ADDIS ABABA UNIVERSITY
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DETERMINANTS OF WASTING AMONG UNDER-FIVE CHILDREN IN ETHIOPIA

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This is to certify that the thesis prepared by Gutu Adugna, entitled: Determinants of wasting among under-five children in Ethiopia and submitted in Partial fulfillment of the requirements for the Degree of Master of Science in Statistics complies with requirements of the university and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Determinants of Wasting Among Under-Five Children in Ethiopia

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Child malnutrition in Ethiopia is one of the most serious public health problems and the highest in the world. Wasting refers to low weight-for-height and measures the body's mass in relation to body length. The objective of this study was to identify determinants of wasting among under-five children in Ethiopia. The study used data collected in the Ethiopian Demographic and Health Survey in 2010/2011. A total of 9611 under-five age children were included in the present study. To analyze the data descriptive statistics, binary logistic regression and multilevel binary logistic regression techniques were employed. The descriptive statistics results indicate that about 11.7 % of under-five children in Ethiopia were wasted. Among demographic, socio-economic and health related factors included in the study: place of residence, household economic status, age of child, sex of child, mother education, body mass index of mother, illness(diarrhea and fever) were significant determinants of children wasting. The results of binary logistic regression and multilevel binary logistic regression indicated that the risk of wasting was highest among male children, small size at birth, children whose parents resided in rural areas, children's of illiterate mothers, children whose mother's body mass index was low, children from poor families and children who had diarrhea and fever two weeks before the date of the survey. The multilevel model showed the existence of significant variations in the prevalence of wasting among the regions in Ethiopia. The study recommended the need for programs related to income generating activities for poor households, improve mother education, caring child in appropriate age. Also, efforts should be made to improve environmental sanitation and personal hygiene to prevent exposures to diarrhea and fever.

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LIST OF ACRONYM

ACC/ SCN	Administrative committee on coordination/sub-committee on nutrition
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMI	Body Mass Index
EDHS	Ethiopian Demographic and Health survey
CSA	Central Statistical Agency
EAs	Enumeration Areas
NCHS	National Centre for Health Statistics
OR	Odds Ratio
SNNP	Southern Nations Nationalities and Peoples
SSA	Sub-Saharan Africa
SE	Standard error
UNICEF	United Nations Children's Fund
USD	United States Agency for International Development
WHO	World Health Organization
W/H	Weight for height
WHZ	Weight for height Z-score

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Malnutrition continues to be a major public health problem in developing countries like Ethiopia. It is an underlying cause of child morbidity and mortality and the most important risk factor for the burden of disease causing about 300, 000 deaths per year directly and indirectly responsible for more than half of all deaths in children (Olaf and Michael, 2005; WHO, 2005). Much of the burden of deaths resulting from malnutrition, estimated to be over half of childhood deaths in developing countries, can be attributed to just mild and moderate malnutrition, varying from 45% for deaths due to measles to 61% for deaths due to diarrhea (de Onis *et al.*, 2004). It is estimated that 53 percent of deaths among pre-school children in the developing world are due to the underlying effects of malnutrition on diseases such as measles, pneumonia, and diarrhea.

Malnutrition can be defined as a lack of proper nutrition. The nutritional status of a child, as with any individual, is assessed through dietary, anthropometric, biochemical and physical observation for signs of malnutrition. These methods of measurement are usually done in combination for more accurate results. When there is a deficiency in the amount and nutritional value of the food consumed, the growth pattern of a child becomes disrupted owing to nutrient deficiencies (Faber and Wenhold, 2007; Labadarios, 2005).

The nutritional status of children under age five is an important outcome measure of children health. The anthropometric data on height and weight collected in the 2011 EDHS provides the measurement and evaluation of the nutritional status of young children. This allows identification of subgroups of the child population that are at increased risk of faltered growth, disease, impaired mental development, and death (EDHS, 2011).

Malnutrition in children is the consequence of a range of factors that are often related to poor food quality, insufficient food intake, and severe and repeated infection diseases, or frequently some combinations of the three. These conditions, in turn, are closely linked to the overall standard of living and whether a population can meet its basic needs, such as access to food, housing and health care. Growth assessment, thus, not only does it serve as a means for evaluating the health and nutritional status of children but also provides an indirect measurement of the quality of life of an entire population (WHO, 2003).

In Ethiopia, child malnutrition rate is one of the most serious public health problems and the highest in the world (Alemu *et al.*, 2005). High malnutrition rates in the country pose a significant obstacle to achieving better child health outcomes. According to the 2011 Ethiopian Health and Demographic survey report (EDHS), at national level, 44 percent of children under age five were stunted, and 21 percent of children are severely stunted, 10 percent of children are wasted, and 3 percent are severely wasted, 29 percent of children under age five were underweight (have low weight-for-age), and 9 percent were severely underweight. This indicates that still there is a great problem of under-five age children malnutrition in Ethiopia (EDHS, 2011).

The magnitude of childhood malnutrition in communities is indicated by the prevalence of weight-for-height deficiency (wasting), weight-for-age deficiency (underweight) and height-for-age deficiency (stunting). In particular, stunting represents low height-for-age, wasting represents low weight-for-height, and underweight scores represent low weight-for-age. Stunting provides an indicator of chronic under-nutrition since it quantifies growth potential restricted; wasting is an indicator of acute under-nutrition since it quantifies weight loss; the degree of underweight is an indicator of both wasting and stunting, combining measures of "the current status of body proportion and linear growth (WHO, 2005).

Wasting refers to low weight-for-height and measures the body's mass in relation to body length. It is, generally, though to reflect the level of acute malnutrition. "As an indicator, wasting is likely to vary over short periods of time due to food availability and disease prevalence" (Silva, 2005).

"The weight-for-height index measures body mass in relation to body length, which shows current nutritional status. Children whose weight-for-height is below minus two standard deviations (-2SD) from the median of the reference population are too thin for their height, or wasted, while those who measure below minus three standard deviations (-3SD) from the reference population median are severely wasted. Wasting represents the failure to receive adequate nutrition during the period immediately, before the survey and usually shows marked seasonal patterns associated with changes in food availability or disease prevalence. It might be the result of recent episodes of illness, particularly diarrhea; improper feeding practices; or acute food shortage." (ORC, 2001)

The incidence of wasting, which reflects the acuteness of malnutrition had been widely used to characterize the nutritional status of children (Wise, 2004; Silva, 2005). Wasting reflects a deficit in weight relative to height due to a deficit in tissue and fat mass. Epidemiological evidence suggests that the first response to a nutritional deficiency and/or disease infectious is weight loss (wasting), and this will be followed by retardation in linear growth (stunting). If the infection persists, children will cease to grow in height and will lose weight, thus augmenting the process and prevalence of wasting (Fernandez *et al.,* 2002; Wise, 2004).

1.2 Statement of the problem

Malnourished children have lowered resistance to infection; they are more likely to die from common childhood illness like diarrheal diseases and respiratory infections; and for those who survive, frequent illness saps their nutritional status, locking them into a vicious cycle of recurring sickness, faltering growth and diminished learning ability. Malnourished children in Ethiopia have a much higher probability of dying.

Although the problem of malnutrition in Ethiopia is relatively well documented, their specific determinants particularly with regard to the relative contribution of different factors for the nutritional status of children are not well addressed (Alemu *et al*., 2005; Christiaensen and Alderman, 2001). National surveys and most small scale studies on child nutrition were descriptive in nature and limited to analysis of association between nutritional status and related variables (Woldemariam and Timotiows, 2002).

According to the 2011 Ethiopian Demographic and Health Survey report nutritional status of children for the period 2000, 2005 and 2011 showed a downward trend in the proportion of children stunted and underweight over the three EDHS surveys. Stunting prevalence decreased by 7 percent between 2000 and 2005 and by an additional 14 percent between 2005 and 2011. The proportion of children underweight dropped by 20 percent from 2000 to 2005 and 12 percent from 2005 to 2011(EDHS, 2011). This indicates that decline in the proportion of stunted and under-weight children show improvement in chronic malnutrition and under-weight over the past eleven years. But the prevalence of wasting in Ethiopia has remained constant over the last 11 years. So to reduce the current rate of acute malnutrition (wasting) one should understand its causes. It is, therefore, important to examine the risk factors for wasting of children. This study attempts to identify the risk factors associated with under-five children wasting in Ethiopia.

1.3 Objective of the Study

1.3.1 General objective

The main objective of this study is to determine factors associated with under-five children wasting in Ethiopia using binary logistic and multilevel logistic regression model.

1.3.2 Specific objectives

- To determine prevalence of under-five children wasting in Ethiopia.
- To identify demographic, socio-economic and health related factors of wasting among under-five children in Ethiopia.
- To examine the extent of the variation in wasting within and between regions of Ethiopia.

1.4 Significance of the study

The results of this study might provide information to government and other concerned bodies in setting policies, strategies and further investigation for reducing problem of under-five child wasting. The results help donors and government to understand risk factors that influence under -five children nutritional status in terms of weight for height.

The result of this study could be used as input and as a source of literature for further studies on children malnutrition.

1.5 Limitation of the study

Although, there are many determinants of wasting among under-five children including different demographic, social, economic, political, cultural, physiological, biological, family planning programs etc., this study is undertaken to explore a few of the, demographic, socio-economic and health related characteristics. The data, we used in this study was the 2011 Ethiopian Health and Demographic survey. Thus, the results may not necessarily reflect the current situation of Ethiopia. Also the study not concerned with the determinants of severe wasting and moderate wasting individually.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concepts and Definitions

The words "nutrition" and "health" are used interchangeably (WHO, 2005) for both outcomes are too related that it is difficult to disentangle one from the other, and thus both may signify the same thing when children are considered. While the word "malnutrition" is associated with both under nutrition and over nutrition (Smith and Haddad, 2000), in this paper it is meant to refer to under-nutrition. Under-nutrition includes being stunted (low height for age), wasted (low-weight-for-height) and underweight (low-weight-for-age) (UNICEF, 2006). The growth of the infants and children is related to socio economic environment in which they live. Children from developing countries grow more slowly and achieve a shorter adult height than those from wealthier regions (Van de Poel, *et al.*, 2008). Wasting is a measure of thinness; a wasted child has suffered from substantial weight loss, usually as a consequence of acute food shortage and/or diseases (UNICEF, 2003). Under-nutrition is influenced by both the height and the weight of the child, and reflects body mass relative to chronological age (ACC/SCN, 2004).

A variety of methods are commonly used for assessing the nutritional status of populations based on anthropometric, clinical, dietary and biochemical measurements. Anthropometric measurements (body dimensions and composition) are often used as proxies for assessing the eventual extent and severity of malnutrition. They are strong and feasible predictors at individual and community level of subsequent ill health, functional impairment and/or mortality. Anthropometry-based nutritional assessment has the advantage of being a universally applicable, inexpensive and noninvasive method. This procedure is also applicable to large sample sizes and helps to identify target groups of population for intervention, as a tool for nutritional surveillance, and in evaluation of success or failure of interventions directed towards economic and environmental factors underlying nutritional deprivation (Simon, 1999; Sununtar, 2005).

Anthropometry refers to body measurements. The basic measurements taken from children include age, sex, weight, length, and height, which are then compared to the sex-specific National Centre for Health Statistics (NCHS) and WHO guided international reference population as a way to assess the level of under-nutrition. Evidence has shown that growth patterns of well-fed, healthy children are the same for all races and ethnicities, so this reference population is used for all areas of the world. It is used for growth assessment and is a single measurement that best defines the health/nutritional status of a child identifying "extreme" or "abnormal" departures from this distribution (Blossner *et al.*, 2005).

According to Cogill (2001), anthropometric assessment was based on four building blocks: age, sex, length (height), and weight. Separately, each of these provides a piece of information about a person. When they were combined together, anthropometric indices result which provide information about nutritional status of a person. The commonly used anthropometric indices in assessing nutritional status of children are weight-for-age, height-for-age, and weight-for-height.

Weight-for-height (W/H) identifies children suffering from current or acute malnutrition. It measures short-term effects such as changes in food supply or short-term nutritional stress brought about by illness (Cogill, 2001). It can develop rapidly and at any age, provides information on mortality risk of children.

2.2 Theoretical Literature

UNICEF (1990, 1998) analyzed the determinants of wasting within a framework that incorporate some underlying causes like inadequate health services, unhealthy environment, inadequate household food security, and inadequate mother and child-caring practices. It was noted that most of the underlying causes were directly linked to some basic factors that were political, legal, and cultural in nature. Chevassus-Ange's (1999) presented a framework for understanding the causes of malnutrition. He identified key factors as access to food, care practices, and health and sanitation as factors ultimately determining nutritional status. Based on the framework, Gunasekara (1999) used anthropometrics indices of weight-for-height to assess the nutritional status of children in Sri Lanka. It was found that employment status of mother, number of living children, the level of education of the mother and non-involvement of the mothers in the rural labour market significantly affected wasting problem in children.

Any comprehensive strategy for resolving the problem of child malnutrition must include actions to address both its underlying and basic causes. Efforts to improve women's education, encourage women's status, raise food supplies (or reduce population growth or both), and create healthful environments should be an important part of strategies for reducing child malnutrition (Lisa, 2000).

The economic status of a household where a child lives has been identified as one of the key determinants of child nutritional status. Smith *et al.* (2005) stated that household economic status significantly affects access to food (a necessary condition for food security). It also dictated possession and utilization of child care resources on a sustainable basis. Relatively better economic status of a household permits more spending on food, clean water, hygiene, and preventive health care (Alderman *et al.*, 2005). In addition, it allowed a more diversified diet and effective child care arrangements. On the other hand, increase in household income at community level leads to improved access to high quality health care, improved water and sanitation systems and greater access to information.

