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STATISTICAL ANALYSIS OF REGIONAL HETEROGENEITY OF UNDER-FIVE CHILD MORTALITY IN ETHIOPIA

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A Thesis Submitted to the Department of Statistics, School of Graduate Studies, College of Natural Science, and Jimma University in Partial Fulfillment for the Requirements of Masters of Science (Msc) Degree in Biostatistics

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As thesis research advisors, we herby certify that we have read and evaluated the thesis prepared by **DECHASA BEDADA** under our guidance, which is entitled **Statistical Analysis of Regional Heterogeneity of Under-Five Child Mortality in Ethiopia.** We recommend that the thesis be submitted as it fulfills the requirements for the degree of Master of Science.

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DEDICATION

This thesis is dedicated to my dear mother who use to give financial and moral support and who suddenly passed way when I was persuading post graduate studies.

STATEMENT OF THE AUTHOR

First, I declare that this thesis is a result of my genuine work and all sources of materials used for writing it have been duly acknowledged. I have submitted this thesis to Jimma University in partial fulfillment for the Degree of Master of Science in Biostatistics. The thesis can be deposited in the library of the university to be made available to borrowers for reference. I solemnly declare that I have not so far submitted this thesis to any other institution anywhere for that award of any academic degree, diploma or certificate.

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LIST OF ACRONYMS

AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
CSA	Central Statistical Agency
EDHS	Ethiopian Demographic and Health Survey
FMOH	Federal Ministry of Health
IMR	Infant mortality rate
LogLik	Log likelihood
MDGs	Millennium Development Goals
OR	Odd ratio
SC	Schwartz Criteria
U5CM	Under five-child mortality
U5MR	Under-five mortality rate
UN	United Nations
UNICEF	United Nations International Children Emergency Fund
UNIGME	UN Inter-Agency Group for Child Mortality Estimation
USAID	United States Agency for International Development
WHO	World Health Organization
PQL	Penalized Quasi Likelihood
AGQ	Adaptive Gaussian Quadrature
NGQ	Non- Adaptive Gaussian Quadrature

ABSTRACT

Introduction: Under-five child mortality is a factor that can be associated with the safety of a population and taken as one of the development indicators of health and socioeconomic status. According to MDGs report in 2013, the rate of decline in under-five child mortality has accelerated globally and in many regions. There is disparity of under-five child mortality rate from region to region in Ethiopia. The core objective of this study was to investigate the existence of regional heterogeneity (differentials) in under-five child mortality and identify important determinant of under-five child mortality in Ethiopia.

Method: Data from the 2011 Ethiopia Demographic and Health Survey were used to determine mortality among under-five children (n=11654) in Ethiopia. Logistic regression and multilevel logistic regression models were used to explore the major risk factors and regional variations in under-five children mortality in Ethiopia using 2011 EDHS data set.

Results: The results obtained from standard logistic and multilevel logistic regression showed that sex of child, family size, mother's education, age at first birth of mother, breast-feeding and using contraceptive methods significantly affect under-five child mortality and there is variation of under-five child mortality from region to region. It was also found that a random coefficient model was the best description of the data set among multilevel logistic regression models.

Conclusion: This study has revealed that **s**ex of the child, family size, education level of mother, age at first birth of mother, breast-feeding, using contraceptive method and region of child were found to be significant determinants of under-five child mortality in Ethiopia. The multilevel logistic model provided interesting relationships that would not be evident from a standard logistic model. There is a variation of under-five child mortality from region to region and there is a variation of under-five child mortality within regions.

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Improvements in child survival have been one of the major targets of development programmers during the past three decades, and child mortality rates have shown substantial and consistent declines in all regions of the world since 1960 (Hill *et al*, 1999). Most countries of the world have agreed to the Millennium Development Goal (MDG) of reducing child mortality by two-thirds by 2015. The UN prepared a report in 2001 on progress towards child-survival goals (UNICEF, 1999). In recent years however, these positive trends have declined, and even reversed in many sub-Saharan African countries while they have continued to improve in other regions (Ahmed *et al* , 2000). Available information clearly shows that unless countries and their technical assistance partners make new resources and refreshed efforts, the MDG will not met.

Under-five child mortality is a factor that can be associated with the safety of a population and taken as one of the development indicators of health and socioeconomic status, and indicates a life quality of a given population, as measured by life expectancy. That is why the reduction of under-five child mortality is a worldwide target and one of the most important key issues in the document of the Millennium Development Goals (MDGs). It is indeed, a very important index for the evaluation and public health strategy. Thus, it was one of the areas on which many researchers have focused, and have attracted the attention of policy makers and program implementers worldwide. One of the most important targets of the Millennium Development Goals (MDGs) was introduced in 2000 at the United Nations Millennium Summit was reducing under-five child mortality rates by two-thirds from the 1990 levels by 2015.

Worldwide, the mortality rate for children under five dropped by 41 percent from 87 deaths per 100 live births in 1990 to 51 in 2011. Despite this enormous accomplishment, more rapid progress needed to meet the 2015 target of a two-thirds reduction in child deaths. In 2011, an estimated 6.9 million children (19,000 a day) died from mostly preventable diseases. The overwhelming majority of these deaths occurred in the poorest regions and countries of the world, and in the most underprivileged areas within countries (MDG report, 2013).

Improvements in child survival are evident in all regions, led by Eastern Asia and Northern Africa, the only regions that have met the target so far. Latin America and the Caribbean, South-Eastern Asia and Western Asia have reduced their under-five mortality rate by more than 50 percent. Sub-Saharan Africa and Southern Asia have achieved reductions of 39 percent and 47 percent, respectively (MDG report, 2013).

According to MDGs report in 2013, the rate of decline in under-five child mortality has accelerated globally and in many regions. Sub-Saharan Africa-with the highest child death rate in the world-has doubled its average rate of reduction from 1.5 percent a year in 1990-2000 to 3.1 percent a year in 2000-2011. In sub-Saharan Africa but also other regions, countries with the highest child mortality rates are motivating the previous decade. Still, the pace of change must accelerate even further, particularly in Sub-Saharan Africa and Southern Asia, if the MDG target is to be met.

As under-five children mortality rates fall in richer developing regions, the majority of child deaths are occurring in the poorest ones sub-Saharan Africa and Southern Asia. In 2011, these two regions accounted for 5.7 million of the 6.9 million deaths in children under five worldwide. This represents 83 percent of the global total in 2011, up from 69 per cent in 1990. Of the 24 countries with an under-five mortality rate above 100 deaths per 1,000 live births in 2011, 23 are in sub-Saharan Africa; the other is in Southern Asia. In sub-Saharan Africa, 1 in 9 children die before age five; in Southern Asia, 1 in 16.

Despite steep challenges, a number of countries with very high rates of child mortality in 1990 have defied the odds, showing that progress for all children is within our grasp. Bangladesh and Liberia, for example, have achieved reductions in under-five mortality of at least two thirds since

1990. Ethiopia, Madagascar, Malawi, Niger, and Rwanda in sub-Saharan Africa, and Bhutan and Nepal in Southern Asia, have seen reductions of at least 60 per cent. (MDG report, 2013)

In 2004 the Ethiopian government prepared child survival strategy and implementation plan to reduce under-five mortality of 140/1000 live births to 67/1000 live births by 2015, this means a reduction of two-thirds of from the 1990 rates of about 200/1000 live births or a 52 percent reduction from 2004 rate of about 140/1000 live births (FMOH, 2005).

A number of studies indicated that the mortality rate especially the mortality rate of children under five in Ethiopia has been declining. The critical forces for this decline are many. The declining of the role of agriculture in the national economy, the increase of urbanization and the launching of globalization which has accelerated the economic performance of the country had significantly changed the trend of mortality rate particularly the mortality rate of children under five (Kenny and Kenny, 2006).

The current levels of mortality rate of children under-five are still high as compared to the expectation of Millennium Development Goals (MDGs) rate. Reducing the mortality rate of children to 67 per 1000 live births was internationally adopted at the 1990 world summit for children. At this time the level of infant and child mortality rate are among a vital indicators of the levels of socioeconomic progress of countries. Children are at greater risk of dying before age five if they are born in rural areas, poor households, or to a mother denied basic education (MDGs Report, 2013).

Similarly, like other developing countries, there is a significant differential in mortality levels among urban and rural resident of Ethiopia. For example, according to the 2005 EDHS report, infant, child and under-five mortality are lowest 66, 32 and 35 per 1000 live births in urban areas while 81, 40 and 41 per 1000 live births in rural areas, respectively. The urban-rural variation even more pronounced in the mortality of children under five. The regional variations are in infant and child mortality rates are also pronounced in Ethiopia (Desta, 2011).

Logistic regression is widely used to model the outcomes of a categorical dependent variable. For categorical variable, it is inappropriate to use linear regression because the response values are not measured on a ratio scale and the error terms are not normally distributed. In addition, the linear regression model can generate as predicted values any real number ranging from negative to positive infinity, whereas a categorical variable can only take on a limited number of discrete values within a specified range. The logistic regression models are supported by variety of link functions, which include the logit, clog-log, log and reciprocal. The type of response variable determines the distribution and link function for the model. Since the response variable for this paper is binary, the logit link function has been used.

In multilevel research, the data structure in the population is hierarchical, and the sample data are a sample from this hierarchical population. Thus, in educational research, the population consists of schools and pupils within these schools, and the sampling procedure often proceeds in two stages: First, we take a sample of schools, and next we take a sample of pupils within each school. Of course, in real research, one may have a convenience sample at either level, or one may decide not to sample pupils but to study all available pupils in the sample of schools. Nevertheless, one should keep firmly in mind that the central statistical model in multilevel analysis is one of successive sampling from each level of a hierarchical population (Hox, 2010).

A potential drawback to multilevel modeling is the additional complexity of coefficients varying by group. It does create new difficulties in understanding and summarizing the model (Gelman, 2006). Multilevel models provide distinct advantages to evaluators seeking to estimate relationships and test hypothesis regarding within and between level linkages between reliability indicators and program outcomes. However, the proper application of the multilevel model, as with any statistical procedure, is dependent upon the resolution of a range of methodological and statistical issues (Zvoch, 2012).

1.2. Statement of the problem

The world is not yet on track to achieve the Millennium Development Goals (MDGs) target of a two-thirds reduction in the rate of child mortality by 2015. Many demographers and scholars do believe and recommend the need to conduct in-depth studies on the various aspects of infant and child health status in a different demographic, economic, and social-cultural setting. Researchers have already come to consensus the importance of conducting research on the socioeconomic, demographic, health and environmental determinants of mortality status of children under five in Ethiopia. Understanding the geographic distribution of mortality of children under five is important to policy interventions. Mortality rate in most parts of the sub-Saharan African and Southern Asia countries tends to cluster by area, often identified as high or low-mortality region (WHO, 2005). Thus, this study tries to assess the regional variation of mortality rate of children under-five and explore the major risk factors of under five age of child death in Ethiopia, taking into consideration various health, socioeconomic and environmental factors based on the 2011 Ethiopia Demographic and Health Survey data. In addition, some researcher attempted to identify the determinant of Under-five age mortality and try to fit logistic regression model. The researcher was trying to fit multilevel models in order to see the variation between and within regions of under five-age mortality rates of children in Ethiopia using the EDHS data set.

Generally, this study tries to answer the following basic research questions:

- Which factors significantly affect the mortality rate of children under-five?
- Which model is appropriate for analyzing the predictors of death rate of children under-five?
- Is there variation in mortality rate of children under five among different National Regional States of Ethiopia?

1.3 Objectives of the study

1.3.1 General objective

In view of the research problem stated above, the general objective of the study is to investigate the existence of regional heterogeneity (differential) in under-five children mortality as well as the extent to which variation is relate to a set of explanatory variables through single and multilevel binary specifications.

1.3.2 Specific objectives

The specific objectives of this study are to:

- Identify the most important factors that are related to the death of children under the age of five in Ethiopia.
- Investigate the different levels of the risk factors and evaluate the probability of each risk level.
- Examine between and within region variations of mortality of children under- five years.

1.4. Significances of the study

This study is useful to understand how important it is to consider the hierarchical structure of the under-five child mortality data whether the magnitude of the random effects is small or large. It also serves as stepping-stone for those who are interested to undertake an in depth research on issues related to the death of children under-five in Ethiopia. It is specifically helpful for those who want to deal with the variation between and within the clusters or groups for cross sectional data set of the factors that affect under-five-child mortality such as the socioeconomic, biological, and demographic. Generally, this research is expected to give idea to those focuses on this area:

- To give emphases on the factors that have strong association with under-five mortality so that policy makers act on accordingly.
- The international community is committed to the MDGs, most of which are closely related to health. In line with this, the results can assist policy makers in the health sector in their effort towards meeting the MDG's related to child mortality.
- The study may also be used as a stepping-stone for further studies.

1.5 Organization of the Study

This study is a presented in five chapters. The first chapter gives a general background of the study, statement of the problem, objective, and its significance of the study. Chapter 2 deals with the review of literature on Under-five child mortality in Ethiopia and the rest of the world, whereas chapter three specifies the data and methodology of the study such as sources of data and variables to be included in the study with their coding and description. Methods of data analysis are also described in this chapter. Chapter 4 reports results from the statistical data analysis and provides discussions. Finally, the last chapter presents conclusion and policy recommendations based on the findings of the study.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Overview of Determinant of under-five child mortality

Child mortality, also known as under-5 mortality, refers to the death of infants and children under the age of five. Under-five mortality rate is the probability per 1,000 that a newborn baby will die before reaching age five.

In 2011, the world average was 51(5.1%), down from 87(8.7%) in 1990. The average was 7 in developing countries and 57 developing countries including 109 in sub-Saharan Africa (UN, 2012). In 2009, there were 31 countries reported in which at least 10% of children under five died. All were in Africa, except for Afghanistan. The highest ten were: Chad, Afghanistan, Democratic Republic of the Congo, Guinea-Bissau, Sierra Leone, Mali, Somalia, Central African Republic, Burkina Faso and Burundi with under –five mortality rate of 20.9%, 19.9%, 19.9%, 19.3%, 19.2%, 19.1%, 18.0%, 17.1%, 16.6% and 16.6% are respectively. About half of child deaths occur in Sub-Saharan Africa (UN, 2012).

