ADDIS ABABA UNIVERSITY

GRADUATE STUDIES PROGRAMME

COLLEGEOF COMPUTIONANAL &NATURAL SCIENCES

DEPARTMENT OF STATISTICS

ANALYSIS OF RISK FACTORS FOR UNDER-FIVE CHILD MALNUTRITION IN ETHIOPIA: MULTI-LEVEL APPROACH

Sintayehu Workineh

A Thesis submitted to

The Department of Statistics

Presented in Partial Fulfillment of the Requirements for the Degree of Masters of Science in

Statistics (Biostatistics)

Addis Ababa University

Addis Ababa, Ethiopia

June, 2016

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Addis Ababa University

School of Graduate Studies

This is to certify that the thesis prepared by Sintayehu Workineh, entitled: *Analysis of Risk Factors for Under-Five Child Malnutrition in Ethiopia: Multi-level Approach* and submitted in partial fulfillment the requirements for Degree on Master of Science in Statistics (Biostatistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining committee:

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Advisor____Signature____________Date_________

Chair of Department or Graduate Program Coordinator

DECLARATION

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

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

Dr.Birhanu Teshome _________________

Advisor‟s Name Signature

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ABSTRACT

Analysis of Risk factors for Under-Five Child Malnutrition in Ethiopia: Multilevel Approach

Sintayehu Workineh

Addis Ababa University, 2016

Although the problem of malnutrition affects the entire population, children are more vulnerable because it reduces their physical growth, proper organ formulation and cognitive development and weakens immune system. Under-nutrition contributes half of all deaths in children under-five in Africa and Asia. The solution of this big public health problem is essential. From this perspective, this study aimed to explore risk factors for under-five child malnutrition in Ethiopia. The data for the study were taken from Ethiopian Mini Demographic and Health Survey (EMDHS) of year 2014. To achieve objectives of the study, two indicators (stunting and wasting) were studied. The two indicators were treated separately due to their biological differences. Statistical models that handle the complexities of correlated data were employed. Generalized Estimating Equations (GEEs), Alternating Logistic Regression (ALR), Proportional Odds Model (POM), Partial Proportional Odds Model (PPOM) and baseline category logit models were used for analysis. Results showed that mothers with less educational level, preceding birth interval less than 24 months, from Tigray, Affar and SNNP regions were associated with higher probability of stunting. Child age in months had positive effect on child stunting. Children from non-educated mothers, from Affar and Somali regions had higher chance of wasting. Two-level ALR analysis indicated strong association ($\alpha_1 = 0.8522$*) between two children from the same households. In conclusion, results suggest that region, mother's education level, wealth index, preceding birth interval and child age were associated with stunting, while region, mother's education level, mother's current marital status, sex and age of child in months were associated with wasting among children under-five in Ethiopia. To reduce under-five child malnutrition, some crucial steps regarding educating mothers and improving economic situation of population as well as supplementary feeding programs should be considered.*

Key Words: *Alternating Logistic Regression (ALR), Generalized Estimating Equations (GEEs), Proportional Odds Model (POM), Partial Proportional Odds Model (PPOM) Baseline Category Logit, Stunting, Wasting.*

ACKNOWLEDGEMENTS

It gives me a great pleasure to come this final point to express my deepest gratitude to all individuals and institutions who contributed in one way or another to my study and realizing of this thesis.

First and foremost I thank almighty God. Secondly, I would like to express my sincere appreciation to my thesis advisor Dr. Birhanu Teshome for his valuable suggestions, comments and patience during the thesis work. I would also like to express my deepest gratitude to the Addis Ababa University, for giving me scholarship to be a student at the Department of Statistics.

Finally, I would like also to thank the Ethiopian central Statistics Agency for providing me with all the relevant secondary data used in this study.

ACRONYMS

ACC/SCN	Administration Committee on Coordination–Sub Committee on Nutrition
ALR	Alternative logistic regression
COHA	Cost of Hunger in Africa
CSA	Central Statistical Agency
EDHS	Ethiopian Demographic and Health Survey
EMDHS	Ethiopian Mini Demographic and Health Survey
GEE	Generalized Estimating Equation
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
MDG	Millennium Development Goal
NGO	Non-Governmental Organizations
POM	Proportional odds Model
PPOM	Partial proportional Odds Model
QIC	Quasi-likelihood Information Criterion
SD	Standard Deviation
UNICEF	United Nations Children‟s Fund
USAID	United States Agency for International Development
WFP	World Food Program
WHA	World Health Assembly
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1.Background of the study

According to world food program (WFP) malnutrition is "a state in which physical function of an individual is impaired to the point where he or she can no longer maintain adequate bodily performance process such as growth, pregnancy, lactation, physical work and resisting recovery from disease."

Adequate nutrition is essential in early childhood to ensure healthy growth, proper organ formation and function, a strong immune system, neurological and cognitive development. Economic growth and human development require well-nourished populations who can learn new skills, think critically and contribute to their communities (UNICEF, WHO-World Bank, 2015). Child malnutrition impacts cognitive function and contributes to poverty through impeding individuals‟ ability to lead productive lives. The reduction of infant and child death between 1990 and 2015 was one of the eight Millennium Development Goals (MDGs). In addition, one of the indicators was child malnutrition (MDG1.C), and it was estimated that more than one-third of under-five deaths in the world are attributable to under nutrition. Stunting rates are dropping but 159 million children (out of 667 million children under 5) around the world were affected in 2014. Wasting still threatens the lives of 50 million children (approximately one out of every 13 children) across the globe. Nearly a third of all wasted children were severely wasted, with a global prevalence of 2.4 percent in 2014 (UNICEF–WHO–World Bank Group joint child malnutrition estimates, 2015).

The combination of malnutrition and infection is the leading cause of death among young children in developing countries. Malnutrition alone is estimated to account for over half of children‟s deaths annually. In developing countries, approximately 183 million children were underweight-for-age, 67 million are underweight-for-height (wasted), and 226 million are low height-for-age (stunted). One in three pre-school children in the developing world were undernourished (Pelletier DL and Frongillo EA, 2003). As a consequence, their human rights are violated. In addition, they are more likely to have impaired immune systems, poorer cognitive development, and lower productivity as adults, and greater susceptibility to diet-related chronic diseases such as hypertension and coronary heart disease later in life. Undernourished female preschoolers are likely to grow into undernourished young women who are more likely to give birth to babies who are undernourished even before they are born, thus perpetuating the inter-generational transmission of deprivation. Reducing these unacceptably high numbers were found to be a tremendous challenge to public policy (Smith *et al.*, 2000). The World Health Assembly adopted a resolution (WHA 65.6) that endorsed the comprehensive implementation plan on Maternal, Infant, and Young children nutrition, which includes global targets for 2025 (WHO, 2012): two of these targets are 40% reduction in child stunting and reduction in child wasting to less than 5%. The underlining causes of malnutrition in developing countries are poverty, lack of access to food, disease, and climate change and lack of safe drinking water (ACF International, 2015).

Ethiopia is one of the developing countries where malnourishment of child continues to be a serious problem. Nationally, 40 percent of children under age of five are stunted, and 19 percent of children are severely stunted. Nine percent of children are wasted, and three percent are severely wasted. A small portion of children (3%) are overweighed. 25 percent of children are underweight, and seven percent are severely underweight (Central Statistics Agency (CSA), 2014), which is one of the most serious public health problem in Ethiopia. The predominant attributes that determine the nutritional status of children indicated by wasting and stunting in Ethiopia were found to be child characteristics, maternal education and other maternal traits, and the economic status of the household (CSA, 2014). To identify risk factors for under-five child malnutrition researches with appropriate statistical modeling are essential.

This study was conducted using Ethiopian mini demographic and health survey (EMDHS) 2014 data. EMDHS data are hierarchical in nature, i.e. children are nested within households and households within regions. For such data, children within a household may be more similar to each other than children in the rest of the households in terms of nutritional status. This rise questions on the efficiency of models that assume independence of observations and calls for a statistical model that takes this correlated nature of the data into account. In this study, to come up with solutions to above stated problem, various statistical models were fitted to estimate household-level socio-economic factors for child malnutrition by taking into account child level characteristics. Methods Generalized Estimating Equations (GEEs) and Alternating Logistic Regression were used. To estimate severity of malnutrition, Proportional Odds Model (POM), Partial Proportional Odds (PPOM) and baseline category logit were fitted. The procedural steps of these models will be discussed in chapter three of this work.

1.2. Statement of the problem

Child malnutrition has long-term negative effects on people‟s lives, most notably in health, education, productivity, and seriously affects labor force on which the economy relies. Even though prevalence and numbers affected are decreasing globally, still under nutrition contributes half of all deaths in children under-five is wide spread in Asia and Africa. According to UNICEF 2015 report, still more than two out of every five children in Ethiopia are stunted, as many as 81% of all cases of child under nutrition and its related pathologies goes untreated, 44% of the health costs associated with under nutrition occur before the child turns one year-old. 28% of all child mortality in Ethiopia is associated with under nutrition, 16% of all repetitions in primary school are associated with stunting. Stunted children achieve 1.1 years less in school education, Child mortality associated with under nutrition has reduced Ethiopia‟s workforce by 8%, 67% of the adult population in Ethiopia suffered from stunting as children. The annual costs associated with child under nutrition are estimated at Ethiopian birr (ETB) 55.5 billion, which is equivalent to 16.5% of GDP. So, researches on child malnutrition are essential. Most of the studies from DHS data in Ethiopia that have examined factors contributing to children malnutrition ignored severity of malnutrition, sampling design and the clustered nature of the EDHS data. This study therefore, aims to fill this gap.

1.3.Objective of the study

1.3.1. General objective

The general objective of this study was to identify most determinant risk factors for under-five child malnutrition in Ethiopia.

1.3.2. Specific objectives

The specific objectives of the study, which were accomplished by achieving the general objective stated above, were the following.

- To identify demographic and socio-economic factors associated with under-five child malnutrition.
- To select models that show relationship between under-five child malnutrition and demographic and socio-economic variables that account for sampling weights clustered nature of data, and ordinarily nature of response.

- To compare under-five child malnutrition across regions of Ethiopia.

1.4.Significance of the Study

Studies done to explore the risk factors for under-five child malnutrition in Ethiopia have identified a variety of risk factors that contribute to malnutrition. Very few of studies from survey data got attention for survey methodology and correlation within cluster during model estimation and data analysis. In the presence of correlated response within cluster, correction must be taken in to account, otherwise, might get incorrect standard errors and hence wrong conclusions. In the presence of positive correlations, we would underestimate the standard errors of the between-subject effects, and overestimate the standard errors of the within-subject effects, resulting in efficient estimation. This study focused in identifying risk factors of under-five child malnutrition taking into account sampling design and correlation within households.

This research might create awareness on the appropriate statistical methods to be used in the presence of correlated data. The results of this study might up raise understanding of policy makers and non-governmental organizations (NGOs) by elucidating the main factors affecting risk of child malnutrition and can serve as an important input for any possible intervention in this area for the future.

1.5.Outline of the study

This thesis work is presented in five chapters; Chapter one highlights major issues relating to child malnutrition at a global level and Ethiopia in particular. The significance and objectives of the study are also described. Chapter two contains both theoretical and empirical literature reviews on factors associated with child malnutrition. Chapter three describes the methodological issues of the study and chapter four gives the results and discussions. Finally, conclusions and recommendations of the study are presented in chapter five.

CHAPTER TWO

LITERATURE REVIEW

In this chapter, we will present a review of the literature on risk factors of under-five child malnutrition. Relevant studies were reviewed giving special focus on findings and methodological issue in developing countries.

2.1. Theoretical literature review

2.1.1. Introduction

The term malnutrition generally refers both to under nutrition and over nutrition. But in Ethiopia only three percent of under-five children are over weighted (CSA, 2014). In this thesis work, we focus on under nutrition which is an important health issue of the country.

According to world food program (WFP) malnutrition is "a state in which physical function of an individual is impaired to the point where he or she can no longer maintain adequate bodily performance process such as growth, pregnancy, lactation, physical work and resisting recovery from disease."

Many factors can cause malnutrition, most of which related to poor diet or severe and repeated infections, particularly in underprivileged populations. Inadequate diet and disease, in turn, are closely linked to the general standard of living, the environmental conditions, and whether a population is able to meet its basic needs such as food, housing and health care. Malnutrition is thus a health outcome as well as a risk factor for disease and exacerbated malnutrition, and it can increase the risk both of morbidity and mortality (WHO, 2005).

2.1.2. Measurement of Malnutrition in Children Under-five years

Physical growth of under-five year‟s children is an accepted indicator of the nutritional well-being of the population they represent. Adults and older children can access proportionally larger reserves of energy than young children during periods of reduced macronutrient intake. Therefore, the youngest individuals are most at risk for malnutrition. For assessment of acute malnutrition, children are more vulnerable to adverse environments and respond rapidly to dietary changes, they are also more at risk of becoming ill, which will result in weight loss. Consequently, their nutritional status is considered a good gauge for population-based malnutrition. For assessment of chronic malnutrition, children during the developmental years are susceptible to skeletal growth failure in ways that adults are not and are a good reflection of long-term nutritional issues. Therefore, the survey results of the under-five-years population are used to draw conclusions about the situation of the whole population, not just of that age group (WFP, 2005).

2.1.3. Expression of Nutrition Indices

Anthropometric indices can be expressed in relationship to the reference population in two different statistical terms: standard deviations from the median or percentage of the median.

Standard deviations or Z-scores

This is the preferred expression for anthropometric indicators in surveys. It is the difference between the value for an individual and the median value of the reference population for the same age or height, divided by the standard deviation of the reference population. In other words, by using the Z-score, you will be able to describe how far a child's weight is from the median weight of a child at the same height in the reference value.

According to WHO and UNICEF in children the three most commonly used anthropometric indices to assess their growth status are weight-for-height, height-for-age and weight-for-age. These anthropometric indices can be interpreted as follows:

Low weight-for-height: Wasting or thinness indicates in most cases a recent and severe process of weight loss, which is often associated with acute starvation and/or severe disease. However, wasting may also be the result of a chronic unfavorable condition. Provided there is no severe food shortage, the prevalence of wasting is usually below 5%, even in poor countries.

Low height-for-age: Stunted growth reflects a process of failure to reach linear growth potential as a result of suboptimal health and/or nutritional conditions. On a population basis, high levels of stunting are associated with poor socioeconomic conditions and increased risk of frequent and early exposure to adverse conditions such as illness and/or inappropriate feeding practices. Similarly, a decrease in the national stunting rate is usually indicative of improvements in overall socioeconomic conditions of a country.

Low weight-for-age: Weight-for-age reflects body mass relative to chronological age. It is influenced by both the height of the child (height-for-age) and his or her weight (weight-for-height), and its composite nature makes interpretation complex. For example, weight-for-age fails to distinguish between short children of adequate body weight and tall, thin children. However, in the absence of significant wasting in a community, similar information is provided by weight-for-age and height-for-age, in that both reflect the long-term health and nutritional experience of the individual or population. Short-term change, especially reduction in weight-for-age, reveals change in weight-for-height. In general terms, the worldwide variation of low weight-for-age and its age distribution are similar to those of low height-for-age.

According to WHO, 1986 there are differences in wasting and stunting in terms of biological, epidemiological and statistical grounds that they indicate different process of malnutrition.

Biological considerations:

Wasting indicates deficit in tissue and fat mass compared with amount expected in a child of same height or length and may result either from failure to gain weight or from actual weight loss. It may be appreciated by infection or other household crises and usually occurs in situations where the family food supply is limited and food intake of children is low. The determinants will differ in various environments. Often seasonal episodes of wasting, related to variations either in food supply or disease prevalence may be documented. One of the main characteristics of wasting is that it can be developed very rapidly, and under favorable conditions can be restored rapidly.

Stunting signifies showing in skeletal growth. The growth rate may be reduced from birth, but significant degrees of stunting, representing the accumulated consequences related growth. Stunting is frequently associated with poor overall economic conditions, especially mild to moderate, chronic or repeated infections, as well as inadequate nutrient intake.

There are several obvious differences between wasting and stunting. In first place, one can fail to gain height but one cannot lose it. Secondly, linear growth is slower process than growth in body mass. A significant degree of stunting, therefore, takes longer to be established. Third, although catch up in the height undoubtedly can occur it takes long time even with favorable environment.

Epidemiological and statistical considerations:

Wasting and stunting are frequently combined; However analysis of number of representative population groups reveal in consistent, mostly insignificant associations between two. The two deficits show different pattern at different ages and different populations (Choudhary, 2004).

