ORDINAL LOGISTIC REGRESSION ANALYSIS FOR IDENTIFYING RISK FACTORS OF CHILD MALNUTRITION IN ETHIOPIA

By:

Woldemariam Erkalo

A Thesis Submitted to the School of Graduate Studies, College of Natural Sciences in Partial Fulfillment of the Requirement for the Degree of Master of Science in Biostatistics

October 2015

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As thesis research advisors, we herby certify that we have read the thesis prepared by Woldemariam Erkalo under our guidance, which is entitled "Ordinal Logistic Regression Analysis for Identifying Risk Factors of Child Malnutrition in Ethiopia", in its final form and have found that (1) its format, citations, and bibliographical style are consistent and acceptable and fulfill University and Department style requirements; (2) its illustrative materials including tables and figures are in place; and (3) the final manuscript is satisfactory to the graduate committee and is ready for submission to the University library.

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As the members of the board of examiners of MSc thesis open defense examination, we certify that we have read and evaluated the thesis and examined the candidate. Hence, we recommend that the thesis be accepted as it fulfills the requirements for the degree of Master of Science in Biostatistics.

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DEDICATION

This thesis is dedicated to my beloved uncle, Erjabo Gobena and his wife who have supported me all the way since the beginning of my studies. Also, this thesis is dedicated to the memory of my mother, Ayelech Burebo who passed away while I was ten years old.

ABSTRACT

Malnutrition is the most common health problem affecting both children and adults in Ethiopia. According to 2014 EDHS mini report nationally, 40 percent of children under age five are stunted, and 18 percent of children are severely stunted. In this thesis, partial proportional odds model would be used to identify the risk factors of malnutrition in children of Ethiopia. The data consisted of 7,738 children of aged 5 years or below. We considered the levels of stunting (malnutrition) as the outcome variable with four ordinal categories (not-stunted, mildly stunted, moderately stunted and severely stunted) as per the specification of WHO to define level of malnutrition. The objective of this study was to identify the risk factors of child malnutrition in Ethiopia using the 2011 EDHS data. To achieve the objective of this study descriptive statistics, chi-square test of association and partial proportional odds model and related tests were used for data analysis using socio-economic, demographic and health related variables as explanatory variables and level of stunting as the response variable. The result of the analysis revealed that the variables child's sex, child's sex, mother's education level, mother's body mass index, place of residence, region, wealth index, previous birth interval, birth order and the number of household members were found to be significant determinants of child malnutrition in Ethiopia and from the result it is revealed that children born with lower previous birth interval (less than 24 months) were more likely to be mildly, moderately and severely stunted than those born within higher birth interval. Children in households who had large number of members were found to be more likely of being mildly, moderately and severely stunted than those who were in households with small number of members. Children of rural Ethiopia were more likely of being mildly, moderately and severely stunted than children of urban Ethiopia. It is suggested that for reducing childhood malnutrition, due emphasis should be given in improving the knowledge and practice of parents on appropriate young child feeding practice and frequent growth monitoring together with appropriate and timely interventions.

Keywords: Ordinal logistic regression model, Proportional odds model, Partial Proportional Odds Model, Generalized Ordered Logit Model, Binary Logistic Regression Model, Anthropometric index, Height-for-age Z score, Child malnutrition, Stunting.

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ACRONYMS

AIC	Akaike's information criterion
BIC	Bayesian information criteria
BMI	Body mass index
COHA	Cost of hunger in Africa
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
EDHS	Ethiopian Demographic and Health Survey
FAO	Food and Agricultural Organization
FDRE	Federal Democratic Republic of Ethiopia
GLM	Generalized Linear Model
GOLOGIT2	Generalized ordered logit two
HAZ	Height-for-age Z score
HKI	Helen Keller International
LR	Likelihood ratio
MDG	Millennium development goal
ML	Maximum Likelihood
MOH	Ministry of Health
NCHS	National Center for Health Statistics
OLOGIT	Ordered logit
SD	Standard Deviation
SNNP	Southern Nation Nationalities and People
UNICEF	United Nations Children's Fund
USAID	United States Agency for International Development
WB	World Bank
WHO	World Health Organization
WMS	Welfare Monitoring Survey

1. INTRODUCTION

1.1. Background of the study

Malnutrition in the Ethiopian context has been described as a long-term year round phenomenon due to chronic inadequacies in food intake combined with high levels of illness (National Nutrition Policy-Draft, 2003). Malnutrition is the most common health problem affecting both children and adults in Ethiopia. Though the word “malnutrition” is associated with both under-nutrition and over-nutrition (Smith & Haddad, 2000), in this study it is meant to refer to under-nutrition.

Under-nutrition is malnutrition due to inadequate food consumption or poor absorption or biological use of nutrients consumed due to illness, disease, or nutrient imbalances. Over-nutrition simply refers to excess intake of macronutrients and micronutrients (HKI, 2001).

Global chronic under-nutrition in children is highly prevalent and remains a big challenge. The United Nations Food and Agriculture Organization estimates that about 805 million people out of 7.3 billion people in the world (one in nine) were suffering from chronic undernourishment in between 2012 and 2014. Almost all the hungry people, 791 million, live in developing countries, representing 13.5 percent, or one in eight, of the population of developing counties. There are 11 million people undernourished in developed countries (FAO, 2014). According to this report, 214 million (23.8%) of all the hungry people of the world are found in sub-Saharan African countries.

Africa has experienced the smallest relative decrease, with underweight prevalence of 17 percent in 2013, down from 23 percent in 1990; Asia reduced underweight prevalence during the same period from 32 percent to 18 percent (UNICEF, 2014).

Hunger and malnutrition are devastating problems, particularly for the poor and unprivileged countries like Ethiopia. About 29.9 percent of the total populations of Ethiopia (30.4% in rural and 25.7% in urban areas) are found to be under the poverty line. In addition 33.6

percent of the Ethiopian population are living below the food poverty line and cannot meet their daily minimum nutritional requirement of 2200 calories (MOFED, 2013).

The poor nutritional status of children continues to be a serious problem in Ethiopia. According to 2014 EDHS mini report nationally, 40 percent of children under age five are stunted, and 18 percent of children are severely stunted. The percentage of children stunted is higher in rural areas (42 percent) than in urban areas (24 percent). Stunting levels are above the national average in Affar (49 percent), Tigray (44 percent), SNNP (44 percent) and Amhara (42 percent), and relatively low in Gambela and Addis Ababa (22 and 23 percent, respectively). Twenty five percent of children under age five are underweight (have low weight for their age), and 7 percent are severely underweight. Rural children are more likely to be underweight (27 percent) than urban children (13 percent). Addis Ababa has the lowest proportion of underweight children, at 7 percent, while Affar has the highest prevalence of underweight children, at 46 percent (CSA, 2014).

Malnutrition among women is likely to have a major impact on their own health and on the health of their children. Besides her own health, a mother's nutritional status affects her capacity to successfully care for her children (Asfaw, 2003). Women in the reproductive age group (15-49 years) and children are most vulnerable to malnutrition due to low dietary intakes, inequitable distribution of food within the household, improper food storage and preparation, dietary taboos and infectious diseases (EDHS, 2011). Particularly for women, the high nutritional costs of pregnancy also contribute significantly to their poor nutritional status (Girma & Genebo, 2002).

Recent illnesses significantly contribute in precipitating malnutrition in marginally nourished children. Diarrhea exerts this influence by depleting the body of fluids. The traditional practice of withholding food from the child suffering from diarrhea diseases also plays an important role. Fever accelerates the onset of malnutrition by reducing food intake and increasing catabolic reactions in the organism (WHO, 1986). Studies in New-Guinea (Han-Am and Sleigh, 1995) and Ethiopia (Genebo *et. al.*, 1999; Gugsa, 1998) revealed that the nutritional status of children based on height-for-age is associated with the presence of recent symptom of illness, fever and diarrhea.

Diarrhea and other infectious diseases manifested in the form of fever affect both dietary intake and utilization, which may have a negative effect on improved child nutritional status. A study on children's nutritional status (Sommerfelt *et. al*., 1994) indicated that stunting was highest among children with recent diarrhea.

Since children are the economic assets to the world and their future development outcome can be influenced by their nutrition and health status, the mechanism and consequences of malnutrition problems need to be understood better. This is true in a country like Ethiopia where malnutrition is common. Therefore, there is a need to assess the factors associated with child malnutrition so that interventions can be planned to children to achieve growth and development. Thus, this study focused on socioeconomic, demographic, health and environmental determinants for prevalence of malnutrition and to rank the significant determinants based on the malnutrition levels defined as severely malnourished, moderately malnourished, mildly malnourished and not malnourished on children aged five years or below by using the ordinal logistic regression models so that, the outcomes of the findings can help in evidence-based decision to develop and control intervention strategies to improve the health status of the children.

1.2. Statement of the problem

Under-nutrition puts children at greater risk of dying from common infections, increases the frequency and severity of such infections, and contributes to delayed recovery. In addition, the interaction between under-nutrition and infection can create a potentially lethal cycle of worsening illness and deteriorating nutritional status. Poor nutrition in the first 1,000 days of a child's life can also lead to stunted growth, which is irreversible and associated with impaired cognitive ability and reduced school and work performance.

High malnutrition rates in Ethiopia pose a significant obstacle to achieve better child health outcomes. Based on the 2004 Welfare Monitoring Survey (WMS), out of all children aged 3 to 59 months, the prevalence of wasted, stunted and underweight (their Z score below -2SD) at country level are reported as 8.3 percent, 46.9 percent and 37.1 percent, respectively.

Few studies were conducted with the objective of identifying the determinants of malnutrition by comparing the health status of the children as undernourished and not undernourished. Thus, this study classifies malnutrition in to four categories according to severity of malnutrition as none, mildly, moderately and severely undernourished based on the specification of WHO to define level of malnutrition. Based on our classification of malnutrition of children, we would then calculate odds ratio and the predictive probability of being at higher level of malnutrition based on ordinal logistic regression models.

In particular, we like to answer the following research questions:

- Which predictors are the most determinant factors for malnutrition?
- What is the likelihood of being at higher level of malnutrition for children at a typical household?
- Does the likelihood of being at higher level of malnutrition vary across region of residence?

1.3. Objective of the study

1.3.1. General Objective

The general objective of this study is identifying risk factors of child malnutrition in Ethiopia.

1.3.2. Specific Objectives

The study specifically needs:

- To identify risk factors of child malnutrition in Ethiopia.
- To determine the likelihood of being at higher level of malnutrition for children at a typical household.
- To compare malnutrition status of children in rural and urban of Ethiopia.

1.4. Significance of the study

The findings from this research are hoped to be useful in many ways. The findings could be helpful for policy making, monitoring and evaluation activities of the government and different concerned agencies. Since the study will attempt to reveal the major responsible factors and their relative contribution to the malnutrition of children, the end user governmental and non-governmental organizations could take intervention measures and set appropriate plans to tackle the existing nutrition problems by identifying and giving priority for the very poor and vulnerable groups.

This study is expected to contribute its part by filling the information gap concerning nutritional status of children aged five and below in the country. Finally, the study could be used as a stepping stone for further studies.

1.5. Limitations of the Study

Although risk factors of malnutrition are many as indicated by different studies in different countries by including different socioeconomic, political, cultural, demographic, physiological, biological, reproductive health rights, family planning policies/programs etc., this study is undertaken to explore a few of the socio-economic, demographic, health and environmental determinants of malnutrition in Ethiopia. And also the data we used for this study is EDHS 2011. In case of this, the results may not necessarily reflect the current situation of Ethiopia.

1.6. Organization of the Study

This study contains five chapters. The first chapter presents the general background of the study, statement of the problem, objectives, its significances and limitations. Chapter two deals with the review of literatures on malnutrition in Ethiopia and the rest of the world, whereas chapter three specifies the data and methodology of the study such as sources of data and variables to be included in the study with their coding and description. Methods of data analysis are also described in this chapter. Chapter four reports results from the statistical data analysis. Finally, the last chapter, chapter five provides discussions, conclusions and policy recommendations based on the findings of the study.

2. LITERATURE REVIEW

2.1. General Concepts and Definitions

Malnutrition refers to deficiencies, excesses or imbalances in intake of energy, protein and/or other nutrients. Contrary to common usage, the term 'malnutrition' correctly includes both under-nutrition and over-nutrition. *Under-nutrition* is the result of food intake that is continuously insufficient to meet dietary energy requirements, poor absorption and/or poor biological use of nutrients consumed. This usually results in loss of body weight. *Over-nutrition* refers to a chronic condition where intake of food is in excess of dietary energy requirements, resulting in overweight and/or obesity (WHO, 2005).

The word “*Anthropometry*” comes from two Greek words; *Anthropo* to mean Human and *Metry/metron* to mean measurement. It is generally meant to represent the measure of people’s growth indicators such as weights and heights (related to their age and sex). It is used for growth assessment and is a single measurement that best defines the health/nutritional status of a child (Blossner and De Onis, 2005). According to this measure, the nutritional/health status of children is determined by comparing growth indicators with the distribution of the same indicators for “healthy” (as reference group), and identifying “extreme” or “abnormal” departures from this distribution. The international reference standard that is most commonly used (and recommended by the WHO) is that of the data on the weights and heights of a statistically valid population (US National Center for Health Statistics (NCHS)) of healthy infants and children in the US.

There are three ways of expressing these comparisons: Z-score (standard deviation (SD) score), percent of median, and percentile. But the interest here is on the SD score (Z-score) and it is defined as the difference between the value for an individual and the median value of the reference population for the same age, height, or weight divided by the standard deviation of the reference population. Based on this comparison method, the three most commonly used anthropometric indicators for infants and children are *stunting*, *wasting* and *underweight*.

Wasting

Wasting indicates body mass in relation to body length, without making use of age data and represents a short-term indicator useful to monitor short-term changes in nutritional status. Children whose *weight-for-height*'s z-scores are below minus two standard deviations (z-scores < -2*SD*) from the median of the reference population are considered wasted (i.e. too thin for their height) which implies that they are acutely undernourished otherwise they are not wasted whilst those with a z-score below -3 are considered severely wasted. Wasting is usually caused by a recent nutritional deficiency and may manifest significant seasonal variations according to changes in the availability of food or disease prevalence (Cogill, 2001).

Stunting

Stunting is an indicator of linear growth retardation relatively uncommon in the first few months of life. However it becomes more common as children gets older. Children with *height-for-age* z-scores below minus two standard deviations from the median of the reference population are considered short for their age or stunted. Furthermore, children with z-scores below minus three standard deviations from the median of the reference population are considered to be severely stunted, while children with z-scores between minus three and minus two standard deviations are known to be moderately stunted. It gives information about chronic malnutrition or 'stunting' which reflects the accumulation of past outcomes (Cogill, 2001).

Underweight

Underweight is a composite index of stunting and wasting. This means children may be underweight if they are either stunted or wasted, or both. In a similar manner to the two previous anthropometric incidences, children may be underweight when their z-score is below minus two standard deviations and they are severely or moderately so if their z-score is lower than two standard deviations.

