exist large variations in fertility between rural and urban areas, regions and various ethnic and religious groups in Ethiopia. These differentials call for urgent attention among both researchers and policy and decision makers.

Ample research shows that fertility intentions predict behavior. Women who report wanting to stop or postpone child-bearing are more likely to use contraception (and less likely to have a child) than women who want a child. Improving measures of fertility motivations would also likely improve understanding of contraceptive and fertility behavior (Hayford and Agadjanian, 2011).

Better prospects of the household economic situation, personal health, etc. would lead to reluctance to stop child-bearing, all else equal, because as the literature suggests, in sub-Saharan Africa, people want to stop child-bearing when times are hard (Lindstrom and Berhanu, 1999).

Kodziand Johnson (2010) identified determinants of the desire to stop child-bearing among women in southern Ghana using fixed effects of logit regression technique. The study revealed that the desire to stop child-bearing was influenced by aging, the number of children born, spousal fertility preferences, concerns about health and household economic welfare. The study showed some determinants of the desire to stop child-bearing at personal level. At personal level, a woman's reproductive history and her husband's preferences were the key factors that determine her desire to stop child-bearing. Women with a child or two children were not likely to want to limit births. Generally, at high parities women were less likely to say they wanted to limit births on grounds of their general health than at lower parities.

Muhoza at el. (2009) conducted a study in Rwanda on desire to stop child-bearing and having unmet need. The data for the study were drawn from 2005 Rwanda DHS with sample of 4,817 women. The objective of the study was to identify factors associated with the desire to limit family size and to determine the individual and contextual constraints associated with non-use of contraceptives by women who want no more children. More than 50 percent of those who wanted to stop having children had an unmet need for modern contraception. Education and wealth seemed to play roles in reducing unmet need, but the effects were limited. Talking about family planning is a taboo in many Rwandan households; the majority of women have never discussed family planning with their husbands or have done so only once or twice, and many were not sure whether their partner approves of it. This turns out to be the major obstacle in the use of modern contraceptives. Negative attitudes toward family planning and failing structures of provision are the dominant constraints on the use of modern contraceptives. Women's socioeconomic status played a negligible role in their demand for means of family limitation. Salaried women were significantly more likely to have a demand for family limitation than those working in agriculture (OR = 1.4). On the contrary religious affiliation did not influence the demand for family limitation. Also rural women were less likely than urban women to have a demand for family limitation (OR = 0.7). A woman's level of education was not strongly associated with her desire to end child-bearing, but the proportion of women who wanted to limit their family size was higher in urban areas, wealthy households, more educated women (Muhoza at el., 2009).

The concept "unmet need" describes the condition of fecund women of reproductive age who do not want to have a child soon or ever but are not using family planning (Concepcion, 1980). Women with unmet need includes all fecund women who are married or living in union, and thus presumed to be sexually active but are not using any form of family planning (unmet need for limiting births) or want to postpone their next birth for at least two years (unmet need for spacing births). The unmet need measure gives an estimate of the proportion of women who might potentially use contraception. Meeting unmet need requires that policy makers and program managers know the characteristics of women with a demonstrated unmet need for family planning, that is, the reasons that some couples do not use contraceptives even when they do not want children and use that information to reduce the health and development consequences of unintended fertility (USAID, 2005).Women whose pregnancies are unwanted or mistimed and who became pregnant because they were not using contraception as well as those who recently gave birth but are not yet at risk of becoming pregnant because they are pregnant or amenorrhea and their pregnancies were unintended are also considered to have unmet need. Unmet need in Sub-Saharan Africa is almost twice for spacing is as high as for limiting (Westoff and Bankole, 1996).

Some consequences of unmet need (Ashford, 2003, RHSC 2009, Mackenzie and Drahota, 2010, WHO, 2010) can:

- increase maternal and child morbidity and mortality, particularly when births cannot be adequately spaced;

- lead to an increase in unsafe abortions;
- contribute to the incidence of HIV and sexually transmitted infections (STIs) (compromises women's abilities to be productive in their communities and national economies;
- force girls and young women to drop out of school due to unplanned pregnancies;
- exacerbates women's lower social status and gender inequality;
- increase poverty and slows economic growth; and
- contribute to unsustainable population growth.

Yohannes (2008) identified age of women, education, number of living children, knowledge of family planning, use of family planning, experiences of child death and exposure to media as the main factors that influence women's intention to limit child-bearing in Oromia Regional State, Ethiopia. Older women (ages 35-49 years) were two times more likely than younger women (15-24 years) to limit child-bearing (OR= 2.15). There was no significant difference in the level of intention to limit child-bearing between young women (15-24 years) and those in the middle of their reproductive years (25-34 years). Household socio-economic status (Wealth Quintile) was another important variable associated with women's intention to limit child-bearing. The odds of the desire to stop child-bearing increased as wealth increased. Women from households in the richest wealth quintile were two and half times more likely to desire to limit child-bearing than women of the poorest wealth category (OR= 2.56). Wealth may indicate a greater exposure of people to new ideas and commodities, and may thus influence fertility intentions of people. Women with two sons were two times more likely to desire to stop child-bearing (OR 2.34) as compared to women with one son. The desire of women who had two daughters was 42 percent higher than those with one daughter.

Samuel Yohannes et al. (2011) conducted a cross sectional study to determine duration and birth interval among women of child-bearing age in southern Ethiopia. They identified rural women were more likely to have shorter birth intervals than urban women [OR= 2.7 (95% CI: 1.4, 5.1)]. Education was considered to be one of the most important socioeconomic factors having an indirect influence on birth interval length. Among mothers with no education (25.5 percent) and primary education (54.8 percent) the length of birth interval was shorter than 3 years when compared to women with secondary and above education (19.7 percent). The length of birth intervals showed a difference by age of mothers in which younger women had shorter birth intervals than older women.

The two studies by Short and Kiros (2002) in Ethiopia by Mohammed and Ringheim (1997) in Pakistan showed that couple's knowledge, and adopting family planning are correlated with the desire not to have additional children.

A study in Malawi revealed that women's intentions to limit child-bearing varied with their knowledge and use of family planning methods. Women who knew at least one method of family planning were 80 percent more likely to desire to stop child-bearing (OR= 1.80) than women who did not know any method of family planning. Women who were using family planning were 50 percent more likely to desire to limit child-bearing (OR= 1.5) than women who were not using family planning. The desire to limit child-bearing also varied with exposure to mass media. Those women with exposure to at least one of the three media (radio, TV and newspapers) were 19 percent more likely to limit child-bearing as compared to women who had no access to any kind of media. Those with exposure to at least two of the media were 31 percent more likely than those with no access to any of the media.

2.2 Intentions to Using Contraceptives Methods

Fertility and modern contraceptive use are two inter-related yet distinct themes. Fertility deals with the number of live births a woman or couple may have, whereas contraceptive use has been identified as a key determinant of fertility.

A woman is considered to have met her need for contraceptives for spacing births when she is using some family planning method and indicates that she wants to conceive sometime in the future but not within the next two years or is undecided; a woman is considered to have met her need for contraceptives to limit births when she is using some method of family planning and states that she wants to have no more children in the future (Creanga et al., 2011).

Creanga et al. (2011) categorized the use of contraceptives into two depending on the purpose of they used: long-term methods (intrauterine devices, implants and sterilization), usually used to limit child-bearing, and short-term methods (pills, condoms, spermicides, injectables, other modern methods and all traditional methods), better suited for women who want to delay but not forfeit having a child. Univariate and bivariate logistic regression analyses were done to examine the associations of interest and trends in contraceptive use and related wealth-inequity over time in 13 sub-Saharan African countries. They investigated the effect of using a long-term rather than a short-term method of contraception as a function of two key covariates namely, women's reproductive intention (spacing versus limiting child-bearing) and household wealth quintile. The finding revealed that women of reproductive age were more likely to use contraception to space rather than to stop child-bearing; so the use of short-term methods has increased. Wealth-related inequalities declined as short-term contraceptive methods increased. When child-bearing intentions were controlled for, women in the richest wealth quintile appeared to be more likely than women in the poorest wealth quintile to use long-term contraception, which is more expensive than short-term contraception and usually provided at clinics. Thus, accordingly closing this particular gap between the rich and the poor in developing countries will entail addressing women's access to contraceptives and making all methods affordable.

The analysis of DHS from Burkina Faso, Ghana and Kenya for1998–1999 arrived at similar results among women who wanted to delay child-bearing but did not practice contraception. Such women need information on short-term methods and about side effects to reduce fears and allay health concerns. It was suggested to put in place outreach programs to change partner and community norms opposing contraceptive use.

A study by (Speizer, 2006) which included women who wanted to limit child-bearing, did not practice contraception and those who said it would be a big problem if they became pregnant soon. It was found that the majority of these women perceived themselves to be in fecund or sub fecund.

As of the early twenty-first century, less than half of women who said that they would like to stop or postpone child-bearing used contraception in developing countries (Sedgh et al. 2007).

Many women in developing countries used family planning methods to prevent unwanted and unplanned pregnancies. Contraceptive use is seen as pivotal to protecting women's health and rights, impacting upon fertility and population growth, and promoting economic development particularly in much of sub-Saharan Africa. Globally, contraceptives help prevent an estimated 2.7 million infant deaths and the loss of 60 million years of healthy life (Darroch et al., 2008). In less developed countries modern contraceptive methods were used by only 43 percent of women of reproductive age overall, and a wide gap in use is seen between the highest and lowest wealth quintiles (52percent versus 35percent, respectively). This gap between the rich and poor in the use of contraception has persisted despite general global improvements in socioeconomic status and the expansion of family planning services.

Contraceptive use is a proximate factor affecting fertility among countries. At the same time, culture and socio-economic conditions have significant roles in the use of contraceptive methods. By and large, an increase in contraceptive prevalence rates was consistent with an increase in the proportion of woman who needs to avoid pregnancy, which then led to a decrease in fertility (Feyisetan and Casterline, 2000).

The prevalence of use of contraceptive methods increased in Pakistan with the increase in the number of living children as well as education level of the respondents (SajidandWhite,2005; Azhar and Pasha, 2008).

A similar association was also found in rural Tanzania where the number of living children and education were the main factors impacting the use of contraception (Marchantet al., 2004).

The situation was the same in Nepal where the sex preference was an important barrier to the increase of contraceptive use and the decline of fertility in the country (Tizianaet al., 2003).

According to Kwame Boadu (2002) the fertility behavior in Ghana was influenced by a multitude of socio-demographic and economic, and cultural factors. These factors, in turn, affected contraceptive practice in a variety of ways. The outcome of the analysis appeared to support the view that knowledge of and contraceptive adoption were gradually making an impact on fertility behavior in Ghana.

Sohail (2010) conducted a cross sectional study in Pakistan, in which 4,064 males and females were interviewed about intentions to use contraceptives. The objective of the study was to identify a range of psychosocial factors that influence males and females intentions to use family planning methods. The study used multinomial logistic regression to identify the factors. The result of the study indicated that, compared to men age 45 and older, the intention to use condoms as well as other modern methods was higher than among those under age 45. Men with six or more children were less likely to use condom than men with three or fewer children (OR= .47). Men with four or five children were more likely to use a modern method other than a condom than men with three or fewer children (OR= 1.63). Women with secondary level of education (OR= 3.02) or matriculate education (OR= 3.00) had higher intentions to use modern methods. The desire to limit child-bearing was associated with higher intentions to use condoms (OR= 2.54) and higher intentions to use any other modern methods other than condoms (OR= 7.78).

Hayford and Agadjanian (2011) conducted a study on contraceptive use and fertility intentions in rural southern Mozambique. The objective of the study was to measure motivation to limit fertility based on data obtained from 14 villages selected with probability proportional to size of survey in rural area. The sample consisted of 1,680 women. It was found that, women in poor economic status preferred to use modern methods of family planning to stop or postpone child-bearing than women who gave other reasons. The results suggested that economic pressure was a strong motivation to prevent additional children than more purely normative reasons such as reaching an adequate family size (OR= 1.67). There was no difference in contraceptive use between women who reported they did not want to have more children and women who wanted to limit child-bearing for spacing reasons. Women who had attained a high level of education were more likely to use family planning than women with less education, and household wealth was also positively associated with use of contraception. However, parity was not associated with contraceptive use among those who wanted to limit child-bearing.

In developing countries the desire to have more children, fear of side effects among contraceptive users and religious prohibitions were some of the reasons reported for the low utilization of family planning methods. More couples used contraceptive methods for birth spacing than for stopping child-bearing and the family planning decision making role was mostly influenced by both couples (Bankole andSingh,1998).

The Ethiopian Demographic and Health Survey of 2005 revealed that knowledge of contraception had remained consistently high in Ethiopia until 2005; 88percent of currently married women said they have heard of at least one method of contraception (CSA and Macro, 2006). As of 2011, 29 percent of married Ethiopian women of child-bearing age used any method of family planning; this was a dramatic increase from 2005 when only 15 percent of married women of child-bearing age were using any form of contraception. According to EDHS 2011 married women in urban areas were twice as likely as their rural counterparts to use any contraceptive method (53 and 23 percent, respectively), to use any modern method (50 and 23 percent, respectively), and to use any traditional method (3 and 1 percent, respectively).

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Source of Data

The data for this study are secondary and were obtained from EDHS 2011 collected by CSA with the aim to provide current and reliable data on fertility and family planning behavior, and child mortality, adult and maternal mortality, children's nutritional status, the utilization of maternal and child services, knowledge of HIV/AIDS and prevalence of HIV/AIDS and anemia. The EDHS 2011 was a follow up to the 2000 and 2005 EDHS surveys and provides updated estimates of basic demographic and health indicators. The investigator took a sub-sample from the EDHS 2011 national data that is representative of rural Ethiopia. The survey covered samples of 16,515 women aged 15-49 years out of which 10,864rural women are included in the study. All rural women (i.e.10,864) were considered in the study.