In many developing countries particularly in Africa, tradition has laid the responsibility of child care on women which begins at conception and continues until infancy, teenage and adulthood (Oyekale and Oyekale, 2000). The implication is that women are key players in the growth and development of a child. In enhancing the quality of care and nutritional status of children, the role of mothers' education is widely recognized.

Smith and Haddad (2000) emphasized that education of women had several positive effects on the quality of care rendered to children since women were the main care takers of children. Their ability to process information, acquire skills, and model positive caring behavior improves with education. Educated women used health care facilities, interact more effectively with health professionals, comply with treatment recommendations, and keep their environment clean. Also, more educated mothers were committed to child care and interact very well with their children.

Silva (2005) also analyzed the determinants of child malnutrition in Ethiopia. The study revealed that child's age, mother's height, household wealth, education of mothers and access to good water explain to a large extent the nutritional status of children.

2.3 Empirical Literature

Rayhan and Khan (2006) used data from Bangladesh Demographic and Health Survey 1999-2000 (BDHS, 1999-2000) to identify the determinants of under-five children malnutrition in Bangladesh. Using logistic regression model, they found that 45 percent of the children under-five age were suffering from chronic malnutrition, 10.5 percent were acutely malnourished and 48 percent had under-weight problem. They concluded that risk of being wasted higher in children small size at birth and children of acute malnourished mother compared to children large size at birth and children of nourished mothers. The results also showed that parent's education had an impact on under-five children malnutrition.

Babatunde *et* al. (2011) examined the prevalence and determinants of malnutrition among under-five children of farming households in Kwara State, Nigeria. Descriptive and logistic regression analyses were used to analyze anthropometrics data collected from 127 children selected randomly from 40 rural villages in the State. The results showed that 23.6%, 22.0% and 14.2% of the sample children were stunted, underweight and wasted respectively. The result also revealed that male and older children were more likely to be wasted. Better education by mothers would reduce the probability of wasting among under-five children. Similarly, children born to mothers with high body mass index were less likely to be wasted.

Salah *et al.* (2006) studied the level of malnutrition and the impact of some socio-economic and demographic factors of households on the nutritional status of children under 3 years of age in Botswana. The study was a cross-sectional descriptive survey using a structured questionnaire and measurements of weight and height. The results showed that the level of wasting, stunting, and underweight in children under three years of age was 5.5 %, 38.7 %, and 15.6 % respectively. The study indicated that wasting was significantly higher among male children than among female children.

According to the findings of the 2000 Ethiopia DHS (CSA and ORC Macro, 2001), the overall prevalence of stunting among Ethiopian children was 51.3 percent and more than one in four children (26%) were severely stunted. This document also showed that 47 percent of the Ethiopian children were underweight (low weight-for-age) and 16 percent were severely underweight. About 11 percent of the children under five years of age were also wasted (thin for their height), and 1 percent were severely wasted. The level of stunting, underweight, and wasting were also higher for rural children than urban children. This showed that Ethiopia had a very high prevalence of stunting, underweight and wasting according to the classification established by the World Health Organization to indicate levels of child malnutrition.

Alemu *et al.* (2005) studied the determinants of child nutritional status using a data collected on eight years old children mainly from food insecure parts of the country namely Tigray, Amhara, Oromiya and SNNP. The multivariate analysis results revealed that household wealth, the highest education level of an adult female in a household, caregiver's membership of a religious group had a strong effect on wasting. In addition, land size a household possesses, food aid received and school feeding programs were found to be a significant determinants of wasting. The number of female adults, access to safe drinking water, and absence of crop failure showed a significant association with nutritional status of children but in opposite direction than normally expected.

Solomon and Zemene (2008) applied Matched case-control study design to identify and determine the risk factors for severe acute malnutrition in children under the age of five. The study was conducted from July 2005 to April 2006 in admitted patients to Gondar University Hospital, Ethiopia. The results revealed that the socioeconomic risk factors for severe acute malnutrition were maternal illiteracy (OR=3.83, 95% CI 1.93-7.67), paternal illiteracy (OR=2.04, 95% CI 1.13–3.71), monthly family income of less than 50 USD (OR =3.44, 95% CI 1.66–7.20) and large family size with the number of children greater than 3 (OR=1.96, 95% CI 1.04 –3.73). Furthermore, the risk for severe acute malnutrition was independently associated with lack of exclusive breastfeeding for the first six months of life (OR=3.22, 95% CI 1.31-7.91) and late initiation of complementary diet (OR=3.39, 95% CI 1.20–9.57) after the effects of other significant risk factors were controlled for. The study concluded that to reduce severe acute malnutrition in children due emphasis should be given in improving the knowledge and practice of parents on appropriate infant and young child feeding practices.

Thanaa *et al.* (2012) performed a cross-sectional descriptive study to investigate the relation between demographic, socio-economic and physical activity factors affecting the nutritional status of young children under five years of age. Logistic regression analysis was employed to estimate the influence of various parameters. The study revealed that the impact of family size on nutritional status of children was significantly different. Birth order was a highly significant factor in relation to nutritional status in WHZ. Further the result showed that the breastfed group was better than the other group with regard to nutritional indicator in children wasting.

A cross-sectional study was conducted in East Jerusalem to assess the factors that might affect the children's nutritional status of children aged 9-18 Months (Salah, 2004). The results showed that 8.5% of the assessed children were wasted. Briefly, findings of this study showed that malnutrition was considered a serious health problem in the early age. The study concluded that stressing on health education program with more focus on nutrition educational sessions mainly for mothers was important in improving children malnutrition.

Oyekale (2012) analyzed the factors predisposing children to wasting in selected Sub-Sahara Africa countries. Probit analysis was used to estimate the effect of different factors on wasting. The results showed that attainment of secondary education by the mothers, urbanization, presence of piped water, vaccination, and mother's access to radio and television significantly reduce the probability of wasting, while infection with diarrhea, fever and age at first polio vaccine significantly increase it. The study concluded that concerted efforts to reduce malnutrition must focus on provision of health facilities in the rural areas, promotion of women education, promotion of enlightenment programs on the need for child immunization and ensuring cleanliness in caring, among others.

Pradhan (2010) used the data from Demographic and Health Survey 2006 conducted in Nepal to identify factors associated to the nutritional status of under-five children. A multinomial logistic regression model was used to study the relation between various factors and nutritional status. The results showed that frequency of listening radio did not show significant association in case of mild and moderate wasting and shown very high unusual odds ratio in case of severe wasting, female children were more likely to be stunted, underweight and wasted as compared to male, and female headed households were more likely to have moderately and mildly stunted children and mixed results were observed for underweight and wasting. Furthermore, the likelihood for all forms of malnutrition was higher among children with smaller than average size at birth as compared to average or bigger size at birth. Mixed results were observed regarding likelihood of different forms of malnutrition among children with mothers having different educational level.

CHAPTER THREE

DATA SOURCE AND RESEARCH METHODOLOGY

3.1 Source of Data

This study used the 2011 Ethiopia Demographic and Health Survey (EDHS, 2011) data. The 2011 EDHS was conducted under the Ministry of Health and was implemented by the Central Statistical Agency and partner organizations from September 2010 through June 2011 with a nationally representative sample of nearly 18,500 households. All women age 15-49 and all men age 15-59 in these households were eligible for individual interview.

The sample for the 2011 EDHS was designed to provide population and health indicators at the national and regional levels. The sampling frame used for the 2011 EDHS was the Population and Housing Census conducted by the Central Statistical Agency (CSA) in 2007. The 2011 EDHS sample was selected using a stratified, two-stage cluster design and Enumeration areas (EAs) were the sampling units for the first stage sampling. The 2011 EDHS sample included 624 EAs, 187 in urban areas and 437 in rural areas.

Households comprised the second stage of sampling. A complete listing of households was carried out in each of the 624 selected EAs from September 2010 through January 2011. A representative sample of 17,817 households was selected for the 2011 EDHS survey.

A total of 11,152 children less than 59 months were identified in the households of selected clusters. From 11,152 children aged less than 59 months by removing missing values and make rearrangements the analysis presented in this study on nutritional status of children in terms of weight for height is based on the 9611 children aged less than 59 months with complete anthropometric measurements.

3.2 Variables included in the study

The variables considered in this study include variables which affect nutritional status of under five children in Ethiopia. Socio-economic, demographic and health related characteristics are considered as the independent variables.

3.2.1 Response variable

The response variable of interest is child nutritional status (wasting). Anthropometric indicators of nutritional status (weight-for-height) were used to define nutritional status of children. Weight and height were measured in kilogram and centimeter respectively.

Weight-for-height z-scores which give the information about wasting was used as measure of health outcomes. In this study, height and weight measurements of children, taking age into consideration, were converted into Z-scores based on new growth standards published by the World Health Organization (WHO). Thus, those below -2 standard deviations of the NCHS median reference for weight-for-height are defined as wasted. This study focuses on wasting which is used to describe the level of child malnutrition problem related to weight and height (EDHS, 2011).

Table 3.1 Description of the response variable

Variable name	Description	Categories
WHZ	Wasting(Weight for Height Z-scores)	(0) Not wasted(≥-2SD) (1) Wasted(<-2SD)

3.2.2 Independent Variables

The choice of explanatory variables for this study was based on literature reviews on the factors affecting children malnutrition. Those variables are demographic, socioeconomic and health related variables.

Table 3.2 Description of the explanatory variables included in the study

Variables name	Description	Categories
SexChild	Sex of child	(0) Female (1) Male
ChildAge	Child's age in months	(0) <6 months (1) 6-11 months (2) 12-23 months (3) 24-35 months (4) 36-47 months (5) 48-59 months
BOD	Birth order number	(0) 1 (1) 2-3 (2) 4-5 (3) 6+
SizeChBir	Size of child at birth	(0) Small (1) Average (2) Large
NHMemb	Number of household member	(0) 1-4 (1) 5-9 (2) 10 and above
REGION	Federal regional state	(1) Tigray (2) Afar (3) Amhara (4) Oromia (5) Somali (6) Ben-gumuz (7) SNNP (8) Gambela (9) Harari

		(10) Addis Ababa (11) Dire Dawa
PlacRes	Place of residence	(0) Rural (1) Urban
MothEduc	Mother's Educational level	(0) No education (1) Primary education (2) Secondary and above
SexHH	Sex of household head	(0) Male (1) Female
WIHh	Wealth index of house hold	(0) Poor (1) Medium (2) Rich
BMIMoth	Body Mass Index of Mother	(0) Thin (1) Normal (2) Overweight
HadDiar	Had diarrhea in last two weeks before survey	(0) No (1) Yes
HadFev	Had fever in last two weeks before survey	(0) No (1) Yes

3.3 Methodology

In this study we have used binary logistic regression and multilevel logistic regression to analyze our data.

3.3.1 Binary Logistic Regression Analysis

Logistic regression is part of a family of models called the Generalized Linear Model used when the response variable is qualitative in nature or categorical and independent variables may be either continuous, categorical or both. Binomial or binary logistic regression is the form of regression which is used when the dependent variable is dichotomous and the independent variables are of any type (Hosmer and Lemeshow, 2000).

3.3.1.1 Assumptions of logistic regression

- Meaningful coding. Logistic coefficients will be difficult to interpret if not coded meaningfully. The convention for binomial logistic regression is to code the dependent class of greatest interest as 1 and the other class as 0.
- Logistic regression does not assume a linear relationship between the dependent and independent variables.
- The independent variables need not be interval, nor normally distributed, nor linearly related, nor of equal variance within each group.
- The categories (groups) must be mutually exclusive and exhaustive; a case can only be in one group and every case must be a member of one of the groups.
- Larger samples are needed than for linear regression. A minimum of 50 cases per predictor is recommended.

3.3.1.2 Model Specification

When the response variable is binary; there is considerable empirical evidence that the shape of the response function should be nonlinear. A monotonically increasing (or decreasing) S-shaped (or reverse S-shaped) function. This function is called the logistic response function and has the form:

$$\pi_i = \frac{\exp(x_i'\boldsymbol{\beta})}{1+\exp(x_i'\boldsymbol{\beta})} = \frac{1}{1+\exp(-x_i'\boldsymbol{\beta})} \qquad (3.1)$$

Where $x_i' = (1, x_{i1}, x_{i2}, ..., x_{ik})$ is a row vector, (i=1, 2, ..., n) and $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_k)'$ is 1*k+1 vector.

The above function can be linearized. Let $\eta_i = x_i'\boldsymbol{\beta}$ (3.2)

be the linear predictor where η_i is defined by the linear transformation

$$\eta_i = \ln\left(\frac{\pi_i}{1-\pi_i}\right) \qquad \text{or} \quad \pi_i = \frac{e^{\eta_i}}{1+e^{\eta_i}} \tag{3.3}$$

The transformation is called the logit transformation of the probability $P(y_i = 1) = \pi_i$ and the ratio $\frac{\pi_i}{1-\pi_i}$ in the transformation is called the odds.

