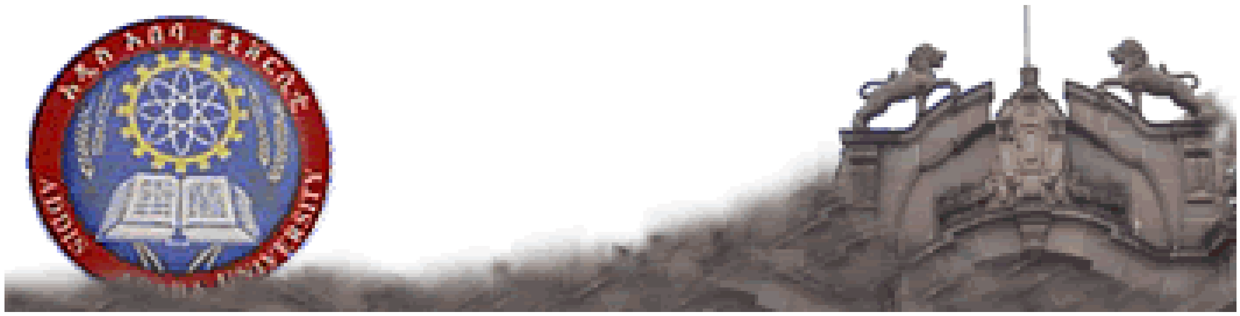

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

DEPARTMENT OF STATISTICS

UNDERNUTRITIONAL STATUS OF CHILDREN IN ETHIOPIA

(Application of Partial Proportional Odds Model)

BY

BELETE ADELO

A Thesis submitted to the Office of Graduate Programs of Addis Ababa University in Partial fulfillment of the requirements for the Degree of Master Science in Statistics

Addis Ababa University

Addis Ababa, Ethiopia

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School of Graduate Studies

This is to certify that the thesis prepared by Belete Adelo, entitled: **UNDERNUTRITIONAL STATUS OF CHILDREN IN ETHIOPIA** and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Statistics complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

Examiner ______________________ Signature ______________Date __________

Examiner _____________________ Signature ______________Date __________

Advisor ______________________ Signature ______________Date __________

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Chair of Department or Graduate Program Coordinator

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DECLARATION

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

Name: Belete Adelo

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Date: ___________________________

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

Name: Dr. Shibru Temesgen

Signature: ______________________

Date: ___________________________

ABSTRACT

UNDERNUTRITIONAL STATUS OF CHILDREN IN ETHIOPIA

Belete Adelo Wobse

Addis Ababa University, 2014

Malnutrition is one of the most important causes for improper physical and mental development of children. This study is an attempt to identify factors affecting the severity status of children malnutrition in Ethiopia by using malnutrition severity models for under age five Ethiopian children. Malnutrition severity is categorized into three levels in order of increasing of severity.

The parallel-lines assumption of commonly applied proportional odds model is usually too restricting. This assumption may be violated only by one or a few of the included variables. A partial proportional odds model where the parallel-lines constraint is relaxed only for those variables when it is not justified is applied in this study.

Partial proportional odds models were used for the severity status of children malnutrition in Ethiopia using 2011 EDHS data. The partial proportional odds models perform consistently better than the other two models (POM and BLR). By using partial proportional odds models, the interpretation of the parameters allows better insight concerning contributing factors, i.e., it revealed the increasing malnutrition severity due to age categories of children and incidence of diarrhea in the last two weeks before the survey.

The significant factors affecting the severity of children malnutrition cover demographic, socio-economic, and health related factors: age of child, sex of child, birth order, education of mother and father, wealth status of household, place of residence, mother's nutritional status, incidence of diarrhea and fever. Mother's education level has been identified as the most significant factor influencing children malnutrition. Thus, based on these findings more efficient countermeasures can be developed to mitigate children malnutrition severity. Furthermore, the influence of these factors can be used in the development of strategies of intervention for reducing severity of child malnutrition.

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LIST OF ABBREVIATIONS

BLR	Binary Logistic Regression
BMI	Body Mass Index
CI	Confidence Interval
CRM	Continuous Ratio Model
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
EDHS	Ethiopian Demographic and Health Survey
FDRE	Federal Democratic Republic Of Ethiopia
LR	Likelihood Ratio
MDG	Millennium Development Goals
MoH	Ministry of Health
ML	Maximum Likelihood
OLR	Ordinal Logistic Regression
OR	Odds Ratio
POM	Proportional Odds Model
PPOM	Partial Proportional Odds Model
PPOM-R	Partial Proportional Odds Model-With Restrictions
PPOM-UR	Partial Proportional Odds Model-Without Restrictions
SD	Standard Deviation
SE	Standard Error
SM	Stereotype Model
UN	United Nations
UNICEF	United Nations Children's Emergency Fund
WB	World Bank
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1. Background of the study

Malnutrition is one of the most important causes for improper physical and mental development of children that continues to be a growing problem in most developing countries (Devi & Geervani, 1994). It could be a consequence of unfavorable conditions and is associated with poor development and disturbances in mental and intellectual capacity (Scrimshaw, 1998). Furthermore, malnutrition in children is the consequence of a range of factors that are often related to poor food quality, insufficient food intake, and severe and repeated infectious diseases, or frequently some combinations of the three.

Malnutrition develops when the body does not get the proper amount of energy (calories), proteins, carbohydrates, fats, vitamins, minerals and other nutrients required to keep the organs and tissues healthy and functioning well. It has been shown through various studies that children and women are the primary victims of malnutrition who suffer the most lasting consequences. When individuals are undernourished, they can no longer maintain natural bodily capacities such as growth resisting infections and recovering from disease, learning and physical work, and pregnancy and lactation in women.

A child can be malnourished by being undernourished or overnourished, but in most parts of the world malnutrition occurs when people are undernourished. Primary reasons for undernourishment, especially of children, are poverty, lack of food, repeated illnesses, inappropriate feeding practices, lack of care and poor hygiene. Inadequate nutrition during the first two years of life can slow a child's physical and mental development for the rest of his or her life. A short period of inadequate nutrition together with illness or infection can quickly make a child dangerously malnourished (UNICEF, 2010).

Poor nutrition during childhood is one important factor impeding child physical and mental development which ultimately propagates the vicious cycle of intergenerational malnutrition.

Thus issue of child malnutrition is critical because its effects are not limited to the boundary of childhood but rather persist into adulthood. Malnutrition at the early stages of life can lower child resistance to infections, increase child morbidity and mortality, and decrease mental development and cognitive achievement and nutritional status is the best global indicator of wellbeing in children (SCUK, 2012). Adequate nutrition is the keystone of survival, health and development not only of current generations but also of the ones to come. Malnutrition is the largest single underlying cause of death worldwide and is associated with over one-third of all childhood deaths (WHO, 2010).

Malnutrition is a silent killer that is under reported, under addressed and, as a result, under prioritized. Every hour and minute of every day, 300 and 5 children die because of malnutrition respectively. In the world today, one child in four is stunted due to malnutrition, and in developing countries this figure is as high as one in three and specifically in Africa two out of five children's would suffer with malnutrition (SCUK, 2012).

The current study focuses on Ethiopia, a country which registers one of the highest child malnutrition rates in Sub-Saharan Africa. These highest malnutrition rates in Ethiopia pose a significant obstacle to achieving better child health outcomes. However, the understanding of its cause's remains limited and hence obtaining a better understanding of the key determinants of child malnutrition in Ethiopia and their relative importance is thus of importance in its own right. As a result, understanding the problem of nutrition in a developing country like Ethiopia and knowing various key causes of malnutrition are deemed essential as background for modeling the severity status of children malnutrition.

Various studies on nutrition have been undertaken and conclusions were reached in the past regarding predictors of nutritional problems. These various studies in different/same countries may find different results over the importance of the determinant factors behind children's nutrition outcomes. Estimates may also differ depending on various factors including the nature of the data and estimating methodology.

Most previous studies have concentrated on the impacts of several of the underlying determinants, particularly maternal education and access to health care, on malnutrition rates using different statistical analysis. Some of the studies that have been done using different statistical analysis in determining the possible risk factors of child malnutrition can be seen in chapter two.

Among various methods applied to uncover the factors of child malnutrition the most preferred method is logistic regression. It considers binary response (nourished and undernourished); consequently the binary logistic regression model was applied in all the cases. However, the nutrition level of a child is usually classified as nourished, moderately malnourished and severely malnourished. Since, the majority of the studies on child nutritional status have never taken into account the order of nutritional status in their analysis which might hide some important information about the severity of child malnutrition. As a result, little is known about the level (severity) of malnutrition in the area. Thus, the current study attempts to fill this gap by utilizing ordered outcome categories in the process of model building.

Commonly determinants of malnutrition and severe malnutrition, two separate binary logistic regressions (BLR) models are required to develop by grouping the response variable into two categories (Rajaretnam & Hallad, 2000). This task is tedious and cumbersome due to estimation of more parameters. However, the researcher can consider the response variable as ordinal response and can apply ordinal logistic regression (OLR) for the same purpose.

The current study aims to describe severity of child malnutrition and identify the determinants of child malnutrition among under-five children.

1.2. Statement of the problem

Malnutrition among under-five children is a chronic problem in developing countries like Ethiopia. Worldwide, ten and a half million children of age under-five die every year, with 98% of these deaths reported to occur in developing countries (UNICEF, 2007). In recognition of the burden of malnutrition among under-five children, four of the eight United Nations Millennium Development Goals (MDGs) are specifically directed towards improving child health outcomes in developing countries. In particular, a reduction in the mortality of children is a key MDG, and a reduction in malnourishment among children is an important indicator of progress towards that goal.

In Ethiopia, child malnutrition is one of the most serious public health problem and the highest in the world (Alemu et al., 2005a). For example, almost one in every 17 babies born in Ethiopia (59 per 1000) does not survive to celebrate its first birthday, and one in every eleven children (88 per 1000) dies before its fifth birthday. As a result, it will be challenging to reach the child survival Millennium Development Goals (reducing child mortality by 3/4) with the current place of mortality reduction (WB, 2011).

According to the 2011 Ethiopia Demographic and Health Survey (EDHS) 29 percent of children under-five are underweight (have low weight-for-age), 44 percent of children under age five are stunted and 10 percent of children are wasted. The figures show the extent to which how much of the country's future potential work force is challenged by malnourishment.

Health and physical consequences of prolonged states of malnourishment among children are: delay in their physical growth and motor development; lower intellectual quotient (IQ), greater behavioral problems and deficient social skills; susceptibility to contracting diseases (Black RE. et al., 2003). The ultimate effect of malnourishment among children might be death of the children or it might propagate into the vicious cycle of intergenerational malnourishment.

Given that good nutritional status is both a human right and a necessary component to address effectively the major children's health problem that Ethiopia faces, what needs to be done to ensure that all Ethiopian children are well-nourished? The first thing is to identify the causes of malnutrition and have a useful understanding of how the severity status of children malnutrition can be effectively analyzed in terms of socio-economic, demographic, health and environmental characteristics. Studies were conducted previously that attempted to identify the causes of malnutrition (Alemu et al 2005a; Woldemariam and Timotiows 2002; Smith et al 2005; Senauer and Garcia 1991; Bilisuma 2004).

Even though the problem of child malnutrition in Ethiopia has been sufficiently documented, the severity and the reasons behind it are still poorly understood. There is also inconsistency across studies regarding the determinant factors behind childhood malnutrition. The inconsistency may be due to inclusion and/or exclusion of some factors. Estimates may also differ depending on various factors including the nature of the data and estimating methodology.

The current study attempts to investigate major socio-economic, demographic, health related determinants of children malnutrition among under age five years old children in Ethiopia by considering the order of child nutritional status into account in the process of analysis.

1.3. Objective of the study

1.3.1. General objective

The general objective of this study is to analyze nutritional data and determine risk factors of child malnutrition in Ethiopia.