3.2 Variables of Interest

3.2.1 The Response Variable

The response/dependent variable in the study was women's intention to limit child-bearing in rural Ethiopia. In order to gather data about the response a total of 10,864 women were asked whether they wanted to have another child soon, after two years, or want no more children (EDHS 2011 questionnaire). On the basis of response to this question, respondents were divided into two categories: those who 'desired to have more children' and those 'desiring to limit child-bearing'. The first category consisted of 7,634 (70.3percent) women who wanted a child within two years, after two years and those who wanted a child but were not sure of the timing; 3,230 (29.7percent) women did not want any more children meaning that they had the 'intention to limit child-bearing' in the context of this study. A total of 352 women who reported that they were sterilized (and thus declared as fecund) were excluded from the analysis. The 2011 EDHS data set used in this study is based on multistage stratified cluster sampling. Here the units at lower level are individuals (women aged 15-49) who are nested within units at higher level (regions). Due to this nested structure, the odds of women experiencing the outcome of interest are not independent, because women from the same cluster (region) may share common exposure to community characteristics. The methodology has two parts: the ordinary logistic regression and multilevel logistic regression methods.

3.2.2 Predictor Variables

Based on the available data and literature review this study considered the following characteristics of women as predictor variable: age, religion, educational attainment, region, wealth index, exposure to media, marital status, number of living children, previous child death, visited by FP workers in the last 12 months, knowledge of family planning, current use of any FP, occupation status of women.

Table 3.1 Description and coding of response and independent variables

The response variable

Variable	Representation of variable	Categories
Intention to limit child-bearing	Y	0= desire to have more children 1= desire to limit child-bearing

Predictor Variables	Representation of variable	Categories
1. Age of a woman	X_1	1=15-29 2=30-39 3=40-49
2. Religion	X_2	1=Coptic orthodox 2=Protestant 3= Muslim 4= Others
3. Educational level of women	X_3	0=No education

		1=Primary 2=Secondary and higher
4. Region	X_4	1=Tigray 2=Affar 3=Amhara 4=Oromiya 5=Somali 6=Ben-Gumuz 7=SNNP 8=Gambela 9=Harari 10=Dire Dawa
5. Wealth index	X_5	1=Poor 2=Middle 3=Rich
6. Exposure to any media	X_6	0=No 1=Yes
7. Number of living children	X_7	0= None 1= 1-3 2= 4+
8. Marital Status	X_8	0=Never married 1=Married/in union 2=Widow/separated
9. Any previous child death	X_8	0=None 1=Died
10. current use any family planning	X_{10}	0=No 1=Yes

11. Knowledge of family planning	X_{11}	0=No 1=Yes
12. Visited by FP worker in last 12 months	X_{12}	0=No 1=Yes
13. Occupation of women	X_{13}	0= Not working 1=Agriculture 2=Non-agriculture

3.3 Methodology

3.3.1 Logistic Regression Analysis

Logistic regression is a statistical technique for predicting the probability of an event, given a set of predictor variables. The procedure is more sophisticated than the linear regression procedure. The binary logistic regression procedure allows one to select the predictive model for dichotomous dependent variables. It describes the relationship between a dichotomous response variable and a set of explanatory variables. The predictor variables may be continuous or discrete or both.

Logistic regression model can be extended to model a categorical response variable with more than two categories. The resulting model is sometimes referred to as the multinomial logistic regression model (in contrast to the 'binomial' logistic regression for a binary response variable).

The choice of explanatory variables will be guided by review of the available literature. The variables will be tested for statistical significance using chi-square tests and those variables that are significant in the bivariate setup ($P<0.05$) will be included in the multiple logistic regression. Logistic regression will be used to examine the impact of social and economic factors on the desire to limit child-bearing. The use of the logistic regression is based on the fact that the response variable is dichotomous (0=desire to have more children, 1=desire to limit child-bearing). A binary response variable is defined here as

$$Y_i = \begin{cases} 0 & \text{if a woman desires to have more children} \\ 1 & \text{if a woman has no desire to have more children} \end{cases}$$

and the response Y_i follows a Bernoulli distribution with success probability π,

$Y_i / \pi \sim$Bernoulli (π), where π= Pr (Y_i= 1), $0 \leq \pi \leq 1$.

3.3.1.1 The Model

Suppose there are k predictors $X_1, ..., X_k$ and we would like to have the probabilities π_i depend on a vector of observed covariates X_i. Then,

$$\pi_i = \frac{exp(\beta_o + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki})}{1 + exp(\beta_o + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki})}$$

gives the probabilities of outcome events given the covariate values $X_{1i}, X_{2i}, \ldots X_{ki}$ and

$$\text{Logit}(\pi_i) = \ln\left[\frac{\pi_i}{1 - \pi_i}\right] = \beta_o + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}$$

where $\pi_i$is the probability that a woman desire to limit child-bearing and $1- \pi_i$is the complement, β_o is the constant; $\beta_1, \beta_2, ..., \beta_k$ stand for the regression coefficients, $X_{1i}, X_{2i}, \ldots X_{ki}$ is the set of independent covariates for the i^{th} woman and the ratio $[\pi_i/1-\pi_i]$ are the odds that a woman desires to limit child-bearing.

3.3.1.2 Parameter Estimation

The maximum likelihood (ML) estimation method is one of several alternative approaches developed for estimating the parameters in a mathematical model. The maximum likelihood equation is derived from the probability distribution of the dependent variable. Let π_i be the probability of success; this is equivalent to the probability that the response variable assumes value one.

$$\pi_i = P(Y_i = 1) = \frac{1}{1 + e^{-x'\beta}}$$

Hence for the i^{th} observation Y_i the Bernoulli distribution is

$$P(Y_i = y_i|\beta) = \pi_i^{yi}(1-\pi_i)^{1-yi}$$

and the likelihood function given by

$$l = \prod_{i=1}^{n} \pi_i^{y_i}(1-\pi_i)^{1-y_i}$$

Then the log likelihood can be written

$$L = \ln l = \sum_{i=1}^{n} y_i ln\left(\frac{\pi_i}{1-\pi_i}\right) + \sum_{i=1}^{n} \ln(1-\pi_i)$$

Therefore, the estimators of β_i will be obtained by differentiating L with respect to β_i's that maximizes L and set the results to zero. In logistic regression, the likelihood equations are non-linear functions of unknown parameters. Therefore, we use a very effective and well known Newton-Raphson iterative method to solve the equations which is known as iteratively reweighted least squares algorithm.

3.3.1.3 Test of Goodness of Fit

Once a model has been developed, we would like to know how effective the model is in describing the outcome variable. This is referred to as goodness-of-fit. In testing the hypothesis that the model fits the data, the common approaches are Pearson's χ^2 statistic and the likelihood-ratio statistic G^2(Agresti, 1996).

3.3.1.3.1 Pearson's Chi-squared statistic

The Pearson chi-squared statistic also compares the model fit to the actual data. The larger the statistic, the poorer the model fits the real data. Let $y_i \sim$binomial (n_i, π_i) for logistic regression the Pearson statistic is

$$\chi^2 = \sum_{i=1}^{k} \frac{(y_i - n_i\hat{\pi}_i)^2}{n_i\hat{\pi}_i(1-\hat{\pi}_i)}$$

where $\hat{\pi}_i$ is the estimated success probability.

3.3.1.3.2 Likelihood ratio test statistic

The likelihood ratio (LR) test is performed by estimating two models and comparing the fit of one model to the fit of the other. Removing predictor variables from a model will almost always make the model fit poor (i.e., a model will have a smaller log likelihood), but it is necessary to test whether the observed difference in model fit is statistically significant. The LRT statistic is

$$G^2 = \sum\left[(observed)log\left(\frac{observed}{Fitted}\right)\right] = -2Ln\left\{\frac{LL_c}{LL_k}\right\}.$$

Here LL_c=maximum likelihood of constant model, and LL_k=maximum likelihood of full model.

For the binary outcome discussed above, if the hypothesis isH_0: β_i=0 against$\beta_i \neq 0$, then for large n, $G^2 \sim \chi^2$with degrees of freedom equal to thenumber of parameters being estimated.

3.3.1.3.3 Hosmer-Lemeshow Statistic

The Hosmer-Lemeshow test is another test for lack of fit. Hosmer-Lemeshow (2000) recommend partitioning the observations into *g* equal sized groups according to their predicted probabilities. Then the Hosmer-Lemeshow statistic is

$$c^2 = \sum_{i=1}^{g}\left(\frac{O_j - E_j}{E_j(1 - \frac{E_j}{n_j})}\right)^2$$

n_j = Number of observations in the jth group

$$O_j = \sum_{i}^{g} y_{ij} = Observed\ number of cases in\ the\ j^{th} group$$

$E_j = \sum_i^g \hat{\pi}_{ij} = Expected\ number\ of\ cases in the j^{th}$ and *g* is the number of groups.

If the observed number of events differs from what is expected, the statistic c^2 will be large and there will be evidence against the null hypothesis that the model is adequate to fit the data. Under the null hypothesis this statistic has an approximate chi-square distribution with (*g*-2) degrees of freedom. If the calculated value of the Hosmer-Lemeshow goodness-of-fit test statistic is greater than the value of 0.05, we will not reject the null hypothesis that there is no difference between observed and model-predicted values, implying that the model estimates are adequate to fit the data at an acceptable level (Hosmer-Lemeshow, 2000).

3.3.1.3.4 Wald test

The Wald test is the usual test for the significance of a single predictor and their null value in relation to their variance (estimated from the inverse of the observed in function). It is also an alternative test which is commonly used to test the significance of the individual logistic regression coefficients for each independent variable (that is, to test the null hypothesis in logistic regression that a particular logit (effect) coefficient is zero i.e. H_0: β_i=0 against$\beta_i \neq 0$).The Wald statistic (W) is

$$W = \frac{\hat{\beta_i}^2}{var(\hat{\beta}_i)}$$

For large sample size this statistic under the null hypothesis has an approximate chi-square distribution with one degree of freedom (Hosmer-Lemeshow, 2000).

3.3.1.3.5 The Lagrange multiplier or score test

As with the Wald test, the Lagrange multiplier test requires estimating only a single model. The difference is that with the Lagrange multiplier test, the model estimated does not include the parameter(s) of interest. If the MLE equals the hypothesized value, β_o, then β_o would maximize the likelihood and U(β_o) = 0. The score statistic measures how far from zero the score function is when evaluated at the null hypothesis. The test statistic for the binary outcome example is

$$S = \frac{U(\beta_o)^2}{I(\beta_o)}$$

The statistic S under the null hypothesis is approximately distributed as chi-square with one degree of freedom (Zhang, 1997).

3.3.1.4 Logistic Regression Diagnostics

After a model has been fit, it is wise to check the model to see how well it fits the data. In linear regression, these diagnostics were building around residuals and the residual sum of squares. Regression diagnostics are techniques for the detection and assessment of potential problems resulting from a fitted regression model that might either support, compromise, or negate the assumptions made about the regression model and/or the conclusions drawn from the analysis of one's data. There are two cases: residual analysis and the identification of influential cases (Menard,2002).

3.3.1.4.1 Logistic Regression Residuals

In logistic regression (and all generalized linear models), there are two kinds of residuals: Pearson residuals and deviance residuals. Pearson residuals are defined to be the standardized difference between the observed frequency and the predicted frequency. Deviance residual is another type of residual and it measures the disagreement between the maxima of the observed and the fitted log likelihood functions.

a. The Pearson residuals

The first kind is called the Pearson residuals, and is based on the idea of subtracting off the mean and dividing by the standard deviation. For a logistic regression model,

$$r_p = \frac{y_i - \hat{\pi}_i}{\sqrt{\hat{\pi}_i(1-\hat{\pi}_i)}}$$

wherey_i is the observed value of Y,$\hat{\pi}_i$ is the predicted or fitted value of Y for a given value of X_i. The Pearson residuals are directly related to the Pearson chi-square goodness-of-fit statistic. Note that, if we ignore the fact that $\hat{\pi}_i$ is an estimate based ony_i, then $r_p$has mean 0 and variance 1.

b. Deviance residuals

The second is the deviance residual for an observation, which is the contribution of the difference between the observed and predicted value for an observation to the total deviance. Deviance residuals can also be useful for identifying potential outliers or misspecified cases in the model. The deviance residual for the ith case is defined as the signed square root of the contribution of that case to the sum for the model deviance as:

$$dr_i = sign(Y_i - \hat{\pi}_i)\sqrt{[-2(Y_i ln(\hat{\pi}_i) + (1 - Y_i)ln(1 - \hat{\pi}_i))]}$$

The Pearson and deviance residuals approximately follow a normal distribution for larger sample sizes when the model is correct; residuals greater than about two indicate lack of fit (Agresti, 1996). When predictor variables are continuous and there is only a single value of Y for each combination of value of the predictor variables, then the large sample size condition will not hold and single residuals will be difficult to interpret. When the predictor variables are categorical and we have reasonable sample size for each combination of predictor variables, then residuals are easier to interpret and we will examine such residuals in the context of contingency tables.

3.3.1.4.2 Detecting Influential Observations

a. Leverage Values

Least squares estimates of parameters in regression models can be strongly influenced by an outlier, especially when the sample size is small. A variety of statistics summarize the influence each observation has. These statistics refer to how much the predicted values $\hat{\pi}_i$or the model parameter estimates change when the observation is removed from the data set. An observation's influence depends on two factors: (1) how far the response on y_i falls from the overall trend in the sample and (2) how far the values of the explanatory variables fall from their means.

The second factor on influence (how far the explanatory variables fall from their means) is summarized by the leverage of the observation. Leverage is a term used in connection with regression analysis and, in particular, in analyses aimed at identifying those observations which have a large effect on the outcome of fitting regression models. Leverage points are those observations, if any, made at extreme or outlying values of the independent variables such that the lack of neighboring observations means that the fitted regression model will pass close to that particular observation. Leverage values are given by the diagonal elements of the $n\times n$ matrix,

$$\hat{H} = \hat{W}^{1/2}X\left(X'\hat{W}X\right)^{-1}X'\hat{W}^{1/2}$$

The ith diagonal element of$\hat{H}$ is $\hat{h}_{ii.}$ In logistic regression it is called hat diagonal or Pregibon leverage and measures the leverage of an observation. More clearly leverage is a measure of the importance of an observation to the fit of the model. In the above, $\hat{W}$ is the $n\times n$ diagonal matrix with elements $\hat{\pi}_i\left(1-\hat{\pi}_i\right)$, X is the $n\times(k+1)$ design matrix and $\hat{\pi}$ is the nx1 vector of linear predictors (Pregibon, 1981).

b. Cook's Statistic

The Cook's distance statistic assesses the influence of individual cases and is a measure of the change in the regression coefficient if an observation is deleted from the model. Cook's distance considers the influence of the ith value on all n fitted values and not on the fitted value of the ith observation. It yields the shift in the estimated parameter from fitting a regression model when a particular observation is deleted. It is a combination measure of the impact of that observation on all regression coefficients. Cook's D_i statistic is defined as:

$$D_i = \frac{\left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)'(X'X)\left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)}{ps^2}$$

where $\widehat{\beta}_i$ is the estimated regression coefficients,$\hat{\beta}_{(i)}$ is the estimated regression coefficients by removing observation i and $s^2$is the mean square error (Belsley et al.,1980).

