JIMMA UNIVERSITY

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RISK FACTORS ASSOCIATED WITH STUNTING AND WASTING LEVELS AMONG UNDER FIVE CHILDREN IN ETHIOPIA

By

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ABSTRACT

Background: Stunting defined as a deficit in height relative to a child's age. Childhood stunting is one of the most significant impediments to human development. Stunting is a major health problem in children under-five years in many low and middle income countries around the world. Wasting is sometimes referred to as acute malnutrition because it is believed that episodes of wasting have a short duration, in contrast to stunting, which is regarded as chronic malnutrition.

Method: The data for the study were taken from Ethiopian Demographic Health Survey (EDHS) of year 2011. For stunting levels parallel line assumption of proportional odds model is violated. Thus, Partial proportional odds model were preferred over proportional odds model, generalized ordered logit model and multinomial logistic regression based on Akaike's Information Criterion evidence. Proportional odds model is used to analyze wasting levels since the parallel assumption of proportional odds model is not violated.

Result: The result indicate that age of child in month, region, place of residence, wealth index, mothers BMI, birth order of child, incidence of diarrhea for two weeks preceding the survey, incidence of fever for two weeks before survey, mothers and husband/partner educational levels are significantly associated with stunting levels. The result also shows that age of child, wealth index, mothers nutritional status, sex of child, incidence of diarrhea and fever for two weeks before survey, type of toilet, husbands/partner and employment status of mothers are significantly associated with wasting levels. Government and other stake holders have to give different priorities to different children age group, family background in terms of their mothers/fathers education level, mother's nutritional status, incidence of diarrhea and fever, household wealth status to control the severity level of children stunting and wasting. Children in rural areas are more likely to be stunted than children in urban areas so special attention should be given for the residence difference.

Key words: Proportional odds model (POM), partial proportional odds model (PPOM), stunting and wasting.

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LIST OF ACRONYMS

AIC	Akaike Information Criteria
AIDS	Acquired Immune Deficiency Syndrome
AOR	Adjusted odd ratio
BIC	Bayesian Information Criteria
BMI	Body Mass Index
CSA	Central Statistical Agency
EDHS	Ethiopian Demographic Health Survey
GLM	Generalized Linear Model
GOM	Generalized ordered logit model
MDG	Millennium Development Goals
MLR	Multinomial logistic regression model
MQL	Marginal Quasi Likelihood
OR	Odd Ratio
POM	Proportional Odds Model
PPOM	Partial Proportional Odds Model
PQL	Penalized Quasi Likelihood
SD	Standard Deviation
SNNPR	Southern Nations, Nationality and People's Region
UN	United Nation
UNICEF	United Nations Children's Emergency Fund
WB	World Bank
WHA	World Health Assembly
WHO	World Health Organization

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Malnutrition is a major public health problem faced by children under-five years as it inhibits their cognitive and physical development as well as contributes to child morbidity and mortality (WHO, 2013). Malnutrition is linked to poverty, low levels of education, poor access to health services and presence of infections. Stunting, wasting and underweight are expressions of protein-energy malnutrition. These malnutrition indicators are caused by an extremely low energy and protein intake, nutrients losses due to infection or combination of both low energy/ protein intake and high nutrient loss by the mother during pregnancy or by the child after birth (WHO, 2000).

Worldwide, over 10 million children under the age of 5 years die every year from preventable and treatable illnesses despite effective health interventions (Mussie A. et al., 2014). In developing countries, malnutrition is a major health problem (Caulfield et al., 2004). Childhood stunting is one of the most significant impediments to human development, globally affecting approximately 162 million children under the age of five years. Stunting, or being too short for one's age, is defined as a height that is more than two standard deviations below the WHO child growth standards median (WHO, 2006). Stunting is a major health problem in children under five years in many low and middle income countries around the world (UNICEF, 2015). It is defined as a deficit in height relative to a child's age (De Onis M. WHO, 2006).

Stunting has long term effects on individuals and societies including diminished cognitive and physical development reduced productive capacity, poor health and an increased risk of degenerative diseases such as diabetes (The state of the world's children, 2013). If current trends continue, projections indicate that 127 million children under five years will be stunted in 2025 (Walker et al., 2007). An estimated 80% of world's stunted children lived in just fourteen countries (India, Nigeria, China, Pakistan, Indonesia, Bangladesh, Ethiopia, Democratic Republic of Congo, Philippines, United Republic of Tanzania, Egypt, Kenya, Uganda and Sudan). Sub-Saharan Africa and South Asia were the home to three fourths of the world's stunted children 40% and 39%, respectively (Desalegne et al., 2016).

Wasting is caused by the same factors that contribute to stunting. Actions focused on prevention such as ensuring that pregnant and lactating mothers are adequately nourished that children receive exclusive breastfeeding during the first six months of life and provision of adequate complementary feeding in addition to breastfeeding for children aged six to twenty three months can help address both stunting and wasting (Bloem M., 2014).

Globally, 52 million children below five years of age were moderately or severely wasted, 11% decrease from 58 million in 1990. More than 29 million children below five years of age an estimated 5% suffered from severe wasting (M. De Onis et al., 2012). Wasting was decreased by 36% from 1990 which was 159 million while 51 million children below five years of age were wasted and 17 million were severely wasted in 2013.

The prevalence in 2013 was 8% and closely a third of that was for severe wasting totaling 3% and approximately two thirds of all wasted children who lived in Asia and one-third in Africa. The prevalence of wasting was the highest in South Asia which was approximately 16%. This moderate or severe wasting was the highest in India which had more than 25 million wasted children (UNICEF, 2013).

In Africa, high prevalence levels of stunting among children under-five years of age (36% or 56 million in 2011). These children have elevated risk of mortality, cognitive deficits and increased risk of adult obesity and non-communicable diseases (De Onis M., 2006). Africa shows rising numbers of stunted children due to population increase and an almost stagnant prevalence of stunting over the past two decades of the 34 countries that account for 90% of the global burden of malnutrition, 22 are in Africa. Some African countries (e.g. Ethiopia, Ghana and Mauritania) have had substantial reductions in stunting but overall in this region little improvement is anticipated in the coming years if recent trends continue (De Onis M., 2006).

In Africa, an estimated 13.4 million children under-five years of age or 8.5% were wasted (W/H <–2SD) in 2011. These children are at substantial increased risk of death. Increasing trends in child overweight in most world regions not just the developed world. In Africa, the estimated prevalence under-five overweight increased from 4% in 1990 to 7% in 2011. This trend is expected to continue (De Onis M., 2006).

According to CSA report in 2011 EDHS nationally 44 percent of children under age five are stunted and 21 percent of children are severely stunted. Male children are slightly more likely to be stunted than female children (46 percent and 43 percent, respectively).

Overall 10 percent of Ethiopian children are wasted and 3 percent are severely wasted. Wasting or acute malnutrition is highest in children age 9-11 months (19 percent) and lowest in children age 36-47 months (6 percent). Male children are slightly more likely to be wasted (11 percent) than female children (8 percent). Ten percent of children in rural areas are wasted compared with 6 percent in urban areas (EDHS, 2011).

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. Among various methods applied to uncover the factors of child stunting and wasting the most preferred method is logistic regression. It considers binary response (stunted and not stunted/wasted and not wasted) consequently, the binary logistic regression model was applied in all the cases. However, the stunting and wasting level of a child is usually classified as stunted, moderately stunted and severely stunted/wasted, moderately wasted and severely wasted. Since, the majority of the studies on child stunting and wasting status have never taken into account the order of status in their analysis which hide important information about the severity of child stunting and wasting. This study aims to describe severity of child stunting and wasting and identify the determinants of child stunting and wasting among under-five children.

1.2. Statement of the problem

Under-nutrition can best be described in Ethiopia as a long term year round phenomenon due to chronic inadequacies of food combined with levels of illness in under five children. 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.

The nutritional and health status of children in Ethiopia are among the worst in the world. 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 (88/1000) 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 pace of mortality reduction (WB, 2011).

The annual costs associated with child under nutrition are estimated at Ethiopian birr (ETB) 55.5 billion which is equivalent to 16.5% of GDP (UNICEF, 2015). So, a research on child stunting and wasting is important. Most of the studies from DHS data in Ethiopia does not included some important variables associated with stunting and wasting and also ignore the severity of stunting and wasting. Therefore, this study attempt to investigate this gap by addressing the following research questions:

- Which covariates are the most determinant factors for stunting and wasting levels of under five age children in Ethiopia?
- Which model is appropriate to stunting and wasting levels of under five age children in Ethiopia?

1.3. Objectives of the study

1.3.1. General Objective

The general objective of this study is to identify determinants of stunting and wasting levels among under five age children in Ethiopia.

1.3.2. Specific Objectives

The specific objectives of the study which should be accomplished to achieve the general objective stated above are:

- To describe the stunting and wasting status of under five children in Ethiopia.
- To identify the most important socio-economic, demographic and environmental factors associated with stunting and wasting level among under-five children in Ethiopia.
- To fit an appropriate statistical model for stunting and wasting level among under-five children in Ethiopia.

1.4. Significance of the study

- To explore the risk factors associated with stunting and wasting levels among under five children in Ethiopia.
- This study also might create awareness on the appropriate statistical methods to be used.
- The result of this study is to provide information to the government program planners, decision makers and other stakeholder who work in these areas.
- Can serve as an important for any possible intervention in this area for the future.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Definition of stunting and wasting

Height-for-age measures linear growth. Children whose height-for-age Z-score below minus two standard deviation (-2SD) from the median of the WHO reference population are considered short for their age. This condition reflects the cumulative effect of chronic malnutrition (UNICEF and WHO, 2012). Stunting is an enormous drain on economic productivity and growth. Economists estimate that stunting can reduce a country's gross domestic product by up to 3%. Stunting reflects chronic under-nutrition during the most critical periods of growth and development in early life (World Bank, 2006).

Stunted growth (shortness) reflects failure to reach linear growth potential as a result of sub-optimal health or nutritional conditions. On a population wide basis, high levels of stunting are associated with poor socio-economic conditions and increased risk of frequent and early exposure to adverse conditions such as illness and/or inappropriate feeding practices. It is assumed to indicate long term, cumulative effects of inadequate nutrition and poor health status (Zemenu et al., 2017).

Wasting represents a low weight-for-height and it is a measure of acute malnutrition, an indicator of short-term fluctuation in nutritional status. Similarly, all the children under-five years whose weight for height Z-score less than minus 2 standard deviation were regarded as wasted. Wasting also refers to the process by which a debilitating disease causes muscle and fat tissue to waste away. Wasting is sometimes referred to as acute malnutrition because it is believed that episodes of wasting have a short duration, in contrast to stunting which is regarded as chronic malnutrition. According to the latest UN estimates, an estimated 52 million children under 5 years of age or 8% were wasted in 2011 (UNICEF and WHO, 2012).

Wasting (thinness) reflects a deficit in tissue and fat mass and indicates that the child don't weight as much as they should for their height. In most cases a recent and severe process of weight loss, which is often associated with acute starvation and/or severe disease. It is the first response to nutritional and/or infectious insult (Zemenu et al., 2017).

Not all children who are stunted are wasted. And not all children who are wasted are stunted. To fully assess the burden of under-five under nutrition, we need to estimate how many children are affected by stunting, wasting or both. In global nutrition report 2015 using data from five countries with a high burden of under nutrition, we provided an snapshot of the prevalence of children 6-59 months old who were stunted, wasted or both (concurrence) (Dolan et al., 2015).

2.2. Causes of stunting and wasting

Factors that contribute to stunted growth and development include poor maternal health and nutrition, inadequate infant and young child feeding practices, and infection. Specifically, these include maternal nutritional and health status before, during and after pregnancy influences a child's early growth and development, beginning in the womb (Özaltin et al., 2010). Intrauterine growth restriction due to maternal under nutrition (estimated by rates of low birth weight) accounts for 20% of childhood stunting (UNICEF and WHO, 2014). Other maternal contributors to stunting include short stature, short birth spacing and adolescent pregnancy which interferes with nutrient availability to the fetus (owing to the competing demands of ongoing maternal growth). As a result of household poverty, caregiver neglect, non-responsive feeding practices, inadequate child stimulation and food insecurity can all interact to impede growth and development.

Wasting can be caused by an extremely low energy intake (e.g. by famine), nutrient losses due to infection or a combination of low intake and high loss. Infection and conditions associated with wasting include tuberculosis, chronic diarrhea, AIDS and superior mesenteric artery syndrome. Caretakers and health providers can sometimes contribute to wasting if the patients are placed on improper diet. Voluntary weight loss and eating disorders are excluded as causes of wasting (https://en.m.wikipedia.org/wiki/wasting, 2017). Children become wasted when they lose weight rapidly, usually as a direct result of a combination of infection and diet that do not cover nutritional needs. The main underlying causes of wasting are; poor access to appropriate timely and affordable health care, inadequate caring and feeding practices (e.g. exclusive breastfeeding or low quantity and quantity of complementary food), poor food security and lack of a sanitary environment including access to safe water, sanitation and hygiene services (WHO, 2014).

2.3. Malnutrition

The term malnutrition generally refers to both under-nutrition and over nutrition (Annette et al., 2005). Proper nutrition is one of the most fundamental aspects of health, but today malnutrition (measured as poor anthropometric status) continues to be a significant health concern and remains as the single largest cause of child mortality around the world. Poor nutrition can have irreversible effects, permanently impacting a child's cognitive development, immune system, and overall growth (WHO, 2000). Malnutrition 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 under-nutrition from either inadequate calories or inadequate specific dietary components for whatever reason (Nikolaos, 2011).

Malnutrition is a serious problem because it causing the deaths of 3.5 million children under five years old per-year in the world, as well as it is at third level in the world of the disease burden in this age group (Black et al., 2008). Roughly 30% of children in the world are undernourished and in fact 60% of children for example who died of common disease like malaria and diarrhea (World Bank, 2006). Malnutrition is one of the leading causes of morbidity and mortality in children under the age of five in developing countries (World Nutrition Situation, 2010). Ethiopia is the second highest rate of malnutrition in sub-Saharan Africa (Getahun et al., 2001).

Malnutrition during childhood is as a result of a wide range of factors, most of which relate to unsatisfactory food intake or severe and repeated infections, or a combinations of the two. The most frequently suggested causes of malnutrition are: poverty, low parental education, lack of sanitation, low food intake, diarrhea and other infections, poor feeding practices, family size, short birth intervals, maternal time availability, child rearing practices and seasonality. There are also economic, social, and cultural causes of malnutrition which underscore the close link between malnutrition (Tibilla M.A, 2007). Wasting stunting is frequently combined however, analysis of number of representative population groups reveal in consistent, mostly insignificant association between two. The two deficits show different pattern at different ages and different populations (Panna Choudhary, 2004).

2.3.1. Child related factors of under-five malnutrition

According to the study done in Nigeria using logistic regression shows that there was significant relationship between sex of a child and malnutrition, male children were more likely to be malnourished than their female counterparts. This is probably due to increased attention paid to female children unlike the male children (Babatunde, 2011). Another study is done in Botswana revealed that stunting, wasting and underweight was also significantly more prevalent among boys than girls (Salah and Nnyepi, 2006). A study done by Olwedo et al. (2008) on the factors associated with malnutrition Uganda indicated that a male child was nearly two times more likely to suffer from acute malnutrition (wasted) compared do a female child (adjusted odds ratio of 1.56 at 95% C.I 1.15-2.13 with p-value =0.004**).

Using logistic regression specific ages, children's nutritional status is associated with feeding, weaning practice, care and exposure to infection. A cumulative indicator of growth retardation (stunting) in children is positively associated with age. A study done in Ethiopia has also shown as an increase in malnutrition with increase in age of the child (Yimer, 2000). The study conducted in vietnam using logistic regression found that the risk of malnutrition increases with age of a child. Children in the youngest age 0-11 months had significantly lower risk of being stunted, underweight and wasted than children in the older age groups (Nguyen and Kam, 2008). Malnutrition increases with the age of the child through the first three years of life before declining in the fourth and fifth year (Uganda Bureau of Statistics and Macro international Inc, 2007; Babatunde, 2011; Kabubo-mariara et al., 2006; Sarmistha, 1999). The finding are plausible considering that many of the younger children are still being breastfed and stunting sets in only after weaning (Babatunde and Qaim, 2010).

The study conducted on children under-five years in Bangladesh using logistic regression, the prevalence of stunting increased with birth order hence most of the children who were of birth order more than two had greater chance of stunting and wasting (Rayhan and Hayat, 2006).

Multilevel analysis reveals that the mothers nutritional status (mother's BMI) is negatively and significantly associated with stunting, suggesting that children in a household where the mother has a low BMI are more likely to be stunted (Olalekan, 2008). Using multilevel analysis male children and mothers with BMI less than 18.5 kg/m^2 were significantly more susceptible to wasting and severe wasting than their female counterparts and mothers with BMI greater than

18.5 kg/m^2. Child's age was also significantly associated with wasting and severe wasting (Blessing et al., 2017) and also the study conducted using multilevel approach reveals that maternal health is associated with higher probability of wasting and stunting (Pendael, 2013).

Using multivariate logistic regression analysis children age 6-59 months those from whose family had middle wealth quintile were 0.53% times less likely to be affected by stunting than children whose family had lowest wealth quintile (AOR=0.53; 95% CI: 0.34-0.82). Similarly children from families who had highest wealth quintile were 0.5 times less likely to be affected by stunting compared to children from lowest wealth quintile families (AOR=0.50; 95% CI: 0.33-0.75) (Birara et al., 2014). Some evidence in developing countries indicated that malnourished individuals that is women with a body mass index (BMI) below 18.5, poor economic status of a household which is an indicator of food supplies, education status of both mother and father, place of residence (whether from rural or urban areas), age of child, birth order show a progressive increase in malnutrition rates and risk of stunting as well as increased risk of illness (Genebo and Girma, 2002).

Mother's education level affects child's nutrition through her choices and health seeking skills related to nutrition, hygiene, preventive care and disease treatment. Many studies (Babatunde and Qaim, 2010; Olwedo et al., 2008; Webb and Block, 2004; Shrimpton et al., 2001) using logistic regression shows that most women with low education spend more time in gardens and feed their children on less nutritious foods. Women who spend more time in gardening get limited time to attend to their children and prepare for them nutritious meals unlike their educated counterparts who normally focus on good child nutrition practices even when they are absent from home most of the time. Education helps the mothers to gain knowledge for adequate intake of food for their children in terms of correct quantity, quality and frequency. It also determines her income and this helps her access proper nutrition for the child as well as health services. The study conducted to Sommerfelt et al. (1994) there is a negative association between the mother's education and under-five child malnutrition.