The cut-off point to define abnormal anthropometry with Z- scores is -2 standard deviations. A more general rule of thumb for evaluating anthropometric Z-scores has been developed by W.H.O, with a score of less than -3 indicating "severe" malnutrition, between -3 and -2.01

"moderate" malnutrition, -2 to -1.01 indicating "mild" malnutrition and -1 and above considered normal.

2.2. Factors associated with Children's Malnutrition

Important determinants of under-nutrition include the education, income, and nutritional situation of the parents, access to clean water and sanitation, and access to primary health care and sex and age of child (MoFED, 1999; Sahn and Stifel, 2003; Christiaensen and Alderman, 2001); Girma, W., & Genebo, T., 2002; Yimer, 2000; Dejen, 2008). Factors that are contributing to malnutrition may differ among regions, communities and over time. Identifying the underlying causes of malnutrition in a particular locality is important to solve the nutritional problems.

Various studies have been made and conclusions were reached by different scholars in the past regarding predictors of health and nutritional status. Survey of available literature indicated that factors like knowledge of health practices and caring level, educational level of parents, access to or interactions of age of the child have strong effect on household and community variables in which the child grows up.

Approximately 10 percent of children born in Ethiopia die before their first birthday and 17 percent will die before their fifth birthday (CSA and ORC Macro, 2001). According to formulas developed by Pelletier *et al*. (1994), 57 percent of under-five mortality in Ethiopia is related to severe and mild to moderate malnutrition (ORC Macro, 2001). The consequences of malnutrition in children also include poor physical development and limited intellectual abilities that diminish their working capacity during adulthood. Some of the socioeconomic, demographic, and health and environmental factors explaining child nutrition according to studies done in different places are reviewed below.

2.2.1. Socioeconomic Characteristics

Socioeconomic characteristics such as household economic status, maternal socioeconomic characteristics (mothers' education, mothers' employment status and their household status relative to men), household size, etc are important in child health outcomes. The economic status of a household where a child lives has been identified as one of the key determinants of child malnutrition status. Smith *et al*. (2005) using logistic analysis showed that household economic status significantly affects access to food (a necessary condition for food security). It also dictates possession and utilization of child care resources on a sustainable basis.

Most of the studies in Ethiopia including Christiaensen & Alderman (2001), SCUK (2002), Girma, W., & Genebo, T. (2002), Bilisuma (2004), Mekonnen *et al*. (2005b), Asfaw (1995), and Silva (2005) found household wealth/income as an important determinant of child nutritional/health status. Because, according to SCUK (2002), for example, better off households have better access to food and higher cash incomes than poor households, allowing them a better quality diet, better access to medical care and more money to spend on essential non-food items such as schooling, clothing and hygiene products. For example, using data from the 1986 Brazilian Demographic and Health Survey, Thomas et al. (1990b) found total income to have a positive and significant effect on child height in both urban and rural sectors and the effect is much larger in magnitude in the rural sector. On the contrary, Kello (1996) was unable to establish a significant relationship between poverty (income) and nutritional status of children in urban Ethiopia.

Using data from four regions of Brazil, Thomas *et al*. (1990b) attempted to estimate the impact of household characteristics on child height and survival. Applying the quasi-maximum likelihood estimation techniques for the binomial model and augmenting income by logarithm of household expenditure and including unearned income, its square and a set of month dummies, income appears to have no effect on child height in all four of the regions.

Consistently, as food availability is one of household resources, both Alderman (1990) and Maxwell *et al*. (2000) did not found it to be a significant factor; rather care and health were found as important inputs. Moreover, Maxwell *et al*. (2000) did not find higher incomes leading to significantly improved care practices and behaviors. In many developing countries particularly in Africa, tradition has laid the responsibility of child care on women which begins at conception and continues until infancy, teenage and adulthood (Oyekale, 2000). The implication is that women are key players in the growth and development of a child. In enhancing the quality of care and nutritional status of children, the role of mothers' education is widely recognized. Education improves the ability of mothers to implement simple health knowledge and facilitates their capacity to manipulate their environment including interaction with medical personnel. Furthermore, educated women have greater control over health choices for their children.

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

Using household data from three consecutive welfare monitoring surveys of Ethiopia over the period 1996-1998, Christiaensen and Alderman (2001) using linear regression analysis found that both female and male adult (parental) education has a strong positive and statistically significant effect on the child's nutritional status, and the effect of female education is about twice as large as that of male education. This study also shows that maternal nutritional knowledge is key determinants of chronic child malnutrition in Ethiopia. Other studies also report similar results from female's education. For example, using Woreda level data on children under age of 24 months, SCUK(2002) confirmed that children whose mothers attended school were less likely to be malnourished than the children of uneducated mothers.

Nevertheless, there are some studies which could not find a significant relationship between female's education and child nutritional status (e.g. Sentayehu, 1994). Various reasons could be attached to this result. According to SCUK (2002), for instance, this could be because, although educating mothers (and other care givers) will undoubtedly lead to an improvement in the way some young children are cared for, many mothers will never be able to act on their new knowledge because they are simply poor. This means that poverty could cause bottlenecks, not allowing other public policies to influence child health (Attansio *et al*., 2004).

Conceptually, the status of women is multidimensional (Mason, 1986). Smith *et al*. (2005) define women's status as the relative power of women in household, communities, and nations they live in. The status of women is an important determinant of two resources for care: their physical and mental health status, and control over household resources (Smith and Haddad, 2000). The physical conditions of women strongly affect the quality of care they provide to their children even before they are born. Poor physical and mental status of women constrains the quality of care rendered to their children which includes the quality of breast feeding. On the other hand, women's control over resources promotes household food security and nutrition because women show a tendency to spend resources on nutrition inputs such as food (Haddad, 1999). Improved control over resources gives women a better opportunity to provide good care which includes better food preparation and storage practices, hygienic practices, improved care for children during illness (including diagnosis of illness, care seeking and home treatment), and motivation for supporting child development.

The effect of maternal employment on the well being of children has been controversial and it appears difficult to determine the net effect. Crepinsek and Burstein (2004) using logistic regression analysis underscored that employment of mothers can have both positive and negative implication on children's dietary intake. On the one hand, employment of mothers adds to family income and this may help to ensure stable supply of quality food through increased expenditure.

On the other hand, employment status of women (care giver) is found to be insignificant in some studies (see Mekonnen *et al*., 2005a; Bilisuma, 2004; Girma, W. & Genebo, T., 2002). It is argued that this could be because the time allocated to earning income may be at the expense of time spent in feeding and caring for children, and thus the net effect of these two opposing effects makes employment status of the caregiver an insignificant variable. The presence of other adults in a household, household's income; net of a mother's earning and age of children are likely to affect the net effect of maternal employment on children nutrition/health status (Crepinsek and Burstein, 2004).

Household size is also important in the analysis of child nutritional and health status for it has direct implications on household resources. Senauer and Garcia (1991) using linear regression analysis found household size to have a significant positive impact on height of children. The authors argue that this could be because household full income is a function of wage rates and the number of economically active family members, and thus this variable may be reflecting a full income effect. On the other hand, as household size gets larger there is a big chance of having economically inactive members in the household and this leads to an adverse impact on the available resources and thereby on child nutrition outcomes. For example, according to Alderman (1990) in Ghana, those children in households with a full sibling less than 2 years of age were found to be significantly shorter than cohorts without such a sibling implying the influence of prenatal conditions or competition for resources.

2.2.2. Demographic Characteristics

Most studies report that demographic characteristics such as age, sex and birth order and previous birth interval are important determinants of malnutrition. Studies show that while the main causes of malnutrition appear to change with age of children, in most cases older children are found to be associated with increased malnutrition. For example, in Ethiopia report on health and poverty by WB and MOH (2005) using descriptive statistical method show that older children have a higher likelihood of being underweight and stunted relative to children who are less than a year old. And also children's nutritional status is more sensitive for some factors at specific age. For example, during the first 4 or 6 months feeding practices and mother's ability to care for the child are the main determinants of child growth.

After the age at which the child starts supplementary feeding (from age 4 to 6 months) through 2 years of age the major influences are exposure to infectious diseases. After 2 years of age household food securities have major effect (UN, 1985). Cumulative indicators of growth retardation, such as stunting and underweight, are positively related to age, with the lower values achieved by less than 6 months age groups (Pelletier, 1991). On the contrary, Christiaensen and Alderman's (2001) study using logistic regression analysis found that a child's standardized height deteriorates up to the age of three, and slightly improves afterwards.

At country level, all the four welfare monitoring surveys from 1996-2004 using descriptive statistics have revealed that boys are more vulnerable to malnutrition than girls with respect to the three indices (wasting, stunting, and underweight). Similar results are also reported from some case studies and official surveys (Sentayehu, 1994; Christiaensen and Alderman, 2001; Mekonnen *et al*. 2005a; Mekonnen *et al*. 2005b). Various reasons behind this gender differential are given in the literature. Mekonnen *et al.* (2005a), for example, argue that this could be due to genetic differences between male and female children and, due to girls' greater access to food through their gender-ascribed role in contributing to food preparation.

However, using the 2000 Ethiopia Demographic and Health Survey data, Silva (2005) did not find the coefficient on the child's gender to be significant in any of the regressions, suggesting there is no gender bias affecting the nutritional status of children in Ethiopia. Similarly, Bilisuma (2004), using probit model, could not find sex of a child to have a significant impact on the probability of being stunted. Finally, considering age and gender together, a relatively different result was reported by Asfaw (1995) using longitudinal analysis. Using data collected from four regions of rural Ethiopia, he studied how poverty affects the health status and the health care demand behavior of households. The finding is that instead of gender and age, relation to the head of the household is an important factor that affects the health status, demand for medical care, and provider choice of households. Since immediate family members are more likely to report illness, to get treatment, and more likely to visit modern health care providers especially private clinics than other family members.

In combination with other factors, high birth order and low birth intervals are reported to have their share in poor childhood nutrition/ health outcomes. According to the draft report on the health sector MDGs needs assessment (FDRE, 2004) and Girma, W. & Genebo, T. (2002) using descriptive and logistic regression analysis, respectively, demonstrated that high birth order and close spacing imply uninterrupted pregnancy and breast feeding and, this depletes women biologically and drains their nutritional resources. These lead to low birth weight which is a key factor in infant and under-five mortalities, death being more prevalent among smaller children. Close spacing may also have a health effect on the previous child, who may be prematurely weaned if the mother becomes pregnant again too early.

Using Young Lives data of children between the age of 6 and 18 months in Peruvian, Mekonnen *et al*. (2005a) did not find birth order to be significantly associated with any of the three indicators considered (wasting, stunting, and underweight) for the whole sample by using logistic regression. However, the results stratified by location show that birth order is associated with wasting and underweight for urban children, while the likelihood of being wasted decreases with higher birth order in rural areas.

On the other hand, unlike expectations, based on the National Rural Nutrition Survey of 1992 on Sidamo, Sentayehu (1994) by using linear regression analysis found positive sign of birth order on height-for-age and weight- for-age equation. The sign is unexpected because high birth order is expected to adversely affect the quantity and quality of resources that could be allocated to the children in the household.

Using data which came from four separate household surveys carried out in three rural provinces of the Philippines in 1983-84 over 800 households, Senauer and Garcia (1991) utilized Weighted Least Square and Fixed Effects models to see the determinants of nutritional and health status of children. In this study, higher birth order children were found to be suffering in terms of the long run health status (height-for-age). The authors argued that this could be presumably due to the increased burden on family resources.

2.2.3. Health and Environmental Characteristics

Health and environmental characteristics including illnesses, sanitation and water, toilet facilities and health care facilities at community as well as at household level is important for their direct and spillover effects on child health/ malnutrition.

Access to unsafe water and unsanitary disposal of wastes are regarded as the main causes of infectious diseases such as diarrhea and intestinal parasites (UNICEF cited in Smith *et al*, 2005). Where there is a better access to safe water and quality sanitation, the incidence of various illnesses will decline (Smith and Haddad, 2000). World Bank (2006) stated that improving access and quality of safe water not only reduces transmission of waterborne diseases but also saves women the extra time they spend on carrying water which can be allotted to child care and feeding or income generating activities.

Silva (2005) examined the impact of access to basic environmental services, such as water and sanitation, on children's nutritional status using Probit analysis and these are found to be insignificant. However, Silva noted that the results for the model including community environmental sample indicate the coefficients on the proportion of households with access to these services are highly significant in the underweight equations suggesting a spillover effect of other household's access to these services.

Christiaensen and Alderman (2001) found possession of a tap and a flush toilet to have a positive effect on child height. However, access to other sources of drinking water which are generally deemed safe such as public taps and protected wells were not found to positively affect children's height. Similar results for underweight are also found by Girma, W. & Genebo, T., 2002; Mekonnen *et al*, 2005a. Considering usage of a tap and a flush toilet, opposite results to Christiaensen and Alderman (2001) are reported in Mekonnen *et al*. (2005a) and Mekonnen *et al* (2005b) for the case of wasting in urban and rural areas, respectively. The reason suggested for the former is that it could be because of the unhealthy conditions of communal latrines in slum areas, while the rural case is assumed that people may still prefer to use the open field rather than unfamiliar pit latrines.

Many studies use the distance between the household's home and the nearest health facility to proxy for access to health care (see Christiaensen and Alderman, 2001; Mekonnen *et al*, 2005a, Mekonnen *et al*, 2005b). In addition to these studies, however, Collier *et al*., 2002 and Asfaw (1995) argue that usage of health services is sensitive not just to the distance to the nearest facility but also the quality (such as availability of material inputs and drugs, the number and qualification of staff, user fees, etc) of care provided.

As a result, studies report the impact of access to healthcare on child nutrition to be either insignificant or give result in the counter-intuitive direction. For example, while Christiaensen and Alderman (2001) found no effect of the proximity of a health clinic on children's height, Mekonnen *et al*. (2005a) found that communities with better access to public health facilities were having a higher incidence of child wasting, stunting and underweight. Based on a qualitative research, Mekonnen *et al*. (2005a) noted that service quality, availability of drugs and affordability of health services have a greater impact on a child's nutritional status than distance to health services. On the other hand, Mekonnen *et al*. (2005b) found distance to a public health clinic to have the expected negative and significant association with weight-for-height in rural areas, but the result is the opposite for urban areas, which is not expected.

Some studies use the number of prenatal care visits of a mother as proxy for access to health services and they found it to be significant for children of lower age group i.e. between 0 and 12 months old. For example, Girma, W. & Genebo, T. (2002) found that the odds of stunting among children whose mothers have had no or (1-4) prenatal care visits were 1.5 times more compared with children whose mothers had five or more prenatal care visits. The authors argue that this is because as the contact of mothers with health services increases, their health seeking behavior improves and therefore they are likely to take appropriate actions to improve the health status of their children, which is also important component of child nutrition.

Using antenatal visits and child vaccinations against measles as proxies for health-seeking behavior, Mekonnen *et al*. (2005a) found children less likely to be wasted and underweight suggesting the importance of the use of health facilities/services in reducing the incidence of underweight and wasting. However, from the qualitative research these authors found that there is still both inadequate understanding of and/or trust in modern scientific healthcare in tackling malnutrition, which is in turn reflected in an unwillingness to replace reliance on spiritual healers with faith in modern medicine.