3.3.1.3 Method of estimation

The general method of estimating logistic regression parameters is called maximum likelihood. The method of maximum likelihood yields values for the unknown parameters which maximize the probability of obtaining the observed set of data. In order to apply this method we first construct a function, called the likelihood function. This function expresses the probability of the observed data as a function of the unknown parameters. The maximum likelihood estimators of these parameters are chosen to be those values that maximize this function. Thus, the resulting estimators are those which agree most closely with the observed data. We now describe how to find these values from the logistic regression model. Since each y_i represents a Bernoulli count in the i^{th} population, the probability distribution function of y_i is given by:

$$f(y_i) = \pi_i^{y_i}(1-\pi_i)^{1-y_i} \tag{3.4}$$

Then the likelihood function is the joint probability distribution of all *n* observation is:

$$l(\beta) = \prod_{i=1}^{n} \pi_i^{y_i}(1-\pi_i)^{1-y_i} \tag{3.5}$$

The principle of maximum likelihood states that we use as our estimate of parameter the value which maximizes the expression in equation (3.5). However, it is easier mathematically to work with the log of equation (3.5). This expression, the log likelihood, is defined as:

$$L(\beta) = \ln[l(\beta)] = \sum_{i=1}^{n} \{y_i \ln(\pi_i) + (1-y_i)\ln(1-\pi_i)\} \tag{3.6}$$

The maximum likelihood estimates are the values for $\boldsymbol{\beta}$ that maximize the likelihood function in equation (3.6). Through maximization of the log-likelihood function we can theoretically estimate the parameter vector $\boldsymbol{\beta}$. But the equation is nonlinear in $\boldsymbol{\beta}$, and as a result the estimates do not have a closed form expression. Therefore, $\boldsymbol{\beta}$ will be obtained by maximizing using iterative algorithm method (Agresti, 1996).

3.3.1.4 Goodness of fit of the model

After fitting a model to a set of data, it is natural to enquire about the extent to which the fitted values of the response variable under the model compare with the observed values. If the agreement between the observations and the corresponding fitted values is good, the model may be acceptable. If not, the current form of model will certainly not be acceptable and the model will need to be revised.

3.3.1.4.1 Pearson chi-square test

The Pearson χ^2 statistic is based on observed (O) and expected (e) observations.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - e_i)^2}{O_i} = \sum_{i=1}^{n} \frac{(y_i - n_i\hat{p}_i)^2}{n_i\hat{p}_i(1-\hat{p}_i)} \qquad (3.7)$$

Where: y_i is the observed value of Y .

$\hat{p}_i$ is the predicted or fitted value of Y for a given of x_i

n_i is the number of observations.

High values of Pearson chi-square for a given independent variables indicates that there is strong association between each of the given independent variables and the dependent variable keeping the effect of the other factors constant. That is, testing the hypothesis:

H_o= There is no association between the variables

H_1= There is association between the dependent and the particular independent variable

3.3.1.4.2 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 almost always make the model fit worse (i.e., a model will have a lower 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 (the one with more variables) 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 statistic is fairly easy to calculate. The likelihood ratio test is performed to test the overall significance of all coefficients in the model on the basis of the test statistic:

$$G^2 = [(-2\ln L_0) - (-2\ln L_1)] \qquad (3.8)$$

Where: L_0 is the likelihood of the null model and L_1 is the likelihood of the saturated model.

Under the global null hypothesis, H_0: $\beta_1 = \beta_2 = ... = \beta_k = 0$, the statistic G^2 follows a chi-square distribution with k-1 degrees of freedom and measures how well the independent variables affect the response variable (Hosmer and Lemeshow, 2000).

3.3.1.4.3 Hosmer-Lemeshow Test

The Hosmer-Lemeshow test is used to check the overall model fit. In this approach, data are divided into g (usually10) groups. From each group, the observed and expected number of events will be computed. Then, the Hosmer-Lemeshow test statistic is given by:

$$\hat{C} = \sum_{j=1}^{g} \frac{(O_j - E_j)^2}{V_j} \qquad (3.9)$$

Where: $E_j = np_j$, $V_j = np_j(1-p_j)$, g is the number of group, O_j is observed number of events in the jth group, E_j is expected number of events in the jth group, and V_j is a variance correction factor for the j[th] group. If the observed number of events differs from what is expected by the model, the statistic $\hat{C}$ 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 (Agresti, 1996).

3.3.1.4.4 Wald Test

A Wald test is used to test the statistical significance of each coefficient (β) in the model. The test statistic is a chi-square statistic with a desirable outcome of non-significance, indicating that the model prediction does not significantly differ from the observed.

The hypothesis to be tested is:

$H_0{:}\beta=0$ Versus $H_A{:}\beta\neq 0$ at α level of significance.

The Wald test statistics, Z, for this hypothesis is

$$Z^2=\left(\frac{\hat{\beta}_i}{S.E(\beta_i)}\right)^2 \sim \chi^2(1) \qquad (3.10)$$

$\hat{\beta}_j^{\,2}$ is the square of the estimated regression coefficient and var($\hat{\beta}_j$) is the variance of $\hat{\beta}_j$.

3.3.1.5 Model Diagnostics

Influential observations and Outliers

Cook's distance is designed to measure the shift in $\hat{\beta}$ when a particular observation is omitted. It is a combined measure of the impact of that observation on all regression coefficients. Cook's distance less than unity shows that an observation had no overall impact on the estimated vector of regression coefficients β.

Cook's D is defined as

$$D=\frac{\left(\hat{\beta}_i-\hat{\beta}\right)\left(X'X\right)\left(\hat{\beta}_i-\hat{\beta}\right)}{p's^2} \qquad (3.11)$$

Computationally, Di is more easily obtained as

$$D = \frac{r_i^2}{p'}\left(\frac{v_{ii}}{1 - v_{ii}}\right) \tag{3.12}$$

Where r_i is the standardized residual and v_{ii} is the i^{th} diagonal element of P computed from the full regression.

DFBETAS: Cook's distance reveals the impact of the i^{th} observation on the entire vector of the estimated regression coefficients. The influential observations for the individual regression coefficients are identified by $DFBETAS_j(i)$, j = 0, 1, 2, . . . , p, where each $DFBETAS_j(i)$ is the standardized change in when $\hat{\beta}_j$ the i^{th} observation is deleted from the analysis. Thus,

$$DFBETAS_{j(i)} = \frac{\hat{\beta}_j - \hat{\beta}_{j(i)}}{si\sqrt{c_{jj}}} \tag{3.13}$$

Where c_{jj} is the $(j+1)^{st}$ diagonal element from$(X'X)^{-1}$.

If DFBETAs is less than unity, this implies no specific impact of an observation on the coefficient of a particular predictor variable (Cook and Weisberg, 1982).

3.3.2 Multilevel Model

Many sets of data collected in human and biological sciences have a multilevel or hierarchical structure. Hierarchy means that units at a certain level (also called micro units) are grouped into, or nested within, higher level (or macro) units. Schooling systems, for instance, present an obvious hierarchical structure, with pupils nested within classrooms, which are themselves nested within schools, and so forth. The techniques used for the statistical modeling and analysis of hierarchically structured data, and this have resulted in a broad class of models known under the generic name of multilevel models (Goldstein, 1995). Multilevel modeling allows relationships to be simultaneously assessed at several levels.

Multilevel analysis is a statistical approach that can be used for clustered sources of variability in multilevel data, which involves units at a higher level. It can take into account the variability associated with each level of the hierarchy (Dai *et al.*, 2010). In data with a hierarchical structure, individuals are not treated as independent, they are considered nested in a larger unit. Thus, multilevel analysis provides an approach to examining the effects of individual-level and group-level variables simultaneously. It can also estimate both between group and within group variations, and help to figure out how those levels interact with each other. Thus, multilevel models were used in order to draw insights regarding the causes of both the inter-individual and the inter-group variations (Duncan *et al*., 1995).

3.3.2.1 Multilevel Logistic Regression Model

Multilevel logistic statistical techniques can be used to predict a binary dependent variable from a set of independent variables. It can be employed in the simplest case without explanatory variables (usually called the empty model) and also with explanatory variables by allowing only the intercept term or both the intercept and slopes (regression coefficients) to vary randomly, and the coefficients are assumed to follow a multivariate normal. To keep the discussion on multilevel logistic regression models simple and taking into account the data to be analyzed in this study we concentrate on the case of two-levels. We note that extensions to the case of three or higher levels is straightforward.

3.3.2.2 Heterogeneous proportions

The basic data structure of the two-level logistic regression is a collection of N groups (regions units at level two) and within-group j (j =1, 2,..., N) a random sample of n_j level-one units (Children). The outcome variable, Nutritional status of children, is dichotomous and is denoted by Y_{ij} for children i in region j (i=1, 2,..., n_j, j=1, 2, ..., N) and Y_{ij} coded as 0(not wasted) and 1(wasted).The total sample size is denoted by $M = \sum_{j=1}^{N} n_j$.For the proper application of multilevel analysis, the first logical step is to test heterogeneity of proportions between the groups (regions). To test whether there are indeed systematic differences between the groups, the well-known chi-square test for contingency table can be used (Snijders and Bosker, 1999). The test statistic is:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{3.14}$$

Where O is observed and E is the expected count in the cell of the contingency table. This can be written as:

$$\chi^2 = \sum_{j=1}^{N} \frac{n_j(\hat{p}_j - \hat{p}_.)^2}{\hat{p}_.} \tag{3.15}$$

Where: $\hat{p}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} Y_{ij}$ is the proportion of children, who are low weight for height (wasted) in region j,

$$\hat{p}_. = \frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{nj} Y_{ij} \tag{3.16}$$

is the overall proportion of children who are wasted.

$M = \sum_{j=1}^{N} n_j$, total number of under five children included in the study

This statistic (χ^2 chi-square statistic) follows approximately central chi-square distribution with N −1 degrees of freedom. Further note that $\hat{p}_j$ is an estimate for the group-dependant probability p_j.

3.3.2.3 Estimation of between and within-groups variance

The true variance between the group-dependent probabilities $\text{var}(p_j)$ can be estimated by (Snijders and Bosker, 1999).

$$\hat{\text{var}}(p_j) = \hat{\tau}^2 = S^2_{between} - \frac{S^2_{within}}{\tilde{n}} \tag{3.17}$$

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

The between-groups variance is closely related to the chi-squared test statistic.

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

The with-in groups' variance is a function of the group averages.

$$S^2_{within} = \frac{1}{M-N}\sum_{j=1}^{N} n_j \hat{p}_j(1-\hat{p}_j)$$

3.3.2.4 The Empty Logistic Regression Model

Empty model is a model that contains no explanatory variables at all that serves as a point of reference with which other models are compared.

The empty two-level model for a dichotomous outcome variable refers to population of groups (level-two units, regions) and specifies the probability distribution for the group-dependent probabilities in equation $Y_{ij} = p_j + \varepsilon_{ij}$, without taking further explanatory variables in to account. The empty two-level logistic regression model is expressed by:

$$\text{logit}(p_j) = \beta_0 + U_{0j} \tag{3.18}$$

Where: Y_{ij} is the outcome for individual i in group j.

p_j is the probability (average proportion of successes) in group j.

ε_{ij} is individual-dependent residual.

β_0 the population average of the transformed probabilities and

U_{0j} the random deviation from this average for group j and distributed as

Normal with mean zero and variance σ_u^2. ($U_{0j} \sim N(0,\sigma_u^2)$)

This model does not include a separate parameter for the level-one residual variance of the dichotomous outcome variable follows directly from the success probability Var(ε_{ij}) $= p_j(1-p_j)$.The residual ε_{ij}' s are assumed to have mean zero and variance σ^2_ε (Snijders and Bosker, 1999).

3.3.2.5 Intra-class Correlation Coefficient (ICC)

The intra-class correlation coefficient (ICC) measures the proportion of variance in the outcome explained by the grouping structure. ICC can be calculated using an intercept-only model based on the following formula:

$$ICC = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_e^2} \quad (3.19)$$

Where: σ_0^2 is between group variance.

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

Since the logistic distribution for the level one residual variance implies a variance of $\pi^2/3 \approx 3.29$ (Snijders and Bosker, 1999) and this formula can be reformulated as:

$$ICC = \frac{\sigma_0^2}{\sigma_0^2 + 3.29} \quad (3.20)$$

3.3.2.6 The Random Intercept Logistic Regression Model

The logistic random intercept model expresses the log-odds, i.e., the logit of p_{ij}, as a sum of a linear function of the explanatory variables and random group-dependent deviation U_{0j}.

Consider K explanatory variables $X_1, X_2, ..., X_k$. The values of $X_h (h = 1,2,...,k)$ are indicated in the usual way by $x_{hij} (h = 1,2,...,k; i = 1,2,...,n; j = 1,2,...,N)$ Since some or all of these variables could be level-one variables, the success probability is not necessarily the same for all individuals in a given groups. Therefore, the success probability depends on the individual as well as on the group, and is denoted by p_{ij}. The outcome variable is expressed as the sum of success probability (expected value of the outcome variable) and a residual term ε_{ij}.

$$\log it(p_{ij}) = \left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \ldots + \beta_k x_{kij} \tag{3.21}$$

By letting $\beta_{oj} = \beta_0 + U_{0j}$ then $\log it(p_{ij}) = \beta_0 + \sum_{h=1}^{k} \beta_h x_{hij} + U_{0j}$

The p_{ij} 's can be written as

$$p_{ij} = \frac{e^{\beta_0 + \sum_{h=1}^{k} \beta_k x_{hij} + U_{0j}}}{1 + e^{\beta_0 + \sum_{h=1}^{k} \beta_k x_{hij} + U_{0j}}} \tag{3.22}$$

Note, that in the above equation $\beta_0 + \sum_{h=1}^{K} \beta_h x_{hij}$ is the fixed part of the model, the remaining U_{0j} is called the random part of the model. Thus, a unit difference between the x_h values of two individuals in the same group is associated with a difference of β_h in their log-odds, or equivalently, a ratio of $\exp(\beta_h)$ in their odds. The deviations U_{0j} mutually independent with zero mean (given the values of all explanatory variables) and a variance σ_0^2. For equation (3.18) does not include a level-one residual because it is an equation for the probability p_{ij} rather than for the outcome Y_{ij} (Snijders and Bosker, 1999).