The higher the level of mothers' education, the lower the percentage of under-five children classified as undernourished. According to Nure et al. (2011) using logistic regression children whose mother had no education or had primary education were more times significantly stunted and underweight than children whose mothers had secondary or higher level. However for wasting, children whose mothers had primary or secondary education had 0.87 times lower odds of wasting than those of mothers with higher education. Education of a mother has several potentially positive effects on the quality of care of children and consequently malnutrition. More educated women are better able to process information, acquire skills and model positive caring behaviors (Lisa, 2000). Mother education is associated with administration of limited household resources, greater availability of health care service, better health promoting behaviours, lower fertility and centered caring practice and all these give a reduction in malnutrition among under-five children (Nguyen and Kam, 2008). On other hand, Shen et al. (1996) have observed that despite economic reforms in both rural and urban China, rural children aged 2 to 5 years were more likely stunted as compared with urban children.

Finding in Ethiopia by using logistic regression reveal that mothers' marital status and under-five child malnutrition is significantly associated with marital status. The study found that under-five child malnutrition is higher among unmarried rural and divorced/separated women compared to married ones (Teller and Yimar, 2000). Married mother was positively associated with good nutrition status among children under-five years in the Volta of Ghana (Appoh and Krekling, 2005). Contrary, the study in Tanzania revealed that mothers who are married were more likely to have undernourished children unlike those that were unmarried perhaps because of the cost of maintaining families hence sometimes these families fail to produce nutritious supplements to the under-five children (Nyaruhucha et al., 2006).

Mothers occupation is one of the factors associated with under-five malnutrition in most developing countries. A study in Vietnam revealed that children from mothers who were labourers or farmers and housewives had a greater prevalence of stunting, underweight and wasting than those from mothers worked in office or housewives (Nguyes and Kam, 2008). Mother's occupation is one of the indicators for access to adequate food supplies, use of health services, availability of improved water sources and sanitation facilities which are prime determinants of child nutritional status (UNICEF, 1990).

A study done on most of the DHS conducted in developing countries especially in the southern nations, nationalities and peoples Region (SNNPR) of Ethiopia using logistic regression shows that under-five children from low economic status households were the most affected by malnutrition (Loaiza, 1997).

The study done in dollo district Ethiopia using logistic regression shows that safe drinking water and child nutritional status especially with stunting are significantly associated. This could be give to the fact clean water avoid water born disease that can negatively affect the health and nutrition of young children (Solomon .D and Amare .W, 2013). And also the study conducted at Sheka Zone, South west Ethiopia using ordinal logistic regression reveals that child feeding status, duration of breast feeding, size of child at birth, had fever in last two weeks, timing of child put to the breast, had diarrhea in the last two weeks and preceding birth interval were significantly associated with malnutrition (Yilkal Messelu and Kassahun Trueha, 2016).

Study by Tadiwos and Degnet (2013) using multivariate logistic regression at Combolcha District of Eastern Hararghein in Ethiopia shows that age of child, sex of child, immunization status and the others use of antenatal care, farm size, household size, water source, latrine use and incidence of morbidity as important factors that associated with child malnutrition.

According to the study on factors associated with stunting among children aged 0 to 59 months from the central region of Mozambique by using multiple logistic regression showed that birth weight, mother's educational status, maternal occupation, living in a rural area, family size, number of children under five years of age in the household, cooking with charcoal, inhabiting wooden or straw housing or housing without proper floors, overall duration of breastfeeding as well as duration of exclusive breastfeeding, and time of initiation of complementary feeding were significantly related to stunting (Loida et al., 2017). And also the study in Nigeria using multilevel analysis revealed that the most consistent factors associated with wasting/severe wasting and underweight/severe underweight are geographical zone (North East, North West and North Central), perceived birth size (small and average), sex of child (male), place/mode of delivery (home delivery and non-caesarean) and a contraction of fever in the two weeks prior to the survey (Blessing et al., 2017).

CHAPTER THREE

3. DATA AND METHODOLOGY

3.1. Source of data and study area

The source of data for this study is the 2011 Ethiopia Demographic and Health Survey (EDHS) which is obtained from Central Statistical Agency (CSA). It is the third major survey designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole, urban and rural area 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).

3.2. Study population

The study populations are all the under five children residents of Ethiopia using the 2011 EDHS data set. In the 2011 EDHS from 11,654 under-five children, total number of children covered in the current study on the stunting and wasting status of children is based on 9370 under-five children with complete anthropometric measurements and the study considered height-for-age and weight-for-height anthropometric index as indicator of a children's stunting and wasting status respectively.

3.3. Study design

The study design for this study was a cross sectional survey conducted in 2011 using population based representative sample.

3.4. Sampling technique

The 2011 EDHS sample was selected using a stratified, clustered and selected in two stages. In the Ethiopia demographic and health survey (EDHS, 2011) a representative sample of approximately 17817 households from 624 clusters was selected. The sample was selected in two stages. In the first stage, 624 Enumeration Areas were selected with probability proportional to the Enumeration Area size and with independent selection in each sampling stratum. In the second stage, a fixed number of 30 households were selected for each Enumeration Area. Among the 624 selected Enumeration Areas, 187 are in urban areas and 437 are in rural areas.

3.5. Variables in the Study

3.5.1. Dependent variable

The outcome variable of interest is stunting and wasting of child less than five year. There are anthropometric indicators of nutritional status such as height-for-age, weight-for-age and weight-for-height. These indices were based on the growth standards published by WHO in 2006. The three indices were expressed as standard deviation units from the median for the reference group. Children who fall below minus two standard deviations (−2 SD) and (-3 SD) from the median of the reference population are regarded as stunted and severely stunted respectively. The height-for-age index provides an indicator of linear growth retardation and cumulative growth deficits in children. Children whose height-for-age Z-score below minus two standard deviations (−2 SD) and (-3 SD) from the median of the WHO reference population are considered short for their age (stunted) and severely stunted or chronically malnourished respectively. Stunting reflects failure to receive adequate nutrition over a long period of time and is affected by recurrent and chronic illness. Height-for-age therefore, represents the long-term effects of malnutrition in a population and is not sensitive to recent, short-term changes in dietary intake. (De Onis M. WHO., 2006).

Weight-for-height index describes current nutritional status. The indicators were categorized in to severely wasted (< -3 Z-score), moderately wasted (-3 to -2 Z-score) and non wasted (≥-2 Z-score).

The response variable of the study is stunting and wasting level, which is categorized into three ordinal categories: severely stunted or wasted, moderately stunted or wasted and if not stunted or wasted.

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

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

3.5.2. Independent variables

The explanatory variables included in this study are mother's education, employment status of the mother, education of husband/partner, household income, household size, place of residence and geographical region, age of the child, sex of the child, birth interval, birth order of the childs, diarrhea and fever in the last two weeks before survey, water supplies and toilet facilities, Incidence of acute respiratory infection (such as cough) in the last two weeks, Mother's nutritional status or Mother's BMI are important factors are included in this study.

Table 3.1: Independent variables of the study

No	Variables	Categories
1	Sex of child	0=female, 1= male
2	Birth interval of the child in month	0=0-24, 1=25-47 and 2=48-59
3	Age of child in month	0=0-11, 1=12-23 and 2=24+
4	Birth order of the child	0=1-3, 1=4-6 and 2=7+
5	Mothers education	0=No education, 1=primary education and 2=secondary and above
6	Employment status of mothers	0=Unemployed and 1=employed
7	Wealth index	0=Poor, 1=medium and 2=rich
8	Education of husband/partner	0=No education, 1=primary education and 2=secondary education and above
9	Number of house hold member	0=1-4, 1=5-9 and 2=10 and above
10	Place of residence	0=urban and 1= Rural
11	Region	1=Tigray, 2=Affar, 3=Amhara, 4=Oromia, 5=Somali, 6=Benishangulgumuz, 7=SNNP, 8=Gambella, 9=Harari, 10=Addis Ababa and 11=Dire Dawa
12	Source of drinking water	0=non improved,1=improved and 2=others
13	Had diarrhea in the two weeks before study	0=No and 1= yes
14	Had fever in the two weeks before survey	0=No and 1=yes

15	Type of toilet facility	0=No facilities,1=Have facilities and 2=others
16	Incidence of cough in the last two weeks	0=No and 1=yes
17	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)

3.6. Statistical method

3.6.1. Logistic regression

Regression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables. It is often the case that the outcome variable is discrete, taking on two or more possible values. Over the last decade the logistic regression model has become in many fields, the standard method of analysis in this situation (Hosmer and lemeshow, 2000).

What distinguishes a logistic regression model from the linear regression model is that the outcome variables in logistic regression have two or more categories. What distinguishes a logistic regression is reflected both in the choice of a parametric model and its assumptions. Once this difference is accounted for the methods employed in an analysis using logistic regression follow the same general principles used in linear regression. Logistic regression is the most important model for categorical response data. It is used increasingly in a wide variety of applications. Early uses were in biomedical studies but the past 20 years have also seen much use in social science research and marketing (Agresti A., 2002).

Regression is a statistical procedure which attempts to predict the values of a given variable, (termed the dependent, outcome, or response variable) based on the values of one or more variables (called independent variables, predictors, or covariates). Regression analysis is model building for the relationship between a dependent and one and/or more independent variables. In the regression if the response variable is continuous we can use the usual linear regression model where as when the response variable is discrete, taking on two or more possible values the appropriate regression model is logistic regression which was proposed as alternative method in the late 1960s and early 1970s (Cabrera, 1994). Such a technique was developed by McCullough and Nelder (1989) and is called generalized linear model (GLM), one of its application is logistic regression (Fox, 1984).

The problem of non normality and hetroscadasticity lead to the model estimation method to be maximum likelihood after natural logarithm transformation of the odd ratio of the response because in logistic the relationship between the response with the set of explanatory variables is not linear hence the procedures used in the linear regression is extended to logistic regression. Logistic regression models are classified according to the type of categories of response variable as follows:-binary logistic regression model, multinomial logistic regression model and ordinal logistic regression models (Hosmer and Lemeshow, 2000). The binary logistic regression model is used to model the binary response variable, whereas the multinomial logistic regression is a simple extension of the binary logistic regression model where the response variable has more than two unordered categories. Ordinal logistic regression models are used to model the relationship between independent variables and an ordinal response variable when the response variable category has a natural ordering.

3.6.1.1. Ordinal logistic regression model

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

Ordinal response models have major importance in social sciences as well as demography and many social phenomena. The responses are discrete or qualitative rather than continuous or quantitative in nature. Many such analyses involve an outcome or dependent variable that is ordinal and in these studies the logistic regression model has become the statistical model of choice. There are several ordinal logistic regression models such as proportional odds model (POM), two versions of the partial proportional odds model-without restrictions and with restrictions, continuous ratio model and stereotype model. The most popular model in ordinal logistic is the Proportional Odds model. In this particular study, logit link function was used. 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).

3.6.1.1.1. Assumption of ordinal logistic regression

When you choose to analyze data using ordinal regression, part of the process involves checking to make sure that the data you want to analyze can actually be analyzed using ordinal regression. You need to do this because it is only appropriate to use ordinal regression if your data "passes" four assumptions that are required for ordinal regression to give you a valid result.

Assumption 1: dependent variable should be measured at the ordinal level.

Assumption 2: one or more independent variables those are continuous, ordinal or categorical (including dichotomous variables). However, ordinal independent variables must be treated as being either continuous or categorical.

Assumption 3: There is no multicollinearity. Multicollinearity occurs when you have two or more independent variables that are highly correlated with each other. This leads to problems with understanding which variable contributes to the explanation of the dependent variable and technical issues in calculating an ordinal regression. Determining whether there is multicollinearity is an important step in ordinal regression. Unfortunately, testing for this assumption can require creating dummy variables for categorical variables (i.e., dummy variables are new variables based on the values of your existing data). However, if you have multiple categorical independent variables, each with three or more groups, you will have to create quite a lot of these dummy variables.

Assumption 4: have proportional odds, which is a fundamental assumption of this type of ordinal regression model. The assumption of proportional odds means that each independent variable has an identical effect at each cumulative split of the ordinal dependent variable.

3.6.1.1.2. Proportional odds model (POM)

The proportional odds model was originally proposed by Walker and Duncan (1967) as the constrained cumulative logit model and later called proportional odds model (McCullagh, 1980; Hosmer and Lemeshow, 2000). The assumption of proportional odds means that each independent variable has an identical effect at each cumulative split of the ordinal dependent variable. In case where the dependent variable is ordinal and parallel lines assumption holds, Proportional Odds Models are commonly used (Brant, 1990; Bender and Grouven, 1998).

Proportional Odds Model is defined by McCullagh(1980) for ordinal logistic regression. The model is based on cumulative distribution function. In proportional odds model, every single cumulative logit has its own threshold value. Coefficients of the equality are independent from dependent variable categories. Thus, coefficients of the independent variable are equal to each other in every cumulative logit model (Kleinbaum and Ananth, 1997; McCullagh and Nelder, 1989). When response categories are ordered logit can directly incorporate the ordering. Define i^{th} cumulative probability that the response Y falls in category *i* or below as:

$$P(Y \leq i) = \pi_1 + \pi_2 + \cdots \pi_c,\ i = 1, \ldots \ldots . . c \tag{3.1}$$

The cumulative probabilities reflect the ordering with

$$P(Y \leq 1) \leq P(Y \leq 2) \leq \ \ldots \ldots \ldots . \leq P(Y \leq i) = 1 \tag{3.2}$$

Models for cumulative probabilities do not use the final one $P(Y \leq i)$ since it equals 1. Let Y takes categorical response variable with c ordered categories, cumulative probability of the first c-1 of Y is $P(Y \leq i) = \pi_i, i = 1, \ldots, c-1$. then, the odds of the first c-1 cumulative are

$$odds\big(pr(Y \leq i)\big) = \frac{pr(Y \leq i)}{1 - pr(Y \leq i)} = \left[\frac{\pi_i}{1-\pi_i}\right] \ , \quad i = 1, \ldots, c-1 \tag{3.3}$$

The proportional odds model the log odds of the first c-1 cumulative probability as:

$$logit[pr(Y \leq i)] = \log\left[\frac{pr(Y \leq i)}{1 - pr(Y \leq i)}\right] = \log\left[\frac{\pi_i}{1-\pi_i}\right] \tag{3.4}$$

And the relationship between the cumulative logits of Y is:

$$\log\left[\frac{\pi_i}{1-\pi_i}\right] = \log\left[\frac{\pi_i}{\pi_{i+1} + \cdots \pi_C}\right] \ , \ i = 1, \ldots . C-1$$

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

$$\pi_i = \frac{\exp\left(\alpha_i + \beta_1 X_1 + \cdots + \beta_p X_p\right)}{\big(1 + \exp\left(\alpha_i + \beta_1 X_1 + \cdots + \beta_p X_p\right)\big)} \tag{3.5}$$

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:

$$\log\left[\frac{pr(Y \leq i)}{1 - pr(Y \leq i)}\right] = \log\left[\frac{\pi_i}{1-\pi_i}\right] = \alpha_i + \beta_1 X_1 + \cdots + \beta_p X_p. \tag{3.6}$$

Equivalent with $\log\left[\frac{\pi_i}{1-\pi_i}\right] = \alpha_i + \sum_{j=1}^{p}\beta_j X_j \qquad i = 1, \ldots, c-1 \ \ and\ j = 1, \ldots, p$

Where: α_i= threshold value, β_j= parameter, X_j = sets of factors or predictors.

The model assumes a linear relationship for each logit and parallel regression lines. Above equation is called proportional odds model and it estimates simultaneously multiple equations of cumulative probability. An equation is solved for each category of the dependent variable except the last one. 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.

Testing parallel lines

In ordinal logistic regression models there is an important assumption which belongs to ordinal odds. According to this assumption parameters should not change for different categories. This means that the dependent variable's categories are parallel to each other. When the assumption does not hold, it means that there is no parallelity between categories (Kleinbaum and Klein, 2010). Test of parallel lines used to determine whether it is reasonable to assume that the values of the location parameters are constant across categories of the response.

The test of parallel lines or planes has two log-likelihood functions; -2loglikelihood for the model that assumes the lines or planes are parallel and -2log-likelihood for the model that assumes the line are separated. For testing parallel lines for POM, the appropriate test statistic used is chi-square statistic. This is the difference between the log-likelihood for the two models. A non significance test is evidence that the logit surfaces are parallel and that the odd ratio can be interpreted as constant across all possible cut point of the response. The intercept term in the equation may vary, but the parameters would be identical for each model. If the lines are parallel, the observed significance level for the change should be large, since the general model does not improve the fit very much. If proportional odds model is not met there are several options (K.A. Adele and A.A. Adepoju, 2010)

- Collapse two or more levels, particularly if some of the levels have small number of observations.
- Use bivariate ordinal logistic analyses, to see if there is one particular independent variable that is operating differently at different levels of the dependent.
- Use partial proportional odds model.
- Use multinomial logistic regression.

3.6.1.1.3. The Generalized ordered logit model

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

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

$$logit\big(P(Y > j/X)\big) = \ln\left(\frac{p(Y>j/X)}{p(Y\leq j/X}\right) = \alpha_j + \beta_{1j}X_1 + \beta_{2j}X_2 + \cdots + \beta_{kj}X_{k,} \qquad (3.7)$$

$$j = 1, \ldots J-1$$

Where, α_j are the intercept or cut points and; $\beta_{1j}, \ \beta_{2j} \ \ldots \beta_{kj}$ are logit coefficients. This model estimates the odds of being beyond a certain category relative to being at or below that category.

Generalized ordered logit model estimates the regression parameters for each explanatory variable on J-1 logit of the probability being beyond the j^{th} category in every logit to have different estimated values. A positive logit coefficient indicates that an individual is more likely to be in a higher category as opposed to a lower category of the outcome variable.

3.6.1.1.4. Partial proportional odds model (PPOM)

Suggested by Peterson and Harrell (1990), Partial Proportional Odds Model can be used when parallel lines assumption holds or not. 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 by the other covariables. The general form of the model is the same as the PO model, but now the coefficients are associated with each category of the response variable.