3. DATA AND METHODOLOGY

3.1. Data source

This study is used secondary data which was obtained from the Ethiopia Demographic and Health Survey (EDHS) 2011. The survey was conducted by the Central Statistical Agency (CSA) under the auspices of the Ministry of Health and it is the third Demographic and Health Survey (DHS) that was conducted in Ethiopia, under the worldwide MEASURE DHS project, a USAID-funded project providing support and technical assistance in the implementation of population and health surveys in countries worldwide.

3.2. Study Population

The 2011 EDHS sample was designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole; urban and rural areas of Ethiopia (each as a separate domain); and 11 geographic areas (9 regions and 2 city administrations), namely: Tigray, Affar, Amhara, Oromiya, Somali, Benishangul-Gumuz; Southern Nations, Nationalities and Peoples (SNNP), Gambela, Harari, Addis Ababa and Dire Dawa. In general, a DHS sample is stratified, clustered and selected in two stages. In the 2011 EDHS a representative sample of approximately 14,500 households from 540 clusters was selected. The sample was selected in two stages. In the first stage, 540 clusters (145 urban and 395 rural) were selected from the list of enumeration areas (EA) from the 2007 Population and Housing Census sample frame (EDHS, 2011). Households comprised the second stage of sampling. A complete listing of households was carried out in each of the 624 selected EAs. A representative sample of 14,500 households was selected for the 2011 EDHS.

The 2011 EDHS used three questionnaires: the Household Questionnaire, the Woman's Questionnaire, and the Man's Questionnaire. The Woman's Questionnaire was used to collect information from all women aged 15-49 from the selected households. The data used to study "Risk Factors of Child Malnutrition" were collected in the birth history section of the Woman's Questionnaire from 16,515 women aged 15-49. The background characteristics of the 14,070 women aged 15-49 was fully obtained in the 2011 EDHS. The study has used the birth history data of the respondents (mothers) from Ethiopian DHS 2011 and the data are reported retrospectively. This study focused on factors related to child malnutrition based on 7,738 children aged five or below after removing incomplete data from the survey.

In this study, height and weight measurements of the children, taking age and sex into consideration, are converted into Z-scores based on new growth standards published by the World Health Organization (WHO) in 2006. Thus, those below (-2) standard deviations of the WHO median reference for height-for-age, weight-for-age and weight-for-height is defined as stunted, underweight, and wasted, respectively.

In this study, stunting provides an indicator of linear growth retardation and cumulative growth deficits in children. Children whose height-for-age Z-score is below minus two standard deviations (−2 SD) from the median of the WHO reference population are considered short for their age (stunted), or chronically malnourished. 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. Therefore, an in-depth analysis was performed on stunting by focusing on factors affecting chronic malnutrition.

Under-nutrition among children is usually determined by assessing the anthropometric status of a child relative to a reference standard. In this study, under-nutrition is considered as measured by stunting or insufficient height-for-age, indicating chronic under-nutrition. Height-for-age score for a child *i* is determined using a Z-score which is defined as

$$Z_i = \frac{AI_i - MAI}{\sigma} \qquad (3.1)$$

where AI_i refers to the i^{th} child anthropometric indicator (height at a certain age in our case), MAI refers to the median of a reference population, and σ *refers* to the standard deviation of the reference population.

3.3. Variables in the Study

3.3.1. Response/ dependent/ Variable

The response variable of this study is height-for-age Z-score (HAZ), which gives information about stunting, will be used as a measure of malnutrition. The variable is split into four categories as per the specification of WHO to define level of malnutrition. We set *normal=1* if HAZ is -1 and above, *mild=2* if HAZ is between -2 and -1.01 SD, *moderate=3* if HAZ is between -3 and -2.01 SD and *severe=4* if HAZ is below -3 SD.

Table 3.1: Description of the response variable

Response variable	Value of the levels
Height-for-age Z score (HAZ) (level of stunting)	Normal=1, Mildly stunted=2, Moderately stunted=3, Severely stunted=4

3.3.2. Explanatory/independent/ variables

Independent variables related to malnutrition among children aged 59 months or below based on various literature reviews and theoretical aspects are given with their respective coding in Table 3.2 below.

Table 3.2. Description of explanatory variables

Variables	Categories
Child's sex (csex)	(0) Female, (1) Male
Child's age (cage)	(0)below 48 months;(1)48 or above
Previous birth interval of child (pbint)	(1) Less than 24 months; (2) 24-47 months (3) 48 or above
Birth order of child (bord)	(0)1-3; (1) 4 or above
Mother's Education level (Medu)	(0) No education ; (1) Primary, (2) Secondary or above
Number of household member (nhhm)	(0) 1-4; (1) 5-9; (2) 10 or above
Wealth index (Windex)	(0) Poor; (1) Medium; (2) Rich

Place of Residence (Plresid)	(0) Rural, (1) Urban
Geographical region (Region)	(1) Addis Ababa ; (2) Afar; (3) Amhara; (4) Oromia;(5) Somali; (6) Benishangul-gumuz; (7) SNNP;(8) Gambela; (9) Harari; (10)Tigray; (11) Dire Dawa
Body Mass Index of Mother (BMI)	(1)Thin(BMI < 18.5), (2) Normal(18.5≤ BMI ≤24.9) ; (3) Overweight/obese (BMI≥25)

3.4. Logistic regression

Regression is a statistical procedure which attempts to predict the values of a given variable, (termed as dependent, outcome, or response variable) based on the values of one or more variables (called independent variables, predictors, or covariates). Regression analysis is model building for the relationship between a dependent and one and/or more independent variables. In the regression, we can use the usual linear regression model if the response variable is continuous whereas when the response variable is discrete, taking on two or more possible values the appropriate regression model is logistic regression which was proposed as alternative method in the late 1960s and early 1970s (Cabrera, 1994). Such a technique was developed by McCullough and Nelder (1989) and is called generalized linear model (GLM), one of its application is logistic regression (Fox, 1984). The problem of non normality and hetroscedasticity lead to the model estimation method to be maximum likelihood after natural logarithm transformation of the odd ratio of the response because in logistic the relationship between the response with the set of explanatory variables is not linear hence the procedures used in the linear regression is extended to logistic regression.

Logistic regression models are classified according to the type of categories of response variable as follows:-binary logistic regression model, multinomial logistic regression model and ordinal logistic regression models (Hosmer and Lemeshow, 2000). The binary logistic regression model is used to model the binary response variable, whereas the multinomial logistic regression is a simple extension of the binary logistic regression model where the response variable has more than two unordered categories. Ordinal logistic regression models are used to model the relationship between independent variables and an ordinal response variable when the response variable category has a natural ordering.

3.4.1. Ordinal logistic regression

Ordinal logistic regression is an extension of binary logistic regression for analyzing ordinal response variable having more than two categories by considering the ordering of the response variable categories. For more than two categories of response, we can build multinomial logistic regression model without considering the natural order of categories. Ordinal logistic regression is used to build a predictive model for ordinal response variable with a set of explanatory variables. It is applicable in biomedical research, epidemiological, biology etc. Ordinal logistic regression models with terms that reflect ordinal characteristics such as monotone trend have improved model parsimony and power. There are different types of ordinal logistic regression models, the most commonly used are: the adjacent-category, the continuation-ratio, the proportional odds models, the unconstrained partial-proportional odds model, the constrained partial-proportional odds model (Hosmer and Lemeshow, 2000).

3.4.1.1. Proportional Odds Model

The proportional odds model (cumulative logit model) for ordinal regression described by McCullough (1980) provides a useful extension of the binary logistic model to situations where the response variable takes an ordered categorical value. Proportional Odds Model is used for modeling the response variable that has more than two levels with K set of explanatory variables by defining the cumulative probabilities, cumulative odds and cumulative logit for the J-1 categories of the response. This model simultaneously uses all cumulative logits. Let $j = 1, 2, \dots, J$ are the ordinal categories of the response variable Y, and the vector of explanatory variable X, and denoted by vector form $X = (X_1,\ X_1, \dots, X_K)'$. For the response variable Y with the J ordinal categories given that of K explanatory variables, the individual probabilities are defined as follows

$$P(Y = j/X) = P_j\,, for\ j = 1, 2, \dots, J$$

and the cumulative probability can be defined as

$$\pi_j(X) = P(Y \leq j/X) = P_1 + P_2 + \ldots + P_j, for\ j = 1, 2, \ldots, J-1 \qquad (3.1)$$

$\pi_j(X)$, is the probability of being at or below category j, given that of K set of predictors. The cumulative probability reflects the ordering with P (Y≤1) ≤ P (Y≤2) ≤…≤ P (Y≤J) =1.

Models for cumulative probability do not use the final one namely, $P(Y \leq J)$ since it necessarily equals one. The odds of the cumulative probabilities of the response variable for the J-1 categories is

$$odds\{\pi_j(X)\} = \frac{\pi_j(X)}{1-\pi_j(X)}, j = 1, 2, \ldots, J-1 \qquad (3.2)$$

The logarithm (natural logarithm) of the odds of the first J-1 cumulative probabilities is

$$\ln[odds\{\pi_j(X)\}] = ln\left[\frac{\pi_j(X)}{1-\pi_j(X)}\right], j = 1, 2, \ldots, J-1 \qquad (3.3)$$

The relationship between the response variable and the set of predictors is not linear in ordinal logistic regression model. The logistic regression function uses the logit transformation of $\pi_j(X)$, cumulative probabilities of the response.

$$\pi_j(X) = P(Y \leq j/X) = \frac{\exp\left(\alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K)\right)}{1 + \exp\left(\alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K)\right)}$$

The logit of the first J-1 cumulative probabilities are:

$$ln\left[\frac{\pi_j(X)}{1-\pi_j(X)}\right] = \ln\left[\frac{P(Y \leq j/X)}{1-P(Y \leq j/X)}\right] = \alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K)$$

$$= \alpha_j - \sum_{k=1}^{K} \beta_k X_k$$

Equivalent to:

$$logit[P(Y \leq j/X)] = \alpha_j - \sum_{k=1}^{K} \beta_k X_k \ , j = 1, 2, \ldots, J-1 \qquad (3.4)$$

Equation 3.4 is called the proportional odds model (POM) to predict cumulative logits across J-1 response categories. The minus sign in the predictor term makes the sign of each component of β have the usual interpretation in terms of whether the effect is positive or negative, but it is not necessary to use this parameterization (Liu & Agresti, 2005).The POM model estimates the logarithm of the odds of being at or below the j^{th}category and assume that there is a linear relationship between the logits and the parallel regression lines and hence this model estimates simultaneously multiple equations of cumulative probability. The model is solved for each category of the dependent variable except the last category.

In the model each logit has its own α_j term called the cut-point or the threshold value and their values do not depend on the values of the independent variables and $\beta_k's$ are the logistic regression coefficients and the estimated values of these parameters show that the direction and the strength of relationship between the explanatory variables and the logit (log odds) of the dependent variable. However, these regression coefficients' interpretations are somewhat different from the usual regression coefficients and the interpretation for categorical explanatory variable is the effect (more likely and less likely) of the estimated category of the independent variables relative to the reference category on the log odds being in higher levels of the categories of the dependent variable. If the effect of each explanatory variable is the same in each logit models, then the model is called proportional odds model. In the POM, cumulative logits are simultaneously modeled using the maximum likelihood estimation method. Prior to fitting POM, it is important to check whether the assumption of proportionality is satisfied by each of the explanatory variables in the model.

Proportional Odds Assumption

This is a key assumption in ordinal regression. The assumption is that the effects of any explanatory variables are consistent (proportional) across the different thresholds (by thresholds we mean the splits between each pair of categories of ordinal outcome variable). SPSS tests this assumption with what it calls the *Test of parallel lines* but it is referring to the same assumption. To test parallel lines assumption, Likelihood Ratio Test, Wald Chi-Square test and the other related tests are used (Agresti, 2002). A non-significance test is evidence that the logit surfaces are parallel and that the odds ratio can be interpreted as constant across all possible cut-point of the response. But, parallel lines assumption sometimes does not hold, in this case Proportional Odds Model gives incorrect results. Therefore, models that consider ordinal structure and relax the assumption are suggested. Partial Proportional Odds Model (PPOM) and Generalized Ordered Logit Model (GOM) are recently used for this purpose.

Likelihood function and parameter estimation

The model:

$$logit[P(Y \leq j/X)] = \alpha_j - \sum_{k=1}^{K} \beta_k X_k \ , j = 1, 2, \dots, J-1$$

can use all J-1 cumulative logits in a single parsimonious model that means its model fit is not the same as fitting separate logit models for each j. To estimate the parameters of the model, define the binary indicator of the response variable for each observation or subject i. Therefore, the likelihood function is defined as follows:

$$l = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \pi_j(X_i)^{y_{ij}} \right] = \prod_{i=1}^{n} \left[\pi_1(X_i)^{y_{i1}} \times \pi_2(X_i)^{y_{i2}} \times \dots \times \pi_J(X_i)^{y_{iJ}} \right] \qquad (3.5)$$

Where, y_{ij}'s are the response variable indicators for fixed i and j = 1,…, J and

$$\pi_j(X_i) = P(Y \leq j/X_i) - P(Y \leq j-1/X_i)$$

And the cumulative probabilities can be written as follows

$$P(Y \leq j/X_i) = \frac{\exp\left(\alpha_j - \sum_{k=1}^{K} \beta_k X_{ik}\right)}{1+\exp\left(\alpha_j - \sum_{k=1}^{K} \beta_k X_{ik}\right)} \text{ and } P(Y \leq j-1/X_i) = \frac{\exp\left(\alpha_{j-1} - \sum_{k=1}^{K} \beta_k X_{ik}\right)}{1+\exp\left(\alpha_{j-1} - \sum_{k=1}^{K} \beta_k X_{ik}\right)}$$

Having these equations the likelihood becomes

$$l(\alpha, \beta) = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} [P(Y \leq j/X_i) - P(Y \leq j-1/X_i)]^{y_{ij}} \right]$$

$$= \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left[\frac{\exp\left(\alpha_j - \sum_{k=1}^{K} \beta_k X_{ik}\right)}{1 + \exp\left(\alpha_j - \sum_{k=1}^{K} \beta_k X_{ik}\right)} - \frac{\exp\left(\alpha_{j-1} - \sum_{k=1}^{K} \beta_k X_{ik}\right)}{1 + \exp\left(\alpha_{j-1} - \sum_{k=1}^{K} \beta_k X_{ik}\right)} \right]^{y_{ij}} \right]$$

$$l(\alpha, \beta) = \prod_{i=1}^{n} \left[\pi_1(X_i)^{y_{i1}} \times \pi_2(X_i)^{y_{i2}} \times \dots \times \pi_J(X_i)^{y_{iJ}} \right]$$

Therefore, the log-likelihood function is:

$$L(\alpha, \beta) = \log l(\alpha, \beta) = \log \left(\prod_{i=1}^{n} \left[\pi_1(X_i)^{y_{i1}} \times \pi_2(X_i)^{y_{i2}} \times \dots \times \pi_J(X_i)^{y_{iJ}} \right] \right)$$

$$= \prod_{i=1}^{n} \left[y_{i1} log\pi_1(X_i) + y_{i2} log\pi_2(X_i) + \dots + y_{iJ} log\pi_J(X_i) \right]$$

$$=\prod_{i=1}^{n}\left[\sum_{j=1}^{J} y_{ij} log\pi_j(X_i)\right]$$

Hence

$$L(\alpha,\beta) = \prod_{i=1}^{n}\left[\sum_{j=1}^{J} y_{ij} log\pi_j(X_i)\right] \tag{3.6}$$

In general, the method of maximum likelihood estimation produces values of the unknown parameters that best match the predicted and observed probability values. McCullagh (1980) provided a Fisher scoring algorithm for ML fitting of all cumulative link models. Hence, it is often used as very effective method to obtain ML estimates for ordinal logistic regression parameters.