2.2. Empirical literature review

A study on social and economic impacts of child under nutrition in Ethiopia shows more than two out of every 5 children in Ethiopia are stunted (COHA, 2012). The annual costs associated with child undernutrition are estimated at Ethiopian birr (ETB) 55.5 billion, which is equivalent to 16.5% of the country‟s GDP. Eliminating stunting in Ethiopia is a necessary step for growth and transformation (COHA, 2012). Some of the socioeconomic and demographic factors explaining child nutrition according to studies done in different places are reviewed below.

A study conducted in Botswana shows all the three types of malnutrition were significantly more prevalent among boys than among girls (Salah E.O. Mahgoub *et al.*, 2006). A study conducted in Mainland Tanzania using Alternating logistic regression and proportional odds model revealed with wasting (Zephania, *et.al*., 2013). that, birth weight, maternal health, age of child, gender, zones and Vitamin A were associated Children‟s nutritional status is also sensitive to factors such as feeding/weaning practices, care, and exposure to infection at specific ages. A cumulative indicator of growth retardation (height-for-age) in children is positively associated with age (Anderson, 1995 as cited in Aschalew, 2000). Local and regional studies in Ethiopia have also shown an increase in malnutrition with increase in age of the child (Yimer, 2000; Genebo *et al.*, 1999; Samson and Lakech, 2000).

Birth spacing effects on childhood under nutrition extend beyond pregnancy and into infancy. Childhood under nutrition is caused by several factors, but birth spacing is often overlooked even though it is strongly associated with stunting, (Gribble *et al.*, 2008). Study conducted by USAID on trends and determinants of malnutrition among children age 0-59 months in Kenya (KDHS 1993,1998, 2003,and 2008-09) shows that size of child at birth is a main factor of malnutrition (ICF International, 2013). According to a study conducted in Sri Lanka birth weight of children, age, and household income significantly affect child‟s nutritional condition (Ekamayake *et al.*, 2006). A study conducted by Yimer shows that economic status of the household was found to be strongly associated with chronic malnutrition (Yimer, 2000).

Local studies show a decreased incidence of malnutrition among young children with an increase in the level of mothers' education (Yimer, 2000; Genebo *et al.*, 1999). A study published in 2004 with regard to this same topic in Ethiopia found that parental education is one of the key determinants of chronic child malnutrition in Ethiopia (Harold and Christiaensen, 2004). A study conducted in Nicaragua shows maternal education has a significant effect on the health outcomes of children when measured by both height-for-age and weight-for-height (Geale, 2010). Some studies have revealed that mothers of the most malnourished children work outside their home (Abbi *et al*., 1991). On the study about mothers‟ marital status and under-five child nutrition, findings in a local study reveal that child's malnutrition is significantly associated with marital status. It was found out that under-five child malnutrition is higher among unmarried rural and divorced/separated women compared to married ones (Teller & Yimer, 2000). Similarly, being a married mother was positively associated with good nutritional status among children under five years in the Volta region of Ghana (Appoh and Krekling, 2005). Contrary to the above, a study in Tanzania revealed that mothers who are married were more likely to have undernourished children unlike those that were unmarried perhaps because of the cost of maintaining families hence sometimes these families fail to produce nutritious supplements to the under-five children (Nyaruhucha *et al.,* 2006).

The results of a study conducted among children 6-59 months of age in Dollo Ado district Ethiopia using logistic regression revealed that there was a significant association between access to safe drinking water and child nutritional status especially stunting. This could be attributed to the fact that clean water will prevent the spread of water-borne diseases that can negatively affect the health and nutrition of young children (Demissie and Worku, 2013).

In 2009, a multivariate multinomial logistic regression study done in rural Bangladesh reveals that mother‟s educational level, poor socio-economic conditions, father‟s education and occupation emerged as important factors (Rahman *et.al.,* 2009).

In 2012, a multilevel logistic regression study done in Ethiopia, revealed that, age of child, mother‟s educational level, wealth index, place of residence, had fever in the two weeks before survey, educational level of partner and geographical regions as important factors for child stunting (Fekade and Mekonnen, 2012).

Multivariate logistic regression study conducted in Combolcha District of Eastern Hararghe, identified child‟s age, gender, immunization status and the other‟s use of antenatal care, farm size, household size, water source, latrine use, and incidence of morbidity as important factors for child malnutrition (Tadiwos and Degnet, 2013).

CHAPTER THREE

DATA AND METHODOLOGY

3.1.Data Source

In this work we utilized data from the EMDHS 2014, particularly data on individual child born in five years preceding the survey.

3.1.1. EMDHS Sample Design, Population, Selection Probabilities and Sampling Weights

The EMDHS sample was drawn in two stages. The first stage of the sample selection involved the selection of approximately 305 sampling units consisting of enumeration areas that was drawn from 2007 population and housing census. The sample was stratified so as to yield adequate representation in urban and rural areas, and for each of the 11 regions. In each of these domains, the sampling units were drawn with probability proportional to their size, and households were drawn with an inverse probability such that the sample is self-weighted within a domain. In the second stage an equal probability systematic selection of 30 households per cluster was carried out from a newly created household listing. The survey interviewers interviewed only the pre-selected households. No replacements and no changes of the pre-selected households were allowed in the implementing stages in order to prevent bias (CSA, EMDHS 2014 final report).

A total of 5,401 children under age of five were eligible to be weighted and measured. Data are presented for 4,893 (4,921 children weighted) of these children, 4.9% had missing values for weight or height and 4 % had weight or height measures considered to be out of range for their ages.

Due to the non-proportional allocation of the sample to the different regions and to their urban and rural areas, sampling weights are required for any analysis using 2014 EMDHS data to ensure representativeness of the survey results at the national and regional level (CSA, EMDHS 2014 report)). Since the EMDHS sample is a two-stage stratified cluster sample, sampling weights was calculated based on sampling probabilities separately for each sampling stage and for each cluster. It should be noted that failure to accommodate survey design might declare effects significant, in fact are not. The fact that cluster‟s population are not equal and members within household have unequal selection probability, sampling weights should be introduced in statistical modeling to account for additional variability that arise due to differences in selection probability. Weights tend to reduce precision of estimates; this can be reflected in large standard errors. In this study, sampling weights were considered to get appropriate estimates.

3.2.Study Variables

3.2.1. Dependent Variable

The outcome variable of interest is child malnutrition status. There are anthropometric indicators of nutritional status such as, height-for-age, weight-for- age and weight-for-height. These indices were based on the growth standards published by WHO in 2006. The three indices were expressed as standard deviation units from the median for the reference group. Children who fall below minus two standard deviations (−2 SD) and (-3 SD) from the median of the reference population are regarded as malnourished and severely malnourished respectively.

The height-for-age index provides an indicator of linear growth retardation and cumulative growth deficits in children. Children whose height-for-age Z-score below minus two standard deviations (−2 SD) and (-3 SD) from the median of the WHO reference population are considered short for their age (stunted) and severely stunted or chronically malnourished respectively. Stunting reflects failure to receive adequate nutrition over a long period of time and is affected by recurrent and chronic illness. Height-for-age, therefore, represents the long-term effects of malnutrition in a population and is not sensitive to recent, short-term changes in dietary intake.

The weight-for-height index measures body mass in relation to body height or length; it describes current nutritional status. Children with Z-scores below minus two standard deviations (−2 SD) and (-3 SD) are considered thin (wasted) and severely wasted or acutely malnourished respectively. Wasting represents the failure to receive adequate nutrition in the period immediately preceding the survey and may be the result of inadequate food intake or a recent episode of illness causing loss of weight and the onset of malnutrition.

Weight-for-age is a composite index of height-for-age and weight-for-height. It takes into account both chronic and acute malnutrition. A child can be underweight for his/her age because he or she is stunted, wasted, or both. Weight-for-age is an overall indicator of a population‟s nutritional health. Children with weight-for-age below minus two standard deviations (−2 SD) and (-3 SD) are classified as underweight and severely underweight respectively.

Due to biological differences, we decided to model stunting and wasting separately. Since underweight is crude effect of wasting and stunting, it was dropped from analysis. Therefore, we have two responses: stunting and wasting status.

The two responses could be defined as multinomial ordinal responses. Let Y_{1i} and Y_{2i} be the observations for the i^{th} child for both stunting and wasting status respectively,

$$Y_{1i} = \begin{cases} 1, \text{if severely stunted}(Z - \text{score} < -3) \\ 2\ , \text{moderately stunted}(-3 \leq Z - \text{score} < -2) \\ 3, \text{if not stunted}(Z - \text{score} \geq -2) \end{cases}$$

$$Y_{2i} = \begin{cases} 1, \text{if severely wasted}(Z - \text{score} < -3) \\ 2, \text{moderately wasted}(-3 \leq Z - \text{score} < -2) \\ 3, \text{if not wasted}(Z - \text{score} \geq -2) \end{cases}$$

Often in many public health studies, binary outcome is preferred as a response of interest for the sake of interpretation. Hence, our two responses were also studied as binary responses: malnourished versus not malnourished.

$$Y_{1i} = \begin{cases} 1 \text{ if stunted } (Z - \text{score} < -2) \\ 0 \text{ if not stunted}(Z - \text{score} \geq -2)\text{i. e normal height for age} \end{cases}$$

$$Y_{2i} = \begin{cases} 1, \text{if low weight for height}(Z - \text{score} < -2) \\ 0, \text{if not wasted}(Z - \text{score} \geq -2) \end{cases}$$

3.2.2. Explanatory variables

A number of explanatory variables at individual (child) and family (household) levels, expected to be associated with child nutritional status are: Region, urban/rural residence, sex, age of child in months, birth order, preceding birth interval, household"s wealth index, household size, Source of drinking water, Mother"s age at first child birth, mother"s current marital status and mother"s educational status. Their description and categories was attached on Appendix 1.

3.3.Statistical Methods

In this section both exploratory (descriptive) and inferential statistical data analysis methods used are discussed.

3.3.1. Exploratory Data Analysis

We started with an exploratory data analysis to gain insight into the dataset. Descriptive statistics were used to observe a possible link between explanatory variables and malnutrition. Univariate associations between potential covariates and the response variable were assessed using frequency tables and by fitting each predictor with each response univariately.

3.3.2. Statistical Data Analysis

As stated in the introduction part, EMDHS data are hierarchical in nature, i.e. children are nested within households and households within regions. With such data, children within a household may be more similar to each other than children belong to other households. This raises the questions on the efficiency of models that assume independence of observations and calls for a statistical model that takes clustered nature of the data into account. Some marginal models were fitted to estimate household-level socio-economic factors for child malnutrition.

3.3.2.1.Analysis Ignoring Nature of Data (Generalized Linear Model (GLM))

Generalized linear models (GLMs) extend ordinary regression models to encompass non-normal response distributions and modeling functions of the mean (Agresti, 2002).

Let Y_i be the response and X_i explanatory variables or covariates for unit i, and define the conditional expectation of the response given the covariates $\mu_i, i.e. \mu_i \equiv E[Y_i|X_i]$.

Generalized linear models are specified as

$$g(\mu_i) = X_i'\beta = \vartheta_{i,} \qquad (3.1)$$

Where the linear combination $\vartheta_i = \beta_0 + \beta_1 x_{i1} + \cdots = X_i'\beta$ is called „linear predictor" and $\boldsymbol{\beta}'s$ are fixed effects. g is a „link function" linking the expected response μ_i to linear predictor ϑ_i. The specification is competed by choosing a conditional distribution for the responses y_i given the covariates $X_i, f(Y_i|X_i)$, from the exponential family distributions.

GLM assumes that the response variables are independent. In clustered data, like the EMDHS data, observations were taken from all under age five children in the selected households, and nutritional status in a household may be correlated. Correlated data requires proper analysis in modeling the association between the response variable and the given set of covariates.

3.3.2.2.Analyses Correcting for the clustered Nature of Data

To obtain efficient estimates of variances and standard errors it is necessary to take into account the hierarchical/cluster effects. Clustered data exhibit intra-class correlation as individuals from the same clusters (households) tend to be more alike than individuals from different clusters. Marginal models and generalized linear mixed models (GLMM) are among the widely used models to study clustered or repeated data. The main interest of our research question was on the marginal effects. Marginal effect models are models in which responses are averaged over all responses; the association structure is then typically captured using a set of association parameters such as correlations, odds ratio, etc. The primary objective of marginal model is to analyze the population-averaged effects of the given factors in the study on the response variable of interest. This means that the covariates are directly related to the marginal expectations (Molenberghs and Verbeke, 2005). In this study, the well-known GEE and ALR were applied techniques.

3.3.2.2.1. Generalized Estimating Equation (GEE)

Generalized estimating equations are extension of GLMs to accommodate correlated data: GEE models a known function of the marginal expectation of dependent variable as linear function of one or more explanatory variables. The GEE methodology provides consistent estimators of the regression coefficients and their variances under weak assumptions about the actual correlation among a subject"s observations. This approach avoids a need for multivariate distributions by assuming only a functional form for marginal distribution at each time point or condition. It relies on independence across subjects to consistently estimate the variance of proposed estimators even when the assumed working correlation structure is incorrect.

For binary data, a GEE approach is used to account for the correlation between responses of interest for subjects from the same cluster (Diggle *et al*., 1994). GEE is non-likelihood method that uses correlation to capture the association within the clusters or subjects in terms of marginal correlations (Molenberghs and Verbeke, 2005). For clustered as well as repeated data, Liang and Zeger (1986) proposed GEE which require only the correct specification of the univariate marginal distributions provided one is willing to adopt “working” assumptions about the correlation structure. The “working” assumptions as proposed by Liang and Zeger (1986) include independence, unstructured, exchangeable and auto-regressive AR (1).

Let $Y_j = (Y_{j1}, \dots, Y_{jnj})^T$ be the response values of observations from j^{th} cluster (from j^{th} household) $j = 1, 2, \dots, m$ with corresponding vector of means $\mu_j = (\mu_{j1}, \dots, \mu_{jnj})$ follow a binomial distribution. i.e. $Y_j \sim Bin(n_j, \mu_j)$ that belongs to exponential family. Let the vector of independent variables for i^{th} individual is $X_{ji} = [x_{ji1}, \dots, x_{jip}]^T$

Then to model the relation between the response and covariates, one can use a regression model similar to the generalized linear model (eqn 3.1)

$$logit(\mu_j) = X_j^T \boldsymbol{\beta}$$

(3.2)

where, $logit(\mu_j) = logit\ link$

$X_j = (n_j \times p)$ dimensional vector of known covariates.

$\boldsymbol{\beta} = (P \times 1)$ dimensional vector of unknown fixed regression parameter to be estimated

$E(Y_j) = \mu_j$ is expected value of responses.

Assume that you have chosen a model that relates a marginal mean to the linear predictor $X_j' \boldsymbol{\beta}$ through a link function. The generalized estimating equations for estimating $\boldsymbol{\beta}$, is given by:

$$\sum_{j=1}^{n} \frac{\partial \mu_j{}^T}{\partial \beta} V_j^{-1} (Y_j - \mu_j) = 0 \quad (3.3)$$

Where V_j is an estimator of covariance matrix of Y_j and it is specified as the estimator

$$V_j = \varphi A_j^{\frac{1}{2}} R_j(\boldsymbol{\alpha}) A_j^{\frac{1}{2}} \quad (3.4)$$

Where

A_j is $n_j X n_j$ diagonal matrix with $v(\mu_{ji})$ as i^{th} diagonal element

$R_j(\boldsymbol{\alpha})$ is $n_j \times n_j$ working correlation matrix of within cluster responses that is fully specified by the vector of parameter $\boldsymbol{\alpha}$. The i, i' element of $R_j(\boldsymbol{\alpha})$ is known, hypothesized, or estimated correlation between Y_{ji} and Y'_{ji}. This working correlation matrix may depend on the vector of unknown parameters $\boldsymbol{\alpha}$, which is the same for all subjects. If $R_j(\boldsymbol{\alpha})$ is the true correlation matrix of Y_j, then V_j is the true covariance matrix of Y_j.

φ is dispersion parameter and is estimated by $\hat{\varphi} = \frac{1}{N-p}\sum_{j=1}^{m}\sum_{i=1}^{n_j} e_{ji}^2$ were $N = \sum_{j=1}^{m} n_j$ is the total number of measurements and p is the number of regression parametres and e_{ji} is the pearson residual given by $e_{ji} = \frac{y_{ji}-\mu_{ji}}{\sqrt{v(\mu_{ji})/w_{ji}}}$.