3.3.2.7 The Random Coefficient Logistic Regression Model

In logistic regression analysis, linear models are constructed for the log-odds. The multilevel analogue, random coefficient logistic regression, is based on linear models for the log-odds that include random effects for the groups or other higher-level units. Consider explanatory variables, which are potential explanations for the observed outcomes. Denote these variables by $X_1, X_2, \ldots, X_k$. The values of $X_h (h = 1,2,\ldots,k)$ are indicated in the usual way by x_{hij}. Since some or all of these variables could be level-one variables, the success probability is not necessarily the same for all individuals in a given group. Therefore, the success probability depends on the individual as well as the group, and is denoted by p_{ij}. Now consider a model with group-specific regressions of logit of the success probability, $\log it(p_{ij})$ on a single level-one explanatory variable X.

$$\log it(p_{ij}) = \left(\frac{p_{ij}}{1-p_{ij}} \right) = \beta_{0j} + \beta_{1j} x_{1ij} \tag{3.23}$$

The intercepts β_{oj} as well as the regression coefficients, or slopes, β_{1j} are group-dependent. These group-dependent coefficients can be split into an average coefficient and the group dependent deviation:

$$\beta_{oj} = \beta_0 + U_{0j}$$

$$\beta_{1j} = \beta_1 + U_{1j} \tag{3.24}$$

Substitution into equation (3.18) leads to the model

$$\log it(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}} \right) = (\beta_0 + U_{0j}) + (\beta_1 + U_{1j}) x1ij \tag{3.25}$$

There are two random group effects, the random intercept U_{0j} and the random slope U_{1j}. It is assumed that the level-two residuals U_{0j} and U_{1j} have means zero given the value of the explanatory variable X. Thus, β_1 is the average regression coefficient and β_0 is the average regression intercept.

The term $\beta_{1j} x1_j$ can be regarded as a random interaction between group and X. This model implies that two random effects characterize the groups: their intercept and their slope. These two group effects U_{0j} and U_{1j} will not be independent, but correlated. Further, it is assumed that, for different groups, the pairs of random effects (U_{0j}, U_{1j}) are independent and identically distributed. Thus, the variances and covariance of the level-two random effects (U_{0j}, U_{1j}) are denoted as follows:

$$\text{var}(U_{0j})=\sigma_{00}=\sigma_0^2$$

$$\text{var}(U_{1j}) = \sigma_{11} = \sigma_1^2$$

$$\text{var}(U_{0j}, U_{1j}) = \sigma_{01}$$

The model for a single explanatory variable discussed above can be extended by including more variables that have random effects. Suppose that there are k level one explanatory variables $X_1, X_2, \ldots, X_k$, the model where all X- variables have varying slopes and random intercept.

That is

$$\log it(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}x_{1ij} + \beta_{2j}x_{2ij} + \ldots + \beta_{kj}x_{kij} \qquad (3.26)$$

Letting $\beta_{0j}=\beta_0+U_{0j}$ and $\beta_{hj}=\beta_h+U_{hj}$ h=1,2,…,k. We get

$$\log it(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \sum_{h=1}^{k} \beta_h x_{hij} + U_{0j} + \sum_{h=1}^{k} U_{hj} x_{hij} \qquad (3.27)$$

The first part of this model, $\beta_0 + \sum_{h=1}^{k} \beta_h x_{hij}$, is the fixed part and the second part,

$U_{0j} + \sum_{h=1}^{k} U_{hj} x_{hij}$, is the random part of the model. (Snijders and Bosker, 1999)

3.3.2.8 Estimation Method

The parameters of generalized linear models are estimated using maximum likelihood methods. Multilevel models are also generally estimated using maximum likelihood methods, and combining multilevel and generalized linear models leads to complex models and estimation procedures.

The most frequently used methods are based on a first-or second order Taylor expansion of the link function. When the approximation is around the estimated fixed part this called marginal quasi-likelihood (MQL), when it is around an estimate for the fixed plus random part it is called Penalized or predictive quasi-likelihood (PQL)(Goldstein,1991; Goldstein and Rasbash,1996).The nonlinear function is linearized using an approximation known as Taylor series expansion. Taylor series expansion approximates a nonlinear function by an infinite series of terms. Often only the first term of the series is used, which is referred to as a first order Taylor approximation. When the second term is also used, we have a second order Taylor approximation, which is generally more accurate. Both MQL and PQL rely on the Taylor expansion to achieve the approximation. Rodriguez and Goldman (1997) compared four approximation estimation procedures (first-order MQL, second-order MQL, first-order PQL, second-order PQL) with the maximum likelihood achieved through high dimensional numerical integration (Snijders and Bosker, 1999). There are different methods of parameter estimations which are implemented by various software packages such as, MLwiN, STATA and SAS. In this study, the multilevel data has been analyzed by the STATA 11 software packages.

3.3.2.7 Significance Testing in Multilevel Regression

For fixed coefficients of multilevel logistic regression tests about parameters are done using the Wald test. Random effects tests examine hypotheses about whether the variance of intercept or slopes is significantly different from zero. The tests of variances and covariances are made using a Wald z-test and chi-square test (Snijders and Bosker, 1999).

3.3.2.9 Multilevel Binary Logistic Regression Model Comparison

Akaike's Information Criterion (AIC): It is the expected estimated relative Kullback-Leibler (K-L) distance, where the K-L distance is the minimum distance between a model and full reality. And it is given as:

$$AIC = -2\ln(L(Model)) + 2K \qquad (3.28)$$

Where: K is number of estimated parameters

L (model) is the likelihood of the model

Bayesian Information Criterion (BIC): It is also known as the Schwarz criterion after Gideon Schwarz and virtually identical to the minimum description length criterion (Taper, 2004). The formula is given as:

$$BIC = -2\ln(L(Model)) + K * \log(n) \qquad (2.29)$$

Where: K is number of estimated parameters

L (model) is the likelihood of the model

n is number of observation

Based on the model selection criterion stated above the model with smallest AIC and BIC value is considered as better fit model.

CHAPTER FOUR

DATA PRESENTATION AND INTERPRETATION

4.1 Descriptive Results

This chapter covers the results and analysis of the study. We begin our data analysis by giving the descriptive statistics for the independent variables considered in the study; we then proceed to logistic regression analysis and multilevel logistic regression analysis.

4.1.1 Nutritional Status of under-five age children according to Weight for Height Z-score (WHZ) for selected Independent variables.

A total of 9,611 under-five age children in Ethiopia were included in the study. Out of this sample, 11.7 percent of children were wasted. The prevalence of child wasting according to selected background characteristics were shown in Table 4.1. About 13.2 % of the male children and 10.2% of female children were wasted. The proportion of wasting children was found highest among the children aged 6-11 months (18.5 %) and lowest among the children aged 36-47 months (7.6 %). There was an inverse relationship between the size of child at birth and the proportion of children who were wasted. Wasting was more common among the children who were small in size at birth (16.4 %) than among children who were average (10.2 %) or larger in size (8.8 %) at birth. The prevalence of wasting with regard to birth orders 1, 2-3, 4-5, 6+ were 9.7%, 10.8%, 12.9% and 13.4%, respectively.

Regionally, the distribution of wasting was highest in Affar (20.3 %) and lowest in Addis Ababa (4 %).There was a difference in the level of wasting for children residing in rural and children residing in urban areas i.e., 12.4 percent of children in rural areas were wasted, compared with 8.4 percent in urban. The mothers' level of education had an inverse relationship with wasting levels. For instance, results from table 4.1 indicate that 13 % the children whose mothers had no education were wasted, whereas 5 % of the children whose mothers with secondary and above education were wasted. Also the mothers' body mass index (BMI) had an inverse relationship with their children's level of wasting. Table 4.1, reveals that 18% of children whose mothers (BMI <18.5) were wasted (18 %) and 5% of children of mothers with BMI ≥25 were wasted. The proportion of wasting was worse for those children of the poor household (14.3 %) compared to children of household with medium wealth index (11.4 %) and children of rich household (8.2%).

Also the proportion of wasting was higher for those children experienced diseases like diarrhea (18.5%) and fever (16.9 %) than those did not experienced diseases two weeks before the date of survey.

Table 4.1 Nutritional status of under-five age according to Weight-for-Height Z-score (WHZ)

Variables	Categories	Nutritional status (Weight-for-Height Z-score)		Total	χ^2	P-value
		Not wasted	Wasted			
Sex of child	Male	4243(86.8%)	647(13.2)	4890	21.465	<0.0001
	Female	4240(89.8%)	481(10.2)	4721		
Age of child in months	< 6	840(83.9%)	161(16.1%)	1001	151.6	<0.0001
	6-11	788(81.5%)	179(18.5%)	967		
	12-23	1492(84.0%)	284(16.0%)	1776		
	24-35	1701(90.6%)	177(9.4%)	1878		
	36-47	1899(92.4%)	156(7.6%)	2055		
	48-59	1763(91.2%)	171(8.8%)	1934		
Birth Order	1	1642(90.3%)	176(9.7%)	1818	19.371	<0.0001
	2-3	2736(89.2%)	331(10.8%)	3067		
	4-5	1952(87.1%)	288(12.9%)	2240		
	6+	2153(86.6%)	333(13.4%)	2486		
Size of child at birth	Small	2531(83.6%)	495(16.4%)	3026	94.311	<0.0001
	Average	3416(89.8%)	389(10.2%)	3805		
	Large	2536(91.2%)	244(8.8%)	2780		

Region	Tigray	963(89.4%)	114(10.6%)	1077	163.4	<0.0001
	Affar	712(79.7%)	181(20.3%)	893		
	Ahmara	958(89.7%)	110(10.3%)	1068		
	Oromiya	1365(90.1%)	150(9.9%)	1515		
	somali	609(80.7%)	146(19.3%)	755		
	Benishangul	749(89.8%)	85(10.2%)	843		
	SNNP	1259(92.0%)	109(8.0%)	1368		
	Gambela	582(85.2%)	101(14.8%)	683		
	Harari	466(91.2%)	45(8.8%)	511		
	AddisAbaba	310(96.0%)	13(4.0)	323		
	DireDawa	510(87.3%)	74(12.7%)	584		
Place of Residence	Urban	1415(91.6%)	130(8.4%)	1545	19.615	<0.0001
	Rural	7068(87.6%)	998(12.4%)	8066		
Number of household members	1-4	3690(89.1%)	451(10.9%)	4141	5.117	0.077
	5-9	4452(87.6%)	631(12.4%)	5083		
	10& above	341(88.1%)	46(4.9%)	387		
Mothers Level of Education	No Educ	5825(87.0%)	871(13.0%)	6696	42.571	<0.0001
	Primary	2214(90.4%)	234(9.6%)	2448		
	Secondary and higher	444(95.1%)	23(4.9%)	467		
Body Mass Index of Mother	Thin	2087(82.0%)	457(18.0%)	2544	141.6	<0.0001
	Normal	5861(90.1%)	643(9.9%)	6504		
	Overweight	535(95.0%)	28(5.0%)	563		
Sex of household head	Male	6984(88.7%)	891(11.3%)	7875	7.504	0.004
	female	1499(86.3%)	237(13.7%)	1736		

Husband educational Level	NoEduc	4285(86.1%)	691(13.9%)	4976	46.299	<0.0001
	Primary	3234(90.4%)	345(9.6%)	3579		
	Secondary and higher	964(91.3%)	92(8.7%)	1056		
Wealth Index household	Poor	4059(85.7%)	678(14.3%)	4737	70.891	<0.0001
	Medium	1410(88.6%)	182(11.4%)	1592		
	Rich	3014(91.8%)	268(8.2%)	3282		
Had Diarrhea	No	7258(89.5%)	850(10.5%)	8108	78.588	<0.0001
	Yes	1225(81.5%)	278(18.5%)	1505		
Had fever	No	6880(89.6%)	802(10.4%)	7682	62.112	<0.0001
	Yes	1603(83.1%)	326(16.9%)	1929		

4.1.1. Test of Association between Under-Five Children Wasting and Predictor Variables

The chi-square test results presented in Table 4.1 above were used to test whether or not there is a significant association between nutritional status of children in terms of height for weight z-score (wasting) and each predictor variables independently. These tests revealed that except number of household members, all other predictor variables showed a significant association with wasting independently.

The result of Pearson chi-square test result showed that all independent variables have significant effect on the nutritional status of under-five children in terms of weight-for-height at 25% level of significance. Thus we included all the variables in the study in the multiple logistic regression model to check the joint effect of those variables on the dependent variable weight-for-height-z-score.

4.2 Logistic Regression Analysis for Nutritional Status of Under-Five Children In case of Weight for Height (Wasting)

Multiple logistic regression was used to analyze the effect of each of the independent variables on nutritional status of under-five age children in terms of weight for height z-score. Stepwise method of variable selection procedure was employed to select the important determinants of wasting with SAS 9.2 software. Differential of wasting among under-five age children were considered by some selected variables related to demographic, socio-economic, child, maternal and health aspects. The significance of individual parameter estimates was checked using Wald test and the results are given in Table 4.2.

The interpretation of the results is given using odds ratio. Odds-ratios less than one indicates, the event was less likely to happen in the comparison than in the base group, an odds-ratio equal to one indicates the event was exactly as likely to occur in the two groups, while odds-ratios more than one indicate the event was more likely to happen than in the base group.

Based on the results of multiple logistic regression presented in the Table 4.2 at the final step of the stepwise method birth order, sex of household head and number of household members, parent's educational level did not have statistically significance effect on children nutritional status in terms of weight for height z-score. Results in Table 4.2 indicates that independent variables sex of children, age of children, size of child at birth, region, place of residence, mothers level of education, body mass index of mother, household wealth index, husband educational level, diarrhea and fever two weeks before survey had a joint significant effect on children nutritional status in terms of weight for height z-score.