Over 70% of all under-five deaths occur in African and South East Asia regions. Children in sub-Saharan Africa are over 16 times more likely to die before the age of five than children in developed region. About half of under-five deaths occur in only five countries: China, Democratic Republic of the Congo, India, Nigeria, and Pakistan (WHO, 2013).

A number of epidemiological factors were being proposed in many researches to explain the specific pattern of high child mortality in sub-Saharan Africa. Drawing from Senegalese surveillance data, (Garenne ML ,1982) attributes the unusual level of child mortality (1 - 4 year age) relative to infant mortality (0-1 year age) to a combination of two main factors: (1) a particular disease environment characterized by high prevalence of malaria, measles, and diarrhea, diseases that appear to generate excess mortality well beyond a child's first birthday; (2) a late age at weaning (centered around 24 months) combined with elevated mortality around weaning because of the loss of protection from breast milk and inadequate weaning foods. Generalized, to seven surveillance sites in areas of sub-Saharan African countries (in Tanzania, Kenya, Burkina Faso, Mozambique, and Ghana) where malaria is endemic, Abdullah et al (2007) it is found that the risk of mortality increases with age following an initial decrease during the first few months of life, and they attributed this increase to malaria mortality. Compared to populations where mortality declines monotonically with age, malaria thus appears to shift the distribution of under-five deaths towards older ages within that interval, contributing to relatively high levels of child mortality (1 - 4 year age).

Guillot, et al (2012) conclude that, on the whole, empirical values of infant mortality (0 - 1 year age) and child mortality (1 to 4 year age) rates fall relatively well within the range provided by Coale and Demeny and UN model life tables, but they also found important exceptions. Sub-Saharan African countries have a tendency to exhibit high values of child mortality (1 to 4 year age) relative to infant mortality (0 to 1 year age), a pattern that appears to arise for the most part from true epidemiological causes. While this pattern is well known in the case of western Africa, they observed that it is more widespread than commonly thought. They also found that the emergence of HIV/AIDS, while perhaps contributing to high relative values of child mortality (1 to 4 year age), does not appear to have substantially modified preexisting patterns of under-five mortality. They also identified a small number of countries scattered in different parts of the world that exhibit unusually low values of child mortality (1 to 4 year age) relative to infant mortality (0 to 1 year age), a pattern that is not likely to arise merely from data errors. Finally, they illustrated that it is relatively common for populations to experience changes in age patterns of infant and child mortality as they experience a decline in mortality. Various researches have identified by determinants of under-five child mortality in some research. Some of these determinants have been discussed as follows:

Birth order number

Modin (2002) states that for boys and girls who were born in the Swedish city of Uppsala during the early part of the 21st century, total mortality at four stages of the life- course differed substantially by birth order. There was a general tendency for individuals who were born late in the sibling ship to have a higher mortality risk than first-born. A positive association between birth order and mortality during childhood has most often been demonstrated using logistic regression for developing countries (Chidambaram et al., 1987; Newcombe, 1965; Ballweg &

Pagtolun-an, 1992; Rutstein, 1984), and studies based on samples from industrialized nations seem to point in the same direction. Modin (2002) suggest that later born children are disadvantaged group within the family during upbringing. This brings into focus the social relations within the family and their material correlates a social environment often ignored in epidemiological research. The relative social disadvantage of later born seems, moreover, to have had long-term consequences for many aspects of these individuals' quality of life.

Breastfeeding

Breastfeeding is almost universal and pro-longed in Ethiopia. Available evidence indicates that close to 97 of every 100 Ethiopian children born are ever breasted, and that slightly over 25% of children are still being breasted at two years of age. Infant and early childhood mortality in Ethiopia is high. According to Markos and Eshetu (2002), the evaluation of age patterns of child mortality indicates that the effects of birth intervals are limited to the age of infancy (i.e. 0- 12 months). The relationship is very weak in the later ages (i.e. ages 1-4). The absence of strong effects suggests that sibling competition is, at best, of secondary importance in explaining the relationship between interval length and early childhood mortality. The population in question is characterized by a predominance of longer birth intervals and prolonged breastfeeding practices. The mean birth intervals are about three years and mean breastfeeding about 24 months.

Markos and Eshetu (2002) clearly indicate that several interrelated areas would foster a more complete understanding of the relationship between child spacing and child survival. The relationships between short birth intervals and maternal health and nutrition have had impact on the growth and development of children in the context of an impoverished society. Another area that needs further clarification is the relationship between short birth intervals and breastfeeding performance. Intervention policies should aim at encouraging longer birth intervals and breast-feeding practices.

Place of residence

Using Demographic and Health Survey (DHS) data, Wang (2002) had investigated the determinants of child mortality in low-income countries like Ethiopia both at the national level, and for rural and urban areas separately. DHS data from over 60 low-income countries between 1990 and 1999 reveal that there is significant gap in child mortality between urban and rural areas. Given that the poor are mainly concentrated in rural areas, the above evidence suggests that health interventions implemented in the past decade may not have been as effective as intended in reaching the poor. She uses both ordinary least square (OLS) and weighted least square (WLS) to check the consistency of the estimates.

In a related study, Wang (2003), using the results from the 2000 Ethiopia DHS, examines the environmental determinants of child mortality. She runs three hazard models, the Weibull, the Piecewise Weibull and the Cox model to examine three age-specific mortality rates: neonatal (under one month), infant (under one year), and under-five mortality by location (urban/rural); and other socioeconomic and health factors such as female education attainment, religious affiliation, income quintile, and access to basic environmental services (water, sanitation and electricity). The estimation results show that children born in rural areas face much higher mortality risk compared to those born in urban areas. Ethiopia is characterized by severe lack of access to basic environmental resources and strong statistical association is found between child mortality rates and poor environmental conditions.

Age at first birth

The age of the mother at the time of the first birth is an important factor for infant and child survival. Mondal *et al.* (2009) tried to show the relationship between the two using multivariable logistic regression analyses. Accordingly, he found that the most significant predictors of neonatal, post-neonatal, and child mortality levels are mother‘s age at birth along with other covariates (immunization, ever breastfeeding, and birth interval). Infant and child mortality are higher for mothers who are under 20 years of age and lower for children whose mothers aged between 20 - 29. Neonatal mortality of the children whose mothers aged below 20 years at the time of the child‘s birth is 9.9 % higher than those children whose mothers are in the age range

20-29 years at the time of giving birth. Consistent with other studies, Aguirre (1995) stated that maternal age has a U-shaped relationship with child mortality. In effect, both coefficients age and age squared are statistically significant and have the expected direction. That is, the risk of child mortality for children under age two is higher when women are either too young or too old, once parity and other reproductive factors are controlled for.

Mother’s Educational Attainment

Maternal education is a major determinant of child survival, influencing care seeking, morbidity and nutritional status. Only 34% of adult Ethiopian women are educated, compared with 49% of men, and 20% fewer girls than boys enroll for primary school. The U5MR for children whose mothers have no schooling is 121% higher than those whose mothers have at least a secondary education (WHO, 2007).

Based on the data obtained from secondary and primary source by interviewing 120 mothers using judgment sampling, Ojikutu asserted that U5MR in Lagos state depends on the educational qualification of mothers. Similarly, the chi square test of independence run by Mahfouz et al. (2009) on Malakal Town – Southern Sudan shows that there is strong association between under five-child mortality and education of mothers.

Belaineh et al. (2007) by case control study on Gilgel Gibe Field Research Center, Southwest Ethiopia, found that among the socio-economic factors, maternal education is significantly associated with under-five mortality. By their study, higher under five mortality was observed among mothers whose educational level was elementary and below as compared to mothers who were above elementary school, the odds ratio (OR) being 11.7 (95% CI: 1.5, 91). Other socio-demographic variables did not show statistically significant association with under-five mortality. Maternal education retained its significance after adjusting for other socio-demographic variables.

Maternal education has a substantial impact on infant and child survival through increased awareness of problems and better feeding habits, among other reasons. Caldwell, (1991) confirmed that mother’s education is a robust determinant of infant and child survival in

Bangladesh. Importantly, Kovsted et al (2002), in a study in Guinea-Bissau, showed that education is only an alternative for actual health knowledge, the real determinant of child health and mortality. Maglad (1993), based on household data from Sudan, revealed that parental education, income per adult and public health programs are significant and negatively correlated with child mortality; maternal education, in particular, is found to have a larger significant effect than that of the father.

Regional variation

Ethiopia is a diverse country and childhood mortality is not evenly distributed throughout the country. Under-5 mortality rates range from a low of 114 per thousand in the capital city of Addis Ababa to a high of 233 per thousand in Gambela and 229 in Afar, two remote regions (Child Health in Ethiopia, 2004).

Patel (1980), on the paper he studied about the effects of the health service and environmental factors on infant mortality, found that regional variations in the infant mortality rates of Sri Lanka are large, ranging from 26 per 1000 live births in Jaffna to 91 per 1000 in Nuwara Eliya, a tea estate district. These differences are more strongly associated with regional variations in environmental determinants of mortality than with regional variations in public health expenditure. The most significant environmental factor associated with interregional infant mortality rates was found to be the source of water supply (i.e. tap water, well water, or river water). Regional government expenditure on health had only a weak association with infant mortality rates.

Economic status of the household or Wealth index

As observed in most studies, household income has significant effect on children survival prospects. Higher mortality rates are experienced in low-income households as opposed to their affluent counterparts. According to Belaineh *et al*. (2007), based on data obtained by using structural questionnaire from Jimma town, Ethiopia, a higher level of wealth score as measured by wealth index has shown a significant reduction in child mortality in a multivariable logistic regression analysis.

Source of water supply

The world has now met the MDG target relating to access to safe drinking water. In 2011, 89% of the population used an improved source of drinking water compared with 76% in 1990. Progress has however been uneven across different regions, between urban and rural areas, and between rich and poor (MDG Report, 2013).

Piped water supply reduces infant mortality directly by reducing the incidence of diarrhea that arises from the ingestion of contaminated water and food, and indirectly when caregivers are able to devote more time to childcare instead of water collection activities (Rabindran *et al.*, 2008).

Patel (1980) found that there was a strong negative relationship between use of well water and regional IMRs in Sri Lanka. High use of well water is associated with low incidence of infant mortality. Well water is the main source of drinking water for 69% of households in Sri Lanka. Multivariate regression analysis yielded a highly significant coefficient of 0.81 and also there was a strong positive association between the extensive usage of river water and the high infant mortality rates of different districts. River water is used directly by 25% of the population of Sri Lanka.

Use of contraceptive methods

Sub-Saharan Africa countries are characterized by low contraceptive prevalence. Low total fertility rate (TFR) can be associated with a high contraceptive prevalence rate. Countries like Kenya with low mean ages at first intercourse, marriage and birth have a lower total fertility rate (TFR) (less than 6) because its contraceptive prevalence rate is higher than 30 percent. It seems that countries with a prevalence rate of more than 40 percent have a total fertility rate (TFR) of less than 5. This is true even for other selected developing countries analyzed in this study (Dobratz, 1998).

2.2 Generalized Linear Models and multilevel logistic regression model

Wong and Mason (1985), Gibbons and Bock (1987), Longford (1993) and Goldstein (2003) describe that the multilevel is extension of generalized linear models. In multilevel generalized linear models, the multilevel structure appears in the linear regression equation of the generalized linear model. The multilevel regression model is more complicated than the standard single-level multiple regression models. One difference is the number of parameters, which is much larger in the multilevel model. This poses problems when models are fitted that have many parameters, and in model exploration. Another difference is that multilevel models often contain interaction effects in the form of cross-level interactions. Interaction effects are complicated, and analysts should deal with them carefully. Finally, the multilevel model contains several different residual variances, and no single number can be interpreted as the amount of explained variance (Hox, 2010).

Multilevel regression models are essentially a multilevel version of the familiar multiple regression model. Using dummy coding for categorical variables, it can be used to analysis of variance (ANOVA)-type of models as well as the more usual multiple regression models. Since the multilevel regression model is an extension of the classical multiple regression model, it too can be used in a wide variety of research problems. It has been used extensively in educational research (Hox, 2010). Other applications have been in the analysis of longitudinal and growth data (Bryk and Rauderbush, 1992; Goldstein, 1996; Goldstein & Rasbash, 1996), the analysis of interview survey data from surveys with complex sampling schemes with respondents nested within sampling units and data from factorial surveys and facet designs. Multilevel regression models for binary and other non-normal data have been described by Wong and Mason (1985), Logford (1993) and Goldstein (1991).

The multilevel regression model has become known in the many research under a variety of names, such as ‘random coefficient model’ (Leeuw & Kreft, 1986; Longford, 1993), ‘variance component model’ (Longford, 1987), and ‘hierarchical linear model’s (Rauderbush & Bryk, 1986). Statistically oriented publications tend to refer to this model as mixed-effects or mixed model.

Multilevel models for covariance structures or multilevel structural equation models (SEM), are powerful tools for the analysis of multilevel data. Recent versions of structural equation modeling software, such as EQS, LISREL, Mplus, all include at least some multilevel features. The general statistical model for multilevel covariance structure analysis is quite complicated (Hox, 2010).

Raudenbush et al. (2000) consider a random slope binary regression model with parameter values close to those matching the Rodriguez-Goldman data, including asymmetric probabilities and correlated random effects. They conclude that PQL estimates are systematically underestimating true values. This negative bias is more prominent for the variance parameters compared to the regression parameters. The bias for Non-Adaptive Gaussian Quadrature (NGQ) and Adaptive Gaussian Quadrature (AGQ) was found to be much smaller. The precision of PQL, NGQ, and AGQ turned out not to differ much. However, they found that the Mean Squared Error for the estimation of the variance components for PQL is substantially lower than for the quadrature methods.

The modern approach to the problem of non-normally distributed variables is to include the necessary transformation and the choice of the appropriate error distribution (not necessarily a normal distribution) explicitly in the statistical model. These classes of statistical models are called generalized linear models (McCullagh & Nelder, 1989).