Thus, score equation used to estimate the marginal regression parameters while accounting for the correlation structure is given by

$$S(\beta) = \sum_{j=1}^{m} \frac{\partial \mu_j{}^T}{\partial \boldsymbol{\beta}} \left[A_j^{\frac{1}{2}} R_j A_j^{\frac{1}{2}}\right]^{-1} \left(Y_j - \mu_j\right) = 0 \tag{3.5}$$

The model-based estimator of $cov(\widehat{\boldsymbol{\beta}})$ is given by $\sum_m(\widehat{\boldsymbol{\beta}}) = \boldsymbol{I_0}^{-1}$

Where $\boldsymbol{I_0} = \sum_{j=1}^{m} \frac{\partial \boldsymbol{\mu_j}^T}{\partial \boldsymbol{\beta}} \boldsymbol{V_j^{-1}} \frac{\partial \boldsymbol{\mu_j}}{\partial \boldsymbol{\beta}}$

The estimator $\sum_e = \boldsymbol{I_0}^{-1} \boldsymbol{I_1} \boldsymbol{I_0}^{-1}$ is called the empirical, or robust, estimator of the covariance matrix of $\widehat{\boldsymbol{\beta}}$, where $\boldsymbol{I_1} = \sum_{j=1}^{m} \frac{\partial \boldsymbol{\mu_j}^T}{\partial \boldsymbol{\beta}} \boldsymbol{V_j^{-1}} cov(Y_j^{-1}) \frac{\partial \boldsymbol{\mu_j}}{\partial \boldsymbol{\beta}}$.

An advantage of the GEE approach is that it yields a consistent estimator of coefficients, even when the working correlation matrix R_j is misspecified. However, severe misspecification of working correlation may seriously affect the efficiency of the GEE estimators (Molenberghs & Verbeke, 2005).

3.3.2.2.2. Alternating Logistic Regression (ALR) Model

This method is very similar to that of GEE, in that they are both quasi-likelihood based and they account for dependency in the data. However, unlike GEE which measures the association among the observed data through the correlation structure; Alternating logistic regression (ALR) measures this association using the odds ratio, which is interpretable and more applicable for binary data. ALR extends beyond classical GEE in the sense that precision estimates follow for both the regression parameters **β** and the association parameters **α**. Moreover with ALR inferences can be made, not only about marginal parameters but about pair wise associations between subjects as well (Molenberghs and Verbeke, 2005).

For cluster $j = 1, 2, \dots, m,\ let\ Y_j = (Y_{j1}, \dots, Y_{nj})'$ be response vector with mean $E(Y_j) = \mu_j$ and let φ_{jkl} be the odds ratio between responses Y_{jk} and Y_{jl} $(1 \le k \le n_j)$ defined by

$$\varphi_{jkl} = \frac{P(Y_{jk}=1,\ Y_{jl}=1)P(Y_{jk}=0,\ Y_{jl}=0)}{P(Y_{jk}=1,\ Y_{jl}=0)P(Y_{jk}=0,\ Y_{jl}=1)} \qquad (3.6)$$

$j = 1, 2, \dots, m,\ k, l = 1, 2, \dots, n_j$, where, Y_{jk} and Y_{jl} represents the j^{th} response values for subjects k and l respectively from the same cluster. Let, γ_{jkl} be the log odds between outcomes Y_{jk} and Y_{jl}, let $\mu_{jk} = P(Y_{jk} = 1)$ and $v_{jkl} = P(Y_{jk} = 1, Y_{jl} = 1)$ then association of two responses (Zeger *et al*, 1993) is defined as

$$logit\ P(Y_{jk} = 1 | Y_{jl} = y_{jl}) = \gamma_{jkl} y_{jl} + \log(\frac{\mu_{jk} - v_{jkl}}{1 - \mu_{jk} - \mu_{jl} + v_{jkl}}) \qquad (3.7)$$

Assume $\gamma_{jkl} = \alpha$. Then the pairwise log odds ratio α is the regression coefficient in logistic regression of Y_{jk} on Y_{jl} as long as the second term on the right-hand side in (3.7) is used as an offset. Generally $log(\varphi_{jkl}) = \gamma_{jkl} = Z'_{jkl}\alpha, where, Z_{jkl}$ is a $q \times 1$ vector of covariates which specifies the form of the association between Y_{jk} and Y_{jl}.

Since alternating logistic regression also not maximum likelihood approach like GEE, parameter estimation is based on the score equation of the approximate likelihood that is based on quasi likelihood approximation.

3.3.2.3. Analysis Ignoring Ordinal Nature of Response

3.3.2.3.1 Baseline Category Logit Model

Ignoring the ordinal nature of the data, we give simultaneous representation (summary) of the odds of being in one category relative to being in designated category called the base line category for all pairs of categories. This is an extension of binary logistic regression model, where we will consider $k-1$ non-redundant logits.

Suppose a set of responses $Y_i = \left(Y_{ij}, Y_{i2}, \dots, Y_{ik}\right)'$ has a multinomial distribution with index $n_i = \sum_{j=1}^{k} y_{ij}$ and parameter$\mu_i = (\mu_{i1}, \mu_{i2}, \dots, \mu_{ik})'$. A set of explanatory variables, $= (X_1,$ $X_2, \dots, X_k)$, the baseline category logit model has an equivalent loglinear model and given by:

$$\log\left(\frac{\mu_{ij}}{\mu_{ij*}}\right) = \alpha_j + x_i'\beta_{j,} \quad j \neq j* \tag{3.8}$$

In our case we have three categories and two equations that determine parameters for logits with other pairs of response categories. That is

$\log\left({}^{\mu_{i1}}/_{\mu_{i3}}\right) = \alpha_1 + x_i'\beta_1 \; and \; \log\left({}^{\mu_{i2}}/_{\mu_{i3}}\right) = \alpha_2 + x_i'\beta_2$. Since $\log\left({}^{\mu_{i1}}/_{\mu_{i2}}\right) = \log\left({}^{\mu_{i1}}/_{\mu_{i3}}\right) -$ $\log\left({}^{\mu_{i1}}/_{\mu_{i3}}\right)$.

Estimating response probabilities:

The equation that expresses multinomial logit models directly in terms of probabilities μ_{ij} is

$$\mu_{ij} = \frac{\exp(\alpha_j + x_i'\beta_j)}{1 + \sum_{j \neq j*}^{J} \exp(\alpha_j + x_i'\beta_{j*})} \tag{3.9}$$

3.3.2.4.Analysis Considering Ordinal Nature of Response

Models briefly discussed in Section 3.3.2.2.1 and 3.3.2.2.2 are limited to binary outcomes. However, our response variables stunting and wasting statuses have three categories and are ordinal in nature, i.e. severe, moderate, and normal status. Therefore, to account for this ordinal nature of responses, proportional odds model partial proportional odds model were used.

3.3.2.4.1. Proportional Odds Model (POM)

Given multinomial responses with K categories a vector of $K-1$ indicators of which k^{th} level is 1 when observation falls in the category k and 0 otherwise (Agresti, 2002). The usual approach for modeling such type of response data to is use logits of cumulative probabilities or proportional odds model given by:

$$logit\left(p\left(Y_{ji} \le k/x_{ji}\right)\right) = \alpha_k + \beta x_{ji}, k = 1, \dots, K-1 \quad (3.8)$$

Where Y_{ji} is the multinomial response with K categories on i^{th} child within j^{th} household, α_k s are intercepts for each logit, X'_{ji} and β are vectors of explanatory variables and slope parameters, respectively.

The cumulative logit model (3.8) satisfies $logit\left(p\left(Y_{j1} \le k/x_{j1}\right)\right) - logit\left(p\left(Y_{j2} \le k/x_{j2}\right)\right)$

$$= \beta(x_{j1} - x_{j2})$$

An odds ratio of cumulative probabilities is called a cumulative odds ratio. The odds of making response$\le k$ at $x_{ji} = x_{j1} are$ $\exp(\beta(x_{j1} - x_{j2}))$ times the odds at $x_{ji} = x_{j1}$.

The important assumption for the PO model of common slope for each logit should be tested before making inferences based on this model. The benefits of utilizing the ordinality of the response variable are for estimating severity status of malnutrition as well as to improve model parsimony, that is, the same fixed effect can apply to each logit and power of the model.

3.3.2.4.2. Partial Proportional Odds Model

The partial proportional odds model (Peterson and Harrel, 1990) allows non-proportional odds for all or subset q of the explanatory variables.

In univariate case,

$$logit[p(Y \le k)] = \alpha_k + \boldsymbol{X^T\beta} + \boldsymbol{Z^T\gamma_k}, \quad k = 1, \dots, K-1$$

Where $\boldsymbol{Z}$ is a $q-$ dimensional vector $(q \le p)$ of explanatory variables for which the proportional odds does not hold and $\boldsymbol{\gamma_k}$ is $q \times 1$ corresponding vector of coefficients and $\boldsymbol{\gamma_1} = \boldsymbol{0}$. When $\boldsymbol{\gamma_k} = \boldsymbol{0}$ for all k, the model reduces to the proportional odds model.

Extension of the partial proportional odds model to clustered data (Donneau *et a*l. , 2010)

In a clustered data setting,

$$logit\left[p\left(Y_{ji} \le k\right)\right] = \alpha_k + \boldsymbol{X^T\beta} + \boldsymbol{Z^T\gamma_k},$$

$$k = 1, \dots, K-1,$$

$$j = 1, \dots, m,$$

$$i = 1, \dots, n_j$$

Where $(\boldsymbol{Z_{j1}}, \dots, \boldsymbol{Z_{jn_j}})^T$ *is* $(n_j \times q)$ matrix, $q \le p$, of subset of $q-$explanatory variables for which the proportional odds assumption does not apply and $\boldsymbol{\gamma_k}$ is $q \times 1$ corresponding vector of regression parameters with $\boldsymbol{\gamma_1} = \boldsymbol{0}$.

Estimation of the regression parameters is by defining a $(K - 1)$ expanded vector of binary responses

$\boldsymbol{Y_{ji}} = (Y_{ji,1}, \dots, Y_{ji,(K-1)})^T$ where $Y_{jik} = 1\ if\ Y_{ji} \leq k\ and\ 0\ otherwise$, then applying GEE discussed in section 3.3.2.2.1.

3.3.3. Model Building Strategy and Selection Used

Model building strategy under GEE, started with all possible covariates that were significant at 20% level of significance in univariate analysis and significant meaningful two-way interactions, under two correlation assumptions (exchangeable and independence) for both stunting wasting responses. We had also tried to consider unstructured correlation, but the hessian matrix did not converge. To select best working correlation structure, Quasi-information criteria was QIC used. The smaller QIC indicates better correlation assumption (Pan, 2001). In order to select the important factors related to the responses, a backward selection procedure was used. We started with full model and the procedure used to remove interaction as well as main effects with non-significant p-values. This means that a variable that do not contribute to the model based on the p-value was eliminated and each time a new model with the remaining covariates was refitted, until we remained with covariates necessary for answering our research question. Variables significant under GEE were taken to fit all ALR, baseline category logit, and POM and PPOM models for both responses.

3.3.4. Model Checking Techniques

After a model is fitted the next important step is checking its model adequacy, assuming that we are primarily satisfied with the final model or model contains variables in their correct functional form. The objective is to look at how closely model fitted responses approximate observed responses. It is based on graphical as well as statistical point of view. There are several steps involved in assessing the appropriateness, adequacy and usefulness of model. First, the overall usefulness was assed. Second, the importance of each explanatory variable was assessed by carrying out statistical tests of significance of coefficients then, detecting influential observations.

3.3.4.1. Goodness of Fit of the Model

The goodness of fit or calibration of a model measures how well the model describes the data. Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values. For likelihood based models, statistical tests like Hosmer-lemeshow test, likelihood ratio and graphical method like fitted versus observed plots could be used. But for correlated (clustered) data, GEE method is quasi-likelihood; there were not readily defined analogs to the fit statistics for maximum likelihood estimation and no procedure included any measure of the assessment of fit. However some model criterion measures were provided to asses over all goodness of fit. The QIC measure was particularly useful tool for choosing the best correlation structure. Similarly the QICu measure was used for model selection (Hardin and Hibbe, 2003).

Test of individual model parameters; as stated above with estimation technique, quasi-likelihood approach, we cannot use likelihood ratio test in particular predictor variables, are more important than others. Instead we use chi-square test statistic adjusted under type3 GEE score test statistic in combination with quasi-information criteria‟s. For small sets of clusters adjusted F-test should be used but, for large set of clusters (usually more than 100 clusters) GEE score test approximates it (Stokes, *et. al.*, 2000). To determine the significance of the predictor variables we can use Wald statistic from empirical (robust) estimates. For PO model before interpreting coefficients estimated, the assumption of common slope was tested using chi-square statistic of proportional odds model assumption for ordinal response.

3.3.4.2. Checking for Influence and outliers

The next important step in marginal model building is to perform an analysis of residuals and diagnostics to study influence of observations. Residuals are used to filter points with outlying response values. For this data set the screening was done at the start of this study based on WHO height-for-age and weight-for-height standard scores. That is Z-scores below minus six and above six were removed from analysis. Therefore we assume no outlying only in responses and since our interest is on coefficients, simply we rush to diagnosis of influential observations. To do this there are two deletion diagnostic approaches for measuring effects of observations on fitted model, deleting individual observations and deleting entire cluster of observations. We use both techniques since the two deletion diagnostic criteria do not summarize the same information in the data. This is done by observing Cook‟s distance versus ordered observations and Cluster Cook‟s distance versus ordered cluster plots whether there are influential observations and clusters respectively (Li and Valliant, 2015).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1.Introduction and Exploratory Data Analysis

Exploratory and marginal models were used for analysis to measure the effects of determinants of malnutrition. The descriptive part provides percentage of malnourished children and some graphs to have insight relationship between responses and predictors. The data are analyzed using SAS and R package.

4.1.1. Exploratory Data analysis

A total of 5,401 children under age five from selected 305 clusters in Ethiopia were eligible to be weighed and measured. Data were presented for 4,893 children of these children.

Approximately equal number of eligible male and female children took part in the weight and height complete measurement, 2287(51.1%) and 2189(48.9%) respectively. 4.9% observations are missing due to refusal, children unavailable during measurement time and extreme measurements. Table 4.1 shows the percentage of children under age five classified as malnourished according to the two anthropometric indices of nutritional status: height-for-age (HAZ, for stunting status), weight-for-height (WHZ, for wasting status) . Over all 39.8% (unweighted 37.7%) of children were stunted while 18.1% were severely stunted. 39.01% and 36.4% of males and females stunted respectively. Of children fourth and fifth place in their birth order 40.35% were stunted while 20.43% were severely stunted. Region wise the highest proportion of stunting observed in Affar region (47.65%) and Tigray region (47.37%) while the lowest proportion observed in Addis Ababa city administration (21.54%). From all children whose mothers were uneducated 41.46% of them were stunted while all of children from mothers with secondary and above educational level 14.5% of them were stunted. Of children living in urban areas 23.8% were stunted. Additionally, information on the socio-economic status (wealth index) was important because it provided information about the welfare of the household. About 12.9% and 19.5% of eligible children lived in households belonging to the fourth (richer) and fifth (richest) wealth indexes respectively, whereas the rest of the children who lived in households in the first three levels (poorest through middle) of socio-economic status. In richer households, 35.7% of children were stunted and 9.36% were wasted. For richest households 24.23% children were stunted.

Wasting as response, overall weighted 9% of children were wasted while 2.6% severely wasted. Region wise the highest proportion of wasting observed in Somali region (26.85%) while the lowest proportion observed in Addis Ababa city administration (3.08%). From all children whose mothers were uneducated 15.6% of them were wasted while all children from mothers with and above educational level, 6.21% of them were wasted. Of children living in urban areas 23.8% were wasted. For richest households 8.76% of children were wasted while 18.43% of children from poorest households were wasted. 4.34% of children were both stunted and wasted. The correlation between these two was found -0.108865.