1.3.2. Specific objectives

The specific objectives of this study are:

1. To describe the nutritional status of children in Ethiopia;
2. To determine prevalence of malnutrition among under-five children;
3. To identify the most important risk factors of children malnutrition;
4. To assess and discuss the effect of multiple covariates in different levels of children nutritional status.

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 identify risk factors and their relative contribution to the malnutrition and health problem of children, the end users governmental and non-governmental organizations could take intervention measures and set appropriate plans to tackle the existing nutrition and health problems.

This study is expected to provide information to fill the gap concerning severity of child malnutrition in the country. Finally, the study could be used as a stepping stone for further studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 The concept of malnutrition

The concept of nutrition and its manifestation as malnutrition involves complex processes at multiple levels, from individual to the household to the community to the national and international levels. UNICEF defined the nutrition conceptual frame work as a set of assumptions designed to facilitate the process of assessing, analysing and deciding on what actions to take at all levels of society to resolve nutrition problems. This is also known as the "Triple A" process (Assessment, Analysis, Action) (Shrimpton and Kachondham, 2003).

Malnutrition is a state of society's nutritional problems (poor nutrition) that can result from insufficient or excessive or unbalanced diet or from inability to absorb foods and it is a situation where there is a category of diseases that includes undernutrition, defined as the outcome of insufficient food intake (hunger) and repeated infectious diseases, obesity and overweight, and micronutrient deficiency among others. However, malnutrition is frequently used to mean undernutrition from either inadequate calories or inadequate specific dietary components for whatever reason (Nikolaos, 2011).

Malnutrition is a broad term commonly used as an alternative to undernutrition, but technically it also refers to overnutrition – to the current epidemic of obesity and related diseases, such as diabetes, in both the industrialized and developing worlds. A UNICEF Policy Review paper states that, from the perspective of developing countries, "malnutrition results from inadequate intake of nutrients and/or from disease factors that affect digestion" among which protein-energy malnutrition, nutritional anemia, vitamin A deficiency, and iodine deficiency disorders are the most serious nutritional problems (UNICEF, 1990).

The current study uses the term malnutrition as undernutrition that encompasses being low weight for one's age (underweight), low height for one's age (stunting), low weight for height (wasting), and deficiencies of essential vitamins and minerals (collectively referred to as micronutrients) which are measured with the aid of anthropometric measurements in children.

The manifestations of malnutrition outcomes are expressed in internationally accepted measurements that reflect the chronic nature of malnutrition. This study utilizes the commonly used anthropometric measures for detecting malnutrition in children: stunting, underweight, and wasting. These measures of malnutrition are often interrelated and children whose measurements fall below two standards deviations from the reference mean are generally considered malnourished. Each measure captures different aspects of malnutrition.

Stunting is considered an indicator of chronic malnutrition. Height-for-age measures linear growth and therefore a low score is indicative of a cumulative growth deficit. Stunting is often the result of inadequate feeding practices over a long period and/or repeated illness. It is likely to persist even after these conditions are eliminated. Wasting measures body mass in relation to body length and is generally considered to reflect acute malnutrition. As an indicator, wasting is likely to vary over short periods of time due to food availability and disease prevalence. Underweight is a composite of height-for-age and weight-for-height. It is generally considered a general indicator of malnutrition, since a child that is underweight could be stunted or wasted, or both stunted and wasted.

2.2. Prevalence of child malnutrition

The cut-off point to define prevalence of malnutrition with Z- scores is two standard deviations below the mean for the international reference population. That means prevalence of malnutrition is the percentage of children under age five whose weight-for-age or height-for-age (stunting) or weight-for-height (wasting) is more than two standard deviations below the mean for the international reference population ages 0-59 months. The data are based on the WHO's new child growth standards released in 2006. A more general rule of thumb for evaluating anthropometric Z-scores has been developed by WHO, with a score of less than -3 indicating “severe” malnutrition, between -3 and -2.01 “moderate” malnutrition, -2 to -1.01 “mild” malnutrition and -1 and above considered normal/or nourished.

According to the 2011 Ethiopia Demographic and Health Survey 44 percent of children under age five are stunted, and 21 percent of children are severely stunted. In general, the prevalence of stunting increases as the age of a child increases, with the highest prevalence of chronic malnutrition found in children age 24-35 months (57 percent) and lowest in children under age six months (10 percent). Male children are slightly more likely to be stunted than female children (46 percent and 43 percent, respectively). With the exception of first order births, there is an inverse relationship between the length of the preceding birth interval and the proportion of children who are stunted. The longer the interval, the less likely it is that the child will be stunted.

Also, the survey found out that 10 percent of Ethiopian children are wasted, and 3 percent are severely wasted, and 29 percent of children under age five are underweight (have low weight-for-age), and 9 percent are severely underweight. The proportion of underweight children generally increases with each age cohort. The proportion of underweight children is highest in the age groups 24-35 months (34 percent) and lowest among those under six months (10 percent). This may be explained by the fact that food for weaning are typically introduced to children in the older age group, thus increasing their exposure to infections and susceptibility to illness. This tendency, coupled with inappropriate or inadequate feeding practices, may contribute to faltering nutritional status among children in these age groups. Also, babies reported as very small or small at birth are much more likely to be underweight later in life (39 percent and 36 percent, respectively) than those reported as average or large at birth (25 percent). Children born to mothers who are thin (BMI less than 18.5) are more than three times as likely to be underweight (39 percent) as children born to mothers who are overweight/obese (12 percent). The proportion of underweight children is eight times higher for those born to uneducated mothers than for those whose mothers have more than secondary education (32 percent versus 4 percent) in Ethiopia (CSA, 2012).

2.3. Determinants of child malnutrition

Several biological and social economic factors contribute to malnutrition. These varieties of factors starting from the national level down to the individual inter play in the causation of malnutrition (UNICEF, 1990). 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.

A global conceptual framework developed by UNICEF in 1990 identifies malnutrition and death in children and women as the result (final outcome) of a long sequence of interconnected events.

These events can be classified as components of three major groups of causes: the basic, the underlying, and the immediate determinants of malnutrition. First, inadequate dietary intake and disease are considered the most significant immediate causes of malnutrition of children and women. Secondly, the underlying causes for inadequate dietary intake and diseases can be numerous. These are context-specific and the most important fall within the three interrelated groupings of insufficient food availability and access, inadequate care for children and mothers, and insufficient health services and inadequate provision of a healthy environment (e.g. clean water and sanitation). Finally, the major basic or structural causes of malnutrition in the hierarchy include economic, technological, political, cultural, and institutional structures and processes, the means of control of physical resources, and the level of human development.

Understanding the problem of nutrition in a developing country like Ethiopia and knowing various determinants of malnutrition are deemed essential as a background for modeling the severity of malnutrition in the area. The current paper focuses on socioeconomic, demographic, and health and environmental determinants of child malnutrition in Ethiopia. The detailed literature review on socioeconomic, demographic, and health and environmental determinants of malnutrition in children presented below.

2.3.1. Demographic characteristics

Most studies report that demographic characteristics such as age, sex and birth order and interval are important determinants of nutrition status.

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, 1994).

On the contrary, Christiaensen and Alderman's (2001) 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; Alemu et al. 2005a; Alemu et al. 2005b). Various reasons behind this gender differential are given in the literature. Alemu 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 child's gender to be significant, 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 Abay 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 behaviour 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 health/nutrition outcomes. According to the draft report on the health sector MDGs needs assessment (FDRE, 2004) and Woldemariam and Timotiows (2002) using descriptive and logistic regression analysis, respectively, demonstrated that high birth order and close spacing depletes women biologically and drains their nutritional resources. These lead to low birth weight which is a key factor of 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, Alemu et al. (2005a) did not find birth order to be significantly associated with any of the three indicators considered (wasting, stunting, and underweight). However, the results 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 Sentayehu (1994) by using linear regression analysis found positive sign for birth order on height-for-age and weight- for-age equation which indicates the higher the birth order of a child the higher the height-for-age and weight- for-age indices. This result 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. The study showed that 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.

2.3.2. 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 has been identified as one of the key determinants of child nutritional 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 and Alderman (2001), SCUK (2002), Woldemariam and Timotewos (2002), Bilisuma (2004), Alemu et al. (2005b), Abay Asfaw (1995), and Silva (2005) found household wealth/income as an important determinant of child nutritional 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. The studies mentioned above proxy wealth/income in either one or the other of the following variables: housing quality, cattle and land ownership/rental, households' access to food, cash income/expenditure etc.

In many developing countries particularly in Africa, tradition has laid the responsibility of child care on women which begins at conception and continues until infancy, teenage and adulthood (Oyekale and Oyekale, 2000). The implication is that women are key players in the growth and development of a child. In enhancing the quality of care and nutritional status of children, the role of mothers' education is widely recognized. 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, acquire skills, and model positive caring behaviour 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. The study showed maternal nutritional knowledge is key determinants of chronic child malnutrition in Ethiopia. Other studies also report similar results from female's education (SCUK, 2002; Woldemariam and Timotiows, 2002; Alemu et al., 2005b; Silva, 2005). 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.

Sentayehu (1994) did not find a significant relationship between female's education and child nutritional status. 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.

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.

Weak control over household resources, tighter constraint on time, restricted access to information and health services, poor mental health, and lack of self confidence and self esteem typically characterize women with relatively lower status which in turn reflect on their children's health and the quality of care provided (Smith et al. (2005)).

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 Alemu et al., 2005a; Bilisuma, 2004; Woldemariam and Timotewos, 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 status (Crepinsek and Burstein, 2004).

Household size is also important in the analysis of child nutritional 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.

2.3.3. 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 nutrition.

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 Woldemariam and Timotiwos (2002) and Alemu et al (2005a).

Considering usage of a tap and a flush toilet, opposite results to Christiaensen and Alderman (2001) are reported in Alemu et al. (2005a) and Alemu 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; Alemu et al, 2005a, Alemu et al, 2005b). In addition to these studies, however, Collier et al. (2002) and Abay 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 (proxied by the distance variable) on child health/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, Alemu 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, Alemu 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, Alemu 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, Woldemariam and Timotiwos (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 behaviour 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 behaviour, Alemu 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.

As we have mentioned above, various studies on nutrition were undertaken and different conclusions were reached regarding predictors of nutritional problems. These differences over the importance of the determinant factors behind children's nutrition outcomes might be due to different nature of data and methodology. The current study has made an effort to identify the predictors of child malnutrition as well as severe malnutrition for under age five Ethiopian children by developing an ordinal logistic regression model.

CHAPTER THREE

DATA AND METHODOLOGY

3.1. Data

This research utilized the Ethiopia Demographic and Health Survey (EDHS) 2011 data on the nutritional status of children by measuring the height and weight of all children under age five that were obtained from Central Statistical Agency.

The 2011 EDHS is the third major survey that were 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 all geographic areas (nine regions namely: Tigray, Affar, Amhara, Oromiya, Somali, Benishangul- Gumuz, Southern Nations, Nationalities and Peoples (SNNP), Gambela and Harari regional states and two city administrations, Addis Ababa and Dire Dawa).

The data were collected to calculate three indices of anthropometric indicators-weight-for-age, height-for-age and weight-for-height. In the 2011 EDHS from 11,654 under-five children only 9,366 are measured for anthropometric measurements height and weight as well as for other related variables. As a result, the current study on the nutritional status of children is based on 9,366 under-five children with complete anthropometric measurements and the study considered only weight-for-age anthropometric index as indicator of a children’s nutritional and health status among the other indices, because weight-for-age anthropometric index is an excellent over all indicator of a population’s nutritional and health status. Moreover, weight-for-age is a composite index of weight-for-height and height-for-age.

3.2. Variables included in the study

As demonstrated in the literature review, socio-economic, demographic, health and environmental characteristics are considered as the most important determinants of nutrition status in under-five children.

3.2.1. The response variable

In different studies the level of malnutrition weight-for-age measurement was expressed in Standard Deviation (SD) units (Z-score) from the mean of the reference population. Children with a measurement of <-2 SD units from the mean of the reference population were considered underweight/undernourished for their age and children with measurement of (≥- 2SD) units from the median of the reference population were normal/nourished.