CHAPTER: THREE

3. DATA AND METHODOLOGY

3.1. Source of Data

For the analysis, the data has been obtained from the Ethiopia Demographic and Health Survey (EDHS) 2011. The Central Statistical Agency (CSA) under the auspices of the Ministry of Health conducted the survey. This is the third Demographic and Health Survey (DHS) conducted in Ethiopia, under the worldwide measure DHS project, a USAID-funded project providing support and technical assistance in the implementation of population and health surveys in countries worldwide. The primary purpose of the EDHS is to furnish policy makers and planners with detailed information on fertility, family planning, infant, child, adult and maternal mortality, maternal and child health, nutrition and knowledge of HIV/AIDS and other sexually transmitted infections.

The 2011 EDHS used three questionnaires: the Household Questionnaire, the Woman's Questionnaire, and the Man's Questionnaire. The Woman's Questionnaire was used to collect information from all women age 15-49 from the selected households. An estimate of childhood mortality was based on information from the birth history section of the questionnaire. The data used for under-five mortality estimation were collected in the birth history section of the Woman's Questionnaire from 16,515 women age 15-49. The birth history section begins with questions about the respondent's experience with childbearing (i.e., the number of sons and daughters living with the mother, the number who live elsewhere, and the number who have died). These questions are followed by a retrospective birth history, in which each respondent is asked to list each of her births, starting with the first birth. For each birth, data were obtained on sex, month and year of birth, and current age, or, if the child is dead, age at death.

3.1.1 Data extracting and Editing

Even if the data was obtain from EDHS as a secondary data source this not means that data is appropriate to use as researcher want for his research in a good manner way. The researcher in order to use this data first of all he was changes the data into appropriate way. Some activities was take place such as recoding, editing data, verifying and arranging data activities be done in order to insert data into computer to make analysis and give meaningful interpretation for response variable and explanatory variables (covariates). To do the activities that mention above the researcher will be need averagely eight person for one week to accomplish all activities that need into arrange the data for 16,515 women age 15 -49 group in appropriate manner for the researcher.

3.2. Variables Description and Measurement

3.2.1 Response variable

The dependent (response) variable is child survival status. One question from the EDHS used to examine the dependent variable, which is child alive at the time of interview "Yes (1) or no (0)". The response was binary: yes or no. As mentioned above, the dependent variables are dichotomous, coded as zero if death has not occurred and coded as 1 if death has occurred (alive =0 and dead =1).

3.2.2 Independent (or Explanatory) variables

Many explanatory variables are used as predictors of under-five child mortality. Broadly, the researcher grouped the variables into three: socioeconomic, biological and maternal, and Environmental health determinants, which contribute to under-five child mortality. Variables that are included in socioeconomic category include place of residence, work status of mother and mother education level. Variables considered under biological and maternal determinants are age of mother, birth order, and sex of a child. Variables that are considered as elements of environmental health include source of drinking water.

Explanatory variables

No	variables	categories	No	Varibles name	Categories
1	place of residence	0= Rural	9	Region	0 = Addis Ababa
		1=Urban			1=Tigre
2	sex of child	0= Male			2= Affar
		1= female			3=Amhara
3	Wealth index	0= Rich			4= Oromia
		1=middle			5=Somali
		2 = poor			6 =Benishangul-G
4	Age of mother	1=15 – 19			7= SNNP
		0= 20 – 29			8 = Gambela
		0 = 30 – 39			9 = Harari
		3 = 40 – 49			10= Dire Dawa
5	source of drinking water	0=Piped			
		1= Spring	10	Smoking status	0 = No
		2= Tube Well Water & others			1 = Yes
6	Breast feeding	0= yes	11	Age of first birth	0 = < 20
		1= no			1 = >=20
7	Birth Order number	1 = 1	12	Using Contraceptive	0 = Yes
		2 = 2,3 or 4			1 = No
		3 = ≥ 5	13	Family size	0 = 1-5
8	Education level	0 = Higher (ref.)			1 = >5
		1 = Primary			
		2 = Secondary			
		3 = No Education			

3.3 Statistical methods

In this study the self reported child survival status is considered as a binary response variable and with this response variable the researcher has examined the effect of explanatory variables with the appropriate model for the under-five child mortality data set. A range of techniques has been developed for analyzing data with categorical response variables. For this study, some extension of generalized linear models such as multilevel model's are applied.

3.3.1 Generalized Linear Models (GLM)

Generalized linear models (GLMs) extend ordinary regression models to include non-normal response distributions and modeling functions of the mean (Agresti, 2002). Three components that specify a generalized linear model are random component which identifies the response variable Y and its probability distribution; a systematic component that specifies explanatory variables used in a linear predictor function; and a link function that specifies the function of expected value of the response variable that the model equates to the systematic component. In general, GLM is a linear model for a transformed mean of a response variable that has distribution in the natural exponential family.

The Exponential Family

A random variable Y follows a distribution that belongs to the exponential family if the density is of the form

$$f(y/\theta, \phi) = \exp\{\phi^{-1}[y\theta - \psi(\theta)] + c(y, \phi\}, \qquad ------------------ \quad (3.1)$$

, for a specific set of unknown parameters θ and ϕ, and for known functions ψ (·) and c (·,·). The parameter θ is called the canonical parameter and represents the location while, ϕ is called the dispersion parameter and represents the scale parameter and for the Poisson and binomial, it is fixed at one (Faraway, 2005). An important property of the GLM is the functional relation between mean and variance.

3.3.1.1 Logistic Regression Model

Binary data are the most common form of categorical data and the most popular model for binary data is logistic regression (Agresti , 2000). Logistic regression is a popular modeling approach when the dependent variable is dichotomous or polytomous as well. This model allows one to predict outcomes from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these. Hosmer and Lemeshow (2000) has described logistic regression focusing on its theoretical and applied aspect. In instances where the independent variables are categorical or a mix of continuous and categorical, logistic analysis is preferred to discriminant analysis (Agresti , 1996). The assumptions required for statistical tests in logistic regression are far less restrictive than those for ordinary least squares regression. There is no formal requirement for multivariate normality, homoscedasticity, or linearity of the independent variables within each category of the response variable. However, the assumptions that apply to logistic regression model include meaningful coding, inclusion of all relevant and exclusion of all irrelevant variables in the regression model, low error in the explanatory variables, no outliers and sampling adequacy.

In the terminology of logistic regression analysis, the odds of success are defined to be the ratio of the probability of a success to the probability of a failure. Hence, if p is the true success probability the odd of a success is p/ (1-p).

Let Y be a dichotomous outcome random vector with categories 1 (child is dead) and 0 (child is alive). Let X be an n x (p+1) matrix that contains the collection of P-predictor variables of Y, i.e.

$$\mathbf{X}= \begin{bmatrix} 1 & X_{11} \cdots & X_{1p} \\ \vdots & \ddots & \vdots \\ 1 & X_{n1} \cdots & X_{np} \end{bmatrix}$$

X without the leading column of 1s' is termed as a predictor data matrix. Then, the conditional probability that the i^{th} child experiences under-five mortality given child characteristics **X**i is given by:

$\pi_i = pr(y_i = 1/x_i)$ -- (3.2)

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

$$\log it(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) \quad \text{--} \quad (3.3)$$

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

$$\text{logit}(\pi_i) = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_p X_{pi} = X_i'\beta \quad \text{---------------------} \quad (3.4)$$

Where, $\beta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_p)'$ are the model parameters and

$X_i = (X_{0i}, X_{1i}, \ldots, X_{pi})'$, with $X_{0i} = 1$, i = 1, 2, 3, . . . , n

The probability of success expressed as

$$\pi_i = p(Y_i = 1/x_{1i}, x_{2i}, \ldots, x_{pi}) = \frac{e^{X_i'\beta}}{1 + e^{X_i'\beta}} \quad \text{---} \quad (3.5)$$

With further rearrangement, we obtain the odds of success

$$odds(Y_i = 1) = \frac{\pi_i}{1-\pi_i} = e^{X_i'\beta} \quad \text{---} \quad (3.\ 6)$$

The above three equations give suitable representations of log-odds, the success probability, and odds, respectively. Indeed, these representations facilitate interpretations of parameter estimates. Regression methods have an important component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables.

3.3.1.1. Parameter Estimation

The goal of logistic regression is to estimate the p +1 unknown parameters β in Eq. 3.4. The most commonly used method of estimating the parameters of a logistic regression model is the method of Maximum Likelihood (ML) instead of Ordinary Least Squares (OLS) method. Mainly for this reason the ML method based on Newton-Raphson iteratively reweighted least square algorithm becomes more popular with researchers (Ryan, 1997). The sample likelihood function is, in general defined as the joint probability function of the random variables whose realizations constitute the sample. Specifically, for a sample of size n whose observations are (y_1, y_2 … y_n), the corresponding random variables are (Y_1, Y_2… Y_n). Since the Y_i is a Bernoulli random variable, the probability mass function of Y_i is:

$$f_i(y_i) = \pi_i^{y_i}(1-\pi_i)^{1-y_i} -------------- (3.7)$$

Y_i = 0 or 1 and i =1, 2, 3, …, n

The joint probability density function in Eq. 3.7 expresses the values of y as a function of known, fixed value of β. (Note that β is related to π by Eq. 3.4). The likelihood function has the same form as the probability density function, except that the parameters of the function reversed: the likelihood function expresses the values of β in term of known, fixed values for y.

$$L(\beta / y) = \prod_{i=1}^{n} \frac{n!}{y_i!(n-y_i)!} \pi_i^{y_i} (1-\pi_i)^{n-y_i} \quad ------------------------------------- (3.8)$$

The maximum likelihood estimates are the values for that maximize the likelihood function in Eq. 3.8. The critical points of a function (maxima and minima) occur when the first derivative equals zero. If the second derivative evaluated at that point is less than zero, then the critical point is a maximum. It is possible to simplify the above equation maximum likelihood function.

First, note that the factorial terms do not contain any of them π_i. As a result, they are essentially constants that can be ignored: maximizing the equation without the factorial terms will come to the same result as if they were included.

$$L(\beta / y) = \prod_{i=1}^{n} \left(\frac{\pi_i}{1-\pi_i} \right)^{y_i} (1-\pi_i)^{n} \quad \text{--} \quad (3.9)$$

Note that after taking e to both sides of Eq. 3.4,

$$\frac{\pi_i}{1-\pi_i} = e^{\sum_{p=0}^{P} x_{ip}\beta_p} \quad \text{--} \quad (3.10)$$

Which, solving π_i becomes,

$$\pi_i = \left(\frac{e^{\sum_{p=0}^{P} x_{ip}\beta_p}}{1 + e^{\sum_{p=0}^{P} x_{ip}\beta_p}} \right) \quad \text{---} \quad (3.11)$$

Substituting Eq. 3.10 for the first term and Eq. 3.11 for the second term, Eq. 3.9 becomes:

$$L(\beta / y) \approx \prod_{i=1}^{n} \left(e^{\sum_{p=0}^{P} x_{ip}\beta_p} \right)^{y_i} \left(1 - \frac{e^{\sum_{p=0}^{P} x_{ip}\beta_p}}{1 + e^{\sum_{p=0}^{P} x_{ip}\beta_p}} \right)^{n} \quad \text{--------------------------} \quad (3.12)$$

Eq. 3.12 can now be written as:

$$L(\beta / y) \approx \prod_{i=1}^{n} \left(e^{y_i \sum_{p=0}^{P} x_{ip}\beta_p} \right) \left(1 + e^{\sum_{p=0}^{P} x_{ip}\beta_p} \right)^{-n} \quad \text{-----------------------------} \quad (3.13)$$

Since the logarithm is a monotonic function, any maximum of the likelihood function will also be a maximum of the log likelihood function and vice versa. Thus, taking the natural log of Eq. 3.13 yields the log likelihood function:

$$l(\beta) = \sum_{i=1}^{n} y_i \left(\sum_{p=0}^{P} x_{ip}\beta_p \right) - n.\log\left(1 + e^{\sum_{p=0}^{P} x_{ip}\beta_p} \right) \quad \text{--} \quad (3.14)$$

To find the critical points of the log likelihood function, set the first derivative with respect to each β equal to zero.

$$\frac{\partial l(\beta)}{\partial \beta_p} = \sum_{i=1}^{n} y_i x_{ip} - n\pi_i x_{ip} = 0 \quad \text{-------------------------------------} \quad (3.15)$$

3.3.1.2 Statistical tests of individual predictors

The statistical significance of individual regression coefficients can be tested using the Wald and Score chi-square statistics. The Wald statistic is a 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.

$H_0: \beta_i = 0$ *against*

$H_1: \beta_i \neq 0$

The Wald test is based on the behavior of the log-likelihood function at the ML estimate $\hat{\beta}$, having chi-squared form. The standard error of the estimate depends on the curvature of the log-likelihood function at the point where it is a maximized with greater curvature giving smaller SE values. For a dichotomous dependent variable, the Wald statistic is:

$$W = \left[\frac{\hat{\beta}}{SE(\hat{\beta})} \right]^2$$

(Hosmer and Lemeshow, 2000) ----------------------- (3.16)

Under the null hypothesis for large sample size, this statistic has an approximate chi-square distribution with one degree of freedom.

The score test or Lagrange Multiplier is based on the behavior of the log-likelihood function at the null value for β of zero. It uses the size of the derivative (slope) of the log-likelihood function evaluated at the null hypothesis value of the parameter. The derivative at β equals to zero tends to be larger in absolute value when $\hat{\beta}$ is further from that null value.

3.3.1.3. Overall Model Evaluation

A logistic model is said to provide a better fit to the data if it demonstrates an improvement over the intercept-only model (also called the null model). An intercept-only model serves as a good baseline because it contains no predictors. Consequently, all explanatory variables are added to the model. An improvement over this baseline is examined by using inferential statistical the likelihood ratio test.

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 usually make the model fit less well (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 likelihood ratio test does this by comparing the log likelihoods of the two models. If this difference is statistically significant, then the less restrictive model is said to fit the data significantly better than the more restrictive model. If one has the log likelihoods from the models, the likelihood ratio test is easy to calculate. The likelihood ratio test performed to test the overall significance of all coefficients in the model based on test statistic:

$$G = \left[\left(-2\ln L_0\right)-\left(-2\ln L_1\right)\right] \qquad \text{-------------------------------- (3.17)}$$

where L_0 is the likelihood of the null model and L_1 is the likelihood of the saturated model. The statistic G is distributed as chi-squared with degrees of freedom equal to the difference in the number of degrees of freedom between the two models and plays the same role in logistic regression as the numerator of the partial F-test does in linear regression.