3.4.1.2. The Generalized ordered logit model

In the case where the proportional odds assumption is violated, the proportionality constraint may be completely or partially relaxed for the set of explanatory variables. Generalized ordered logit model is an ordinal logistic regression which considers order of category of the response variable with k set of explanatory variables. This model results J-1 logits without constrained the effect of each explanatory variable is equal across the logits.

The model can be expressed as proposed by Fu (1998) and Williams (2006) as follows:

$$logit[P(Y > j/X)] = \ln\left[\frac{P(Y > j/X)}{P(Y \leq j/X)}\right] = \alpha_j + \sum_{k=1}^{K} \beta_{kj} X_k \quad , j = 1, 2, \ldots, J-1 \tag{3.7}$$

Where, $\alpha_j's$ are the intercepts or cut points and $\beta_{kj}'s(for\ k = 1, 2, \ldots, K)$ are logit coefficients. This model estimates the odds of being beyond a certain category relative to being at or below that category. A positive logit coefficient indicates that an individual is more likely to be in a higher category as opposed to a lower category of the outcome variable. Generalized ordered logit model estimates the regression parameters for each explanatory variable on J-1 logit of the probability being beyond the j^{th} category in every logit to have different estimated values. Hence, because of the model have too many parameters, different interpretation will be given for the k^{th} explanatory variable in the J-1 logit. As discussed above, the generalized ordered logit model relaxes the proportionality assumption for all explanatory variables so that it is less parsimonious model. So, there is another model that allows some variables to be proportional across all logits and the other variables to vary across logits. This model is called Partial proportional odds model.

3.4.1.3. Partial proportional odds model

The partial proportional odds model (Peterson and Harrell, 1990; Fu, 1998; Williams, 2006) is a natural extension of the proportional odds model, which allows $\beta's$ varying across logit equations. Suppose one set of predictors X_1 has p_1 parameters that satisfy the parallel line assumption or equal slope assumption and the remaining set of predictors X_2 has p_2 parameters that do not satisfy parallel line assumption but they have unequal slopes and also depend on the j^{th} category of the response. PPOM is obtained by modifying Equation 3.7 and written as follows

$$logit[P(Y > j/X)] = \alpha_j + \sum_{k=1}^{p_1} \beta_k X_{1k} + \sum_{r=1}^{p_2} \beta_{rj} X_{2r} \quad , j = 1, 2, \dots, J-1 \qquad (3.8)$$

Equation 3.8 is PPOM; it should also be modified for the cases where, if the explanatory variables are categorical with more than two categories, some of the estimated categories may varies across the J-1 logits while other to be equal in such a case the proportionality is tested related to the categories of the explanatory variables. Generally speaking, the generalized ordinal logistic regression model constrained for all explanatory variables estimates equal for J-1 logits called proportional odds model and partial proportional odds model is generalized ordinal logistic regression constrained for some of the variables to be equal across the J-1 logits and relaxed for the other which violate the parallel line assumption.

3.5. Odds Ratio

In logistic regression the relationship between the response variable and the set of explanatory variables is not linear. Let the logistic probabilities from a model containing one dichotomous covariate coded 0 and 1, the odds of the response being present among individuals with x=1 and x=0 given below respectively (Hosmer and Lemeshow, 2000)

$$\mathrm{odds}(x = 1) = \frac{P(Y/X=1)}{1-P(Y/X=1)} \quad \text{and} \quad \mathrm{odds}(x = 0) = \frac{P(Y/X=0)}{1-P(Y/X=0)} \qquad (3.9)$$

The *odds ratio*, denoted OR, is the ratio of the odds for x=1 to the odds for x=0, given as follows

$$\mathrm{OR} = \frac{\mathrm{odds}(\mathrm{x} = 1)}{\mathrm{odds}(\mathrm{x} = 0)}$$

The odds of the response are multiplied by OR = e^{β} for change from reference category to the estimated category of the given explanatory variable and OR less than one indicate that the occurrence is less likely than non occurrence and if the OR greater than one indicate the occurrence is more likely than non occurrence.

3.6. Model Selection Criteria

In regression analysis fitting a model is the main issue and we should give more care for selecting model that well fit the data. To achieve these task, selection criteria's such as R-square, Adjusted R-square, PseudoR^2, BIC and AIC should be considered. It is much better to compare models based on their results, reasonableness, and fit as measured; we can make comparisons among the possible models using the above selection criteria. In the case of logistic regression the model selection criteria will be taken as AIC. The AIC computation is based on the likelihood of the fit and the number of parameters in the model is considered. Therefore, if the model contains many variables there will be many parameters to be estimated; therefore, this may penalize the AIC criteria. If we fit a model that contains all the possible variables under study it needs much computation time and resources, the collinearities of the variables may affect the model fit and also less important variables might be included in the model or if the model contains few variables, it may not well explain the outcome (response) and the error of the model becomes large due to exclusion of important variables. The variables included in the model should be selected based on their significance and relationship with the response variable. Therefore, the issue of inclusion and exclusion of explanatory variables are called variable selection problem. Methods such as forward, backward and stepwise selection are commonly used.

In this study, the model selection criteria used is AIC (Akaki information criterion) and the model with minimum AIC value is chosen as the best model to fit the data (Agresti, 2002). AIC is defined as

$$AIC = -2L(\alpha, \beta) + 2P$$

Where $L(\alpha, \beta)$ the maximized log likelihood function, P is the number of free parameters in the model (the penalty component) which is a measure of complexity or the compensation for the bias in the lack of fit when the maximum likelihood estimators are used. $-2L(\alpha, \beta)$ is the lack of fit component.

3.7. Test of overall model fit

3.7.1. Likelihood ratio test

After the model is selected the first step is to check whether a model fits the data well or not. The null hypothesis is their all the regression parameters are zero, and under the alternative hypothesis at least one regression coefficient (parameter) is not zero .To keep use of the selected model, the null hypothesis must be rejected and possibility for examining the significance for the individual parameters. In binary and ordinal logistic regression models, the overall model fit can be based on the difference between the –2log likelihood for the model with only the intercept and the –2log likelihood for the selected model that follows chi-square distribution under the null hypothesis. Moreover, models could be compared by the –2loglikelihood; a model which has small -2LL are more preferred than for model that has large -2LL value.

The likelihood-ratio test statistic is given by (Agresti, 2002):

$$\mathrm{G}^2 = -2\log\Lambda = -2(\mathrm{LL}_0 - \mathrm{LL}_1), \mathrm{G}^2 \sim \mathrm{X}^2_{\mathrm{P}-(\mathrm{J}-1)} \quad (3.10)$$

Where, P and J are the number of parameter and number of category of the response variable respectively, and LL_0 and LL_1 are the maximized log-likelihood functions of the null model and the selected model respectively.

3.7.2. Pseudo R^2 measures

In the linear regression model, the coefficient of determination R^2 summarizes the proportion of variance in the dependent variable associated with the predictor (independent) variables, with larger R^2 values indicating that more of the variation is explained by the model. For regression models with a categorical dependent variable, it is not possible to compute a single R^2statistic that has all of the characteristics of R^2 in the linear regression model, so these approximations are computed instead. McFadden's pseudo R-squared statistic is based on the log likelihood for the model with predictors compared to the log likelihood for the model without predictors.

However, with categorical outcomes, it has a theoretical maximum value of less than one, even for a "perfect" model. McFadden's pseudo R-squared statistic is given by (McFadden, 1974):

$$R_{MC}^2 = \frac{\mathrm{LL}_0 - \mathrm{LL}_1}{\mathrm{LL}_0} \tag{3.11}$$

3.8. Test of a single predictor

Wald test

The Wald test is used to see the significance of a single explanatory variable in the model. The Wald test statistic is the square of the ratio of the estimated coefficient to its standard error and is defined as:

$$W = \left[\frac{\widehat{\beta_i}}{SE(\widehat{\beta_i})}\right]^2 \tag{3.12}$$

Under the null hypothesis $H_0 : \beta_i = 0 , for\ i = 1, 2, \ldots, k$ and W has a chi-square distribution with one degree of freedom.

3.9. Goodness-of-Fit Measures

As in linear regression, goodness of fit in logistic regression attempts to get at how well a model fits the data. It is usually applied after a “final model” has been selected. Most of the goodness of fit literature is based on the following hypothesis:

H_0: The model fit the data well *and* H_A: the model does not fit the data well

The measure of goodness of a fit done by testing whether a model fits is to compare observed and expected values. From the observed and expected frequencies, we can compute the usual Pearson and Deviance goodness-of-fit measures. For a sample of n independent observations, the deviance and Pearson chi-square for a model with p degrees of freedom, both $\chi^2$and D has chi-square distribution with (n-p) degrees of freedom.

The Pearson goodness-of-fit statistic is:

$$\chi^2 = \sum\sum\left(\frac{O_{ij} - E_{ij}}{E_{ij}}\right)^2 \tag{3.13}$$

The deviance measure is:

$$D = 2\sum\sum O_{ij}\, ln\left(\frac{O_{ij}}{E_{ij}}\right) \tag{3.14}$$

Where O_{ij} is the observed frequency from i^{th} row and j^{th} column of the cross tabulation. E_{ij} is the expected frequency from i^{th} row and j^{th} column of the cross tabulation. The observed frequency is obtained from the data on the response but the expected frequency is obtained from the estimated probabilities of the response. Both goodness-of-fit statistics should be used only for models that have reasonably large expected values in each cell. If we have a continuous independent variable or many categorical predictors or some predictors with many values, we may have many cells with small expected values. If our model fits well, the observed and expected cell counts will be similar, the value of each statistic will be small, and the observed significance level will be large. We shall reject the null hypothesis that the model fits the data well if the observed significance level for the goodness of- fit statistics is small. Good models have large observed p- values.

Hosmer-Lemeshow goodness of fit test

The recommended test for overall fit of a binary logistic regression model is the Hosmer-Lemeshow test (Hosmer and Lemeshow, 1980; Hosmer and Lemeshow, 2000). This test is preferred over classification tables when assessing model fit. The Hosmer-Lemeshow goodness of fit test divides subjects into deciles based on predicted probabilities, and then computes a Chi-square from observed and expected frequencies. Then a probability (p) value is computed from the Chi-square distribution to test the fit of the logistic model. If the p value of H-L goodness-of-fit test statistic is greater than .05, as we want for well-fitting models, we do not reject the null hypothesis that there is no difference between observed and model predicted values, implying that the model's estimates fit the data at an acceptable level.

Note that the number of groups, g, can be smaller than 10 if there are fewer than 10 patterns of explanatory variables. There must be at least three groups for the Hosmer-Lemeshow statistic to be computed. The Hosmer-Lemeshow goodness-of-fit statistic is obtained by calculating the Pearson chi-square statistic from the 2 × g table of observed and expected frequencies, where g is the number of groups. The statistic is written as

$$\chi^2_{HL} = \sum_{i=1}^{g} \frac{(O_i - N_i\pi_i)^2}{N_i\pi_i(1-\pi_i)} \tag{3.15}$$

Where N_i is the total frequency of the subjects in the i^{th} group, O_i is the total frequency of the event outcomes in the i^{th} group, and π_i is the average estimated predicted probability of an event outcome for the i^{th} group. Under the null hypothesis the H-L test statistic has χ^2_{HL} distribution with (g-2) degree of freedom. Large values of χ^2_{HL} (and small p-values) indicate lack of fit of the model.

3.10. Model adequacy checking

Model building is not the final goal in regression analysis. The model adequacy checking is the main step of regression analysis after a model is fitted. It can be measured based on diagnosing residuals and measure of influence.

3.10.1. Residuals

Residuals are the difference between the observed and predicted value of the response variable. Residuals are useful in identifying observations that are not explained well by the model. For logistic regression diagnostics the residuals are calculated in a similar way as usual. However, since the variables are categorical we have to consider contingency tables.

The pattern of lack of fit revealed in cell-by-cell comparisons of observed and fitted (expected) counts may suggest a better model. For a model with categorical predictors, the residuals are computed from the observed and expected counts of the contingency table. Let Y_i denote the binomial variate for n_i trials at setting i of the explanatory variables, i =1,…, N. Let $\hat{\pi_i}$ denote the model estimate of P(Y=1). Then $n_i \hat{\pi_i}$ is the fitted number of successes.

The Pearson residual is defined by (Agresti, 2002):

$$e_i = \frac{Y_i - n_i \hat{\pi_i}}{\sqrt{\hat{var}(Y_i)}} = \frac{Y_i - n_i \hat{\pi_i}}{\sqrt{n_i \hat{\pi_i}(1-\hat{\pi_i})}} \tag{3.16}$$

with $\hat{\pi_i}$ replaced by π_i in the numerator of the Pearson residual, e_i is the difference between a binomial random variable and its expectation, divided by its estimated standard deviation; for large $n_i \geq 30$, e_i has an approximate N (0, 1) distribution. Since is π_i estimated by $\hat{\pi_i}$ and $\hat{\pi_i}$ depend on Yi, The Pearson residuals do not have unit variance since no allowance has been made for the inherent variation in the fitted value. A better procedure is to further adjust the Pearson residuals by their estimated standard deviation that contains variation due to the effect of leverage value is called standardized Pearson residual.

The Standardized Pearson residual is slightly larger in absolute value than e_i and is approximately N (0, 1) when the model holds. It's similar to the Pearson residual but the only difference is standardized residuals uses the leverage from an estimated hat matrix that means for an observation i with leverage value$\hat{h_i}$. Observations with absolute standardized residual values greater than 3 may indicate lack of fit (Rawlings, 1998). The standardized Pearson residual is given (Agresti, 2002):

$$r_i = \frac{e_i}{\sqrt{1-\hat{h_i}}} = \frac{Y_i - n_i \hat{\pi_i}}{\sqrt{n_i \hat{\pi_i}(1-\hat{\pi_i})(1-\hat{h_i})}} \tag{3.17}$$

Deviance residuals are used to check for lack of fit by considering the i^{th} observation. Logistic regression is a type of generalized linear model, if the model fits poorly based on the overall goodness-of-fit test, examination of residuals highlights where the fit is poor. This residual uses the components of the deviance statistic. The deviance residual for observation i is defined as:

$$\sqrt{d_i} \times sign(Y_i - n_i\, \widehat{\pi_i}) \tag{3.18}$$

Where,

$$d_i = 2\left(Y_i \log \frac{Y_i}{n_i\, \widehat{\pi_i}} + (n_i - Y_i) \log \frac{n_i - Y_i}{n_i - n_i \widehat{\pi_i}}\right)$$

The deviance residual can have negative sign when $n_i\, \widehat{\pi_i}$ is greater than Y_i and positive sign if Y_i exceeds $n_i\, \widehat{\pi_i}$. Observations with absolute deviance residual values greater than 3 may indicate lack of fit (Rawlings, 1998), each squared deviance residual is a component of D^2 , deviance statistic test for goodness of fit is given by

$$D^2 = \sum_{i=1}^{N} {d_i}^2$$

3.10.2. Measure of influence

An outlier is an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism. An observation is influential if it is individually or together with several other observations, has a demonstrably larger impact on the calculated values of various estimates than is the case for most of the other observations (Belsley *et al*., 2005). Diagnostics are certain quantities computed from the data with the purpose of pinpointing influential points after which these influential points can be removed or corrected. The standard logistic regression model, we should check for the effect of individual observations on model estimates and fit. We are interested in identifying subjects with high leverage, large residuals, or a large degree of influence on the model estimates.