To determine the severity of child malnutrition, child nutritional status was expressed as an ordinal outcome variable based on malnourishment level as severely undernourished category if the standardized weight-for-age measurement(Z-score) is less than to -3 SD, moderately undernourished category if the standardized weight-for-age measurement(Z-score) is between -3 and-2 SD, and normal/nourished category if the standardized weight-for-age measurement(Z-score) is greater than or equal to -2 SD.

3.2.2. The explanatory variables

The predictor variables (risk factors) to be included as determinants of child malnutrition are grouped into demographic, socio-economic, and health related factors.

Table 3.1 Description of the variables and coding

The response variable

Response Variable	**Representation of variables**	**Factor categories**
Nutritional Status	Y	0, Not malnourished/Nourished 1, Moderately undernourished 2, severely undernourished

The explanatory variables

1) **Demographic Variables**

Variables	**Categories**
Age of child in months (AGCH)	0=0-11 1=12-23 2=24+
Sex of child (SECH)	0=Female 1=Male
Birth order of child (BOCH)	0=1-3 1=4-6 2=7+
Total number of children ever born (NCH)	0= 1-4 1= 5-9 2=10 and above
Number of household members (NHH)	0= 1-4 1= 5-9 2=10 and above
Sex of the head of the household (SEHH)	0=Female 1=Male
Age of the head of the household (AGHH)	0=14-38 1=39-63 2=64+

2) Socio-Economic Variables

Variables	**Categories**
Mother's highest educational level (EDU)	0= No education 1=Primary education 2=Secondary 3=Higher
Husband/partner's education level (HEDU)	0= No education 1=Primary education 2=Secondary 3=Higher
Household wealth status (WI)	0=Poor 1=Medium 2=Rich
Place of residence (RES)	0= Rural 1= Urban

3) Health related Variables

Variable	Categories
Mother's nutritional status or Mother's BMI (BMI)	0= Thinness (MBI<18.5) 1= Normal (MBI 18.5-24.9) 2=Overweight/Obese (MBI≥25)
Incidence of diarrhea in the last two weeks (DIARRHEA)	0= No 1= Yes
Incidence of fever in the last two weeks (FEVER)	0= No 1= Yes
Incidence of cough in the last two weeks (COUGH)	0= No 1= Yes
Source of drinking water (SORDW)	0= non improved sources (surface water, tanker truck, unprotected well/spring) 1= improved sources (piped water, public tap, protected well/spring, rain water, bottled water)
Toilet facilities (TOILET)	0= no facilities (bush/field toilet, hanging toilet) 1= have facilities (pit toilet, flush toilet)

3.3. Methodology

When examining literature it becomes clear that there is no unique approach in identifying the determinants of malnutrition. But, it is accepted that malnutrition is usually determined by several demographic, social economic and health related factors.

Authors had used different statistical methods to analyze determinants of malnutrition. These methods include descriptive and logistic regression analysis, Weighted Least Square and Fixed Effects models, probit model (Alemu et al., 2005a; Woldemariam and Timotiows, 2002; Smith et al., 2005; Senauer and Garcia, 1991; Bilisuma, 2004).

Regression methods such as linear, logistic, and ordinal regression are useful tools to analyze the relationship between multiple explanatory variables. These methods also permit researchers to estimate the magnitude of the effect of the explanatory variables on the outcome variable. If researchers wish to study the effect of explanatory variables on all levels of the ordered categorical outcome, an ordinal regression method must be appropriately chosen to obtain the valid results (Chen and Hughes, 2004).

This study utilized ordinal regression method of analysis to meet the objectives set since the response variable in the study has three ordered categories (severely undernourished, moderately undernourished, and nourished) and the value of each category has a meaningful sequential order.

3.3.1. Ordinal logistic regression model

The application of the ordinal regression model is dependent, in large part, on the measurement scale of the variables and the underlying assumptions. Ordinal logistic regression model is a type of logistic regression model that are used to analyze ordinal dependent variables. For instance, if the dependent variable (outcome variable) is in ordinal scale (ordered child nutritional status as severely undernourished, moderately undernourished, and nourished as in our case), the ordinal regression model is a preferred modeling tool which does not assume normality or constant variance, but requires the assumption of parallel lines across all levels of the outcome variable (McCullagh and Nelder, 1989).

The ordinal logistic regression procedure empowers one to select the predictive model for ordered dependent variables. It describes the relationship between an ordered response variable and a set of explanatory variables which may be continuous or discrete (or any type).

Ordinal regression model is embedded in the general framework of generalized linear models for analyzing ordinal response variables. Different models can be resulted from the use of different link functions. Among different link functions, *logit* and *cloglog* links are the two major link functions.

In this particular study, we would use *logit* link function. The *logit* link is generally suitable for analyzing the ordered categorical data when all categories are evenly distributed. The *cloglog* link may be used to analyze the ordered categorical data when higher categories are more probable (SPSS, Inc. 2002).

If the logit link is applied, the general form of ordinal regression model may be written as follows

$$f\left(\gamma_j(X)\right) = log\left(\frac{f\left(\gamma_j(X)\right)}{1 - f\left(\gamma_j(X)\right)}\right) = \log\left(\frac{pr(Y \leq j \setminus X)}{pr(Y > j \setminus X)}\right) = \alpha_j + \beta X, j = 1,2 \ldots k - 1$$

$$\gamma_j(X) = \frac{e^{\alpha_j + \beta X}}{1 + e^{\alpha_j + \beta X}}$$

Where j indexes the cut-off points for all categories (*k*) of the response variable, the function $f\left(\gamma_j(X)\right)$ is the link function that connects the systematic components (i.e. $\alpha_j + \beta X$) of the linear model, the alpha α_j represents a separate intercept or threshold for each cumulative probability and β represents the regression coefficient (McCullagh and Nelder, 1989).
If multiple explanatory variables are applied to the ordinal regression model, βX is replaced by the linear combination of $(\alpha_j + \beta_1 X_{j1} + \beta_2 X_{j2} + \cdots + \beta_p X_{jp})$.

There are several ordinal logistic regression models such as proportional odds model (POM), two versions of the partial proportional odds model-without restrictions (PPOM-UR) and with restrictions (PPOM-R), continuous ratio model (CRM), and stereotype model (SM). In this study we would use the first two.

3.3.1.1. The proportional odds model (POM)

Agresti (2002) details that the proportional odds model is used as a tool to model the ordinal nature of a dependent variable by defining the cumulative probabilities instead of considering the probability of an individual event. POM considers the probability of that event and all events that are ordered before it. When response categories are ordered, logits can directly incorporate the ordering. The cumulative probabilities are the probability that the response Y falls in category i or below, for each possible i the i^{th} cumulative probability is $pr(Y \le i) = p_1 + p_2 + ... + p_i$.

The proportional odds model assumes that the cumulative logits can be represented as parallel linear functions of independent variables. That is, for each cumulative logit the parameters of the models are the same, except for the intercept. Consequently, according to the proportional odds assumption, odds ratio is the same for all categories of the response variable (Agresti (2002)).

The POM, however, has some appealing features. Firstly, it is invariant under several categories, as only the signs of the regression coefficient change. Secondly, it is invariant under collapsibility of the ordered categories, as the regression coefficients do not change when response categories are collapsed or the category definitions are changed. Thirdly, it produces the most easily interpretable regression coefficients, as $\exp(\beta)$ is homogeneous odds ratio over all cut-off points summarizing the effects of the explanatory factor X on the response Y in one single frequently used measure. Due to these reasons, the POM is by far the most used regression model for the ordinal data.

Let Y be response variable with k ordered categories and assume $pr(Y=1)$ is p_1, $pr(Y=2)$ is p_2, ..., $pr(Y=i)$ is p_i; for $i=1,...,k$. Cumulative probability reflect the ordering, with $pr(Y \le 1) \le pr(Y \le 2) \le ... \le pr(Y \le k) = 1$ and let the cumulative probability of the first $k-1$ of Y is $pr(Y \le i) = \pi_i$, $i = 1,...,k-1$.

Then the odds of the first $k-1$ cumulative probabilities are

$$odds(pr(Y \le i)) = \frac{pr(Y \le i)}{1 - pr(Y \le i)} = \left[\frac{\pi_i}{1-\pi_i}\right] \; i = 1,...,k-1 \qquad ... (1)$$

Given that the outcome categories of the dependent variable appear to be ordered in terms of the severity of malnutrition, a typical approach is to use the standard ordered logit model which is also called proportional odds model.

The proportional odds model is the log odds of the first $k-1$ cumulative probabilities as:

$$\operatorname{log}it\left[pr(Y \leq i)\right] = \log\left[\frac{pr(Y \leq i)}{1 - pr(Y \leq i)}\right] = \log\left[\frac{\pi_i}{1 - \pi_i}\right] \qquad \text{... (2)}$$

And the relationship between the cumulative logits of Y is:

$$\log\left[\frac{\pi_i}{1-\pi_i}\right] = \log\left[\frac{\pi_i}{\pi_{i+1} + \ldots + \pi_k}\right]; \; i = 1,\ldots,k-1$$

Consider a collection of p explanatory variables denoted by the vector $X' = \left(X_1, X_2, \ldots, X_p\right)$. The relationship between the predictors and response variable is not a linear function in logistic regression; instead, the logistic regression function is used, which is the logit transformation of π.

$$\pi_i = \frac{\exp\left(\alpha_i + \beta_1 X_1 + \ldots + \beta_p X_p\right)}{1 + \exp\left(\alpha_i + \beta_1 X_1 + \ldots + \beta_p X_p\right)} \qquad \text{... (3)}$$

Then the logit or log-odds of having $pr(Y \leq i) = \pi_i$ is modeled as a linear function of the explanatory variables as:

$$\lambda_i(X) = \operatorname{log}it\left[pr(Y \leq i)\right] = \log\left[\frac{pr(Y \leq i)}{1 - pr(Y \leq i)}\right] = \log\left[\frac{\pi_i}{1-\pi_i}\right] = \alpha_i + \beta_1 X_1 + \ldots + \beta_p X_p, 0 \leq \pi_i \leq 1,$$

$$i = 1,\ldots,k-1 \qquad \text{... (4)}$$

Where:

α_i = threshold value

β_j = parameter

X_j =sets of factors or predictors

Equation (4) is called proportional odds model. This model assumes a linear relationship for each logit and parallel regression lines and it estimates simultaneously multiple equations of cumulative probability. An equation is solved for each category of the dependent variable except the last one (Agresti, 2002).

In this model each logit has its own α_i term called the threshold value and their values do not depend on the values of the independent variable for a particular case. Logistic regression coefficients indicate the direction and strength of the relationship between independent variables and the log odds of the dependent variable. However, these logistic regression coefficients are a little bit more complicated to intuitively gauge, as they present the influence of a unit change in the independent variable on the log odds of the dependent variable. The influence determines the rate of increase or decrease in the log odds of the dependent variable. This means that the effect of the independent variable is the same for different logit functions, that's also the reason why the model is called the proportional odds model.

Testing of Parallel Lines

For our ordinal regression model to hold, we need to ensure that the assumption of parallel lines of all levels of the categorical data is satisfied since the model does not assume normality and constant variance (Bender and Benner, 2000).

Since, the response variable "nutritional status" is ordinal in nature. We would fit an ordinal logistic regression model, assuming that all logit surfaces are parallel. If the data do not fulfill the assumption, results of a regression applied to them can be misleading or have no meaning at all.

That means the results from the proportional odds model would only be valid if the parallel lines assumption is met. Thus, the assumption of parallel lines must be tested.

Here the test of parallel lines helps us to determine whether it is reasonable to assume that the values of the location parameters are constant across categories of the response. If there is evidence to reject the null hypothesis that the logit surfaces are parallel, it is possible that the link function selected is incorrect or that the relationships between the independent variables and logits are not the same for all logits.