Table 4.1: Descriptive statistics and for categorical determinant factors of under-five child malnutrition in Ethiopia

Explanatory Variable	Stunting status			Wasting status		
	Severely stunted (%)	Moderately stunted (%)	Not stunted (%)	Severely wasted (%)	Moderately wasted (%)	Not wasted (%)
Sex: Male	438 (19.07)	457 (19.9)	1402 (61.04)	106 (4.61)	219 (9.53)	1972 (85.85)
Female	397 (18.06)	404 (18.38)	1397 (63.56)	93 (4.23)	183 (8.33)	1922 (87.44)
Birth order: 1	122 (14.39)	158 (18.63)	568 (66.99)	35 (3.77)	65 (7.67)	751 (88.56)
2-3	279 (19.69)	247 (17.43)	891 (62.88)	55 (3.88)	125 (8.82)	1237 (87.30)
4-5	236 (20.43)	229 (19.83)	690 (59.74)	53 (4.59)	96 (8.31)	1006 (87.10)
6+	198 (18.42)	227 (21.12)	650 (60.47)	59 (5.49)	116 (10.79)	900 (83.72)
Preceding birth interval: First birth	122 (14.39)	158 (18.63)	568 (66.98)	32 (3.77)	65 (7.67)	751 (88.56)
<24	232 (28.33)	156 (19.05)	431 (52.63)	52 (6.35)	80 (9.77)	687 (83.88)
24-47	361 (19.03)	377 (19.87)	1159 (61.10)	87 (4.59)	183 (9.65)	1627 (85.77)
48+	119 (12.89)	168 (18.20)	636 (68.91)	28 (3.03)	73 (7.91)	822 (89.06)
Residence:Urban	73 (9.00)	120 (14.80)	618 (76.20)	24 (2.96)	56 (6.91)	731 (90.14)
Rural	762 (20.68)	741 (20.11)	2181 (59.20)	175 (4.75)	346 (9.39)	3163 (85.86)
Region: Tigray	78 (19.55)	111 (27.82)	210 (52.63)	22 (5.51)	38 (9.52)	339 (84.96)
Affar	141 (31.54)	72 (16.11)	234 (52.35)	39 (8.73)	71 (15.88)	337 (75.39)
Amhara	67 (14.16)	133 (28.12)	273 (57.72)	11 (2.33)	33 (6.98)	429 (90.69)
Oromiya	102 (17.77)	113 (19.69)	359 (62.54)	11 (1.92)	33 (5.75)	530 (92.33)
Somali	83 (18.57)	81 (18.12)	283 (63.31)	47 (10.51)	73 (16.33)	327 (73.15)
Benishangul-Gumuz	82 (22.34)	61 (16.62)	224 (61.04)	23 (6.27)	37 (10.08)	307 (83.65)
SNNP	135 (22.73)	118 (19.87)	341 (57.41)	12 (2.02)	30 (5.05)	552 (92.93)
Gambela	42 (11.9)	47 (13.31)	264 (74.79)	16 (4.53)	40 (11.33)	297 (84.14)
Harari	41 (13.67)	42 (14.00)	217 (72.33)	3 (1.00)	13 (4.33)	284 (94.67)
Addis Ababa	7 (3.59)	35 (17.95)	153 (78.62)	2 (1.02)	4 (2.05)	189 (96.92)
Dire Dawa	57 (16.47)	48 (13.87)	241 (69.65)	13 (3.76)	30 (8.67)	303 (87.57)
Water source						
Non-Improved	461(21.56)	426(19.93)	1251(58.51)	125 (5.85)	230 (10.76)	1783 (83.40)
Improved	363(15.99)	423(18.63)	1484(65.37)	70 (3.08)	164 (7.22)	2036 (89.69)
Other	11(12.64)	12(13.79)	64(73.56)	4 (4.60)	8 (9.19)	75 (86.21)
Mother's education level: No education	626 (21.05)	607 (20.41)	1741 (58.54)	158 (5.31)	306 (10.29)	2510 (8.44)
Primary	193 (16.31)	221 (18.68)	769 (65.00)	33 (2.79)	83 (7.02)	1067 (90.19)
Secondary and Above	16 (4.73)	33 (9.76)	289 (85.50)	8 (2.37)	13 (3.85)	317 (93.79)
Wealth index: Poorest	361 (25.02)	276 (19.13)	806 (55.86)	99 (6.86)	167 (11.57)	1177 (81.57)

Poorer	168 (19.13)	200 (22.78)	510 (58.09)	50 (5.69)	75 (8.54)	753 (85.76)
Middle	140 (19.50)	132 (18.38)	446 (62.12)	17 (2.37)	62 (8.64)	639 (89.00)
Richer	88 (15.25)	118 (20.45)	371 (64.30)	11 (1.91)	43 (7.45)	523 (90.64)
Richest	78 (8.87)	135 ()15.36	666 (75.77)	22 (2.50)	55 (6.26)	802 (91.24)
Mother's marital status: Married	794 (18.74)	808 (19.07)	2636 (62.20)	195 (4.60)	378 (8.92)	3665 (86.48)
Single	41 (15.95)	53 (20.62)	163 (63.42)	4 (1.56)	24 (9.34)	229 (89.11)
Overall unweighted	835 (18.56)	861 (19.15)	2799 (62.27)	199 (4.43)	402 (8.94)	3894 (86.63)
Overall weighted	810 (18.10)	971 (21.70)	2694 (62.20)	114 (2.60)	290 (6.50)	4071 (91.00)
Cumulative	18.1	39.8	100	2.6	9	100
Missing (weighted)	232(4.9)			232(4.9)		

The graphs of proportions of children malnourished by the covariates were made to have a hint of how malnutrition is associated to these covariates. From Figure 1 (a-b), proportion of children stunted for both severe and moderate statuses seems increasing with age, but, proportion of wasting seems almost constant.

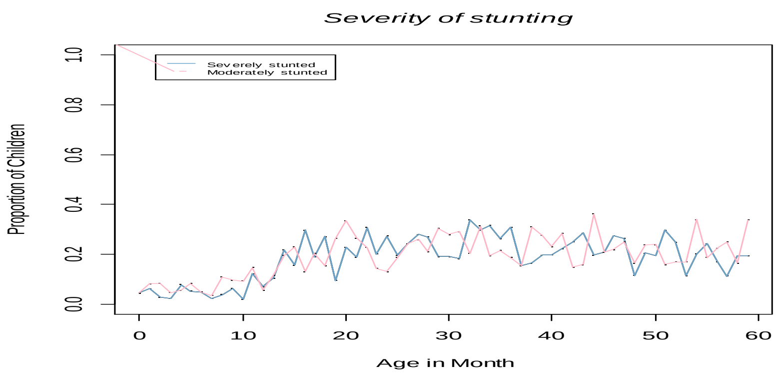


Figure1 (a), Proportion of children stunted by severity stunting with child age in months

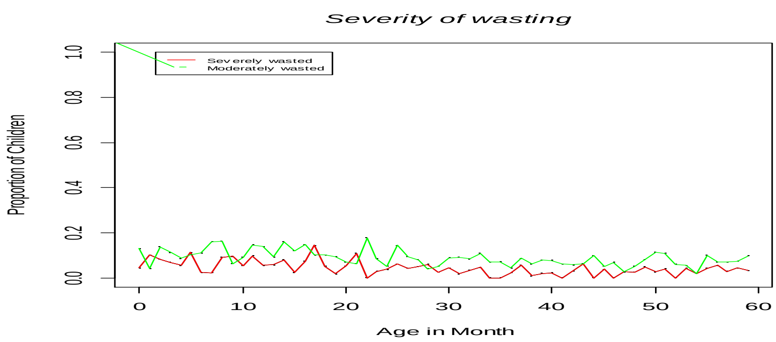


Figure1 (a), Proportion of children wasted by severity wasting with child age in months

From Figure 1(c-d), age was categorized and severity statuses (severe and moderate) were merged, the proportions of males malnourished were observed to be higher at all age group points compared to their female counterparts, these proportion seem to be relatively increasing over higher age groups for stunting cases, while proportion of children wasted decreases for higher age groups. We categorized age to have more points that enable to explain interims of proportion. This was done only for this in sight purpose only. In the analysis part age was considered in its continuous scale. Figure 1(a-b) shows proportion of two malnutrition types through age groups by sex and

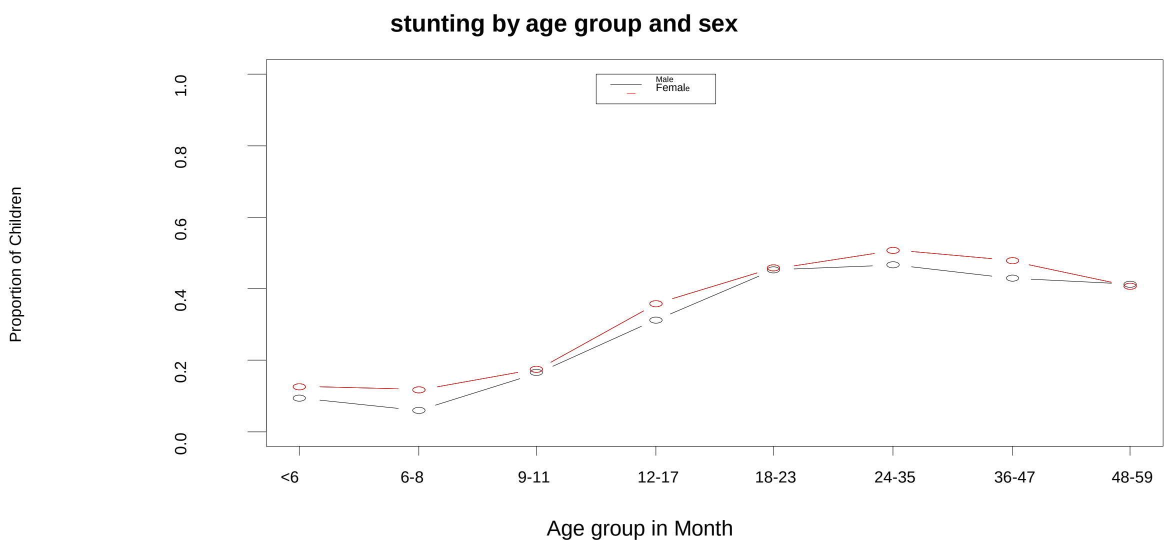


Figure 1(c) Proportion of Stunted Children by Age Group and Sex

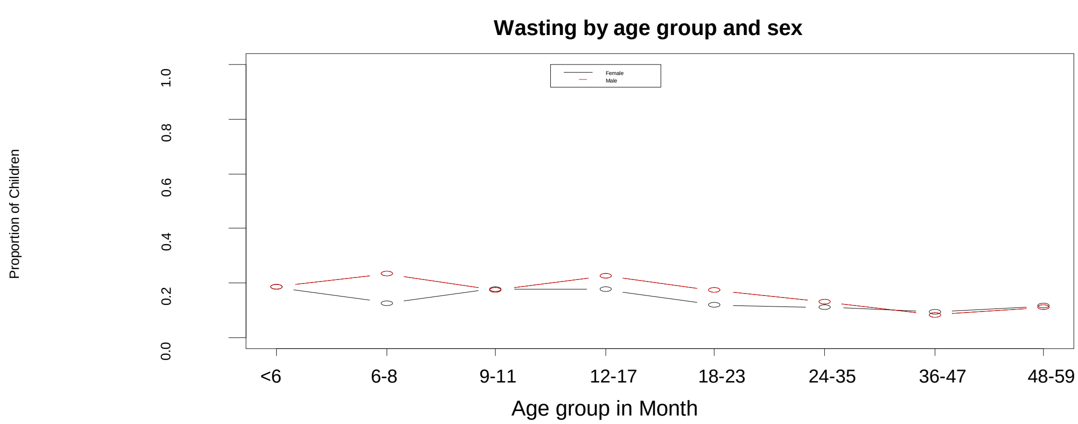


Figure 1(d) Proportion of wasted Children by Age Group and Sex

From Figures 1(e-f), malnutrition seems to vary across regions for both two responses. The highest proportion of malnutrition observed in Affar and Tigray regions. While the smallest level of malnutrition observed in Addis Ababa.

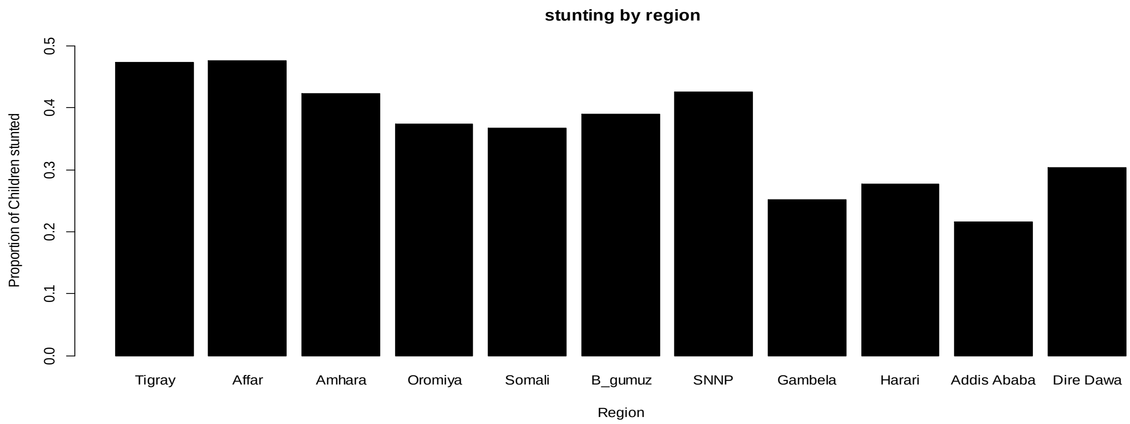


Figure 1(e) proportion of children stunted by region

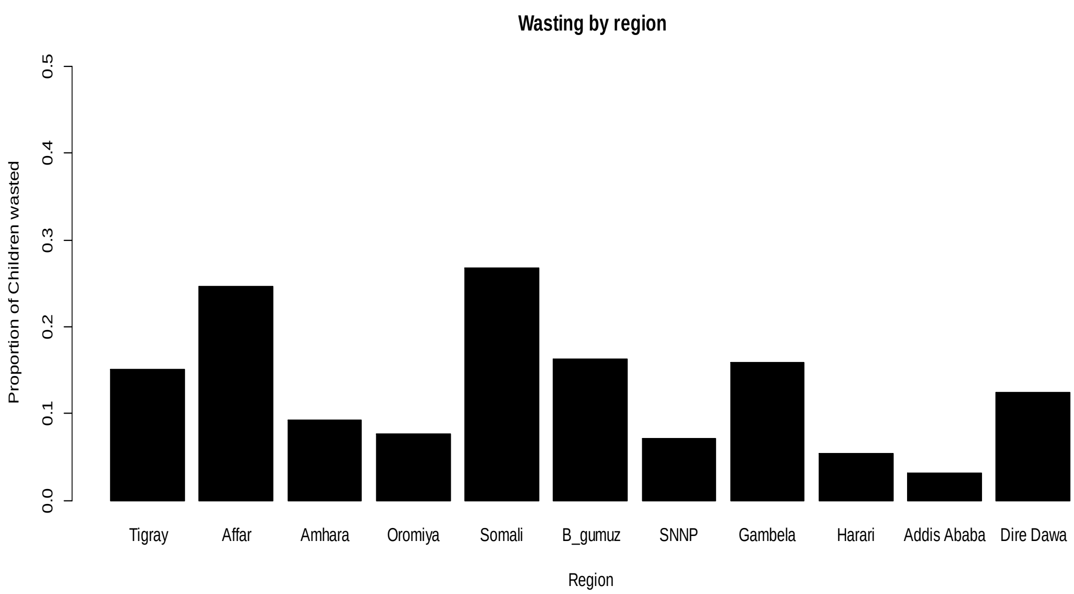


Figure1 (f) proportion of wasted children by regions

To have more insight on strength of association between each covariate with both and responses, we had fitted GEE for each covariate separately. At 20% level of significance, region, urban-rural residence, wealth-index, education level of mother, mother‟s age at first child birth, birth order, previous birth interval and child‟s age in months were found to be significantly related with under-five child stunting while sex, current marital status of mother and household size were not significantly associated with stunting. For wasting as response region, sex, education level of mother, birth order, current marital status of mother, child age in months and water source were found to be significantly associated with wasting. Result of unvariate analysis was attached on Appendix 3 and 4.

4.2. Statistical Analysis

4.2.1. Model Building and Selection

4.2.1.1. Marginal Models

In a situation, when the likelihood function cannot be fully specified, e.g., as in the GEE case, the Akaike‟s Information Criterion (AIC) cannot be directly applied for model selection procedures. Instead, one can use the modified Akaike‟s Information Criterion (QIC) which is based on the quasi-likelihood function (McCullagh and Nelder, 1989). Additionally, QIC is also applicable in selecting a working correlation structure under GEE settings.

Firstly, under the GEE, model building strategy started by fitting a model containing all significant covariates in univariate analysis at 20% level of significance and meaningful two-way interaction terms. This was done by considering two different working correlation assumptions (exchangeable, independence). We had also tried to consider unstructured correlation structure, but the hessian matrix did not converged. In order to select the important factors related to child stunting and wasting, the backward selection procedure was used. In this case the procedure was used to remove interactions as well as main effects with non-significant p-values that improve overall fit (i.e. minimize QIC and QICu).