The findings of this study revealed that female children were 28.8% (OR=0.712, 95% CI: 0.624, 0.811) less likely to be wasted than male children controlling other variables in the model. Also, wasting was highest for children in age group 6-11 months (OR=2.206; 95% CI: 1.742, 2.795) compared to children in age group 48-59 months controlling other variables in the model. Children in age groups 0-5 months and 12-23 months were 88.2% and 76.6% more likely to be wasted than children in age groups 48-59 months. Small in size children were 71.6% more likely to be wasted than large size children at birth (OR=1.716, 95% CI: 1.444, 2.038). On the other hand no significant difference was observed for the children in age groups 24-35 months and 36-47 months compared to the reference category group 48-59 months.

The odds of wasting for children whose parents reside in SNNP compared to children whose parents resided in Dire Dawa region were lower by 50.7% (OR: 0.493; 95%CI: 0.355, 0.684), controlling for other variables in the model. Children whose parents resides in Tigray, Oromiya, Amhara, Benishangul-Gumuz regions were less likely to be wasted compared to children whose parents reside in Dire Dawa region. Children whose parents resided in Somali region were 27% more likely to be wasted than children whose parents reside in Dire Dawa region. However, the odds of being wasted in Addis Ababa, Affar, Harari and Gambela were not significantly different from the reference region Dire Dawa. Children whose parents resided in rural area were 1.375 times more likely to be wasted than children whose parents reside in urban area (OR: 1.375; CI: 1.048, 1.805).

Children from poor households were about 43.7% more likely to be wasted than those children who live in rich households controlling for other variables in the model (OR: 1.437; 95%CI: 1.193, 1.730). The odds of wasting for children born to mothers body mass index was thin (BMI< 18.5) was higher by a factor of 2.66 compared to children whose mothers body mass index of overweight (BMI>=25) controlling for other variables in the model. On the other hand, children of normal body mass index mothers were about 54.4% more likely to be wasted than children of overweighed body mass index mothers controlling for other variables in the model.

Children whose mother had no education were 2.258 times more likely to be wasted (OR=2.258; 95% CI 1.334, 3.821) compared to children whose mothers had secondary or higher education controlling for other variables in the model, while children whose mothers had primary education were 78.2% more likely to be wasted compared to children whose mother had secondary or higher education controlling for other variables in the model.

Children who had diarrhea and fever in the preceding two weeks of the survey had 44.8% (OR: 1.448, CI: 1.221, 1.718) and 36.4% (OR: 1.364; CI: 1.164, 1.599) higher risk of being wasted than those children who did not have these illnesses, respectivel

Table 4.2 Logistic Regression Analysis for Weight-for-Height Z-score (Wasting)

Variables	DF	Estimate	S.E	Wald chi-square	Pr>chisquare	OR	95%Wald CL	
Intercept	1	-4.0340	0.3460	135.9272	<.0001*			
SEXOFCH	1			26.0508	<.0001*			
Female	1	-0.3404	0.0667	26.0508	<.0001*	0.712	0.624	0.811
Male(Ref)								
CHILDAGE	5			117.8723	<.0001*			
6< months	1	0.6322	0.1220	26.8665	<.0001*	1.882	1.482	2.390
6-11 months	1	0.7913	0.1206	43.0353	<.0001*	2.206	1.742	2.795
12-23 months	1	0.5690	0.1076	27.9718	<.0001*	1.766	1.431	2.181
24-35 months	1	-0.0222	0.1161	0.0367	0.8480	0.978	0.779	1.228
36-47 months	1	0.1648	0.1178	1.9553	0.1620	0.848	0.673	1.068
48-59 (Ref)								
SIZECHBIR	2			44.7713	<.0001*			
Small	1	0.5313	0.0878	36.6225	<.0001*	1.701	1.432	2.021
Average	1	0.1416	0.0890	2.5320	0.1116	1.152	0.968	1.372
Large(Ref)								
REGION	10			78.8427	<.0001*			
Tigray	1	-0.5041	0.1663	9.1918	0.0024*	0.604	0.436	0.837
Affar	1	0.0847	0.1592	0.2828	0.5948	1.088	0.797	1.487
Ahmara	1	-0.5297	0.1670	10.0555	0.0015*	0.589	0.424	0.817
Oromiya	1	-0.4727	0.1579	7.8623	0.0050*	0.642	0.471	0.875
Somali	1	0.2394	0.1206	3.9393	0.0472*	1.270	1.003	1.692
Benishangul-Gumuz	1	-0.5398	0.1765	9.3577	0.0022*	0.583	0.412	0.824
SNNP	1	0.7078	0.1671	17.9517	0.0001*	0.493	0.355	0.684

Gambela	1	-0.3117	0.1775	3.0825	0.0791	0.732	0.517	1.037
Harari	1	-0.3429	0.2076	2.7276	0.0986	0.710	0.472	1.066
Addis Ababa	1	-0.4608	0.3305	1.9447	0.1632	0.631	0.330	1.205
DireDa(Ref)								
PLACRES	1			5.2834	0.0215*			
Rural	1	0.3187	0.1387	5.2834	0.0215*	1.375	1.048	1.805
Urban(Ref)								
MOTHEDUC	2			14.5362	0.0007*			
No Education	1	0.8145	0.2684	9.2093	0.0024*	2.258	1.334	3.821
Primary	1	0.5775	0.2701	4.5710	0.0325*	1.782	1.049	3.025
Second(Ref)								
BMIMoth	2			68.4087	<.0001*			
Thin	1	0.9785	0.2120	21.3027	<.0001*	2.660	1.756	4.031
Normal	1	0.4345	0.2083	4.3511	0.0370*	1.544	1.027	2.323
Overw(Ref)								
WIHH	2			7.2080	0.0272*			
Poor	1	0.3626	0.0947	14.6463	0.0001*	1.437	1.193	1.730
Medium	1	0.2381	0.1150	4.2886	0.0384*	1.269	1.013	1.590
Rich(Ref)								
HADDIAR	1			18.0786	<.0001*			
Yes	1	0.3705	0.0871	18.0786	<.0001*	1.448	1.221	1.718
No(Ref)								
HADFEV	1			14.6482	0.0001*			
Yes	1	0.3105	0.0811	14.6482	0.0001*	1.359	1.164	1.599
No(Ref)								

(* significant at 5% level of significance)

3.2.1 Model Goodness of Fit Statistics

The overall logistic regression model was significant at the 5% level of significance as indicated by the Likelihood ratio, Wald and Score tests of the global null hypothesis that the model parameters were significant (Table 4.3)

Table 4.3 Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	603.9743	27	<.0001
Score	612.7832	27	<.0001
Wald	543.7176	27	<.0001

The Hosmer-Lemeshow Goodness-of-Fit Test tests the hypothesis:

H_o: The model is a good fit, vs.

Ha: The model is not a good fit

The value of the Hosmer-Lemeshow goodness-of-fit statistic was $\hat{C}$=10.1816 and the corresponding p-value computed from the chi-square distribution with 8 degrees of freedom was 0.2525. A large p-value (>0.05) usually suggests that the fitted model is an adequate. In this case, the p-value = 0.2525>0.05, so we do not reject the null hypothesis, and the model predicts the data at an acceptable level (Table 4.4).

Table 4.4 Hosmer-Lemeshow Goodness-Of-Fit Test

Chi-Square	DF	Pr > ChiSq
10.1816	8	0.2525

All of the goodness of fit tests suggests that the model was significant and adequate. The AIC, SBC and - 2Log likelihood (lower the better) values indicate that the model with the selected covariates was superior to the model with intercept only (Table 4.5).

Table 4.5 Models Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	6953.500	6403.525
SC	6960.670	6604.304
-2 Log L	6951.500	6347.525

3.2.3 Model diagnostic checking

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 were presented in Appendix A, TableA2. The DFBETAs for model parameters including the constant term and Cook's influence statistics were both less than unity. DFBETAs less than unity implies no specific impact of an observation on the coefficient of a particular predictor variable while Cook's distance less than unity showed that an observation had no overall impact on the estimated vector of regression coefficients ($\hat{\beta}$). Thus, from the above goodness of fit tests and diagnostic checking, we can say that our model is adequate.

4.3 Determinants of Under-Five Children Wasting In Ethiopia: Multilevel Logistic Regression Model

In this study we consider multilevel logistic regression models to allow for and to explore between-region variance of nutritional status of under-five children in terms of weight-for-height z-score (wasting). The data have a two-level hierarchical structure with 9,611 under-five age children at level 1, nested within 11 regions at level 2. This is based on the idea that there might be differences in under-five children wasting between regions that are not captured by the explanatory variables and hence might be regarded as unexplained variability within the set of all regions.

Before starting to multilevel analysis, one has to test for the heterogeneity of under-five children wasting among regions of Ethiopia. A chi-square test statistic was applied to assess heterogeneity in the proportion of wasted children among the regions in Ethiopia. The test yields a Pearson chi-square χ^2=163.736 which is greater than χ^2_{tab} (10) = 18.30704, and P =0.0001is less than 0.05 level of significance. Thus, there is evidence for heterogeneity among the regions with respect to wasting in under-five children in Ethiopia.

The multilevel analysis is a stepwise process. The first step examines the null model of overall probability of child wasted without considering any predictors. The second step includes both the analysis of single and multilevel model for random intercept and fixed slope multilevel analysis. The third step considers a model for two level random intercept and random slope (random coefficient) multilevel logistic regression analysis.

4.3.1 Multilevel empty logistic regression model analysis

The empty binary logistic regression model presented in Table 4.6 contained only region random effect. The deviance based Chi-square=114.148 was the difference in -2*log likelihood between an empty model without random effect (-2LL= 6951.5) and an empty model with random effect (-2LL =6837.352) was greater than χ^2_{tab}(1)=3.8414 with a corresponding p-value<0.0001 at 5% level of significance (See Appendix B, Table B1). This implies that an empty logistic regression model with random intercept was much better than an empty model without random intercept.

From the model estimated without considering explanatory variable, the estimated average log-odds of wasted children in an 'average' region (one with u_{0j} = 0) is estimated as $\hat{\beta}_0$= -2.080627. The intercept for region j was -2.080625 $+u_{0j}$ and the between region variance of under-five children wasting was estimated as $\hat{\sigma}^2_{u0}$=0.4231626 which was significant at 5% level of significance, indicating the variations of under-five children wasting among regions of Ethiopia was non-zero. This indicates that there were regional differences in under-five children wasting across regions in Ethiopia.

The intracorrelation coefficient (ICC) from the empty model was estimated at 0.05162 which was found to be significant at 5% level of significance, suggesting that about

5.162% of the variance in under-five children wasting in Ethiopia could be attributed to differences across regions.

Table 4.6 Result of Random empty two-level binary logistic regression model

Fixed Part	Coefficient	S.E	Z-value	P-value	[95% CI]
β_0=Intercept	-2.080627	.1332478	-15.61	0.000*	-2.341788 -1.819466
Random Part					
$\hat{\sigma}^2_{u0}$	.4231626	.1038034	4.08	0.002*	.2616401 .6844003
ICC(ρ_u)	.05162	.0240179	2.15	0.032*	.0203838 .1246328
AIC	6841.351				
BIC	6855.693				

(*significant at 5% level of significance)

4.3.2 Two-Level Random Intercept and Fixed Slope Binary Logistic Regression Model

The random intercept and fixed slope model is allows the intercept is to vary across regions and coefficients for covariates of under-five children wasting were fixed. The random intercept binary logistic regression model for under-five children wasting is significant based on deviance based Chi-square, the difference between log-likelihood of two-level empty binary logistic and two-level random intercept binary logistic regression model. The deviance based chi-square χ^2= 458.99 was greater than $\chi^2_{tab}(17)$ =27.587 with corresponding P-value=0.0000 at 5% level of significance (See Appendix B, Table B2). This suggests that, after controlling all indicators of under-five children wasting, the intercept varied across regions (i.e., the variations of under-five children wasting among regions of Ethiopia was non-zero).

The overall average log-odds of wasted children estimated at -4.3526, which was lower by about 2.27 as compared to empty model thus, indicating that inclusion of explanatory variables decreased overall mean of under-five child wasting. The variance component for the constant term was found significant at 5% significant level, indicating strong evidence of the variations across regions for under-five children wasting was non-zero (Table 4.7).

The intracorrelation coefficient was found to be 0.0211 implying that the percentage of the variance of under-five child wasting could be attributed to the differences between regions. The between-region (level two) variance of constant term for under-five child wasting was estimated at 0.2663 which is decreased by about 0.157 as compared to empty model indicating that, there was a contribution of those significant factors on under-five children variations across regions.

The two-level random intercept and fixed slope binary logistic regression has less AIC and BIC compared to random empty logistic regression model (Table 4.7). This indicates the random intercept and fixed slope model was a better fit compared to the empty model for predicting variation of under-five children wasting among regions in Ethiopia.

The results revealed that child age, sex of child, size of child at birth, type of place of residence, mothers educational level, body mass index of mothers, diarrhea and fever were found to be statistically significant (at 5% level of significance) indicating strong effects on under-five children wasting and also contributing to under-five children wasting variations among regions in Ethiopia (Table: 4.7).

The results of below are based on Table 4.7 for the random intercept and fixed slope logistic regression. Results of fixed part of coefficients can be interpreted similarly as binary logistic regression. The odds of under-five children wasting for female child was reduced by a factor of 0.711 (OR: 0.711; CI (0.624, 0.810)) compared to male child, controlling other variables in the model. Children in age groups: 0-5months, 6-11months, 12-23months, 24-37 were 1.889(OR: 1.889; CI (1.486, 2.396), 2.198(OR: 2.198; CI (1.736, 2.784) and 1.763(OR: 1.763; CI (1.428, 2.177) times more likely to be wasted compared to children aged 48-59months respectively, controlling the other variables in the model. The probability of wasting among children age groups 24-37 and 38-47months were not significantly different from children in age group 48-59 at 5% level of significance. Small size children are 70.9% more likely to be wasted (OR: 1.709; CI

(1.439, 2.029)) than large size child at birth. While the probability of wasting for average size child at birth was not statistically different from large size children at birth.