Computationally, D_i is more easily obtained as

$$D_i = \frac{r^2}{p}\left(\frac{\hat{h}_{ii}}{1-\hat{h}_{ii}}\right)$$

Where r_i is the studentized residual and $\hat{h}_{ii}$ is the ith diagonal element of $\widehat{H}$ computed from the full regression and p is the number of unknown parameters. Notice that D_i is large if the standardized residual is large and if the data point is far from the cancroids of the X-space that is, if $\widehat{h}_{ii}$ is large (Cook 1977).

c. Dfbetas

Most statistical software reports other diagnostics that depend on the studentized residuals and the leverages. For a given observation, Dfbeta summarizes the effect on the model parameter estimates of removing the observation from the data set.

The influential observations for the individual regression coefficients are identified by $Dfbetas_{j(i)}$, $j = 0, 1, 2, \ldots, p$, where each $Dfbetas_{j(i)}$ which measures the standardized change in estimated logistic regression coefficients $\hat{\beta}_j$ when the i^{th} observation is deleted from the analysis.

$$Dfbetas_{j(i)} = \frac{\beta_j - \beta_{j(i)}}{s_i\sqrt{c_{jj}}}$$

wherec_{jj} is the $(j + 1)^{st}$ diagonal element from $(X'X)^{-1}$. Dfbetasj(i) measures the change in $\hat{\beta}_j$ in multiples of its standard error. Although this looks like a t-statistic, it should not be interpreted as a test of significance. Values of Dfbetasj(i) greater than 2 would certainly indicate a major, but very unlikely, impact from a single point. The cutoff point of $2/\sqrt{n}$ is suggested as the point that will tend to highlight the same proportion of influential points across data sets (Belsley et al., 1980).

3.3.2 Multilevel Logistic Regression

3.3.2.1 The Two-Level Model

This introduction is taken from Snijders and Bosker (2011).

A multilevel logistic regression model also referred to as a hierarchical model, can account for lack of independence across levels of nested data (i.e., individuals nested within groups). Conventional logistic regression assumes that all experimental units are independent in the sense. Multilevel modeling relaxes this assumption and allows the effects of these variables to vary across groups. One way to do this uses a generalization of the model developed. We consider two level models for two level data structure: at single woman level and regional level. Assume that there are $j = 1, \ldots, N$ level 2 units and $i= 1, \ldots, n_j$ level 1 units are nested within each level 2 unit. The total number of level 1 observation across level 2 units is given by:

$$n = \sum_{j=1}^{N} n_j$$

Let the response variable for the ith individual in group j be coded as $Y_{ij}= 0$ for the response "desire to have more children";$Y_{ij}= 1$ for the responses "desire to limit child-bearing". We define the probability ofthe response equal to one as $\pi_{ij} = pr(y_{ij}= 1)$ and let π_{ij} be modeled using a logit link function. The standard assumption is that y_{ij} has a Bernoulli distribution. Then the two-level model can be written as:

$$\text{Log}\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_o + \beta_i x_i + U_j(\text{combined model}) \text{ ....(i)}$$

where $U_j$is the random effect at level two. Without U_j, equation (i) would be a standard logistic regression model. Model (i) is often described alternatively as:

$$\text{logit}\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{oj} + \beta_i x_i(\text{level 1 model}) \text{ ....(ii)}$$

and

$$\beta_{oj} = \beta_o + U_j \ \ (\text{level 2 model }) \text{..(iii)}$$

Relative to equations (ii) and (iii), equation (i) is the so-called combined model (Snijders and Bosker, 2011).

Multilevel models are statistical models, which allow not only independent variables at any level of a hierarchical structure, but also at least one random effect above level one. Multilevel models take account of the variability at each level of the hierarchy and thus allow the provider effects to be analyzed within the models. Thus, multilevel logistic regression analyses allow us to deal with the micro-level of individuals and the macro-level of groups or contexts simultaneously.

If one does not take explanatory variables into account, the probability of success is constant in each group. The success probability in group j is denoted by π_i. In a random coefficeint model, the groups are considered as being taken from a population of groups and success probabilities in the group,π_i are regarded as random variables defined in this population. The dichotomous outcome can be represented as the sum of this probability and a residual, $Y_{ij} = \pi_i + R_{ij}$ (refers to the empty model).

The outcome of individual *i* in group *j*, which is either 0 or 1, is expressed as the sum of the probability (average proportion of success) in this group plus some individual-dependent residual. This residual has (like all residuals) mean zero but for these dichotomous variables it has the peculiar property that it can assume only the values -$\pi_i$and 1-π_i. Further, given the value of the probabilityπ_i, the variance of the residual is var(Rij)= $\pi_i(1-\pi_i)$.Since the outcome variable is coded 0 and 1, the group average

$$\bar{Y}_{.j} = \frac{1}{n_j}\sum_{i=1}^{n_j} \mathrm{Y_{ij}}$$

is the proportion of successes in group *j*. This is an estimate for the group-dependent probabilityπ_i. Similarly, the overall proportion of success is

$$\hat{\pi}. = \bar{\mathrm{Y}}.. = \frac{1}{\mathrm{M}}\sum_{\mathrm{j=1}}^{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{n_j}} \mathrm{Y_{ij}}.$$

In the above equation M is total sample size (Snijders and Bosker, 2011).

3.3.2.2 Testing Heterogeneity of Proportions

To test whether there are indeed systematic differences between the groups, the well-known chi-squared test can be used. It can be written as

$$\chi^2 = \sum_{j=1}^{N} n_j \frac{(\bar{Y}_{.j} - \hat{\pi}_.)^2}{\hat{\pi}_.(1-\hat{\pi}_.)}$$

It can be tested with chi-squared distribution with N-1 degree of freedom. This chi-squared distribution is an approximation valid if the expected numbers of success and of failures in each group, $n_j\bar{Y}_{.j}$ and $n_j(1-\bar{Y}_{.j})$, respectively, all are at least one while 80 percent of them are at least 5 (Agresti, 1990).

Another test of heterogeneity of proportions was proposed by Commenges and Jacqmin (1994). The test statistic is

$$\mathrm{T} = \frac{\sum_{j=1}^{N}\{n_j{}^2(\bar{Y}_{.j} - \hat{\pi}.)^2\} - M\hat{\pi}.(1-\hat{\pi}.)}{\hat{\pi}.(1-\hat{\pi}.)\sqrt{2\sum \mathrm{n_j}(\mathrm{n_j}-1)}}$$

where M is total sample size. Large values of this statistic are an indication of heterogeneous proportions. The true variance between the group-dependent probabilities i.e. the population of $\mathrm{var}(\pi_j)$ can be estimated by

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

where $\tilde{n}$ is defined as $\tilde{n} = \frac{1}{N-1}\left\{M - \frac{\sum n_j{}^2}{M}\right\} = \bar{n} - \frac{s^2(n_j)}{N\bar{n}}$

For a dichotomous outcome variable, the observed between-group variance is closely related to the chi-squared test statistic. i.e.

$$S^2{}_{between} = \frac{\hat{\pi}.(1-\hat{\pi}.)}{\tilde{n}(N-1)}\chi^2$$

The within-groups variance in the dichotomous case is a function of the group average,

$$S^2{}_{within} = \frac{1}{MN}\sum_{j=1}^{N} n_j\bar{Y}_{.j}(1-\bar{Y}_{.j})$$

3.3.2.3 Types of Multilevel logistic regression models

It must be decided on two aspects, first including which predictors are to be included in the analysis, if any. Secondly, it must be decided whether parameter values (i.e., the elements that will be estimated) will be fixed or random. Fixed parameters are composed of a constant over all the groups, whereas a random parameter has a different value for each of the groups. Additionally, it must be decided whether to employ a maximum likelihood estimation or a restricted maximum likelihood estimation type (Long and Jeremy, 2006).

3.3.2.3.1 The empty model

The null or empty two level model is a model with only an interceptβ_0 and random intercepts U_{oj}

$$Logit\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta o + U_{oj}$$

The intercept $\beta o$is shared by all groups while the random effect U_{oj} is specific to group j. The random effect is assumed to follow a normal distribution with variance $\delta^2{}_{01}$ (Kreft and De Leeuw, 1998).

3.3.2.3.2 Random intercepts model

A random intercepts model is a model in which intercepts are allowed to vary, and therefore, the scores on the dependent variable for each individual observation are predicted by the intercept that varies across groups. This model assumes that slopes are fixed (the same across different contexts). In addition, this model provides information about intra class correlations, which are helpful in determining whether multilevel models are, required in the first place (Long and Jeremy, 2006).

The random intercept model expresses the log-odds, i.e. the log*it* of π_{ij}as a sum of a linearfunction of the explanatory variables. That is,

$$Logit(\pi_{ij}) = \beta oj + \sum_{h=1}^{k} \beta_h X_{hij}$$

where the intercept term $\beta oj$is assumed to vary randomly and is given by the sum of anaverage intercept $\beta o$and group-dependent deviations ,$U_o$that is

$$\beta oj = \beta o + U_{oj}$$

As a result

$$Logit(\pi_{ij}) = \beta o + \sum_{h=1}^{k} \beta_h X_{hij} + U_{oj}$$

Solving for π_{ij}

$$\pi_{ij} = \frac{e^{\beta o + \sum_{h=1}^{k} \beta_h X_{hij} + U_{oj}}}{1 + e^{\beta o + \sum_{h=1}^{k} \beta_h X_{hij} + U_{oj}}}$$

Thus, a unit difference between the $X_h$values of two individuals in the same group is associated with a difference of $\beta_h$in their log-odds, or equivalently, a ratio of exp (β_h)in their odds. The second equation does not include a level-one residual because it is an equation for the probability π_{ij} rather than for the outcome Y_{ij}. The level-one is already included in the first. Note that the first part of the right-hand side of, incorporating the regression coefficients $\beta o + \sum_{h=1}^{k} \beta_h X_{hij}$is the *fixed part* of the model, because the coefficients are *fixed.* The remaining part,U_{0j} , is called the random part of the model. It is assumed that the residual, U_{0j}, are mutually independent and normally distributed with mean zero and variance $\delta_o{}^2$ (Snijders and Bosker, 2011).

3.3.2.3.3 Random slope model

Notice that now the slope is also allowed to vary across regions. The slopes equation specifies that the slope coefficient is a linear combination of the average slope (β) and the regional effect (U).

The random intercept logistic regression model can be extended to a random slope model. Assume that there are k explanatory variables X_1 to X_k. Assume that the effect of the first one, X_1, is variable across groups, and accordingly has a random slope.

$$Logit(\pi_{ij}) = \beta o + \sum_{h=1}^{k} \beta_h X_{hij} + U_{oj} + U_{1j} X_{1ij}$$

Then there are two random group effects, the random intercepts $U_{oj}$and the slopeU_{1j}. It is assumed that both have a zero mean. Their variances are denoted by $\delta^2{}_0$, $\delta^2{}_1$ and their covariance is δ_{01}. The model for a single explanatory variable discussed above can be extended by including more variables that have random effects. Suppose that there are level-one explanatory variables X_1, X_2, …, X_k. We consider the model where all X-variables have varying slopes and a random intercept

$$Logit(\pi_{ij}) = \beta_{oj} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \cdots + \beta_{kj}X_{kij}.$$

by setting $\beta oj = \beta_0 + U_{oj}$ and $\beta hj = \beta_h + U_{hj}$, h= 1, 2, ..., k.

Then

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

The first part of equation$\boldsymbol{\beta_o} + \sum_{h=1}^{k} \boldsymbol{\beta_h X_{hij}}$ is called the fixed part of the model and the second part, $\boldsymbol{U_{oj}} + \sum_{h=1}^{k} \boldsymbol{U_{hj} X_{hij}}$, is called the random part.

3.3.2.4 Estimation and Testing Techniques for multilevel logistic model

Parameter estimation for multilevel logistic model is not straightforward like the methods for ordinary logistic regression. The most common methods for estimating multilevel logistic models are based on likelihood. Among the methods, Marginal Quasi Likelihood or MQL [Goldstein(1991), Goldstein and Rasbash (1996)] and Penalized Quasi Likelihood or PQL [Laird (1978) and Breslow and Clayton (1993)] are the two prevailing approximation procedures. Both MQL and PQL are based on Taylor series expansion to achieve the approximation. Based on the usage of first and second term of Taylor expansion, MQL and PQL are often known as first order MQL and second-order MQL respectively. After applying these quasi likelihood methods, the model is then estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) [Goldstein (2003)].Besides, there are other estimation methods: Maximum Likelihood Method (several simulation based; McCulloch (1997)), Bayesian methods using Markov Chain Monte Carlo (MCMC), adaptive Gaussian quadrature (AGQ) and the Iterative Bootstrap method. Using MCMC simulation technique has come to the forefront of statistical research over the last one and half decade [Gelfand et al. (1990)] and also it is being used with greater extent in multilevel modeling recently. An important part of modeling involves testing parameters and models to see which parts of the multilevel model are statistically important. For fixed coefficients of multilevel logistic regression tests about parameters are done using the Wald test. The random part of multilevel logistic regression parameters is estimated based on t-test or Z-test. Parameter estimation in hierarchical generalized linear models is more complicated than the hierarchical linear models. The most frequently used kind of approximation method used is based on a first-order or second-order Taylor series expansion of the link function(Snijders andBosker, 2011). There are different methods of parameter estimations which are implemented by various software packages such as, MLwiN, STATA and SAS. In this study, the multilevel data will be analyzed by the Stata and SAS software packages.