This means that the variables that did not contribute to the model based on the highest p-value were eliminated sequentially and each time a new model with the remaining covariates was refitted, until we remained with covariates necessary for answering our research question.

None of the interaction terms were found to be significant. It turned out that, model with region, preceding birth interval, child age in months, wealth index, and education level of mother as covariates was found to be the most parsimonious model. This model is considered as the best model because the corresponding QIC value is the smallest and this is true for both correlation structures. Finally we compared QIC from two correlation structures, almost they were equal. Also as a customary, comparison of empirical and model based standard errors for the parameter estimates obtained based on the two working correlation assumptions (in this study exchangeable and independence) was performed. The distance between empirical and model based standard error of estimates from exchangeable correlation structure was somehow closer. Authors Stokes et, al. (2000) suggested the choice of working correlation structures depends on what the researcher(s) believe most realistic for a particular data. For clustered correlated data, when the correlations are small, it is natural to consider exchangeable correlation structure (Agresti, 2007). For this particular data, we assumed exchangeable correlation structure for the final analysis. Our proposed final model from the two-level model for stunting response was given as;

$$logit(\hat{\mu}_{ji}) = \hat{\beta}_0 + \hat{\beta}_1 Reg_{1i} + \hat{\beta}_2 Reg_{2i} + \cdots + \hat{\beta}_{10} Reg_{10i} + \hat{\beta}_{11} WI_{11i} + \hat{\beta}_{12} WI_{12i} + \hat{\beta}_{13} WI_{13i} + \hat{\beta}_{14} WI_{14i} + \hat{\beta}_{15} PBI_{15i} + \hat{\beta}_{16} PBI_{16i} + \hat{\beta}_{17} PBI_{17i} + \hat{\beta}_{18} Age_i + \hat{\beta}_{19} EDL_{19i} + \hat{\beta}_{20} EDL_{20i}$$

Where $Reg_{1i} = 1$ if region = Addis Ababa, $Reg_{2i} = 1$ if Region = Affar, $Reg_{3i} = 1$ if region= Amhara, $Reg_{4i} = 1$ if region= Benshangul-Gumuz, $Reg_{5i} = 1$ if region= Dire Dawa, $Reg_{6i} = 1$ if region= Gambela, $Reg_{7i} = 1$ if region= Harari, $Reg_{8i} = 1$ if region= Oromiya, $Reg_{9i} = 1$ if region= SNNP, $Reg_{10i} = 1$ if region= Somali, $WI_{11i} = 1$ if Wealth index = Poorer, $WI_{12i} = 1$ if Wealth index = Poorest, $WI_{13i} = 1$ if Wealth index = Richer, $WI_{14i} = 1$ if Wealth index = Richest, $PBI_{15i} = 1$ if Preceding birth interval = 48+, $PBI_{16i} = 1$ if Preceding birth interval <24, $PBI_{17i} = 1$ if Preceding birth interval = First birth, Age_i is the age of i^{th} child in months, $EDL_{19i} = 1$ if Education level of mother = No education, $EDL_{20i} = 1$ if Education level of mother = Secondary & above for i^{th} child. $i = 1, 2, \ldots, 4487$

Additionally, using selected covariates, a two-level ALR model which provides information about pairwise association of observations between two different individuals (children) within the same household was fitted. Later this model was extended to a three-level ALR model to accommodate the association of pairs of responses from two different households within the same cluster. Based on the QIC (Appendix 5) values of 5718.9296 and 5725.0931 for the two and three-levels ALR models respectively, it was concluded that the two-level ALR model was a better model in explaining the population-averaged association between under-five child stunting and the selected predictor variables. Thus, our interpretation will be based on the two-level ALR model. Table 4.2 shows parameter estimates, model-based (naive) standard errors and empirically corrected standard errors with p-values from GEE and two-level ALR. Each parameter reflects the effects of factor on the log odds of being stunted, statistically controlling for all other factors. Slight difference in the parameter estimates where observed, that could be due to the fact that ALR takes into account associations, whereas GEE treats the association nuisance parameter. Effect of assumption considered, correlated response (stunting status) within households was reflected by higher standard error and larger p-values than that of naïve (model-based) methods. This could have impact on inference of the parameters. Standard errors from empirical and model based methods of ALR were closer than that of GEE. This suggests, exchangeable correlation assumption under ALR was better for this data set.

Analysis under ALR (Appendix 6B) suggests that child characteristics; child age in months, preceding birth interval, wealth index and education level of mother are significantly related to stunting. It was observed that every month increase in age multiplies the odds of stunting by = 1.0248. Also we observed that children who had preceding birth interval less than 24 months had =1.4613 times estimated odds of stunting of children who had between 24 and 47 months previous birth interval. With respect to socio-economic effect, wealth index of household was significantly related to child stunting. It was observed that children from poorest household had 1.649 times estimated odds of stunting of children who were from middle wealth indexed households. The odds of children stunting from poorer, richer and richest households were not significantly different from that of middle wealth indexed households. It was also observed that education level of mother significantly related to children stunting. Children whose mothers were educated secondary and above had 0.5462 (i.e. 1-0.4538) times lower odds of stunting than children whose mother‟s educated primary education only. It was found that there were no significant difference between uneducated mothers and mothers who were educated primary education only in terms of estimated odds of children stunting. Moreover, it was observed that the estimated odds of stunting from regions Addis Ababa, Benishangul-Gumua, Amhara, Dire Dawa Gambela, Harari, Oromiya and Somali were 0.5921, 0.8035, 0., 0.4491, 0.3333, 0.5373, 0.6663, and 0.50 times the estimated odds of stunting children who were living in Tigray region respectively. The estimated odds of stunting children who were from Affar region and SNNP region were not significantly different from that of Tigray region.

Table 4.2 also presents the estimated constant log odds ratio (α), which provides information about association between individuals (children) within household. This means that, the estimated pairwise odds ratio relating two responses from same household was found to have small (weak) positive association (0.0104).

Table 4.2: Parameter estimates, empirical standard (Es.e) errors and model-based standard errors (MBs.e) for GEE and two-level ALR for stunting response

		GEE, with independence correlation structure		GEE, with exchangeable correlation structure		ALR, with exchangeable correlation structure	
Effect	Par	Est. (Es.e, MBs.e)	E.p-value	Est.(Es.e, MBs.e)	E.p-value	Est.(Es.e, MBs.e)	E.p-value
Intercept	$\hat{\beta}_0$	-1.0017 (0.1940, 0.1629)	<.0001	-1.0017 (0.19541, 0.1632)	<.0001	-0.1008 (0.1940, 0.1630)	<.0001
Region: Addis Ababa	$\hat{\beta}_1$	-0.5244 (0.2606, 0.2783)	0.0442	-0.5230 (0.2606, 0.2788)	0.0448	-0.5241 (0.2606, 0.2784)	0.0443
Affar	$\hat{\beta}_2$	-0.2807 (0.1727, 0.3318)	0.1040	-0.2799 (0.1727, 0.3331)	0.1050	-0.2805 (0.1727, 0.3321)	0.1042
Abhara	$\hat{\beta}_3$	-2192(0.01523, 0.1401)	0.1500	-0.2173 (0.1523, 0.1405)	0.1537	-0.2187 (0.1523, 0.1402)	0.0159
Ben-Gumuz	$\hat{\beta}_4$	-0.3443 (0.1653, 0.3314)	0.0372	-0.3446 (0.1654, 0.3324)	0.0372	-0.3443 (0.1653, 0.3316)	0.0372
Dire Dawa	$\hat{\beta}_5$	-0.8007 (0.1737,0.5547)	<.0001	-0.7997 (0.1736, 0.5565)	<.0001	-0.8005 (0.1737, 0.5550)	<.0001
Gambela	$\hat{\beta}_6$	-1.0988 (0.02101, 0.5418)	<.0001	-1.0983 (0.2104, 0.5432)	<.0001	-1.0986 (0.2102, 0.5420)	<.0001
Harari	$\hat{\beta}_7$	-0.6213 (0.1883, 0.7421)	0.0010	-0.6210 (0.1884, 0.7444)	0.0010	-0.6212 (0.1883, 0.7425)	0.0010
Oromiya	$\hat{\beta}_8$	-0.4062 (0.1417, 0.1332)	0.0041	-0.4055 (0.1418, 0.1336)	0.0042	-0.4060 (0.1417, 0.1333)	0.0042
SNNP	$\hat{\beta}_9$	-0.2572 (0.1438, 0.1413)	0.0736	-0.2578 (0.1438, 0.1417)	0.0729	-0.2574 (0.1438, 0.1414)	0.0374
Somali	$\hat{\beta}_{10}$	-0.6936 (0.1793, 0.2291)	0.0001	-0.6918 (0.1789, 0.2300)	0.0001	-0.6932 (0.1792, 0.2293)	0.0001
Wealth Index: Poorer	$\hat{\beta}_{11}$	0.2783 (0.1479, 0.0953)	0.0599	0.2793 (0.1480, 0.0956)	0.0592	0.2785 (0.1479, 0.0954)	0.0598
Poorest	$\hat{\beta}_{12}$	0.4293 (0.1425, 0.0958)	0.0026	0.4303 (0.1426, 0.0961)	0.0025	0.4295 (0.1426, 0.0958)	0.0026
Richer	$\hat{\beta}_{13}$	0.0064 (0.1462, 0.1044)	0.9691	0.0058 (0.1643, 0.1047)	0.9718	0.0062 (0.1642, 0.1045)	0.9698
Richest	$\hat{\beta}_{14}$	-0.0673 (0.2004, 0.1254)	0.7372	-0.0654 (0.2007, 0.1257)	0.7444	-0.0669 (0.2005, 0.1255)	0.7388
Preceding birth interval: 48+	$\hat{\beta}_{15}$	-02508 (0.1283, 0.0849)	0.0506	-0.2506 (0.1283, 0.0849)	0.0508	-0.2508 (0.1283, 0.0849)	0.0506
<24	$\hat{\beta}_{16}$	0.3782 (0.1545, 0.0934)	0.0144	0.3828 (0.1546, 0.0934)	0.0133	0.3793 (0.1545, 0.0934)	0.0141
First birth	$\hat{\beta}_{17}$	-0.1802 (0.1452, 0.0939)	0.2147	-0.1804 (0.1453, 0.0939)	0.2145	-0.1803 (0.1453, 0.0939)	0.2146
Child age	$\hat{\beta}_{18}$	0.0245 (0.0028, 0.0019)	<.0001	0.0245 (0.0028, 0.0019)	<.0001	0.0245 (0.0028, 0.0019)	<.0.0001
M.Educ.level:No educ.	$\hat{\beta}_{19}$	0.0558 (0.1137, 0.0762)	0.6237	0.0566 (0.1138, 0.0764)	0.6188	0.0560 (0.1137, 0.0763)	0.6225
Second.& above	$\hat{\beta}_{20}$	-0.7901 (0.3043, 0.1932)	0.0094	-0.7901 (0.3044, 0.1934)	0.0094	-0.7901 (0.3043, 0.1932)	0.0094
Alpha	$\hat{\alpha}_1$					0.0104 (0.1418)	0.9417

For wasting as response, none of interaction terms were found to be significant. Only Variables region, Sex of child, education level on mother, child age in months and mother‟s current marital status left in the final most parsimonious model. This model was considered as the best model because the corresponding QIC value is the smallest and this is true for both correlation structures. Finally we compared QIC from two correlation assumption (exchangeable and independence), almost they were equal. With the same reasoning that of stunting, we selected exchangeable correlation structure for the final analysis. Our proposed final model from two-level ALR model for wasting response is given as;

$$logit(\hat{\mu}_{ij}) = \hat{\beta}_0 + \hat{\beta}_1 Reg_{1i} + \hat{\beta}_2 Reg_{2i} + \cdots + \hat{\beta}_{10} Reg_{10i} + \hat{\beta}_{11} sex_{11i} + \hat{\beta}_{12} EDL_{12i} + \hat{\beta}_{13} EDL_{13i} + \hat{\beta}_{14} Age_i + \hat{\beta}_{15} CMS_{15i}$$

Where $Reg_{1i} = 1$ if region = Addis Ababa, $Reg_{2i} = 1$ if Region = Affar, $Reg_{3i} = 1$ if region= Amhara, $Reg_{4i} = 1$ if region= Benshangul-Gumuz, $Reg_{5i} = 1$ if region= Dire Dawa, $Reg_{6i} = 1$ if region= Gambela, $Reg_{7i} = 1$ if region= Harari, $Reg_{8i} = 1$ if region= Oromiya, $Reg_{9i} = 1$ if region= SNNP, $Reg_{10i} = 1$ if region= Somali, $sex_{11i} = 1$ if Sex = Male, $EDL_{12i} = 1$ if Education level of mother = No education, $EDL_{13i} = 1$ if Education level of mother = Secondary & above, Age_i is age in months for i^{th} child, $CMS_{15i} = 1$ if Marital status = Married, 0 other wize.

Additionally, using selected covariates, a two-level ALR model which provides information about pairwise association of observations between two different individuals (children) within the same household was fitted. Later this model was extended to a three-level ALR model to accommodate the association of pairs of responses from two different households within the same cluster. Based on the QIC (Appendix 5) values of 2607.7595 and 2615.2877 for the two and three-levels ALR models respectively, it was concluded that the two-level ALR model was a better model in explaining the population-averaged association between under-five child wasting and the selected predictor variables. Thus, our interpretation was based on the two level ALR model. Table 4.3 shows parameter estimates, model-based (naive) standard errors and empirically corrected standard errors with p-values from GEE and two-level ALR. Each parameter reflects the effects of factor on the log odds of being wasted, statistically controlling for all other factors. Under two-level ALR, region, sex, education level of mother, age of child in months and marital status of mother were found to be significantly related to child wasting. The result (Appendix 7B) showed that the estimated odds of wasting for children who were from regions Addis Ababa, Affar, Amhara, Harari, Oromiya, SNNP and Somali were 0.2325, 1.6479, 0.6233, 0.3731, 0.5144, 0.4677 and 1.9897 times the estimated odds of wasting of children who were from Tigray region. It was also observed that an estimated odd of wasting for male children was 1.4167 times estimated odds of wasting female children (i.e. an estimated odds wasting for male children was 0. 4167 times higher than that of female children.). Moreover, odds of wasting for children whose mothers were uneducated was 1.9257 times the estimated odds of wasting for children mothers with primary educational level. The result also suggested that every month increase in age multiplies the odds of wasting by 0.9817. With respect marital status (singlehood) of mother, estimated odds of wasting for children who belong to married mother (formally married and living with partner) was 1.9178 times the estimated odds wasting for children whose mothers were single (never married, widowed and divorced). From the estimated constant log odds ratio (α), the estimated pairwise odds ratio relating two responses from same household was found to have large (strong) positive association (0.8522).

Table 4.3: Parameter estimates, model-based standard errors and empirical standard errors for GEE and two-level ALR for wasting.