3.3.1.4. Hosmer-Lemeshow Goodness-of-Fit test

The Hosmer-Lemeshow test is one of the recommended tests for overall fit of a binary logistic regression model. This goodness-of-fit statistic is used to assess the fit of a logistic regression model. Hosmer and Lemeshow‟s goodness of fit test divides subjects into deciles based on predicted probabilities and then computes a chi-square from observed and expected frequencies. Using this grouping strategy, the Hosmer-Lemeshow goodness-of-fit statistic, Ĉ is obtained by calculating the Pearson chi-square statistic from the gx2 Table of observed and estimated expected frequencies. A formula defining the calculation of Ĉ is as follows:

$$\hat{C} = \frac{\sum_{k=1}^{g}(O_k - E_k)^2}{V_k}$$, Where $E_k = nP_k$, $V_k = nP_k(1-P_k)$, k = 1, 2, …, g, where g is the number of group , O_k is observed number of events in the k^{th} group, E_k is expected number of events in the k^{th} group, and V_k is a variance correction factor for the k^{th} group. If the observed number of events differs from what is expected by the model, the statistic $\hat{C}$ is will be large and

there will be evidence against the null hypothesis that the model is adequate to fit the data. 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 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.

3.3.1.5. Validations of Predicted Probabilities.

The resultant predicted probabilities using logistic model can be revalidated with the actual outcome to determine if high probabilities are indeed associated with events and low probabilities with nonevents. The degree to which predicted probabilities agree with actual outcomes is expressed as either a measure of association or a classification Table. The predictive ability of the model was assessed using the following four measures of association.

1. Somers' D: Somer's D is used to determine the strength and direction of relation between pairs of variables. Its values range from -1.0 (all pairs disagree) to 1.0 (all pairs agree). It is defined as

$$Somers\, D = \frac{n_c - n_d}{t} \quad \text{---} \ (3.18)$$

Where n_c is the number of pairs that are concordant, n_d the number of pairs that are discordant, and t is the total number of pairs with different responses.

2. Gamma: The Goodman-Kruskal‟s Gamma method does not penalize for ties on either variable. Its values range from -1.0 (no association) to 1.0 (perfect association). Because it does not penalize for ties, its value will generally be greater than the values for Somer's D. Its value is calculated as follows.

$$Gamma = \frac{n_c - n_d}{n_c + n_d} \quad \text{---} \ (3.19)$$

3. Tau-a: Kendall's Tau-a is a modification of Somer's D that takes into account the difference between the number of possible paired observations and the number of paired observations with a different response. It is defined to be the ratio of the difference between the number of concordant pairs and the number of discordant pairs to the number of possible pairs.

$$Tau - a = \frac{2(n_c - n_d)}{N(N-1)} \text{ --- (3.20)}$$

Usually this value is much smaller than Somer's D since there would be many paired observations with the same response.

4. C: it is equivalent to the well-known measure ROC. C ranges from 0.5 to 1, where 0.5 corresponds to the model randomly predicting the response, and a 1 corresponds to the model perfectly discriminating the response.

$$C = \frac{[n_c + 0.5(t - n_c - n_d)]}{t} \text{ -- (3.21)}$$

Where, N is the total number of observation, i.e. number of children, in the study, t is the number of children pairs having different response values, n_c is the number of pairs which are concordant and n_d is the number of discordant.

3.3.1.6. Model Diagnostics

Regression model building is often an iterative and interactive process. The first model we try may prove to be inadequate. Regression diagnostics are used to detect problems with the model and suggest improvements.

There are three ways that an observation can be considered as unusual, namely outlier, influence, and leverage. In logistic regression, observations whose values deviate from the expected range, produce extremely large residuals, and may indicate a sample peculiarity called **outliers**. These outliers can unduly influence the results of the analysis and lead to incorrect inferences. An observation said to be **influential** if removing the observation substantially changes the estimate of coefficients. Influence can be thought of as the product of leverage and outliers. An observation with an extreme value on a predictor variable is called a point with high leverage. **Leverage** is a measure of how far an independent variable deviates from its mean. In fact, the leverage indicates the geometric extremeness of an observation in the multi-dimensional covariate space. These leverage points can have an unusually large effect on the estimate of logistic regression coefficients (Cook, 1998).

To identify if an observation is outlier or influential, the following rules of thumbs were employed in this study.

- **Residuals: S**tandardized, Standard, deviance and Pearson residuals are obtained using different software Observations with values larger than three in absolute values are considered as outliers (Agresti, 2007).

- **Leverage Values (Hat Diag):** Measure of how far an observation is from the others in terms of the levels of the independent variables (not the dependent variable). Observations with values larger than$(2p/n)$ are considered potentially highly influential. Where p is number of parameter in the fitted model and n is sample size.

- **Cook's D**: Measures of aggregate impacts of each observation on the group of regression coefficients, as well as the group of fitted values. In logistic regression, a case is identified as influential if its Cook's distance is greater than 1.0 (Hosmer and Lemeshow, 2000).

3.3.2 Multilevel logistic regression model

The main statistical model of multilevel analysis is the hierarchical generalized linear model, an extension of the generalized linear model that includes nested random coefficients. Multilevel/hierarchical modeling explicitly accounts for the clustering of the units of analysis, individuals nested within groups. Such data structures are viewed as a multistage sample from a hierarchical population. Multilevel analysis is a methodology for the analysis of data with complex patterns of variability, with a focus on nested sources of variability. The best way to the analysis of multilevel data is an approach that represents within group as well as between groups relations within a single analysis, where "group‟ refers to the units at the higher levels of the nesting hierarchy. Very often, it makes sense to use probability models to represent the variability within and between groups, in other words, to consider the unexplained variation within groups and the unexplained variation between groups as random variability. In this study not only unexplained variation between children but also unexplained variation between regions is regarded as a random variable. Such variation can be analyzed through statistical models known as random coefficients models.

3.3.2.1. Two Level Model

For simplicity of presentation two-level models are used for this study, i.e., models accounting for children-level and regional -level effects. In this data structure, level-1 is the children level and level-2 is the regional level. Within each level-2 unit there are n_j children in the j th region. We further simplify the presentation by assuming there is a children-level predictor and regional-level factor. To provide a familiar starting point, we first consider a two-level model for binary outcomes with a single explanatory variable. Conceptually, the basic (two level) multilevel model for a binary response is equivalent to model (3.6) except for the notation in the outcome variable. Suppose we have data consisting of children, (level one) grouped into regions (level two). Let Yij be the binary response for child i in region j and X ij, an explanatory variable at the children level. We define the probability of the response equal to one as π_{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

$$\log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_0+\beta_1 X_{ij}+U_j \quad \text{--- (3.22)}$$

Where $U_j \sim IID(0,\delta^2)$, U_j is the random effect at level two. Without U j, Equation (3.22) would be a standard logistic regression model. Conditional on U_j, the Y_{ij} is assumed to be independent. The model (3.22) is often described as follows.

$$\operatorname{logit}(\pi_{ij}) = \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_{0j}+\beta_1 X_{ij} \qquad \text{[Level 1 model]}$$

and, $$\beta_{0j} = \beta_0 + U_j \qquad \text{[Level 2 model]}$$

3.3.2.2. Heterogonous Proportion

For the proper application of multilevel analysis, the first logical step is to test heterogeneity of proportions between groups. The most commonly used test statistic to check for heterogeneity of proportions between groups is the chi-square. To test whether there are indeed systematic differences between the groups, the well-known chi-square test can be used. The test statistic of the chi-squared test for contingency table is often given in familiar form:

$$X^2 = \frac{\sum_i (O-E)^2}{E} \quad \text{-- (3. 23)}$$

Where O is the observed and E is the expected counts in the cell of contingency table. It can also be written as:

$$X^2 = \sum_{j=1}^{g} n_j \frac{(\bar{Y}_{.j}-\hat{P}_{.})^2}{\hat{P}_{.}(1-\hat{P}_{.})} \quad \text{--- (3.24)}$$

Where the group average, $\bar{Y}_{.j} = \frac{1}{n_j}\sum_{i=1}^{n_j} Y_{ij}$ is the proportion of successes in-group j, which is an estimate for the group-dependent probability Pj. Similarly, the overall average

$\hat{P}. = \bar{Y}.. = \frac{1}{M}\sum_{j=1}^{g}\sum_{i=1}^{n_j} Y_{ij}$ Here is the overall proportion of successes. g is number of group

The decision is based on the chi-square distribution with (g-1) degrees of freedom. This chi-square distribution is an approximation valid if the expected number of success and of failures in each group, $n_j\overline{Y_{.j}}$ and $n_j\left(1-\overline{Y_{.j}}\right)$ respectively, all are at least 1 while 80 percent of them are at least 5 (Agresti, 2002).

Estimation of between and within group variance: the theoretical variance between the group dependent probabilities, i.e., the population value of Var (Pj), was estimated by:

$$\tau^2 = S^2_{between} - \frac{S^2_{within}}{n} \qquad \text{--- (3.25)}$$

Where n is given by

$$n = \frac{1}{n-1}\left\{ n - \frac{\sum_{j=1} n_j^2}{n} \right\} = \bar{n} - \frac{S^2(n_j)}{g\bar{n}} \qquad \text{And}$$

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

For binary outcome variables, the observed between-groups variance is closely related to the chi-squared test statistic (3.19). They are connected by the formula

$$S^2_{between} = \frac{\hat{p}(1-\hat{p})}{\bar{n}(N-1)} X^2 \qquad \text{--- (3.26)}$$

The within-group variance in the binary case is a function of the group averages, via,

$$S^2_{within} = \frac{1}{M-N}\sum_{j=1}^{N} n_j \overline{Y}_{.j}\left(1-\overline{Y}_{.j}\right) \qquad \text{-- (3.27)}$$

3.3.2.3. The Random Intercept-Only Model

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

$$\log it(p_j) = \beta_0 + U_{0j} \qquad \text{-- (3.28)}$$

$$U_{0j} \sim IID\left(0, \sigma_0^2\right)$$

Where β_0 is the population average of the transformed probabilities and U_{0j} is the random deviation from this average for group j.

3.3.2.4. The Random Intercept and Fixed Slope Model

A random intercept model is a model in which intercepts allow varying, and therefore the scores on the dependent variables for each individual observation was predicted by the intercept that varies across groups. This model assumes that slope was fixed. In addition, this model provides information about intra-class correlations, which are helpful in determining whether multilevel models were required in the first place (Fidell, 2007). Let y_{ij} be the response of child i in region *j*. Then the model can be write as follows:

for child *i* in region *j*, Z_j is latent variable in region j.

$$\log it(\pi_{ij}) = \beta_{0j} + \beta_{10} X_{ij} \qquad \text{Level 1 model} \qquad \text{---------------------------- (3.29)}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + \delta_{0j}$$
$$\delta_{0j} \sim N(0, \tau_{00})$$
$$\beta_{10} = \gamma_{10}$$

Level 2 model (Snijders and Boskers, 1999)

$$\log it(\pi_{ij}) = \gamma_{00} + \gamma_{01} Z_j + \gamma_{10} x_{ij} + \delta_{oj}$$

or

Mixed model ---------------------------------- (3.30)

$$\pi_{ij} = \frac{\exp(\gamma_{00} + \gamma_{01} Z_j + \gamma_{10} x_{ij} + \delta_{oj})}{1 + \exp(\gamma_{00} + \gamma_{01} Z_j + \gamma_{10} x_{ij} + \delta_{oj})}$$

3.3.2.5. Random Intercepts and Slope Models

A model that includes both random intercepts and random slopes is likely the most realistic type of model, although it is also the most complex. In this model, both intercept and slopes are allowed to vary across regions, meaning that they are different in different regions. Let y_{ij} is the response of child *i* in region *j*. Then the model can be written as follows:

For child *i* in region *j*, Z_j is latent variable in region j

$$\log it\left(\pi_{ij}\right) = \beta_{0j} + \beta_{1j} X_{ij}$$

level-1 model ---------(3.31)

$$\beta_{0j} = \gamma_{00} + \gamma_{01} z_j + \delta_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11} z_j + \delta_{1j}$$
$$\begin{pmatrix} \delta_{0j} \\ \delta_{1j} \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00} & \tau_{10} \\ \tau_{01} & \tau_{11} \end{bmatrix}\right)$$
$$\sim N\left(0 ,\quad \tau\right)$$

Level-2 Model (Snijders and Boskers, 1999)

$$\log it\left(\pi_{ij}\right) = \gamma_{00} + \gamma_{01} z_j + \gamma_{10} X_{ij} + \gamma_{11} z_j X_{ij} + \delta_{0j} + \delta_{1j} X_{ij}$$

or Mixed model----- (3.32)

$$\pi_{ij} = \frac{\exp\left(\gamma_{00} + \gamma_{01} z_j + \gamma_{10} X_{ij} + \gamma_{11} z_j X_{ij} + \delta_{0j} + \delta_{1j} X_{ij}\right)}{1 + \exp\left(\gamma_{00} + \gamma_{01} z_j + \gamma_{10} X_{ij} + \gamma_{11} z_j X_{ij} + \delta_{0j} + \delta_{1j} X_{ij}\right)}$$

3.3.2. 6. Estimation of Multilevel Logistic Regression Model

Parameter estimation for a multilevel logistic model is not straightforward like the methods for logistic regression. The most common methods for estimating multilevel logistic models and the once that will be use in this study, are based on likelihood. Among the methods, Marginal Quasi Likelihood (MQL) (Goldstein, 1991; Goldstein and Rasbash, 1996) and Penalized Quasi Likelihood (PQL) (Laird, 1978); Breslow and Clayton, 1993) are the two prevailing approximation procedures. After applying these quasi likelihood methods, the model will be estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) (Goldstein, 2003). Second-order PQL method can be used throughout the multi-level analyses since this method approximates well compared to the other PQL and MQL methods (Goldstein, 2003). Mainly the PQL method is used. Bayesian methods using Markov chain Monte Carlo (MCMC) have also been used for parameter estimation.