Table 4.7 Result of Random Intercept and fixed slope logistic regression analysis for wasting

Fixed Part	Coeff.	Std.Er.	Z	P>|Z|	OR	[95% Conf. Interval]	
SEXOFCH							
Female	-.3414957	.0666344	-5.12	0.000*	.7107065	.6236932	.8098593
Male(Ref)							
CHILDAGE							
<6months	.6348096	.1218391	5.21	0.000*	1.886663	1.485883	2.395543
6-11months	.7876073	.1205055	6.54	0.000*	2.198131	1.735717	2.783736
12-23months	.5671441	.1074899	5.28	0.000*	1.763224	1.428275	2.176723
24-37months	-.0195534	.1159501	-0.17	0.866	.9806365	.781288	1.23085
38-47months	-.1655524	.1177466	-1.41	0.160	.8474255	.6727837	1.067401
48-59(Ref)							
SIZECHBI							
Small	.5359115	.0876259	6.12	0.000*	1.709005	1.439316	2.029227
Average	.1414412	.0888236	1.59	0.111	1.151933	.9678773	1.370989
Large(Ref)							
PLACRES							
Female	.3049475	.1359692	2.24	0.025*	1.356554	1.039202	1.770819
Male (Ref)							
MOTHEDUC							
No education	.8376684	.2677302	3.13	0.002*	2.310972	1.367421	3.905594
Primary	.5841527	.2696145	2.17	0.030*	1.793471	1.057299	+3.04222
Sec (Ref)							
BMIMOTH							
Thin	.9714337	.2115657	4.59	0.000*	2.641729	1.745031	3.999202

Normal	.4171865	.2080642	2.01	0.045*	1.517686	1.009432	2.281846
Overw (Ref)							
WIHH							
Poor	.3719709	.094096	3.95	0.000*	1.450591	1.206286	1.744374
Medium	.234963	.1147365	2.05	0.041*	1.264862	1.010135	1.583824
Rich(Ref)							
HADDIAR							
Yes	.3680754	.0869798	4.23	0.000*	1.444951	1.218473	1.713525
No(Ref)							
HADFEV							
Yes	.3110238	.0809412	3.84	0.000*	1.364822	1.164605	1.599459
No(Ref)							
Constant	-4.352597	.3336679		0.000*			
Random Part							
	Coeff.	S.E	Z-value	P-value		[95% Conf. Interval]	
$\hat{\sigma}_0^2$	.2663028	.0666957	3.99	0.002*		.1630016	.4350705
ICC (ρ_u)	.0211014	.0103467	2.04	0.041*		.0080115	.0544058
AIC	6416.359						
BIC	6552.602						

(Ref =reference category) (*= significant at 5% level of significance)

4.3.3 Two-level Random Coefficient Binary Logistic regression model

Random coefficient logistic regression model allows the effect that the coefficient of the covariates to vary from region to region. First we run this model for each covariate separately to check the significance effect of those variables. We used a deviance-based chi-square test to test whether the effect of sex of child, age of child, size of child at birth, place of residence, mother level of education, body mass index of mothers, household wealth index, illness(diarrhea and fever) varies across regions. The null hypothesis is that the random factors have no effect.

The calculated deviance-based chi-square test for each variable was as follows: sex of child (χ^2 = 0.17, d.f = 2, p-value = 0.9200), age of child (χ^2= 8.31, d.f=2, p-value = 0.157), size of child (χ^2= 0.12, d.f=2, p-value= 0.9428), place of residence (χ^2= 3.03, d.f=2, p-value= 0.2202), mothers level of education (χ^2 = 0.52, d.f=2, p-value= 0.7700), body mass index of mothers (χ^2= 0.20, d.f =2, p-value = 0.9027), household wealth index (χ^2= 2.11, d.f=2, p-value= 0.3482), illness diarrhea (χ^2= 0.06, d.f=2, p-value= 0.9680) and fever(χ^2=1.90, d.f=2, p-value = 0.3873) See Appendix B, Table B4. The results showed that the random factor parts of all variables were not significantly different from zero at 5% level of significance. We concluded that the coefficients of all variables do not indeed vary across regions. Therefore, considering multiple logistic regression models for those variables having random slope coefficients has no significant importance. The AIC, BIC result for random intercept and fixed intercept model was less than for random coefficient logistic regression model result (Appendix B, Table B4). This indicated that the random intercept and fixed slope binary logistic regression model was more appropriate model for variation of under-five children wasting in Ethiopia compared to other two-level binary logistic regression model.

CHAPTER FIVE

DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

5.1 Discussion

This study had the objective to identify the determinants of wasting among under-five children wasting based on 2011 EDHS data. This study revealed that about 11.7% of under-five children in Ethiopia were wasted (low weight for height z-score).

The results from binary logistic regression analysis should that the factors sex of child, age of child, size of child at birth, place of residence, region, mother's body mass index, mothers level of education, household wealth index, illness(diarrhea and fever two weeks before survey) had significant effects on wasting of under-five children at 5% significance level. Birth order, sex of household head, number of household members and parent's level of educations had no significant effect on under-five children wasting. Children in Somali region were more likely wasted compared to Dirre Dawa. But, under-five children in SNNP, Tigray, Oromiya, Amhara, Benishangul-Gumuz regions were less likely wasted compared to children whose parents resided in Dirre Dawa region. However, under-five children wasting for children in Addis Ababa, Affar, Harari and Gambela were not significantly different from those in Dire Dawa.

The results of random intercept binary logistic regression model revealed that the overall mean of under-five children wasting varied across the regions in Ethiopia. Based on loglikelihood deviance based Chi-square, AIC and BIC the two-level random intercept binary logistic regression fitted the data set well.

The findings of this study revealed that female children were less likely to be wasted than males. A study in Botswana showed that male children were at high risk of wasting than female (Salah *et al*, 2006). Another study in Sub-Sahara Africa (SSA) showed that male children in Niger and Central Africa Republic had significantly higher probability of wasting whereas the study in Swaziland showed that female children were more likely wasted than male children (Oyekale, 2012).

The study showed that the risk of wasting was highest for children in the age group 6-11 months and children less than 6 months. Also the study in Sub-Saharan Africa showed that, as the children grow older it was observed that wasting significantly reduced in Niger and Comoros Oyekale (2012). Wise (2004) had a similar finding and explained that due to high vulnerability of children to illness at the early stage of growth. This result is not consistent with the study conducted in Kwara state, Nigeria (Babatunde *et al.*, 2011) that examined the prevalence and determinants of malnutrition among under-five children of farming households in Kwara State, Nigeria. The study revealed that older children were more likely wasted.

Children who are small in size at birth were more likely wasted than large size children at birth. A study in Bangladesh indicated that size of children at birth was an important factor of wasting and the risk of being wasted is higher in children small size at birth than large size at birth (Rayhan and Khan, 2006). A study in Nepal revealed that the likelihood of wasting was higher among children with smaller than average size at birth as compared to average or bigger size at birth (Pradhan, 2010).

Children whose parents resided in rural area were more likely wasted than children whose parents resided in urban area. Also, according to the findings of the 2000 Ethiopia DHS (CSA and ORC Macro, 2001) wasting was higher among children in rural areas than children in urban areas. Food Consumption and Nutrition Division International Food Policy Research Institute (Lisa, 2004) reported weight-for-height z-score (WHZ) wasting was generally higher in urban areas. This common pattern has been previously documented (Ruel *et al.* 1998). The urban areas offer more favorable living conditions and opportunities and that this is reflected in better health and nutrition outcomes for children.

Children who lived in poor households were more likely to be wasted than that of children who live in rich households. The result was similar with studies (Alemu *et al.*, 2005). Increase in household income at community level leads to improved access to high quality health care, improved water and sanitation systems and greater access to information which affect the nutritional status of children.

The present study showed that the hazard of wasting for children whose mothers body mass index +(BMI< 18.5) was higher by a factor of 2.66 compared to children whose mothers body mass index were overweight (BMI>=25). A similar study in Nigeria (Babatunde *et al.*, 2011) revealed that children born to mothers with high body mass index were less likely to be wasted.

Children whose mother had no education were more likely to be wasted compared to children whose mothers' had secondary and higher education. A study by Oyekale (2012) showed that attainment of mother's secondary education reduces the probability of wasting. Also a study in Gondar university hospital, Ethiopia showed that the risk of children wasting were higher for those children born to illiterate mothers (Solomon and Zemene, 2008).

Babatunde *et al.* (2011) showed that better education by mothers significantly reduced the risk of wasting among under-five children. Education was expected to broaden the knowledge of the mothers on the best way to take care of children. In enhancing the quality of care and nutritional status of children, the role of mothers' education is widely recognized. Also Smith and Hadad (2000) showed that more educated mothers are committed to child care and interact very well with their children.

The findings of this study also revealed that prevalence of wasting was higher among children who had diarrhea and fever two weeks before the date of the survey than those who had not diarrhea and fever. This result is consistent with other studies (Frogillo *et al*, 1997; Oyekale, 2012). Diarrhea affects dietary intake and utilization, which may have a negative effect on improved child nutritional status and associated with body dehydration.

5.2 Conclusions

The study employed binary logistic regression and two-level binary logistic regression model to determine the determinants of wasting among under-five children in Ethiopia. The result from descriptive statistics showed that 11.7% of under-five children in Ethiopia wasted (low weight-for-height z-score). Results based on binary logistic regression and two-level binary logistic regression model revealed that the following variables are important determinants of wasting of under-five children: Sex of child, age of child, size of child at birth, place of residence, mothers body mass index, mothers level of education, household wealth index, had diarrhea and fever two weeks before date of survey. The multilevel model showed the existence of significant variations in the prevalence of wasting among the regions in Ethiopia. Based on loglikelihood deviance based Chi-square, AIC and BIC the two-level random intercept binary logistic regression fitted the data set well.

5.3 Recommendations

Based on the findings of this study, we recommend the following:

- It is useful to strengthen health care and food security programs in rural areas to directly address food insecurity and wasting problems of the poor and vulnerable communities in rural parts of the country.
- Special attention should be paid to children at appropriate age.
- Mothers should be educated to improving the quality of care and attention they can provide to their children.
- Efforts should be made to improve environmental sanitation and personal hygiene to prevent exposures to diarrhea and fever.
- Further studies, should be conducted to identify others determinants of wasting among under-five children by considering severe wasting.

REFERENCES

ACC/SCN, *5th Report on the World Nutrition Situation* (2004). United Nations. Administrative commitee on Coordination/ sub-Commitee on Nutrition.

Agresti, A. (1996). An Introduction to Categorical data Analysis. John Wiley and Sons, Inc., New York.

Alderman, H., Hoogeveen, H. and Rossi, M. (2005) 'Reducing Child Malnutrition in Tanzania-Combined Effects of Income Growth and Program Intervention' World Bank Policy Research Working Paper 3567

Alemu, M., Nicola, J. and Belele, T. (2005). Tackling child malnutrition in Ethiopia; Young lives project working paper No 19; Save the children UK.

Babatunde, O. R., Olagunju, F. I., Fakayode, S. B. and Sola-Ojo, F. E. (2011). Prevalence and Determinants of Malnutrition among Under-five Children of Farming Households in Kwara State, Nigeria. *Journal of Agricultural Science* **3**(3).

Blossner, M. and de Onis, M. (2005). Malnutrition: Quantifying the Health Impact at National and Local Levels. Environmental Burden of Diseases Series, No. 12.

Central Statistical Authority (CSA) [Ethiopia] and ORC Macro. 2001. *Ethiopia Demographic and Health Survey 2000.* Addis Ababa, Ethiopia, and Calverton, Maryland, USA: Central Statistical Authority and ORC Macro.

Chevassus-Agnès, S. (1999). Anthropometric, health and demographic indicators in assessing nutritional status and food consumption Special: Population, poverty and environment FAO Food and Nutrition Division with the collaboration of Alain Marcoux, FAO Population Programme Service.

Christiaensen, L. and Alderman, H. (2001). Africa region working paper series. Child malnutrition in Ethiopia; Can maternal knowledge augment the role of income? No. 22.

Cogill, B. (2001). Anthropometric Indicators Measurement Guide: Food and Nutrition Technical Assistance Project. European Journal of Clinical Nutrition 58, 532–540.

Cook, R. and Weisberg, S. (1982). Residuals and Influence in Regression. Chapman and Hall, New York.

Dai, J., Li. Z., & Rocke, D. (2010). Hierarchical logistic regression modeling with SAS Glimmix. www. Lexjansen.com.

de Onis M, Blössner MB, Borghi E. Estimates of global prevalence of childhood underweight in 1990 and 2015. JAMA. 2004;291:2600–06.

Duncan, C., Jones, K., and Moon, G. (1995). Psychiatric morbidity: a multilevel approach to regional variations in the UK. *Journal of Epidemiol Community Health*, 49(3), 290-5.

EDHS (2005). Ethiopian Demographic and health survey (EDHS), Addis Ababa, Ethiopia and Carverton, Mary land, USA.

EDHS (2011). Ethiopian Demographic and health survey (EDHS), Addis Ababa, Ethiopia and Carverton, Mary land, USA.

Faber, M. and Wenhold, F. 2007. Nutrition in contemporary South Africa. *Water South Africa*, 33(3):393-399. (Special Edition) 2007.

Fernandez., Isabel, D., John, H., Mercedes, H. and de Onis. (2002). Prevalence of nutritional wasting in populations: building explanatory models using secondary data Bull World Health Organ vol.80 no.4 Genebra.