Partial proportional odds model can be classified as unrestricted and the restricted one. 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:

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

$$\lambda_i = \alpha_i + \{(\beta_1 + \gamma_{i1})X_1 + \cdots + (\beta_q + \gamma_{iq})X_q + (\beta_{q+1}X_{q+1}) + \cdots (\beta_p X_q)\}, i = 1, \dots, k-1 \quad (3.8)$$

It is normally expected that there is 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_{kl} 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 ith logit. The model becomes (Peterson and Harrell, 1990).

$$\lambda_i = ln\left\{\frac{pr(Y=1/X)+\cdots+pr(Y=i/X)}{p(Y=i+1/X)+\cdots+pr(Y=k/X)}\right\} = ln\left\{\frac{\sum_1^i pr(Y=i/X)}{\sum_{i+1}^k pr(Y=i/X)}\right\} \quad (3.9)$$

$$\lambda_i = \alpha_i + \{\tau_i((\beta_1 + \gamma_{i1})X_1 + \cdots + (\beta_q + \gamma_{iq})X_q + (\beta_{q+1}X_{q+1}) + \cdots (\beta_p X_q))\}, i = 1, \dots, k-1$$

3.6.1.2. Multinomial Logistic Regression model

In multinomial logistic regression, dependent variable has more than two nominal categories which do not have an ordinal structure. Multinomial logistic regression models how multinomial response variable Y depends on a set of k explanatory variables, X = X_1, X_2, X_3… X_K. Also this dependent variable is multinomially distributed. Shortly, it is an expanded form of binary logistic regression model for J categories. A multinomial logistic model with J categories must have J − 1 logistic regressions. In a multinomial logistic regression model, dependent variable's probability of being in category J $\pi_j = p(Y = j)$ is expressed by equation below (Liao, 1994).

$$\pi_j = \frac{\exp\left(\sum_{k=1}^K \beta_{jk}X_k\right)}{1+\sum_{j=1}^{J-1}\left(\sum_{k=1}^K \beta_{jk}X_k\right)} , \qquad j = 1,2, \dots J-1 \quad (3.10)$$

3.6.2. Odds Ratio

Odds ratio is a statistic that measures the odds of an event compared to the odds of another event. The odds of the response being present among individuals with x=1 and x=0 given is given by:

$$odds(x = 1) = \frac{p(Y|X=1)}{1-p(Y|X=1)} \quad and\ odds(x = 0) = \frac{p(Y|X=0)}{1-p(Y|X=0)} \quad (3.11)$$

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

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

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

3.6.3. Model Selection Criteria

In regression analysis fitting a model is the main issue and should give more care for selecting model that well fit the data. To achieve this task selection criterion's such as R-square, adjusted R-square, Pseudo R^2, BIC, AIC, etc should be considered. It is much better to compare models based on their results, reasonableness, and fit as measured; we can make comparisons among the possible models using the above selection criteria. In the case of logistic regression the model selection criteria was taken as AIC. The AIC computation is based on the likelihood of the fit and the number of parameters in the model is considered.

Therefore, if the model contains many variables there are many parameters to be estimated; therefore, this may penalize the AIC criteria. If we fit a model that contains all the possible variables under study it needs much computation time and resources, the co-linearity of the variables may affect the model fit and also less important variables might be included in the model or if the model contains few variables, it may not well explain the outcome (response) and the error of the model becomes large due to exclusion of important variables. The variables included in the model should be selected based on their significance and relationship with the outcome variables or response variable. Therefore, the issue of inclusion and exclusion of explanatory variables are called variable selection problem. Methods such as forward, backward and stepwise selection are commonly used.

In this study to select the best model AIC (Akaki information criterion) was used. The model with small value of AIC is the optimal model, that means a model that close to actual one (Agresti, 2002) and the model which have few parameters to be estimated. AIC and BIC is defined as

$$AIC = -2 * \ln(likelihood) + 2k$$

$$BIC = -2 * \ln(likelihood) + \ln(N) * k$$

Where k is the model degrees of freedom calculated as the rank of variance–covariance matrix of the parameters and N is the number of observations used in estimation or, more precisely, the number of independent terms in the likelihood. AIC and BIC can be viewed as measures that combine fit and complexity. Fit is measured negatively by -2 * ln (likelihood); the larger the value, the worse the fit. Complexity is measured positively, either by 2 *k (AIC) or ln (N) * k (BIC). Given two models fit on the same data, the model with the smaller value of the information criterion is considered to be better (Akaike, 1974; Schwarz, 1978).

3.6.4. 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 $-2 \times \log 1=0$ (Agresti, 2002).

The likelihood-ratio test statistic is given by (Hosmer and Lemeshow, 2000)

$$G^2 = -2\, ln\left(\frac{likelihood\ without\ the\ variable}{likelihood\ with\ the\ variable}\right) \tag{3.12}$$

3.6.5. Goodness-of-Fit Measures

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 c form a second outcome. This shows that c categories of response collapsed in to binary out come. Again let $(Y_{j1}, \dots Y_{jc})$ 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:

$$L = \prod_{j=1}^{n}\left[\prod_{i=1}^{c}\pi_i(X_j)^{Y_{ij}}\right] = \prod_{j=1}^{n}\left[\prod_{i=1}^{c}(p(Y \le i/X_j) - p(Y \lesssim i-1/X_j))^{Y_{ij}}\right]$$

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

$$l(\beta^*) = \prod_{i=1}^{c}[\pi_1(X_j)^{Y_{1j}}\pi_2(X_j)^{Y_{2j}} \times \dots \pi_c(X_j)^{Y_{cj}}]$$

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

$$L(\beta^*) = \sum_{j=1}^{n} Y_{1j}\ln\left[\pi_1(X_j)\right] + Y_{2j}\ln\left[\pi_2\left(X_j\right)\right] + \cdots + Y_{cj}\ln\left[\pi_c(X_j)\right] \quad (3.13)$$

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

H_0. The model fit the data well Vs H_A: The model does not fit the data well.

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

Pearson goodness of fi statistic is $X^2 = \frac{\sum\sum(o_{ij} - e_{ij})^2}{e_{ij}}$ and

deviance measure is $D = 2\sum\sum O_{ij}\ln\left(\frac{O_{ij}}{E_{ij}}\right)$ (3.14)

Where O_{ij} is the observed frequency and e_{ij} is the expected frequency.

The observed frequency is obtained from the data on the response but the frequency is obtained from the estimated probabilities of the response.

Both goodness-of-fit statistics should be used only for models that have reasonably large expected values in each cell. If we have a continuous independent variable or many categorical predictors or some predictors with many values, we may have many cells with small expected values. If our model fits well, the observed and expected cell counts are similar, the value of each statistic is small, and the observed significance levels are large. We shall reject the null hypothesis that the model fits the data well if the observed significance level for the goodness of-fit statistics is small. Good models have large observed p-values.

3.6.6. Model adequacy checking

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

Residuals

Residuals are the difference between the observed and predicted value of the response variable Residuals are useful in identifying observations that are not explained well by the model. For logistic regression diagnostics the residuals are calculated in a similar way as usual. However, since the variables are categorical we have to consider contingency tables. The pattern of lack of fit revealed in cell-by-cell comparisons of observed and fitted (expected) counts may suggest a better model. For a model with categorical predictors, the residuals are computed from the observed and expected counts of the contingency table. Let Yi denote the binomial variate for ni trials at setting i of the explanatory variables, i=1,2,…N. Let $\hat{\pi}_i$ denote the model estimate of p(Y=1). Then $ni\hat{\pi}_i$ is the fitted number of successes.

The person residual is defined as:

$$e_i = \frac{(Y_i - N\hat{\pi}_i)}{(var(Y_i))^{1/2}} \tag{3.15}$$

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

Pearson residuals by their estimated standard deviation that contains variation due to the effect leverage value is called standardized Pearson residual.

The Standardized Pearson residual is slightly larger in absolute value then e_i, and is approximately N (0, 1) when the model holds. It's similar to the Pearson residual the only difference is standardized residuals uses the leverage from an estimated hat matrix that means for an observation *i* with leverage value $\hat{h}_i$.

Observations with absolute standardized residual values in excess of 3 may indicate lack of fit (Rawlings, 1998). The standardized Pearson residual is given (Agresti, 2002):

$$r_i = \frac{e_i}{(1-\hat{h}_i)^{1/2}} \tag{3.16}$$

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

$$\sqrt{d_i} \times sign(Y_i - n_i\hat{\pi}_i)$$

$$where \quad d_i = 2\left(Y_i log\frac{Y_i}{n_i\hat{\pi}_i} + (n_i - Y_i)log\frac{n_i - Y_i}{n_i - n_i\hat{\pi}_i}\right) \tag{3.17}$$

Measure of influence

Influence measure indicates 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 the leverage and outliers. It may be informative to report the fit of the model after deleting one or more 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:

$h_i = n_i\hat{\pi}(X_i)[1 - \hat{\pi}(X_i)(1, X_j')(X'VX)^{-1}(1, X_j')']$, Where $\hat{V} = diag\{\hat{\pi}(1-\hat{\pi})\}$ and $\hat{\pi}$ 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 an independent variable deviates from its mean. These leverage points can have an effect on the estimate of regressions 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 $(N-1)/N$ and a leverage value greater than 2 or 3 times of average leverage is considered as large. 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:

$CD_i = \frac{Z^2{}_i h_i}{1-h_i}$ Where Z_i is Standardized 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).

DFBETA(S): is a diagnostic measure which measures the change in the logit coefficients for a given variable when a case is dropped. If DFBETA(S) is less than unity, this implies no specific impact of an observation on the coefficient of a particular predictor variable, while DFBETA of a case greater than 1.0 and implied the observation is outlier (cook and weisberg, 1982).

CHAPTER FOUR

RESULT AND DISCUSSION

The objective of this chapter is to provide analysis of results on socioeconomic (mothers highest educational level, husband/partner educational level, employment status of mothers, wealth index, region, place of residence), demographic (age of child, sex of child, birth order of child) and health related (mothers nutritional status, incidence of diarrhea, incidence of fever, type of toilet) determinant of stunting and wasting. The analysis was done using SPSS version 20 and STATA version 12.

4.1. Descriptive statistics

The data used in this study were the national wide Ethiopia Demographic and Health Survey (EDHS) 2011 collected data on the stunting and wasting status of children. The analysis presented in the study is based on 9370 under-five children with complete height-for-age and weight-for-height anthropometric index as indicator of children's stunting and wasting status respectively. Table 4.1 below, shows that the relative frequency distributions of the stunting and wasting status of child. 16.5% are severely stunted, 20.6% are moderately stunted and 62.9% are not stunted. Table below also shows that 1.4% of children are severely wasted, 9% are moderately wasted and 89.6% are not wasted.

Table 4.1: stunting and wasting status of children

Stunting status	Frequency	Percent
Not stunted	5891	62.9
Moderately stunted	1930	20.6
Severely stunted	1549	16.5
Total	9370	100
Wasting status		
Not wasted	8398	89.6
Moderately wasted	840	9.0
Severely wasted	132	1.4
Total	9370	100

From Table 4.10 (see appendix) show that 38.09% and 36.12% of males and females stunted respectively. With regards to child age, the highest proportion of stunted children was observed among those whose age group 24+ months (42.96 percent) as opposed to the smallest percentage (13.1 percent) of stunted children which was observed among those whose age group is 0-11 months. The highest proportion of stunting observed in Affar region (45.46%) and Tigray region (45.68%) while the lowest proportion observed in Addis Ababa city administration (15.21%).

The proportion of stunted children, as can be seen in Table 4.10, differs by type of place of residence: urban and rural. Accordingly, 40.19% of the stunted children reside in rural areas while a relatively smaller proportion of the stunted children (20.93 percent) reside in urban centers. Table 4.10 also shows that the proportion of the children found stunted varies by the household wealth index. The highest proportion of the stunted children was from poor households (42.25 percent) whereas the lowest proportion of the stunted children (28.85 percent) was recorded from children residing in rich households.

Likewise, as Table 4.10 shows, the proportion of stunted children varied by educational status of mothers. The highest proportion of the stunted children was observed for children whose mothers have no education (40.09 percent) as opposed to the lowest prevalence of the stunted children which was recorded for children whose mothers have secondary and above education level (15.24 percent). Additionally, highest prevalence (41.5 percent) of the stunted children was observed for children whose husband/partners have no education as opposed to the lowest prevalence of child stunting which was recorded for children whose mothers husband/partner have secondary and above education level (18.79 percent).

Table 4.10 also shows that the proportion of the children found stunted varies by the mothers BMI. The highest proportion of the stunted children was from thinness (40.66 percent) whereas the lowest proportion of the stunted children (20.37 percent) was recorded from overweight mothers BMI. The highest proportion of stunting observed in children who had diarrhea in the last two weeks (40.38%) children who had no diarrhea in last two weeks were 36.52%. Table 4.10 also shows children who had fever in the last two weeks had highest proportion of stunting (39.41%) and children who had no fever in the last two weeks were 36.56%.

The proportion of severely wasted and moderately wasted children were found higher among the children aged 12-23 months (2.58% and 14.94%), being male (1.57% and 9.64%), having 4-6 birth order (1.63% and 9.84%), Mother with no formal education (1.59% and 9.8%) and mothers with thinness BMI (2.14% and 13.76%), who resides in rural (1.52% and 9.37%), and experienced with diarrhea (2.81% and 13.62%) , fever (2.52% and 12.65%), poor wealth index(1.81%,10.52%) and being unemployed of mothers (1.50% and 9.59%).

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 stunting and wasting. The variables in this study are stunting and wasting levels of under five age children as the response and age of a child, region, place of residence, source of drinking water, type of toilet, wealth index, mothers BMI, birth order, sex of a child, diarrhea in last two weeks before survey, fever in the two weeks before survey, incidence of cough in the last two weeks, mothers educational levels, husband/partner education, number of household member, birth interval and employment status of mother are the explanatory variables that related to stunting and wasting based on different literatures. In initial selection of variables, risk factors that clearly demonstrated in different previous research performed. Before building the logistic regression model for analyzing the categorical data, first checked the association of each explanatory variable with response using Pearson chi-square test.

All variable are significantly associated at 15% level of significance with stunting levels except incidence of cough in the last two weeks before survey and employment status of mothers. Therefore, all these explanatory variables entered into the proportional odds model (Hosmer and Lemeshow, 2000) except incidence of cough in the last two weeks before survey and employment status of mothers. Since this two explanatory variables are insignificantly associated with stunting level at 15% level of significance. After these factors were identified, the ordinal logistic regression procedure was used in combination with the stepwise selection method. Accordingly, age of child, region, place of residence, wealth index, mothers BMI, birth order of child, incidence of diarrhea in the last two weeks, incidence of fever in the last two weeks, mothers' educational level and husband/partner's education level are included in the final model for stunting.

For wasting from it was found that all the explanatory variables are significantly associated at 15% level of significance. Hence, all these explanatory variables entered into the proportional odds model (Hosmer and Lemeshow, 2000) since all the explanatory variables are significantly associated with wasting level. After these factors were identified, the ordinal logistic regression procedure employed with the stepwise selection method. Accordingly, age of child, wealth index, mothers BMI, sex of child, husband/partner's education level, employment status of mothers, type of toilet, incidence of diarrhea and incidence of fever in the last two weeks are included in the in the final model for wasting.

4.2.1. Proportional odds model for wasting

Ordinal regression models take advantage of the ordinality in the outcome by summarizing the relationships between explanatory variables and the outcome in a single parsimonious model. However, the most popular approach to ordinal regression is the proportional odds (PO) model that makes a substantial simplifying assumption that the odd ratios associated with each explanatory variable are the same over the cumulative splits in the outcome. This assumption has to be tested if ordinal models are to be applied appropriately. We have noted that the statistical test of the PO assumption is over-conservative and the PO assumption is frequently rejected particularly when the number of explanatory variables is large (Brant, 1990), the sample size is large or there is a continuous explanatory variable in the model (Allison, 1999). Where the PO assumption is justified ordinal regression models can be a powerful means of summarizing relationships that utilizes all the information present in the ordinal outcome.

As shown in table below (Table 4.3) fitted proportional odds model, Test procedure produced an insignificant chi-square value of 14.675 with 14 degree of freedom (p-value=0.401) indicating that a parallel lines assumption is appropriate for the data. Hence, the proportional odds model was appropriate to analyze the wasting levels of children. Results of proportional odds model for wasting indicates that all covariates are significantly associated with wasting status (see Table 4.2).

Table 4.2: Result proportional odds model for wasting

Covariate		Coef.	Standard error	Z	P>|z|	95% Confidence Interval	
						Lower	Upper
Age of child in month (0-11 as reference)	12-23	0.682	0.107	6.38	0.000	0.472	0.891
	24+	-0.110	0.100	-1.10	0.271	-0.307	0.086
Wealth index (Poor as a reference)	Medium	0.040	0.099	0.41	0.685	-0.153	0.233
	Rich	-0.213	0.096	-2.23	0.026	-0.401	-0.025
Mothers BMI (Thinness as reference)	Normal	-0.599	0.072	-8.29	0.000	-0.741	-0.458
	Overweight	-1.080	0.225	-4.78	0.000	-1.522	-0.637
Sex of child (Female as reference)	Male	0.178	0.069	2.55	0.011	0.041	0.314
Incidence of diarrhea (No as reference)	Yes	0.392	0.090	4.34	0.000	0.215	0.569
Type of toilet (No facilities as reference)	Have facilities	-0.281	0.082	-3.41	0.001	-0.443	-0.120
	Other	-0.413	0.298	-1.39	0.166	-0.996	0.171
Incidence of fever (No as reference)	Yes	0.357	0.084	4.22	0.000	0.191	0.522
Husband/partner education (No education as reference)	Primary education	-0.270	0.078	-3.48	0.001	-0.423	-0.118
	Secondary and above	-0.357	0.136	-2.62	0.009	-0.624	-0.090
Employment status of mother (unemployed as reference)	Employed	-0.217	0.080	-2.70	0.007	-0.375	-0.059
/cut1	-	1.739	0.141	-	-	1.512	1.966
/cut2	-	3.880	0.116	-	-	3.603	4.156

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 368.90, df = 14, p-value = 0.0000, Pseudo R^2 = 0.0526

Table 4.3: test of parallel lines

Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	2666.507			
General	2651.831	14.675	14	0.401

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories Link function: Logit

Table 4.4: Odd ratio estimates and confidence interval of POM for wasting

Covariate		Coef.	OR	P>|z|	95% Confidence Interval for OR	
					Lower	Upper
Age of child in month (0-11 as reference)	12-23	0.682	1.978	0.000	1.603	2.438
	24+	-0.110	0.896	0.271	0.736	1.090
Wealth index (Poor as a reference)	Medium	0.039	1.040	0.685	0.858	1.262
	Rich	-0.213	0.808	0.026	0.670	0.975
Mothers BMI (Thinness as reference)	Normal	-0.599	0.549	0.000	0.477	0.633
	Overweight	-1.079	0.340	0.000	0.218	0.529
Sex of child (Female as reference)	Male	0.177	1.194	0.011	1.042	1.369
Incidence of diarrhea (No as reference)	Yes	0.392	1.480	0.000	1.240	1.766
Type of toilet (No facilities as reference)	Have facilities	-0.281	0.755	0.001	0.642	0.887
	Other	-0.412	0.662	0.166	0.369	1.186
Incidence of fever (No as reference)	Yes	0.357	1.429	0.000	1.210	1.685
Husband/partner education (No education as reference)	Primary education	-0.270	0.763	0.001	0.655	0.889
	Secondary and above	-0.357	0.700	0.009	0.536	0.914
Employment status of	Employed	-0.217	0.805	0.007	0.687	0.942

mother (unemployed as reference)						
/cut1	-	1.739		-		
/cut2	-	3.880		-		

4.2.2. Proportional odds model for stunting

For stunting the results of the proportional odds model are given in Table 4.5. Having fitted proportional odds model, a test procedure was run to see whether the fitting of a proportional odds model is appropriate for the data. Test procedure produced a significant chi-square value of 97.385 with 25 degree of freedom (p-value=0.000) indicating that a parallel lines assumption is no longer appropriate for the evidence that we see in our data. Hence, the proportional odds model was not appropriate to analyze the severity of stunting status of children.