Perhaps the most frequently used methods are based on first- or second- order Taylor expansions. Marginal quasi-likelihood (MQL) involves expansion around the fixed part of the model, whereas penalized or predictive quasi- likelihood (PQL) additionally includes the random part in its expansion (Goldstein & Rasbash, 1996).

More recently, Raudenbush *et al*. (2000) proposed an approach that uses a combination of a fully multivariate Taylor expansion and a Laplace approximation. This method yields accurate results and is computationally fast. Also, as opposed to the MQL and PQL approximations, the deviance obtained from this approximation can be used for likelihood-ratio tests.

3.4 Model Comparison

There are generally many options available when modeling a data structure, and once we have successfully fit a model, it is important to check its fit to data. It is also often necessary to compare the fits of different models. When fitting several models to the same data set, it can be helpful to compare those using summary measures of fit. A standard summary of some software has given deviance, which is -2 times the log-likelihood; that is, -2 times the logarithm of the probability of the data given the estimated model parameters (Gelman, 2006).

3.4.1 Deviance and Akaike Information Criterion

The residual deviance is defined to be twice the difference between the maximum achievable log likelihood and that attained under the fitted model. Under any given model, H_0 , with fitted probabilities $\hat{\pi}$, the log likelihood is

$$L(\hat{\pi};\, y) = \sum \left\{ y_i \log \hat{\pi}_i + (m_i - y_i) \log(1 - \hat{\pi}_i) \right\},$$

The maximum achievable log likelihood attained at point $\tilde{\pi}_i = \frac{y_i}{m_i}$

, but this point does not usually occur in the model space under H_0. The deviance function is therefore

$$D(y;\, \hat{\pi}) = 2l(\tilde{\pi}; y) - 2l(\hat{\pi}; y)$$

$$= 2 \sum \left\{ y_i \log\left(\frac{y_i}{\hat{\mu}_i}\right) + (m_i - y_i) \log\left(\frac{m_i - y_i}{m_i - \hat{\mu}_i}\right) \right\}$$

In classical generalized linear models, adding a parameter to a model is expected to increase the fit even if the new parameter represents pure noise. Adding a noise predictor is expected to reduce the deviance by one, and adding k predictors that are pure noise is expected to reduce by an amount corresponding to a chi-square distribution with k degrees of freedom. Thus, if k predictors are added and the deviance declines by significantly more than k, then we can conclude that the observed improvement in predictive power is statistically significant. Thus,

Adjusted deviance = deviance + number of parameters

can be used as an adjusted measure that approximately accounts for the increase in fit attained simply by adding predictors to a model (The analogy in simple linear regression is the adjusted R^2).

Akaike information criterion is defined as

AIC = deviance + 2 (number of predictors)

= adjusted deviance + number of predictors

In classical regression or generalized linear modeling, a new model is estimated to reduce out-of- sample prediction error if the AIC decreases.

The ideas of deviance and AIC apply to multilevel also, but with the difficulty that the "number of parameters" is not so clearly defined. Roughly speaking, the number of parameters in a multilevel model depends on the amount of pooling a batch of J parameters corresponds to one parameter if there is complete pooling, J independent parameters if there is no pooling, and something in between with partial pooling. In case of this study, with varying intercept random models, the coefficients for N group indicators represent something fewer than N independent parameters. Especially for the group's small samples sizes, the group level regression explains much of the variation in the intercepts, so that in the multilevel model they are not estimated independently. When the model is improved and the group level variance decreases, the effective number of independent parameters also decreases.

3.6 Ethical Consideration

Ethical clearance which is used to be provided previously by the Ethiopian Health and Nutrition Research Institute (EHNRI) Review Board, the National Research Ethics Review Committee (NRERC) at the Ministry of Science and Technology, the Institutional Review Board of ICF International, and the Centers for Disease Control and Prevention (CDC) currently conferred to Jimma University. Accordingly, the Research Ethics Review Board of Jimma University has provided an ethical clearance for the study. The data for analysis was brought from EDHS, and to do so the department of statistics asked to write an official co-operation letter to the Central Statistical Agency of Ethiopia from where data will be obtained.

CHAPTER FOUR

4. RESULT AND DISCUSSION

The data analysis is done using STATA 11 and SAS statistical (software) packages. The results of the analysis are divided into the following sections: descriptive analysis results, results of logistic analysis and results of multilevel analysis. These results and their discussions are presented in the following sections.

4.1. Descriptive Analysis

The major demographic and socio-economic characteristics of the respondents with under-five children mortality are presented in Table 4.1 below. The total number of children covered in the present study is 11654. Among these, 846 (7.26%) were dead where as 10808 (92.74%) were alive at the date of the survey.

Table 4.1.Distribution of Demographic and Socioeconomic Factors on Mortality Status of Children under- Five in Ethiopia

Covariates (Explanatory	Under-five child mortality (U5CM) status			
	Live	Death	Total	% of U5CM status
Regions				
Tigray	1123	79	1202	6.6
Affar	1033	97	1130	8.6
Amhara	1203	91	1294	7.0
Oromiya	1637	124	1761	7.0
Somali	951	76	1027	7.4
Benishangul-Gumuz	925	95	1020	9.3
SNNP	1491	123	1614	7.6
Gambela	782	69	851	8.1
Harari	616	43	659	6.5
Addis Ababa	386	14	400	3.5
Dire Dawa	661	35	696	5.0
Total	10808	846	11654	7.26
Place of Residence				
Urban	1865	121	1986	6.1
Rural	8943	725	9668	7.5
Sex of children				
Male	5515	472	5987	7.9
Female	5293	374	5667	6.6
Age of mother				
15-19	463	51	514	9.92

20 _29	5562	420	5982	7.02
30- 39	3871	289	4160	6.95
40 -49	912	86	998	8.62
Birth order				
1	2130	173	2303	7.5
2,3 or 4	4820	358	5178	6.9
≥ 5	3858	315	4173	7.5
Family size				
1-5	4694	480	5174	9.3
>5	6114	366	6480	5.6
Wealth index				
Poor	5277	462	5739	8.1
Middle	1738	134	1872	7.2
Rich	3793	250	4043	6.2
Source of Drinking water				
Piped	2803	171	2974	5.7
Spring	2861	234	3095	7.6
Tube Well Water and others	5144	441	5585	7.9
Educational level				
No Education	7839	636	8475	7.5
Primary	2500	191	2691	7.1
Secondary	278	14	292	4.8
Higher	191	5	196	2.6
Breastfeeding				
No	3367	502	3869	13.0
Yes	7441	344	7785	4.4
Age of first birth				
< 20	6627	549	7176	7.7
>=20	4181	297	4478	6.6
Using contraceptive method				
Yes	2306	119	2425	4.9
No	8502	727	9229	8. 6

The proportion of the death status of children under-five varied from one region to the other in Ethiopia. For example, the highest percentage of death of children under-five was observed in Benishangul-Gumuz (9.3%) followed by Afar (8.6%) while the lowest percentage of death was recorded in Addis Ababa (3.5%) and followed by Dire Dawa (5.0%). Hence, there appears to be some variation in the proportion of mortality of children under-five amongst children in different regions.

Similarly, the proportion of the death of a child under-five as observed in table 4.1 differs by place of residence: Urban and Rural. Accordingly, higher number of death of under-five children (7.5%) was recorded in rural areas, and relatively small number of death of under-five children (6.1%) recorded in urban areas.

The proportion of death of children under-five as observed in table 4.1 also differs with the age of their mothers. For instance, higher proportion of death of children under-five was observed for women 15-19 year (9.92%) and the lowest proportion of mortality of children under-five was a found in the age group between 30 -39 years (6.95%).

Table 4.1 also shows that the proportion of the death of children under-five vary by wealth index (households economic status), sex of children (gender) and breastfeeding. The highest percentage of death of child under-five that was observed among children from poor households (8.1%) as opposed to children residing among rich households (6.2%). With regard to sex of children, the higher percentage of death of children under-five was observed among male children (7.9%) compared to female children (6.6%) of the same age. Likewise, the death of children under-five was assessed, and found to be higher among breastfeeding children (4.4%) compared to non-breastfeeding children (13.0%).

Table 4.1 also reveals that the number of death of children under-five varies by their educational levels of mothers. The highest percentage of death of under-five child that was observed in women who have no education (7.5%) as opposed to the lowest percentage of death of under-five child that was recorded for women who have higher education level (2. 6%).

The number of death of under-five children also varies according to family size and age of first birth. A higher percentage of death of under five child was observed in family size below five (9.3%) as opposed to the lowest percentage of death of under-five child was observed in family size is greater than or equal to five (5. 6%). About 7.7% die before the age of five children that were observed in age of first birth of mother was less than 20 year while 6.6% of die before the age of five children were an observed in age of first birth of mother was greater than or equal to 20 year.

As Table 4.1 shows the number of deaths of children under-five differs between contraceptive method using and non-contraceptive using families. Accordingly, a higher percentage of death of children under-five happened to children coming from non- contraceptive method using households (8. 6%) as opposed to children coming from contraceptive method using households (4.9%).

The number of death of children under-five also varies in line with the sources of drinking water of households. A higher percentage of death of children under-five was observed among households using well tube and others source of drinking water (7.9%) as opposed to households using pipe source of drinking water (5.7%).

4.2. Logistic Regression Analysis of Under-Five Child Mortality

In this section, the logistic regression analysis results obtained by using stepwise inclusion of variables, overall model evaluation, statistical tests of individual predictors and goodness-of-fit statistics are presented.

The Initial Log Likelihood function, (-2 Log Likelihood or -2LL) is a statistical measure like total sums of squares in regression. If the independent variables have a relationship with the dependent variable, we will improve our ability to predict the dependent variable accurately, and the log likelihood value will decrease. The initial –2LL value is 6066.966 at step 0, before any variables was added to the model.

The statistical significance of individual regression coefficients is tested using the Wald and score chi-square statistic. In this section, we identify the statistically significant predictor variables and determine the direction of relationship with and contribution to the dependent variable.

A negative sign in column labeled Estimate indicates an inverse relationship of explanatory variable with the log odds of the dependent variable. In contrast a positive coefficient column labeled Estimate indicates a positive relationship to the log odds of the dependent variable.

Table 4.2 Test of Significance of Independent Variables Using Wald Test

Parameter	Estimate	Standard error	Pr > ChiSq	OR	[95% C. Interval of OR]	
Intercept	-3.2141	0.3444	0.000	-	-	
Sex of Child						
Male (ref.)						
Female	- 0.1737	0.0734	0.018	0.8405	0.7279	0.9705
Family size						
1-5 (ref.)						
>5	-0.5715	0.0748	0.000	0.5647	0.4877	0.6538
Education level						
Higher (ref.)						
No Education	0.7448	0.2430	0.002	2.1060	1.3081	3.3906
Primary	0.6369	0.2481	0.010	1.8906	1.1626	3.0747
Secondary	0.3272	0.3617	0.366	1.3871	0.6827	2.8182
Breast feeding						
No (ref.)						
Yes	-1.2459	0.0750	0.000	0.2877	0.2483	0.3333
Use of Contraceptive						
Yes (ref.)						
No	0.5621	0.1081	0.000	1.7543	1.4192	2.1684
Age of first Birth						
< 20(ref.)						
>=20	-0.1693	0.0774	0.029	0.8442	0.7254	0.9825
Region						
A.Ababa(ref.)						
Tigray	0.4559	0.3066	0.137	1.5776	0.8649	2.8775
Affar	0.5551	0.3068	0.070	1.7422	0.9548	3.1787
Amhara	0.7040	0.3057	0.021	2.0218	1.1106	3.6805
Oromia	0.6800	0.2993	0.023	1.9739	1.0979	3.5491
Somali	0.4996	0.3118	0.109	1.6481	0.8946	3.0364
Benishangul-G	0.9046	0.3057	0.003	2.4709	1.3572	4.4986
SNNP	0.7732	0.2994	0.010	2.1667	1.2048	3.8964
Gambela	0.8939	0.3100	0.004	2.4446	1.3314	4.4885
Harari	0.5434	0.3234	0.093	1.7218	0.91343	3.2455
Dire Dawa	0.1533	0.3328	0.645	1.1656	0.60713	2.2396

The statistical significance of individual regression coefficients is tested using the Wald and LRT (see in the appendix for this result table 4.12). According to the above Table 4.2, Region, breastfeeding, sex of children, family size, education level, contraceptive method, and age of first birth of mothers were found to be significant predictors of under-five children mortality at 5% level of significance. But, secondary education level, Tigray region, Affar region, Somali region, Harari region and Dire dawa are not significant when compare to Addis Ababa. Thus, the estimated model is given by:

$$\log it\left(\hat{p}\right) = -3.2141 - 0.1737 Sexch_{female} - 0.5715 F.size_{1} + 0.7448 Educ_{no educ}$$
$$+0.6369 Educ_{\Pr im} + 0.3272 Educ_{Seco} - 1.2459 Br.feed_{Yes}$$
$$+0.5621 C.method_{No} - 0.1693 Agebirth_{\geq 20} + 0.4559 \operatorname{Re} gion_{Tigray}$$
$$+ 0.0115 \operatorname{Re} gion_{Affar} + \quad .... + 0.5434 \operatorname{Re} gion_{Harari} + 0.1533 \operatorname{Re} gion_{Dire.Dawa}$$

Where: $\hat{p}$ = predicted probability of under-five child mortality, β_0 = constant, $\mathbf{Sexch_i}$ = Sex of child i, $\mathbf{F.size_j}$ = Family size j, $\mathbf{Educ_m}$ = Education level m, $\mathbf{Agebirth_l}$ = Age of first birth of mother l, $\mathbf{Br.feed_r}$ = Breast feeding r , $\mathbf{C.method_n}$ = Mother use contraceptive method n and $\mathbf{Region_k}$ = children's region k.

The value of explanatory variable for each category is taken as 1 if this variable falls in the corresponding category. For example,

$\mathbf{Agebirth_l = 1}$ for women's age of first birth l and $\mathbf{Agebirth_l = 0}$ for others age groups.

$\mathbf{Region_k = 1}$ for children's region k and $\mathbf{Region_k = 0}$ for others region.