Frogillo EA. de Onis M. and Hauson K.M.P. Socio-economic and demographic factors are associated with worldwide patterns of stunting and wasting of children. The Journal of Nutrition 1997;127. (12): 2302-2309.

Goldstein, H. (1991). Nonlinear multilevel models with an application to discrete response data. *Biometrika* 78:45–51.

Goldstein, H. (1995). Multilevel Statistical Models. London: Edward Arnold/New York: Halsted.

Goldstein, H. and Rasbash, J. (1996). Improved approximations for multilevel models with binary responses. *J. Roy. Statist. Soc. A,* 159:505–513.

Gunasekara, H. R. (1999). Nutrition Status of Children in Sri Lanka. *Sri Lankan Journal of Population Studies* 1(12):57-73.

Hosmer, D. and Lemeshow, S. (2000). Applied Logistic Regression. John Wiley and Sons Inc., New York.

Labadarios, D. 2005. Malnutrition in the developing world: The triple burden. *South African Journal of Clinical Nutrition (SAJCN),* 18(2):119-121, September 2005.

Lisa, C., Smith and Lawrence, H. (2000). Cross country analysis of child malnutrition in developing countries. International Food Policy Research Institute Washington, DC.

Olaf, M. and Michael, K. (2005). Malnutrition and health in developing countries. *Canadian medical Association Journal* 173 (3): 20-25.

ORC Macro. Measure DHS+STAT compiler (2001). Available at: www.measuredhs.com

Oyekale, A. S. and Oyekale, T. O. (2000). Do Mother's Education Levels Matter in Child Malnutrition and Health Outcomes in Gambia and Niger? Department of Agricultural Economic, University of Ibadan, Nigeria.

Oyekale, S. A. (2012). Factors Explaining Acute Malnutrition among Under-Five Children in Sub-Sahara Africa (SSA). *Life Science Journal* **9**(4): 2101-2107.

Pradhan, A. (2010). Factors associated with nutritional status of the under five children. *Asian Journal of Medical Sciences* 1: 6-8

Rayhan, I. M. and Khan, H. S. M. (2006). Factors Causing Malnutrition among under Five Children in Bangladesh. *Pakistan Journal of Nutrition* 5 (6): 558-562.

Ruel, M. J. Garrett, S. Morris, D. Maxwell, A. Oshaug, P. Engle, P. Menon, A.Slack, and L. Haddad. 1998. "Urban Challenges to Food and Nutrition Security: A Review of Food Security, Health and Care-Giving in the Cities." FCND Discussion Paper 51. Washington DC: International Food Policy Research Institute.

Salah, E.O., Mahgoub., Nnyepi, M. and Bandeke, T. (2006). Factors Affecting Prevalence of Malnutrition among Children Under Three Years of Age In Botswana. *African Journal Food Agriculture Nutrition and Development* **6**.

Salah, M. J. A. (2004). Factors that Affect the Nutritional Status of Children Aged 9-18 months in Jerusalem. Un-published Msc thesis AN-Najah. National University, Nablus, Palestine.

Silva, P. (2005). Environmental Factors and Children's Malnutrition in Ethiopia. World Bank Policy Research Working Paper, 3489.

Simon, C. (1999); Anthropometric, health and demographic indicators in assessing nutritional status and food consumption; FAO Food and Nutrition Division.

Smith, L. C., Ruel, M. T. and Ndiaye, A. (2005). Why is Child Malnutrition Lower in Urban than in Rural Areas? Evidence from 36 Developing Countries' World Developmen*t*, Vol. 33, No. 8, 1285-1305.

Smith, L.C. and Haddad, L. (2000).Explaining Child Malnutrition in Developing Countries: A Cross-Country Analysis." IFPRI Research Report 111. Washington D.C. International Policy Research Institute.

Snijders, T. and Bosker, R. (1999). Multilevel Analysis: an Introduction to Basic and Advanced Multilevel Modeling. London/ Thousand Oaks/ New Delhi: Sage Publications.

Solomon Amsalu and Zemene Tigabu (2008). Risk factors for severe acute malnutrition in children under the age of five: A case-control study. *Ethiop.J.Health Dev.* **22**(1): 21-25.

Sununtar, S. (2005). Child malnutrition as poverty indicator, an evaluation in the context of different development interventions in Indonesia.

Taper, M. L. 2004. Model Identification from Many Candidates. The Nature of Scientific Evidence. M. L. Taper and S. R. Lele, Editors. The University of Chicago Press, Chicago, IL, USA. P 3-16.

Thanaa, A., El-kholy., Naglaa, H. M., Hassanen, R. M. H. and Anter, S. (2012). Nutrient Intakes Affecting the Nutritional Status of preschool Children by Nationality Compared with RDA in Jeddah KSA. *Life Science Journal* **9**(4): 3338-3346.

UNICEF (1990). *Strategy for Improved Nutrition of Children and Women in Developing Countries*. New York.

UNICEF (1998). *The State of the World's Children 1998*. New York.

UNICEF (2003). *Strategy to reduce maternal and child undernutrition*, United Children's Fund East Asia and Pacific Regional Office: Bangkok.

UNICEF, *Progress for children*. (2006) United Nations Children's Fund: New York.

Van de Poel E, Hosseinpoor AR, Speybroeck N, Van Ourti T, Vega J. (2008). *Socioeconomic inequality in malnutrition in developing countries.* Bull World Health Organ, 86(4):282-91.

WHO (2003). Global Database on Child Growth and Malnutrition: Methodology and applications. *International Journal of Epidemiology* 32:518-526.

WHO (2005). Nutrition for health and development, protection of the human environment, Geneva.

Wise, V. (2004). Nutritional Situation of Young Children in Rwanda: An Analysis of Anthropometric data collected by the Household Living Conditions Survey 1999 –2001. Research Report, Food Security Research Project (FSRP) and Division of Agricultural Statistics (DSA) Ministry of Agriculture, Livestock, and Forestry.

Woldemariam, G. and Timotiows, G. (2002). Determinants of nutritional status of Women and children in Ethiopia; EHNRI Addis Ababa, Ethiopia.

World Health Organization (2005). The World Health Report - Make Every Mother and Child Count.

APPENDIX

Appendix A

Table A1 Results of Binary logistic regression using SAS 9.2

Summary of Stepwise Selection

Step	Effect Entered	Effect Removed	DF	Number In	Score Chi-Square	Pr > ChiSq
1	BMIMOTH		2	1	141.5896	<.0001
2	CHILDAGE		5	2	149.9409	<.0001
3	REGION		10	3	135.1346	<.0001
4	SIZECHBIR		2	4	50.4026	<.0001
5	WIHH		2	5	41.4438	<.0001
6	HADDIAR		1	6	37.4586	<.0001
7	SEXOFCH		1	7	25.8888	<.0001
8	MOTHEDUC		2	8	18.3333	0.0001
9	HADFEV		1	9	14.8182	0.0001
10	PLACRES		1	10	5.3091	0.0212

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
REGION	10	78.8427	<.0001
PLACRES	1	5.2834	0.0215
MOTHEDUC	2	14.5362	0.0007
WIHH	2	14.7616	0.0006
BMIMOTH	2	68.4087	<.0001
SIZECHBIR	2	44.7713	<.0001
HADDIAR	1	18.0786	<.0001
HADFEV	1	14.6482	0.0001
CHILDAGE	5	117.8723	<.0001
SEXOFCH	1	26.0508	<.0001

Analysis of Maximum Likelihood Estimates

				Standard	Wald
Parameter	DF	Estimate	Error	Chi-Square	Pr > ChiSq
Intercept	1	-4.0340	0.3460	135.9272	<.0001
REGION Addis Ababa	1	-0.4608	0.3305	1.9447	0.1632
REGION Affar	1	0.0847	0.1592	0.2828	0.5948
REGION Amhara	1	-0.5297	0.1670	10.0555	0.0015
REGION Benishangul-Gumuz	1	-0.5398	0.1765	9.3577	0.0022
REGION Gambela	1	-0.3117	0.1775	3.0825	0.0791
REGION Harari	1	-0.3429	0.2076	2.7276	0.0986
REGION Oromiya	1	-0.4427	0.1579	7.8623	0.0050
REGION SNNP	1	-0.7078	0.1671	17.9517	<.0001
REGION Somali	1	0.2394	0.1206	3.9393	0.0472
REGION Tigray	1	-0.5041	0.1663	9.1918	0.0024
PLACRES Rural	1	0.3187	0.1387	5.2834	0.0215
MOTHEDUC No education	1	0.8145	0.2684	9.2093	0.0024
MOTHEDUC Primary	1	0.5775	0.2701	4.5710	0.0325
WIHH Midium	1	0.2381	0.1150	4.2886	0.0384
WIHH Poor	1	0.3626	0.0947	14.6463	0.0001
BMIMOTH Normal	1	0.4345	0.2083	4.3511	0.0370
BMIMOTH Thin	1	0.9785	0.2120	21.3027	<.0001
SIZECHBIR Average	1	0.1416	0.0890	2.5320	0.1116
SIZECHBIR Small	1	0.5313	0.0878	36.6225	<.0001
HADDIAR Yes	1	0.3705	0.0871	18.0786	<.0001
HADFEV Yes	1	0.3105	0.0811	14.6482	0.0001
CHILDAGE 12-23 months	1	0.5690	0.1076	27.9718	<.0001
CHILDAGE 24-35 months	1	-0.0222	0.1161	0.0367	0.8480
CHILDAGE 36-47 months	1	-0.1648	0.1178	1.9553	0.1620
CHILDAGE 6-11months	1	0.7913	0.1206	43.0253	<.0001
CHILDAGE <6 months	1	0.6322	0.1220	26.8665	<.0001
SEXOFCH Female	1	-0.3404	0.0667	26.0508	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
REGION Addis Ababa vs Dire Dawa	0.631	0.330	1.205
REGION Affar vs Dire Dawa	1.088	0.797	1.487
REGION Amhara vs Dire Dawa	0.589	0.424	0.817
REGION Benishangul-Gumuz vs Dire Dawa	0.583	0.412	0.824
REGION Gambela vs Dire Dawa	0.732	0.517	1.037

REGION Harari vs Dire Dawa	0.710	0.472	1.066
REGION Oromiya vs Dire Dawa	0.642	0.471	0.875
REGION SNNP vs Dire Dawa	0.493	0.355	0.684
REGION Somali vs Dire Dawa	1.270	1.003	1.692
REGION Tigray vs Dire Dawa	0.604	0.436	0.837
PLACRES Rural vs Urban	1.375	1.048	1.805
MOTHEDUC No education vs Secondary and above	2.258	1.334	3.821
MOTHEDUC Primary vs Secondary and above	1.782	1.049	3.025
WIHH Midium vs Rich	1.269	1.013	1.590
WIHH Poor vs Rich	1.437	1.193	1.730
BMIMOTH Normal vs Overweight	1.544	1.027	2.323
BMIMOTH Thin vs Overweight	2.660	1.756	4.031
SIZECHBIR Average vs large	1.152	0.968	1.372
SIZECHBIR Small vs large	1.701	1.432	2.021
HADDIAR Yes vs No	1.448	1.221	1.718
HADFEV Yes vs No	1.364	1.164	1.599
CHILDAGE 12-23 months vs 48-59 months	1.766	1.431	2.181
CHILDAGE 24-35 months vs 48-59 months	0.978	0.779	1.228
CHILDAGE 36-47 months vs 48-59 months	0.848	0.673	1.068
CHILDAGE 6-11months vs 48-59 months	2.206	1.742	2.795
CHILDAGE <6 months vs 48-59 months	1.882	1.482	2.390
SEXOFCH Female vs Male	0.712	0.624	0.811

Partition for the Hosmer and Lemeshow Test

Group	Total	WHZ = Wasted		WHZ = Not Wasted	
		Observed	Expected	Observed	Expected
1	963	18	25.75	945	937.25
2	963	38	42.52	925	920.48
3	963	54	54.87	909	908.13
4	961	76	67.70	885	893.30
5	960	70	81.47	890	878.53
6	962	100	98.38	862	863.62
7	960	133	118.70	827	841.30
8	962	153	147.57	809	814.43
9	961	202	190.55	759	770.45
10	956	284	300.49	672	655.51

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
10.1816	8	0.2525

Table A2 Results of diagnostic tests for outliers and influential values for binary logistic regression model

Descriptive Statistics

	N	Minimum	Maximum
Analog of Cook's influence statistics	9611	.00001	.12123
DFBETA for constant	9611	-.01863	.05339
DFBETA for REGION(1)	9611	-.01567	.01206
DFBETA for REGION(2)	9611	-.01605	.01037
DFBETA for REGION(3)	9611	-.01567	.01366
DFBETA for REGION(4)	9611	-.01587	.00962
DFBETA for REGION(5)	9611	-.01621	.01016
DFBETA for REGION(6)	9611	-.01569	.01431
DFBETA for REGION(7)	9611	-.01584	.01184
DFBETA for REGION(8)	9611	-.01889	.01522
DFBETA for REGION(9)	9611	-.01687	.02518
DFBETA for REGION(10)	9611	-.02550	.08288
DFBETA for MothEduc(1)	9611	-.05635	.02020
DFBETA for MothEduc(2)	9611	-.05442	.02105
DFBETA for WIHh(1)	9611	-.00653	.00628
DFBETA for WIHh(2)	9611	-.00622	.00843
DFBETA for BMIMoth(1)	9611	-.04041	.01064
DFBETA for BMIMoth(2)	9611	-.04035	.01056
DFBETA for PartEduc(1)	9611	-.01788	.01165
DFBETA for PartEduc(2)	9611	-.01632	.01164
DFBETA for SizeChBir(1)	9611	-.00441	.00557
DFBETA for SizeChBir(2)	9611	-.00388	.00358