Table 4.5: Result of POM for stunting as three ordered response categories

Covariate		Coef.	Standard Error	Z	P>|z|	95% Confidence Interval	
						Lower	Upper
Age of child in month (0-11 as reference)	12-23	1.431	0.090	15.99	0.000	1.256	1.607
	24+	1.690	0.081	20.80	0.000	1.531	1.849
Region (Tigray as reference)	Affar	0.045	0.093	0.48	0.630	-0.137	0.226
	Amhara	-0.088	0.087	-1.01	0.314	-0.258	0.083
	Oromia	-0.305	0.082	-3.72	0.000	-0.465	-0.144
	Somali	-0.708	0.107	-6.65	0.000	-0.917	-0.500
	Ben-gumuz	0.031	0.093	0.33	0.742	-0.152	0.214
	SNNP	-0.140	0.084	-1.66	0.096	-0.304	0.025
	Gambella	-0.912	0.113	-8.10	0.000	-1.133	-0.692
	Harari	-0.652	0.125	-5.22	0.000	-0.897	-0.407
	Addis Ababa	-0.586	0.187	-3.13	0.002	-0.953	-0.219
	Dire Dawa	-0.145	0.110	-1.32	0.188	-0.360	0.071
Place of residence (urban as reference)	Rural	0.401	0.090	4.48	0.000	0.225	0.576

Wealth index (poor as reference)	Medium	-0.152	0.062	-2.47	0.014	-0.272	-0.031
	Rich	-0.249	0.060	-4.17	0.000	-0.366	-0.132
Mothers BMI (thinness as reference)	Normal	-0.152	0.050	-3.04	0.002	-0.249	-0.054
	Overweight	-0.514	0.122	-4.20	0.000	-0.754	-0.275
Birth order of child (1-3 as reference)	4-6	0.141	0.050	2.83	0.005	0.043	0.239
	7+	0.068	0.062	1.11	0.267	-0.052	0.189
Incidence of diarrhea (No as reference)	Yes	0.296	0.064	4.60	0.000	0.170	0.422
Incidence of fever (No as reference)	Yes	0.143	0.058	2.46	0.014	0.029	0.258
Mothers education (No education as reference)	Primary education	-0.043	0.057	-0.75	0.453	-0.154	0.069
	Secondary and above	-0.323	0.157	-2.06	0.040	-0.632	-0.015
Husband/partner education (No education as reference)	Primary education	-0.066	0.050	-1.31	0.191	-0.164	0.033
	Secondary and above	-0.473	0.103	-4.57	0.000	-0.675	-0.270
/cut1		1.861	0.143			1.584	2.138
/cut2		3.048	0.141			2.767	3.329

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 1126.04, df = 25, p-value = 0.0000, Pseudo R2 = 0.0657

Table 4.6: result of Test of parallel lines

Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	9013.673			
General	8916.288	97.385	25	.000

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

As we can see from the above table (Table 4.6) the assumption of proportional odds model is violated for the stunting. If the POM assumption is violated there are different alternatives. Therefore, in order to overcome this problem the partial proportional odds model fitted by the GOLOGIT2 with option AUTOFIT (Williams, 2006) using STATA12 provides a good alternative model than the other models like POM with strict assumption of parallel line for all explanatory variables, GOM relaxed the assumption of parallel line for all explanatory variables and multinomial logistic regression which ignore ordering nature of the variable (see result of MLR in appendix Table 4.12).

In case where the dependent variable is ordinal, parallel lines assumption sometimes does not hold. In this case generalized ordered logit model applied which uses cumulative logit to build the model and does not hold the parallel lines assumption. Therefore, the effects of the independent variable's odds to dependent variables are not equal and coefficients are different for every single category of the dependent variable (Fu, 1998). The most significant difference between POM and GOM is that GOM has different parameters for every single category of the dependent variable (see result of GOM in appendix Table 4.11).

4.2.3. Partial proportional odds model (PPOM) for stunting

Partial Proportional Odds Model can be used when parallel lines assumption holds or not. Partial Proportional Odds Model bears the same characteristics with both Proportional Odds Model and Generalized ordered logit model (Peterson and Harrell, 1990; Ananth and Kleinbaum, 1997). The study used STATA12 with 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 < 0.01534), region (p-value < 0.01421), birth order (p-value < 0.02592) and husband/partner education (p-value < 0.02446) 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 4.7 as shown below with Wald test of parallel-lines assumption. Results of PPOM show that all the covariates have significant influence on the response variable. Global Wald test for the final model indicates that the final model does not violate the proportional odds assumption with p-value (0.2598). Also the marginal effects for the model are reported in Table 4.8.

Table 4.7: Result of partial proportional odds models

		Not stunted Vs (Moderately and Severely stunted)				(Not stunted and Moderately) Vs Severely stunted			
Covariate		Coeff.	Std. Er	OR	P>|z|	Coeff.	Std.Er.	OR	P>|z|
Age of child in month (0-11 as reference)	12-23	1.457	0.090	4.293	0.000	1.304	0.103	3.684	0.000
	24+	1.676	0.081	5.344	0.000	1.676	0.081	5.344	0.000
Region (Tigray as reference)	Affar	-0.105	0.096	0.900	0.275	0.336	0.106	1.399	0.001
	Amhara	-0.091	0.088	0.913	0.298	-0.091	0.088	0.913	0.298
	Oromia	-0.323	0.083	0.724	0.000	-0.323	0.083	0.724	0.000
	Somali	-0.786	0.109	0.456	0.000	-0.471	0.136	0.624	0.001
	Ben-gumuz	-0.111	0.097	0.895	0.252	0.337	0.108	1.401	0.002
	SNNP	-0.238	0.087	0.788	0.006	0.102	0.099	1.107	0.306
	Gambella	-0.986	0.114	0.373	0.000	-0.698	0.150	0.498	0.000
	Harari	-0.689	0.126	0.502	0.000	-0.689	0.126	0.502	0.000
	Addis Ababa	-0.642	0.188	0.526	0.001	-0.642	0.188	0.526	0.001
	Dire Dawa	-0.227	0.113	0.797	0.045	0.062	0.136	1.064	0.648
Place of residence (urban as reference)	Rural	0.398	0.090	1.489	0.000	0.398	0.090	1.489	0.000
Wealth index (poor as reference)	Medium	-0.151	0.062	0.860	0.014	-0.151	0.062	0.860	0.014
	Rich	-0.251	0.060	0.778	0.000	-0.251	0.060	0.778	0.000
Mothers BMI (thinness as reference)	Normal	-0.153	0.050	0.858	0.002	-0.153	0.050	0.858	0.002
	Overweight	-0.515	0.122	0.598	0.000	-0.515	0.122	0.598	0.000
Birth order of child(1-3 as reference)	4-6	0.141	0.050	1.151	0.005	0.141	0.050	1.151	0.005
	7+	0.031	0.064	1.031	0.629	0.167	0.076	1.182	0.028
Incidence of diarrhea	Yes	0.297	0.064	1.346	0.000	0.297	0.064	1.346	0.000

(No as reference)									
Incidence of fever (No as reference)	Yes	0.139	0.058	1.149	0.017	0.139	0.058	1.149	0.017
Mothers education (No education as reference)	Primary education	-0.044	0.057	0.957	0.445	-0.044	0.057	0.957	0.445
	Secondary and above	-0.334	0.157	0.716	0.034	-0.334	0.157	0.716	0.034
Husband/partner education (No education as reference)	Primary education	-0.032	0.052	0.969	0.535	-0.155	0.065	0.856	0.017
	Secondary and above	-0.465	0.103	0.628	0.000	-0.465	0.103	0.628	0.000
Cons		-1.797	0.142	0.166	0.000	-3.140	0.147	0.043	0.000

Wald test for the proportional odds assumption: Chi-square = 19.17, df = 16, p-value = 0.2598

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 1204.26, df = 34, p-value = 0.0000, Pseudo R2 = 0.0702

4.3. Marginal effects

Table 4.8 presents the marginal effects which are computed at a representative value. In PPOM the probability of a single level of the response variable is not possible. The sign of the coefficients does not always determine the direction of the effect of the intermediate outcomes (Washington et al., 2003; Wooldridge, 2002). Marginal effect is used to measure the magnitude and types of association between the levels of the explanatory variable on the probability of levels of the response variable. Table 4.8 shows that age of child in month variable has the largest magnitude of marginal impact on the outcome probabilities. Children who had age 12-23 and 24 and above months were more likely to be moderately stunted by 14.4% and 16.5% respectively compared to those children aged 0-11 months; they were more likely to be severely stunted by 20.1% and 17.5% respectively compared to children aged 0-11.

Table 4.8: Marginal effects for stunting levels based on PPOM

		Stunting levels					
		Not stunted		Moderately stunted		Severely stunted	
Covariate		MER	P>z	MER	P>z	MER	P>z
Age of child in month (0-11 as reference)	12-23	-0.346	0.000	0.144	0.000	0.201	0.000
	24+	-0.340	0.000	0.165	0.000	0.175	0.000
Region (Tigray as reference)	Affar	0.023	0.268	-0.067	0.000	0.044	0.004
	Amhara	0.020	0.293	-0.010	0.300	-0.011	0.286
	Oromia	0.070	0.000	-0.035	0.000	-0.035	0.000
	Somali	0.156	0.000	-0.108	0.000	-0.048	0.000
	Ben-gumuz	0.025	0.245	-0.069	0.000	0.043	0.004
	SNNP	0.052	0.005	-0.065	0.000	0.012	0.318
	Gambella	0.188	0.000	-0.121	0.000	-0.066	0.000
	Harari	0.138	0.000	-0.073	0.000	-0.065	0.000
	Addis Ababa	0.129	0.000	-0.068	0.000	-0.061	0.000
	Dire Dawa	0.050	0.038	-0.057	0.002	0.008	0.654
Place of residence (urban as reference)	Rural	-0.086	0.000	0.043	0.000	0.043	0.000
Wealth index (poor as reference)	Medium	0.034	0.012	-0.016	0.014	-0.017	0.011
	Rich	0.056	0.000	-0.027	0.000	-0.029	0.000
Mothers BMI (thinness as reference)	Normal	0.035	0.002	-0.016	0.002	-0.018	0.003
	Overweight	0.107	0.000	-0.056	0.000	-0.052	0.000
Birth order of child(1-3 as reference)	4-6	-0.032	0.005	0.015	0.005	0.017	0.006
	7+	-0.007	0.630	-0.014	0.228	0.021	0.035
Incidence of diarrhea (No as reference)	Yes	-0.069	0.000	0.031	0.000	0.038	0.000
Incidence of fever (No as reference)	Yes	-0.032	0.018	0.015	0.016	0.017	0.021
Mothers education	Primary	0.010	0.443	-0.005	0.446	-0.005	0.441

(No education as reference)	education						
	Secondary and above	0.072	0.024	-0.036	0.033	-0.035	0.017
Husband/partner education (No education as reference)	Primary education	0.007	0.535	0.011	0.259	-0.018	0.016
	Secondary and above	0.099	0.000	-0.050	0.000	-0.048	0.000

Note: MER = Marginal effects computed at a representative value

4.4. Model comparison and Goodness of fit of model

The model fit statistics AIC for the four models POM, GOM, PPOM and MLR for stunting are given below.

Table 4.9: AIC for POM, GOM, PPOM and MLR

Model	AIC
POM	16070.71
GOM	16023.33
PPOM	16010.49
MLR	16017.82

For stunting status of under five children data, proportional odds model, generalized ordered logit model, multinomial logistic regression and partial proportional odds model were fitted by including all the covariates those are significant in the univariate analysis at 5% level of significance. To compare the efficiency of different models, the AIC was used. It is the most common applicable criterion to select model. Based on AIC, a model having the minimum AIC value was preferred. Accordingly, partial proportional odds model (AIC=16010.49) found to be the best model for the stunting status of under five children data set.

For stunting the Likelihood ratio 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 (p-value =0.0000) indicate that the null hypothesis is strongly rejected, i.e., at least one of the coefficients in the model has an impact on stunting status of children. When we see POM overall goodness-of-fit, for wasting significant p-values (p-value=0.0000) indicate that estimates of the model adequately fit the data.

4.5. Model adequacy checking

After the model has been fitted, it is desirable to determine whether a fitted model adequately describes the data or not. 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).

Then a binary logistic regression model is fitted after which it is possible to apply model adequacy checking in this study the response has three categories. By collapsing the two categories into one including severe and moderate these can be called stunted and the other category is not stunted. The same applies to wasting i.e severe and moderate wasting is as wasted and the other category is not wasted. We could calculate residuals, measures of influence and the predicted probabilities of the data. The plots of standardized Pearson residuals, deviance residuals, DFBETA, Cook's distance, leverage value with predicted probability can then be used to see the pattern of all cases. The residuals and measure of influence plots against the predictive probabilities showed that the model is adequate.

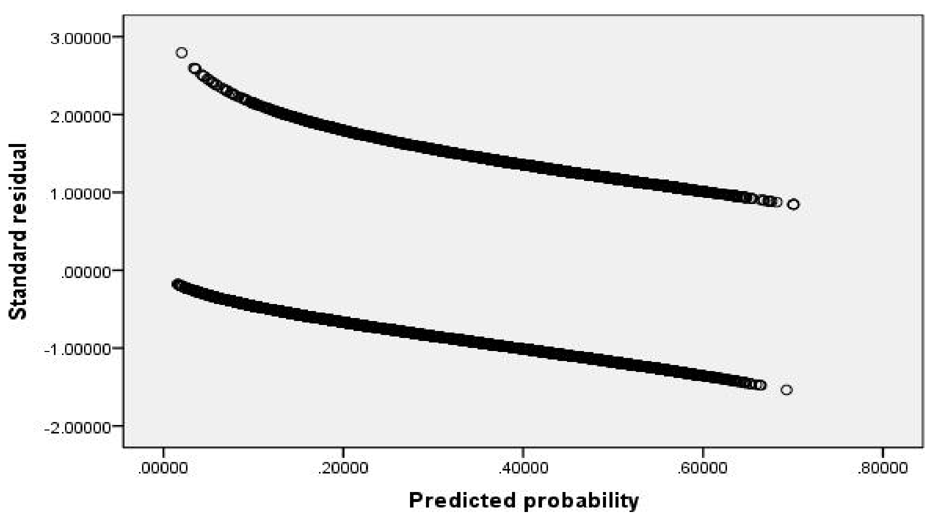

Figure 4.1: Plots of standard residual versus predicted probability for stunting.

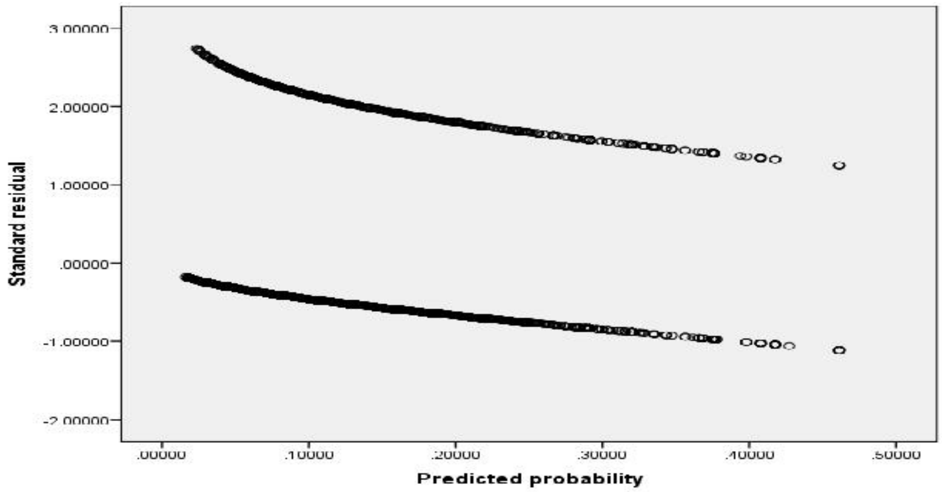

Figure 4.2: Plots of standard residual versus predicted probability for wasting.

Figure 4.1 and 4.2 is the plot of standard residuals versus predicted probabilities of all observations. There are few observations far from the others. However, the computed standard residuals do not influencing the model that means all standard residuals are less than three (see from Y- axis).

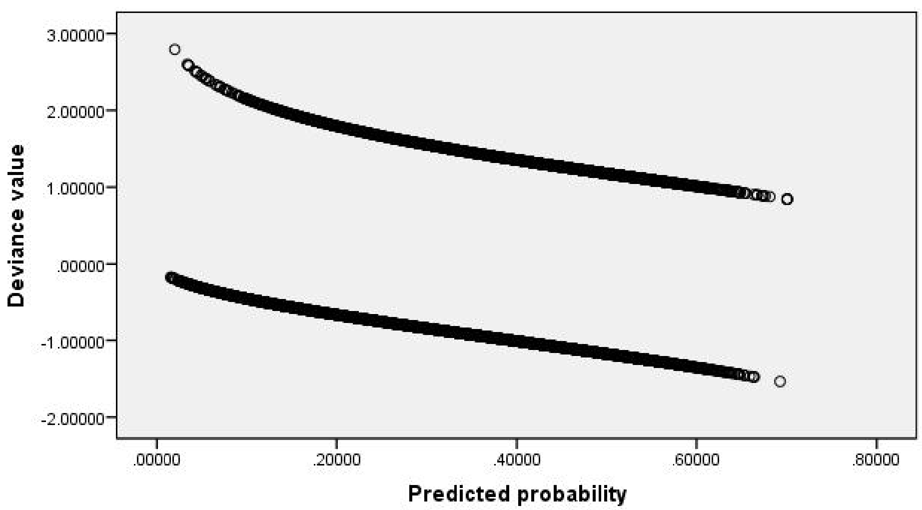

Figure 4.3: Plots of deviance residual versus predicted probability for stunting.