The test of parallelism contains: -2 log-likelihood for the constrained model, the model that assume the planes or surfaces are parallel across the category of the response variable and -2 log-likelihood for the general model that assumes planes or surfaces are separated across the category.

The chi-square statistic is the log-likelihood difference between the two models. If the lines or planes are parallel, the observed significance level for the change should be large, since the general model doesn't improve the fit very much and the parallel model is adequate. If there is evidence to reject the null hypothesis, it is possible that the link function selected is incorrect or that the relationships between the independent variables and logits are not the same for all logits.

In general, this assumption can be checked by allowing the location parameters (coefficients) to vary, estimating them and determining if they are all equal. The unknown parameters such as threshold (α_i) and the regression coefficient (β_j) can be estimated by means of the maximum likelihood method (Bender and Benner, 2000). So, our maximum likelihood parameter estimates, diagnostic and goodness of fit statistic, residuals and odds ratios would be obtained from the final fitted ordinal logistic regression model.

The current study would assess the proportional odds and parallel slopes assumptions with the help of brant test procedure (Brant, 1990), to see whether the main assumption was violated or not, and also this procedure enable us to identify which covariates violate the stated assumption.

As the proportional odds assumption is difficult to achieve in practice, a parsimonious alternatives may be used such as Partial Proportional Odds Model (PPOM).

3.3.1.2. Partial Proportional Odds Model (PPOM)

This model allows some covariables with the proportional odds assumption to be modeled, but for those variables in which this assumption is not satisfied it is increased by a coefficient (γ), which is the effect associated with each i^{th} cumulative logit, adjusted for the other covariables. The general form of the model is the same as the POM, but now the coefficients are associated with each category of the response variable.

Partial proportional odds model can be classified as unrestricted PPOM-UR and the restricted PPOM-R. The unrestricted partial proportional odds model is used when proportional chances assumption is not valid and the coefficients are associated with each category of the response variable (in the case of both parallel and linear assumption are not fulfilled).

The model has the form (Peterson and Harrell 1990):

$$\lambda_i(X) = \log\left\{\frac{pr(Y=1\setminus X)+\ldots+pr(Y=i\setminus X)}{pr(Y=i+1\setminus X)+\ldots+pr(Y=k\setminus X)}\right\} = \log\left\{\frac{\sum_1^i pr(Y=i\setminus X)}{\sum_{i+1}^k pr(Y=i\setminus X)}\right\}$$

$$\lambda_i(X) = \alpha_i + \{(\beta_1+\gamma_{i1})X_1 + \ldots + ((\beta_q+\gamma_{iq})X_q) + (\beta_{q+1}X_{q+1}) + \ldots + (\beta_p X_p)\},\ i = 1,\ldots,k-1 \qquad \ldots (5)$$

It is normally expected that there will be a type of linear trend between each OR of the specific cut-off points and the response variable. If there is then a set of restrictions γ_{k1} may be included in the model to clarify this linearity. When these restrictions are included this model is called the restricted partial proportional odds model. The τ_i parameters are fixed scale parameters which take the form of restrictions allocated to the parameters. In this case for a given covariable X_m, α_m does not depend on the cut-off points, but is multiplied by τ_i for each i^{th} logit.

The model becomes (Peterson and Harrell 1990):

$$\lambda_i = \log\left\{\frac{pr(Y=1/X)+\cdots+pr(Y=i/X)}{pr(Y=i+1/X)+\cdots+pr(Y=k/X)}\right\} = \log\left\{\frac{\sum_1^i pr(Y=i/X)}{\sum_{i+1}^k pr(Y=i+1/X)}\right\}$$

$$\lambda_i = \alpha_i + \left\{\tau_i\left((\beta_1+\gamma_{i1})X_1+\cdots+\left(\beta_q+\gamma_{iq}\right)X_q+\left(\beta_{q+1}X_{q+1}\right)+\cdots+\left(\beta_pX_p\right)\right)\right\},$$

$$i = 1, \ldots, k-1 \qquad \ldots (6)$$

3.3.2. Odds Ratio

The odds ratio is a value which measures the strength of effect of each independent variable in the model on the log odds of the dependent variable.

The odds of some event happening is defined as the ratio of the number of occurrences to the number of non occurrences. That is, the odds of the event, E is given by

$$\mathrm{odds(E)} = \frac{\mathrm{pr(E)}}{\mathrm{pr(not\ E)}} = \frac{\mathrm{pr(E)}}{1-\mathrm{pr(E)}} \qquad \ldots (7)$$

The odds of the response are multiplied by e^{β} for every unit increment of x. That is, the odds at level $x + 1$ equal the odds at x multiplied by e^{β} and odds less than one indicate the occurrence is less likely than non occurrence.

3.3.3. Model Selection

Methods such as forward, backward, and stepwise selection are available, but, in logistic as in other regression methods are not to be recommended, because they give incorrect estimates of the standard errors and p-values; can discard variables that are important to be included in the model (Harrell, 2001). It is much better to compare models based on their results, reasonableness, and fit as measured, by the Akaike Information Criterion (AIC). Other criteria besides significance tests can help select a good model in terms of estimating quantities of interest. The best known is the Akaike information criterion. It judges a model by how close its fitted values tend to be to the true values, in terms of a certain expected value. Even though a simple model is farther from the true model than is a more complex model, it may be preferred because it tends to provide better estimates of certain characteristics of the true model, such as cell probabilities. Thus, the optimal model is the one that tends to have fit closest to reality. Given a sample, Akaike showed that this criterion selects the model that minimizes

$$AIC = -2(maximized\ log\ likelihood - number\ of\ parameters\ in\ model)$$

This penalizes a model for having many parameters. With models for categorical Y, this ordering is equivalent to one based on an adjustment of the deviance, $(G^2 - 2(d.f.))$, by twice its residual degree of freedom (Agresti, 2002); where G^2 is deviance statistic.

Test of Overall Model Fit

For the selected model before proceeding to examine the individual coefficients, we should look at an overall test of the null hypothesis that the location coefficients for all of the variables in the model are 0. It can base this on the change in -2 log-likelihood when the variables are added to a model that contains only the intercept. The change in likelihood function has a chi-square distribution even when there are cells with small observed and predicted counts. This value provides a measure of how well the model fits the data.

The log likelihood statistic is analogous to the error sum of squares in multiple linear regressions. As such it is an indicator of how much unexplained information remains after fitting the model. The larger the value of the log likelihood the more unexplained observations there are and a poorly fitting model. Therefore, a good model means a small value for -2LL. If a model fits perfectly, the likelihood is 1 and -2 × log 1=0 (Agresti, 2002).

3.3.4. Goodness-of-Fit Measures

A good-fitting model has several benefits. The structural form of the model describes the patterns of association and interaction. The sizes of the model parameters determine the strength and importance of the effects. Inferences about the parameters evaluate which explanatory variables affect the response variable Y, while controlling effects of possible confounding variables. Finally, the model's predicted values smooth the data and provide improved estimates of the mean of Y at possible explanatory variable values.

For logistic regression, the model coefficients are estimated by the maximum likelihood method and the likelihood equations are non-linear explicit function of unknown parameters. The ordinal logistic regression model is fitted to the observed responses using the maximum likelihood approach. In general, the method of maximum likelihood produces values of the unknown parameters that best match the predicted and observed probability values. Therefore, it usually used a very effective and well known Fisher scoring algorithm to obtain ML estimates.

A model for logit$(pr(Y \leq i))$ alone is ordinary logit model for a binary response in which categories 1 to i form one outcome and categories $i + 1$ to k form a second outcome. This shows that k categories of response collapsed in to binary outcome. Again let (Y_{j1},…, Y_{jk}) be binary indicators of the response for subject j.

The likelihood function L is viewed as a function of β and α_i parameters. The parameters are estimated by maximizing the likelihood, or more usually, by maximizing the logarithm of the likelihood. The likelihood function is given by the equation (Agresti, 2002):

$$L = \prod_{j=1}^{n} \left[\prod_{i=1}^{k} \pi_i(X_j)^{Y_{ij}} \right] = \prod_{j=1}^{n} \left[\prod_{i=1}^{k} \left(pr(Y \leq i/X_j) - pr(Y \leq i - 1/X_j) \right)^{Y_{ij}} \right]$$

$$= \prod_{j=1}^{n} \left[\prod_{i=1}^{k} \left(\frac{exp(\alpha_i + \beta' X_j)}{1 + exp(\alpha_i + \beta' X_j)} - \frac{exp(\alpha_{i-1} + \beta' X_j)}{1 + exp(\alpha_{i-1} + \beta' X_j)} \right)^{Y_{ij}} \right]$$

$$L(\beta^*) = \prod_{j=1}^{n} \left[\pi_1(X_j)^{Y_{1j}} \pi_2(X_j)^{Y_{2j}} \ldots \pi_k(X_j)^{Y_{kj}} \right]$$

Here β^* is used imprecisely to denote both the slope coefficients and intercept coefficients. It follows that the log-likelihood function is:

$$\ell(\beta^*) = \sum_{j=1}^{n} Y_{1j} \ln[\pi_1(X_j)] + Y_{2j} \ln[\pi_2(X_j)] + \cdots + Y_{kj} \ln[\pi_k(X_j)] \qquad \ldots (8)$$

The maximum possible value of the likelihood for a given data set occurs if the model fits the data exactly. This occurs if observed counts are close to predicted. The difference between the log-likelihood functions for two models is a measure of how much one model improves the fit over the other. A special case of this is defined as the deviance.

The deviance is defined as minus twice the log of the ratio of the likelihood for a model to the maximum likelihood.

Deviance for model comparison is (Agresti, 2002):

$$D = -2\log\left[\frac{likelihood\ of\ the\ current\ model}{likelihood\ of\ the\ saturated\ model}\right], \text{ This simplifies to}$$

$$D = -2[\log(likelihood\ of\ the\ current\ model) - \log(likelihood\ of\ the\ saturated\ model)]$$

$$= \{(-2\log likelihood\ of\ the\ current\ model) - (-2\log likelihood\ of\ saturated\ model)\}$$

It can be shown that the likelihood of this saturated model is equal to 1 yielding a log-likelihood equal to 0. For a sample of n independent observations, the deviance for a model with *p* degrees of freedom (that is, *p* parameters estimated, including the threshold or constant) has (*n* - *p*) degrees of freedom.

Since the deviance is effectively -2 times the log of the likelihood ratio, it has an asymptotic distribution null distribution that is chi-squared with degrees of freedom equal to (*n* - *p*).

This deviance is also used to construct a goodness-of-fit test for the model. The goodness of fit statistics for ordinal logistic regression has a form:

$$D = 2\sum\sum O_{ij}\log\left(\frac{O_{ij}}{E_{ij}}\right)$$

Likewise, the Pearson chi-square statistic also compares the model fit to the actual data, defined by:

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

E_{ij} is the expected value for the i^{th} observation.

Both goodness-of-fit statistics should be used only for models that have reasonably large expected values in each cell. If the model fits well, the observed and expected cell counts are similar, the value of each statistic is small, and the observed significance level is large. As usual large χ^2 and D value provide the evidence of lack of fit. When the fit is poor, residuals and other diagnostic measures describe the influence of individual observation on the model fit and highlight reason for the inadequacy.

3.3.5. Model Adequacy

One important topic in logistic regression is regression diagnostics. In logistic regression, some of the usual diagnostic statistics are the residuals and measures of influence.

Model Evaluation- Residuals

Residuals are the basic building blocks for logistic regression diagnostics. They can be useful for identifying potential outliers (observations not well fit by the model) or misspecification models and another use for residuals is in checking normality. For log linear models this can be thought of checking how well the asymptotic theory holds (Agresti, 2002).