		GEE, with independence correlation structure		GEE, with exchangeable correlation structure		ALR, with exchangeable correlation structure	
Effect	Par	Est. (Es.e, MBs.e)	E.p-value	Est.(Es.e, MBs.e)	E.p-value	Est.(Es.e, MBs.e)	E.p-value
Intercept	$\hat{\beta}_0$	-2.5048 (0.4057, 0.3459)	<.0001	-2.5236 (0.4064, 0.3486)	<.0001	-2.5473 (0.4071, 0.3509)	<.0001
Region							
Addis Ababa	$\hat{\beta}_1$	-1.5001 (0.4768, 0.5829)	0.0017	-1.4801 (0.4747, 0.5883)	0.0018	-1.4588 (0.4762, 0.5870)	0.0022
Affar	$\hat{\beta}_2$	0.4720 (0.2038, 0.3880)	0.0205	0.4847 (0.2035, 0.3962)	0.0172	0.4995 (0.2020, 0.4093)	0.0144
Abhara	$\hat{\beta}_3$	-0.5058 (0.2265, 0.2002)	0.0255	-0.4894 (0.2267, 0.2037)	0.0309	-0.4727 (0.2272, 0.2075)	0.0375
Ben-Gumuz	$\hat{\beta}_4$	0.0785 (0.2187, 0.4319)	0.7197	0.0946 (0.2184, 0.4391)	0.6650	0.1099 (0.2187, 0.4486)	0.6152
Dire Dawa	$\hat{\beta}_5$	-0.2112 (0.2338, 0.7386)	0.3664	-0.2075 (0.2338, 0.7545)	0.3748	-2018 (0.2341, 0.7694)	0.3887
Gambela	$\hat{\beta}_6$	0.0928 (0.2492, 0.6774)	0.7095	0.0978 (0.2491, 0.6895)	0.6947	0.1023 (0.2491, 0.7022)	0.6814
Harari	$\hat{\beta}_7$	-1.0309 (0.3062, 1.4146)	0.0008	-1.0071 (0.3058, 1.4339)	0.0010	-0.9858 (0.3060, 1.4354)	0.0013
Oromiya	$\hat{\beta}_8$	-0.7261 (0.2253, 0.1906)	0.0013	-0.6905 (0.2242, 0.2167)	0.0021	-0.6647 (0.2229, 0.1976)	0.0030
SNNP	$\hat{\beta}_9$	-0.8042 (0.2243, 0.2133)	0.0003	0.6854 (0.2021, 0.2689)	0.0005	-0.7600 (0.2242, 0.2201)	0.0007
Somali	$\hat{\beta}_{10}$	0.6787 (0.2028, 0.2629)	0.0008	0.3446 (0.1562, 0.1072)	0.0007	0.6880 (0.2021, 0.2784)	0.0007
Sex: Male	$\hat{\beta}_{11}$	0.3434 (0.1572, 0.1076)	0.0289	0.3434 (0.1572, 0.1076)	0.0274	0.3483 (0.1553, 0.1068)	0.0249
M.Educ.level:No educ.	$\hat{\beta}_{12}$	0.6432 (0.2065, 0.2935)	0.0018	0.6496 (0.2073, 0.1367)	0.0017	0.6553 (0.2081, 0.1372)	0.0016
Second.& above	$\hat{\beta}_{13}$	0.1255 (0.2065, 0.2935)	0.7577	0.1267 (0.4074, 0.2949)	0.7558	0.1288 (0.4080, 0.2954)	0.7523
Child age	$\hat{\beta}_{14}$	-0.0181 (0.0047, 0.0031)	0.0001	-0.0184 (0.00046, 0.0031)	<.0001	-0.0185 (0.0046, 0.0031)	<0.0001
Current marital status							
Married	$\hat{\beta}_{15}$	0.6413 (0.3083, 0.2742)	0.0375	0.6462 (0.3083, 0.2755)	0.0361	0.6512 (0.3098, 0.2764)	0.0356
Alpha	$\hat{\alpha}_1$					0.8522 (0.2341)	0.0003

4.2.1.2. Baseline Logit Model

For both stunting responses, baseline-category logit model for nominal responses which uses separate binary logit for each pair of response to describe the effects of predictors was considered. The effects of predictors vary according to the response paired with the baseline. Baseline category logit model was fitted to investigate the effects of region, wealth index of household, education level of mother, preceding birth interval and child age in months on stunting.

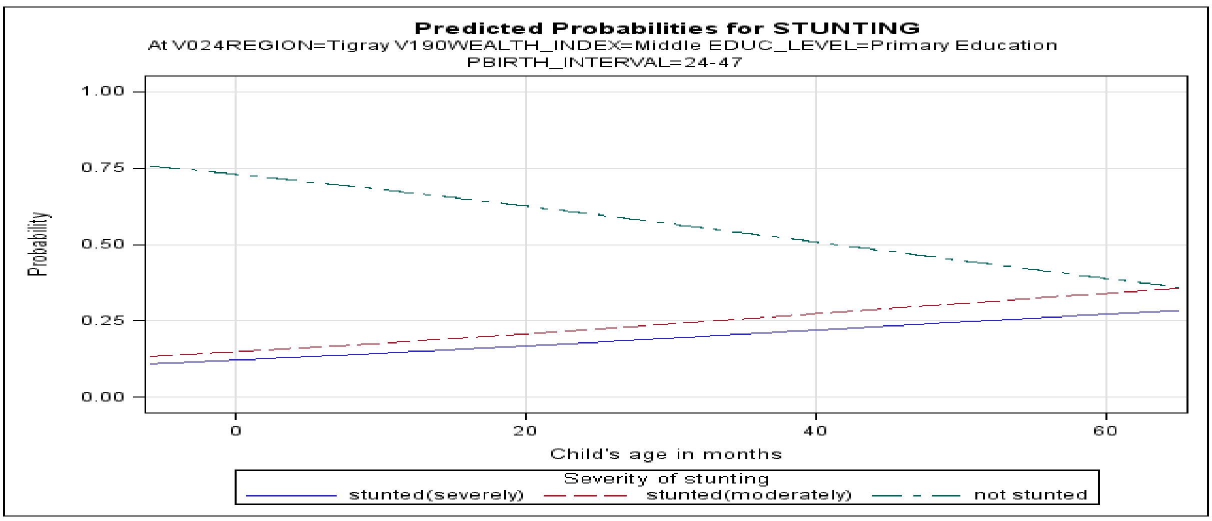
Table 4.4 presents the analysis under a baseline logit model. The result suggests that region is significantly related with stunting. Given other effects held constant region effect indicate that the estimated odds of sever stunting instead of moderate stunting for children who live in Gambela region are exp (-0.8297+1.1.0699) = 1.2715, which is 27.15% more than the estimated odds for children who live in Tigray region. Moreover, wealth-index of households was found to be significantly related to stunting. The estimated odds of sever stunting instead of moderate stunting for children belong to poorest households were 1.1585 times (15.85% more than) the estimated odds of children who belong to middle wealth households. With respect to preceding birth interval, it was found to be significantly related to stunting. This implied that, the estimated odds of sever stunting instead of severe stunting for children who are first birth for their mothers are 0.9281 times the estimated odds of children who had between 24 and 47 months(24-47) previous birth interval. With respect to age of child in months, it was found to be significantly related to stunting. That is for one month child age increase, the estimated odds of sever stunting instead of moderate stunting increases by 0.7%. For wasting response the result is attached on Appendix 10.

Table 4.4. Estimated baseline logit model for stunting

Logit(moderately stunted vs not stunted)			Logit(severely stunted vs not stunted)	
Effect	Par.	Est.(s.e)	Par.	Est.(s.e)
Intercept	$\hat{\alpha}_1$	-0.7919(0.2299)*	$\hat{\alpha}_2$	-1.2603(0.2484)*
Region : Affar	$\hat{\beta}_{12}$	-0.5969(0.2082)*	$\hat{\beta}_{13}$	0.1176(0.2138)
Benishangul-Gumuz	$\hat{\beta}_{22}$	-0.6221(0.1985)*	$\hat{\beta}_{23}$	0.0609(0.2103)
SNNP	$\hat{\beta}_{32}$	-0.3790(0.1680)*	$\hat{\beta}_{33}$	0.0466(0.1856)
Somali	$\hat{\beta}_{42}$	-0.6941(0.2071)*	$\hat{\beta}_{43}$	-0.4344(0.2263)
Oromiya	$\hat{\beta}_{52}$	-0.4992(0.1692)*	$\hat{\beta}_{53}$	-0.1607(0.1914)
Dire Dawa	$\hat{\beta}_{62}$	-0.9832(0.2094)*	$\hat{\beta}_{63}$	-0.4233(0.2247)
Harari	$\hat{\beta}_{72}$	-0.7844(0.2244)*	$\hat{\beta}_{73}$	-0.2372(0.2568)
Addis Ababa	$\hat{\beta}_{82}$	-0.3243(0.2885)	$\hat{\beta}_{83}$	-1.0714(0.4663)*
Gambela	$\hat{\beta}_{92}$	-1.0699(0.2335)*	$\hat{\beta}_{93}$	-0.8297(0.3088)*
Amhara	$\hat{\beta}_{102}$	-0.0622(0.1677)	$\hat{\beta}_{103}$	-0.4085(0.2075)*
Wealth-Index: Poorer	$\hat{\beta}_{112}$	0.4291(0.1688)*	$\hat{\beta}_{113}$	0.1010(0.1886)
Poorest	$\hat{\beta}_{122}$	0.3378(0.1721)*	$\hat{\beta}_{123}$	0.4849(0.1779)*
Richest	$\hat{\beta}_{132}$	0.1282(0.2403)	$\hat{\beta}_{133}$	-0.2656(0.2758)
Richer	$\hat{\beta}_{142}$	0.2031(0.1812)	$\hat{\beta}_{143}$	-0.2263(0.2424)
Preceding birth interval: <24	$\hat{\beta}_{152}$	-0.3422(0.1812)	$\hat{\beta}_{153}$	-0.1011(0.2010)
48+	$\hat{\beta}_{162}$	-0.6036(0.1517)*	$\hat{\beta}_{163}$	-0.5268(0.1699)*
First birth	$\hat{\beta}_{172}$	-0.4544(0.1673)*	$\hat{\beta}_{173}$	-0.5290(0.1957)*
Child age in months	$\hat{\beta}_{182}$	0.00439(0.0035)	$\hat{\beta}_{183}$	0.0114(0.0.00358)*
Educ.level of Mother:No edc.	$\hat{\beta}_{192}$	0.0520(0.1389)	$\hat{\beta}_{193}$	0.0693(0.1482)
Secondary and above	$\hat{\beta}_{202}$	-0.5867(0.3549)	$\hat{\beta}_{203}$	-1.2949(0.4408)*

*Significant with p-value<0.05

From predicted probabilities plot 3 (Figure 3), we observed that, older children had higher probabilities of both two lower categories (severe stunting and moderate stunting) than younger children. This also in line with what we had observed in exploratory data analysis (Figure 1 (a) and 1 (c)).



Plot 3 Predicted probabilities of stunting at reference category of predictors with age.

4.2.1.3. Proportional odds Model

Marginal ordinal logistic regression model with an extension of GEE technique to accommodate ordering level of response (malnutrition status) and correlation of within households. Stunting and wasting statuses could be further categorized using three point ordinal scale: 1-stunted (severely), 2-stunted (moderately), 3-not stunted and 1-wasted (severely), 2-wasted (moderately), 3-not wasted respectively.

Before inference could be made, the assumption of common slope for proportional odds model had to be tested first. The score test for the null hypothesis of constant slope for stunting response gave $\mathrm{Chi-square} = 72.5455, \mathrm{d\,f} = 20, \mathrm{p-value} = < .0001$. We fail to accept the null hypothesis (i.e. that the PO assumption fails). Therefore, PO model was not appropriate for stunting response. Further partial proportional odds model was considered in Section 4.2.1.3. For wasting response similar score test for the null hypothesis of common slope performed and we got $C\mathrm{h-square} = 5.901, \mathrm{df} = 15, \mathrm{p-value} = 0.9813$. There is no statistical evidence to reject null hypothesis (i.e. that the PO assumption holds) and we proceeded examining model output. Table 4.5 summarized results of fitted ordinal logistic regression model. The estimated cumulative log odds ratios and 95% confidence interval for the log odds ratios for the selected predictor variables, the results suggested that region, child in months, current marital status of mother and education level of mother were significant predictors in the cumulative logit for wasting response as their 95% confidence intervals for the log odds ratio do not include 0. It was observed that (Appendix 8B), the estimated cumulative odds for children who were from Addis Ababa, Affar, Amhara, Harari, Oromiya, SNNP, and Somali being in severe category relative to normal category were 0.2266, 1.7255, 0.5758, 0.3387, 0.4523 , 0.4289and 2.0855 times odds Tigray region their counter parts . With respect to sex it was observed that, the cumulative odds that male children in sever category of wasting relative to normal category was 0.9659 times cumulative odds for females being in severe category relative to normal (not wasted) category. Moreover, marital status of mothers was negatively related to child wasting. This implied that the estimated cumulative odds for children whose mothers were married being in the severe category relative to normal (not wasted) category was 1.9176 times cumulative odds of children whose mothers were single being in sever category relative to not stunted category. Age was found to be positively related to child wasting. For a unit month increase in child age, cumulative odds of sever category relative to normal category multiplied by 1.0172. It was also observed that cumulative odds for children whose mothers were not educated being in sever category of wasting relative to normal category was 1.7074 times odds of children from mothers with primary educational level being sever wasting category relative to normal category. This interpretation also holds in reverse direction, since assumption of common slope holds.

Table 4.5. Estimated cumulative logit model for wasting

Effect	Par.	Estimate(s.e)	Cumulative Log Odds Ratio OR[95% CI]
Intercept1	$\hat{\alpha}_0$	-4.6426(0.4310)	[-5.4874, -3.7978]
Intercept2	$\hat{\alpha}_1$	-3.2790(0.4166)	[-4.0955, -2.4624]
Region : Addis Ababa	$\hat{\beta}_1$	-1.4846(0.4770)	[-2.4194, -0.5498]
Affar	$\hat{\beta}_2$	0.5455(0.2033)	[0.1470, 0.9440]
Amhara	$\hat{\beta}_3$	-0.5520(0.2267)	[-0.9963, -0.1077]
Ben-Gumuz	$\hat{\beta}_4$	0.0855(0.2195)	[-0.3447, 0.5158]
Dire Dawa	$\hat{\beta}_5$	-0.2329(0.2393)	[-0.7020, 0.2362]
Gambela	$\hat{\beta}_6$	-0.0730(0.2581)	[-0.5787, 0.4328]
Harari	$\hat{\beta}_7$	-1.0826(0.3103)	[-1.6909, -0.4744]
Oromiya	$\hat{\beta}_8$	-0.7935(0.2274)	[-1.2391, -0.3478]
SNNP	$\hat{\beta}_9$	-0.8583(0.2268)	[-1.3028, -0.4138]
Somali	$\hat{\beta}_{10}$	0.7350(0.2018)	[0.3395, 1.1305]
Sex : Male	$\hat{\beta}_{11}$	-0.0347(0.1549)	[-0.3384, 0.2689]
Current marital status of mother			
Married	$\hat{\beta}_{12}$	0.6511(0.3025)	[0.0582, 1.2440]
Child age in months	$\hat{\beta}_{13}$	0.0171(0.0049)	[0.0076,0.0267]
Mother's education level			
No education	$\hat{\beta}_{14}$	0.5350(0.2064)	[0.1304, 0.9395]
Secondary and Above	$\hat{\beta}_{15}$	0.2115(0.4104)	[-0.5929, 1.0160]

From predicted cumulative probability plot (Figure 2), it was observed that severity of wasting was higher for younger children. This matches with the result of observed proportion of children proportion of children wasted, which is presented in exploratory part (figure 1 (d)).

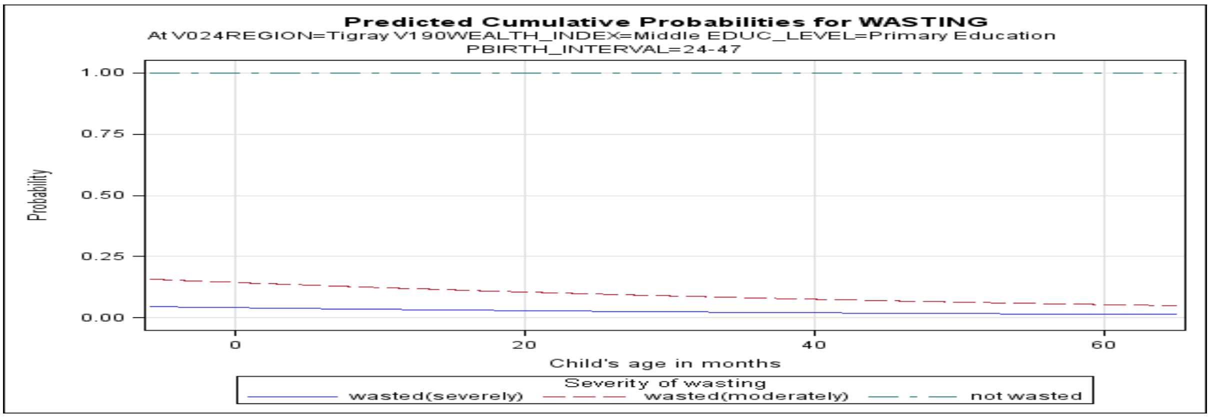


Figure 2 Predicted Cumulative probabilities for severity of wasting with age

4.2.1.4. Partial Proportional odds Model

Before fitting partial proportional odds model, we assessed weather we had adequate number counts in each cell. We formed two- way cross-classifications of explanatory variables with the response variable, the counts for each cell was greater than five.

We created two logits for each observation that compare level 1 versus 2 and 3 (severely stunted versus moderately and not stunted), level 1 and 2 versus 3 (severely and moderately stunted versus not stunted). The type of logit is contained in the variable logtype with values 3 and 2 to represent cut point, and the new response variable stunting status was assigned 1 if that observation"s value meets that cut point and is 0 otherwise. Two observations were created from each observation, one for each logit.

The interaction terms logtype*education level of mother and logtype*wealth index were not significant. The final model assumes proportional odds for education level of mother and wealth index.