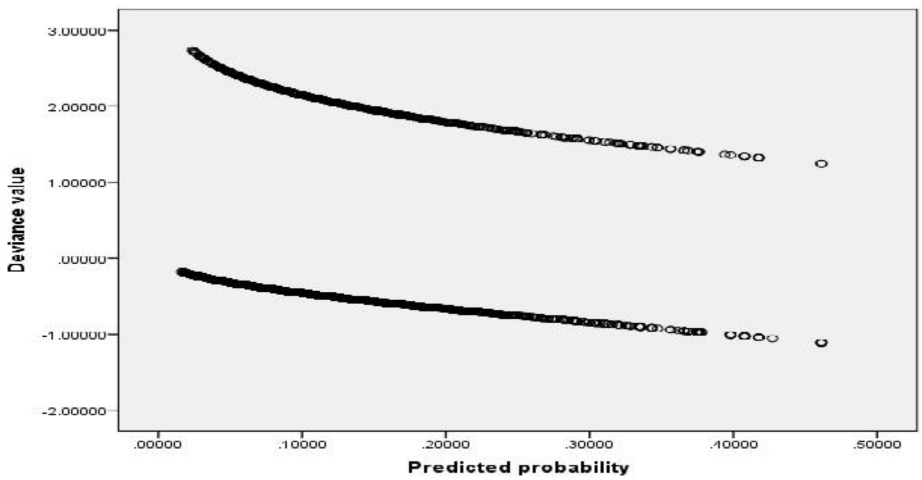

Figure 4.4: Plots of deviance residual versus predicted probability for wasting.

The figures 4.3 and 4.4 above are the plots of deviance residuals versus predicted probabilities of all observations. Apparently there are few observations that lie far away from the rest but all deviance residuals are less than three. Therefore, there is no lack of fit.

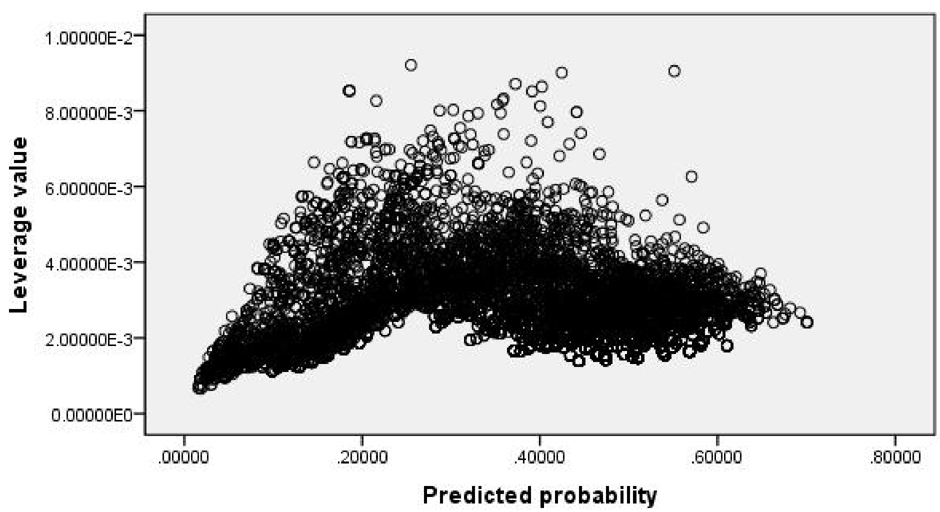

Figure 4.5: Plots of leverage value versus predicted probability for stunting.

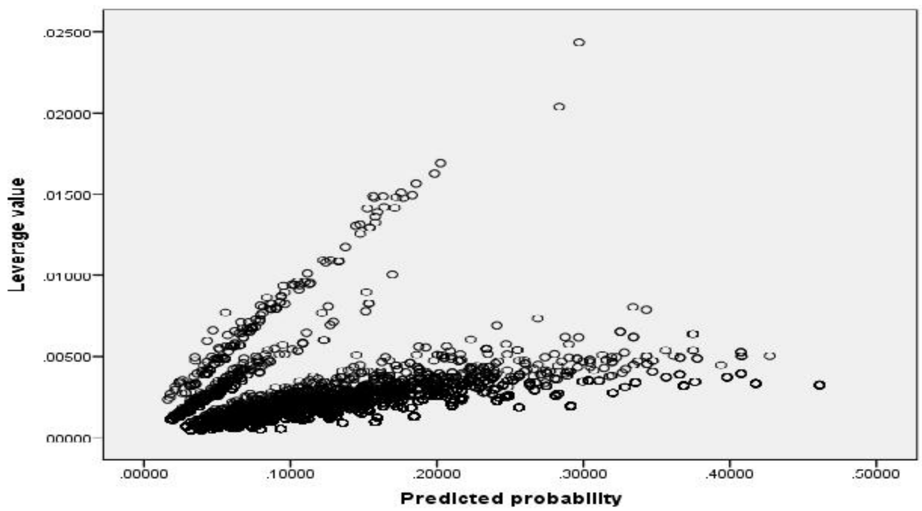

Figure 4.6: Plots of leverage value versus predicted probability for wasting.

Figure 4.5 and 4.6 the plots of leverage value versus the predicted probabilities of all observations. It was observed that leverage values of the above plots are less than one. Therefore, there are no outliers.

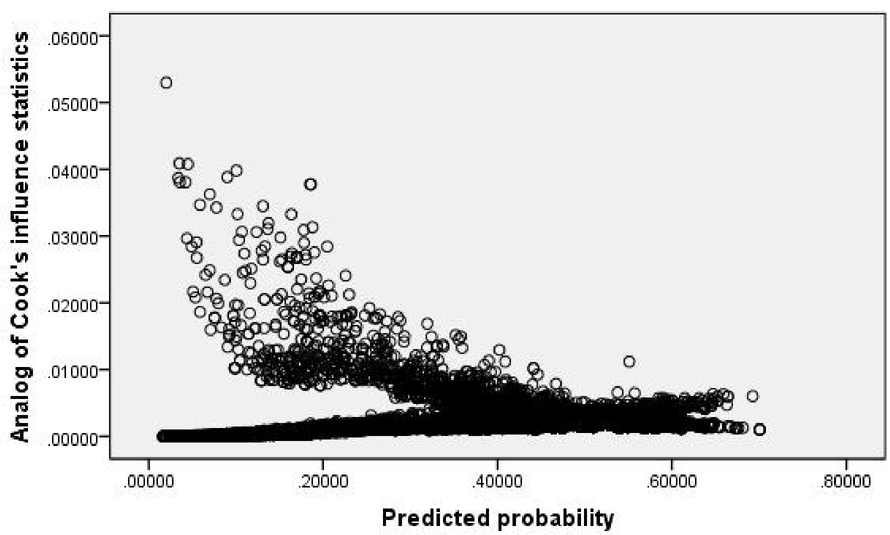

Figure 4.7: Plots of Analog of Cook's influence statistic versus predicted probabilities for stunting

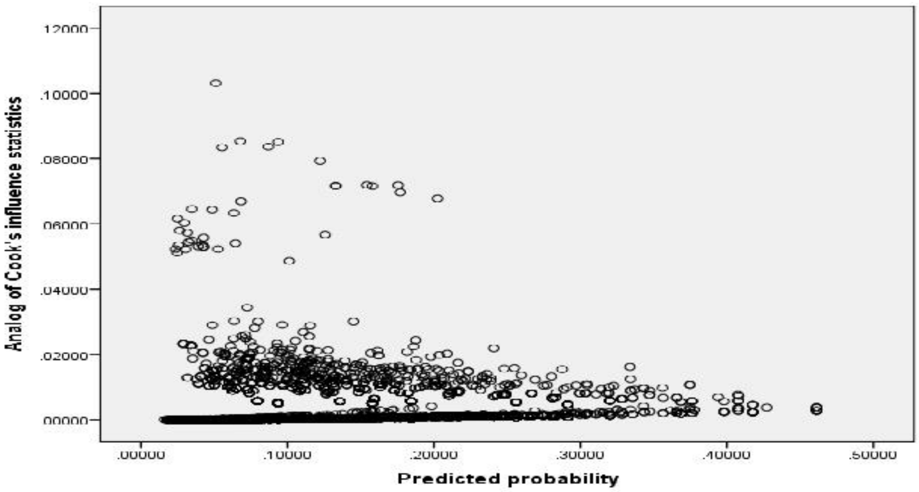

Figure 4.8: Plots of Analog of Cook's influence statistic versus predicted probabilities for wasting.

Figure 4.7 and 4.8 is the plot of Analog of Cook's influence statistic versus the predicted probabilities of all observations. There are observations a little far away from the others. These are not influential observations since all Cook's influence statistic are less than one. (See on Y-axis of the graph). Plots of DFBETA(S) of all explanatory variables versus predicted probability are given in Figures found in appendix where it is shown that all the DFBETA(S) of all explanatory variables are less than one. This is an indication that there is no serious problem with the fitted model.

4.6. Interpretation of result of proportional odds model for wasting

When the assumption of proportionality/parallelism holds, the coefficients of explanatory variables in an ordinal logistic regression model are interpreted in terms of the logarithm of the ratio of the odd of a particular category to the reference category. Interpretation of the parameters corresponding to the significant variables is presented below.

Age of child in month significantly influences the wasting status of children. Children whose age is 12-23 months are (OR=exp(0.682)) 1.978 times severely/moderately wasted as compared to those in the age group 0-11 months, holding all other variable constant. From this we can see that children in the age group 12-23 months were more likely severely/moderately wasted as compared to children aged group 0-11 months. This could be because of breastfeeding in the early stages of child growth, mother's ability to care for the child and also due to the care that parents give to older children that may decline especially if there are younger children in the family (UN, 1985). The odds could be as minimum as 1.603 and as maximum as 2.438 with 95% confidence.

Children from rich households are (OR=exp(-0.213)) 0.808 times less likely severely/moderately wasted as compared to those children from poor household, holding all other variables constant. Compared with children from rich households, the chances of having worse wasting status was found to increase with decrease of household wealth condition. The 95% confidence interval for odds ratio also suggests that odds could be as minimum as 0.670 and as maximum as 0.975.

Mother's nutritional status significantly influences the wasting status of children. Children from normal level (BMI 18.5-24.9) and overweight (BMI≥25) mothers were 0.549 and 0.340 times less likely severely/moderately wasted respectively as compared to thinness level (BMI<18.5) mothers, controlling all other variables constant. This means that children from thinness level (BMI<18.5) mothers were more likely to severely/moderately wasted when we compare with normal level (BMI 18.5-24.9) and overweight (BMI≥25) mothers. The 95% confidence interval odds ratio also suggests that odds for children from normal mothers BMI could be as minimum as 0.477 and as maximum as 0.633 and odds for children from overweight mothers BMI could be as minimum as 0.218 and as maximum as 0.529.

Sex of child is also significantly effect on the wasting status of children. Controlling all other variable constant, children whose sex is male are 1.194 times severely/moderately wasted as compared to female children. That means male children have greater chance of severely/moderately wasted as compared to female. The odds could be as minimum as 1.042 and as maximum as 1.369 with 95% confidence.

Children who had incidence of diarrhea in the last two weeks are 1.480 times severely/moderately wasted as compared to children who had no diarrhea, controlling all other variable constant. 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 being severely/moderately wasted than children who had no diarrhea in the two weeks preceding the survey. The 95% confidence interval also suggests that the odds of severely/moderately wasting are 1.240 times as low and 1.766 times as high as compared to those not wasted.

Children who had incidence of fever in the last two weeks are 1.429 times severely/moderately wasted as compared to children who had no fever, controlling all other variable constant. This means among children under age five who had fever in the two weeks preceding the survey, have greater chance of being severely/moderately wasted than children who had no fever in the two weeks preceding the survey. The 95% confidence interval also suggests that the odds of severely/moderately wasting are 1.210 times as low and 1.685 times as high as compared to those not wasted.

When we see type of toilet facilities, children from household who had no toilet facilities were 1.324 times more likely severely/moderately wasted as compared to children from household who had toilet facilities, while holding all other variables constant. The 95% confidence interval could be as minimum as 1.127 and as maximum as 1.557.

Husband/partner educational levels had significant influence on the wasting status of child. Children from husband/partner who had no formal education were (OR=exp(0.270)) 1.309 times severely/moderately wasted as compared to children from husband/partner who had primary education. Moreover, Children from husband/partner who had no formal education were (OR=exp(0.357)) 1.429 times severely/moderately wasted as compared to children from husband/partner who had secondary and above educational levels. In other word, the risk of having worse wasting status was found highest for children having husband/partner with no formal education compared with higher level educated husband/partner children. The odds could be as minimum as 1.125 and as maximum as 1.526 corresponding to husband/partner who had primary education and the odds could be as minimum as 1.094 and as maximum as 1.866 corresponding to husband/partner who had secondary and above education with 95% confidence.

With respect to employment status of mothers it was observed that, children whose mothers are unemployed are 1.242 times severely/moderately wasting compared to children whose mothers are employed, controlling all other variables constant. That means children from mothers who had job are less likely to be wasted as compared to children from mothers who had no job. The odds could be as minimum as 1.061 and as maximum as 1.455 with 95% confidence.

4.7. Interpretation of results of partial proportional odds model for stunting

As we can see from Table 4.9 above the model which have smallest value of AIC is partial proportional odds model. In PPOM, all independent variables in the model were found to be significant predictors of child stunting status.

It is clear that the odds ratios for the children aged 12-23 months and 24+ months compared to children age group 0-11 months were about 4.293 and 5.344 respectively when not stunted is compared with moderate and severely stunted states implying that children belonging the age group 12-23 and 24+ had 4.293 and 5.344 times greater risk of being moderately or severely stunted respectively compared with age group 0-11 months. When not stunted state and moderate stunting state are compared with severely stunting state the odds ratio were found about 3.684 and 5.344 respectively for children belonging to the age group 12-23 and 24+ month compared to children age group 0-11 months implying that children belonging to the age group 12-23 and 24+ months had 3.684 and 5.344 times greater risk of being severely stunted respectively compared with children age group 0-11 months.

From PPOM when not stunted and moderate stunting state are compared with severely stunting state the odds ratio were found about 1.399 and 1.401 respectively for children lived in Affar and Ben-gumuz region compared to children lived in Tigray region implying that children lived in Affar and Beni-gumuz had 1.399 and 1.401 times greater risk of being severely stunted respectively compared with children lived in Tigray region. These results were confirmed by the positive marginal effects for severely stunted as shown in Table 4.8.

Specifically, odds ratios for the children whose birth order 4-6 compared to children whose birth order 1-3 were about 1.151 when not stunted is compared with moderate and severely stunted states implying that children belonging to the birth order 4-6 had 1.151 times greater risk of being moderately or severely stunted respectively compared with whose birth order 1-3.When not stunted state and moderate stunted state are compared with severely stunted state the odds ratio were found about 1.151 and 1.182 respectively for children whose birth order 4-6 and 7+ compared to 1-3 birth order implying that children whose birth order are 4-6 and 7+ had 1.151 and 1.182 times greater risk of being severely stunted respectively compared with children whose birth order are 1-3.

Husband/partner educational levels had significant influence on the stunting status of child. Specifically, when not stunted is compared with severely and moderately stunting status, children from husband/partner who had no formal education compared to children from higher education had 1.592 times being moderately or severely stunted. When not stunted and moderately is compared with severely stunted, children from husband/partner who had no formal education compared to children from husband/partner of primary education and secondary and higher had 1.168 and 1.592 times being severely stunted respectively. In other word, the risk of having worse stunting status was found highest for children having husband/partner with no education compared with higher level educated husband/partner children.

Mother's educational levels had significant influence on the stunting status of child. Children from mothers who had no formal education were 1.397 times severely/moderately stunted as compared to children from mothers who had secondary and above educational levels. That means the risk of having worse stunting status was found highest for children having mothers with no formal education compared with higher level educated mothers children.

Place of residence of child is also significant effect on the stunting status of children. Controlling all other variable constant, children who reside in rural area are 1.489 times severely/moderately stunted as compared to children reside in urban area. That means children who reside in rural area have greater chance of severely/moderately stunting as compared to children who reside in urban area.

Children from poorest households are 1.163 and 1.285 times severely/moderately stunted as compared to those children from medium and richest household, holding all other variables constant. Compared with children from medium and rich households, the chances of having worse stunting status was found to increase with decrease of household wealth condition. Thus, children from poorest households have greater risk of severity of stunting as we compare with medium and rich households.

Mother's nutritional status significantly influences the stunting status of children. Children from thinness level ($BMI<18.5$) mothers were 1.165 and 1.674 times severely/moderately stunted as compared to normal level (BMI 18.5-24.9) and overweight ($BMI\geq25$) mothers respectively, controlling all other variables constant. This means that children from thinness level ($BMI<18.5$)

mothers were more likely to severely/moderately stunted when we compare with normal level (BMI 18.5-24.9) and overweight (BMI≥25) mothers.

Children who had incidence of diarrhea in the last two weeks before survey are 1.346 times severely/moderately stunted as compared to children who had no diarrhea, controlling all other variable constant. 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 being severely/moderately stunted than children who had no diarrhea in the two weeks preceding the survey.

Children who had incidence of fever in the last two weeks are 1.149 times severely/moderately stunted as compared to children who had no fever, controlling all other variable constant. This means among children under age five who had fever in the two weeks preceding the survey have greater chance of being severely/moderately stunted than children who had no fever in the two weeks preceding the survey.

4.8. Discussion

This study attempts to develop a method that can help to identify factors that affect the severity status of stunting and wasting. Accordingly Proportional odds model, generalized ordered logit models, multinomial logistic regression model and Partial proportional odds model were fitted for stunting. At first sight the POM becomes inappropriate model for analyzing the considered data for stunting as test of parallel line is significant at 5% level of significance indicating proportional odds assumption is violated but POM is appropriate for wasting status as proportional odds assumption is not violated. For stunting status for each covariate, we have assessed for which covariate the assumption was violated. The test for each covariate shows that the assumption is violated for age of child in month, region, birth order of children and husband/partner education.

