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RISK FACTORS FOR ANEMIA LEVELS AMONG PREGNANT WOMEN IN ETHIOPIA: ORDINAL LOGISTIC REGRESSION AND MULTILEVEL MODELS

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BY

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Declaration

The undersigned, I, declare that this thesis is my original work and has not been submitted for achieving any diploma or degree award to other universities or institutions. All materials and sources used for this thesis have been properly acknowledged. The thesis has been submitted in partial fulfillment for the requirements of Master of Science in biostatistics, Bahir Dar University.

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

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Approval Sheet

We, the undersigned, members of the board of examiners of MSc thesis open defense, have read and evaluated the candidate and certify that the thesis entitled "**Risk Factors for Anemia Levels among Pregnant Women in Ethiopia: Ordinal Logistic Regression and Multilevel Models**"prepared by Kassahun Animut, has been accepted in partial fulfillment of the requirement for the degree of master of science in Biostatistics.

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List of Acronyms

ACM	Adjacent Category Model
AIC	Akaike Information Criterion
BIC	Bayesian information Criterion
CRM	Continuation Ratio Model
EDHS	Ethiopian Demographic and Health Survey
GOM	Generalized Ordered Logit Model
ICC	Intra-Class Correlation Coefficient
LRT	Likelihood Ratio Test
ML	Maximum Likelihood
MQL	Marginal Quasi Likelihood
POM	Proportional Odds Model
PPOM	Partial proportional Odds Model
PPOM-R	Restricted partial proportional Odds Model
PPOM-UR	Unrestricted Partial Proportional Odds Model
PQL	Penalized Quasi Likelihood
UNFPA	United Nations Population Fund
UNICEF	United Nations children's Fund
WHO	World health organization

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Abstract

***Background**: Lower concentration of the blood hemoglobin than the normal level is defined as anemia. It is a public health problem for all countries having different income levels with significant consequences of health and economic growth. About 95.7% of the global load of prenatal anemia is originated from developing countries. The main purpose of this study was to identify factors of anemia levels among pregnant women under ordinal logistic regression models by considering regional discrepancy of anemia levels in Ethiopia.*

***Methods**: The EDHS 2016 conducted by the CSA of Ethiopia was used as main data source. The survey considered 1122 pregnant women at the reproductive age; of which 1053 pregnant women with complete anemia levels were included in this study. Ordinal logistic regression and multilevel models were employed to explore factors of anemia levels among pregnant women.*

***Results:** From the total pregnant women included in this study 3.04% were severe, 20.32% were severe or moderate and 37.51% were severe, moderate or mild anemic. Under single level ordinal analysis partial proportional odds model was best fitted the pregnant women data. Ordinal logistic regression model the best model for the data as PPOM was selected as it had smallest AIC value. The anemia levels of pregnant women vary among regions of Ethiopia and random intercept multilevel PPOM was best fitted the data. The intercept variance decreased from 0.531 in null to 0.165 in random intercept PPOM indicating the predictive power of the predictors. Rural pregnant women were more anemic, taking iron was 3.71 times decreased the risk of anemia. Education level had invers relation with risk of anemia while parity had direct relation.*

***Conclusions:** The prevalence of anemia levels of pregnant women among regions indicated that the proportions of severe anemia were 10.98%, 4.08% and 3.51% in pregnant women from Somali, Dire Dawa and Afar respectively. Education, iron take, wealth index, residence, births in 5 years, parity, visit health facility and antenatal visit were significant factors of anemia level. Polices and strategies established by the government will better to enhance women education by considering regional variability of anemia and women should participate in different decisions, which affects their health status due to anemia.*

***Keywords:** Anemia levels, Ordinal logistic regression, PPOM, Ethiopia, Multilevel, Region*

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Anemia is a universal public health problem distressing over1.62 billion people, heavy bleeding during menstruation and parasitic infection like malaria and HIV are basic causes of anemia during pregnancy by decreasing hemoglobin concentration of the blood (Benoist et al., 2008). About 95.7% of the global load of prenatal anemia is originated from developing countries(Van Den Broek, 2003). In Africa closely half (46.3%) of anemia occurred during pregnancy (Organization, 2015a). Anemia reduce levels of hemoglobin favor changes in placental angiogenesis, limiting the availability of oxygen to the fetus and consequently causing potential restriction of intrauterine growth and low birth weight (Figueiredo et al., 2018).

Anemia is a low blood hemoglobin concentration, the basic indication of public health problem that touches countries having low, middle and high-income and has significant adverse health consequences, on pregnant women as well as adverse influences on social and economic growth. Although the greatest consistent pointer of anemia at the population level is concentration of blood hemoglobin, quantities of this concentration alone do not determine anemia sources and anemia is evaluated by measuring hemoglobin levels, rather than by clinical signs, which are less observable than for vitamin A deficiency and disorders of iodine scarcity (United Nations System, 2010).