Table 4.6 contains results of Type 3 analysis of the final model. All main effects and interaction terms were significant; no further reduction.

Table 4.6 Score Statistics for Type 3 GEE Analysis for final Model for Stunting Response

Score Statistics For Type 3 GEE Analysis			
Source	DF	Chi-Square	Pr>Chisq
Logtype	1	69.25	<.0001
Region	10	73.12	<.0001
Wealth index	4	24.73	0.0005
Preceding birth interval	3	35.86	<.0001
Age in months	1	135.42	<.0001
Education level of mother	2	26.38	<.0001
logtype *Region	10	63.41	<.0001
logtype *preceding birth interval	3	9.09	0.0281
Age in months* logtype	1	13.12	0.0003

Finally Table 4.7 contains the final parameter estimates. The main effects pertain to effects corresponding factors for severely and moderately stunted versus not stunted, and interaction are increments to the main effects to obtain the effects corresponding severely stunted versus moderately and not stunted. For example, $\hat{\beta}_7$ =-1.1241 is the estimated log odds ratio for Gambela region versus Tigray region for severely and moderately stunted relative to not stunted , and -1.1241+0.4278 is the estimated log odds ratio for Gambela versus Tigray region for severely stunted relative to moderately and not stunted. Thus, exp(-1.1241) = 0.3249 means Gambela region had lower odds of stunting than Tigray region. Exp (-1.1241+0.4278) = 0.4984, the odds of severe stunting of those children from Gambella region was 0.4984 times odds of severely stunted from Tigray region. With respect to wealth index, proportional odds were assumed. The estimated log odds of severe stunting for children from poorest and richest households were 0.2791 and -0.2821 respectively compared to children from middle wealth households. This interpretation also holds for moderate stunting category. With respect to preceding birth interval, the estimated log odds of severe and moderate stunting category relative to normal category for children who had <24 and 48+ months preceding birth interval were 0.3836 and -0.2494 respectively compared to children who had preceding birth interval between 24 and 47 months. The estimated log odds of stunting relative to both moderate and not stunted category for children who had who had <24 and 48+ months preceding birth interval were 0.3836+0.1556 and -0.2494-0.0802 respectively compared to children who had preceding birth interval between 24 and 47 months. The result also suggest that a unit month increase in child age had positive effect, estimated log odds ratio of severe and moderate stunting relative to normal category was 0.0217, and 0.0217-0.0063 estimated log odds being severely stunted relative to both moderate and normal category. The proportional odds were also assumed for education level of mother. The estimated log odd of being severely stunted for children from mothers with secondary and above education level was -0.8989 compared to children from mothers with primary education only. This interpretation also holds for moderate stunting.

Table 4.7 Parameter Estimates under PPOM for stunting

Analysis of GEE Parameter Estimates Empirical Standard Error Estimates			
Variable	Parameter	Estimate (s.e)	P-value
Intercept	$\hat{\alpha}_1$	-0.7908 (0.1509)	<.0001
	$\hat{\alpha}_2$	-1.1291 (0.1319)	<.0001
Region: Affar	$\hat{\beta}_1$	-0.4993 (0.1498)	0.0009
Amhara	$\hat{\beta}_2$	-0.2434 (0.1447)	0.0926
Oromiya	$\hat{\beta}_3$	-0.4617 (0.1376)	0.0008
Somali	$\hat{\beta}_4$	-0.9397 (0.1537)	<.0001
Ben-Gumuz	$\hat{\beta}_5$	-0.6140 (0.1536)	<.0001
SNNP	$\hat{\beta}_6$	-0.3793 (0.1361)	0.0053
Gambela	$\hat{\beta}_7$	-1.1241 (0.1697)	<.0001
Harari	$\hat{\beta}_8$	-0.6716 (0.1752)	0.0001
Addis Ababa	$\hat{\beta}_9$	-0.4902 (0.2338)	0.0360
Dire Dawa	$\hat{\beta}_{10}$	-0.7090 (0.1611)	<.0001
Wealth Index: Poorest	$\hat{\beta}_{11}$	0.2791 (0.1004)	0.0055
Poorer	$\hat{\beta}_{12}$	0.1173 (0.1071)	0.2735
Richest	$\hat{\beta}_{13}$	-0.2821 (0.1339)	0.0351
Richer	$\hat{\beta}_{14}$	-0.0681 (0.1212)	0.5740
Preceding birth interval: 48+	$\hat{\beta}_{15}$	-0.2494 (0.0882)	0.0047
<24	$\hat{\beta}_{16}$	0.3836 (0.0896)	<.0001
First birth	$\hat{\beta}_{17}$	0.0033 (0.0973)	0.9727
Age in months	$\hat{\beta}_{18}$	0.0217 (0.0018)	<.0001
Education level of mother: No Educ.	$\hat{\beta}_{19}$	0.0123(0.0806)	0.8784
Secondary and Above	$\hat{\beta}_{20}$	-0.8989 (0.1983)	<.0001
Interaction: logtype3* Affar	$\hat{\gamma}_{2,1}$	0.6777 (0.1380)	<.0001
Logtype3*Amhara	$\hat{\gamma}_{2,2}$	-0.1549 (0.1672)	0.3541
Logtype3*Oromiya	$\hat{\gamma}_{2,3}$	0.3032 (0.1460)	0.0378
Logtype3*Somali	$\hat{\gamma}_{2,4}$	0.3971 (0.1552)	0.0105
Logtype3*Ben-Gumuz	$\hat{\gamma}_{2,5}$	0.5371 (0.1542)	0.0005
Logtype3*SNNP	$\hat{\gamma}_{2,6}$	0.4023 (0.1446)	0.0054
Logtype3*Gambela	$\hat{\gamma}_{2,7}$	0.4278 (0.1761)	0.0151
Logtype3*Harari	$\hat{\gamma}_{2,8}$	0.4369 (0.1815)	0.0161
Logtype3*Addis Ababa	$\hat{\gamma}_{2,9}$	-0.6017 (0.3520)	0.0874
Logtype3*Dire Dawa	$\hat{\gamma}_{2,10}$	0.5061 (0.1623)	0.0018
Logtype3*48+	$\hat{\gamma}_{2,15}$	-0.0802 (0.0955)	0.4009
Logtype3*<24	$\hat{\gamma}_{2,16}$	0.1556 (0.0761)	0.0408
Logtype3*first birth	$\hat{\gamma}_{2,17}$	-0.1181 (0.0971)	0.2240
Age in months* logtype3	$\gamma_{3,18}$	-0.0063 (0.0017)	0.0002

4.3. Model Diagnostic Results

After model fitting, the next in model building is to perform analysis of residuals and diagnostics to study influence of observations and taking appropriate remedial measures. A failure to detect outliers and hence influential observations can have severe distortion on the validity of the inferences drawn from a model. It would be reasonable to use diagnostics to check if the model is adequate or not.

Cook"s distance is proposed to measure the effect of excluding any specific observation observation on the set of parameter estimates. Cook (1977) gave the value of D, D>1 identifies cases that might be influential. From individual observation and cluster Cook"s distance plot (Appendix 10), there were no large of Cook"s distance ($D_i > 1$) for both individual observations and clusters. This means that there were no influential cases an effect on the model. Thus we can say that both models were not distorted.

4.4. Discussion

For stunting as response variable, both marginal models led to the same conclusion that region, wealth index of household, previous birth interval, education level of mother and child age in months were significantly related to stunting. Affar, SNNP and Tigray regions were associated with high probability of stunting. For previous birth interval, children who had below 24 months birth interval had higher chance of stunting. With respect to household wealth index, children who belong to the poorest households had higher probability of stunting than children who belong to middle wealth indexed households. Age was positively associated with stunting. Increase in age was associated to more possibility of stunting. Moreover, education of mother had negatively related with stunting. That is, children whose mothers had secondary and above educational status had lower possibility of stunting than those belong to mother with lower educational level.

For wasting as response, region, sex, age of child in month(s), education level of mother and current marital status of mother were found to be significantly related to wasting. Affar, Gambela, Benishabgul-Gumuz and Somali regions were associated with high probability of wasting. Educational level of mother was found to be negatively associated with wasting. That is, children from mothers with no education had higher probability of wasting than children from mothers with primary and above educational level. Opposite to stunting, age of child was negatively associated with wasting. That implies as age increases the likelihood of children being wasted decreases and vice versa for stunting. With respect to mothers marital status (single hood), children whose mothers were married (married formally or living with partner) had higher chance of wasting than children whose mothers were single (never married, divorced or widowed). This is in line with stunting response variable.

From proportional odds model, we concluded that sex (male) was associated with decreasing risk of wasting (not severe) while non-education of mother and older children were associated with increasing risk of wasting. Affar and Somali regions were associated with sever wasting.

From partial proportional odds model, the interaction terms (increments to the main effects) between newly created responses (logtype) and two explanatory variables wealth index and education level of mother were not significant, hence partially proportional odds model was assumed to these two variables.

Additionally, the two-level alternating regression indicated high positive association (0.8522, P-value=0.0003) between any two pairs of responses from the same households for wasting response and small positive (0.0104) between any two pairs of responses from the same households for stunting response. This implies high positive association between children within household‟s in terms of wasting and small positive association in terms of stunting.

Finally our findings were compared with previous researches done in the area. Stunting and wasting were more prevalent to boys than girls (Salah E.O. Mahgoub *et al.*, 2006, Mandefro *et.al.*, 2015). The result of our study in line with the wasting case but, there was no significant difference between male and female children in terms risk of stunting. A cumulative indicator of growth retardation (stunting) in children was positively associated with age (Anderson, 1995 as cited in Aschalew, 2000). Local and regional studies in Ethiopia have also shown an increase in malnutrition with increase in age of the child (Yimer, 2000; Genebo *et al.*, 1999; Samson and Lakech, 2000; Dereje and Ayele, 2015). This agrees with the result we found for risk of stunting. Study conducted by USAID on the effects of preceding birth Intervals on neonatal, infant, and under-5-years mortality and nutritional status in developing countries indicated that the relationship between the preceding birth-to-pregnancy interval and under-five mortality was highly significant (Macro International Inc, 2008). This also matched with our result, preceding birth interval was highly associated with child stunting. Economic status of the household was found to be strongly associated with chronic malnutrition (Yimer, 2000). This was in line with our result that, children from wealthier household had lower risk of stunting. On studies about mothers‟ marital status and under-five child nutrition, findings of a local study revealed that child's malnutrition was significantly associated with marital status. It was found out that under-five child malnutrition was higher among unmarried rural and divorced/separated women compared to married ones (Teller & Yimer, 2000). Contrary to the above, a study in Tanzania revealed that mothers who are married were more likely to have undernourished children unlike those who were unmarried perhaps because of the cost of maintaining families hence sometimes these families fail to produce nutritious supplements to the under-five children (Nyaruhucha *et al.,* 2006). Result from our study agrees with the second, that under-five children wasting were higher among married than single (unmarried, divorced or separated).

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

For this thesis work we used the 2014 mini demographic and health survey data to identify risk factors associated with under-five children malnutrition in Ethiopia. Stunting and wasting were considered as indicators of malnutrition. The first indicator (stunting) is a long term malnourishment effect indicator while the second (wasting) is a short term malnourishment effect indicator. These two indicators might be differently distributed within as well as across households, as they indicate different mechanism by which such nutritional deficits are acquired.

The findings of this study demonstrated that the prevalence of under-five child malnutrition in Ethiopia is still high, as clearly shown by two indicators: stunting and wasting. The result of this study showed that risk factors for child malnutrition were mostly socio-economic, demographic and maternal related.

The major risk factors for stunting were region, mother‟s education level, wealth index of household, preceding birth interval and age of child in months. Mother‟s education level, wealth index of household and preceding birth interval had negative effects on stunting. That is, children who belong to mothers with secondary and above education level were less likely to be stunted than children who belong to mothers with educated primary education and less education. In addition, household wealth had very significant impact on child stunting, children who belong to wealthier households had less chance of stunting. Children who with wider preceding birth interval had less chance of stunting. Age of child in months had positive effect on stunting that implies as age increases, the risk of stunting also increases. There is also a significant regional difference in terms of stunting. Children from regions, like Affar and SNNP have more chance of being stunted as compared to Tigray region.

For the other important indicator, wasting status, region, mother‟s education level, mother‟s current marital status, sex and age of child in months were major risk factors. Education level of mother had negative effect on child wasting. That implies children from uneducated mothers had higher chance of being wasted than children who belong to mothers educated to primary and above. With respect to age, as age of child increases, the likelihood of being wasted decreases, but the likelihood of being severely wasted increases. Male children had higher chance of wasting than females, but no significant difference was observed in terms of severity of wasting. Significant regional differences were observed in terms of wasting. Children from Affar and Somali regions had more chance of being wasted compared to Tigray region. The probability of severe wasting was also higher in these two regions.

5.2. Recommendations

Based on the significant variables, wealth index and previous birth interval, for stunting and education level of mother for both stunting and wasting:

- It would be important for the government and other stakeholders to improve mothers" formal education as well as awareness on birth spacing (or family planning).
- It is also recommend that improving the economic status of the population at household level in the long term as well as nutritional programs related to food insecurity.
- Additionally, it was observed that the risk of being stunted or wasted depends on age, sex and regions. However, it is worth noting that the probability of being stunted or wasted could also be associated with other factors such as breast feeding duration, status of diarrhea, maternal health and nutrient intake. Data collection of such factors is recommended for future studies.
- For wasting status, under two-level alternating logistic regression indicated strong association between two pairs of responses from the same household. For household based studies involving more than one child from the household, it is to be recommended to consider appropriate modeling to account for within household correlations.

5.3. Scope and limitation of the study

This study uses secondary data collected by Central Statistical Agency (CSA), i.e., the Ethiopian Mini demographic and Health Survey of the year 2014 (EMDHS, 2014). The study uses information on under-five children in Ethiopia who born in five years preceding the survey. Like any other source of data, the EMDHS 2014 has its own limitations. A major limitation of the data is that some important potential predictors to child malnutrition, for example, child weight at birth, breast feeding duration, status of diarrhea, genetic factors and maternal health like Body Mass Index of mother at child birth have not been covered.

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APPENDIXES

Appendix 1. Description and catagories of explanatory variables

No.	Variable	Categories
1	Region	1=Tigray 2= Affar 3=Amhara 4= Oromiya 5= Somali 6= Benishangul-Gumuz 7=SNNP 8=Gambela 9=Harari 10=Addis Ababa 11=Dire Dawa
2	Urban-Rural residence	1=Urban 2=Rural
3	Sex of a child	1=Male 2=Female
4	Age of child in month(s)	In continuous scale
5	Birth order	1=first 2=2-3 3=4-5 4=6+
6	Preceding birth interval	1=First 2=" <24", 3=24-47 4=48+
7	Household economic status/wealth index	1=Poorest 2=Poor 3=Middle 4=Rich 5=Richest
8	Household size	Continuous variable
9	Source of drinking water	0=Non-improved source 1= Improved source 3= Others
10	Mother‟s age at first child birth	In continuous scale
11	Marital status of mother	1=Married (formally married, living with partner)

		2=Single(never married, widowed, divorced or separated)
12	Education of mother	0=No education 1=Primary 2=Secondary and Above secondary

Appendix 2. Model information for responses

Information	Response	
	Stunting	Wasting
Number of observations read	4893	4893
Number of observations used	4487	4495
Sum of weights	4471.205	4475.683
Number of events	1692	601
Number of trials	4487	4495
Missing Values	406	398
Number of clusters	3406	3406
Cluster with missing values	343	335
Correlation matrix dimension	4	4
Maximum cluster size	4	4
Minimum cluster size	1	1

Appendix 3. Associations of each covariate with stunting from univariate covariate score statistics at 20% level of significance for type3 GEE analysis.

Variable	DF	Chi-square	Pr>Chisq
Region	10	94.83	<0.0001
Urban-Rural residence	1	22.07	<0.0001
Sex	1	0.53	0.4667
Wealth-Index	4	34.71	<0.0001
Educ-Level	2	30.30	<0.0001
Birth order	3	12.35	0.0063
Preceding Birth-Interval	3	32.97	<0.0001
Current marital status	1	0.40	0.5250
HHsize	1	0.85	0.3552
M other‟s age-at-first birth	1	9.14	0.0025
Age-in months	1	85.33	<0.0001
Water-Source	2	4.54	0.1033

Appendix 4. Associations of each covariate with wasting from univariate covariate score statistics at 20% level of significance for type3 GEE analysis.