In linear regression, the diagonal elements of the hat matrix are called the leverage values and are proportional to the distance of x_i to the mean of the data, $\overline{x}$. Similarly, for logistic regression leverage values are the diagonal element of the hat matrix. These values show as the distance between individual observations to the mean, if the distance is large or as individual observation are far from the mean it may have considerable influence on the values of the estimated parameters.

Pregibon (1981) derived a linear approximation to the fitted values which yields a hat matrix for logistic regression. This matrix is

$$H = V^{1/2}X(X'VX)^{-1}X'V^{1/2}$$

Where, V is $n \times n$ diagonal matrix with general diagonal element

$$v_i = m_i \hat{\pi}(x_i)[1 - \hat{\pi}(x_i)]$$

Leverage values for logistic regression are the diagonal elements of the hat matrix and denoted by h_i is given below (Hosmer and Lemeshow, 2000).

$$h_i = m_i \hat{\pi}(x_i)[1 - \hat{\pi}(x_i)]x'_i(X'VX)^{-1}x_i \tag{3.19}$$

Where,

$$\hat{v}_i = m_i \hat{\pi}(x_i)[1 - \hat{\pi}(x_i)]$$

And $x'_i = (1, x_{1i}, x_{2i}, \dots, x_{pi})$ is the vector of the covariate values defining the i^{th} covariate pattern.

The hat matrix for the logistic regression as a n× n matrix the diagonal element is bounded from the above by $1/m_i$, where m_i is the total number of subject with the same covariate pattern. When the hat matrix is based upon data grouped by covariate pattern, the upper bound for any diagonal element is one that means the centered leverage values ranges from 0 to $(n-1)/n$ and the leverage value greater than one for the i^{th} observation indicates that observation is influential (Belsley *et al*., 1980).

Another useful diagnostic statistic is one that examines the effect that deleting all subjects with a particular covariate pattern has on the value of the estimated coefficients and the overall summary measures of fit χ^2 and D^2 . The change in the value of the estimated coefficients is analogous to the measure proposed by Cook (1977, 1979) for linear regression (Hosmer and Lemeshow, 2000). It is obtained as the standardized difference between the estimated coefficient with i^{th} observation and without the i^{th} observation, where this represents the maximum likelihood estimates computed using all i covariate patterns and excluding the m_i subjects with pattern x_i respectively, and standardizing via the estimated covariance matrix of the estimators.

The Analog Cook's influence statistic for logistic regression is given as follow

$$\Delta\hat{\beta}_i = \left(\hat{\beta} - \hat{\beta}_{-i}\right)'(X'VX)^{-1}\left(\hat{\beta} - \hat{\beta}_{-i}\right)$$

Computationally, the i^th^ Cook's distance, CD_i, is more easily obtained as:

$$CD_i = \frac{{r_i}^2 h_i}{(1-h_i)} \tag{3.20}$$

Where, r_i is the standardized residual and h_i is the i^{th} diagonal element of H matrix computed from the full logistic regression with K explanatory variables.

Cook's distance is the difference between the estimated coefficient with the i^{th} observation and after deleting the i^{th} observation. This is based on the squared value of standardized Pearson residual and leverage value. If Cook's distance is large for i^{th} observation it is considered to be influential. The suggested cut off values for i^{th} observation to be influential such as outlier, if the CD_i is greater than "one" (CD_i> 1) (Hosmer and Lemeshow, 2000, Rawlings, 1998).

4. ANALYSIS AND RESULTS

4.1. Descriptive statistics

Of the 7,738 children who were included in this study, 50.7% were male and 49.3% were female children. Out of these children, 67.3% male children and 66.4% female children were stunted (malnourished). Tables 4.1, 4.2 and 4.3, which are placed below, present the cross tabulation of prevalence of malnutrition (frequency and percentages) by level of stunting. Prevalence of stunting with regard to region of residence shows that Amhara has the highest percentage of stunting cases. Of the 862 children in Amhara, only 20.5% are non-stunted and the remaining 79.5% have some form of stunting (25.3% severe, 25.9% moderate and 28.3% mild). Tigray falls next to Amhara with about 79% stunting cases (23.4% severe, 29% moderate and 26.6% mild). Benshangul-Gumuz falls next to Tigray with about 73.5% stunting cases (28.9% severe, 21.1% moderate and 23.5% mild). Affar falls next to Benshangul-Gumuz with about 68.7% stunting cases (31% severe, 20.5% moderate and 17.2% mild). SNNP falls next to Affar with about 67.8% stunting cases (23.4% severe, 21.3% moderate and 23.1% mild). Oromiya falls next to SNNP with about 65.4% stunting cases (16.9% severe, 23.9% moderate and 24.6% mild). Dire Dawa falls next to Oromiya with about 62.8% stunting cases (19.9% severe, 18.6% moderate and 24.3% mild). Somali falls next to Dire Dawa with about 54.7% stunting cases (17% severe, 16.9% moderate and 20.8% mild). Addis Ababa falls next to Somali with about 54.2% stunting cases (6.6% severe, 19.9% moderate and 27.7% mild). Harari falls next to Addis Ababa with about 51.6% stunting cases (12.5% severe, 16.7% moderate and 22.4% mild) while Gambela has the lowest percentage of stunting cases (50.9%). Among the severely stunted children, 31% are in Affar, 28.9% in Benshangul-Gumuz followed by 25.3% in Amhara. Tigray has the most moderately stunted children (29%) followed by Amhara (25.9%) and Oromiya (23.9%). Among the non-stunted children, 49.1% are in Gambela followed by 48.4% in Harari (See Table 4.1).

Table 4.1.Cross-table of prevalence of stunting (malnutrition) by region of residence

Predictors (Independent variables)		Stunting levels (%)				Total
		normal	mild	moderate	severe	
Region	Addis Ababa	76 (45.8)	46 (27.7)	33 (19.9)	11 (6.6)	166
	Affar	226 (31.3)	124 (17.2)	148 (20.5)	224 (31.0)	722
	Amhara	177 (20.5)	244 (28.3)	223 (25.9)	218 (25.3)	862
	Oromiya	431 (34.6)	306 (24.6)	298 (23.9)	210 (16.9)	1245
	Somali	303 (45.3)	139 (20.8)	113 (16.9)	114 (17.0)	669
	Benshangul-Gumuz	181 (26.5)	161 (23.5)	144 (21.1)	198 (28.9)	684
	SNNP	364 (32.2)	262 (23.1)	241 (21.3)	265 (23.4)	1132
	Gambela	270 (49.1)	124 (22.5)	88 (16.0)	68 (12.4)	550
	Harari	186 (48.4)	86 (22.4)	64 (16.7)	48 (12.5)	384
	Tigray	182 (21.0)	231 (26.6)	251 (29.0)	203 (23.4)	867
	Dire Dawa	170 (37.2)	111 (24.3)	85 (18.6)	91 (19.9)	457

The prevalence of child stunting (malnutrition) levels varies by place of residence: for rural children 31.3%, 23.2%, 22.4%, and 23.1% are normal (non-stunted), mildly stunted, moderately stunted and severely stunted respectively while for urban children 44.7%, 27.1%, 18.2% and 10% are normal (non-stunted), mildly stunted, moderately stunted and severely stunted showing that the proportions of moderate and severe stunting levels in urban residence children are smaller than for those children who were rural residence. Interestingly, the prevalence of moderate and severe stunting is lower with increased levels of child's mother education and body mass index (BMI). (See Table 4.2).

Table 4.2.Cross-table of prevalence of stunting (child malnutrition) by socioeconomic and demographic variables

Predictors (Independent variables)		Child stunting levels (%)				
		normal	mild	moderate	severe	Total
Child's sex	Female	1282 (33.6)	931 (24.4)	833 (21.8)	769 (20.2)	3815
	Male	1284 (32.7)	903 (23.0)	855 (21.8)	881 (22.5)	3923
Child's age	Below 48	2190 (35.4)	1392 (22.5)	1292 (20.9)	1309 (21.2)	6183
	48 or above	376 (24.2)	442 (28.4)	396 (25.5)	341 (21.9)	1555
Previous birth interval	Less than 24	463 (28.5)	366 (22.5)	353 (21.7)	443 (27.3)	1625
	24 up to 47	1453 (33.1)	1016 (23.2)	993 (22.6)	926 (21.1)	4388
	48 and above	650 (37.7)	452 (26.2)	342 (19.8)	281(16.3)	1725
Birth order	1up to 3	1064 (35.0)	753 (24.8)	666 (21.9)	559 (18.4)	3042
	4 and above	1502 (32.0)	1081 (23.0)	1022 (21.8)	1091 (23.2)	4696
Mother's	No education	1790 (30.8)	1355 (23.3)	1300 (22.4)	1364 (23.5)	5809

education	Primary	655 (38.2)	421 (24.6)	364 (21.2)	273 (15.9)	1713
	Secondary/ above	121 (56.0)	58 (26.9)	24 (11.1)	13 (6.0)	216
Number of household member	1up to 4	396 (32.6)	318 (26.2)	256 (21.1)	246 (20.2)	1216
	5 up to 9	1914 (32.7)	1376 (23.5)	1289 (22.0)	1277 (21.8)	5856
	10 and above	256 (38.4)	140 (21.0)	143 (21.5)	127 (19.1)	666
Place of residence	Rural	2095 (31.3)	1548 (23.2)	1496 (22.4)	1545 (23.1)	6684
	Urban	471 (44.7)	286 (27.1)	192 (18.2)	105 (10.0)	1054
Mother's Body Mass Index	Thin	646 (31.3)	478 (23.1)	456 (22.1)	485 (23.5)	2065
	Normal	1692 (32.4)	1253 (24.0)	1156 (22.1)	1121 (21.5)	5222
	Overweight	228 (50.6)	103 (22.8)	76 (16.9)	44 (9.8)	451

Household economic status is categorized based on their wealth index status. Of the severely stunted children, 24.9% are from poor households, 22.7% are from medium, and 14.7% are from rich households (See Table 4.3).

Table4.3.Cross-table of prevalence of stunting (child malnutrition) by wealth index

Predictors		Stunting levels (%)				Total
		normal	mild	moderate	severe	
Wealth index	Poor	1217 (30.6)	875 (22.0)	892 (22.4)	990 (24.9)	3974
	Medium	420 (31.8)	318 (24.1)	282 (21.4)	300 (22.7)	1320
	Rich	929 (38.0)	641 (26.2)	514 (21.0)	360 (14.7)	2444

4.2. Results of the ordinal logistic regression

Ordinal logistic regression is an appropriate model for a response variable with more than two categories by considering the ordering of the categories. This model is simply an extension of binary logistic regression (only two categories). This model is based on the estimation of log (odds) cumulative probability for the response which has a linear relationship to the set of explanatory variables. Proportional odds model is a set of logit model estimated simultaneously by assuming the effects of explanatory variables equal in all logits.

Univariate analysis

The variables in this study are level of stunting (malnutrition) of children aged five or below as the response and child's sex, child's age, mother's education, number of household members, previous birth interval, birth order, body mass index, wealth index, place of residence and region are the explanatory variables that related to stunting (malnutrition) based on different literatures. Before building the logistic regression model for analyzing the categorical data, we first checked the association of each explanatory variable with response using Pearson chi-square test. Consequently, it was found that all the explanatory variables are significantly associated at 15% level of significance. (See Table A1). Hence, all these explanatory variables are entered into the proportional odds model (Hosmer and Lemeshow, 2000) since all the explanatory variables are significantly associated with level of stunting (malnutrition). Owing to this, we investigate the relationship between level of stunting (malnutrition) and the variables cited above using ordinal logistic regression models.

The proportional odds model can be estimated for all significantly associated variables by descending option in logistic procedure using SAS 9.2. Results of the fit showed that all possible independent variables (i.e. child's sex, child's age, mother's education level, previous birth interval, birth order, number of household members, mother's body mass index, wealth index, place of residence and region) are significant at 5% level of significance. It is also possible to use variable selection procedure in fitting POM. Thus, in order to select the important independent variables related to level of stunting (child's malnutrition), the three variable selection procedures such as backward, forward and stepwise selections were used using SAS 9.2. Final models for the three selection procedures are virtually the same and all effects or variables have been entered into the final model.

The fit of POM model for the selected explanatory variables was done using SAS 9.2, by including "aggregate scale=none" option to test the overall goodness of fit test by the Pearson (p=0.063) and Deviance (p=0.188) chi-squares (See Table A2). These goodness-of-fit tests support that the model fits the data well since the p-value for both goodness-of-fit tests is greater than 5% level of significance. In fitting POM, test of the proportionality assumption is performed using score test which has p value less than 0.05 showing that the assumption is violated (See Table A2). To confirm the predictors that violate the assumption of POM, single score tests of the proportional odds assumption for each predictor were conducted. The p-values of the single score tests are shown in the last column of Table A2. A significant test statistic provides evidence that the proportionality assumption has been violated. Thus, the test results suggest that child's sex, child's age and birth order are especially problematic with regards to the proportionality assumption, but the other predictors do not appear to violate the assumption.

If the POM assumption is violated, there are two different alternatives that have been discussed in chapter three. Therefore, in order to overcome this problem the partial proportional odds model fitted by the GOLOGIT2 with option AUTOFIT (Williams, 2006) provides a good alternative model than the other models like POM (with strict assumption of parallel line for all explanatory variables) and GOM (with relaxed the assumption parallel line for all explanatory variables).

4.3. Results of partial proportional odds model (PPOM)

This model can be fitted using the GOLOGIT2 with AUTOFIT option of STATA user written command (Williams, 2006). Using AUTOFIT option to estimate a model in which some variables are constrained to meet the parallel lines assumption while others are not. In simple words, PPOM is a model that relaxes the constraints for those variables that violate the assumption of POM. Based on the above PPOM with AUTOFIT option, a series of Wald tests are also used to check the assumption of proportionality for all categories of each explanatory variable and finally all the categories of the explanatory variables that pass the Wald test are tested using global Wald test with degrees of freedom equal to the number of parameters that pass the assumption of proportional odds model.