The residuals for logistic regression model are typically defined as the difference between observed response, and the estimated probability of the response, conditional on the covariates. This simplifies with categorical predictors of Y, it is useful to form residuals to compare observed and fitted counts. Let Y_i denote the binomial variate for n_i trials at setting i of the explanatory variables $i = 1, ..., \mathrm{N}$. Let π_i denote the model estimate of $pr(Y_i = 1)$. Then $n_i \hat{\pi}_i$ is the fitted number of successes. However, in logistic regression we have binomial errors and, as a result, the error variance is a function of the conditional mean. For a GLM with binomial random component, the Pearson residual for this fit is (Agresti, 2002)

$$e_i = \frac{Y_i - n_i \hat{\pi}_i}{[v\hat{a}r(Y_i)]^{1/2}} = \frac{Y_i - n_i \hat{\pi}_i}{\sqrt{\left(n_i \hat{\pi}_i (1 - \hat{\pi}_i)\right)}}$$

which standardized by dividing the difference by the estimated binomial standard deviation of Y_i (Agresti, 2002). These residuals relate to the Pearson goodness-of fit statistics by

$$\chi^2 = \sum_{i=1}^{N} {e_i}^2$$

Each squared Pearson residual is a component of χ^2. Pearson residual values fluctuate around zero, following approximately a normal distribution when n_i *is* large. When the model holds these residuals are less variable than standard normal (that is e_i has an approximate *N* (0, 1)), however, because the numerator must use the fitted value $n\hat{\pi}$ rather than the true mean $n\pi$ (Agresti, 2002).

Since the sample data determine the fitted value, $Y_i - n_i\hat{\pi}_i$ tends to be smaller than $Y_i - n_i\pi_i$. The Pearson residual divided by its estimated standard error is called an adjusted residual. Adjusted residual larger than about 2 in absolute value are worthy of attention, though one expect some values of this size by chance alone when the number of categories is large. Adjusted residuals are preferable to Pearson residuals (Agresti, 1996).

Deviance residual is another type of residual. It measures the disagreement between the maxima of the observed and the fitted log likelihood functions. The deviance residual is useful for determining if individual points are not well fit by the model. The deviance residual for the i^{th} observation is the signed square root of the contribution of the i^{th} case to the sum for the model deviance, for the i^{th} observation, and is given by

$$D_i = \pm\{-2[Y_i \log \hat{\pi}_i + (1 - Y_i) \log(1 - \hat{\pi}_i)]\}^{1/2}$$

Where the sign is positive when $Y_i \geq \hat{\pi}_i$ and negative otherwise. An observation with a residual that is far from 0 (that is greater than two in either direction) is an indication of poor fit.

Influence Measures

Influence measures show the effect that deleting an observation has on the regression parameters or the goodness-of-fit statistics. An observation is said to be influential if removing the observation substantially changes the estimate of coefficients. Influence can be thought of as the product of leverage and outlierness. It may be informative to report the fit of the model after deleting one or two observations, if the fit with them seems misleading.

Leverages are the diagonal elements of the logistic equivalent of the hat matrix in general linear regression. The i^{th} diagonal element of the logistic equivalent of the hat matrix is calculated as:

$h_i = n_i\hat{\pi}(X_i)\left[1-\hat{\pi}(X_i)(1,X_j')(X'\hat{V}X)^{-1}(1,X_j')'\right]$, Where $\hat{V} = diag\{\hat{\pi}_i(1-\hat{\pi}_i)\}$ and $\hat{\pi}_i$ is the expected proportional response with n_i number of trials of the i^{th} covariate pattern. An observation with an extreme value on a predictor variable is called a point with high leverage. Leverage is a measure of how far (proportional distances of) an independent variable deviates from its mean. These leverage points can have an effect on the estimate of regression coefficients and its value measures the influence of a point on the fit of the model. The centered leverage ranges from 0 (no influence on the fit) to $\frac{N-1}{N}$, and a leverage value greater than 2 or 3 times of average leverage is considered as large (Agresti, 2002).

The logistic regression analog of Cook's influence statistic is a measure of how much the residual of all cases would change if a particular case were excluded from the calculation of the regression coefficients. Cook’s distance is a direct influence measure relative to the fitted regression coefficients and observation with higher Cook's distance is the more influential point.

For logistic regression the Cook’s distance has the form:

$$CD_i = \frac{{z_i}^2 h_i}{1-h_i}, \quad \text{where } z_i \text{ is Standard Residual.}$$

A large Cook's distance indicates that excluding a case from computation of the regression statistics changes the coefficients substantially. The lowest value of Cook’s distance can assume is zero but for logistic regression, a case is identified as influential if its Cook's distance is greater than one (Hosmer and Lemeshow, 2000).

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1. Descriptive statistics

This research utilized the national wide Ethiopia Demographic and Health Survey (EDHS) 2011 collected data on the nutritional status of children. The analysis presented in the study is based on 9,366 under-five children with complete weight-for-age anthropometric index as indicator of a children's nutritional and health status among other indices, since it is an excellent overall indicator of a population's nutritional and health status. Table 4.1, below, shows that the relative frequency distributions of the severity status of child malnutrition; 69.8% are nourished (Not malnourished), 20.4% are moderately malnourished and 9.8% are severely malnourished.

Table 4.1 proportion of severity status of children malnutrition

severity status of child malnutrition	Freq.	Percent
nourished	6,540	69.83
moderate malnourished	1,906	20.35
severe malnourished	920	9.82
Total	9,366	100.00

In 2005 the percentage of undernourished children was 33% and 10% were severely undernourished. Though the percentage of undernourished children reduced a little in 2011 (29%), the levels are still very high (CSA, 2012).

The prevalence of child malnutrition according to selected background characteristics are shown in Table 4.2. The proportion of severely malnourished and moderately malnourished children were found higher among the children aged 12-23 months (11% and 21%), being male (10% and 22%), having 4-6 birth order (12% and 22%), with illiterate (11% and 22%) and acutely malnourished (thinness or BMI<18.5) mothers (14% and 25%), who resides in rural (11% and 22%), and experienced with several diseases like diarrhea, and fever (near about 38% malnourished separately). Moreover, near about 37 percent of the total number of children who lived in poor households were most vulnerable to malnutrition. All the selected independent variables were significantly associated with the children's nutrition status (Chi-square statistics and p-values are mentioned in Table 4.2).

Table 4.2 Children's nutrition status according to selected independent variables

Co-variables		Nutrition status according to weight-for-age z-score (WAZ)				Pearson chi-square (p-value)
		Severely Malnourished (WAZ<-3.00)	Moderately Malnourished (-3.00≤WAZ≤-2.01)	Nourished (Adequate) (WAZ≥-2.00)	Total	
Age of child in months	0-11	5.61	10.71	83.68	1,924	227.652 (0.000)
	12-23	10.94	20.66	68.40	1,728	
	24+	10.90	23.50	65.59	5,714	
Sex of child	Female	9.36	18.87	71.77	4,595	16.613 (0.000)
	Male	10.27	21.78	67.95	4,771	
Birth order of child	1-3	8.14	19.22	72.64	4,740	46.360 (0.000)
	4-6	11.87	21.84	66.29	3,008	
	7+	10.94	20.89	68.17	1,618	
Mother's highest educational level	No education	11.44	22.29	66.27	6,540	187.501 (0.000)
	Primary	6.82	17.73	75.45	2,375	
	Secondary	3.04	7.43	89.53	296	
	Higher	0.65	3.23	96.13	155	
Husband/partner's education level	No education	12.29	22.76	64.96	4,908	188.431 (0.000)
	Primary	7.93	19.67	72.40	3,457	
	Secondary	5.15	12.08	82.77	621	
	Higher	2.89	8.95	88.16	380	
Household wealth status	Poor	12.72	23.82	63.46	4,614	239.504 (0.000)
	Medium	9.76	21.26	68.98	1,557	
	Rich	5.67	14.90	79.44	3,195	
Place of residence	Rural	10.82	22.03	67.15	7,875	169.522 (0.000)
	Urban	4.56	11.47	83.97	1,491	

Mother's nutritional status (MBI)	Thinness	14.29	24.88	60.84	2,464	212.082 (0.000)
	Normal	8.69	19.64	71.67	6,361	
	Overweight	2.77	8.13	89.09	541	
Incidence of diarrhea in the last two weeks	No	8.69	20.09	71.22	7,898	81.963 (0.000)
	Yes	15.94	21.73	62.33	1,468	
Incidence of fever in the last two weeks	No	8.64	19.91	71.45	7,498	70.987 (0.000)
	Yes	14.56	22.11	63.33	1,868	
Total		9.82	20.35	69.83	100%	

4.2. Ordinal logistic regression analysis

This section focuses on regression analysis undertaken to test the relative predictive power of demographic, socio-economic and health related covariates with severity status of children malnutrition.

In this study ordinal logistic regression is selected for analyzing the nutritional data using the explanatory variables associated with the dependent variable. In order to appropriately address all factors that, through extensive research performed, are believed to affect the level of malnutrition, the following was done. In our initial selection of variables, we looked for risk factors that clearly demonstrated in different previous extensive research performed and also for variables significant for bivariate analysis with Pearson chi-square association measure. After these factors were identified, the ordinal logistic regression procedure was used in combination with the stepwise selection method. This enabled us to select those significant variables which contribute to malnutrition. Accordingly, age of child in months (AGCH), sex of child (SECH), birth order of child (BOCH), mother's highest educational level (EDU), husband/partner's education level (HEDU), household wealth status (WI), place of residence (RES), mother's nutritional status or Mother's BMI (BMI), incidence of diarrhea (DIARRHEA) and incidence of fever in the last two weeks (FEVER) are included in the model.

Partial proportional odds model with logit function was developed for nutrition status of children. To identify the risk factors of child malnutrition and to estimate their effect, the study fitted partial proportional odds models by a user-written program gologit2 (Williams, 2006). For comparison, POM and Separate Binary Logistic Regressions were also fitted. At first competence of the models are described and then the results of the models are interpreted.

4.2.1. Proportional odds model (POM)

The results of the proportional odds model are given in Table 4.3. Having fitted proportional odds model, a test procedure (Brant, 1990) was run to see whether the fitting of a proportional odds model is appropriate for the data. Brant's (1990) test procedure produced a significant chi-square value of 37.48 with 18 degree of freedom (p-value=0.005) indicating that a parallel lines assumption is no longer appropriate for the evidence that we see in our data. After conducting the Brant test of the parallel regression (proportional odds) assumption for status of children malnutrition, we identified two important predictors, age of child (for 24+) and incidence of diarrhea in the last two weeks before the survey, which were found to violate the proportional odds assumption. Hence, the proportional odds model was not appropriate to analyze the severity status of children malnutrition. The results of Brant tests are shown in the last column of Table 4.3 which reveals that all the variables except age of child in months and incidence of diarrhea in the last two weeks were found insignificant.

Table 4.3 Results of POM using children nutrition status as three ordered response categories

Co-variable		Regression Coefficient	P-value	Estimated OR	95% CI for OR	Brant test (p-value)
Age of child in months [0-11 as ref]	12-23	0.829	0.000	2.291	1.951, 2.691	0.084
	24+	1.031	0.000	2.805	2.448, 3.213	0.004
Sex of child [Female as ref]	Male	0.173	0.000	1.189	1.087, 1.302	0.131
Birth order of child [1-3 as ref]	4-6	0.155	0.003	1.167	1.054, 1.293	0.131
	7+	0.047	0.467	1.048	.923, 1.191	0.307
Mother's educational	No edu	1.424	0.001	4.155	1.767, 9.771	0.760

level [higher as ref]	Primary	1.258	0.004	3.518	1.502, 8.244	0.822
	Secondary	0.859	0.065	2.361	.9491, 5.871	0.668
Husband/partner's education level [higher as ref]	No edu	0.556	0.002	1.743	1.221, 2.489	0.567
	Primary	0.374	0.038	1.453	1.021, 2.069	0.891
	Secondary	0.162	0.422	1.176	0.792, 1.746	0.606
Household wealth status [Rich as ref]	Poor	0.443	0.000	1.558	1.378, 1.762	0.487
	Medium	0.242	0.002	1.274	1.096, 1.482	0.736
Place of residence [Rural as ref]	Urban	-0.231	0.011	0.794	0.664, 0.949	0.414
Mother's nutritional status[Normal as ref]	Thinness	0.440	0.000	1.553	1.407, 1.713	0.551
	Overweight	-0.772	0.000	0.462	0.347, 0.616	0.984
Incidence of diarrhea [No as ref]	Yes	0.388	0.000	1.473	1.296, 1.675	0.012
Incidence of fever [No as ref]	Yes	0.315	0.000	1.370	1.219, 1.539	0.154
/cut1		4.083		-	-	-
/cut2		5.549		-	-	-

Over all brant test of parallel regression assumption: Chi-square = 37.48, df = 18, p-value = 0.005

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 878.48, df = 18, p-value = 0.000, Pseudo R2 = 0.0584

As a consequence, a partial proportional odds model was fitted. Without making a final decision we proceed to analyze the data using separate binary logistic regressions for the dichotomized response. Such analysis is required to assess the correct functional form of the covariates to build models with adequate goodness-of-fit (Das and Rahman, 2011).