Variable	DF	Chi-square	Pr>Chisq
Region	10	129.88	<0.0001
Urban-Rural	1	0.02	0.8988
Sex	1	5.11	0.0238
Wealth-Index	4	3.85	0.4263
Educ-Level	2	17.04	0.0002
Birth order	3	5.80	0.1215
Preceding Birth-Interval	3	2.76	0.4301
Current marital status	1	5.41	0.0200
HHsize	1	1.19	0.2746
Mother‟s age-at-first birth	1	0.01	0.9247
Age-in months	1	13.90	0.0002
Water-Source	2	3.98	0.1368

Appendix 5. Quasi-information Criteria for the final mean structure

Responses	Correlation Structure	QIC	QICu	Correlation (ρ)
Stunting status	Independence under GEE Exchangeable under GEE Exchangeable Under two-Leve1 ALR	5718.0520 5718.9891 5718.9296	5693.2794 5693.2766 5693.2717	- 0.0105 -
Wasting Status	Independence under GEE Exchangeable under GEE Exchangeable Under two-Level ALR Exchangeable Under three-Level ALR Independence under POM	2607.8046 2607.7595 2607.9296 5725.0931 3105.3558	2600.6799 2600.4540 2600.5753 5699.3886 3096.0986	- 0.05415 - -

Appendix 6A. Score statistics for type3 GEE for stunting response under two-level ALR

Source	DF	Chi-square	Pr>Chisq
Region	10	48.38	<.0001
Wealth index	4	14.05	0.0071
Preceding birth interval	3	15.32	0.0016
Child age in months	1	71.25	<.0001
Education level of Mother	2	8.51	0.0142

Appendix 6B: Empirical parameter estimates with their standard errors, Odds ratios with their standard errors and 95% confidence limits, for stunting response under two-level ALR model

Effect	Par	Est.(Es.e)	Exp(estimate) or Odds Ratio (s.e)	95% Confidence Limits for Odds Ratio
Region				
Addis Ababa	$\hat{\beta}_1$	-0.5241 (0.2606)	0.5921 (0.1543)	[0.3552, 0.9868]
Affar	$\hat{\beta}_2$	-0.2805 (0.1727)	0.7554 (0.1304)	[0.5385, 1.0596]
Abhara	$\hat{\beta}_3$	-0.2187 (0.1523)	0.8035 (0.1224)	[0.5962, 1.0830]
Ben-Gumuz	$\hat{\beta}_4$	-0.3443 (0.1653)	0.7087 (0.1171)	[0.5126, 0.9798]
Dire Dawa	$\hat{\beta}_5$	-0.8005 (0.1737)	0.4491 (0.0780)	[0.3195, 0.6312]
Gambela	$\hat{\beta}_6$	-1.0986 (0.2102)	0.3333 (0.0701)	[0.2208, 0.5033]
Harari	$\hat{\beta}_7$	-0.6212 (0.1883)	0.5373 (0.1012)	[0.3715, 0.7771]
Oromiya	$\hat{\beta}_8$	-0.4060 (0.1417)	0.6663 (0.0944)	[0.5047, 0.8796]
SNNP	$\hat{\beta}_9$	-0.2574 (0.1438)	0.7731 (0.1111)	[0.5832, 1.0247]
Somali	$\hat{\beta}_{10}$	-0.6932 (0.1792)	0.5000 (0.0896)	[0.3519, 0.7103]
Wealth Index: Poorer	$\hat{\beta}_{11}$	0.2785 (0.1479)	1.3212 (0.1955)	[0.9886, 1.7656]
Poorest	$\hat{\beta}_{12}$	0.4295 (0.1426)	1.5364 (0.2190)	[1.1619, 2.0317]
Richer	$\hat{\beta}_{13}$	0.0062 (0.1642)	1.0062 (0.1653)	[0.7293, 1.3884]
Richest	$\hat{\beta}_{14}$	-0.0669 (0.2005)	0.9353 (0.1875)	[0.6314, 1.3855]
Preceding birth interval: 48+				
<24	$\hat{\beta}_{15}$	-0.2508 (0.1283)	0.7782 (0.0998)	[0.6052, 1.0007]
First birth	$\hat{\beta}_{16}$	0.3793 (0.1545)	1.4613 (0.2258)	[1.0794, 1.9782]
	$\hat{\beta}_{17}$	-0.1803 (0.1453)	0.8351 (0.1213)	[0.6281, 1.1101]
Child age	$\hat{\beta}_{18}$	0.0245 (0.0028)	1.0248 (0.0029)	[0.0189, 0.0301]
M.Educ. level No educ.	$\hat{\beta}_{19}$	0.0560 (0.1137)	1.0576 (0.1203)	[0.8462, 1.3217]
Second.& above	$\hat{\beta}_{20}$	-0.7901 (0.3043)	0.4538 (0.1381)	[0.2499, 0.8239]

Appendix 7A. Score statistics for type3 GEE for wasting response under two-level ALR

Source	DF	Chi-square	Pr>Chisq
Region	10	90.91	<.0001
Age of child in months	1	15.12	0.0001
Sex	1	4.94	0.0262
Education level of Mother	2	11.83	0.0027
Current marital status of Mother	1	5.89	0.0152

Appendix 7B: Empirical parameter estimates with their standard errors, Odds ratios with their standard errors and 95% confidence limits, for wasting response under two-level ALR model

Effect	Par	Est.(s.e,)	Exp(estimate) or Odds Ratio (s.e)	95% Confidence Limits for Odds Ratio
Region				
Addis Ababa	$\hat{\beta}_1$	-1.4588 (0.4762)	0.2325 (0.1107)	[0.0914, 0.5912]
Affar	$\hat{\beta}_2$	0.4995 (0.2020)	1.6478 (0.3362)	[1.1047, 2.4580]
Abhara	$\hat{\beta}_3$	-0.4727 (0.2272)	0.6233 (0.1417)	[0.3993, 0.9731]
Ben-Gumuz	$\hat{\beta}_4$	0.1099 (0.2187)	1.1162 (0.2441)	[0.7271, 1.7136]
Dire Dawa	$\hat{\beta}_5$	-2018 (0.2341)	0.8173 (0.1913)	[0.5166, 1.2930]
Gambela	$\hat{\beta}_6$	0.1023 (0.2491)	1.1077 (0.2760)	[0.6798, 1.8050]
Harari	$\hat{\beta}_7$	-0.9858 (0.3060)	0.3731 (0.1142)	[0.2048, 0.6797]
Oromiya	$\hat{\beta}_8$	-0.6647 (0.2229)	0.5144 (0.1152)	[0.3317, 0.7979]
SNNP	$\hat{\beta}_9$	-0.7600 (0.2242)	0.4677 (0.1048)	[0.3014, 0.7257]
Somali	$\hat{\beta}_{10}$	0.6880 (0.2021)	1.9897 (0.4021)	[1.3390, 2.9565]
Sex: Male	$\hat{\beta}_{11}$	0.3483 (0.1553,)	1.4166 (0.2200)	[1.0449, 1.9206]
M.Educ. level:No educ.	$\hat{\beta}_{12}$	0.6553 (0.2081)	1.9257 (0.4008)	[1.2806, 2.8958]
Second.& above	$\hat{\beta}_{13}$	0.1288 (0.4080)	1.1375 (0.4641)	[0.5112, 2.5308]
Child age	$\hat{\beta}_{14}$	-0.0185 (0.0046)	0.9817 (0.0045)	[0.9729, 0.9905]
Current marital status				
Married	$\hat{\beta}_{15}$	0.6512 (0.3098)	1.9179 (0.5942)	[1.0450, 3.5200]

Appendix 8A. Score statistics for type3 GEE for wasting response under POM

Source	DF	Chi-square	Pr>Chisq
Region	10	103.97	<.0001
Age of child in months	1	12.86	0.0003
Sex	1	0.05	0.8228
Education level of Mother	2	7.77	0.0206
Current marital status of Mother	1	6.54	0.0106

Appendix 8B: Empirical parameter estimates with their standard errors, Odds ratios with their standard errors and 95% confidence limits, for wasting response under POM

Effect	Par.	Estimate(s.e)	Exp(estimate) or Odds Ratio (s.e)	95% Confidence Limits for Odds Ratio
Region :				
Addis Ababa	$\hat{\beta}_1$	-1.4846(0.4770)	0.2266 (0.1081)	[0.0890, 0.5771]
Affar	$\hat{\beta}_2$	0.5455(0.2033)	1.7255 (0.3508)	[1.1583, 2.5703]
Amhara	$\hat{\beta}_3$	-0.5520(0.2267)	0.5758 (0.1305)	[0.3692, 0.8979]
Ben-Gumuz	$\hat{\beta}_4$	0.0855(0.2195)	1.0893 (0.2391)	[0.7084, 1.6750]
Dire Dawa	$\hat{\beta}_5$	-0.2329(0.2393)	0.7923 (0.1896)	[0.4956, 1.2665]
Gambela	$\hat{\beta}_6$	-0.0730(0.2581)	0.9296 (0.2399)	[0.5606, 1.5416]
Harari	$\hat{\beta}_7$	-1.0826(0.3103)	0.3387 (0.1051)	[0.1844, 0.6223]
Oromiya	$\hat{\beta}_8$	-0.7935(0.2274)	0.4523 (0.1028)	[0.2896, 0.7062]
SNNP	$\hat{\beta}_9$	-0.8583(0.2268)	0.4239 (0.0961)	[0.2718, 0.6611]
Somali	$\hat{\beta}_{10}$	0.7350(0.2018)	2.0855 (0.4209)	[1.4043, 3.0973]
Sex : Male	$\hat{\beta}_{11}$	-0.0347(0.1549)	0.9658 (0.1496)	[0.7129, 1.3085]
Current marital status of mother :Married	$\hat{\beta}_{12}$	0.6511(0.3025)	1.9176(0.5801)	[1.0599, 3.4694]
Child age in months	$\hat{\beta}_{13}$	0.0171(0.0049)	1.0173 (0.0050)	[1.0076, 1.0270]
Mother‟s education level				
No education	$\hat{\beta}_{14}$	0.5350(0.2064)	1.7074 (0.3524)	[1.1393, 2.5588]
Secondary and Above	$\hat{\beta}_{15}$	0.2115(0.4104)	1.2356 (0.5071)	[0.5527, 2.7621]

Appendix 9. Model fit statistics for baseline category logit

Criterion	Intercept only	Intercept and covariates
AIC SC -2 Log L	8464.990 8477.808 8460.990	8244.294 8513.294 8160.119

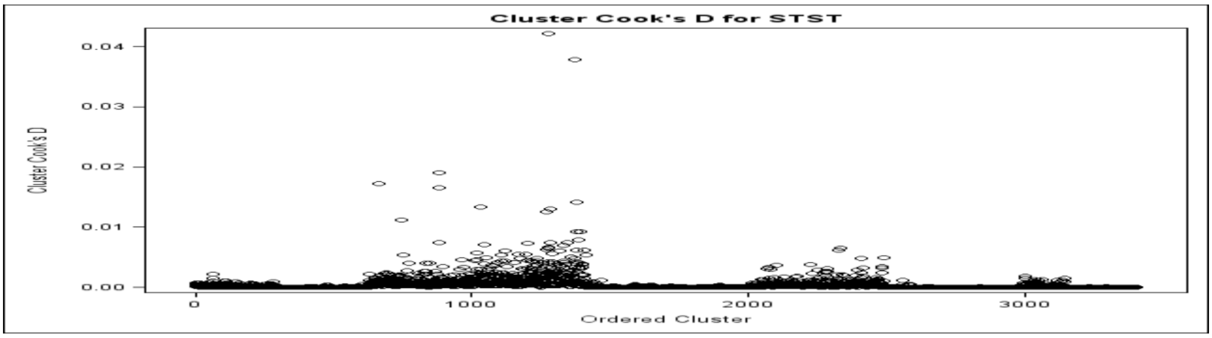
Testing Global Null Hypothesis: BETA=0			
Test	Ch-Square	DF	Pr> chisq
Lilelihood Ratio Score Wald	300.8716 285.6529 220.4797	40 40 40	<.0001 <.0001 <.0001
Type 3 analysis of Effects			
Effect	DF	Wald Chi-square	Pr>Chisq
Region	20	83.6704	<.0001
Wealth index	8	22.3670	0.0043
Preceding birth interval	6	27.4656	0.0001
Age of child	2	10.1455	0.0063
Education level of mother	4	11.1101	0.0254

Appendix 10 Baseline category logit for wasting response

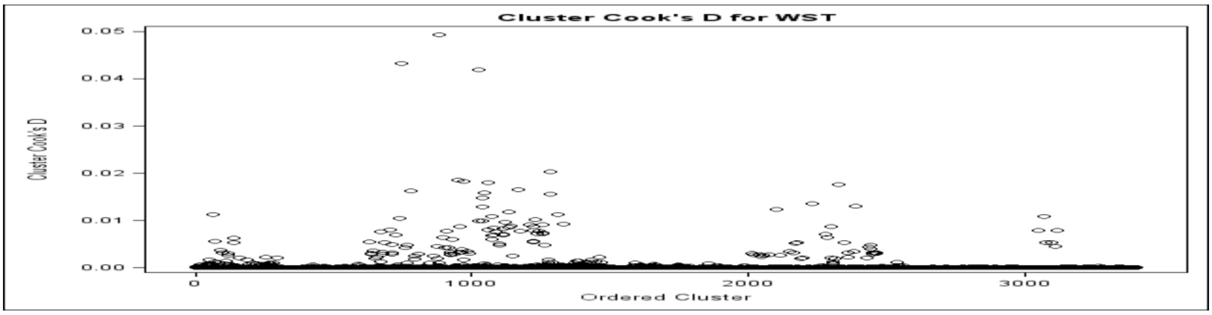
Logit(moderately stunted vs not stunted)			Logit(severely stunted vs not stunted)	
Effect	Par.	Est.(s.e)	Par.	Est.(s.e)
Intercept	$\hat{\alpha}_1$	-3.4143(0.4637)*	$\hat{\alpha}_2$	-5.5793(0.8498)*
Region : Affar	$\hat{\beta}_{1,2}$	0.5303(0.2510)*	$\hat{\beta}_{1,3}$	0.5573(0.3092)
Benishangul-Gumuz	$\hat{\beta}_{2,2}$	0.0831(0.2670)	$\hat{\beta}_{2,3}$	0.0708(0.3303)
SNNP	$\hat{\beta}_{3,2}$	-0.7289(0.2728)*	$\hat{\beta}_{3,3}$	-1.1265(0.3857)*
Somali	$\hat{\beta}_{4,2}$	0.6507(0.2472)*	$\hat{\beta}_{4,3}$	0.8165(0.2989)*
Oromiya	$\hat{\beta}_{5,2}$	-0.6312(0.2677)*	$\hat{\beta}_{5,3}$	-1.1263(0.3940)*
Dire Dawa	$\hat{\beta}_{6,2}$	-0.1676(0.2913)	$\hat{\beta}_{6,3}$	-0.3522(0.4004)
Harari	$\hat{\beta}_{7,2}$	-0.8247(0.3554)*	$\hat{\beta}_{7,3}$	-1.7437(0.6438)*
Addis Ababa	$\hat{\beta}_{8,2}$	-1.4916(0.5793)*	$\hat{\beta}_{8,3}$	-1.4671(0.8115)
Gambela	$\hat{\beta}_{9,2}$	0.0565(0.2936)	$\hat{\beta}_{9,3}$	-0.3284(0.4119)
Amhara	$\hat{\beta}_{10,2}$	-0.3878(0.2726)	$\hat{\beta}_{10,2}$	-0.8848(0.3899)*
Sex: Male	$\hat{\beta}_{11,2}$	-0.0459(0.1816)	$\hat{\beta}_{11,3}$	0.0008(0.2606)
Marital Status of Mother Married	$\hat{\beta}_{12,2}$	0.3963 (0.3290)	$\hat{\beta}_{12,3}$	1.7666 (0.6505)*
Age in moths	$\hat{\beta}_{13,2}$	0.0163 (0.0056)*	$\hat{\beta}_{13,3}$	0.0188 (0.00903)*
Educ.level of Mother :No educ. Secondary and above	$\hat{\beta}_{14,2}$ $\hat{\beta}_{15,2}$	0.4960 (0.2446)* 0.0928(0.4816)	$\hat{\beta}_{14,3}$ $\hat{\beta}_{15,3}$	0.6268 (0.3554) 0.4704 (0.7276)
*Significant with p-value<0.05				

Appendix 11. Diagnostics plot of ALR.

Appendix11A. Cluster Cook"s distance



STST=Stunting



WST= Wasting

Appendix 11B: Observation Cook"s Distance