CHAPTER FOUR

STATISTICAL DATA ANALYSIS

4.1 Introduction

This chapter presents the analysis of the effect of different socio-economic, demographic and other proximate factors affecting women's intention to limit child-bearing in rural Ethiopia using the data from the 2011 Ethiopian Demographic and Health Survey. The response variable considered in this study is binary assuming two outcomes (0 = Want more children, 1 = desire to limit the number of children). Accordingly, in the first section results of descriptive statistics are presented; the second section presents the results of ordinary logistic regression obtained with the help of Statistical Package for Social Sciences (SPSS) version 20. Multilevel logistic regression methods are used to measure the effects of the determinants of limiting child-bearing by region using Stata and SAS software.

4.2 Summary of descriptive statistics

Table 4.1 Descriptive statistics of intention to limit child-bearing

Variables	Categories	Desire for more children				
		no more		more		Total
		count	percent	count	Percent	count
Age of women	15-29	955	14.8%	5483	85.2%	6438
	30-39	1158	41.1%	1658	58.9%	2816
	40-49	1117	69.4%	493	30.6%	1610
Region	Tigray	341	25.8%	979	74.2%	1320
	Affar	132	13.1%	876	86.9%	1008
	Amhara	664	38.0%	1084	62.0%	1748
	Oromia	569	33.0%	1155	67.0%	1724
	Somali	62	10.6%	521	89.4%	583
	Beni-Gumuz	333	32.1%	705	67.9%	1038
	SNNP	601	34.0%	1166	66.0%	1767

	Gembela	261	29.6%	620	70.4%	881
	Harari	133	30.9%	298	69.1%	431
	Dire Dawa	134	36.8%	230	63.2%	364
Educational level of women	No education	2402	35.0%	4466	65.0%	6868
	Primary	796	21.8%	2858	78.2%	3654
	Secondary and higher	32	9.4%	310	90.6%	342
Knowledge of FP methods	No	208	18.9%	892	81.1%	1100
	Yes	3022	31.0%	6742	69.0%	9764
Wealth index	Poor	2098	32.3%	4389	67.7%	6487
	Middle	935	26.5%	2596	73.5%	3531
	Rich	197	23.3%	649	76.7%	846
No. of living children	None	284	9.1%	2828	90.9%	3112
	1-3	833	21.7%	2999	78.3%	3832
	4 and more	2113	53.9%	1807	46.1%	3920
Visited by FP worker within the last12 months	No	2405	27.4%	6380	72.6%	8785
	Yes	825	39.7%	1254	60.3%	2079
Previous child death	No	2452	30.3%	5633	69.7%	8085
	Yes	778	28.0%	2001	72.0%	2779
Marital status	Never in union	237	10.7%	1982	89.3%	2219
	Currently in union	2408	31.9%	5137	68.1%	7545
	Widowed/separated	585	53.2%	515	46.8%	1100
Exposure to any media	No	1571	27.5%	4148	72.5%	5719
	Yes	1659	32.2%	3486	67.8%	5145
Religion	Coptic Orthodox	1271	33.4%	2538	66.6%	3809
	Protestant	721	31.6%	1559	68.4%	2280
	Muslim	1099	24.8%	3333	75.2%	4432

	Others	139	40.5%	204	59.5%	343
Current use of any methods of FP	No	2575	27.6%	6739	72.4%	9314
	Yes	655	42.3%	895	57.7%	1550
Occupation of women	Not working	1642	30.2%	3787	69.8%	5429
	Agricultural	885	29.5%	2116	70.5%	3001
	Non-agricultural	703	29.9%	1731	71.1%	2434

The following discussion is based on the results provided in Table 4.1.

Out of a total of 10,864 interviewed women 3,230 (29.7 percent) intended to limit child-bearing while 7,634 (70.3 percent) did not intend to limit child-bearing at the time of the survey.

More than half of the women with intention to limit child-bearing are older ages (40-49) 69.4 percent whereas only 30.6 percent did not want to limit child-bearing followed by the age 30-39 (41.1 percent), and the lowest percentage (14.8 percent) with intention to limit child-bearing was observed in the age group 15-29.

Women who lived in different regions also had different levels of desire to limit children. The lowest proportion of desire to limit child-bearing was observed in Somali region (10.6 percent) followed by Affar (13.1 percent).The highest was observed in Amhara region (38.0 percent) followed by Dire Dawa (36.8 percent).

The results based on education showed that 35 percent of women with no formal education had desire to limit child-bearing. Women with secondary and higher education who did not want any more children were only 9.4 percent. The uneducated or less educated women, who wanted to limit child-bearing, might already have many children than the educated. Thus the effect of education might diminish when analysis is done based on their number of living children.

Most women, that is 9,764 (89.9 percent of the total), knew some form of family planning methods. About 69 percent of the women with knowledge of family planning methods wanted more children and about 31 percent wanted to limit child-bearing. It is believed that exposure to any kind of mass media like radio, TV and newspapers and magazines would enhance intention to limit child-bearing. Women who were exposed to any kind of mass media (32.2 percent) were found to have desire to limit child-bearing than those who were not (27.5 percent).

Some 39.7 percent of the rural women who had been visited by family planning workers during the last 12 months before the survey and only 27.4 percent of those who had not been visited by family planning workers were intending to limit child-bearing. Of those women who had used any family planning methods, 42.3 percent had the desire to limit child-bearing; only 27.6 percent of those women did not use any methods desire to limit child-bearing.

Wealth index also showed effect on the status of desire to limit child-bearing. Around 32.3 percent of the poor, 26.5 percent of the middle level and 23.3 percent of rich women intended to limit child-bearing. About 30.2 percent of women who did not have work wanted to limit child-bearing; women who were employed in agriculture intended to limit children (29.5 percent) and 29.9 percent of non-agricultural employed showed desire to limit children.

The number of living children is a variable that is strongly associated with the desire to limit child-bearing. Women with a large number of living children wanted to limit child-bearing (53.9 percent). Women with 1-3 children showed a desire to limiting child-bearing (21.7 percent), and women with no children had lower intention to limit child-bearing (9.1 percent).

Among rural women who never lost a single child, 30.3 percent wanted to limit child-bearing; about 28.0 percent of women who lost a child showed less intention to limit child-bearing in rural area of Ethiopia.

The highest percentage intentions to limit child-bearing were observed among women living with a partner or were married (53.2 percent); the lowest percentage of intention to limit child-bearing was observed among not married women (10.7 percent).

With regards to religion, the intention to limit child-bearing of women was highest for the category "others" (traditional, catholic and others) (40.5 percent) followed by (33.4 percent) of Coptic orthodox. The lowest intention to limit child-bearing (24.8 percent) of women was recorded for followers of Muslim religions. However, we observe that absolute number of women in this category ("others") was 343, which is very insignificant compared to the three other religions groups.

4.3 Results based on Ordinary Logistic Regression Analysis

The logistic regression model was used to identify factors influencing the desire to limit child-bearing. The regression results revealed that predictors of the desire to limit child-bearing in rural Ethiopia were age of a woman, religion of a woman, educational level of women, residence of region, number of living children, marital status, status of wealth, exposure to mass media, experience of child death, and visits by FP worker during the last 12 months. Current use of any contraceptive methods and knowledge of family planning were also found to be significant. Results of the logistic regression are presented in Table 4.2. The model building procedure used was the ENTER method. The reference categories of all variables (except the variable education of women) are set by SPSS as the last category.

We would like to point out that the discussion of the logistic regression analysis assumed that a result about a factor /variable is given by controlling the effects of the remaining predictors (actors/variables) in the model.

The model revealed that the likelihood of intention to limit child-bearing of women was lowest for age group 15-29 compared to the age group 40-49 (OR= 0.124; 95% CI: 0.104-0.147). Also, women in the age group 30-39 were 73.6 percent less likely to limit child-bearing as compared to women in the reference age group 40-49 (OR= 0.264; 95% CI: 0.227-0.306).

While making comparisons based on regions we have left out Somali and Affar because of the relative low absolute figures of women intending to limit child-bearing. The odds of intention to limit child-bearing compared to those who do not intend to limit decreased by factor 0.191women who lived in Tigray (OR= 0.191; 95% CI: 0.138-0.264); 0.450 women who lived in

Beni-Gumuz were times less likely intend to limit child-bearing than women in Dire-Dawa region (OR= 0.450; 95%CI: 0.337-0.600). Women who lived in Amhara and Gambela regions were 54.9 percent and 52.8 percent less likely intended to limit child-bearing when compared to the reference Dire- Dawa with (OR= 0.451; 95% CI:0.339-0.601) and (OR= 0.472; 95% CI:0.339-0.657), respectively.

Women with secondary and higher education were 45.8 percent less likely to have a desire to limit child-bearing compared to women with no formal education (OR= 0.542; 95% CI: 0.362-0.812); women who had primary education had almost the same level of intention to limit child-bearing compared to the reference women with no formal education (OR=1.06595% CI: 0.936-1.212).

Women who were not exposed to any kind of media were 13.3 percent less likely to have an intention to limit child-bearing compared to women who were exposed to any media (reference category) (OR=0.867; 95% CI: 0.779-0.965). Women who were not visited by FP worker during the past 12 months before the survey were 0.746 times less likely to want to limit child-bearing compared to women who were visited by FP worker during the past 12 months before the survey (OR=0.746; 95% CI: 0.659-0.845).

Intending to limit child-bearing was found to be associated significantly with religion. Women who were followers of the Muslim religion were 0.615 times less likely to have a desire to limit child-bearing than the followers of protestant (reference category) (OR=0.615; 95% CI: 0.530-0.715).Coptic orthodox followers were 1.334 times more likely to have a desire to limit child-bearing than the followers of protestant religion (OR=1.334; 95% CI: 1.130-1.576).

Women who were married at the time of the survey were 0.260 times less likely to desire limiting child-bearing than women who were widowed/separated (OR=0.260; 95% CI: 0.220-0.307).

The desire to limit child-bearing also varied with wealth status of women. Women whose economic status was poor were39.8 percent times more likely to want to limit child-bearing than women in the rich economic status. Those in middle economic status have almost the same level of intention to want to limit child-bearing as women in rich economic status (OR=1.398; 95%

Table 4.2 Estimates from the logistic regression analysis for factors associated with women's desire to limit child-bearing, rural Ethiopia

Covariates	$\widehat{\beta}$	S.E($\widehat{\beta}$)	Wald	d.f.	P-value	$\widehat{OR}$	95% C.I. for OR	
							Lower	Upper
Age of women			576.798	2	.000			
15-29	-2.088	.088	566.063	1	.000	.124	.104	.147
30-39	-1.333	.075	312.217	1	.000	.264	.227	.306
40-49 (ref)								
Region			186.142	7	.000			
Tigray	-1.654	.165	100.191	1	.000	.191	.138	.264
Amhara	-.796	.146	29.714	1	.000	.451	.339	.601
Oromiya	-.365	.147	6.185	1	.013	.694	.521	.926
SNNP	-.311	.154	4.091	1	.043	.733	.542	.990
Beni-Gumuz	-.799	.147	29.589	1	.000	.450	.337	.600
Gambela	-.750	.168	19.867	1	.000	.472	.339	.657
Harari	-234	.179	1.710	1	.191	.791	.557	1.124
Dire-Dawa (ref)								
Education of women			11.399	2	.003			
No education (ref)								
Primary	.063	.066	.913	1	.339	1.065	.936	1.212
Secondary and above	-.612	.207	8.750	1	.003	.542	.362	.814
Religion			124.431	2	.000			
Coptic orthodox	.288	.085	11.564	1	.001	1.334	1.130	1.576
Muslim	-.486	.077	40.274	1	.000	.615	.530	.715
Protestant (ref)								
Wealth index			27.609	2	.000			

Poor	.335	.105	10.283	1	.001	1.398	1.139	1.716
Middle	.064	.114	.316	1	.574	1.066	.852	1.334
Rich (ref)								
Number of living children			456.632	2	.000			
None	-2.696	.146	340.908	1	.000	.067	.051	.090
1-3	-1.141	.068	282.959	1	.000	.320	.280	.365
4 and more (ref)								
Knowledge of family planning								
No	-.493	.098	25.413	1	.000	.611	.504	.740
Yes (ref)								
Use of family planning								
No	-.478	.071	45.284	1	.000	.620	.539	.713
Yes (ref)								
Media exposure								
No	-.143	.055	6.803	1	.009	.867	.779	.965
Yes (ref)								
Any death of children								
No	1.054	.063	276.657	1	.000	2.870	2.535	3.250
Yes (ref)								
Marital status			265.685	2	.000			
Never in union	-.234	.152	2.372	1	.124	.791	.587	1.066
Married	-1.347	.085	252.662	1	.000	.260	.220	.307
Widowed/separated (ref)								
Visited by FP worker								
No	-.293	.063	21.302	1	.000	.746	.659	.845
Yes (ref)								
Occupation of women			3.580	2	.167			
Not working	.121	.065	3.433	1	.064	1.128	.993	1.281

Agricultural	.062	.073	.725	1	.395	1.064	.922	1.228
Non-agricultural (ref)								
Constant	2.478	.297	69.636	1	.000	11.918		

* Statistically Significant at ($p<0.05$) ref. = reference category

CI: 1.139-1.716) and (OR=1.066; 95% CI: 0.852-1.334), respectively.

Women who were not working were more likely to want to limit child-bearing than the reference category women who were working in non-agriculture. Women working in agriculture had the same level of intention to limit child-bearing with women who were working in non-agriculture (OR=1.128; 95% CI: 0.993-1.281) and OR=1.064; 95% CI: 0.922-1.228), respectively.

Women with no children were 93.3 percent less likely to want to limit child-bearing as compared to women with four or more children (OR=0.067; 95% CI: 0.051-.090) and the odds of intention to limit for women with 1-3 children was 68.0 percent less likely compared to the odds for those women with four or more children (OR= 0.320; 95% CI: 0.280-0.365).

With regards to child mortality, it was observed that those women who never lost a child were 2.870 times more likely to intend to limit child-bearing as compared to those who lost child (OR= 2.870; 95% CI: 2.535-3.250).

Women who had no knowledge about family planning were 39 percent less likely to want to limit child-bearing than women who had knowledge about family planning (OR= 0.610; 95% CI: 0.504-0.740). The odds of intention to limit child-bearing among women who have never used any family planning methods was 38 percent less likely than the odds of intention to limit child-bearing among women who had used family planning (OR= 0.620; 95% CI: 0.539-0.713).