Generally speaking, we can say that the PPOM fitted the data very well relatively minimum AIC value compared to POM, GOM and MLR due to this we stick discussion with PPOM results as follows for stunting status. Variables that are significant determinant of stunting levels are age of child in month, region, place of residence, wealth index, mothers BMI, birth order of children, incidence of diarrhea in the last two weeks, incidence of fever in the last two weeks, mother educational level and husband/partner education. For wasting status significant variables are age of a child in month, wealth index, mothers BMI, sex of a child, incidence of diarrhea in that last two weeks before survey, type of toilet, incidence of fever, husband/partner educational level and employment status of mothers. Finally our findings were compared with previous researches done in the area.

The results of the study indicate that age of child is one of determinant associated with stunting and wasting status of children in Ethiopia. The severity of stunting and wasting was higher in children aged greater than 12 months than the age 0-11 groups. This finding is consistent with the studies conducted by Shrimpton et al. (2001); Kabubo-Mariara et al. (2006); Nguyen and Kam (2008); Alemu et al. (2014); which revealed a rapid fall in children's height from birth to 59 months; although stunting continues after 24 months and children in the youngest age 0-11 months had significantly lower risk of being stunted, underweight and wasted than children in the older age groups. This could be as a result of weaning and lower breast milk intakes, which make them prone to childhood stunting.

Mother's highest educational level was identified to be the most significant factor to reduce the occurrence of children stunting. The findings of this study showed that there is a significant difference in the severity status of stunting in children by mothers' educational level. The risk of worse level stunting 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 is consistent with other studies Nure et al. (2011); Semali et al. (2015); Blessing et al. (2017). 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. This finding also suggests that severity status of stunting and wasting status was found highest for the children having father's/partner with no education when compared with higher level educated fathers' children. The finding is similar to those study by Nguyes and Kam (2008); Blessing et al. (2017). Study conducted by Nguyes and Kam (2008) also reveals that children whose mothers are unemployed are severity status of wasting compared to children whose mothers are employed. This finding is consistent with the study by Nguyes and Kam (2008).

The risk of stunting is significantly higher in child whose birth order is more than four when we compare with children whose birth order is 0-3. This study is consistent with the study Sommerfelt et al. (1994); Jeyaseelan (1997); Rayhan and Hayat (2006). This study is inconsistent with the study by Habaasa Gilbert (2010) which reveals stunting was more among children of birth order 1-4 than those of order 5 and above.

The study revealed that under-five children from poor households are at a higher risk of stunting and wasting than children from rich households. This finding is similar with studies Genebo and Girma (2002); Smith et al. (2005); Alemu et al. (2014). Place of residence were found to be significant determinants of stunting status in under five children. The analysis also showed that children whose parents reside in rural areas more likely to be stunted when compared to those children whose parents reside in urban areas. This study is similar to the study conducted by Shen et al. (1996); Fotso JC and Kuate-Defo B. (2005); Loida et al. (2017).

Mother's nutritional status significantly influences the stunting and wasting status of children. Children from thinness level (BMI<18.5) mothers higher severity of stunting and wasting as compared to normal level (BMI 18.5-24.9) and overweight (BMI≥25) mothers. This finding is consistent with study conducted by Pendael Zephania Machafuko (2013); Semali et al. (2015) which reveals that mother's nutritional status had positive effect indicating that children belong to thinness level (BMI<18.5) mothers are associated with high probability of stunting and wasting.

Male children have greater risk of severity of stunting and wasting than female children (Salah E.O. Mahgoub et al. (2006); Mandefro et al. (2015)). The result of this finding is consistent with these studies but, the covariate genders of a child are insignificant factor for stunting status. This finding also similar with the studies conducted by Salah and Nnyepi (2006). The result of this study indicates that children who had incidence of diarrhea in the last two weeks are significant factor for stunting/severity of stunting and wasting/severity of wasting as compared to children who had no diarrhea. This study is consistent with the study Alemu et al. (2014); Blessing et al. (2017). The result of this study suggests that children who had incidence of fever in the last two weeks are significant factor for stunting and wasting status. This study is consistent with the studies conducted by Blessing et al. (2017). Type of toilet facilities is important factors that associated with child malnutrition (Tadiwos and Degnet, 2013). The result of this finding is consistent with these studies.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

PPOM fitted the data adequately in predicting severity status of stunting because of POM assumption is violated but POM is appropriate for wasting status. Consequently, from the results of PPOM for stunting status and based on POM for wasting status we have drawn the following conclusions.

The study examined the demographic, socio-economic and health related determinants of child stunting and wasting in Ethiopia. The result of PPOM showed that for stunting levels age of child, region, birth order of child, child place of residence, household wealth status, mother's nutritional status, incidence of diarrhea and fever, mother's educational level and husband/partner's educational level have statistically significant effect of stunting. The result of POM reveals for wasting levels age of child, wealth status of household, mother's nutritional status, sex of child, incidence of diarrhea, incidence of fever, type of toilet, husband/partner's educational level and employment status have statistically significant effect.

Children younger than 11 months had low risk of stunting and wasting status than other age groups. This could be because of breastfeeding in the early stages of child growth. Children from regions, like Affar and Beni-gumuz have more chance of being stunted as compared to Tigray region. Household wealth had very significant impact on child stunting and wasting, children who belong to wealthier (richest) households had less chance of stunting and wasting. Children whose husbands/partners and mothers had secondary and higher levels of education are low risk of stunting. And also children whose husband/partner had no education are greater risk of wasting as we compare with husband/partner who had secondary and higher levels of education.

The risk of stunting is higher for children whose birth order were more than four than that of child whose birth order are 0-3. The risk of having worse wasting was found significantly higher for male children compared to female children. It is observed that the risk of having high risk of stunting 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 stunting and wasting severity. Children from thinness level ($BMI<18.5$) mothers higher severity of stunting and wasting as compared to normal level (BMI 18.5-24.9) and overweight ($BMI\geq25$) mothers. Children who had diarrhea are significantly vulnerable to stunting and wasting than those who did not. A similar result was also obtained for children who had fever.

5.2. Recommendations

Based on the finding the following recommendation should be given to reduce the prevalence of stunting and wasting by taking the following in to consideration.

- The concerned bodies (government and other stakeholders) have to give different priorities to different children age group, family background in terms of their mothers/fathers education level, mother's nutritional status, incidence of diarrhea and fever, household wealth status to control the severity level of children stunting and wasting. Additionally being wasted depends on gender of children. The concerned bodies give attention for gender difference.
- Since we have shown that children in rural areas are more likely to be stunted than children in urban areas, special attention should be given for the residence difference.
- Since the prevalence of stunting status differs among regions, the concerned body should give special attention to regions like Affar and Ben-gumuz.

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APPENDIX

Table 4.10: Descriptive statistics for categorical determinant factors of stunting and wasting of under-five children in Ethiopia

Variables		**Stunting status**			**Wasting status**		
		Severely stunted (%)	**Moderately stunted (%)**	**Not stunted (%)**	**Severely wasted (%)**	**Moderately wasted (%)**	**Not wasted (%)**
Sex of child	Female	751(16.37)	906(19.75)	2930(63.88)	57(1.24)	379(8.26)	4151(90.5)
	Male	798(16.68)	1024(21.41)	2961(61.91)	75(1.57)	461(9.64)	4247(88.79)
Age of child in months	0-11 months	77(4.97)	126(8.13)	1346(86.9)	16(1.03)	134(8.65)	1399(90.32)
	12-23 months	290(15.26)	443(23.30)	1168(61.44)	49(2.58)	284(14.94)	1568(82.48)
	24+ months	1182(19.97)	1361(22.99)	3377(57.04)	67(1.13)	422(7.13)	5431(91.74)
Region	Tigray	175(16.79)	301(28.89)	566(54.32)	13(1.25)	80(7.68)	949(91.07)
	Affar	232(26.30)	169(19.16)	481(54.54)	26(2.95)	126(14.29)	730(82.77)
	Amhara	182(17.60)	280(27.08)	572(55.32)	15(1.45)	87(8.41)	932(90.14)
	Oromia	209(13.99)	326(21.82)	959(64.19)	17(1.14)	111(7.43)	1366(91.43)
	Somali	87(12.13)	109(15.20)	521(72.66)	20(2.79)	111(15.48)	586(81.73)
	B-gumuz	198(24.44)	158(19.51)	454(56.05)	9(1.11)	61(7.53)	740(91.36)
	SNNP	257(19.11)	270(20.07)	818(60.82)	10(0.74)	89(6.62)	1246(92.64)
	Gambella	65(9.77)	98(14.74)	502(75.49)	12(1.80)	68(10.23)	585(87.97)
	Harari	40(8.05)	80(16.1)	377(75.86)	4(0.80)	33(6.64)	460(92.56)
	Addis Ababa	12(3.88)	35(11.33)	262(84.79)	0(0)	10(3.24)	299(96.76)
	Dire Dawa	92(16)	104(18.09)	379(65.91)	6(1.04)	64(11.13)	505(87.83)
Place of residence	Urban	105(7.07)	206(13.86)	1175(79.07)	12(0.81)	101(6.8)	1373(92.4)
	Rural	1444(18.32)	1724(21.87)	4716(59.82)	120(1.52)	739(9.37)	7025(89.10)
Type of toilet	No facilities	933(18.44)	1082(21.39)	3044(60.17)	95(1.88)	541(10.69)	4423(87.43)
	Have facilities	591(14.25)	806(19.44)	2749(66.30)	37(0.89)	286(6.9)	3823(92.21)
	Other	25(15.15)	42(25.45)	98(59.39)	0(0)	13(7.88)	152(92.12)
Wealth index	Poor	943(20.37)	1013(21.88)	2674(57.75)	84(1.81)	487(10.52)	4059(87.67)
	Medium	266(17.23)	335(21.7)	943(61.08)	21(1.36)	148(9.59)	1375(89.05)
	Rich	340(10.64)	582(18.21)	2274(71.15)	27(0.84)	205(6.41)	2964(92.74)

Mothers BMI	Thinness Normal Overweight	449(18.11) 1061(16.71) 39(7.22)	559(22.55) 1300(20.47) 71(13.15)	1471(59.34) 3990(62.82) 430(79.63)	53(2.14) 76(1.2) 3(0.55)	341(13.76) 479(7.54) 20(3.70)	2085(84.11) 5796(91.26) 517(95.74)
Birth order	1-3 4-6 7+	672(14.16) 568(18.95) 309(19.02)	968(20.39) 641(21.38) 321(19.75)	3107(65.45) 1789(59.67) 995(61.23)	60(1.26) 49(1.63) 23(1.42)	389(8.19) 295(9.84) 156(9.6)	4298(90.54) 2654(88.53) 1446(88.98)
Incidence of diarrhea in the last two weeks	No Yes	1261(15.94) 288(19.71)	1628(20.58) 302(20.67)	5020(63.47) 871(59.62)	91(1.15) 41(2.81)	641(8.10) 199(13.62)	7177(90.74) 1221(83.57)
Incidence of fever in the last two weeks	No Yes	1188(15.83) 361(19.36)	1556(20.73) 374(20.05)	4761(63.44) 1130(60.59)	85(1.13) 47(2.52)	604(8.05) 236(12.65)	6816(90.82) 1582(84.83)
Mother education	No education Primary education Secondary and above	1237(18.9) 290(12.24) 22(4.86)	1407(21.19) 476(20.09) 47(10.38)	3904(59.62) 1603(67.67) 384(84.77)	104(1.59) 24(1.01) 4(0.88)	642(9.80) 181(7.64) 17(3.75)	5802(88.61) 2164(91.35) 432(95.36)
Education of husband /partner	No education Primary education Secondary and above	972(19.97) 512(14.67) 65(6.43)	1048(21.53) 757(21.68) 125(12.36)	2848(58.5) 2222(63.65) 821(81.21)	92(1.89) 30(0.86) 10(0.99)	499(10.25) 276(7.91) 65(6.43)	4277(87.86) 3185(91.23) 936(92.58)
Employment status of mother	Unemployed Employed	1115(16.95) 434(6.6)	1347(20.47) 583(8.86)	4118(62.58) 1773(26.95)	99(1.50) 33(0.50)	631(9.59) 209(3.18)	5850(88.91) 2548(38.72)

Table 4.11: Result of GOM for stunting of children

Covariate		Stunting levels: Not stunted Coeff.	Std. Err.	P>|z|	Moderately stunted Coeff.	Std. Err.	P>|z|
Age of child in month (0-11 as reference)	12-23	1.462	0.091	0.000	1.196	0.133	0.000
	24+	1.681	0.082	0.000	1.558	0.122	0.000
Region (Tigray as reference)	Affar	-0.134	0.098	0.171	0.414	0.118	0.000
	Amhara	-0.114	0.093	0.218	-0.028	0.120	0.812
	Oromia	-0.375	0.087	0.000	-0.153	0.115	0.183
	Somali	-0.815	0.110	0.000	-0.385	0.147	0.009
	Ben-gumuz	-0.136	0.099	0.170	0.410	0.119	0.001
	SNNP	-0.265	0.089	0.003	0.176	0.112	0.116
	Gambella	-1.022	0.116	0.000	-0.594	0.161	0.000
	Harari	-0.737	0.129	0.000	-0.529	0.189	0.005
	Addis Ababa	-0.683	0.190	0.000	-0.551	0.329	0.094
	Dire Dawa	-0.266	0.115	0.021	0.163	0.146	0.264
Place of residence (urban as reference)	Rural	0.404	0.091	0.000	0.404	0.131	0.002
Wealth index (poor as reference)	Medium	-0.154	0.064	0.016	-0.146	0.080	0.069
	Rich	-0.233	0.062	0.000	-0.319	0.081	0.000
Mothers BMI (thinness as reference)	Normal	-0.177	0.052	0.001	-0.089	0.065	0.170
	Overweight	-0.522	0.125	0.000	-0.542	0.183	0.003
Birth order of child (1-3 as reference)	4-6	0.116	0.052	0.026	0.213	0.065	0.001
	7+	0.025	0.064	0.693	0.188	0.079	0.017
Incidence of diarrhea (No as reference)	Yes	0.290	0.067	0.000	0.310	0.083	0.000
Incidence of fever (No as reference)	Yes	0.115	0.061	0.058	0.200	0.075	0.008
Mothers education (No education as reference)	Primary education	-0.026	0.059	0.659	-0.104	0.079	0.188

	Secondary and above	-0.343	0.159	0.031	-0.257	0.248	0.300
Husband/partner education (No education as reference)	Primary education	-0.035	0.052	0.507	-0.146	0.067	0.028
	Secondary and above	-0.464	0.105	0.000	-0.523	0.155	0.001
Constant		-1.753	0.145	0.000	-3.181	0.203	0.000

Goodness-of-fit test of overall model (Likelihood Ratio): Chi-square = 1223.42, df = 50, p-value = 0.0000, Pseudo R2 = 0.0714

Table 4.12: Result of multinomial logistic regression model

		Stunting levels					
		Moderately stunted			Severely stunted		
Covariate		Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|
Age of child in month (0-11 as reference)	12-23	1.428	0.110	0.000	1.513	0.136	0.000
	24+	1.511	0.100	0.000	1.919	0.124	0.000
Region (Tigray as reference)	Affar	-0.478	0.120	0.000	0.271	0.125	0.030
	Amhara	-0.130	0.106	0.223	-0.072	0.127	0.572
	Oromia	-0.439	0.100	0.000	-0.285	0.120	0.018
	Somali	-0.902	0.132	0.000	-0.659	0.151	0.000
	Ben-gumuz	-0.467	0.120	0.000	0.277	0.127	0.028
	SNNP	-0.475	0.105	0.000	0.043	0.118	0.713
	Gambella	-1.079	0.137	0.000	-0.920	0.165	0.000
	Harari	-0.760	0.148	0.000	-0.721	0.195	0.000
	Addis Ababa	-0.727	0.216	0.001	-0.719	0.332	0.030
	Dire Dawa	-0.485	0.138	0.000	0.040	0.153	0.796
Place of residence (urban as reference)	Rural	0.350	0.108	0.001	0.495	0.135	0.000
Wealth index (poor as reference)	Medium	-0.120	0.077	0.122	-0.190	0.084	0.024
	Rich	-0.133	0.074	0.072	-0.367	0.085	0.000
Mothers BMI (thinness as	Normal	-0.192	0.063	0.002	-0.151	0.069	0.028

reference)	Overweight	-0.463	0.147	0.002	-0.638	0.187	0.001
Birth order of child (1-3 as reference)	4-6	0.042	0.062	0.500	0.229	0.069	0.001
	7+	-0.072	0.078	0.354	0.162	0.083	0.051
Incidence of diarrhea (No as reference)	Yes	0.200	0.082	0.014	0.387	0.087	0.000
Incidence of fever (No as reference)	Yes	0.036	0.074	0.630	0.214	0.079	0.006
Mothers education (No education as reference)	Primary education	0.011	0.070	0.876	-0.100	0.082	0.221
	Secondary and above	-0.357	0.187	0.056	-0.306	0.255	0.231
Husband/partner education (No education as reference)	Primary education	0.049	0.063	0.435	-0.149	0.070	0.033
	Secondary and above	-0.367	0.125	0.003	-0.613	0.158	0.000
Constant		-2.034	0.172	0.000	-3.052	0.213	0.000

Plots of DFBETA(S) with each explanatory variable for stunting

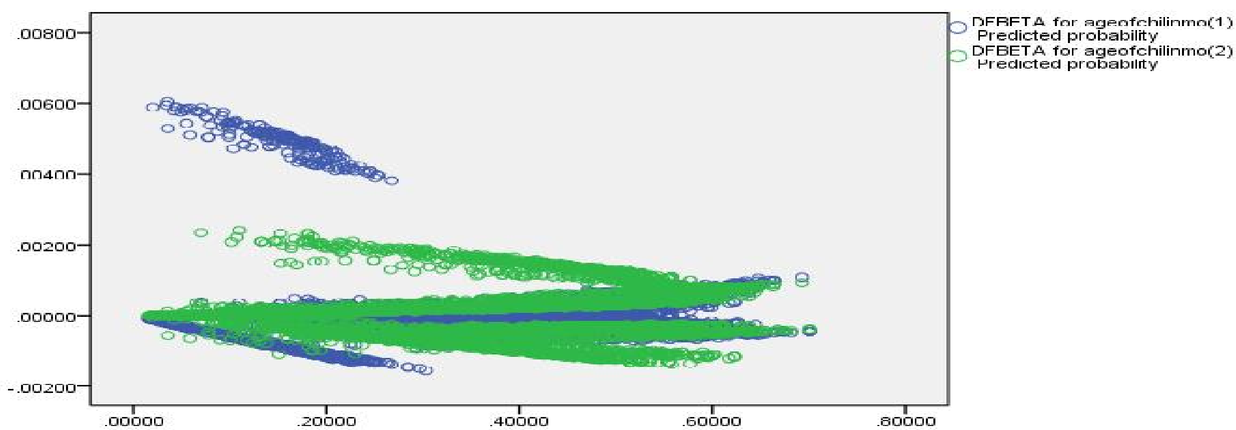

Figure 4.9: Plots of DFBETA(S) for age of children in month versus predicted probability