4.2.2. Separate binary logistic regressions (BLR)

Results of two separate binary logistic regression models are shown in Table 4.4. Hosmer-Lemeshow test for both models indicate that both fit the data adequately (p-value > 0.36). The regression coefficients and odds ratios in the two separate models for all the categories of each of the covariates are found homogeneous. Age of children and incidence of diarrhea in the last two weeks that failed to satisfy the proportional odds assumption have significant influence on both models. However, significance levels varied for some covariates in the two BLR models. In the first BLR model with response variable "at least moderate malnutrition" all the variables are found to be significant. On the other hand, sex of child, mothers' highest educational level, and place of residence are found insignificant in the other BLR model with response variable "at least severe malnutrition". Thus the covariates show similar result with some differences in significance level. Since these regression models do not consider the restriction of ordinal response and consider more parameters, we proceeded to construct PPOM, which represents a joint model of the response categories (Cox C, 1995), a powerful method based upon maximum likelihood procedures for ordinal response (Cox C, 1997).

Table 4.4 Results of two separate multiple binary logistic regression models using child nutrition status as binary response

Co-variable		Nourish vs. (moderately & severely malnourished)			(Nourish & moderately malnourished) vs. severely malnourished		
		B_1	OR_1	p-value	B_2	OR_2	p-value
Intercepts		-4.068	-	<.0001	-5.854	-	<.0001
Age of child	12-23	0.838	2.311	<.0001	0.647	1.910	<.0001
	24+	1.050	2.859	<.0001	0.777	2.175	<.0001
Sex of child	Male	0.191	1.211	<.0001	0.095	1.100	**0.1817**
Birth order of child	4-6	0.142	1.153	0.0081	0.251	1.285	0.0018
	7+	0.037	1.038	0.5774	0.128	1.137	0.1976
Mother's educational level	No edu	1.420	4.135	0.0011	1.707	5.514	**0.0958**
	Primary	1.261	3.530	0.0037	1.473	4.364	**0.1499**
	Secondary	0.837	2.310	0.0717	1.255	3.510	**0.2383**
Husband education level	No_hedu	0.533	1.704	0.0037	0.704	2.022	0.0345
	Primaryh	0.374	1.454	0.0392	0.415	1.515	0.2107
	Secondaryh	0.144	1.155	0.4777	0.312	1.367	0.3928
Household wealth status	Poor	0.437	1.547	<.0001	0.501	1.650	<.0001
	Medium	0.239	1.270	0.0023	0.277	1.319	0.0275
Residence	Urban	-0.242	0.785	0.0086	-0.131	0.878	**0.3971**
Mother's nutritional status	Thinness	0.434	1.544	<.0001	0.474	1.607	<.0001
	Overweight	-0.767	0.464	<.0001	-0.772	0.462	0.0046
Incidence of diarrhea	Yes	0.347	1.415	<.0001	0.554	1.740	<.0001
Incidence of Fever	Yes	0.296	1.344	<.0001	0.406	1.501	<.0001
Hosmer and Lemeshow Goodness-of-Fit Test: p-value = 0.5186					p-value =0.3652		

4.2.3. Partial proportional odds model (PPOM)

The results of STATA command GOLOGIT2 are similar to the series of binary logistic regressions and can be interpreted in the same way. The main problem with the results of both processes is that they include many more parameters than POM. These methods free all the variables from the parallel-lines constraint, even though the assumption may be violated only by one or a few of them. So the study used AUTOFIT option with GOLOGIT2 to fit partial proportional odds models, where the parallel-lines constraint is relaxed only for those variables where the assumption was not justified and parallel-lines constraint is considered for the other variables which satisfy the assumption (Liu, 2008).

Parallel-lines assumption for each variable was tested using a series of Wald tests to see whether its coefficients differ across equations. The variables, age of child in months (p-value < 0.0139) and incidence of diarrhea in the last two weeks (p-value < 0.0010) were found significant i.e., the proportional odds assumption is violated. Partial proportional odds model with logit function was fitted with these variables changing across equations while other variables were imposed to have their effects meet parallel-lines assumption.

The results for the partial proportional odds model with logit function are presented in Table 4.5 with Wald test of parallel-lines assumption. Global Wald test for the final model indicates that the final model does not violate the proportional odds assumption with high p-value (0.5375). Also the marginal effects for the model are reported in Table 4.6. From Table 4.4 and Table 4.5 we can see that there are only 21 unique β coefficients or odds ratios need to be explained in PPOM compared to the 36 coefficients produced by separate BLR models.

Results of PPOM show that all the covariates have significant influence on the response variable. In addition, the deviance (defined as the difference in the likelihood ratios between POM and PPOM) is chi-square = 23.19 (901.67-878.48) with 3 d.f. (21-18), favoring the PPOM as a better fit to the data than POM (Ananth & Kleinbaum, 1997). The pseudo R^2 of POM (0.0584) and PPOM (0.0600) also reflect the same result.

Table 4.5 Results of PPOM using child nutrition status as response with three ordered categories

Co-variable		Nourish vs. (moderately & severely malnourished)			(Nourish & moderately malnourished) vs. severely malnourished		
		B_1	OR_1	p-value	B_2	OR_2	p-value
Intercepts		-4.075	-	0.000	-5.569	-	0.000
Age of child	12-23	0.815	2.258	0.000	0.815	2.258	0.000
	24+	**1.043**	**2.838**	0.000	**0.877**	**2.404**	0.000
Sex of child	Male	0.173	1.188	0.000	0.173	1.188	0.000
Birth order of child	4-6	0.155	1.168	0.003	0.155	1.168	0.003
	7+	0.046	1.047	0.481	0.046	1.047	0.481
Mother's educational level	No edu	1.432	4.186	0.001	1.432	4.186	0.001
	Primary	1.264	3.541	0.004	1.264	3.541	0.004
	Secondary	0.857	2.356	0.065	0.857	2.356	0.065
Husband education level	No_hedu	**0.535**	**1.707**	0.003	**0.679**	**1.973**	0.000
	Primaryh	0.375	1.456	0.037	0.375	1.456	0.037
	Secondaryh	0.160	1.174	0.427	0.160	1.174	0.427
Household wealth status	Poor	0.443	1.557	0.000	0.443	1.557	0.000
	Medium	0.243	1.276	0.002	0.243	1.276	0.002
Residence	Urban	-0.233	0.792	0.011	-0.233	0.792	0.011
Mother's nutritional status	Thinness	0.440	1.552	0.000	0.440	1.552	0.000
	Overweight	-0.775	0.461	0.000	-0.775	0.461	0.000
Incidence of diarrhea	Yes	**0.336**	**1.400**	0.000	**0.582**	**1.789**	0.000
Incidence of Fever	Yes	0.311	1.365	0.000	0.311	1.365	0.000

Score test for the proportional odds assumption: Chi-square = 13.84, df = 15, p-value = 0.5375

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 901.67, df = 21, p-value = 0.0000, Pseudo R2 = 0.0600

4.3. Marginal effects

Table 4.6 presents the marginal effects which are computed at a representative value, i.e., at the mode values of dummy variables. Table 4.6 shows that in general, the marginal effects have larger magnitudes of impact on the first two outcomes, nourished and moderate level of malnourishment, and smaller impact on the last outcome, severe level of malnourishment.

Table 4.6 shows that mother's highest educational level (EDU) variable has the largest magnitude of marginal impact on the outcome probabilities. A child born to a mother with no education experienced a larger increase in the probability of having a moderate level of malnutrition, i.e., an increase by about 16 percent, while the probability of having a severe level of malnutrition increases by about 9 percent.

Table 4.6 Marginal effects for severity status of children malnutrition based on PPOM

variable		Nourished		Moderately malnourished		Severely malnourished	
		MER	P>z	MER	P>z	MER	P>z
Age of child	12-23	-.178867	0.000	.1037724	0.000	.0750944	0.000
	24+	-.196775	0.000	.1360182	0.000	.0607571	0.000
Sex of child	Male	-.034553	0.000	.0218251	0.000	.0127276	0.000
Birth order of child	4-6	-.03143	0.003	.0197196	0.003	.0117114	0.004
	7+	-.009223	0.484	.005806	0.481	.0034165	0.487
Mother's education level	**No edu**	**-.247715**	0.000	**.1603736**	0.000	**.087341**	0.000
	Primary	**-.278624**	0.005	**.1550713**	0.001	**.1235524**	0.023
	Secondary	-.196084	0.088	.1076851	0.037	.0883993	0.163
Partner's education level	No_hedu	-.106290	0.003	.0563028	0.014	.0499873	0.000
	Primaryh	-.076754	0.040	.0477988	0.037	.0289556	0.047
	Secondaryh	-.03306	0.440	.0205301	0.432	.0125299	0.453
Household wealth status	Poor	-.088751	0.000	.0558237	0.000	.0329276	0.000
	Medium	-.050483	0.002	.0312353	0.002	.0192474	0.003
Residence	Urban	.044955	0.008	-.028871	0.009	-.016085	0.006

Mother's nutritional status (BMI)	Thinness	-.091875	0.000	.0563568	0.000	.0355184	0.000
	Overweight	.130258	0.000	-.087014	0.000	-.043244	0.000
Incidence of diarrhea	Yes	-.070673	0.000	.0197331	0.102	.0509397	0.000
Incidence of fever	Yes	-.064873	0.000	.0399815	0.000	.0248916	0.000

Note: MER = Marginal effects computed at a representative value, i.e., at mode values of dummy variables.

4.4. Determinants of severity status of children malnutrition

In PPOM, all independent variables in the model were found to be significant predictors of child malnutrition. The covariates were also found significant in both separate BLR models except sex of child, place of residence, and mother's highest educational level in the 2nd BLR model with the response variable "at least severe malnutrition". The results support the use of PPOM instead of BLR models to determine the predictors of child malnutrition as well as severe malnutrition.

The results of POM reveal that the risk of having worse malnutrition status were 2.29 and 2.80 times higher among the children belonging to the age group 12-23 and 24+ months respectively, when compared with the infants(age group 0-11) (Table 4.3). Since the proportional odds assumption is violated for the variable, this interpretation may be invalid. However, from separate BLR models and PPOM it is clear that the odds ratios for the children aged 12-23 months and 24+ months compared to infants were about 2.26 and 2.84 respectively when nourished state is compared with moderate and severe malnutrition states implying that children belonging to the age group 12-23 and 24+ months had 2.26 and 2.84 times greater risk of being moderately or severely malnourished respectively compared with infants (age group 0-11) (Table 4.5). When nourished and moderate malnutrition states are compared with severe malnutrition state, the odds ratios were found about 2.26 and 2.40 respectively for children belonging to age group 12-23 and 24+ months compared to infants implying that children belonging to the age group 12-23 and 24+ months had 2.26 and 2.40 times greater risk of being severely malnourished respectively compared with infants (Table 4.5).