The Wald chi-square statistic tests the unique contribution of each predictor, holding the other predictors constant, that is, eliminating any overlap between predictors. Each predictor (except occupation of women) must meet the conventional 0.05 standard for statistical significance at this stage.

4.4 Goodness of Fit and Model Diagnostics

4.4.1 Goodness of Fit

In order to check the goodness-of-fit of an estimated multiple logistic regression model one should assume that the model contains those variables that should be in the model and have been entered in the correct functional form. The goodness-of-fit measures how effectively the model describes the response variable. The most common assessment of overall model fit in logistic regression are the likelihood ratio test, Hosmer-Lemeshow and score test of fit (Long, 1997).

The likelihood ratio test is simply the chi-square difference between the null model (i.e., with the constant only) and the model containing the predictors. Under model summary in Table 4.3 we see that the -2Log Likelihood statistics is 9671.731. This statistic measures how poorly the model predicts the use of intention to limit children. The smaller the statistic the better the model. SPSS does not give this statistic for the model that has only the intercept; we know it to be (9671.731+3551.272 =13223.003). When we add predictors' value of the -2 Log Likelihood statistic became smaller by 13223.003 – 9671.731= 3551.272, which is the statistic for omnibus test. If the model with the predictors is significantly different from the model with only the intercept we use the omnibus test of model coefficients test. The difference of these two yields a chi-square statistic which is a measure of how well factors /predictor variables affect the outcome variable. The value of χ^2=3551.272 with d.f= 26, p-value < 0.001, shows that there is adequate fit of the data to the model, meaning that at least one of the predictors is significantly related to the response variable. This means the null hypothesis that there is no difference between the model with only a constant and model with predictor variables was rejected (see Table 4.3).

Table 4.3 Omnibus Tests of Model Coefficients and Model summary

Omnibus Tests of Model Coefficients

		Chi-square	d.f.	Sig.
	Step	3551.272	26	.000
Step 1	Block	3551.272	26	.000
	Model	3551.272	26	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9671.731[a]	.279	.396

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

The Hosmer-Lemeshow statistic measures the goodness-of-fit by creating 10 ordered groups of subjects and then compares the number actually in each group (observed) to the number predicted by the logistic regression model (predicted). Thus, the test statistic is a chi-square statistic with a desirable outcome of non-significance, indicating that the model prediction does not significantly differ from the observed. The p-value of Hosmer-Lemeshow test is 0.086 showing that we fail to reject the null hypothesis that there is no difference between observed and predicted values, implying that the model adequately fits the data at a 0.05 level of significance (see Table 4.4).

Table 4.4 Hosmer-Lemeshow Test

Hosmer-Lemeshow Test

Step	Chi-square	df	Sig.
1	13.844	8	.086

Contingency Table for Hosmer-Lemeshow Test

		Desire for more children = want more children		Desire for more children = Desire to limit		Total
		Observed	Expected	Observed	Expected	
Step 1	1	1046	1052.480	40	33.520	1086
	2	1000	1016.483	86	69.517	1086
	3	985	984.611	101	101.389	1086
	4	941	944.608	140	136.392	1081
	5	901	904.356	184	180.644	1085
	6	860	837.537	224	246.463	1084
	7	759	727.841	329	360.159	1088
	8	582	582.653	503	502.347	1085
	9	387	397.649	699	688.351	1086
	10	173	185.783	924	911.217	1097

The score test is used to estimate the improvement in model fit if additional variables were included in the model. The test statistic is the expected change in the chi-squared statistic for the model if a variable or set of variables is added to the model. Because it tests for improvement of model fit if variables that are currently omitted are added to the model. The score test is sometimes also referred to as a test for omitted variables. Score test measures how much -2LL would drop if a single variable were added to the model with intercept only (Pampel, 2000).

We can see from Table 4.5 that each of the predictors would be statistically significant except for occupation of women, that is, including all predictors except occupation of women in the model would create a statistically significant improvement in model fit.

The p-value is below the typical cutoff of 0.05, suggesting that including all variables except 'occupation of women' in the model would create a statistically significant improvement in model fit (see Table 4.5).

Table 4.5 Variables not in the equation

Variables		Score	Df	Sig.
Variables	age	2070.199	2	.000
	age(1)	1678.713	1	.000
	age(2)	236.090	1	.000
	region	33.734	7	.000
	region(1)	10.927	1	.001
	region(2)	1.273	1	.259
	region(3)	10.510	1	.001
	region(4)	3.039	1	.082
	region(5)	3.309	1	.069
	region(6)	.005	1	.943
	region(7)	.273	1	.601
	education	268.764	2	.000
	education(1)	245.645	1	.000
	education(2)	166.434	1	.000
	religion	64.846	2	.000
	religion(1)	35.326	1	.000
	religion(2)	63.526	1	.026
	wealth	55.848	2	.000
	wealth(1)	52.516	1	.000
	wealth(2)	26.472	1	.000
	Numberof	1845.935	2	.000
	Numberof(1)	886.332	1	.000

Numberof(2)	181.053	1	.000
Knowledge of(1)	68.613	1	.000
Currentuse(1)	135.798	1	.000
media(1)	29.560	1	.000
Anychildren(1)	5.384	1	.020
Maritalstatus	692.260	2	.000
Maritalstatus(1)	484.429	1	.000
Maritalstatus(2)	56.384	1	.000
Visitedby(1)	121.868	1	.000
work	1.609	2	.447
work(1)	1.371	1	.242
work(2)	.115	1	.734
Overall Statistics	3279.990	26	.000

The classification table is another method to evaluate the predictive accuracy of a logistic regression model. In a classification table the observed values for the dependent outcome and the predicted values (at a user defined cut-off value, for example p=0.50) are cross-classified. The independent variables could be characterized as useful predictors distinguishing observation respondents who wanted no more children from observation respondents who wanted more children if the classification accuracy rate was substantially higher than the accuracy attainable by chance alone. Operationally, the classification accuracy rate should be 25percent or higher than the proportional by chance accuracy rate (Bayaga, 2010).

Table 4.6 Classification table for block zero

Classification Table[a,b]

Observed			Predicted		
			Desire for more children		Percentage Correct
			want more children	Desire to limit	
Step 0	Desire for more children	want more children	7634	0	100.0
		Desire to limit	3230	0	.0
	Overall Percentage				70.3

a. Constant is included in the model.
b. The cut value is .500

The proportional by chance accuracy rate is a proportional chance criterion that uses as a standard for assessing model's accuracy rate. Even if the predictor variables had no relationship to the dependent variable, it would be expected to be correct in the predictions of group membership some percentage of the time (Chan, 2005). The proportional by chance accuracy rate was computed by first calculating the proportion of cases for each group based on the number of cases in each group in the classification table at Step 0 which includes no predictors and just the intercept. The proportion in the "want no more" group is 3,230/10,864 = 0.2973. The proportion in the "want more children" group is 7,634/10,864 = 0.7027. The proportional by chance accuracy rate is $0.2973^2 + 0.7027^2 = 0.5822$.

Table 4.7 Classification table for block one

Classification Table[a]

Observed			Predicted		
			Desire for more children		Percentage Correct
			want more children	Desire to limit	
Step 1	Desire for more children	want more children	6955	679	91.1
		Desire to limit	1465	1765	54.6
	Overall Percentage				80.3

a. The cut value is .500

The accuracy rate computed by SPSS was 80.3percent which was greater than the proportional by chance accuracy criteria of 72.7percent (1.25 x 58.2% = 72.7%).

The classification table (Table 4.7) given above shows that of 10,864 women included in the analysis 80.3percent were correctly classified providing evidence that the model fits the data well.

4.4.2 Diagnostic checking: checking for outliers and influential values

An outlier is an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism. An observation is influential if it is individually or together with several other observations, has a demonstrably larger impact on the calculated values of various estimates than is the case for most of the other observations (Belsleyet al, 1980). In logistic regression outliers may occur as alteration (misclassification) between the binary (1, 0) responses. Misclassification may refer to points which are on the wrong side of the hyperplane/classifier (Scholkopfand Smola, 2002).

Detection of outliers and influential cases and taking a corresponding treatment is a very crucial task of any modeling exercise. Failure to detect outliers and hence influential cases can have severe distortion on the validity of the inferences drawn from such modeling exercise.

The diagnostic test results for detection of outliers and influential values are presented in Appendix 1.2. The Dfbetas for model parameters including the constant term and Cook's influence statistic were both less than unity. Dfbetas less than unity imply no specific impact of an observation on the coefficient of a particular predictor variable, while a Cook's distance less than unity shows that an observation has no overall impact on the estimated vector of regression coefficients β. A value of the leverage statistic less than one shows that no subject has a substantial large impact on the predicted values of model. Thus, from the above goodness of fit tests and diagnostic checking, we can say that our model is adequate (Belsley et al., 1980).

4.5 Results of Multilevel Logistic Regression Analysis

For multilevel analysis involving two levels (e.g. women nested within region), the model can be conceptualized as a two-stage system of equations in which the variation of limiting child-bearing among women within each region is explained by a woman level equation, and the variation across region in the region-specific regression coefficients is explained by a region-level equation.

A chi-square test statistic was applied to assess heterogeneity in the proportion of women who had intention to limit children among the rural regions of Ethiopia. The test yield χ^2= 378.290. Thus, there is evidence of heterogeneity between regions with respect to intention to limit child-bearing of women.

4.5.1 The Empty Logistic Regression Model

We first fit a simple model with no predictors i.e. an intercept-only model that predicts the probability of intention to limit child-bearing. That is a random intercept or variance components model that allows the overall probability of intention to limit child-bearing to vary across the regions.

From the model estimate for β_0 for a region with U_{oj}= 0 is $\hat{\beta}_0$= -0.986. This estimating of the intercept provides information that the average probability ofintention to limit child-bearing in rural area is exp(-0.986)/ [1+exp(-0.986)] = 0.2717. Then for region j we have -0.986+U_{oj}, where the variance of U_{oj} is estimated as $\hat{\delta}^2{}_{u0}$= 0.521 revealing that there is a significant difference in intention to limit child-bearing across regions (Somali and Affar left out) (see Table 4.8). This implies that multilevel modeling is appropriate.

The deviance-based chi-square (deviance = 329.09) indicated in Table 4.8 is the difference -2LL in deviance between an empty model without random effect and an empty model with random effect. This implies that an empty model with random intercept is better than an empty model without random intercept.

The residual intra-class correlation or ICC is the correlation between two individuals who are in the same higher level unit. The computed ICC= 0.0861 shows that 8.61 percent of the variation in the intention to limit child-bearing can be explained by region (level two). The remaining

(100-8.61= 91.9 percent) of the variation of intention to limit child-bearing is explained within the same region.

Table 4.8 Results of empty random intercept Logistic regression model analysis

Fixed part	**Coefficient.**	**S.E.**	**Z-value**	**P-value**	**[95% Conf. Interval]**	
β_0 = intercept	-.9858039	.1667186	-5.91	0.000	-1.312566	-.6590415

Random-part	**Estimate**	**Std. Err.**	**Z-value**	**P-value**
Level-two variance, $\delta^2{}_0$=var(U_{oj})	.5205567	.121401	4.288	0.001
Deviance-based chi-square	329.09			0.000

4.5.2 The Random Intercept Model

Here we analyze a model with all lower level explanatory variables fixed. This means that the corresponding variance components of the slopes are fixed at zero. All variables except education of women (no education), religion (Muslim), marital status (married) and occupation of women (not working) were found to have a significant effect of variation in intention to limit child-bearing in all regions with respect to the corresponding reference categories (see Table 4.9).The results of two-level random intercept model presented in Table 4.9 show that the deviance based chi-square test for significance of random effects (χ^2=325.36, *df*=1, P<0.05) is reduced; this is an indication of that the model fits better than the previous model.

The variance of random intercept is estimated at 0.423; this is due to the inclusion of fixed predictor variables indicating that the additional predictors did not increase the percentage of variance explained by the model. Therefore, the model shown in Table 4.9 should be selected as it is the more parsimonious than the empty logistic regression model. The results of estimate coefficient of random intercept model and random coefficients are similar to the interpretation in the ordinary logistic regression of Section 4.3.

Table 4.9 Results of random intercept and fixed coefficient logistic regression model

l effects	Estimate					
ıriate	Coefficient	S.E.	Z-value	P-value	[95% Conf. Interval]	
Age of women						
15-29	.7175397	.0713768	10.05	0.000	.5776438	.8574356
30-39	2.0693	.0892281	23.19	0.000	1.894416	2.244184
40-49(ref)						
Education of Women						
No education	.036286	.066194	0.55	0.584	-.093452	.1660239
Primary	-.550234	.2065048	-2.66	0.008	-.954976	-.145492
condary and +(ref)						
Religion						
Coptic orthodox	-.7514086	.0719684	-10.44	0.000	-.892464	-.6103532
Muslim	-.2754712	.0846004	-3.26	0.001	-.4412849	-.1096575
Protestant (ref)						
Wealth index						
Poor	-.1323214	.0618608	-2.14	0.032	-.2535665	-.0110764
Middle	-.2404195	.1053156	-2.28	0.022	-.4468343	-.0340047
Rich(ref)						
lumber of living children						
0	1.565296	.136623	11.46	0.000	1.297519	1.833072
1-3	2.777635	.1467199	18.93	0.000	2.490069	3.0652
4+(ref)						
owledge about FP						
No	.2878815	.1004253	2.87	0.004	.0910515	.4847115
Yes(ref)						

of family planning						
No	.4173939	.0716307	5.83	0.000	.2770003	.5577875
Yes(ref)						
lia exposure						
No	.1314136	.0552017	2.38	0.017	.0232202	.239607
Yes(ref)						
death of children						
No	-1.070416	.0644502	-16.61	0.000	-1.196736	-.9440961
Yes(ref)						
ital status						
:r in union	-1.094243	.1496438	-7.31	0.000	-1.387539	-.8009462
ied	.2342075	.1525438	1.54	0.125	-.0647729	.5331879
owed						
arated(ref)						
ted by FP worker						
No	.2240519	.0641807	3.49	0.000	.0982601	.3498438
Yes(ref)						
upation of women						
Not working	-.0460879	.0610828	-0.75	0.451	-.1658081	.0736323
Agricultural	-.1610138	.0658635	-2.44	0.014	-.2901038	-.0319238
n-agricultural(ref)						
Constant	-2.438153	.2509097	-9.72	0.000	-2.929927	-1.946379
Random Part	**Estimate Variance Component**	**S.E.**		**Z-value**	**P-value**	
Random rcept:$\delta^2{}_0$=var(U_{oj})	**.4233538**	**.1969515**		**2.149**	**0.032**	
Deviance-based chi-square	**325.36**			**0.000**		

4.5.3 Random Coefficients

This section provides information about the variability of intention to limit child-bearing among regions, taking into consideration the estimated coefficients. We find out that the effect of number of living children, current use of FP, media exposure and being visited by FP workers vary across regions. So, we need to include random coefficients to the model containing number of living children, current use of FP, media exposure and being visited by FP workers to vary randomly across regions. Based on the results in Table 4.10 it can be concluded that although the fixed part of the random coefficients are significant there is a large uncertainty about the variance of random parts.