DFBETA for HadDiar(1)	9611	-.00445	.00668
DFBETA for HadFev(1)	9611	-.00434	.00557
DFBETA for ChildAge(1)	9611	-.00807	.00846
DFBETA for ChildAge(2)	9611	-.00793	.00775
DFBETA for ChildAge(3)	9611	-.00764	.00506
DFBETA for ChildAge(4)	9611	-.00719	.00708
DFBETA for ChildAge(5)	9611	-.00663	.00720
DFBETA for SexofCH(1)	9611	-.00224	.00286
Valid N (listwise)	9611		

APPENDIX B Multilevel Logistic Regression Anlysis Using Stata 11

Table B1 Empty Logistic Regression Model With Out Random Effect

```
. logit WHZ

Iteration 0:   log likelihood = -3475.7499
Iteration 1:   log likelihood = -3475.7499

Logistic regression                               Number of obs   =       9611
                                                  LR chi2(0)      =       0.00
                                                  Prob > chi2     =          .
Log likelihood = -3475.7499                       Pseudo R2       =     0.0000
```

WHZ	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	-2.017618	.0316924	-63.66	0.000	-2.079734	-1.955502

```
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	-3475.75	-3475.75	1	6953.5	6960.67

Note: N=Obs used in calculating BIC; see [R] BIC note

Table B2 Two-Level Random Empty Binary Logistic Regression Model For Under-Five Children Wasting

```
. . xtlogit WHZ , i(REGION)

Fitting comparison model:

Iteration 0:   log likelihood = -3475.7499
Iteration 1:   log likelihood = -3475.7499

Fitting full model:

tau =  0.0     log likelihood = -3475.7499
tau =  0.1     log likelihood = -3419.3241
tau =  0.2     log likelihood = -3417.9045
tau =  0.3     log likelihood = -3427.0305

Iteration 0:   log likelihood = -3418.9905
Iteration 1:   log likelihood = -3418.7118
Iteration 2:   log likelihood = -3418.6757
Iteration 3:   log likelihood = -3418.6756

Random-effects logistic regression              Number of obs      =      9611
Group variable: REGION                          Number of groups   =        11

Random effects u_i ~ Gaussian                   Obs per group: min =       323
                                                               avg =     873.7
                                                               max =      1515

                                                Wald chi2(0)       =         .
Log likelihood  = -3418.6756                    Prob > chi2        =         .
```

WHZ	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	-2.080627	.1332478	-15.61	0.000	-2.341788	-1.819466
/lnsig2u	-1.719998	.4906076			-2.681571	-.7584245
sigma_u	.4231626	.1038034			.2616401	.6844003
rho	.05162	.0240179			.0203838	.1246328

```
Likelihood-ratio test of rho=0: chibar2(01) =   114.15 Prob >= chibar2 = 0.000
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3418.676	2	6841.351	6855.693

Note: N=Obs used in calculating BIC; see [R] BIC note

Table B3 Two-Level Random Intercept and Fixed Slope Binary Logistic Regression Model For Under-Five Children Wasting

```
. . xtlogit WHZ i.SEXOFCH i.CHILDAGE i.SIZECHBI i.PLACRES i.MOTHEDUC i.BMIMOTH i. WIHH i.HADDIAR i.HADFEV, i(REGION)

Fitting comparison model:

Iteration 0:   log likelihood = -3475.7499
Iteration 1:   log likelihood = -3236.5707
Iteration 2:   log likelihood = -3212.5274
Iteration 3:   log likelihood = -3212.3667
Iteration 4:   log likelihood = -3212.3665

Fitting full model:

tau =  0.0     log likelihood = -3212.3665
tau =  0.1     log likelihood = -3192.1829
tau =  0.2     log likelihood = -3196.1344

Iteration 0:   log likelihood = -3192.1709
Iteration 1:   log likelihood = -3189.2205
Iteration 2:   log likelihood = -3189.1796
Iteration 3:   log likelihood = -3189.1796

Random-effects logistic regression              Number of obs      =      9611
Group variable: REGION                          Number of groups   =        11

Random effects u_i ~ Gaussian                   Obs per group: min =       323
                                                               avg =     873.7
                                                               max =      1515

                                                Wald chi2(17)      =    423.23
Log likelihood  = -3189.1796                    Prob > chi2        =    0.0000
```

WHZ	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.SEXOFCH	-.3414957	.0666344	-5.12	0.000	-.4720967	-.2108948
CHILDAGE						
1	.7876073	.1205055	6.54	0.000	.5514208	1.023794
2	.5671441	.1074899	5.28	0.000	.3564677	.7778204
3	-.0195534	.1159501	-0.17	0.866	-.2468114	.2077046
4	-.1655524	.1177466	-1.41	0.160	-.3963314	.0652266
5	.6348096	.1218391	5.21	0.000	.3960093	.8736099
SIZECHBI						
1	.1414412	.0888236	1.59	0.111	-.03265	.3155323
2	.5359115	.0876259	6.12	0.000	.3641679	.7076551
1.PLACRES	.3049475	.1359692	2.24	0.025	.0384527	.5714423
MOTHEDUC						
1	.5841527	.2696145	2.17	0.030	.055718	1.112587
2	.8376684	.2677302	3.13	0.002	.3129268	1.36241
BMIMOTH						
1	.4171865	.2080642	2.01	0.045	.0093881	.8249849
2	.9714337	.2115657	4.59	0.000	.5567725	1.386095
WIHH						
1	.234963	.1147365	2.05	0.041	.0100837	.4598424
2	.3719709	.094096	3.95	0.000	.1875462	.5563956
1.HADDIAR	.3680754	.0869798	4.23	0.000	.1975981	.5385527
1.HADFEV	.3110238	.0809412	3.84	0.000	.1523819	.4696657
_cons	-4.352597	.3336679	-13.04	0.000	-5.006574	-3.69862
/lnsig2u	-2.646243	.5009011			-3.627991	-1.664494
sigma_u	.2663028	.0666957			.1630016	.4350705
rho	.0211014	.0103467			.0080115	.0544058

```
Likelihood-ratio test of rho=0: chibar2(01) =    46.37 Prob >= chibar2 = 0.000

. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3189.18	19	6416.359	6552.602

Note: N=Obs used in calculating BIC; see [R] BIC note

Odds Ratio

```
. xtlogit, or

Random-effects logistic regression              Number of obs      =      9611
Group variable: REGION                          Number of groups   =        11

Random effects u_i ~ Gaussian                   Obs per group: min =       323
                                                               avg =     873.7
                                                               max =      1515

                                                Wald chi2(17)      =    423.23
Log likelihood  = -3189.1796                    Prob > chi2        =    0.0000
```

WHZ	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.SEXOFCH	.7107065	.0473575	-5.12	0.000	.6236932	.8098593
CHILDAGE						
1	2.198131	.2648869	6.54	0.000	1.735717	2.783736
2	1.763224	.1895288	5.28	0.000	1.428275	2.176723
3	.9806365	.1137049	-0.17	0.866	.781288	1.23085
4	.8474255	.0997814	-1.41	0.160	.6727837	1.067401
5	1.886663	.2298693	5.21	0.000	1.485883	2.395543
SIZECHBI						
1	1.151933	.1023189	1.59	0.111	.9678773	1.370989
2	1.709005	.1497531	6.12	0.000	1.439316	2.029227
1.PLACRES	1.356554	.1844496	2.24	0.025	1.039202	1.770819
MOTHEDUC						
1	1.793471	.4835458	2.17	0.030	1.057299	3.04222
2	2.310972	.6187171	3.13	0.002	1.367421	3.905594
BMIMOTH						
1	1.517686	.3157761	2.01	0.045	1.009432	2.281846
2	2.641729	.5588993	4.59	0.000	1.745031	3.999202
WIHH						
1	1.264862	.1451258	2.05	0.041	1.010135	1.583824
2	1.450591	.1364947	3.95	0.000	1.206286	1.744374
1.HADDIAR	1.444951	.1256816	4.23	0.000	1.218473	1.713525
1.HADFEV	1.364822	.1104704	3.84	0.000	1.164605	1.599459
/lnsig2u	-2.646243	.5009011			-3.627991	-1.664494
sigma_u	.2663028	.0666957			.1630016	.4350705
rho	.0211014	.0103467			.0080115	.0544058

```
Likelihood-ratio test of rho=0: chibar2(01) =    46.37 Prob >= chibar2 = 0.000
```

Table B4 Result Of Random Slope Logistic Regression Model for Slope(Random Part Effect)

.Sex of Child

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(SEXOFCH)	.0006829	.0033666	4.35e-08	10.73231
var(_cons)	.0769793	.0411114	.0270261	.2192625
cov(SEXOFCH,_cons)	-.0072504	.0188083	-.044114	.0296131

```
LR test vs. logistic regression:     chi2(3) =    46.54   Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3189.096	21	6420.192	6570.776

```
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. est store m4

. lrtest m1 m4

Likelihood-ratio test                                 LR chi2(2)  =      0.17
(Assumption: m1 nested in m4)                         Prob > chi2 =    0.9200
```

Child age

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(CHILDAGE)	.0076343	.0058086	.0017184	.0339163
var(_cons)	.0602419	.0437829	.0144963	.2503452
cov(CHILDAGE,_cons)	-.0075637	.0129723	-.032989	.0178616

LR test vs. logistic regression: chi2(3) = 54.68 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3185.025	21	6412.051	6562.635

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m4

. lrtest m1 m4

Likelihood-ratio test LR chi2(2) = 8.31
(Assumption: m1 nested in m4) Prob > chi2 = 0.157

Size of child at birth

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(SIZECHBI)	.0002034	.0011877	2.18e-09	18.96578
var(_cons)	.0802601	.0485073	.0245501	.2623893
cov(SIZECHBI,_cons)	-.0040408	.0125995	-.0287354	.0206538

LR test vs. logistic regression: chi2(3) = 46.49 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3189.121	21	6420.241	6570.825

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m3

. lrtest m1 m3

Likelihood-ratio test LR chi2(2) = 0.12
(Assumption: m1 nested in m3) Prob > chi2 = 0.9428

Mothers educational level

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(MOTHEDUC)	.0150008	.0212706	.0009314	.2415964
var(_cons)	.0605598	.0315186	.021836	.1679563
cov(MOTHEDUC,_cons)	.0301404	.0230687	-.0150734	.0753542

LR test vs. logistic regression: chi2(3) = 48.48 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3188.125	21	6418.249	6568.833

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m2

. lrtest m1 m2

Likelihood-ratio test LR chi2(2) = 2.11
(Assumption: m1 nested in m2) Prob > chi2 = 0.3482

Body Mass index of Mothers

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(BMIMOTH)	.0007837	.0034666	1.35e-07	4.563512
var(_cons)	.060827	.0376254	.0180956	.2044654
cov(BMIMOTH,_cons)	.0069044	.0143341	-.0211899	.0349987

LR test vs. logistic regression: chi2(3) = 46.58 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3189.077	21	6420.154	6570.738

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m4

. lrtest m1 m4

Likelihood-ratio test LR chi2(2) = 0.20
(Assumption: m1 nested in m4) Prob > chi2 = 0.9027

Huosehold wealth index

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(WIHH)	.0096622	.0143388	.0005271	.1771198
var(_cons)	.0531658	.0297458	.0177579	.1591741
cov(WIHH,_cons)	.0132658	.0145782	-.0153069	.0418386

```
LR test vs. logistic regression:      chi2(3) =     49.40   Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3187.666	21	6417.333	6567.917

```
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. est store m2

. lrtest m0 m1

Likelihood-ratio test                                 LR chi2(17) =     458.99
(Assumption: m0 nested in m1)                         Prob > chi2 =     0.0000

. lrtest m1 m2

Likelihood-ratio test                                 LR chi2(2)  =       3.03
(Assumption: m1 nested in m2)                         Prob > chi2 =     0.2202
```

Place of Residence

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(PLACRES)	.0077407	.0218515	.0000306	1.957331
var(_cons)	.1190982	.0946749	.025076	.5656552
cov(PLACRES,_cons)	-.0303628	.0537642	-.1357388	.0750131

```
LR test vs. logistic regression:      chi2(3) =     46.90   Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3188.918	21	6419.837	6570.42

```
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. est store m7

. lrtest m1 m7

Likelihood-ratio test                                 LR chi2(2)  =       0.52
(Assumption: m1 nested in m7)                         Prob > chi2 =     0.7700
```

Had diarrhea two weeks before survey

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(HADDIAR)	.0004192	.0033011	8.30e-11	2118.02
var(_cons)	.0686024	.035692	.0247447	.1901941
cov(HADDIAR,_cons)	.0053625	.0208722	-.0355464	.0462713

LR test vs. logistic regression: chi2(3) = 46.44 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3189.147	21	6420.294	6570.878

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m3

. lrtest m1 m3

Likelihood-ratio test LR chi2(2) = 0.06
(Assumption: m1 nested in m3) Prob > chi2 = 0.9680

Had fever two weeks before survey

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
REGION: Unstructured				
var(HADFEV)	.0101641	.0155835	.0005035	.2051737
var(_cons)	.0577796	.0312695	.0200039	.1668912
cov(HADFEV,_cons)	.0242337	.0193681	-.0137271	.0621946

LR test vs. logistic regression: chi2(3) = 48.27 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	9611	.	-3188.231	21	6418.462	6569.046

Note: N=Obs used in calculating BIC; see [R] BIC note

. est store m3

. lrtest m1 m3

Likelihood-ratio test LR chi2(2) = 1.90
(Assumption: m1 nested in m3) Prob > chi2 = 0.3873

Declarations

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

Name: Gutu Adugna

Signature: ____________________

Date: June, 2013

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

Advisor: Prof M.K.Sharma

Signature: ________________________

Date: June, 2013