Similarly, each of the other variables takes value 1 if it falls within the corresponding level of category. Based on the above result, the regression equation consisting of the significant variables is given by:

As can be seen in Table 4.2 at the final step, all independent variables are added to the logistic regression equation in a stepwise manner. The addition of these variables reduced the initial log likelihood value (-2 Log Likelihood) of 6066.966 to 5652.523.

Table 4.3: Result of Model Fit Statistics for Intercept only and Full Model

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6068.966	5690.523
SC	6076.329	5830.428
-2 Log L	6066.966	5652.523

G = -2ln (likelihood of the reduced model) + 2ln (likelihood of the full model)

= 6066.966 - 5646.568 = 420.398

$X^2_{0.95,17} = 27.58711$ (table value of chis-square)

Since, the calculated deviance is greater than the chi-squared critical values; the null hypothesis will rejected, further supporting the significance of the fit full model to the data set.

The difference between these two measures is the model chi-square value or likelihood ratio (414.443 = 6066.966 - 5652.523) that is tested for statistical significance. This test is analogous to the F-test for R^2 or change in R^2 value in multiple regressions that tests whether or not the improvement in the model associated with the additional variables is statistically significant.

Table 4.4: Test of Significance of the Relationship between the Dependent and Independent Variables.

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	414.4425	18	<0.0001
Score	426.0795	18	<0.0001
Wald	390.8171	18	<0.0001

In Table 4.4 the model Chi-Square value of 414.4425 has a P-Value of less than 0.001. Similarly, score and Wald tests also have P-values less than 0.05 and are significant. These indicate that all three tests yield similar conclusions, that is, the final model with explanatory variables was more effective than the null model. So, we conclude that there is a significant relationship between the dependent variable and the set of independent variables.

The Hosmer-Lemeshow goodness of fit test was employed and the result is presented in Table 4.5. A good model fit is indicated by a none-significant chi-square value.

Table 4.5: Test of Significance of Hosmer-Lemeshow Goodness of Fit Statistics

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
7.2878	8	0.5059

The better model fit is indicated by a smaller difference in the observed and predicted classification. The Hosmer-Lemeshow Goodness-of-fit test tests the hypotheses:

Ho: the model is a good fit, vs.

Ha: the model is not a good fit

Since the P-value in Table 4.5 P-value = 0.5059 is larger than 0.05, we do not reject the null hypothesis, and we conclude that the model is a good fit.

Finally, the four measures of association for assessing the predictive ability of the model are presented in Table 4.6.

Table 4. 6: Association of Predicted Probabilities and Observed Responses

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	68.8	Somers' D	0.392
Percent Discordant	29.6	Gamma	0.398
Percent Tied	1.5	Tau-a	0.053
Pairs	9143568	C	0.696

The value of the Gamma statistic is 0.398 (see Table 4.6) implying that 39.80% fewer prediction errors are by using the estimated probabilities than by chance alone. The value of C statistic is 0.696. This means that for 69.6% of all possible pairs of children's the model correctly assigned a higher probability to those who were under five child mortality.

A more appealing way to interpret the regression coefficient in logistic model is using odds ratio. The odds ratio indicates the effect of each explanatory variable directly on the odds of under-five children mortality rather than on the odds of survival of under-five children. Estimates of odds greater than 1.0 indicate that the risk of is greater than that for the reference category. Estimates less than 1.0 indicate that the risk of death of under-five child is less than that for the reference category of each variable. Therefore, the final model presented in Table 4.2 is interpreted in terms of odds ratio as follows.

Children whose gender was female were 16% (OR = 0.84.05) less likely to die before the age of five compared to children who gender was male controlling for other variables in the model. Similarly, children from family size greater than or equal to five were 43.5% (OR = 0.5646) less likely to die compared to children from family size less than five controlling for other variables in the model.

The odds of U5CM of children who were from non- educated mother were 2.1 (OR = 2.1) times higher than the odds of U5CM of children from higher educated mother while children from primary educated mother were 89.1% (OR =1.891) more likely to die compared to children from higher educated mother controlling for other variables in the model.

Children who get breast feed were 71.2% (OR = 0.288) less likely to die before the age of five compared to children who do not get breast feed, controlling for other variables in the model. Similarly, children who are from family not using contraceptive methods are 75.4% (OR = 1.754) more likely to die compared to children from family using contraceptive methods, controlling for other variables in the model.

Children who are from mothers age of first birth greater equal to 20 years were 15.6% (OR = 0.844) less likely to die compared to children from mothers age of first birth less than 20 years, controlling for other variables in the model.

The odds of die of children under-five in Amhara, Oromia, Benishangul- Gumez, SNNP and Gambela National Regional State were 2.02, 1.974, 2.47, 2.167 and 2.445 times higher than the odds of die of children under-five in Addis Ababa respectively by controlling others variables in the model.

4.2.1. Model Diagnostics

Regression model building is often an iterative and interactive process. Model diagnostics are used to detect problems with the model and suggest improvements. A failure to detect outliers and influential cases can have severe distortion on the validity of the inferences. It would be reasonable to use diagnostics to check if the model is adequate or not. The adequacy of the fitted model was checked for possible presence and treatment of outliers and influential values. The diagnostic test results for detection of outliers and influential values are presented using figure below. The residuals like Studentized, Pearson and standardized residuals are also use in order to check model diagnostic. The Cook.s distance less than unity showed each observation had no impact on the group of regression coefficients. A value of the leverage statistic show's that no observation is far apart from the others in terms of the levels of the independent variables (not the dependent variable). Thus, from the above goodness of fit tests and diagnostic checking, we can say that our model is adequate.

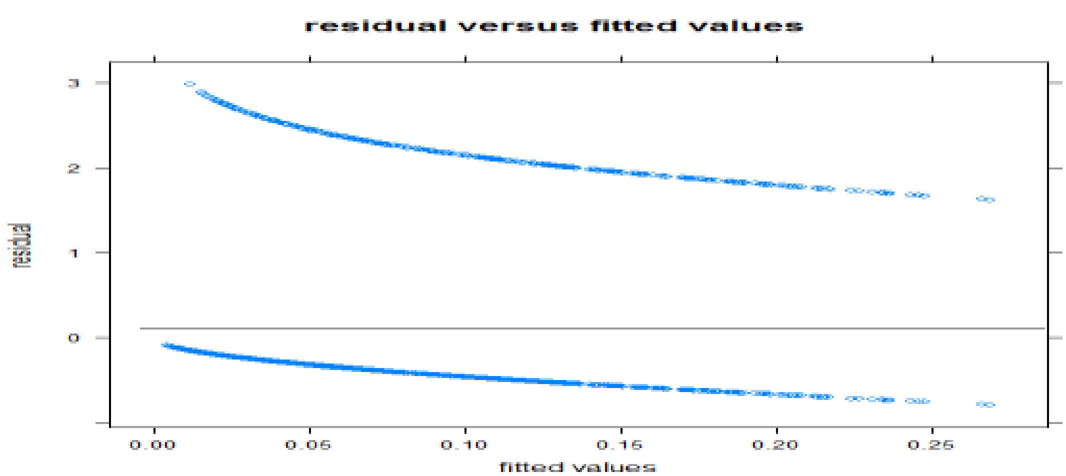

Figure 4.1 plot of residual versus fitted values of U5CM in Ethiopia

Figure 4.1 show that Residual versus fitted value plot for final logistic model. It does not show any systematic pattern. This points out that the model fits the data well

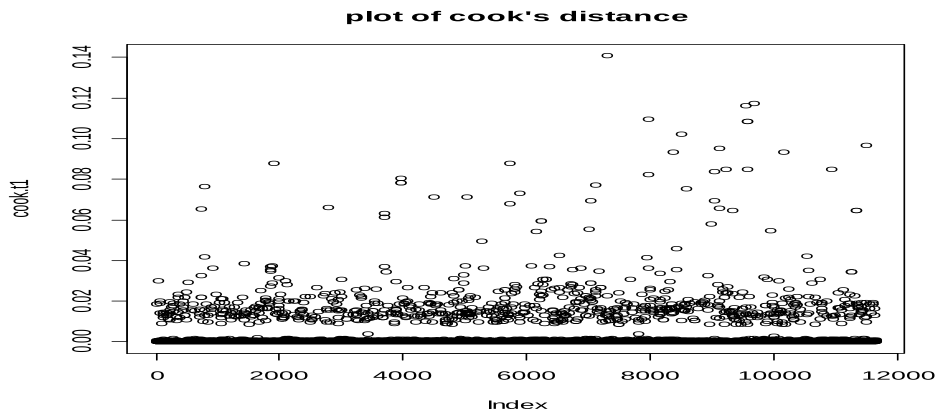

Figure 4.2 plot of index cook's distance

Figure 4.2 shown that one observation (# 7297) is large cook's distance from others. But, all not point within 0.25 inches.

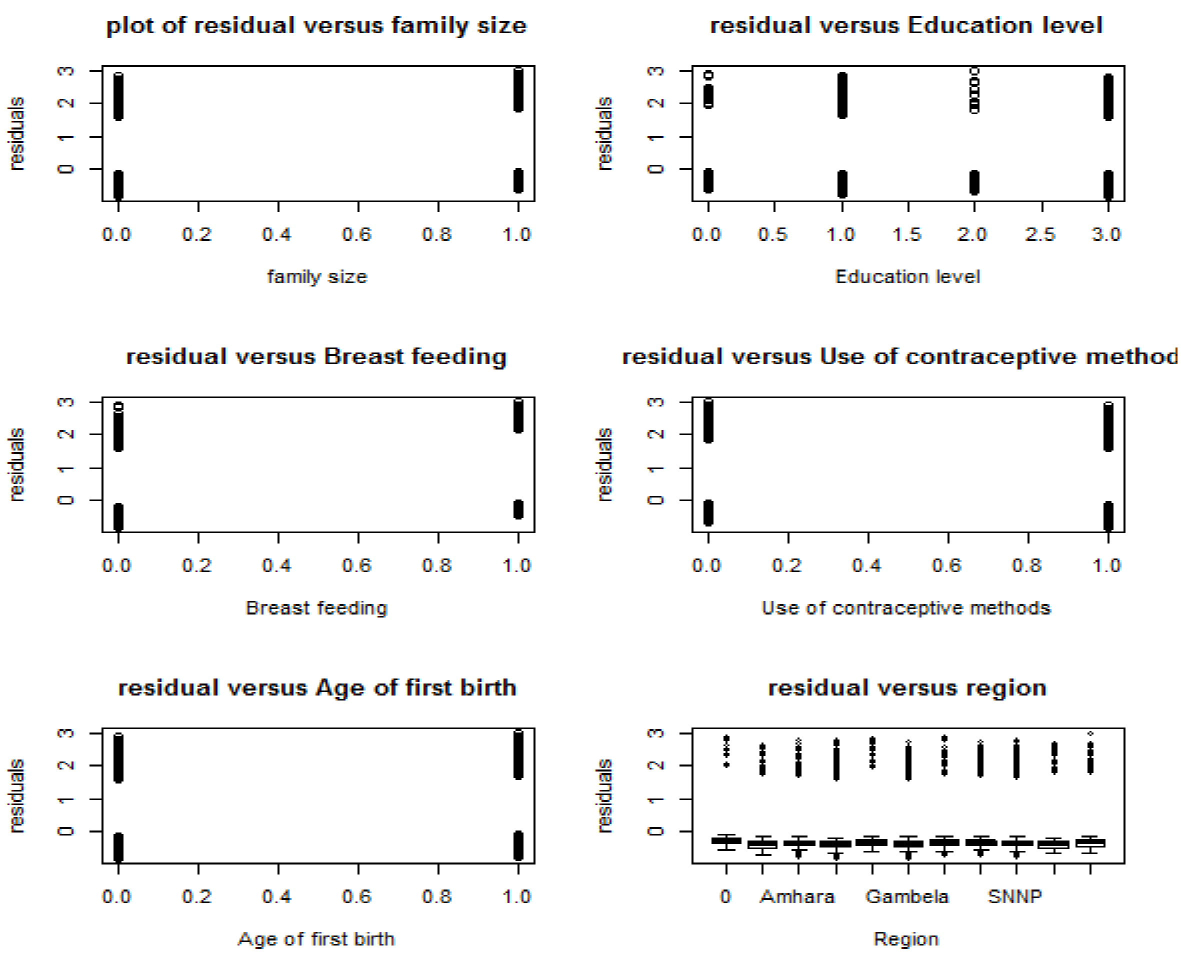

Figure 4.3 plots of residual versus each categorical predictor

Furthermore, the residual versus each categorical predictor recommended that there is a uniformity of residuals across each level of covariates specifies that homogeneity of error variances.

4.3. Multilevel Logistic Analysis of Under-Five Child Mortality

The data used in this study have a hierarchical structure. Units at one level are nested within units at the next higher level. Here, the lower level (level-1) units are the individual child, and the higher level (level-2) units are the regions that constitute the groups into which the children are clustered or nested. The nesting structure is children within regions that resulted in a set of 11 regions with 11654 children. The data used in this study consist of variables describing individuals as well as variables describing regions. Therefore, the statistical model used has to describe the data at both levels in order to find the effect on under-five child mortality of both the individual children and the regions.

As mentioned above, multilevel models were developed to analyze hierarchically structured data. These models contain variables measured at different levels of the hierarchy. Unobserved heterogeneity is modeled by introducing random effects. Random intercepts are used to model unobserved heterogeneity in the overall response; random coefficients model unobserved heterogeneity in the effects of explanatory variables on the response variable. As one of the aims of this study was to model the heterogeneity between regions, a random intercept model was used. This allows the overall probability of under-five child mortality to vary across regions. The chi-square test was applied to assess heterogeneity between regions mean. The test yields X^2 = 37.4332 with d.f 10 (P<0.0001). Thus, there is evidence of heterogeneity among the regions.

Children's in this study were selected from different regions of Ethiopia. Thus, there are two kinds of random variability in the data, that is, between different children in a single region and that between different regions. The advantages of using a multilevel model include the ability to fully explore the variability at all levels of the data hierarchy, and estimation of correct standard errors in the presence of clustered data. Children from the same region would tend to be more similar compared to children chosen at random from different regions. The model takes into account the correlation structure of the data, enabling correct inferences to be made.