Table 4.10 Results for Fixed and Random Effects of Random Coefficient Model

:d effects ariates	Estimate Coefficient	S.E.	Z-value	P-value	[95% Conf. Interval]	
Age of women						
15-29	.7268753	.0715981	10.15	0.000	.5865456	.867205
30-39	2.08301	.0895935	23.25	0.000	1.90741	2.25861
40-49(ref)						
Education of Women						
No education	.040087	.0663911	0.60	0.546	-.0900372	.1702112
Primary	-.5263264	.2064841	-2.55	0.011	-.9310277	-.121625
condary and +(ref)						
Religion						
Coptic orthodox	-.1770092	.0970581	-1.82	0.068	-.3672396	.0132212
Muslim	.0713672	.1586927	0.450	.653	-.2396649	.3823992
Protestant(ref)						

Wealth index						
Poor	-.1104355	.0622494	-1.77	0.076	-.2324421	.011571
Middle	-.2557662	.1056282	-2.42	0.015	-.4627938	-.0487386
Rich(ref)						
umber of living children						
0	1.587104	.1376412	11.53	0.000	1.317333	1.856876
1-3	2.812961	.1479974	19.01	0.000	2.522892	3.103031
4+(ref)						
owledge about FP						
No	.2481655	.1011803	2.45	0 .014	.0498558	.4464751
Yes(ref)						
Use of family planning						
No	.6696582	.209211	3.20	0.001	.2596123	1.079704
Yes(ref)						
dia exposure						
No	.1437524	.0554316	2.59	0.010	.0351084	.2523963
Yes(ref)						
death of dren						
No	-1.076499	.064644	-16.65	0.000	-1.203199	-.9497993
Yes(ref)						
rital status						
er in union	-1.109264	.1506582	-7.360	.000	-1.404549	-.8139794
ried	.2224802	.1530745	1.45	0.146	-.0775404	.5225007
lowed						
arated(ref)						

ted by FP worker						
	.3583604	.123987	2.89	0.004	.1153504	.6013704
ref)						
upation of						
ıen						
working	-.0472824	.0612622	-0.77	0.440	-.1673542	.0727893
.cultural	-.1583281	.0660396	-2.40	0.017	-.2877634	-.0288928
-agricultural(ref)						
stant	-2.490773	.2646522	-9.41	0.000	-3.009482	-1.972064
)eviance-based chi-square	**348.65**	**0.0000**				

ındom Part	**Coefficient**	**S.E.**	**Z-value**	**P-value**
$^{2}{}_{0}=\mathrm{var}(U_{oj})$	.5488397	.2510176	2.186	0.028*
$^{2}{}_{1}=\mathrm{var}(U_{1j})$	.2302183	.1161744	1.982	0.047*
$^{2}{}_{2}=\mathrm{var}(U_{2j})$	.3415622	.2694778	1.268	0.206
$^{2}{}_{3}=\mathrm{var}(U_{3j})$	.0100119	.0089538	1.124	0.258
$^{2}{}_{4}=\mathrm{var}(U_{4j})$	.1038323	.0916692	1.133	0.250
$^{2}{}_{01}=\mathrm{cov}(U_{oj,}U_{1j})$	-.1481443	.1181134	-1.254	0.209
$^{2}{}_{02}=\mathrm{cov}(U_{oj,}U_{2j})$	-.3159409	.2074782	-1.522	0.128
$^{2}{}_{03}=\mathrm{cov}(U_{oj,}U_{3j})$	-.0627359	.0277311	-2.263	0.023*
$^{2}{}_{04}=\mathrm{cov}(U_{oj,}U_{4j})$	.0485594	.0712069	0.682	0.494
$^{2}{}_{12}=\mathrm{cov}(U_{1j,}U_{2j})$	-.1092356	.0946522	1.154	0.250
$^{2}{}_{13}=\mathrm{cov}(U_{1j,}U_{3j})$	-.0175383	.0290591	0.742	0.515
$^{2}{}_{14}=\mathrm{cov}(U_{1j,}U_{4j})$	-.1296805	.0800627	-1.621	0.128
$^{2}{}_{23}=\mathrm{cov}(U_{2j,}U_{3j})$	.0220243	.0244806	0.899	0.373
$^{2}{}_{24}=\mathrm{cov}(U_{2j,}U_{4j})$	.1882359	.1432247	1.314	0.183

$^2{}_{34}$=cov($U_{3j,}U_{4j}$)	.0137496	.0176246	0.780	0.435

* Statistically Significant at (p<0.05)

In Table 4.10 above, the value of Var (U_{0j}), Var (U_{1j}), Var (U_{2j}), Var (U_{3j}) and Var (U_{4j}) are the estimated variance of intercept, slope of number living of children, slope of use of family planning, slope of media exposure and slope of visited by FP worker in the last 12 months respectively. The overall variance constant term is found to be statistically significant. Also, we observed that the random effect of the slope of number of living children vary significantly at 0.05 levels of significance across regions. Using FP methods, exposure to any media and women who were visited by FP workers have no almost variation across the regions (i.e. not significant at the level of 0.05) (see Table 4.10).

The correlation matrix contains the estimated correlations between random intercepts and slopes (see Table 4.11). The correlation between the intercept and random slope of visited by FP workers is 0.2034, meaning that women who were visited by FP workers within 12 monthsbefore the survey had the intention to limit child-bearing than those who did not by a larger factor at regions with higher intercepts compared to regions with lower intercepts. The negative sign for the correlation between intercepts and slopes implies that regions with higher intercepts tend to have on average lower slopes on the corresponding predictors. Women who had access to use any family planning methods through mass media and who had been visited by FP worker were more likely to desire to limit number of children.

Table 4.11 the correlation matrix of the random coefficients

	Intercept	No of living children	Use of FP	Media	Visited by FPW
ept	1.000				
living children	-0.4167	1.000			
f FP	-0.7297	-0.3901	1.000		
a	-0.8469	-0.3656	0.4330	1.000	
d by FPW	0.2034	-0.8389	0.9991	0.4270	1.000

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to select parsimonious statistical models. In a model selection application, the optimal fitted model is identified by the minimum value of AIC and BIC. The lower the AIC/BIC value the better the model. The number of classes is increased until the AIC and BIC minimum are found (Hurvich and Tsai, 1989).The AIC value of random intercept and fixed coefficient is smaller than that of empty model with random intercept (AIC=9571.541<12900.47). Additionally, BIC for random intercept and fixed coefficient is less than that of empty model (BIC=9731.991<12915.06), implying that a random intercept and fixed slope model performed better than the empty model with random intercept in predicting intention to limit child-bearing in a region. Similarly, for a random intercept and fixed coefficient (AIC=9571.541 and BIC= 9731.991) and for the random coefficients model (AIC= 9484.219) and (BIC= 9681.135) showed that the random coefficient model is better compared to a random intercept and fixed coefficient (see Table 4.12).

Table 4.12 Multilevel logistic regression model Selection Criteria

Model selection Criteria	**Multilevel empty model**	**Multilevel random intercept model**	**Multilevel random Coefficient model**
Deviance based			
chi-squared	329.09	325.36	348.65
Log LL	-6448.235	-4763.770	-4715.109
AIC	12900.47	9571.541	9484.219
BIC	12915.06	9731.991	9681.135

CHAPTER FIVE

DISCUSSION, CONCLUSION AND RECOMANDTIONS

5.1 Discussion and Conclusion

In order to reduce unrestrained population growth in Ethiopia and associated problems with it, it is important to study the effects of influential factors to limit child-bearing. Accordingly, this study attempted to examine factors that influence women's intention to limit child-bearing in rural Ethiopia, using data from the 2011 Ethiopian DHS. For that purpose descriptive analysis, binary logistic regression and multilevel logistic regression techniques were used. The results of the analysis are discussed as follows.

The descriptive analysis revealed from a total of 10,864 women 3,230 (29.7 percent) were intending to limit child-bearing while the remaining 7,534 (70.3 percent) did not. Age, religion, educational attainment, knowledge about family planning methods, wealth index, exposure to media, number of living children, previous child death, visited by FP workers during the last 12 months, marital status, current usage of any FP method, occupation status of women were found to be the major predictors of women's intention to limit child-bearing in rural Ethiopia. Although the study was undertaken only in rural areas there are differences in intention to limit child-bearing among rural areas of the regions. The lowest intentions to limit child-bearing were observed in Somali (10.6 percent) and Affar (13.1 percent) regions. This means that the intention to limit child-bearing was not significant in Affar and Somali regions. Muslim women had low intention to limit child-bearing. Women who live in Somali and Affar are predominantly Muslims. The majority of the women with the intention to limit children belonged to the ages 40-49 (69.4 percent) and those women who had four or more living children (53.9 percent). This observation is not surprising because the fertility behavior of older women is more consistent with intentions than that of younger women (De Silva, 1991).

Results of the multiple logistic regression analysis showed that those women who desired to have more children were: rich, not visited by family planning workers during the last 12 months, had no access to media, had no children, had little information/knowledge about use of family planning, and were working in non-agriculture sector. This finding is similar to those by Short and Kiros (2002) and Yohannes (2008).

Women who lost a child or children due to death were more likely to have more children. A study done in Butajira showed women who lost one or more children7.39 likely to have more children (Fitaw et al, 2004). Women who experienced child mortality might want more children to replace those who died and to achieve their desired fertility. This supports the existing hypothesis that behavioral reaction to child mortality involves replacement of a child who has died, and adjustment of fertility to ensure the survival of some children to adulthood (Bhargava, 2007 and Ramesh, 2010).

Women with no formal education were more likely to desire to limit child-bearing. This was also observed in Guatemala (Pepley et al., 1989) and Ethiopia (Bhargava, 2007 and Yohannes, 2008), where the probability of wanting additional children increased as educational attainment of women increased. The uneducated or less educated women, who wanted to limit child-bearing, might already have many children than the educated. Thus the effect of education might diminish when analysis is done based on their number of living children. Derebessa (2002) showed that education has been considered as an index of socio-economic development and modernization used to convey new ideas in innovation-diffusion theory: an indicator of women's status. Educated women had lower fertility compared with those uneducated women (Dejene, 2000).

Intention to limit child-bearing showed differences by age of the mother, in which younger women had less intention to limit than older ones. This finding is similar to studies conducted in Malawi (Palamuleni, 2009) and in Oromiya, Ethiopia (Yohannes, 2008).

Women whose economic status was poor were more likely to limit child-bearing. This finding is in agreement with Hayford and Agadjanian (2012).To the contrary Yohannes (2008) showed that the desire to stop child-bearing increased as wealth increased. Women who were not working were 12.8 percent times more likely to want to limit child-bearing than women who were working in non-agriculture sector.

The desire to limit child-bearing also varied with exposure to the mass media. Those women with no exposure to any media (radio, TV and newspapers) were 13.3 percent less likely to desire to limit child-bearing compared to women who had access to any kind of media. The association between mass media (particularly those promoting family planning) and fertility desires and intentions also has been reported by Gupta et al (2003) and Westoff and Bankole (1995) (as cited by Basten, 2010). They found that women who were exposed to mass media regularly had greater family planning knowledge than women with less mass media exposure.

As expected, women's intention to limit child-bearing varied with their knowledge and use of family planning methods. Women who knew about any of family planning methods were more likely to desire to stop child-bearing than women who did not know any method of family planning. Similarly, women who were using family planning were more likely to desire to limit child-bearing as women who were not using family planning. Previous studies in Ethiopia (Short and Kiros, 2002) showed that couple's knowledge, approval and use to family planning were associated with the desire to have or not to have additional children

Results from the random effect multilevel analysis took into account the hierarchical structure of the data as well as the variability within each region and individual levels to estimate the levels of association of the study factors with the outcome. In general, the fixed effects of the explanatory variables included in the multilevel models had somewhat similar interpretation as the results of the multiple logistic regressions as discussed above. The random intercept and the coefficients provided additional information. The overall variance of the constant term in the empty model with random intercept only, in random intercept and fixed slope model indicated the existence of differences in intention to limit child-bearing among women in rural areas. A random intercept and fixed slope model was also employed to compare the status of limiting child-bearing among regions. The deviance-based chi-square test for significance of random effects indicated that the random intercept model with the fixed slope provided a better fit compared to the empty model. The inclusion of fixed predictor variables indicated that all predictors had significant effect to determine the variation in limiting child-bearing among regions.

The software package used did not allow for more variables to be included in the analysis. Due to this limitation only four variables were considered in the random coefficient model. Among these, the effect of the random part associated with number of living children was significantly different across the regions. Further, depending on the model selection criterion the model with a random coefficient was found to be more appropriate to explain the regional variation than a model with fixed coefficients or an empty model with random effects.

5.2 Recommendations

This analysis indicated that there is desire for limiting child-bearing among women in rural Ethiopia, particularly among older women and those who had large families.

On the basis of the findings the following recommendations are made:

- Provide family planning services to women who have achieved their fertility goals would be important for reducing unwanted fertility.
- Enhance information and communication activities regarding family planning services using media, health extension workers and health centers in rural Ethiopia.
- Family planning programs should focus on women with unmet need, particularly those who want to limit child-bearing; avail more information, education and communication about small family norms and the benefits of family planning to achieve the goals of wanted fertility is needed.
- Further study is required to assess the quality related to limit child-bearing in the whole Ethiopia.