Similarly, for incidence of diarrhea within last two weeks before the survey the proportional odds assumption was violated .Thus the interpretation with POM reveals that the risk of having worse malnutrition status were 1.47 times higher among children who experienced diarrhea compared with children having no such problems within last two weeks before the survey (Table 4.3) may be misleading. However, from separate BLR models and PPOM it is clear those children who experienced diarrhea within last two weeks before the survey had 40% higher risk of being malnourished compared with the children having no such problems (Table 4.5). Moreover, the severity increased for children experienced with diarrhea when nourished and moderate malnutrition states are compared with severe malnutrition state. This means among children under age five who had diarrhea in the two weeks preceding the survey, there has been a noticeable increase in the chance of getting worse malnutrition which was masked using the PO model as shown in Table 4.3. The marginal effects also showed that incidence of diarrhea in the last two weeks before the survey (Yes vs no) had positive effects on severe level of children malnutrition (0.051). Since all other covariates did not violate the proportional odds assumption and PPOM performed better than POM as well as separate BLR models, the results for other covariates are described from Table 4.5 and 4.6.

Mother's highest educational level (EDU) was identified to be the most significant positive factor for the contributions to decrease of children malnutrition. In this study, the different forms of mother's educational level were tested for investigating their effect on severity status of child malnutrition, which include no education, primary education, secondary education, and higher. The results showed that children having mothers with low level of education, specifically mothers with no education, levels of malnutrition tended to be more severe (Coef. = 1.43; *p*-value = 0.001). In other word, the risk of having worse malnutrition status was found highest for children having mothers with no education (about 4.2 times) compared with higher level educated mothers' children. These results were confirmed by the positive marginal effects for moderate and severe malnutrition as shown in Table 4.6. Similarly, the risk of having worse malnutrition status was found highest for the children having father's with no education (about 1.71 times) compared with higher level educated fathers' children.

The risk of having severe malnutrition compared to nourished and moderately malnourished was found significantly higher for male children compared to female children, i.e. the risk of male children being severely malnourished compared to nourished and moderately malnourished had 19% higher risk of being malnourished compared to females.

Children having birth order 4-6 had 1.17 times greater risk of having worse malnutrition status compared with children having 1-3 birth order (Table 4.5).

Compared with children from rich households, the chances of having worse malnutrition status was found to increase with decrease of household wealth condition (1.6 for children from poor households and 1.3 for those from medium households).

The risk of having worse malnutrition was found significantly higher for the children in rural areas compared to those in urban areas. From Table 4.6 the negative marginal effect for urban residence (-0.016) confirms that children in rural areas are more likely to be malnourished than children in urban areas.

Mother's nutritional status had a significant effect on malnutrition severity of children. Compared to children with normal level (nourished or BMI 18.5-24.9) mothers, children belonging to acutely malnourished (thinness or BMI<18.5) mothers were 1.55 times more likely to be malnourished moderately or severely. That means, children with acutely malnourished mothers had 1.55 times greater risk of being malnourished compared to those of nourished mothers. However, children belonging to overweighed/obese mothers (BMI≥25) were less likely to be malnourished moderately or severely.

Experiencing fever within last two weeks before the survey had significant effect on children malnutrition severity. Children who experienced fever within last two weeks before the survey had 1.37 times higher risk of being malnourished compared with children having no such problems.

4.5. Model specification tests

This section checks for the adequacy of the PPOM in terms of how well the model fits the data. These tests, as listed in Table 4.7, are imperative as an inappropriately specified model leads to misleading inferences.

The Wald chi-square test is a test of the PPOM's overall goodness-of-fit. It tests for the null hypothesis that all the coefficients in the model are simultaneously equal to zero, i.e., having no effect on the dependent variable. The significant p-values as shown in Table 4.7 indicate that the null hypothesis is strongly rejected, i.e., at least one of the coefficients in the model has an impact on nutrition status of children.

The general model specification test, also known as a link test, is a test of appropriate functional form of the model. This test is the nonlinear counterpart of Ramsey's (1969) RESET test for linear regression models. If a model is properly specified, then no nonlinear functions of the explanatory variables, such as the quadratic function, should be significant when added to the model. Here, the nonlinear functions of the explanatory variables are represented by the '_hatsq' variable. This variable is tested insignificant for each J–1 equation, i.e., the insignificant p-values. This indicates no functional form misspecification.

Table 4.7 Model specification tests

Tests	Results
Wald chi-square test	p-value = 0.0000
General model specification test	
i. Not malnourished: _hatsq	p-value = 0.290
ii. Moderately malnourished: _hatsq	p-value = 0.128
Threshold parameter test	
i. Alpha_1	p-value = <0.0001
ii. Alpha_2	p-value = <0.0001

As mentioned in the Chapter 3, the alpha terms in a PPOM are cut points or threshold parameters along the continuum of the unobserved propensity to malnutrition. With three outcome categories, there are two cut points to be tested. The results of the threshold parameter test indicate that the two cut points are significant at the 1 percent significance level. That is, the two cut points are relevant to the model, indicating that the three observed outcome categories are indeed ordinal in nature and are well-placed along the continuous scale of the unobserved propensity to malnutrition. The significant cut points also suggest that the three outcome categories should not be collapsed into two categories. Further adequacy checking and comparisons of partial proportional odds model and other ordinary logistic regression can be seen from Appendix 1 and Appendix 2 respectively.

4.6. Discussion

In this study an attempt has been made to develop a method that can help to identify factors that affect the severity status of children malnutrition. Accordingly, Proportional odds model, Separate binary logistic models and Partial proportional odds model were fitted.

At first sight the POM becomes inappropriate model for analyzing the considered data since the p-value of chi-squared Brant test for overall model is significant at 5% level of significance indicating proportional odds assumption is violated, but all of the considered variables were found significant in the POM.

Since, the proportional odds assumptions for overall model was violated, by using Brant test for each covariate, we have assessed for which covariate the assumption was violated. The Brant test for each covariate shows that the assumption is violated for age of child and incidences of diarrhea in the last two weeks before the survey. This condition was also checked with separate BLR models which indicate the coefficients and the odds ratios for each age and incidence of diarrhea categories varied in the models.

In the case of all other variables, coefficients and odds ratios are not identical but almost close. In PPOM, coefficients and odds ratios for the variables ‘age of child’ and 'incidence of diarrhea in the last two weeks before the survey’ are almost same with the result of BLR models. However, the coefficients and odds ratios for other covariates in PPOM are slightly different compared to separate binary logistic regression models, but almost identical with those of POM. Moreover, all the variables are significant in PPOM but in the separate binary logistic regression models few of them found to be insignificant.

Generally speaking in comparing separate binary logistic regression models and partial proportional odds models for two main outcomes of children malnutrition, we found that the results were quite similar, but the partial proportional odds model was preferred due to the more parsimonious model principle, and as a result for easier interpretation of models in terms of fewer parameters. Due to that we stick our discussion with PPOM results as follows.

Mother's highest educational level (EDU) was identified to be the most significant factor to reduce the occurrence of children malnutrition. The findings of this study showed that there is a significant difference in the severity status of malnutrition in children by mothers' educational level. The risk of worse level malnutrition is significantly higher for children whose mothers have no education and primary education level than children whose mothers have secondary and 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. Similarly, the risk of having poor malnutrition status was found highest for the children having father's with no education when compared with higher level educated fathers' children.

In addition, our study revealed that the chances of having poor malnutrition status was found to increase with decrease of household wealth condition, i.e. under-five children from poor households are at a higher risk of malnutrition than children from rich households. This finding is consistent with other studies (Smith et al., 2005; Woldemariam and Timotewos, 2002).They indicated that better off households have better access to food and higher cash incomes than poor households, allowing them quality diet, better access to medical care and more money to spend on essential nonfood items such as schooling, clothing and hygiene products.

Age of child is also one important determinant associated with status of children malnutrition in Ethiopia. Children up to 11 months (infants) have better nutrition status than other age groups. 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).

Another important demographic factor which affects status of children malnutrition in Ethiopia is sex of child. The risk of having worse malnutrition was found significantly higher for male children compared to female children, i.e. male children had 1.19 times higher risk of being malnourished compared to females. Similar results are also reported from other studies (Christiaensen and Alderman, 2001; Alemu et al., 2005(a, b)). 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.

CHAPTER FIVE

CONCLUSIONS AND RECOMENDATIONS

5.1. Conclusions

Despite some differences in the results of the fitted models, the result of PPOM is reasonably comparable with those of separate BLR models. PPOM fitted the data adequately in predicting severity status of child malnutrition, due to the nature of the response variable (grouped continuous variable). Furthermore, PPOM had a better fit better for the data than POM. Consequently, from the results of PPOM we have drawn the following conclusions.

The study examined the demographic, socio-economic and health related determinants of child malnutrition in Ethiopia. The findings based on PPOM of the study showed that factors such as age of child, sex of child, birth order of child, mother's educational level, partner's educational level, household wealth status, child place of residence, mother's nutritional status, incidence of diarrhea and fever have statistically significant effect on the status of malnutrition.

High educational level was identified to be a very significant factor for the occurrence of children malnutrition in Ethiopia.

Children younger than 11 months (infants) had better nutrition status than other age groups. This could be because of breastfeeding in the early stages of child growth.

The risk of having worse malnutrition was found significantly higher for male children compared to female children.

It is observed that the risk of having poor malnutrition was found significantly higher for the children in rural areas compared to those in urban areas.

Mother's nutritional status had significant effect on children malnutrition severity. Compared to children belonging to nourished mothers, children belonging to acutely malnourished mothers were more likely to be malnourished moderately or severely.

Children who had diarrhea are significantly vulnerable to malnutrition than those who did not. A similar result was also obtained for children who had fever.

5.2. Recommendations

We learn from this study that in addition to the efforts being made to reduce the frequency of malnutrition in general, specific attention should be given to reduce the prevalence of malnutrition by taking the following in to consideration.

- ✓ The concerned bodies have to give different priorities to different children age categories, residence category, family background in terms of their mothers/fathers education level, wealth status to curb the severity level of children malnutrition.
- ✓ Since we have shown that children in rural areas are more likely to be malnourished than children in urban areas, special attention should be given for the residence difference.
- ✓ Further study can be made on the area of malnutrition at different level by considering detail and accurate information on various variables.

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APPENDICES

Appendix 1: Further adequacy checks of ordinal Regression models

When the cumulative logit model fit well, it also fits well with similar effects for any collapsing of the response categories. Since diagnostic for ordinal and multinomial model is very difficult, one way to examine model adequacy is to check each of the binomial models separately (Hosemor and Lemshow, 2000). Therefore, diagnostic is performed using binary outcome by collapsing moderate and severe malnutrition in to at least moderate malnutrition. Finally, the outcome variable becomes binary with moderate and severe malnutrition.

Model diagnostic is performed for both outliers and influential points. To observe the model adequacy, one way of looking at them is to graph them against predicted probabilities.

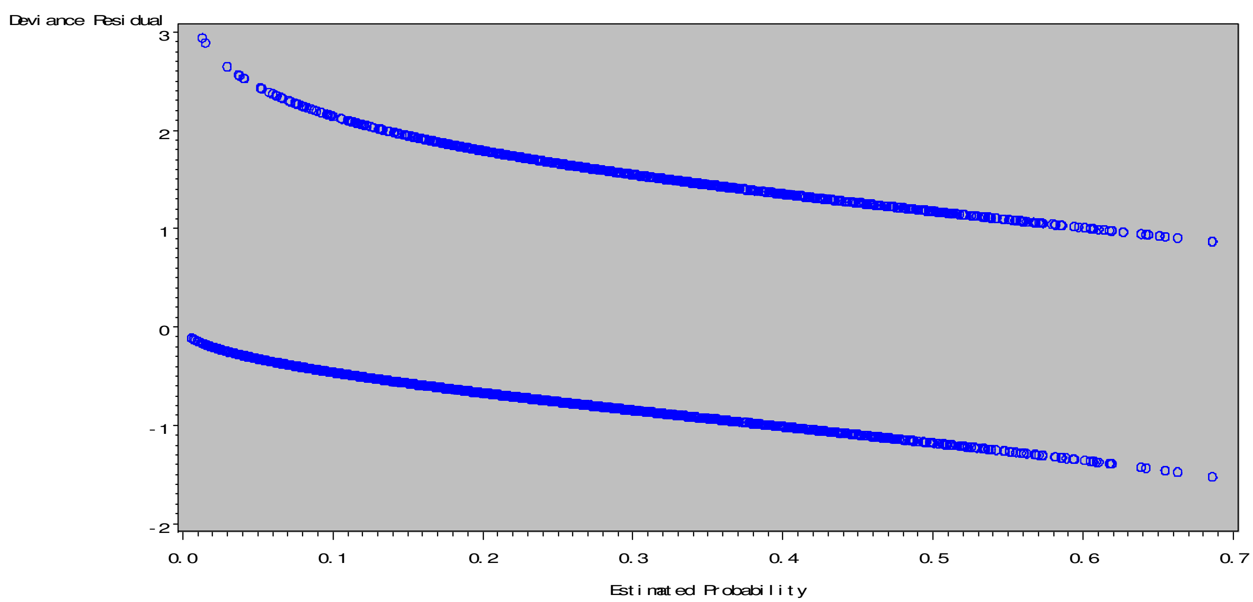

Figure 1 Plots of Deviance residual by predicted probability.