Maternal anemia is associated with adverse maternal and fetal outcomes such as increase rats of maternal and prenatal mortality, premature delivery, low birth weight and certain anomalies. There are numerous effects of anemia during pregnancy on both the mother and the fetus may leads to low birth weight preterm deliveries and even neonatal death (Ahmed et al., 2015). Universally, anemia occurrence at the time of pregnancy has been expected to be 41.8%, corresponding to a total of 56.4 million women (McLean et al., 2007). Anemia during pregnancy is reported to have negative maternal and child health effect and increase maternal and prenatal mortalities as a whole. The negative health effects for the mother include fatigue, poor work capacity and impaired immune function (Stephen et al., 2018).

Anemia can be described by hemoglobin (Hb) cut off significance adjusted to sea level altitude on the origins of gestational age and to categorize the degree of harshness using the standard of WHO. The value of Hemoglobin is lower than 11.0 g/dl at both first and third trimesters and below10.5 g/dl at second trimester, was used to explain anemia. Depending on the severity, women having hemoglobin value of between 10 and 11g/dl at first and third trimesters and (10 g/dl≤ Hb < 10.5 g/dl) at second trimester were considered as mild anemic. Pregnant women having Hb value of (7 g/dl≤ Hb < 10g/dl) and (Hb <7g/dl) were grouped as moderate and severe anemic, respectively, irrespective of their gestational age (Organization, 2011).

Defined as a blood hemoglobin concentration under 110 g/L, anemia is the biosphere's second foremost cause of disability, and one of the most serious global public health problems, with 38% worldwide popularity among pregnant women. Clinical valuation (examination of the conjunctiva for pallor) is a usual method of detecting anemia but has been shown to be fairly inexact. In the healthcare incident command system (HICs), which is performing a full blood count and quantifies the blood Hb level, is part of routine of African national congress (ANC). However, including this and other existing tests may be expensive, complex or difficult to practice or impractical for use in rural LMIC settings (WHO, 2018).

Anemia can be defined as a situation in which there is below the normal body hemoglobin level, which minimizes red blood cells oxygen-carrying capacity to the tissues in pregnant women (Organization, 2001). Anemia is one of the major population health problem hurting both developed and developing nations with major consequences for human wellbeing specially on pregnant women in addition to social and economic development since it occurs at all phases of the life cycle (Gupta and Gadipudi, 2018).

Average hemoglobin improved in the global level somewhat between 1995 and 2011, starting from 125 g/L to 126 g/L in non-pregnant women, from 112 g/L to 114 g/L in pregnant women, and from 109 g/L to 111 g/L in children. In 2011, the average hemoglobin concentrations were to be lowest, but in south and central Asia as well as west Africa anemia prevalence was highest (Stevens et al., 2013). The mechanisms underlying to these effects are unknown, but they may have a chance to be related to the reducing oxygen delivery to the placenta and fetus, maximize rates of infection, or adverse consequence of iron deficiency on brain development

(Grieger and Clifton, 2014) and (Melku et al., 2014), Anemia is a major and one of the greatest prevalent nutritional deficiency problems disturbing pregnant women. In pregnancy anemia prevalence differs significantly due to the reasons of difference in socioeconomic conditions, lifestyles, and health-seeking behaviors with respect to different cultures (Zehra et al., 2014) and (Melku et al., 2014).

Anemia is an illness in which the oxygen carrying capacity of red blood cells is insufficient to encounter the physiological needs. It has been considered as a public health problem that affects low, middle and high income countries and has significant adverse health and socio-economic consequences (Patience, 2016).The most reliable indicator of anemia at the population level is hemoglobin concentration although it does not indicate the cause (WHO, 2011).

Anemia in pregnant women may due to from iron shortage adversely affects reasoning and motor development, causes tiredness and low productivity and, when it occurs in pregnancy, may be related with low birth weight and maximized the risk of maternal and perinatal mortality (Shulman et al., 1996). In developing countries, maternal and neonatal mortality were accountable for 3.0 million deaths in 2013 and are important contributors to overall worldwide mortality. It has been additionally further estimated that 90 000 deaths in both males and females for all age categories are because of iron deficiency anemia alone. All of the strategy applied to prevent or treat anemia should be tailored to local conditions, by taking consideration of the specific etiology and prevalence of anemia in a given setting and population group (Mbule et al., 2013b).

Anemia is one of the major and highly spread public health problems in developing countries including Ethiopia. It leads to different complications and difficulties on the fetus and mother at the pregnancy period. According to Ethiopian demographic and health survey report, about one fourth of women at the reproductive aged 15-49, (17%) are anemic with severe, moderate and mild anemia accounting for 1%, 3% and 13% respectively (Demographic, 2011) and (Hall et al., 2008). Micronutrient Initiative (MI) (Gebremedhin and Enquselassie, 2011), estimated in Ethiopia27.0 percent and 30.6 percent were the existence of anemia among women at the reproductive age and pregnant women, respectively.

1.2. Statement of the problem

Anemia is major population health problem in the world, particularly related with pregnant women at the reproductive age in developing nations. In pregnancy the universal occurrence of anemia is projected approximately 41.8% fluctuating from 5.7% in USA to 75% in Gambia (Chathuranga et al., 2014). However, the prevalence of anemia in developing countries is about four times larger than the developed nations(Hu et al., 2014). In less developed countries, anemia shakes above 50% of pregnant women (Mbule et al., 2013b). It existed almost in all stages of the life cycle but it is more prevalent among pregnant women and young children (Benoist et al., 2008).