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Appendixes

Appendix 1: Logistic Regression SPSS Output

Appendix 1.1 Results of binary logistic regression analysis SPSS output factors influencing women's intentions to limit child-bearing.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	10,864	100.0
	Missing Cases	0	.0
	Total	10,864	100.0
Unselected Cases		0	.0
Total		10,864	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
want more children	0
Desire to limit	1

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			Desire for more children		Percentage Correct
			want more children	Desire to limit	
Step 0	Desire for more children	want more children	7634	0	100.0
		Desire to limit	3230	0	.0
	Overall Percentage				70.3

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.860	.021	1679.163	1	.000	.423

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	3551.272	26	.000
	Block	3551.272	26	.000
	Model	3551.272	26	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	9671.731[a]	.279	.396

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	13.844	8	.086

Contingency Table for Hosmer and Lemeshow Test

		Desire for more children = want more children		Desire for more children = Desire to limit		Total
		Observed	Expected	Observed	Expected	
Step 1	1	1046	1052.480	40	33.520	1086
	2	1000	1016.483	86	69.517	1086
	3	985	984.611	101	101.389	1086
	4	941	944.608	140	136.392	1081
	5	901	904.356	184	180.644	1085
	6	860	837.537	224	246.463	1084
	7	759	727.841	329	360.159	1088
	8	582	582.653	503	502.347	1085
	9	387	397.649	699	688.351	1086
	10	173	185.783	924	911.217	1097

Classification Table[a]

Observed			Predicted		
			Desire for more children		Percentage Correct
			want more children	Desire to limit	
Step 1	Desire for more children	Want more children	6955	679	91.1
		Desire to limit	1465	1765	54.6
	Overall Percentage				80.3

a. The cut value is .500

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
	age			576.798	2	.000			
	age(1)	-2.088	.088	566.063	1	.000	.124	.104	.147
	age(2)	-1.333	.075	312.217	1	.000	.264	.227	.306
	region			186.142	7	.000			
	region(1)	-1.654	.165	100.191	1	.000	.191	.138	.264
	region(2)	-.796	.146	29.714	1	.000	.451	.339	.601
	region(3)	-.365	.147	6.185	1	.013	.694	.521	.926
	region(4)	-.311	.154	4.091	1	.043	.733	.542	.990
	region(5)	-.799	.147	29.589	1	.000	.450	.337	.600
	region(6)	-.750	.168	19.867	1	.000	.472	.339	.657
	region(7)	-.234	.179	1.710	1	.191	.791	.557	1.124
	education			11.399	2	.003			
	education(1)	.612	.207	8.750	1	.003	1.843	1.229	2.765
	education(2)	.675	.203	11.034	1	.001	1.964	1.319	2.924
	religion			124.431	2	.000			
	religion(1)	.288	.085	11.564	1	.001	1.334	1.130	1.576
ep 1[a]	religion(2)	-.486	.077	40.274	1	.000	.615	.530	.715
	wealth			27.609	2	.000			
	wealth(1)	.335	.105	10.283	1	.001	1.398	1.139	1.716
	wealth(2)	.064	.114	.316	1	.574	1.066	.852	1.334
	numberof			456.632	2	.000			
	numberof(1)	-2.696	.146	340.908	1	.000	.067	.051	.090
	numberof(2)	-1.141	.068	282.959	1	.000	.320	.280	.365
	knoledgeof(1)	-.493	.098	25.413	1	.000	.611	.504	.740
	currentuse(1)	-.478	.071	45.284	1	.000	.620	.539	.713
	media(1)	-.143	.055	6.803	1	.009	.867	.779	.965
	Anychildren(1)	1.054	.063	276.657	1	.000	2.870	2.535	3.250
	maritalsta			265.685	2	.000			
	maritalsta(1)	-.234	.152	2.372	1	.124	.791	.587	1.066
	maritalsta(2)	-1.347	.085	252.662	1	.000	.260	.220	.307
	visitedby(1)	-.293	.063	21.302	1	.000	.746	.659	.845
	occup			3.580	2	.167			
	occup(1)	.121	.065	3.433	1	.064	1.128	.993	1.281

occup(2)	.062	.073	.725	1	.395	1.064	.922	1.228
Constant	2.478	.297	69.636	1	.000	11.918		

Variable(s) entered on step 1: age, region, education, religion, wealth, numberof, knoledgeof, currentuse, ›dia, Anychildren, maritalsta, visitedby, occup.

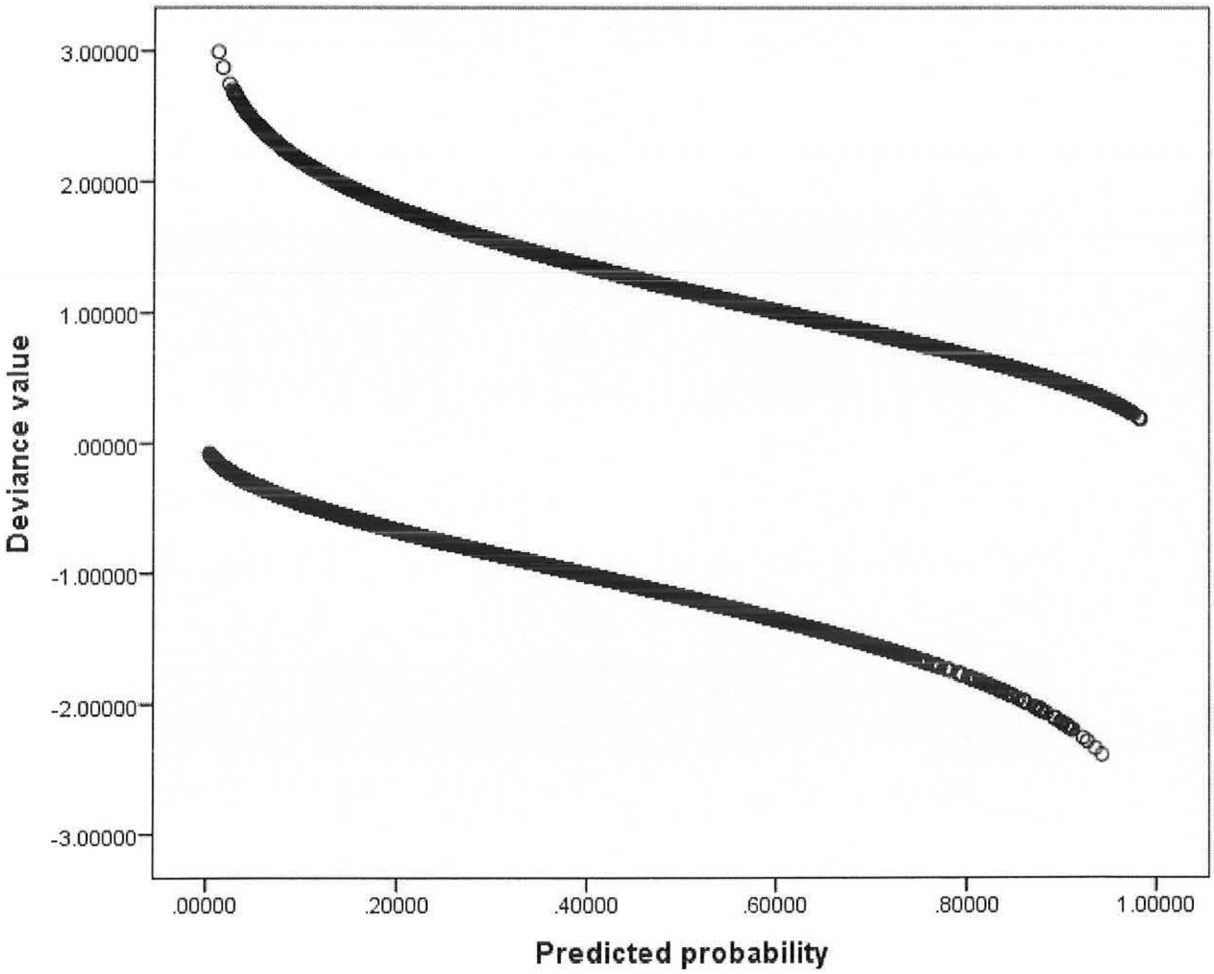
Appendix 1.2 Result of diagnostic tests for outliers and influential values

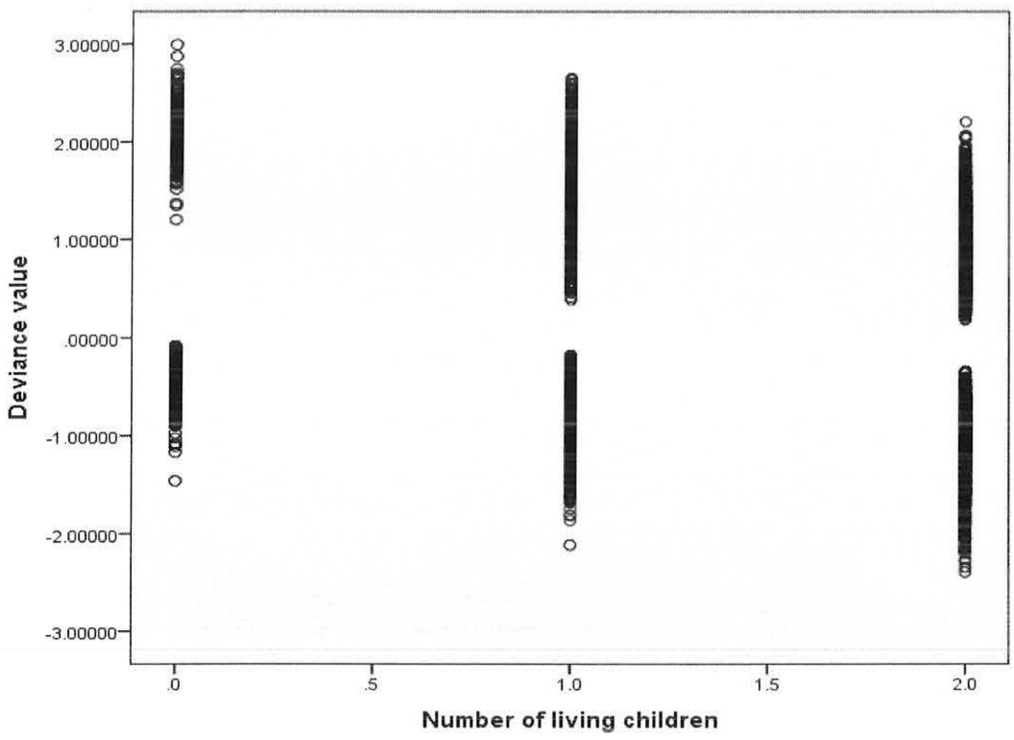
Descriptive Statistics

	N	Minimum	Maximum
Analog of Cook's influence statistics	10864	.00000	.06169
Leverage value	10864	.00014	.01689
Normalized residual	10864	-4.07022	9.33880
Deviance value	10864	-2.39416	2.99324
DFBETA for constant	10864	-.02066	.03857
DFBETA for age(1)	10864	-.00512	.00583
DFBETA for age(2)	10864	-.00300	.00425
DFBETA for region(1)	10864	-.01558	.01619
DFBETA for region(2)	10864	-.01617	.01494
DFBETA for region(3)	10864	-.01579	.01414
DFBETA for region(4)	10864	-.01619	.01426
DFBETA for region(5)	10864	-.01591	.01449
DFBETA for region(6)	10864	-.01748	.01512
DFBETA for region(7)	10864	-.01581	.01422
DFBETA for education(1)	10864	-.03898	.01587
DFBETA for education(2)	10864	-.03834	.01530
DFBETA for religion(1)	10864	-.00559	.00483
DFBETA for religion(2)	10864	-.00477	.00435
DFBETA for wealth(1)	10864	-.01020	.00858
DFBETA for wealth(2)	10864	-.01138	.00927
DFBETA for number of(1)	10864	-.01324	.01844
DFBETA for number of(2)	10864	-.00276	.00388
DFBETA for knowledgeof(1)	10864	-.00849	.00880
DFBETA for currentuse(1)	10864	-.00430	.00413
DFBETA for media(1)	10864	-.00281	.00232
DFBETA for Anychildren(1)	10864	-.00374	.00198
DFBETA for maritalsta(1)	10864	-.01721	.01410
DFBETA for maritalsta(2)	10864	-.00501	.00633

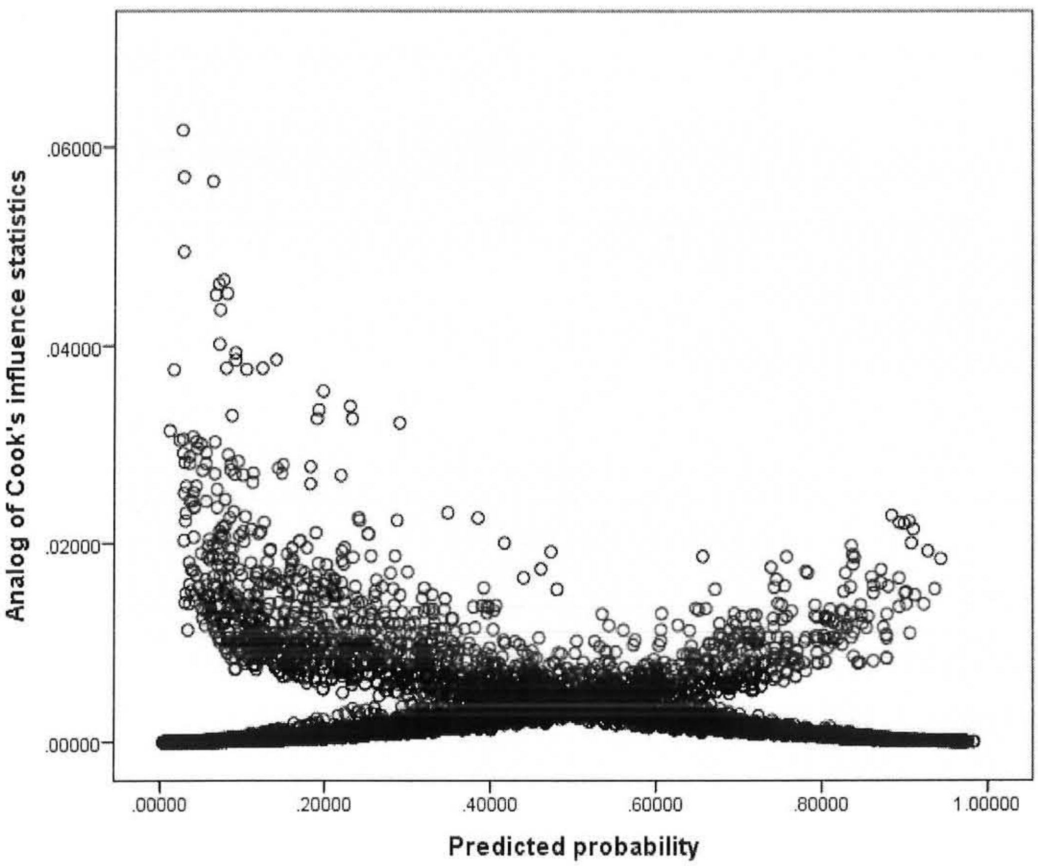
DFBETA for visitedby(1)	10864	-.00359	.00325
DFBETA for occup(1)	10864	-.00344	.00272
DFBETA for occup(2)	10864	-.00347	.00279
Valid N (listwise)	10864		

Change in Deviance against Predicted probabilities





3.00000
2.00000
1.00000
.00000
-1.00000
-2.00000
-3.00000
Deviance value
.0
.5
1.0
1.5
2.0
Number of living children



.06000
.04000
.02000
.00000
Analog of Cook's influence statistics
.00000
.20000
.40000
.60000
.80000
1.00000
Predicted probability

Appendix 2: Multilevel logistic regression STATA output

Appendix 2.1: Empty model with random intercept analysis STATA output.