4.3.1. Random Intercept-Only Model (Empty Model with Random Intercept)

We first fit a simple model with no predictors i.e. an intercept-only model that predicts the probability of death of child under five. The functional form of the model is:

$$\log it\left(\hat{p}\right) = \beta_0 + U_{0j}$$

The estimates of parameters and standard errors are presented in Table 4.7. The maximum likelihood estimate of the empty model of standard logit model is -2.57269 with standard error 0.0357009. The ML estimate from the standard logit model of the ratio of death to alive is exp (-2.57269) = 0.07632994, which is the same as the sample ratio of 846 death to 11654 alive. It is in fact the estimated odds-ratio when no predictors have been considered in the model.

Table 4.7: Result of Parameter Estimate of Intercept-Only Model with Random Effect

Fixed effect estimated					
Covariates	Estimate	Std. Err.	Z	P>|z|	[95% Conf. Interval]
Intercept	-2.57269	0.0598923	-42.96	0.000	-2.690076 -2.455303

Random effects Parameters estimated			
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
region (Intercept) **Var(U₀ⱼ) =** $\boldsymbol{\sigma_0^2}$	0.1456168	0.0679959	0.0583099 0.3636476

LR test vs. logistic regression: chibar2(01) = 3.22 Prob>=chibar2 = 0.0364

AIC = 6067.748, logLik = -3031.874, Deviance = 6063.748

The variance of the regional level residuals errors, symbolized by $\boldsymbol{\sigma_0^2}$ is estimated to be 0.1456. This parameter estimate is larger than the corresponding standard errors and the 95% confidence interval of the estimate shows that it is significant since the lower bounder of confidence interval is does not close to zero. The significance of this residual term indicates that there are regional differences in the U5CM status in Ethiopia. LR test comparing the model with the one-level binomial regression model favors the random-intercept model, indicating that there is a significant variation in U5CM between regions.

4.3.2. Random Intercept And Fixed Effect Model

We will now extend our model to allow for regional effects on the probability of death of child under five. We begin with a random intercept or variance components model that allows the overall probability of U5CM to vary across regions. The results of two-level random intercept and fixed slope model are presented in table 4.8

Table 4.8: Result of Parameter Estimate of random intercept and fixed slope multilevel logistic model

Fixed effect parameter estimated						
Covariates	Estimate	Std. Err.	P>|z|	OR	[95% Conf. Interval of OR]	
Intercept	-2.695492	0.25255	0.000	-	-	
Sex of child						
Male (ref.)						
2.Sexchild	-0.173795	0.07331	0.018	0.8404689	0.7279794	0.9703406
Family size						
1-5(ref.)						
>5	-0.568499	0.07451	0.000	0.566375	0.4894237	0.6554252
Education level						
Higher(ref.)						
No education	0.8129527	0.2414	0.001	2.254555	1.404739	3.61848
primary	0.7108574	0.24775	0.004	2.035736	1.252671	3.308307
Secondary	0.3383056	0.3609	0.349	1.402569	0.6913994	2.845244
Breast feeding						
No						
Yes	-1.22664	0.07515	0.000	0.293276	0.2531109	0.3398146
Use of Contraceptive						
Yes (ref.)						

No	0.575436	0.10734	0.000	1.777906	1.440584	2.194214
Age of 1st Birth						
<20 (ref).						
>=20	-0.185863	0.07736	0.016	0.8303878	0.71356	0.9663431

Random-effects Parameters estimated				
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
region: Identity var(**Uoj**) $=\boldsymbol{\sigma_0^2}$	0.0284344	0.0223343	0.0060989	0.1325667
LR test vs. logistic regression: chibar2(01) = 5.62 Prob>=chibar2 = 0.0089				
AIC = 5694.739, loglik = -2837.369, Deviance = 5674.738				

In table 4.8, the variance component representing variation between regions has decreased from 0.1456 in the empty model with random intercept to 0.0284344 in the random intercept and fixed slopes multilevel logistic regression model. The 95% confidence interval of the estimate shows that it is significant since the lower bounder of confidence interval is does not close to zero. The significance of this residual term indicates that there are regional differences in the U5CM status in Ethiopia. Likelihood Ratio(LR) test comparing the model with the one-level binomial regression model favors the random-intercept model, indicating that there is a significant variation in U5CM between regions.

The deviance-based Chi-square (deviance = 389.012) is the difference in deviance between the empty model with random intercept (deviance = 6063.750) and fixed slope model with random intercept (deviance = 5674.738). This value is compared to chi-square distribution with 10 degree of freedom. The significant of it (X^2 = 389.012, df = 10, P-value = 0.000) implies that fixed slope model with random intercept model is better than empty model with random intercept. Therefore, this model is a better fit as compared to the empty model with random intercept.

Moreover, the AIC and Deviance value for fixed slope model with random intercept (AIC= 5694.739, and Deviance = 5674.738) are less than the empty model with random intercept (AIC = 6067.750, and Deviance =6063.750). This indicates that fixed slope model with random intercept is a better fit as compared to the empty model with random intercept model.

Test of random intercept significance is Ho: $\boldsymbol{\sigma_0^2}$ = 0 versus $\boldsymbol{\sigma_0^2}$ ≠ 0, according to table 4.8 the 95% confidence interval of the estimate of random intercept shows that it is significant since the lower bounder of confidence interval is does not close to zero. This indicates that there is enough evidence that reject Ho: $\boldsymbol{\sigma_0^2}$ = 0, which means that random intercept is different from zero.

4.3.3. The Random Coefficient Model

It is essential to determine whether the explanatory variables included in the study have different influence on the response variable (U5CM) among regions. A multilevel model with a random intercept and a random slope is therefore fitted.

Because of the limitations of MLwiN software, we will examine the influence of use of contraceptive methods of mothers; and breast-feeding separately on U5CM between regions. Thus, two separate analyses conducted. Firstly, the effect of use of contraceptive methods of mothers (allowing it to randomly vary between regions) with other fixed effects (by setting the variance of other coefficients zero) on U5CM is examined (table 4.9). Secondly, the effect of breast-feeding (allowing them to randomly vary between regions) with other fixed effects (by setting the variance of other coefficients zero) on U5CM is examined (table 4.10). Therefore, the table includes fixed effect coefficients and an overall (level-2) or regional variance constant term ($\boldsymbol{\sigma_{0u}^2}$)together with variance and covariance terms for their corresponding variables

a) Models when coefficients of use of contraceptive methods of mothers vary

In comparison to the model with random intercept and fixed explanatory variables, the model with random intercept and random coefficients was found to be a best fit in explaining regional differences in under-five death ($\chi_{cal}^2 = 5674.738 - 5667.928 = 6.81$ with p-value=0.0091). The results of fitted random intercept and random coefficient model are given in Table 4.9. According to the results, the overall region variance constant term and the variance terms for use of contraceptive methods of mothers are found to be significant. The fixed effect of Sex of child, family size, education level of (no education and primary education) and use of contraceptive methods of mothers and age at first birth are significant (p-values<0.05) while from education level secondary education level is found to be insignificant.

Table 4.9: Result of Parameter Estimate of Random Coefficient Multilevel Model for use of contraceptive method

			Fixed effect parameter estimation			
Covariates	Estimate	Std. Err.	P>|z|	OR	[95% Conf. Interval of OR]	
Intercept	-2.79782	0.29712	0.000	-	-	
Sex of child						
Male (Ref.)						
Female	-0.174407	0.073337	0.017	0.839955	0.727497	0.969797
Family size						
1-5(Ref.)						
>5	-0.570643	0.074313	0.000	0.5651621	0.4885602	0.6537745
Education level						
Higher(Ref.)						
No Education	0.81066	0.24078	0.001	2.249391	1.403176	3.605932
primary	0.70890	0.24741	0.004	2.031749	1.251056	3.299615
Secondary	0.35704	0.36209	0.324	1.429099	0.7028293	2.90586
Breast feeding						
No (Ref.)						
Yes	-1.22492	0.07483	0.000	0.2937804	0.2537046	0.3401866
Use of Contraceptive						
Yes (Ref.)						
No	0.70188	0.17377	0.000	2.017544	1.435188	2.836202
Age of 1st birth						
<20 (Ref.)						
>=20	-0.18430	0.0772	0.017	0.839955	0.727497	0.969797

	Random effects parameter estimated			
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
region: Unstructured				
$var(U_{7j})$	0.1443751	0.1264733	0.025932	0.8038017
$Var(U_{0j})$	0.2422144	0.1686619	0.06187	0.9482429
$cov(U_{7j},U_{0j})$	-0.187002	0.1449916	-0.4711803	0.0971764

LR test vs. logistic regression: chi2(3) = 12.43 Prob > chi2 = 0.0060

Ref.= Reference Category.

AIC = 5691.928, loglik = -2833.964, Deviance = 5667.928

Random-effects covariance matrix for region level

$$\tau = \begin{bmatrix} \tau_{00} & \tau_{70} \\ \tau_{07} & \tau_{77} \end{bmatrix} = \begin{bmatrix} 0.2422144 & -0.18700 \\ -0.18700 & 0.14438 \end{bmatrix}$$

Hypothesis test for random effect part:

H0: $\tau_{00} = 0$ versus Ha: $\tau_{00} \neq 0$, according to table 4.9 the 95% confidence interval of the estimate of random intercept shows that it is significant since the lower bounder of confidence interval is does not close to zero. This indicates that random intercept of region is significant. This means that under-five-child mortality varies from region to region.

H0: $\tau_{77} = 0$ versus Ha: $\tau_{77} \neq 0$, according to table 4.9 the 95% confidence interval of the estimate of random slope of use of contraceptive estimated shows that it is significant since the lower bounder of confidence interval is does not close to zero. This indicates that random slope of no use of contraceptive methods in the region is significant. This means that under-five child mortality varies from mother's use contraceptive method and from region to region.

In Table 4.9, the value of Var (U_{0j}) and Var (U_{7j}) are the estimated variance of intercept and slope of use of contraceptive methods of mothers respectively. These estimated variances are significant suggesting that intercept and slope of use of contraceptive methods of mothers vary significantly. Therefore, there is a significant variation in the effect of use of contraceptive methods of mothers across regions in Ethiopia. Likelihood ratio (LR) test comparing the model with the one-level binomial regression model favors the random coefficient model, indicating that there is a significant variation in U5CM between regions.

The effect of the intercept on region j is estimated to be -2.79782 (0.29712) +U_{0j} and their variance 0.2422144 (Standard error 0.1686619). The intercept variance of 0.2422144 (Standard error 0.1686619) is interpreted as the variance between-regions when all other variables are held constant (i.e. equal to zero). Their mean is -2.79782 (standard error 0.29712) and their variance is 0.2422144 (Standard error 0.1686619). The between-region variance of slope of use of contraceptive methods of mothers is estimated to be 0.1443751 (standard error 0.1264733). The individual region slopes of use of contraceptive methods of mothers vary about with a variance 0.1443751 (standard error 0.1264733).

The quantities AIC can be used to make an overall comparison of this more complicated model with the random intercept model with fixed slope model. We see that the value of fit statistics for random coefficient model (AIC = 5691.928) is less than random intercept model (AIC= 5694.739). This indicates that the random coefficient model is a better fit as compared to the random intercept and fixed effect model. The random coefficient model involves two extra parameters, the variance of the slope residuals (i.e. use of contraceptive methods of mothers), U_{7j} and their covariance with the intercept residuals U_{0j} and the change (which is also the change in deviance) can be regarded as a χ^2 value with 1 degrees of freedom under the null hypothesis that the extra parameters have population values of zero. The value of deviance based chi-square is given by (5674.738 - 5667.928 = 6.81, P-Value = 0.0091) which shows that the addition of this fixed effects and one random coefficient has significantly improved the fit of the more elaborate model to the data.

b) Models when coefficients of Breast feeding variables vary

In comparison to the model with random intercept and fixed explanatory variables, the model with random intercept and random coefficients was found to have a better fit in explaining regional differences in under-five death $X_{cal}^2 = 5674.738 - 5662.672 = 12.066$ with p-value = 0.00051). Table 4.10 shows that the overall region variance constant term and the variance for breast feeding are found to be significant. Both the covariance between the random intercept and the random slope for breast feeding show a negative sign, estimated as -0.2235281, suggesting that there is an inverse relation between the random intercept and the corresponding random slope. This indicates that regions with higher intercepts tend to have shallower slopes.

In general, the results of the multilevel logistic regression suggest that there exists difference in the U5CM among the regions in Ethiopia and the effect of breast feeding on U5CD differs from region to region.

Table 4.10: Result of Parameter Estimate of Random Coefficient Multilevel Model for breast-feeding.

Covariates	Coef.	Std. Err.	P>|z|	OR	[95% Conf. Interval]	
Fixed effect parameter estimate						
Intercept	-2.74226	0.26600	0.000	-	-	
Sex of Child						
Male (ref.)						
Female	-0.17372	0.07342	0.018	0.8405	0.7279	0.9706
Family size						
1-5(Ref.)						
>5	-0.57188	0.074576	0.000	0.5645	0.4877	0.6533
Education level						
Higher(ref.)						
No Education	0.8254	0.2417	0.001	2.2828	1.4215	3.6658
Primary	0.70960	0.2478	0.004	2.0332	1.2509	3.3045
Secondary	0.32907	0.3617	0.363	1.3897	0.6840	2.8233
Breast feeding						
No (ref.)						
Yes	-1.1576	0.12901	0.000	0.31423	0.2440	0.4046
Use of contraceptive						
Yes (ref.)						
No	0.59698	0.10747	0.000	1.81663	1.4716	2.2426
Age of 1st Birth						
< 20(Ref.)						
>=20	-0.18203	0.0773	0.019	0.8336	0.7164	0.9700

Random-effects Parameters

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
region: Unstructured				
var(U_{6j})	0.1149	0.0810	0.0288	0.4577
Var(U_{0j})	0.4348	0.2709	0.1282	1.4744
cov(U_{6j},U_{0j})	-0.2235	0.1470	-0.5117	0.0647

LR test vs. logistic regression: chi2(3) = 17.69 Prob > chi2 = 0.0005

Ref. = reference category

AIC = 5686.672, loglik = -2831.336, Deviance = 5662.672

$$\tau = \begin{bmatrix} \tau_{00} & \tau_{06} \\ \tau_{60} & \tau_{66} \end{bmatrix} = \begin{bmatrix} 0.4348301 & -0.2235281 \\ -0.2235281 & 0.1149065 \end{bmatrix}$$

Hypothesis test of random effect:

H0: $\tau_{00} = 0$ versus Ha: $\tau_{00} \neq 0$, according to table 4.10 the 95% confidence interval of the estimate of random intercept shows that it is significant since the lower bounder of confidence interval is does not close to zero. This indicates that random intercept of region is significant. This means that under-five-child mortality varies from region to region.