The following is the format of PPOM for level of stunting (malnutrition) and the estimated model is given in Table 4.1.

$$ln\left[\frac{\pi_j(X)}{1-\pi_j(X)}\right] = \alpha_j + \beta_{1jm}CSEX_m + \beta_{2ja}CAGE_a + \sum_{e=2}^{3}\beta_{3e}MEDU_e + \sum_{h=2}^{3}\beta_{4h}NHHM_h + \sum_{i=2}^{3}\beta_{5i}PBINT_i + \beta_{6jo}BORD_o + \sum_{w=2}^{3}\beta_{7w}WINDEX_w + \sum_{b=2}^{3}\beta_{8b}BMI_b + \beta_{9u}PLRESID_u + \sum_{r=2}^{11}\beta_{10r}REGION_r$$

where, $\pi_j(X) = P(Y > j/X)$ is the sum of all probabilities of the response above the j^{th} category.

When the model is fitted using STATA 12 for categorical explanatory variables the first category of each explanatory variables are considered as reference category. Results of the fitted PPOM are given in Table 4.4. The categories, child's sex female, child's age below 48 months, previous birth interval less than 24 months, birth order between 1 and 3, no education, number of household members between 1 and 4, wealth index poor, urban residence, Addis Ababa and BMI less than 18.5 (thin mothers) were used as reference categories. Table 4.4 and 4.5 provide a variety of PPOM estimates (parameters estimate, p-value, odds ratios, 95% CI's for odds ratios).

Table 4.4: The parameters estimate of PPOM model

Predictors (independent variables)		Normal (Not- stunted)		Mildly stunted		Moderately stunted	
		Coef.	P(> |z|)	Coef.	P(> |z|)	Coef.	P(> |z|)
Child's sex	male	0.050	0.014	0.111	0.017	0.152	0.007
Child's age	≥48 months	0.534	0.000	0.184	0.002	-0.010	0.881
Mother's education	Primary	-0.195	0.020	-0.195	0.020	-0.195	0.020
	Secondary/above	-0.605	0.000	-0.605	0.000	-0.605	0.000
No of HH members	5-9 members	0.158	0.012	0.158	0.012	0.158	0.012
	≥10 members	0.270	0.143	0.270	0.143	0.270	0.143
P. birth interval	24-47	-0.394	0.000	-0.394	0.000	-0.394	0.000
	≥48	-0.649	0.000	-0.649	0.000	-0.649	0.000
Birth order	4 or above	0.113	0.044	0.125	0.019	0.237	0.000
Wealth index	Medium	-0.244	0.017	-0.244	0.017	-0.244	0.017
	Rich	-0.164	0.002	-0.164	0.002	-0.164	0.002
Mother's BMI	Normal	-0.148	0.012	-0.148	0.012	-0.148	0.012
	Overweight	-0.600	0.000	-0.600	0.000	-0.600	0.000
Residence	Urban	-0.471	0.000	-0.471	0.000	-0.471	0.000
Region	Affar	-0.159	0.418	-0.159	0.418	-0.159	0.418
	Amhara	0.530	0.007	0.530	0.007	0.530	0.007
	Oromiya	-0.214	0.254	-0.214	0.254	-0.214	0.254
	Somali	-0.122	0.000	-0.122	0.000	-0.122	0.000
	Ben-Gumuz	0.143	0.000	0.143	0.000	0.143	0.000
	SNNP	-0.081	0.668	-0.122	0.556	0.320	0.355
	Gambela	-0.809	0.000	-0.820	0.000	-0.415	0.251
	Harari	-0.680	0.000	-0.655	0.003	-0.310	0.401
	Tigray	0.508	0.028	0.508	0.028	0.508	0.028
	Dire Dawa	-0.220	0.534	-0.220	0.534	-0.220	0.534
	Cons	1.294	0.000	0.321	0.144	-1.031	0.004

Table 4.5: Odds ratio estimates of PPOM for the risk factors of malnutrition levels

Predictors (independent variables)		Normal (Not- stunted)			Mildly stunted			Moderately stunted		
		Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI	
			Lower	Upper		Lower	Upper		Lower	Upper
Child's sex	male	1.051	0.954	1.158	1.117	1.019	1.224	1.164	1.042	1.299
Child's age	≥48months	1.705	1.497	1.942	1.202	1.071	1.347	0.990	0.862	1.136
Mother's education	Primary	0.822	0.727	0.930	0.822	0.729	0.927	0.822	0.706	0.957
	Secondary^{+}	0.546	0.398	0.747	0.546	0.371	0.802	0.546	0.301	0.987
No of HH members	5-9	1.171	1.012	1.356	1.171	1.012	1.356	1.171	1.012	1.356
	≥10	1.310	1.055	1.627	1.310	1.055	1.627	1.310	1.055	1.627
P. birth interval	24-47	0.674	0.592	0.767	0.674	0.599	0.758	0.674	0.589	0.771
	≥48	0.522	0.447	0.609	0.522	0.451	0.604	0.522	0.438	0.622
Birth order	≥4	1.120	1.002	1.250	1.133	1.020	1.258	1.267	1.115	1.440
Wealth index	Medium	0.783	0.681	0.901	0.783	0.681	0.901	0.783	0.681	0.901
	Rich	0.848	0.743	0.968	0.848	0.743	0.968	0.848	0.743	0.968
Mother's BMI	Normal	0.862	0.768	0.967	0.862	0.768	0.967	0.862	0.768	0.967
	Overweight	0.549	0.436	0.689	0.549	0.436	0.689	0.549	0.436	0.689
Residence	Urban	0.624	0.522	0.746	0.624	0.522	0.746	0.624	0.522	0.746
Region	Affar	0.853	0.580	1.254	0.853	0.580	1.254	0.853	0.580	1.254
	Amhara	1.699	1.155	2.498	1.699	1.155	2.498	1.699	1.155	2.498
	Oromiya	0.807	0.558	1.166	0.807	0.558	1.166	0.807	0.558	1.166
	Somali	0.885	0.606	1.292	0.885	0.606	1.292	0.885	0.606	1.292
	B/Gumuz	1.154	0.781	1.702	1.154	0.781	1.702	1.154	0.781	1.702
	SNNP	0.922	0.635	1.338	0.922	0.635	1.338	0.922	0.635	1.338
	Gambela	0.445	0.301	0.656	0.445	0.301	0.656	0.445	0.301	0.656
	Harari	0.506	0.341	0.752	0.506	0.341	0.752	0.506	0.341	0.752
	Tigray	1.662	1.134	2.437	1.662	1.134	2.437	1.662	1.134	2.437
	D.Dawa	0.802	0.545	1.181	0.802	0.545	1.181	0.802	0.545	1.181
	Cons	3.647	2.430	5.473	1.378	0.895	2.121	0.356	0.177	0.717

4.4. Marginal effects

In PPOM the probability of a single level of the response variable is not possible. The sign of the coefficients does not always determine the direction of the effect of the intermediate outcomes (Washington *et al.*, 2003; Wooldridge, 2002). Therefore, there is a need to find another way of determining the contribution of each explanatory variable on the categories of the response which can be done by computing marginal effects. Marginal effect is used to measure the magnitude and types of association between the levels of the explanatory variable on the probability of levels of the response variable. In Table A3, the effect of the levels of the explanatory variables on stunting (malnutrition) levels are given.

Male children were more likely to be mildly, moderately and severely stunted by 17.6%, 11.3% and 1% respectively as compared to female children. Also children living in urban areas were less likely to be mildly, moderately and severely stunted by 4%, 3.8% and 3.6% respectively as compared to their rural counterparts.

Children with birth order of 4 or above were more likely to be mildly stunted by 3.4% as compared to children with birth order first to third; they were more likely to be moderately stunted by 2.5% as compared to children with birth order first to third. Children with birth order of 4 or above were more likely to be severely stunted by 2.4% as compared to children with birth order first to third.

Children belonging to mothers with primary education were less likely to be mildly, moderately and severely stunted by 5.6%, 3.7% and 3.5% respectively as compared to children whose mothers weren't educated. Also, children belonging to mothers with secondary education or above were less likely to be mildly, moderately and severely stunted by 25.3%, 15.2% and 14.3% respectively as compared to children whose mothers weren't educated. Besides, children in 5-9 and 10 or above household members were more likely to be mildly stunted by 3.9% and 6.3% respectively as compared to those children in 1-4 household members.

Children from Tigray, Amhara and Benishangul-Gumuz were more likely to be mildly stunted by 18.4%, 19.3% and 15%, respectively as compared to children in Addis Ababa; they were more likely to be moderately stunted by 19.6%, 17.9% and 11.63% respectively as compared to Addis Ababa. Children from Tigray, Amhara and Benishangul-Gumuz were more likely to be severely stunted by 14.9%, 17.4% and 19% respectively as compared to children from Addis Ababa.

4.5. Result of test of overall model fit

The model fit statistics (AIC, likelihood ratio (LR) test and Pseudo R^2) for the two alternative models; PPOM and GOM are given in Table 4.6 and Table 4.7 below.

Table 4.6: AIC and BIC for PPOM and GOM

Model	Observations	AIC	BIC
PPOM	7738	20551.29	21072.83
GOM	7738	20564.88	21332.42

Table 4.7: Likelihood ratio test and computed Pseudo R^2 for PPOM and GOM

Model	LL(null)	LL(model)	DF	LR chi2	Pr>Chi2	Pseudo R^2
PPOM	-10592.65	-10318.95	33	547.39	0.0000	0.0358
GOM	-10592.65	-10198.44	72	788.42	0.0000	0.0372

PPOM contains fewer parameters than GOM. A model with small AIC is preferred therefore; PPOM has the smallest AIC which is 20,551.29.

The final fit for the two models are significant compared to their null model (only intercept term) evidenced from deviance LR test all the P=0.0000 and again the Pseudo R^2 of PPOM model is a little bit smaller than Pseudo R^2 of GOM.

Partial proportional odds model (PPOM) is a series of logit models estimated simultaneously, the only way to perform goodness of a fit is by separately fitting all logits and perform goodness of fit test for each binary model. For ordinal response variable with J ordinal category we can obtain a J-1 Binary Logistic Regression (BLR) models which make a series of binary comparisons. For example, a four-category ordered variable Y coded as 1, 2, 3 and 4 can be represented as three possible separate binary comparisons.

BLR 1: not-stunted vs mildly stunted or moderately stunted or severely stunted: -

$$ln\left[\frac{\pi_1(X)}{1-\pi_1(X)}\right] = \alpha_j + \beta_{1jm}CSEX_m + \beta_{2ja}CAGE_a + \sum_{e=2}^{3}\beta_{3je}MEDU_e + \sum_{h=2}^{3}\beta_{4jh}NHHM_h + \sum_{i=2}^{3}\beta_{5ji}PBINT_i + \beta_{6jo}BORD_o + \sum_{w=2}^{3}\beta_{7jw}WINDEX_w + \sum_{b=2}^{3}\beta_{8jb}BMI_b + \beta_{9ju}PLRESID_u + \sum_{r=2}^{11}\beta_{10jr}REGION_r$$

where, π_1 is the probability of stunting (at least mild) given that of the set of explanatory variables.

BLR 2: not-stunted or mildly stunted vs moderately stunted or severely stunted: -

$$ln\left[\frac{\pi_2(X)}{1-\pi_2(X)}\right] = \alpha_j + \beta_{1jm}CSEX_m + \beta_{2ja}CAGE_a + \sum_{e=2}^{3}\beta_{3je}MEDU_e + \sum_{h=2}^{3}\beta_{4jh}NHHM_h + \sum_{i=2}^{3}\beta_{5ji}PBINT_i + \beta_{6jo}BORD_o + \sum_{w=2}^{3}\beta_{7jw}WINDEX_w + \sum_{b=2}^{3}\beta_{8jb}BMI_b + \beta_{9ju}PLRESID_u + \sum_{r=2}^{11}\beta_{10jr}REGION_r$$

where, π_2 is the probability of stunting (at least moderate) given that of the set of explanatory variables.

BLR 3: not-stunted or mildly stunted or moderately stunted vs severely stunted: -

$$ln\left[\frac{\pi_3(X)}{1-\pi_3(X)}\right] = \alpha_j + \beta_{1jm}CSEX_m + \beta_{2ja}CAGE_a + \sum_{e=2}^{3}\beta_{3je}MEDU_e + \sum_{h=2}^{3}\beta_{4jh}NHHM_h + \sum_{i=2}^{3}\beta_{5ji}PBINT_i + \beta_{6jo}BORD_o + \sum_{w=2}^{3}\beta_{7jw}WINDEX_w + \sum_{b=2}^{3}\beta_{8jb}BMI_b + \beta_{9ju}PLRESID_u + \sum_{r=2}^{11}\beta_{10jr}REGION_r$$

where, π_3 is the probability of severely stunting given that of the set of explanatory variables.

After fitting the above three separate binary logistic regression models, the Hosmer-Lemeshow goodness-of-fit test for those binary logit models were performed using SAS 9.2 (See Table A6). The three logit models' results of H-L test are insignificant showing all the three binary logits well fit the data. Since H-L test cannot be used for proportional odds model, candidate binary logits were well fitted. Hence, the proportional odds model that contains all binary logits also well fit the data because partial proportional odds model is a set of binary logits which are simultaneously modeled.

4.6. Interpretation of partial proportional odds model

The results in Table 4.4 regarding the partial proportional odds model provide estimated coefficient, standard error and p-value for each explanatory variable category. The coefficients of the explanatory variables in the model are interpreted as the log odds of the response variable being in higher categories as opposed to the lower categories. In logistic regression, the interpretations of the model estimates are based on odds ratios and their confidence interval (See Table 4.5). On the basis of Table 4.5, the interpretations are given as follow.

From the results of PPOM, it is revealed that children aged 48 months or above were 1.705 times more likely to be at least mildly stunted (as opposed to not-stunted) compared to children aged below 48 months. Children aged 48 months or above were 1.202 times more likely to be at least moderately stunted (as opposed to not-stunted or mildly stunted) compared to children aged below 48 months. When not-stunted, mildly and moderately stunted are opposed to severely stunted, children aged 48 months or above were 1.2 times more likely to be severely stunted as compared to children aged below 48 months. In general, the prevalence of stunting increases as the age of a child increases, with the highest prevalence of chronic malnutrition found in children aged 48 months or above and lowest in children aged below 48 months.

Male children had 1.051 times higher risk of being at least mildly stunted status (as opposed to not-stunted status) as compared to female children. Male children had 1.117 times higher risk of being at least moderately stunted status (as opposed to not-stunted or mildly stunted status) compared to female children. Similarly, male children had 1.164 times higher risk of being severely stunted status (as opposed to not-stunted or mildly stunted or moderately stunted status) as compared to female children. That means male children were more likely of being in higher levels of stunting than lower levels of stunting compared with female children.

Previous birth interval is a significant determinant of stunting status. Children having birth interval 24-47 and 48 months or above had 32.6% and 47.8% less risk of being at worse stunting status respectively as compared to children having birth interval less than 24 months. That means the longer the interval, the less likely it is that the child will be stunted. Generally, birth interval has an inverse relationship with stunting levels.