___ ____ ____ ____ ____ (R)
/__ / ____/ / ____/
___/ / /___/ / /___/ 11.1 Copyright 2009 StataCorp LP
Statistics/Data Analysis StataCorp
4905 Lakeway Drive
Special Edition College Station, Texas 77845 USA
800-STATA-PC http://www.stata.com
979-696-4600 stata@stata.com
979-696-4601 (fax)
Single-user Stata license expires 31 Dec 9999:
Serial number: 71606281563
Licensed to: STATAForAll
STATA
Notes:
1. (/m# option or -set memory-) 500.00 MB allocated to data
2. (/v# option or -set maxvar-) 5000 maximum variables
running C:\Users\user\Documents\reta\Stata11\profile.do ...
unable to change to D:\Research\CRA\
r(170);
. use "C:\Users\user\Documents\reta\rdata.dta", clear
. xtmelogit desire region:, intpoints(7)
Note: single-variable random-effects specification; covariance structure set to identity
Refining starting values:
Iteration 0: log likelihood = -6451.0894
Iteration 1: log likelihood = -6449.8365
Iteration 2: log likelihood = -6448.5676
Performing gradient-based optimization:
Iteration 0: log likelihood = -6448.5676
Iteration 1: log likelihood = -6448.5153
Iteration 2: log likelihood = -6448.2349
Iteration 3: log likelihood = -6448.2346
Mixed-effects logistic regression Number of obs = 10864

Group variable: region					Number of groups = 8
					Obs per group: min = 364
					avg = 1358.0
					max = 2756
Integration points = 7					Wald chi2 (0) = .
Log likelihood = -6448.2346					Prob > chi2 =.

desire	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_cons	-.9858039	.1667186	-5.91	0.000	-1.312566	-.6590415

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
region: Identity				
var(_cons)	.5205567	.121401	.3295903	.8222516
LR test vs. logistic regression:	chibar2(01) = 326.53		Prob>=chibar2 = 0.0000	

Appendix 2.2: Random Intercepts and fixed coefficients Model Stata output

xtmelogit desire i. age i. educatio i. religion i. wealth i. numberof i. knoledge i. current i. media i. Anychild i. >marital i. visited i. work region:,cov(unstr)var	
Note: single-variable random-effects specification; covariance structure set to identity	
Refining starting values:	
Iteration 0: log likelihood = -4791.4617 (not concave)	
Iteration 1: log likelihood = -4783.3501	
Iteration 2: log likelihood = -4764.6002	
Performing gradient-based optimization:	
Iteration 0: log likelihood = -4764.6002	
Iteration 1: log likelihood = -4763.7905	
Iteration 2: log likelihood = -4763.7705	
Iteration 3: log likelihood = -4763.7704	
Mixed-effects logistic regression	Number of obs = 10864
Group variable: region	Number of groups = 8
	Obs per group: min = 364
	avg = 1358.0
	max = 2756

Integration points = 7					Wald chi2(20) = 2306.60	
Log likelihood = -4763.7704					Prob > chi2 = 0.0000	

desire	Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]	
age						
2	.7175397	.0713768	10.05	0.000	.5776438	.8574356
3	2.0693	.0892281	23.19	0.000	1.894416	2.244184
education						
1	.036286	.066194	0.55	0.584	-.093452	.1660239
2	-.550234	.2065048	-2.66	0.008	-.954976	-.145492
religion						
2	-.2437256	.0951649	-2.56	0.010	-.4302455	-.0572058
3	-.3337298	.0834528	-4.00	0.000	-.4972942	-.1701654
4	.0046513	.1564168	0.03	0.976	-.30192	.3112226
wealth						
1	-.1323214	.0618608	-2.14	0.032	-.2535665	-.0110764
2	-.2404195	.1053156	-2.28	0.022	-.4468343	-.0340047
numberof						
1	1.565296	.136623	11.46	0.000	1.297519	1.833072
2	2.777635	.1467199	18.93	0.000	2.490069	3.0652
knoledge	.2878815	.1004253	2.87	0.004	.0910515	.4847115
currentu	.4173939	.0716307	5.83	0.000	.2770003	.5577875
media	.1314136	.0552017	2.38	0.017	.0232202	.239607
Anychild	-1.070416	.0644502	-16.61	0.000	-1.196736	-.9440961
maritals						
1	-1.094243	.1496438	-7.31	0.000	-1.387539	-.8009462
2	.2342075	.1525438	1.54	0.125	-.0647729	.5331879
visitedb	.2240519	.0641807	3.49	0.000	.0982601	.3498438
work						
1	-.0460879	.0610828	-0.75	0.451	-.1658081	.0736323
2	-.1610138	.0658635	-2.44	0.014	-.2901038	-.0319238
_cons	-2.438153	.2509097	-9.72	0.000	-2.929927	-1.946379

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
region: Identity			

var(_cons)	.4233538	.1969515		.1701022 1	.053652
LR test vs. logistic regression:	chibar2(01) =	325.36	Prob>=	chibar2 = 0.0000	

. xtmelogit,or						
Mixed-effects logistic regression					Number of obs = 10864	
Group variable: region					Number of groups = 8	
					Obs per group: min = 364	
					avg = 1358.0	
					max = 2756	
Integration points = 7					Wald chi2(20) = 2261.69	
Log likelihood = -4763.7704					Prob > chi2 = 0.0000	
desire	Odds Ratio	Std. Err.	Z	P>z	[95% Conf. Interval]	
age						
2	2.049385	.1462785	10.05	0.000	1.781835	2.357108
3	7.919277	.7066221	23.19	0.000	6.648665	9.432714
educatio						
1	1.036952	.0686401	0.55	0.584	.9107817	1.180601
2	.5768148	.119115	-2.66	0.008	.3848214	.8645968
religion						
2	.7837026	.074581	-2.56	0.010	.6503494	.9443997
3	.7162473	.0597728	-4.00	0.000	.608174	.8435253
4	1.004662	.157146	0.03	0.976	.7393972	1.365093
wealth						
1	.8760593	.0541938	-2.14	0.032	.7760282	.9889847
2	.786298	.0828095	-2.28	0.022	.6396499	.966567
numberof						
1	4.784088	.6536167	11.46	0.000	3.660205	6.253065
2	16.08094	2.359394	18.93	0.000	12.06211	21.43876
1.knoledge	1.333599	.1339271	2.87	0.004	1.095325	1.623706
1.currentu	1.5180	.1087354	5.83	0.000	1.319167	1.746803
1.media	1.140439	.0629542	2.38	0.017	1.023492	1.27075
1.Anychild	.3428658	.0220978	-16.61	0.000	.3021789	.389031
maritals						
1	.334793	.0500997	-7.31	0.000	.249689	.448904

2	1.263907	.1928012	1.54	0.125	.9372803	1.704357
1.visitedb	1.251136	.0802988	3.49	0.000	1.10325	1.418846
work						
1	.954958	.0583315	-0.75	0.451	.8472088	1.076411
2	.8512803	.0560683	-2.44	0.014	.7481859	.9685804

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
region: Identity				
sd(_cons)	.6506565	.1513483	.4124344	1.026475
LR test vs. logistic regression: chibar2(01) = 325.36 Prob>= chibar2 = 0.0000				

Appendix 2.2: Random coefficients Model Stata output

. xtmelogit desire i. age i. educatio i. religion i. wealth i. numberof i. knowledge i. current i. media i. >Anychild i. marital i. visitedb i. work ||region: numberof currentu visited media, cov(unstr)var

Refining starting values:

Iteration 0: log likelihood = -4760.1878 (not concave)

Iteration 1: log likelihood = -4752.4272 (not concave)

Iteration 2: log likelihood = -4746.3176

Performing gradient-based optimization:

Iteration 0: log likelihood = -4746.3176 (not concave)

Iteration 1: log likelihood = -4727.1853 (not concave)

Iteration 2: log likelihood = -4723.2428 (not concave)

Iteration 3: log likelihood = -4720.0242 (not concave)

Iteration 4: log likelihood = -4717.0568 (not concave)

Iteration 5: log likelihood = -4716.3608 (not concave)

Iteration 6: log likelihood = -4716.1556 (not concave)

Iteration 7: log likelihood = -4716.029 (not concave)

Iteration 8: log likelihood = -4715.9687 (not concave)

Iteration 9: log likelihood = -4715.882 (not concave)

Iteration 10: log likelihood = -4715.8025 (not concave)

Iteration 11: log likelihood = -4715.5782

Iteration 12: log likelihood = -4715.3397

Iteration 13: log likelihood = -4715.131

Iteration 14: log likelihood = -4715.1129

Iteration 15: log likelihood = -4715.1093

Iteration 15: log likelihood = -4715.1093					
Mixed-effects logistic regression					Number of obs = 10864
Group variable: region					Number of groups = 8
					Obs per group: min = 364
					avg =1358.0
					Max = 2756
Intgration points = 7					Wald chi2(20) = 1191.90
Log likelihood = -4715.1093					Prob > chi2 = 0.0000
desire	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]
age					
2	.7268753	.0715981	10.15	0.000	.5865456 .867205
3	2.08301	.0895935	23.25	0.000	1.90741 2.25861
educatio					
1	.040087	.0663911	0.60	0.546	-.0900372 .1702112
2	-.5263264	.2064841	-2.55	0.011	-.9310277 -.121625
religion					
2	-.1770092	.0970581	-1.82	0.068	-.3672396 .0132212
3	-.2940844	.0841365	-3.50	0.000	-.4589889 -.1291799
4	.0713672	.1586927	0.45	0.653	-.2396649 .3823992
wealth					
1	-.1104355	.0622494	-1.77	0.076	-.2324421 .011571
2	-.2557662	.1056282	-2.42	0.015	-.4627938 -.0487386
numberof					
1	1.587104	.1376412	11.53	0.000	1.317333 1.856876
2	2.812961	.1479974	19.01	0.000	2.522892 3.103031
knoledge	.2481655	.1011803	2.45	0.014	.0498558 .4464751
currentu	.6696582	.209211	3.20	0.001	.2596123 1.079704
media	.1437524	.0554316	2.59	0.010	.0351084 .2523963
1.Anychild	-1.076499	.064644	-16.65	0.000	-1.203199 -.9497993
maritals					
1	-1.109264	.1506582	-7.36	0.000	-1.404549 -.8139794
2	.2224802	.1530745	1.45	0.146	-.0775404 .5225007
visitedb	.3583604	.123987	2.89	0.004	.1153504 .6013704
work					
1	-.0472824	.0612622	-0.77	0.440	-.1673542 .0727893

2	-.1583281	.0660396	-2.40	0.017	-.2877634	-.0288928
_cons	-2.490773	.2646522	-9.41	0.000	-3.009482	-1.972064

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
region: Unstructured				
var(numberof)	.2302183	.1161744	.085625	.6189836
var(currentu)	.3415622	.2694778	.0727627	1.60336
var(media)	.0100119	.0089538	.0017349	.0577773
var(visitedb)	.1038323	.0916692	.0184011	.5858985
var(_cons)	.5488396	.2170958	.2527838	1.191631
cov(numberof,_cons)	-.1481443	.1181134	-.3796423	.0833537
cov(currentu,_cons)	-.3159409	.2074782	-.722590	.0907089
cov(media,_cons)	-.0627359	.0277311	-.1170879	-.0083839
cov(visitedb,_cons)	.0485594	.0712069	-.0910036	.1881223
cov(currentu,visitedb)	.1882359	.1432247	-.0924792	.4689511
cov(currentu,numberof)	-.1092356	.0946522	-.2947505	.0762794
cov(media,numberof)	-.0287526	.0331079	-.0936429	.0361377
cov(visitedb,numberof)	-.1296805	.0800627	-.2866006	.0272396
cov(currentu,media)	.0220243	.0244806	-.0259568	.0700054
cov(visitedb,media)	.0137496	.0176246	-.0207941	.0482932
LR test vs. logistic regression:	chi2(6) = 348.65	Prob > chi2 = 0.0000		
Note: LR test is conservative and provided only for reference.				

Declaration

I, the undersigned, declare that the thesis is my original work, has not been presented for a degree in any other university and that all sources of material used for the thesis have been duly acknowledged.

Declared by

Name: **Reta Lemessa**

Signature: ______________________

Date: March 12/03/13

Addis Ababa University

This thesis has been submitted for examination with my approval as a University Advisor.

Name: **Professor Eshetu Wencheko**

Signature: ______________________ Eshetu W.

Date: March 12/03/2013

Addis Ababa University