H0: $\tau_{66} = 0$ versus Ha: $\tau_{66} \neq 0$, according to table 4.10 the 95% confidence interval of the estimate of random slope of breast feed estimated shows that it is significant since the lower bounder of confidence interval is does not close to zero. This indicates that random slope of get breast feed within the region is significant. This means that under-five child mortality varies from child get chance of breast feed and from region to region.

In Table 4.10, the value of Var (U_{0j}) and Var (U_{6j}) are the estimated variance of intercept and slope of breast feed respectively. These estimated variances are significant suggesting that intercept and slope of breast feed vary significantly. Therefore, there is a significant variation in the effect of breast feed across regions in Ethiopia. Likelihood ratio (LR) test comparing the model with the one-level binomial regression model favors the random coefficient model, indicating that there is a significant variation in U5CM between regions.

The effect of the intercept on region j is estimated to be -2.74226 (0.26600) $+U_{0j}$ and their variance 0.4348301 (Standard error 0.2708911). The intercept variance of 0.4348301 (Standard error 0.2708911) is interpreted as the variance between-regions when all other variables are held constant (i.e. equal to zero). Their mean is -2.74226 (standard error 0.26600) and their variance is 0.4348301 (Standard error 0.2708911). The between-region variance of slope of breast feed is estimated to be 0.1149065 (standard error 0.0810236). The individual region slopes of breast feed vary about with a variance 0.1149065 (standard error 0.0810236).

The quantities AIC can be used to make an overall comparison of this more complicated model with the random intercept model with fixed slope model. We see that the value of fit statistics for random coefficient model (AIC = 5686.672) is less than random intercept model (AIC= 5694.739). This indicates that the random coefficient model is a better fit as compared to the random intercept and fixed effect model. The random coefficient model involves two extra parameters, the variance of the slope residuals (i.e. breast feeding of mothers), U_{6j} and their covariance with the intercept residuals U_{0j} and the change (which is also the change in deviance) can be regarded as a χ^2 value with 1 degrees of freedom under the null hypothesis that the extra parameters have population values of zero. The value of deviance based chi-square is given by ($5674.738 - 5662.672 = 12.066$, P-Value = 0.00051) which shows that the addition of this fixed effects and one random coefficient has significantly improved the fit of the more elaborate model to the data.

4.3.4. Comparison of Multilevel Logistic Models

Table 4.11 show that the comparison of the fit multilevel logistic regression models using the summary of the fitted model. The model which has small AIC is best model for the data set of under five child mortality in Ethiopia.

Table 4.11: Comparison of multilevel logistics models using AIC, loglik and Deviance

Model	AIC	Loglik	Deviance
Only random intercept	6067.748	-3031.874	6063.748
Random intercept and fixed slope	5694.739	-2837.369	5674.738
Random coefficient(contraceptive)	5691.928	-2833.964	5667.928
Random coefficient (Breast feeding)	5686.672	-2831.336	5662.672

According to table 4.11, the multilevel logistic model with small AIC is best when compared to others models. The random coefficient of breast-feeding model with small AIC =5686.672 was an improved fit as compared to the rest models for any combination of variables in the data set.

According to table 4.10 the result of parameters of observed variables can be interpreted much the same way as those from the standard logit model. Thus, everything else being equal except slight difference on random effect in the model, the odds of deaths of under-five child from noneducated mother were 2.28 (OR=2.283) times higher than the odds of death of under-five child who from higher educated mother controlling for other variables in the model and random effect at level two. The odds of death of under-five child from primary educated mothers were 2.03 (OR = 2.033) times higher than the odds of death of under-five child from higher educated mothers controlling for other variables in the model and random effect at level two.

Children whose gender is female were about 16% less likely to die before the age of five than that of child whose gender is male controlling for the other variables in the model and random effect at level two. Similarly, children who are from household size greater than five were about 43% (OR = 0.5645) less likely to die before the age of five than that of child from household size less than five controlling for other variables in the model and random effect at level two.

Breast fed children were 69% (OR = 0.3142) less likely to die before the age of five than non-breast-fed children controlling for other variables in the model and random effect at level two. Similarly, children who are from on-contraceptive using mothers were 82% (OR =1.8166) more likely to die before the age of five than children from mothers using contraceptive method controlling for other variables in the model and random effect at level two.

Children whose age of mother at first birth greater than or equal to 20 year were 16% (OR = 0.83357) less likely to die before the age of five than age of mother at first birth less than 20 year children controlling for other variables in the model and random effect at level two.

4.4 Discussion

The purpose of this paper was to examine the regional heterogeneity in under-five children death in Ethiopia using single and multilevel logistic regression procedure. The study uses the 2011 Ethiopian Demographic and Health survey (EDHS) data to identify some of the factors that are responsible for regional differences in under-five child mortality. Accordingly, descriptive analysis, multiple logistic regressions, and multilevel logistic regression techniques were used. Multiple logistic regressions were applied for national level. The results, obtained have been discussed as follows.

This study has indicated that some of the demographic and socio-economic variables considered have significant influence on the under-five children mortality rate. Sex of the child, family size, education level of mother, age of mother, breast-feeding and the use of contraceptive method and region of child were found to be among the determinants of under-five child mortality in Ethiopia.

According to the results, mother's education level is an important socio-economic predictor of under-five child mortality, that is, mortality rate decreases with increase in mother's education level. Many studies showed that the higher the level of maternal education, the lower the infant and child mortality. Caldwell (1991) provided three explanations for the phenomenon: mothers that are more educated become less fatalistic about their children' illnesses, they are more capable of manipulating available health facilities and personnel and they greatly change the traditional balance of familial relationships with profound effects on childcare. In addition to these, they are more likely to have received antenatal care to give birth with some medical attendance, and to take their children at some time to see a physician. In this study, even after controlling for other variables, education of mother remained significant in the regression equations. This finding is consistent with Belaineh et al. (2007) and other studies.

The risk of death of under-five female children was significantly different from that of male children. Risk of death in under-five female children was less than in under-five male children. This finding is complementary with Hill and Upchurch (1995) findings.

Household wealth in Ethiopia was a significant determinant of under-five children mortality. According to our finding, households with greater wealth were less likely to have under-five children deaths compared with children of the poor households. This finding is consistent with Kimani and Ettarh (2012) and Blaineh et al. (2007).

The finding of the study showed that the risk of death of under-five children from mothers using contraceptive is significantly less than child is from non- contraceptive methods using mothers. Similarity, the finding of the study showed that the risk of die before the age of five children from mother's age at first birth is greater than or equal to 20 years was significantly less than child is from mothers age at first birth is less than 20 years. This finding is almost consistent with result of Modal et al, 2009 and Aguirre, 1995.

Concerning the regional disparity in under-five child mortality, the results of study showed that children who live in Amhara, Benishangul-gumaz, Gambela, Oromia and SNNP National Regional States are at a higher risk of death than children who live in Addis Ababa.

In the multilevel analysis, children are considering as nested within the various regions in Ethiopia. There are three multilevel models: empty model, random intercept and random slope or random coefficient model were fitted in order to explain regional differences in the under-five mortality.

Most of the time multilevel model building starts from empty models, which is fitted without any covariates but with random intercept only. This model is used in order to see the significance of multilevel model over empty model without random effect. The second model is random intercept model, which include covariates and random intercept. Lastly, we build random coefficient model that varies at lower level (child) and higher level (regional). This study shown that the random intercept model is significant, which means there is a variation of under-five child mortality from region to region in Ethiopia.

The multilevel logistic model provided interesting relationships that would not be evident from a standard logistic model (or single-level analysis of logistic regression). We showed that there is a significant variation of under-five mortality between regions. This may suggest differences in lifestyle, culture, ethnic or environmental determinants between different regions. Because of these potential cultural, socio-economic, and environmental differences, under-five child mortality exhibits a significant variation among regions of Ethiopia. Similarly, Khan and Ewart (2011) study found using Bangladesh DHS data the multilevel effects are significant and have to be taken into consideration in logistic regression modeling, which leads to multilevel logistic regression modeling. As a result, this multilevel analysis enables the proper investigation of the effects of all explanatory variables measured at different levels (clusters and divisions) on the response variable currently using contraception. A major reason for significant multilevel effects for such data might be dependencies between individual observations.

Because of MLwiN software limitation our study does not further demonstrated the tendency for the standard logistic model to seriously bias the parameter estimates of observed covariates when analyzing multilevel data. However, Khan and Ewart (2011) and Guo and Zhao (2000) and other findings demonstrated the tendency for the standard logistic model to seriously bias the parameter estimates of observed covariates when analyzing. However, the estimated bias generally differs depending on the estimation procedure used for the multilevel logistic model.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The results of this study suggested the need to use individual level (child) and region level disparities in the likelihood of under-five child mortality. This study found evidences that verify some demographic and socioeconomic variables considered in this study have significant influence on the under-five child mortality. Sex of the child, family size, education level of mother, age at first birth of mother, breast-feeding and the use of contraceptive method and regions of children were found to be determinant of under-five child mortality in Ethiopia.

The multilevel logistic model provided interesting relationships that give more evidence than standard logistic model. We showed that there is a significant variation of under-five mortality between regions. This may suggest differences in lifestyle, culture, ethnic or environmental determinants between different regions. Because of these potential cultural, socio-economic, and environmental differences, under-five children mortality exhibits a significant variation among regions of Ethiopia.

It is possible to conclude that there are variations in terms of under-five child mortality among regions and within the region.

All models of multilevel logistic regression model (Empty model with random intercept, Random intercept model with fixed slope and Random coefficient model) are better than standard logistic regression model since the fitted models of multilevel logistic regression have smaller AIC and deviance

Among multilevel logistic regression models, the random coefficient model with breast feeding was an improved fit as compared to the rest models for any combination of variables in the data set.

5.2 Recommendation

Based on finding and results this study, the following recommendations can be made:

- Educational level of mothers plays an important role in child survival. This is, however, requires a long-term investment. As an alternative, in the short term, health programs need to focus on supporting women with little or no education.
- Breast-feeding plays an important role in child survival. Government and concerned bodies should give attention to teaching mothers in relation to the importance of breast feeding to children as much as possible.
- Under-five children mortality differentials among regions are significant. This is an indication that the severity of U5CD varies from one region to another. Thus, in order to have a bearing on policy recommendations, future studies should focus on identifying risk factors of U5CD for each region of Ethiopia separately.

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Appendix:

Appendix: A

Table 4.12: Test of Significance of Individual Predictors for Logistic Regression Using Score Test

Summary of Stepwise Selection			
Effect Step Entered Removed	DF	Score Chi-Square	Wald Pr > ChiSq
BREASTFE	1	281.0451	<.0001
FAMILYSI	1	42.2957	<.0001
CONTMETH	1	43.5021	<.0001
REGION	10	37.4332	<.0001
AGEBIRTH	1	5.8948	0.0152
SEXCHILD	1	5.5555	0.0184
EDUCATIO	3	8.7738	0.0325

Table 4.13: Type three Analysis of effects for logistic regression model

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Sexchild	1	5.4255	0.0198
Region	10	30.9535	0.0006
Familysi	1	57.1006	<.0001
Educatio	3	8.1591	0.0428
Breastfe	1	274.9308	<.0001
Contmeth	1	28.8778	<.0001
Agebirth	1	4.8677	0.0274

Table 4.14: Partition for the Hosmer and Lemeshow Test for goodness of fit of logistic regression model.

Partition for the Hosmer and Lemeshow Test					
		NEWLIFE = 0		NEWLIFE = 1	
Group	Total	Observed	Expected	Observed	Expected
1	1157	28	22.72	1129	1134.28
2	1154	42	35.46	1112	1118.54
3	1146	47	41.68	1099	1104.32
4	1167	45	47.77	1122	1119.23
5	1146	52	54.23	1094	1091.77
6	1152	57	66.91	1095	1085.09
7	1193	75	85.18	1118	1107.82
8	1176	114	111.22	1062	1064.78
9	1156	143	148.69	1013	1007.31
10	1207	243	232.14	964	974.86

SAS code for logistic regression Analysis:

```
proc logistic data=fz2;
class sexchild region place familysi Birthord Wealth Drinking toiletfa
             educatio agegrp5 Breastfe contmeth smokings agebirth;
model newlife=sexchild region place familysi Wealth Drinking toiletfa
              educatio agegrp5 Breastfe contmeth smokings
              agebirth/SELECTION=STEPWISE;
run;
```

Appendix: B

Code for plot graph

plot(resid(Dech))

abline(h=0, lty=2)

r.pearson<-resid(Dech, type="pearson")

plot(resid(Dech, type="pearson"))

qqnorm(resid(Dech, type="pearson"))

abline(0,1)

```
hii <- hatvalues(Dech)

 r.adjusted <- r.pearson/sqrt(1 -hii)

 plot(r.adjusted)

 plot(r.adjusted)

 abline(h = 0, lty = 2)

par(mfrow=c(2,2))

#### hat values of best model ###########

hii <- hatvalues(Dech)

list(sum(hii))

plot(hii,ylim=c(-0.025,0.025),main="plot of hat values")

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abline(0.003432298,0,col="red")

abline(-0.003432298,0,col="red")

### Cook’s distance plot

p.t1 <- length(coef(Dech))

cook.t1 <- ((r.pearson^2) * hii)/((1 - hii)^2)

cook.t11 <- cooks.distance(Dech) * p.t1

plot(cook.t1,main="plot of cook's distance")

identify(1:11654,cook.t1)
```