Birth order is a significant determinant of stunting status. In some of previous studies, the order of birth has been recorded into four categories assumed that a higher order births are associated with a high risk of malnutrition (with the exception of first order births). In this study, birth order is recorded into two categories: first to third birth, and higher. Children with birth order 4 or above had 1.12 times higher risk of being at least mildly stunted (as opposed to not-stunted status) compared to children with birth order first to third. Children with birth order 4 or above had 1.13 times higher risk of being at least moderately stunted (as opposed to not-stunted or mildly stunted) as compared to children with birth order first to third. Children with birth order 4 or above had 1.267 times higher risk of being severely stunted status (as opposed to not-stunted or mildly stunted or moderately stunted status) as compared to children with birth order first to third. That means as the birth order number increases the likely to be stunted will increases.

The mother's level of education generally has an inverse relationship with stunting levels. Children of mothers with primary and secondary education or above had 17.8% and 45.4% less risk of being at worse stunting status respectively as compared to children of mothers with no education. That means the risk of having stunting status was found highest for the children having mothers with no education. As the mother's education level improves, the stunting (malnutrition) status of children become less and less when compared with children whose mother was not educated.

Children in 5-9 and 10 or above household members had 1.171 and 1.310 times greater risk of being at worse stunting status respectively as compared to those children in 1-4 household members, holding all other variables constant. This result is also confirmed by marginal effect, children in 5-9 and 10 or above household members had positive marginal effect (see Table A3) implying that children in 5-9 and 10 or above household members were more likely of being in the mildly stunted as compared to children in 1-4 household members.

The mother's nutritional status, as measured by her body mass index (BMI), also has an inverse relationship with her child's level of stunting. Children of normal mothers (BMI between 18.5 and 24.9) had 13.8% less risk of being at worse stunting status as compared to children of thin mothers (BMI < 18.5). Children of overweight mothers (BMI ≥ 25.0) were less likely of being in higher categories of stunting. The estimated odds ratio (OR=0.549) reveals that children of overweight mothers had 45.1% less risk of being at worse stunting status as compared to children of thin mothers. The 95% confidence interval also suggests that odds ratio could be as minimum as 0.436 and as maximum as 0.689.

A similar inverse relationship is observed between the household wealth index and the stunting levels of children. Children of the medium wealth households had 21.7% less risk of being at worse stunting status as compared to children of the poor households. Children of the rich households were less likely of being in higher categories of stunting. The estimated odds ratio (OR=0.848) reveals that children of the rich households had 15.2% less risk of being at worse stunting status as compared to children of the poor households. The 95% confidence interval also suggests that odds ratio could be as minimum as 0.743 and as maximum as 0.968; that is, the chance of having worse stunting was found to decrease with increase of household wealth condition.

Place of residence is a significant determinant of stunting status, showing that urban children had 37.6% less risk of being at worse stunting status as compared with rural children. That means rural children were more likely of being in higher levels of stunting than lower levels of stunting compared with urban children.

Regional variation in the prevalence of stunting in children is substantial. Children lived in Amhara, Benishangul Gumuz and Tigray had 1.699, 1.154 and 1.662 times higher risk of being at worse stunting status respectively as compared with those lived in Addis Ababa.

4.7. Model adequacy checking

Model adequacy checking includes diagnosing residuals and measures of influence. This is difficult to do in ordinal and multinomial logistic models. In order to reduce the difficulty, the ordinal response variable categories can be changed to binary categories by collapsing two or more categories. Then a binary logistic regression model is fitted after which it is possible to apply model adequacy checking. In this study, the response variable has four categories. By collapsing the three categories such as mildly, moderately and severely stunted into one and called as stunted. The other category would be not-stunted. Therefore, the diagnostics performed in binary logistic regression model is the same for the partial proportional odds model (ordinal logistic regression). We could calculate residuals, measures of influence and the predicted probabilities of the data. The plots of standardized Pearson residuals, deviance residuals, Cook's distance and leverage value with predicted probability can then be used to see the pattern of all cases using the software SAS 9.2. The residuals and measure of influence plots against the predictive probabilities revealed that the model is adequate.

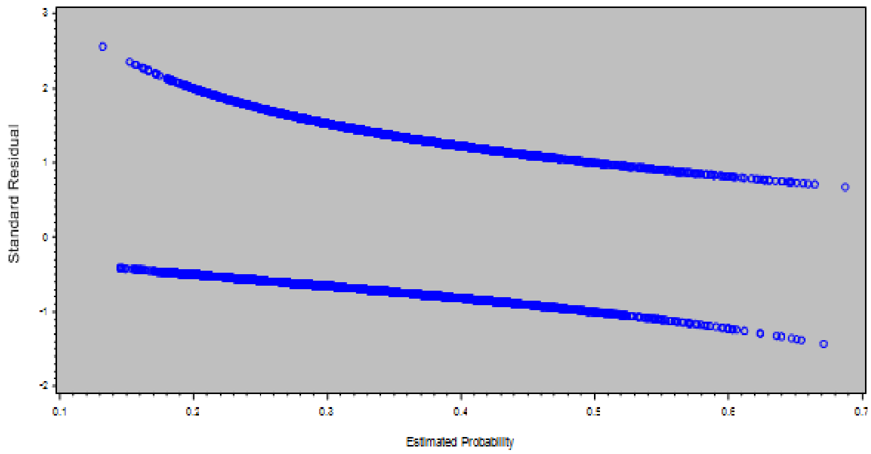

Figure 4.1: Plots of Standard Residual vs Estimated Probability

Figure 4.1 is the plot of standard residuals vs estimated probabilities of all observations. There are few observations far from the others. However, the computed standard residuals do not influencing the model that means all standard residuals are less than three (see from Y-axis).

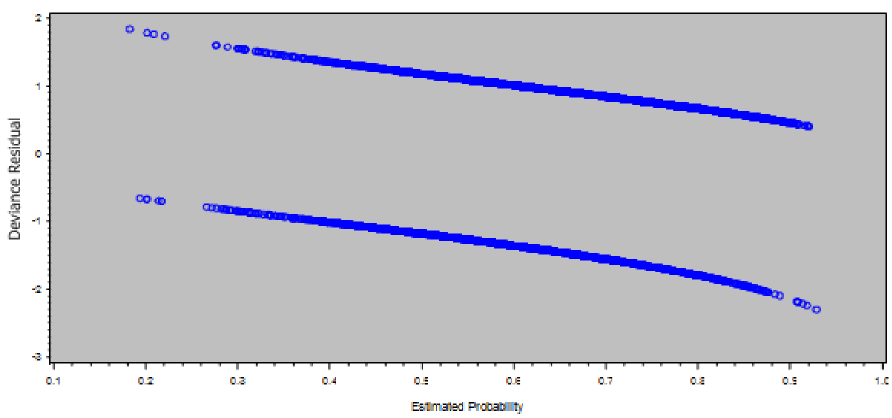

Figure 4.2: Plots of Deviance Residual vs Estimated Probability

Figure 4.2 above is the plots of deviance residuals vs estimated probabilities of all observations. Apparently, there are few observations that lie far away from the rest but all absolute deviance residuals are less than three. Therefore, there is no lack of fit.

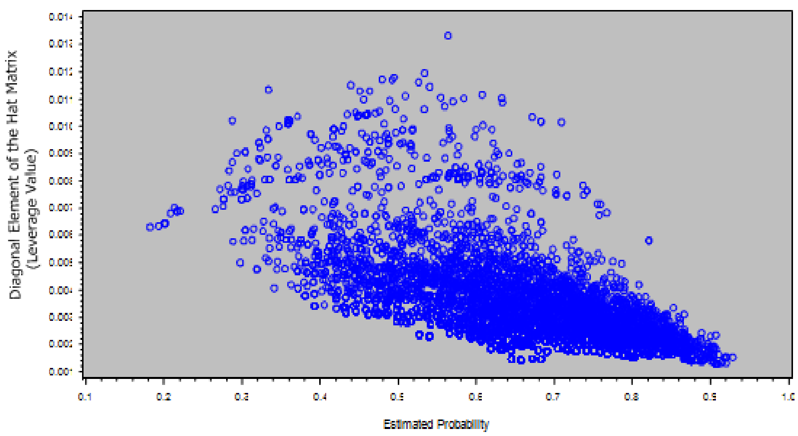

Figure 4.3: Plots of Leverage Value vs Estimated Probability

Figure 4.3 the plots of leverage value vs the estimated probabilities of all observations. It was observed that leverage values of the above plots are less than one. Therefore, there are no outliers.

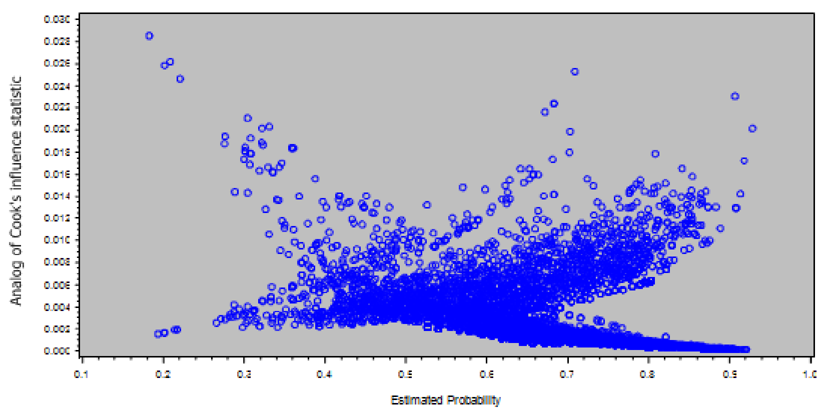

Figure 4.4: Plots of Analog of Cook's influence statistic vs Estimated Probability

Figure 4.4 is the plot of Analog of Cook’s influence statistic vs the estimated probabilities of all observations. There are observations a little far away from the others. These are not influential observations since all Cook’s influence statistic are less than one. (See on Y-axis of the graph).

5. DISCUSSION, CONCLUSION AND RECOMMENDATION

5.1. Discussion

This study was intended to identify the risk factors of the stunting status (malnutrition) of children aged five years or below in Ethiopia based on EDHS 2011 data. The stunting status was measured by the height-for-age z scores. Accordingly, we can say that the PPOM fitted the data very well with very small p value and relatively minimum AIC value compared to GOM. In this study, child's sex, child's age, mother's education, number of household members, previous birth interval, birth order, mother's body mass index, wealth index, place of residence and region were considered as predictors. Results of PPOM show that all the predictors have significant influence on malnutrition of children aged five or below in Ethiopia. The results obtained are discussed as follows.

Finding of this study showed that the risk of stunting increased with age of children. Children whose age were 48 months or above (48-59 months) had significantly higher risk of being at worse stunting as compared with children aged below 48 months. This could be because of breastfeeding in the early stages of child growth, mother's ability to care for the child and also due to the care that parents give to older children that may decline especially if there are younger children in the family (UN, 1985). This result is consistent with other studies conducted in Ethiopia and other developing countries, which showed the prevalence of stunting positively associated with child age (Otgonjargal *et al.*(2012); Asres & Eidelman (2011); Teshome *et al.*(2006); Mulugeta *et al*. (2005)). This result is also consistent with national EDH 2011 which indicated that the prevalence of stunting increases as the age of child increases (EDHS, 2011). The prevalence of diseases and stunting rises with age (Paramita *et al.* (2010)). But, this is inconsistent with studies conducted by Joseph *et al.* (2002); Panda *et al*. (1993). They have found highest prevalence of malnutrition is in children aged 12-23 months.

Similarly, this study revealed that male children were more likely to be at worse stunting status as compared to female. These sex-related differences require further study. One report from Ghana suggested that boys were more influenced by environmental stress (Hien N &

Hoa N., 2009). This is also supported by the report of EDHS 2011 indicated that male children are slightly more likely to be stunted than female children (46 % and 43%, respectively). Similar results are also reported from other studies (Christiaensen & Alderman, 2001; Mekonnen *et al*. (2005)). They argued that this could be due to genetic differences between male and female children and, due to girls' greater access to food through their gender-ascribed role in contributing to food preparation.

Household economic status, which is categorized based on their wealth index status, is also an important determinant of child malnutrition. Children in poor households are found to be, on average, at a higher risk of stunting (malnutrition) than children from rich households. This finding is consistent with other studies (Smith *et al*., 2005; SCUK, 2002; Girma & Genebo, 2002). They indicated that better households have better access to food and higher cash incomes than poor households, allowing them a quality diet, better access to medical care and more money to spend on essential non-food items such as schooling, clothing and hygiene products.

The findings of this study also show that there is a significant difference in the risk of stunting (malnutrition) in children by mothers' educational level. The risk of stunting (malnutrition), on average, significantly higher for children whose mothers with no education and primary education level than children whose mothers have secondary or higher level of education. This finding seemed to be consistent with other studies (Oyekale and Oyekale, 2000; Smith and Haddad, 2000). They indicated that education improves the ability of mothers to implement simple health knowledge and facilitates their capacity to manipulate their environment including health care facilities, interact more effectively with health professionals, comply with treatment recommendations, and keep their environment clean. Furthermore, educated women have greater control over health choices for their children.

Previous birth interval showed highly significant and inverse relationship with the prevalence of stunting. Children with longer previous birth interval had lower risk of being stunted. Our analysis shows that both birth interval groups (24 to 47 months and greater than 48 moths) are found statistically significant. Thus, as the birth interval increases the likelihood to be stunted decreases. This finding is confirmed by most of previous studies (Kandela, 2001;

Khalid, 2007; Mohammed, 2008; Dejen, 2008). The significant and higher risk of stunting among children of lower birth interval could be due to uninterrupted pregnancy and breastfeeding, since this drains women's nutritional resources (Sommerfelt and Stewart, 1994). Close-spacing may also have a health effect on the previous child who may be prematurely weaned if the mother becomes pregnant too early again. In this study, rural children were found to be the most affected by stunting status (malnutrition). This may be due to close spacing and low contraceptive prevalence rate in the rural areas.

Birth order showed highly significant and direct relationship with the prevalence of stunting. Children with higher birth order had higher risk of being stunted (undernourished). Our analysis shows that birth order 4 or above is found statistically significant. Thus, as birth order increases the likelihood to be stunted (undernourished) increases. This finding is consistent with most of previous studies (Senauer and Garcia, 1991; Sentayehu, 1994). The significant and higher risk of stunting among children of higher birth order could be due to the increased burden on family resources (Senauer and Garcia, 1991). This is not consistent with the study conducted by Mekonnen *et al.*, 2005. They didn't find birth order to be significantly related with stunting for the whole sample by using logistic regression.

As the study has revealed that, household size is an important risk factor for malnutrition. The prevalence of stunting (malnutrition) increased with increasing household size. Households with 5-9 and 10 or above members had a higher percentage of stunted children compared with households with between 1 and 4 children. Large household size is not conducive for better nourishment of children. However, we may interpret that while larger households provide more care to children (mostly by elder members of the household in a joint or extended family setting), there seemed to be a simultaneous competition for resources within the same larger household size. This competition for limited resources may be responsible for worsening of nutritional status for the children of a larger household size. This result is in agreement with a study under taken by Rahman, A. & Chowdhury, S. (2007) which stated that children living in a household with only one child have a lower risk of nutrition than children who live in households with more than one child. The total number of children within a household influences the resources available to each child, in terms of financial, time and attention. In a crowded household, exposure of an individual child to infection is also increased. (Sereebutra *et al*., 2006).