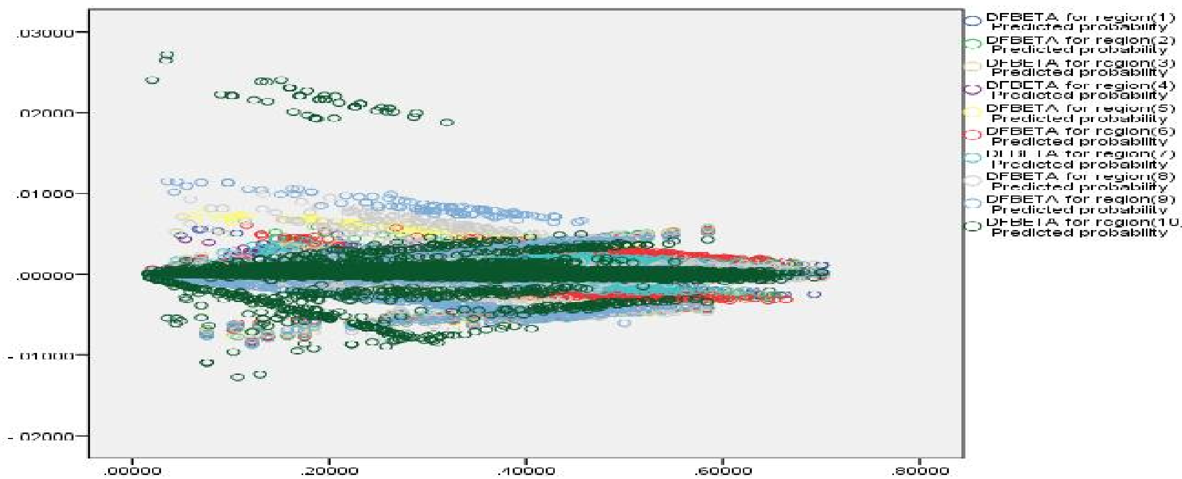

Figure 4.10: Plots of DFBETA(S) for Regions versus predicted probability

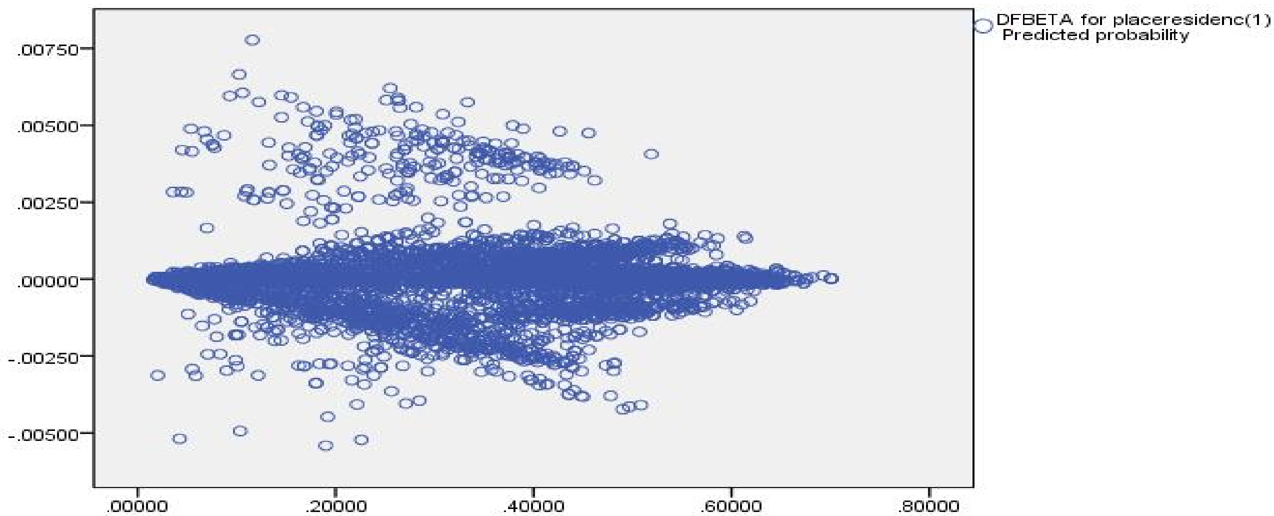

Figure 4.11: Plots of DFBETA(S) for place of residence versus predicted probability.

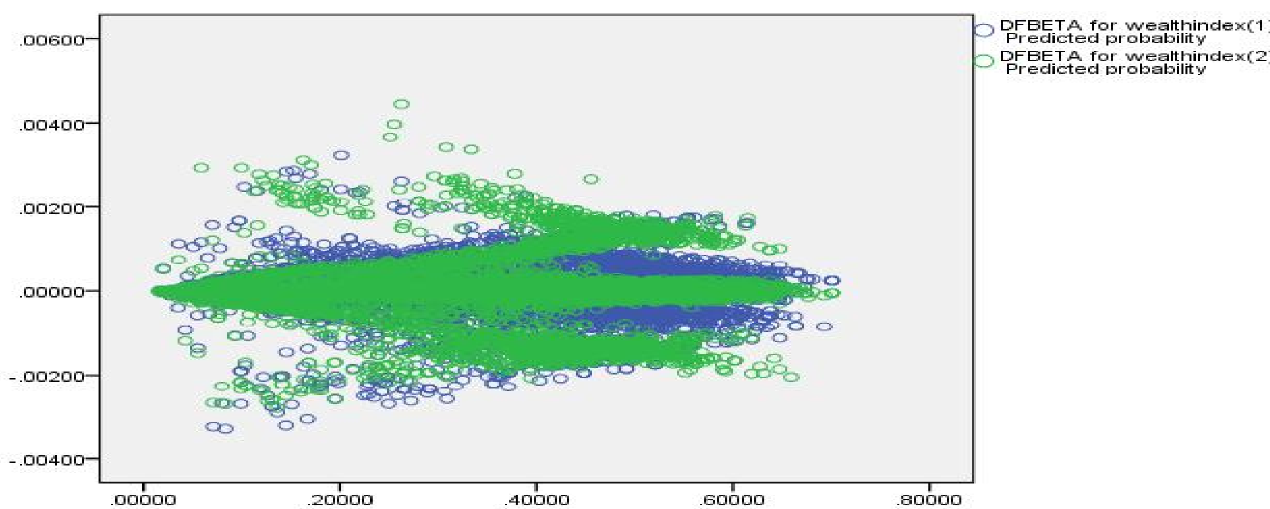

Figure 4.12: Plots of DFBETA(S) for wealth index versus predicted probability

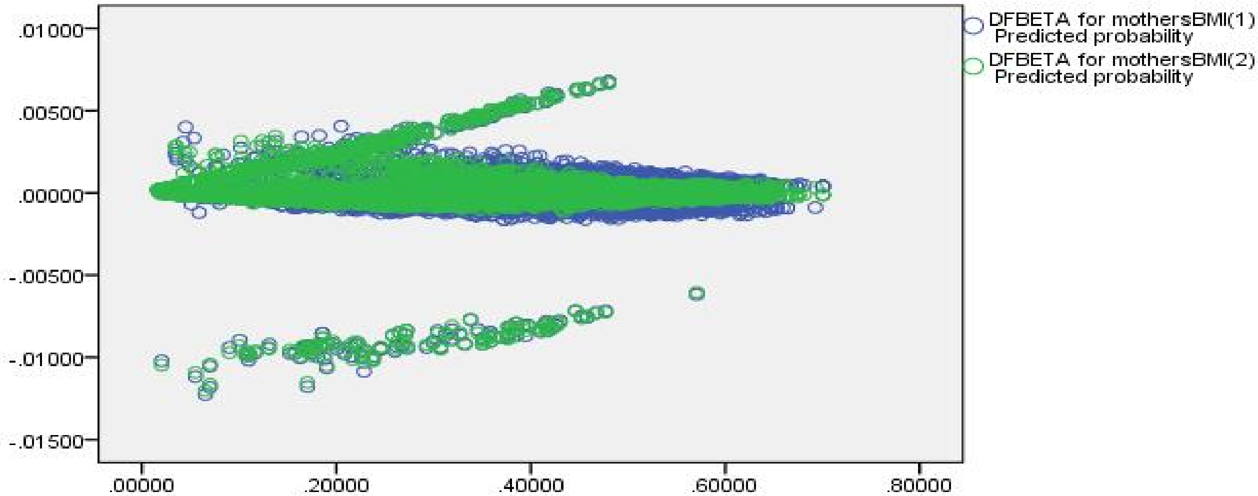

Figure 4.13: Plots of DFBETA(S) for mothers BMI versus predicted probability

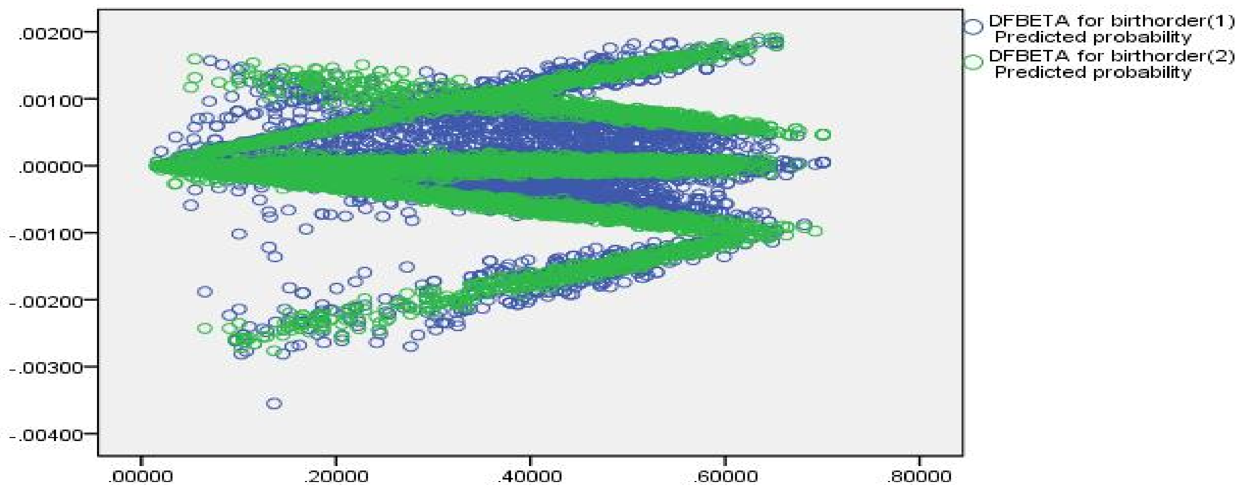

Figure 4.14: Plots of DFBETA(S) for birth order versus predicted probability

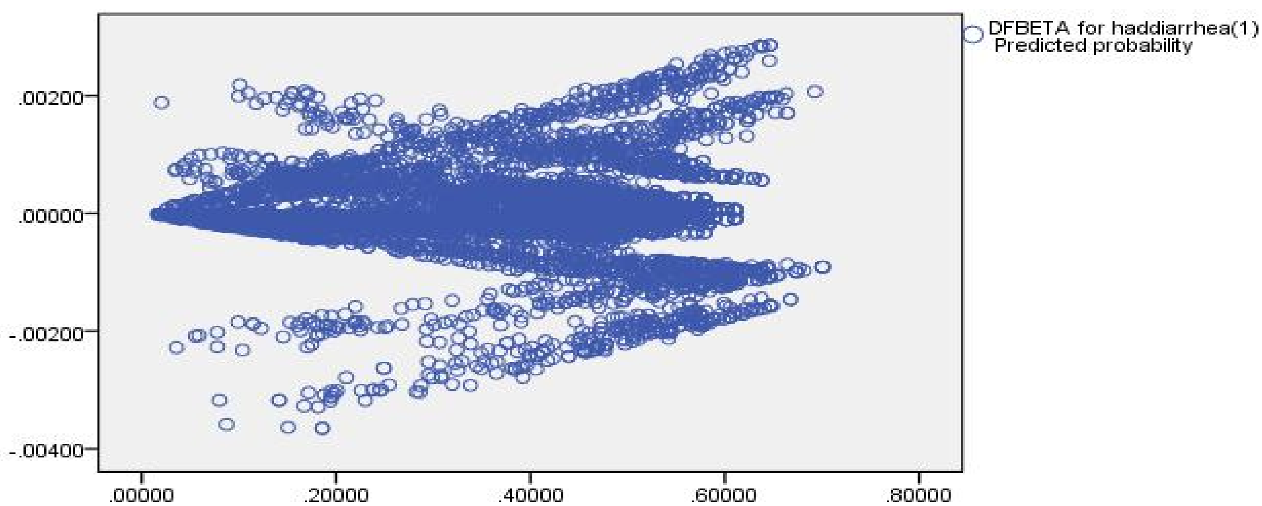

Figure 4.15: Plots of DFBETA(S) for incidence of diarrhea in the last two month versus predicted probability

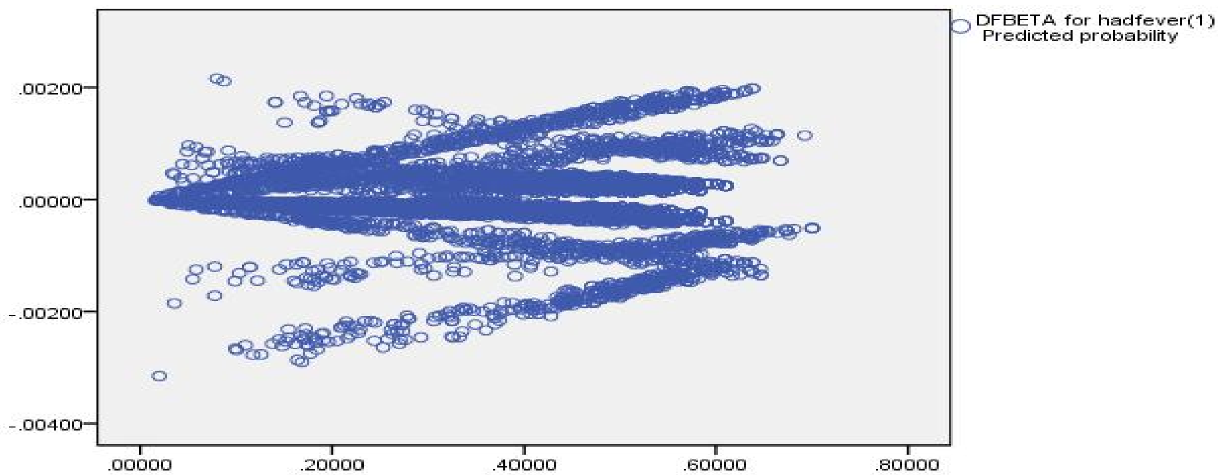

Figure 4.16: Plots of DFBETA(S) for incidence of fever in the last two month versus predicted probability

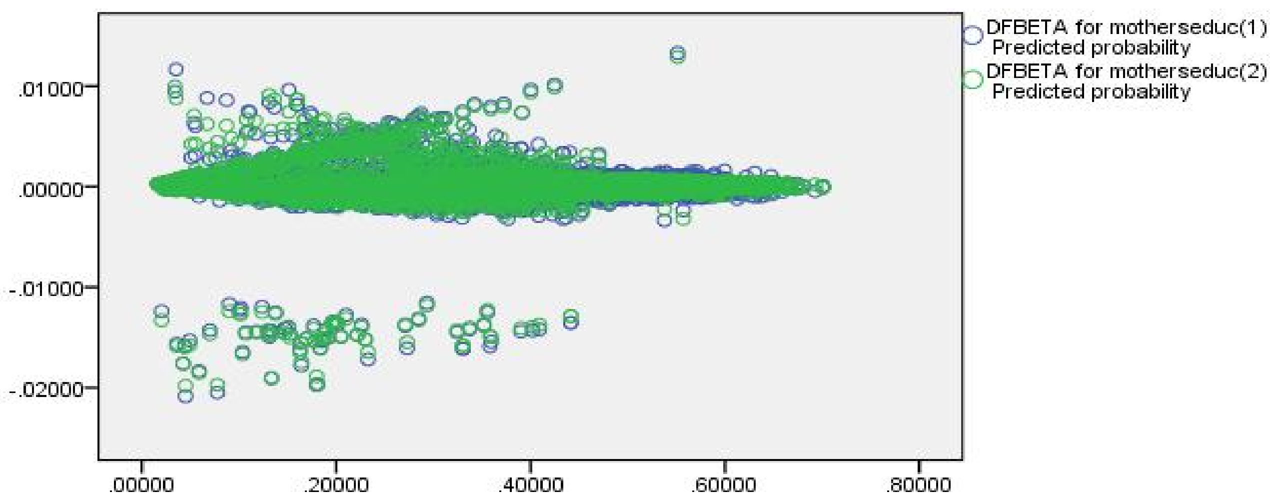

Figure 4.17: Plots of DFBETA(S) for mother's education level versus predicted probability

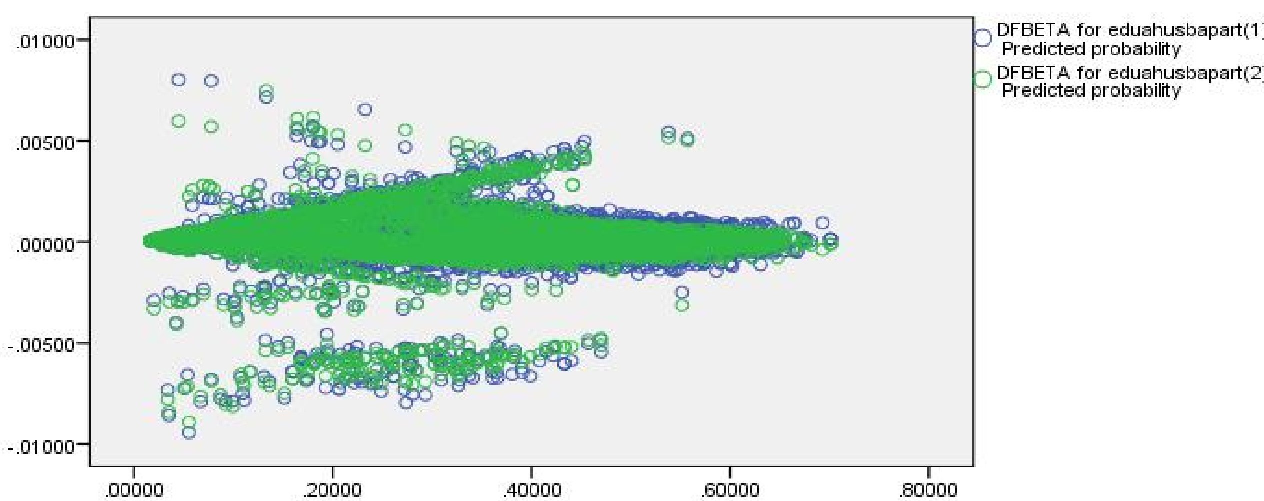

Figure 4.18: Plots of DFBETA(S) for husband/partner education versus predicted probability