Figure 1 shows that the density of points are higher on the lower curve for fitted values less than 0.5, with residuals approaching 0. Similarly, the density of points on the upper curve is higher at fitted values less than 0.5, again with residuals near 0. Thus, none of the observation has deviance residuals larger than 3 in absolute. As a result no observation can take worthy attention.

This indicates the values for the independent variable are not in an extreme region. In addition observed responses for those points have similar form with the predicted probability of the response. Therefore individual points are well fitted by the model.

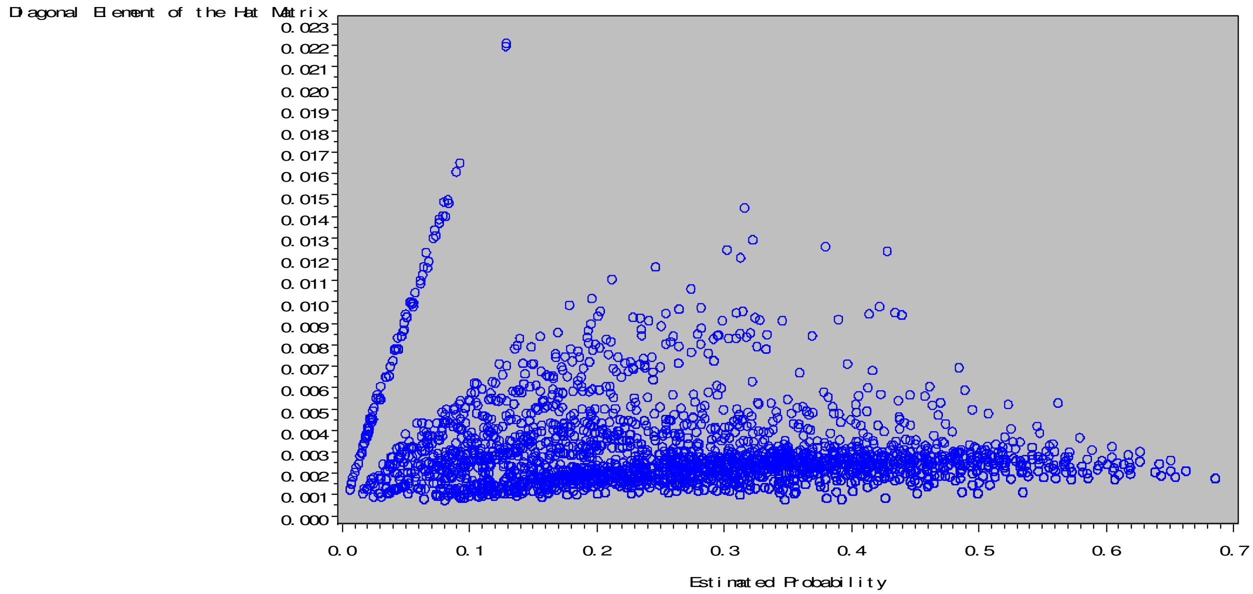

Figure 2 Plots of leverage value by predicted probability.

Plot of leverage against predicted probability is presented in Figure 2 and this identifies observations that have a strong influence on the estimated regression coefficients. The computed value of center of leverage is between 0 and 0.9996. The above plot shows that no point has large leverage value than two or three fold of 0.4998, which is average leverage. This indicates no observation is highly deviate from its mean and there is no observation with an extreme value on a predictor variable. In other words, the points have no undue influence on the parameter estimates of the fitted model. Therefore, the parameters are estimated properly and points are well fitted by the model.

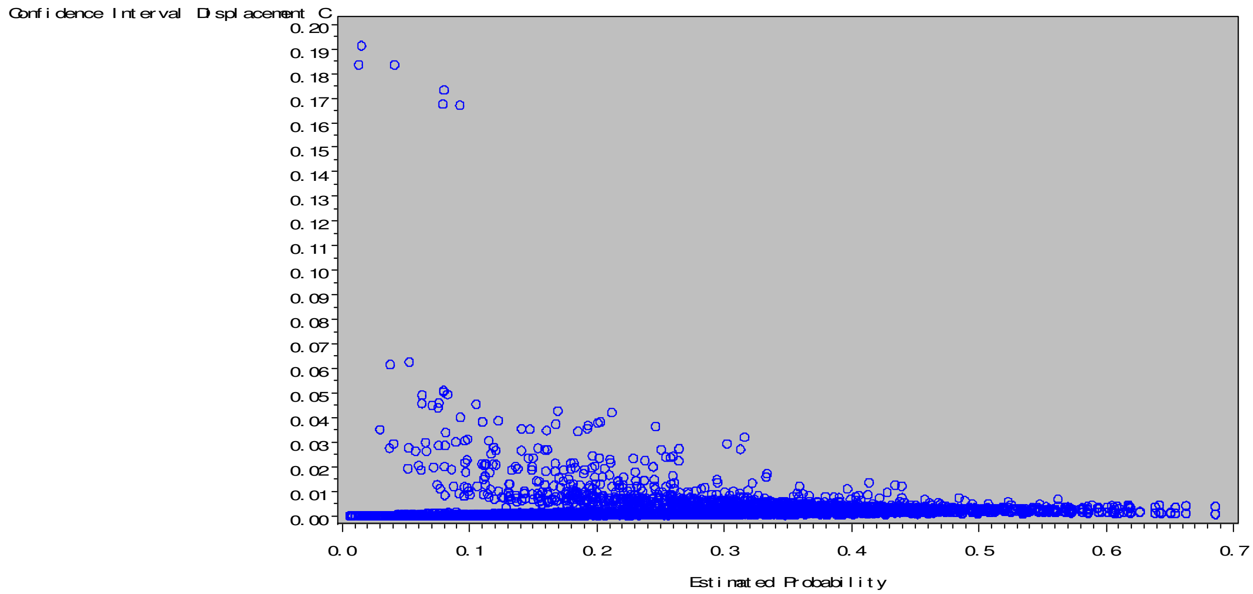

Figure 3: plots of cook's influence by predicted probability.

When looking at the plot of points in Figure 3 relatively few predicted values were found to be far from most of the other predicted values. Even if they are far away they may not be considered as real influential because no observation has values of Cook's distance greater than one. Therefore there is no observation with real influence and points are well fitted by the model.

Appendix 2: Comparisons of multinomial and partial proportional odds models

The multinomial logistic regression model and partial proportional odds model were compared in terms of goodness of fit, interpretation and parsimony. For severity status of children malnutrition, the partial proportional odds model had slightly lower AIC (Table 4.8) which indicated that the partial proportional odds model fitted the data better.

Table 4.8 Model fit characteristics: AIC for children malnutrition severity status

Model	AIC
Proportional odds model	14197.85
Multinomial model	14197.74
Partial proportional odds model	14180.66

As mentioned previously, the numbers of parameters in these two models were quite different. In the partial proportional odds model, there were 21 parameters while the multinomial model had 36 parameters. Therefore, the partial proportional odds model was more parsimonious than the multinomial model, and because it had fewer parameters, interpretation of the results of the partial proportional odds model was simpler than that of the multinomial model. You can see the results of multinomial logistic regression if you needed below.

Multinomial logistic regression model:

The results of the multinomial logistic regression analysis for status of children malnutrition are displayed in Table 4.9. Compared with not malnourished level, children in 12-23 months age category were more likely to be moderately malnourished (RR=2.336, 95%CI 1.93-2.82) or to be severely malnourished (RR=2.265, 95%CI 1.76-2.92) than those in the infants age category. This means that having different age categories had effect in terms of increasing children malnutrition status. We can interpret the other predictors in similar fashion.

Table 4.9 Risk ratios of child malnutrition (multinomial logistic regression model)

severity	Outcome Category	RR	P-value	95% CI RR
age of child in months				
12-23	moderate	2.336	0.000	1.93-2.82
24+		2.913	0.000	2.48-3.42

12-23	severe	2.265	0.000	1.76-2.92
24+		2.749	0.000	2.21-3.42
sex of child				
male	moderate	1.233	0.000	1.11-1.37
male	severe	1.165	0.036	1.01-1.34
Birth order of child				
4-6	moderate	1.083	0.192	.961-1.22
7+		.9942	0.939	.857-1.15
4-6	severe	1.317	0.001	1.12-1.55
7+		1.136	0.209	.931-1.39
mother’s highest educational level				
no_edu	moderate	3.799	0.005	1.49-9.70
primary		3.386	0.010	1.33-8.61
secondary		2.077	0.155	.759-5.68
no_edu	severe	6.083	0.078	.814-45.5
primary		4.675	0.132	.628-34.81
secondary		3.573	0.232	.442-28.90
Husband/partner's education level				
no_hedu	moderate	1.531	0.039	1.02-2.29
primaryh		1.401	0.097	.940-2.09
secondh		1.079	0.739	.689-1.69
no_hedu	severe	2.220	0.017	1.15-4.279
primaryh		1.620	0.148	.843-3.114
secondah		1.385	0.376	.673-2.848
Household wealth status				
poor	moderate	1.443	0.000	1.25-1.66
medium		1.228	0.021	1.03-1.46
poor	severe	1.815	0.000	1.48-2.226
medium		1.385	0.011	1.08-1.778
place of residence				
urban	moderate	.7645	0.010	.622-.939
urban	severe	.8329	0.239	.614-1.129
mother’s nutritional status (mother's body mass index)				
thinness	moderate	1.437	0.000	1.27-1.61
overweighed		.4846	0.000	.349-.672
thinness	severe	1.787	0.000	1.54-2.077
overweighed		.4132	0.001	.242-.7055
Incidence of diarrhea in the last two weeks				
dyes	moderate	1.220	0.012	1.04-1.42
dyes	severe	1.842	0.000	1.53-2.222
Incidence of fever in the last two weeks				
fyes	moderate	1.230	0.004	1.07-1.41
fyes	severe	1.594	0.000	1.34-1.899
_cons	moderate	.0153	0.000	.006-.039
_cons	severe	.0023	0.000	.000-.0179

Note: RR is Risk Ratio, CI is Confidence Interval

Appendix 3: Stata code for modelling and model comparison:

- ✓ **Stata code for proportional odds model**

```
xi: ologit severity i.agch i.sech i.boch i.edu i.hedu i.wi i.res i.bmi i.diarrhea i.fever

. brant
```

- ✓ **Stata code for multinomial model**

```
. xi: mlogit severity i.agch i.sech i.boch i.edu i.hedu i.wi i.res i.bmi i.diarrhea i.fever, baseoutcome(0) rrr

. estat ic
```

- ✓ **Stata code with gologit2**

```
. xi: gologit2 severity i.agch i.sech i.boch i.edu i.hedu i.wi i.res i.bmi i.diarrhea i.fever, auto lrf store(gologit2) or

. estat ic
```