In this study mother's body mass index, which is defined as her weight in kilogram divided by square of her height in meters, was found to be highly related with malnutrition. Thin Mothers (BMI < 18.5) are themselves malnourished and are therefore likely to have stunted (undernourished) children. The same finding is also found in a number of studies. Mothers with low BMI, on average, are giving birth to babies of low birth weight. (Mohammad. A, 2008). This finding also consistent in some of studies in Africa (MOFED, 1999; Sahn & Stifel, 2002; Christiaensen & Alderman, 2004) a mother's nutritional status affects her ability to successfully carry, deliver, and care for her children and is of great concern in its own right. Women who are malnourished (thinness or obesity) may have difficulty during childbirth and may deliver a child who can be malnourished. The results indicate that there is an association between the thinness condition of the mother and the nutritional status of the child.

As shown in the analysis, urban children were less likely to be stunted (malnourished) than their rural counterparts because the quality of health environment and sanitation is better in urban areas, whereas, the living condition in rural areas were associated with poor health condition, and lack of personal hygiene, which were the risk factors in determining malnutrition. This is consistent with some studies, where mothers' place of residence has a statistical significant effect on children nutritional status. (Girma & Genebo , 2002; Kandala *et al*.,2006).

Based on findings of this study, Tigray, Amhara and Benishangul-Gumuz regions children aged five years or below show high risk of stunting (malnutrition). The observed higher risk of malnutrition in Tigray, Amhara and Benishangul-Gumuz regions may be due to differences in economic levels, and cultural and dietary practices. Earlier surveys have also shown a very high prevalence of stunting in these regions (CSA, 1998; CSA, 2007). According to 2013 MOFED report in terms of food poverty, the highest poverty is observed in Amhara followed by Tigray and Beneshangul Gumuz (MOFED, 2013). These figures are consistently similar in extent of malnutrition of children in the country. One reason to have high malnutrition prevalence in Amhara, Tigray and Benishangul Gumuz may be due to food poverty prevalence in the regions. In contrast, those regions like Harari, Gambela and Addis Ababa Administration children have low risk to be stunted, because these regions are relatively better in economy and food access according to 2013 MOFED report. The present finding was also in line with the study done by Girma, W. & Genebo, T. (2002).

5.2. Conclusion

Despite some differences in the results of the fitted models, the results of PPOM are reasonably compared with that of GOM. The PPOM is fitted better for the data than GOM. From the results of PPOM it is clear that all the considered variables in the study are significant predictors of child malnutrition as previous researchers done.

The study showed that children from uneducated mother, low mother's body mass index, economically poor household and large household size are more vulnerable to stunting problem in Ethiopia. Children with lower previous birth interval (less than 24 months) and higher birth order were at higher risk of stunting. Children from rural residence of mother were more likely to be at worse stunting level. The findings of this study also showed that male children are more vulnerable to stunting problem than female children. Children from Tigray, Amhara and Benishangul Gumuz regions were more likely to be at worse stunting status (to be at higher level of malnutrition). This implies that the likelihood of being at higher level of malnutrition vary across regions.

5.3. Recommendation

Based on the results of this study, the following recommendations are suggested.

- For reducing childhood malnutrition, due emphasis should be given in improving the knowledge and practice of parents on appropriate young child feeding practice and frequent growth monitoring together with appropriate and timely interventions.
- Since the prevalence of child's malnutrition differs among regions, the Ministry of Health should give special attention to regions Tigray, Amhara and Benishangul Gumuz.

- Since children in higher number of household members were at higher risk of malnutrition, we recommend that the government and health centers should advice the households about family planning.
- Since children born with lower previous birth interval were at higher risk of malnutrition, the government and health centers should advice the households about bearing child with better spacing.
- Governments should improve socioeconomic conditions. Because, if living standards are improved, there will be better health care and reduction of infants' and children's malnutrition, diseases and mortality.
- The government and other concerned bodies should pay attention to the above suggestions and make appropriate efforts to tackle problems that contribute to malnutrition.

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APPENDICES

Table A1: Chi- square test of association between explanatory variables with response variable

Predictors (independent variables)	Pearson Chi-square (p value)
Child's sex	0.078
Child's age	0.000
Mother's education	0.000
Number of household members	0.023
Previous birth interval	0.000
Birth order	0.000
Mother's body mass index(BMI)	0.000
Wealth index	0.000
Place of residence	0.000
Region	0.000
All these variables are significantly associated with child malnutrition at 15%	

Table A2: POM maximum likelihood estimates, Goodness of fit Statistics and Score test of proportionality using SAS 9.2.

Predictors	**Estimate**	**Standard Error**	**Odds ratio**	**p-value**	**Single score Test (p-value)**
Intercept 1	-1.334	0.185	-	0.000	-
Intercept 2	-0.298	0.184	-	0.106	-
Intercept 3	0.779	0.185	-	0.000	-
Child's sex [Female as reference]					
Male	-0.094	0.041	0.910	0.023	0.002
Child's age [Below 48 months as reference]					
48 or above	-0.256	0.052	0.774	0.000	0.003
Mother's education [No education as reference]					
Primary	0.157	0.0537	1.170	0.003	0.651
Secondary or above	0.588	0.150	1.800	0.000	
No. of Household members [1-4 as reference]					
5-9	0.074	0.062	1.077	0.234	0.113
10 or above	0.196	0.094	1.216	0.038	
Previous birth interval [Less than 24 as reference]					
24-47	0.349	0.053	1.418	0.000	0.568
48 or above	0.555	0.066	1.742	0.000	
Birth Order [1-3 as reference]					
4 or above	-0.146	0.047	0.864	0.002	0.001
Wealth status [Poor as reference]					
Medium	0.091	0.059	1.095	0.120	0.654
Rich	0.141	0.056	1.151	0.012	
Mother's BMI [Thin as reference]					
Normal	0.146	0.048	1.157	0.003	0.118
Overweight	0.542	0.105	1.719	0.000	
Place of residence [Rural as reference]					
Urban	0.247	0.080	1.280	0.002	0.875
Region [Addis Ababa as reference]					
Affar	-0.083	0.174	0.920	0.641	0.597

Table A2: POM maximum likelihood estimates, Goodness of fit Statistics and Score test of proportionality using STATA 12 (Continued)

Amhara	-0.286	0.174	0.751	0.100
Oromiya	0.253	0.170	1.288	0.138
Somali	0.633	0.176	1.883	0.000
Ben-Gumuz	-0.168	0.177	0.845	0.342
SNNP	0.051	0.172	1.052	0.764
Gambela	0.783	0.181	2.188	0.000
Harari	0.631	0.185	1.879	0.000
Tigray	-0.271	0.173	0.762	0.117
Dire Dawa	0.183	0.179	1.200	0.306

Goodness of fit Statistics

Criteria	**Value**	**df**	**Value/df**	**Pr> ChiSq**
Deviance	9648.70	9362	1.0306	0.188
Pearson	9706.77	9362	1.0368	0.063

Score test for the Proportional Odds Assumption

Chi-square	**df**	**Pr> ChiSq**
103.542	20	0.000

Table A3: Marginal effect (ME) of each predictor on stunting (child malnutrition) levels probabilities

Predictors (independent variables)		Normal (Not- stunted)		Mildly stunted		Moderately stunted		Severely stunted	
		ME	P(>|z|)	ME	P(>|z|)	ME	P(>|z|)	ME	P(>|z|)
Child's sex	male	-0.021	0.023	0.176	0.033	0.113	0.057	0.010	0.305
Child's age	≥48 months	-0.054	0.000	0.210	0.000	0.111	0.000	0.108	0.000
Mother's education	Primary	0.035	0.004	-0.056	0.018	-0.037	0.007	-0.035	0.009
	Secondary+	0.138	0.000	-0.253	0.048	-0.152	0.040	-0.143	0.000
No of HH members	5-9 members	0.016	0.018	0.039	0.012	0.027	0.069	0.025	0.097
	≥10members	0.043	0.040	0.063	0.014	0.065	0.035	0.061	0.013
P. birth interval	24-47	0.072	0.000	-0.057	0.000	-0.072	0.000	-0.068	0.000
	≥48	0.119	0.000	-0.111	0.000	-0.114	0.000	-0.107	0.000
Birth order	≥4	-0.032	0.002	0.034	0.050	0.025	0.046	0.024	0.045
Wealth index	Medium	0.020	0.017	-0.024	0.014	-0.020	0.211	-0.019	0.210
	Rich	0.031	0.012	-0.058	0.025	-0.011	0.452	-0.019	0.444
Mother's BMI	Normal	0.031	0.002	-0.023	0.019	-0.043	0.018	-0.031	0.009
	Overweight	0.124	0.000	-0.130	0.000	-0.132	0.000	-0.125	0.000
Residence	Urban	0.056	0.000	-0.040	0.000	-0.038	0.007	-0.036	0.009
Region	Affar	-0.020	0.037	0.001	0.470	0.387	0.411	0.036	0.399
	Amhara	-0.056	0.013	0.193	0.034	0.179	0.002	0.174	0.003
	Oromiya	0.055	0.113	-0.006	0.692	-0.048	0.262	-0.046	0.259
	Somali	0.147	0.000	-0.230	0.000	-0.166	0.000	-0.157	0.000
	B/Gumuz	-0.034	0.041	0.150	0.028	0.116	0.010	0.191	0.013
	SNNP	0.011	0.006	0.050	0.034	0.022	0.025	0.028	0.610
	Gambela	0.184	0.000	-0.113	0.000	-0.190	0.000	-0.179	0.000
	Harari	0.146	0.000	-0.143	0.006	-0.161	0.001	-0.152	0.001
	Tigray	-0.053	0.000	0.184	0.006	0.196	0.004	0.149	0.005
	Dire Dawa	0.397	0.284	-0.083	0.251	-0.058	0.249	-0.051	0.237

Table A4: Test of parallel lines (using SPSS 20) for POM

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	12603.506			
General	12399.318	204.188	48	.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Table A5: The Generalized Ordered Logistic Regression Model (GOM) for risk factors of level of stunting (malnutrition)

Predictors (independent variables)		Normal		Mildly stunted		Moderately stunted	
		Coef.	P(> |z|)	Coef.	P(> |z|)	Coef.	P(> |z|)
Child's sex	male	0.157	0.017	0.178	0.010	0.118	0.090
Child's age	≥48 months	-0.394	0.000	0.242	0.004	0.187	0.028
Mother's education	Primary	-0.275	0.002	-0.157	0.091	-0.132	0.163
	Secondary[+]	-0.932	0.003	-0.381	0.097	-0.060	0.871
No of HH members	5-9 members	0.138	0.016	0.036	0.026	0.09	0.04
	≥10 members	0.361	0. 000	0.016	0.047	0.239	0.141
P. birth interval	24-47	0.545	0.000	0.326	0.000	0.302	0.001
	≥48	0.864	0.000	0.624	0.000	0.399	0.000
Birth order	4 or above	0.272	0.000	0.211	0.008	0.242	0.003
Wealth index	Medium	-0.106	0.247	-0.089	0.354	-0.036	0.717
	Rich	-0.234	0.010	-0.316	0.001	-0.212	0.028
Mother's BMI	Normal	0.230	0.002	0.129	0.106	0.086	0.283`
	Overweight	0.876	0.000	0.437	0.032	0.368	0.081
Residence	Urban	-0.499	0.000	-0.505	0.001	-0.320	0.040
Region	Affar	-0.346	0.344	0.725	0.058	0.739	0.060
	Amhara	0.781	0.033	0.166	0.658	0.379	0.331
	Oromiya	-0.203	0.576	-0.130	0.728	-0.051	0.895
	Somali	-0.526	0.152	-0.006	0.987	-0.384	0.335
	Ben-Gumuz	0.568	0.121	0.439	0.247	0.699	0.075
	SNNP	-0.217	0.549	-0.267	0.476	0.501	0.198
	Gambela	-0.828	0.029	-0.333	0.399	-0.165	0.688
	Harari	-0.641	0.096	-0.166	0.681	-0.200	0.633
	Tigray	0.688	0.060	0.159	0.673	0.209	0.591
	Dire Dawa	-0.058	0.876	-0.201	0.601	-0.538	0.179
	Cons	0.545	0.138	0.647	0.069	0.066	0.867

Table A6: The three Binary Logit Regression models and their Hosmer and Lemeshow goodness-of-fit test

Stunting (Malnutrition) levels							
Predictors (independent variables)		BLR 1		BLR 2		BLR 3	
		Coef.	P(> |z|)	Coef.	P(> |z|)	Coef.	P(> |z|)
Child's sex	male	0.0513	0. 0356	0.1024	0.0302	0.1506	0.0082
Child's age	≥48 months	0.5484	0.0000	0.1865	0.0015	-0.0015	0.9827
Mother's education	Primary	-0.4761	0.0031	-0.6640	0.0009	-0.4195	0.0174
	Secondary+	-0.6437	0.0000	-0.8128	0.0000	-0.6186	0.0438
No of HH members	5-9 members	0.1537	0.0111	0.1198	0.8908	0.1166	0.4467
	≥10 members	0.1625	0.0196	0.1722	0.4078	0.1482	0.1681
P. birth interval	24-47	-0.3345	0.0000	-0.3007	0.0000	-0.4059	0.0000
	≥48	-0.5005	0.0000	-0.5554	0.0000	-0.6541	0.0000
Birth order	4 or above	0.1142	0.0447	0.1169	0.0299	0.2429	0.0002
Wealth index	Medium	-0.1943	0.0348	-0. 242	0.0485	-0.2495	0.0395
	Rich	-0.1652	0.0443	-0.1609	0.0121	-0.2525	0.0015
Mother's BMI	Normal	-0.1531	0.0101	-0.1417	0.0102	-0.1568	0.0160
	Overweight	-0.5651	0.0000	-0.4910	0.0000	-0.6211	0.0005
Residence	Urban	-0.1713	0.0637	-0.3125	0.0010	-0.4576	0.0005
Region	Affar	-0.6811	0.0000	0.1783	0.0869	0.2283	0.0519
	Amhara	0.0301	0.8026	0.0494	0.6152	0.0910	0.4263
	Oromiya	-0.7278	0.0000	0.5073	0.0000	-0.4474	0.0000
	Somali	-1.2178	0.0000	0.8466	0.0000	-0.4731	0.0005
	Ben-Gumuz	0.3739	0.0022	0.1577	0.1297	0.2239	0.0588
	SNNP	-0.6097	0.0000	0.3399	0.0002	-0.0249	0.8192
	Gambela	-1.3124	0.0000	1.0420	0.0000	-0.7727	0.0000
	Harari	-1.1938	0.0000	0.8751	0.0000	-0.6252	0.0005
	Tigray	0.5114	0.0092	0.2241	0.2844	0.3289	0.3424
	Dire Dawa	-0.7521	0.0000	0.4759	0.0000	-0.1027	0.4841
	Cons	0.9990	0.0000	0.5436	0.0139	-1.6637	0.0000
		H-L test p-value=0.0975		H-L test p-value=0.1779		H-L test p-value=0.4056	