Plots of DFBETA(S) with each explanatory variable for wasting

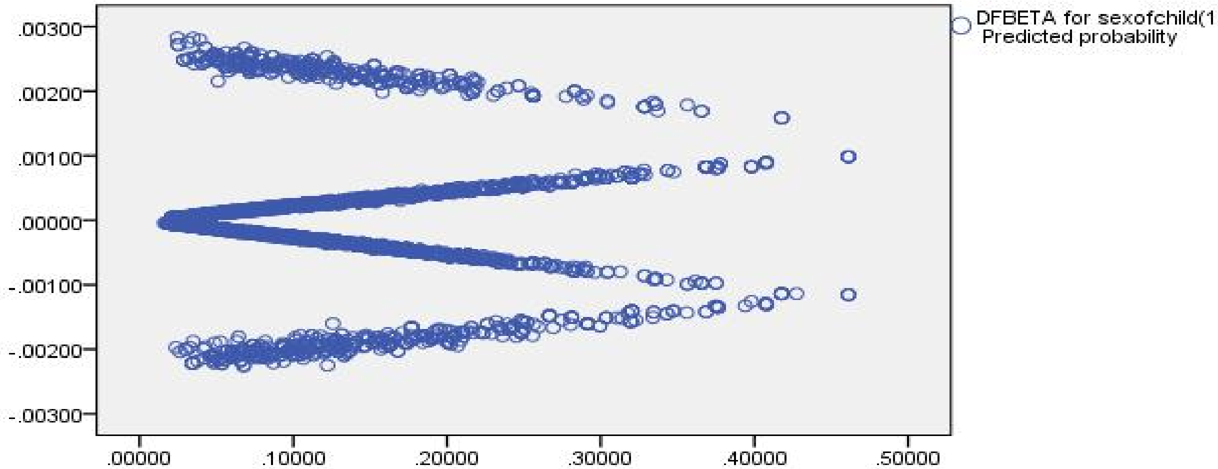

Figure 4.19: Plots of DFBETA(S) for sex of child versus predicted probability

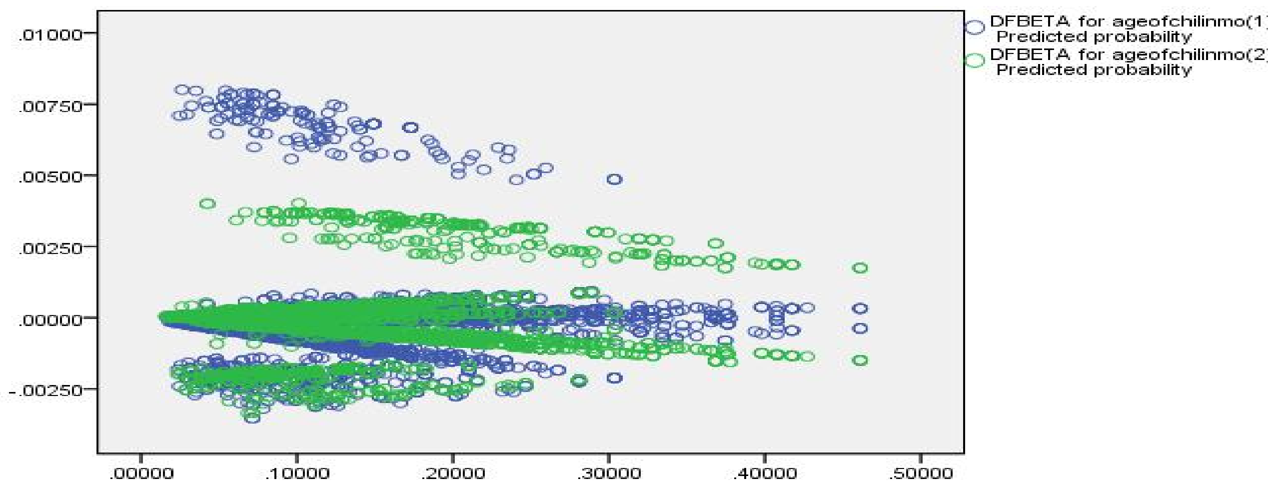

Figure 4.20: Plots of DFBETA(S) for age of children in month versus predicted probability

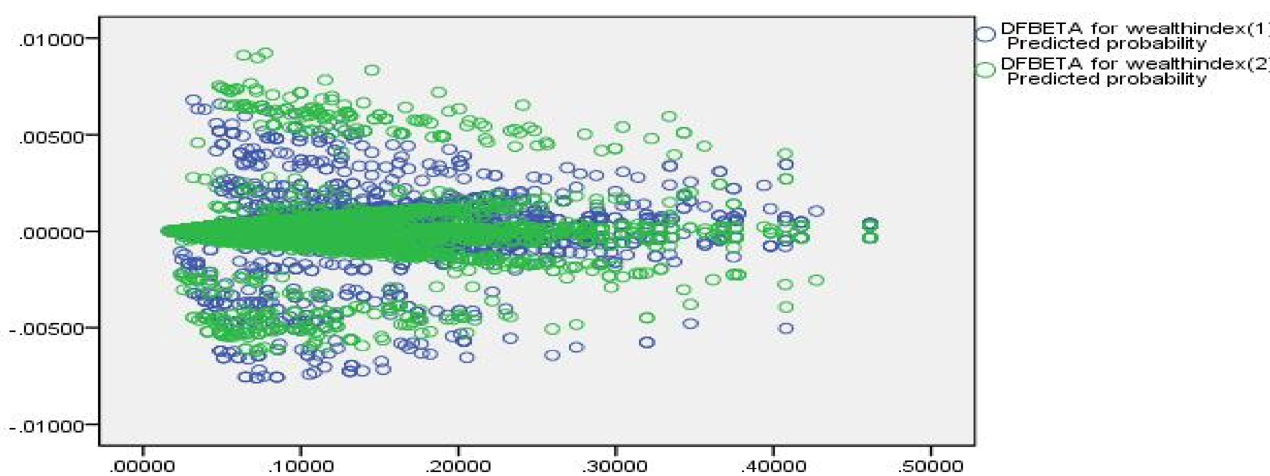

Figure 4.21: Plots of DFBETA(S) for wealth index versus predicted probability

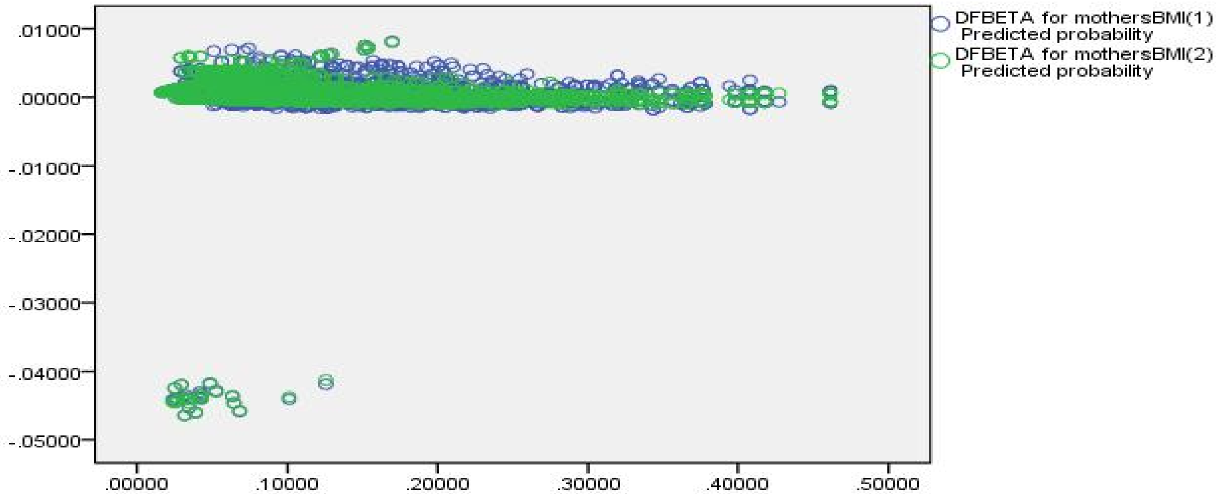

Figure 4.22: Plots of DFBETA(S) for mothers BMI versus predicted probability

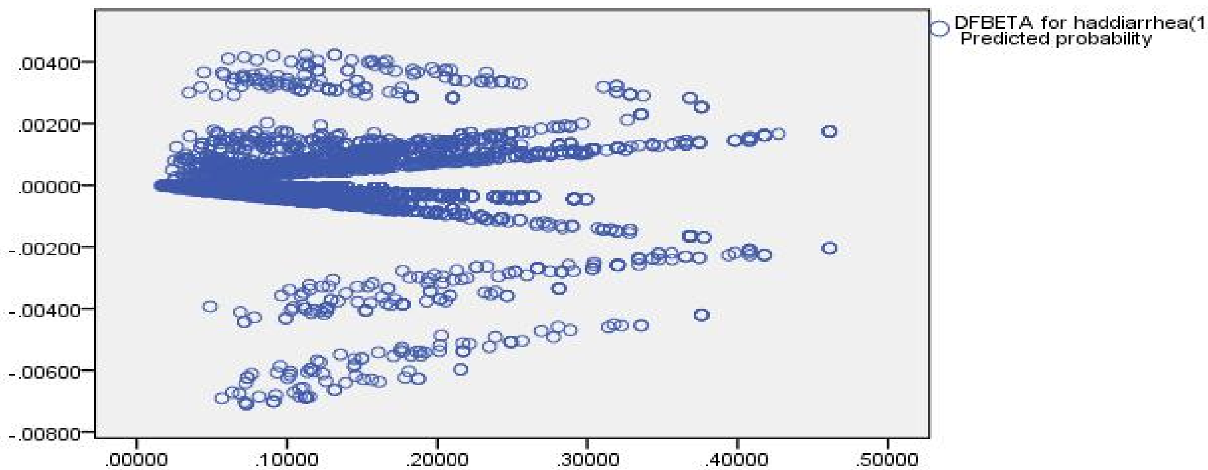

Figure 4.23: Plots of DFBETA(S) for incidence of diarrhea in the last two weeks versus predicted probability

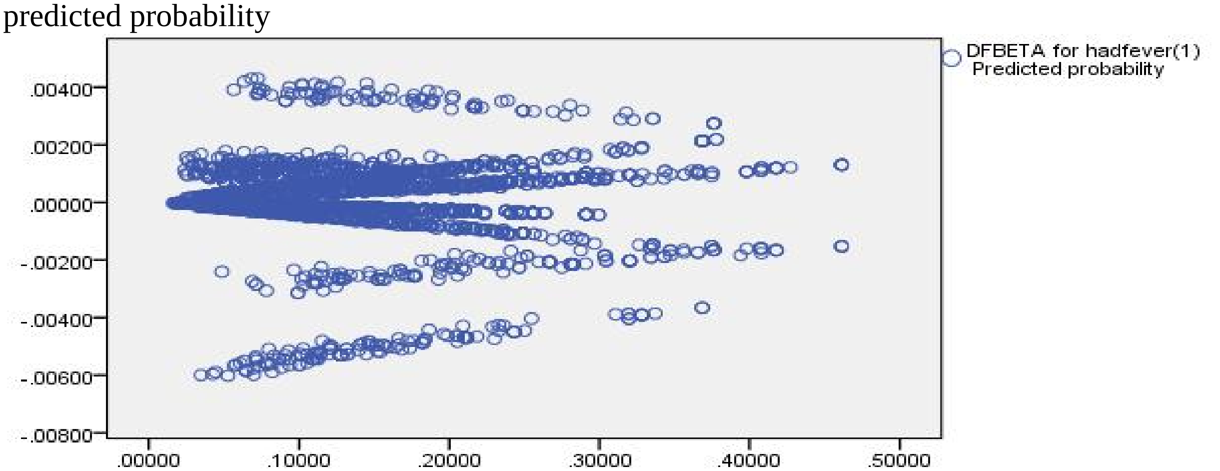

Figure 4.24: Plots of DFBETA(S) for incidence of fever in the last two weeks versus predicted probability

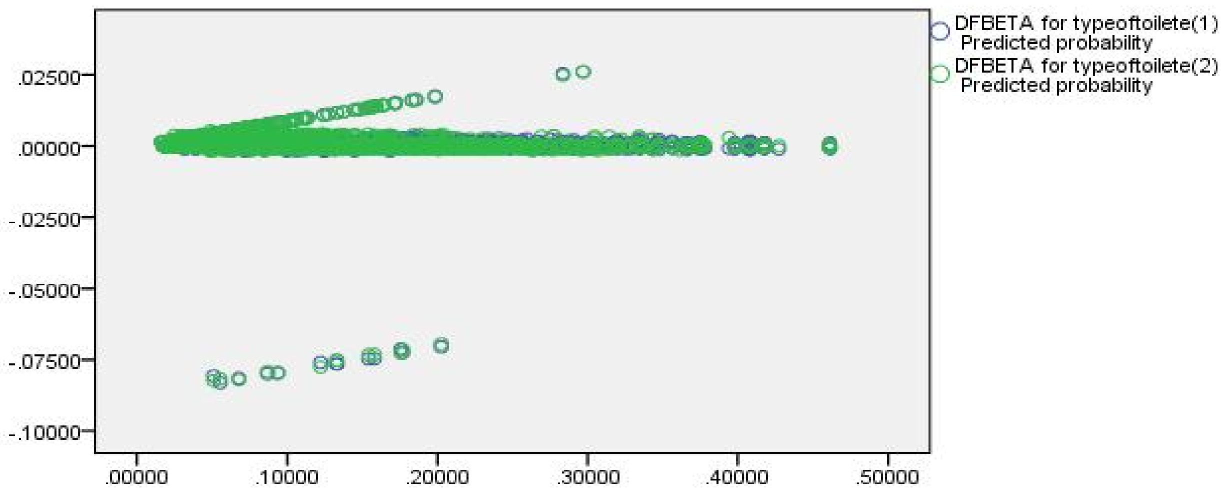

Figure 4.25: Plots of DFBETA(S) for type of toilet versus predicted probability

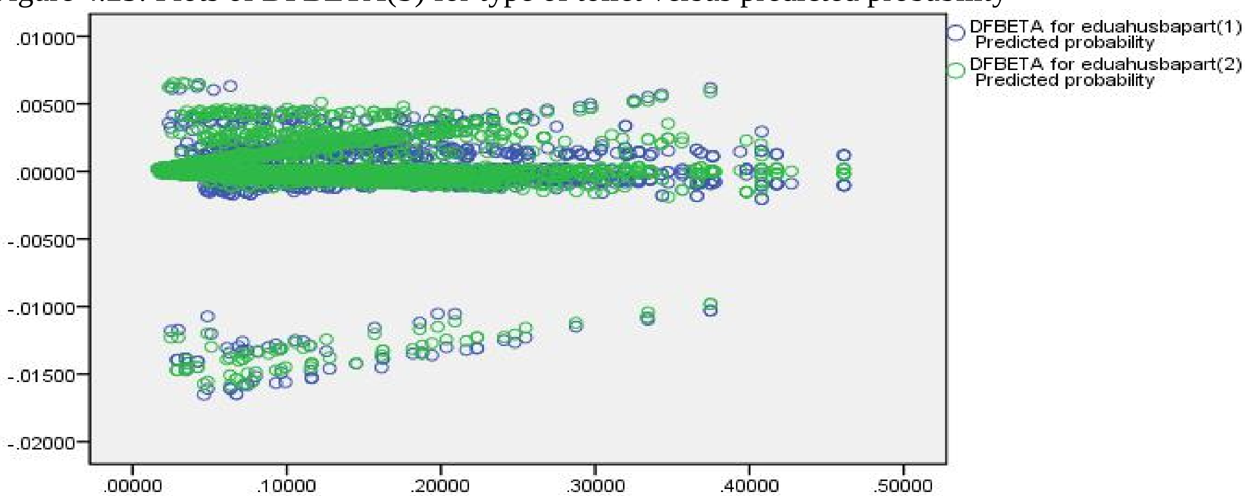

Figure 4.26: Plots of DFBETA(S) for husband/partner education versus predicted probability

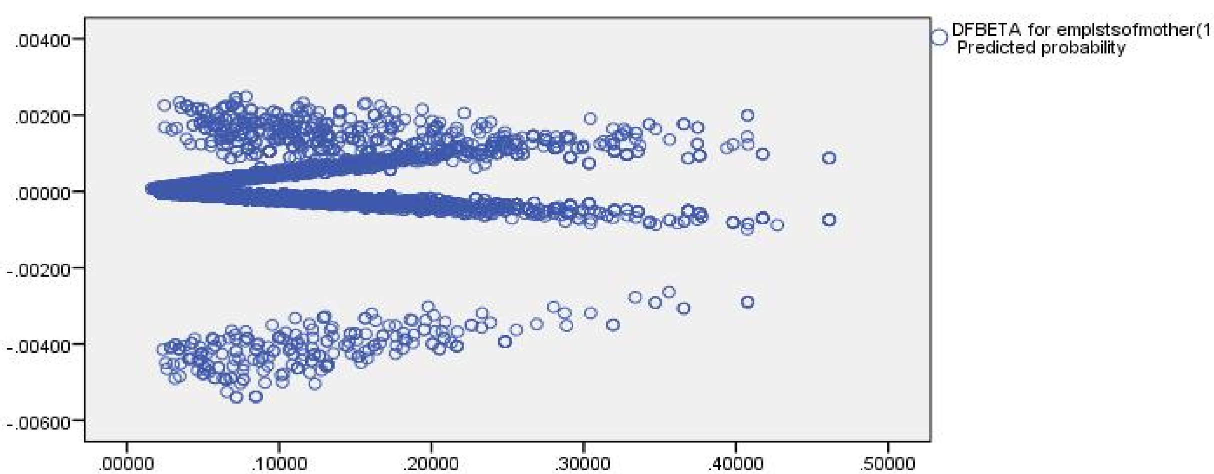

Figure 4.27: Plots of DFBETA(S) for mother's employment status versus predicted probability