In 2011, anemia in pregnancy exaggerated above half billion women wide-reaching, with a prevalence of 29 percent for non-pregnant women and 38 percent for pregnant women. Anemia is a moderate to severe public health problem in 142 republics worldwide, affecting both health and productivity of pregnant women (Stevens et al., 2013) and (Targets, 2014). A number of studies that have been conducted to investigate the determinant risk factors of anemia levels in pregnant women across different countries in the world including, developing countries like Ethiopia, (Derso et al., 2017) and(Tadesse et al., 2017, Charles et al., 2010). However, in Ethiopia, many types of research have conducted on minimal survey data as well as inadequate number of variables.

Moreover, studies assessed anemia risk factors among pregnant women through binary logistic regression (Worku Takele et al., 2018) and (Obse et al., 2013, Acheampong et al., 2018). However, binary logistic regression accounts the status of anemia. Besides, binary logistic regression cannot deliver sufficient information for studying the pattern of different anemia levels. A study conducted in India on reproductive risk factors assessment for anemia among pregnant women using a multinomial logistic regression model by categorized the anemia level as (normal, mild and moderate to severe)without considering natural ordering (Perumal, 2014).

There is also a study done in Ethiopia on the determinant risk factors of anemia level of women by using ordinal logistic regression under proportional and partial proportional model (Birhane, 2014). Majority of the past studies were done by using single level binary logistic and multiple logistic regressions together with studies mentioned above, but on childhood anemia status varies across different community, ecological, and political structures within countries. Such contextual determinant is the regional or community environment (Ntenda et al., 2017, Kawo et al., 2018) and a study conducted on anemic status of Ethiopian pregnant women using multilevel marginal model for binary outcome variable, showed that the occurrence of anemia is varied in different regions of the country and to analyze the population-averaged effects of the given factors and the study depends on binary response variable of interest (Assaye, 2014).

This study assumed that regions has an effect on modeling the risk factors of anemia levels among pregnant women, because of the heterogeneity between regions by considering ordinal categories of anemia levels. Multilevel ordinal logistic regression model allows the simultaneous examination of the effects of regional level and individual level predictors and also to examine the variations of anemia levels of pregnant women among regions of Ethiopia (Goldstein, 2011).

According to the Ethiopian Demographic and Health Survey (EDHS, 2016) report, 24% of women at the reproductive age were estimated to be anemic and 29% of the pregnant or breastfeeding women are anemic. Among women who had a live birth five years earlier than the survey, prevalence of anemia decreased from 20% in 2005 to 13% in 2011 and the data for 2011 revealed a much broader gap in the prevalence of anemia between pregnant (29.9%) and non-pregnant women (10.8%) (WHO, 2012).

The main aim of this study was try to address the regional variation of anemia levels among pregnant women and discover the major risk factors by considering various socioeconomic, maternal, health related and environmental factors. Therefore, the present study seeks to identify determinant factors of anemia levels among pregnant women in Ethiopia based on EDHS 2016 data. In this concern, the research questions of interest were:

1. Which ordinal logistic regression model is better to analyze anemia levels of pregnant women?
2. What are the determinant risk factors of anemia level among pregnant women in Ethiopia?
3. Is there a significant variation of anemia level among pregnant women across regions in Ethiopia?

1.3. Objectives of the Study

1.3.1 General Objective

The general objective of this study was to identify determinants of anemia level among pregnant women at the reproductive age in Ethiopia using EDHS 2016 data.

1.3.2 Specific objectives of the study

1. To identify the best ordinal logistic regression model to analyze the anemia levels of pregnant women
2. To study and examine the effect of determinants on anemia levels among pregnant women in Ethiopia.
3. To identify the factors that may explain the variation in anemia level of pregnant women between regions of Ethiopia.

1.4. Significance of the study

The basic significant of this study will be, to create awareness about anemia and to identify the common risk factors related with anemia level of pregnant women in addition to understanding socio-economic and demographic differentials on anemia levels. The results of this study may use as a source for concerned bodies for setting policies, strategies and further investigation to decrease the severity of anemia among pregnant women in Ethiopia and give emphases on the factors those have strong association with anemia level of pregnant women, so that policy makers act on accordingly. Lastly this study will also use as a bridge for additional studies.

1.5 Limitation of the study

The EDHS 2016 data used for this study and there were missing values on the variables like taking status of vitamin A that affects the estimation result. The data was collected in 2016 before two years; therefore it may not reflect the current prevalence of anemia level for pregnant women in Ethiopia. We did not explore variables like gestational age and HIV status with respect to anemia levels of pregnant women. They may be important cofactors in the relationship between anemia levels and socioeconomic status.

CHAPTER TWO

LITERATURE REVIEW

2.1 Definition and causes of Anemia During pregnancy

At the time of pregnancy anemia is a condition characterized by inadequate red blood cell volume and a low concentration of hemoglobin in the blood. Commonly anemia is the final outcome of a nutritional deficiency of iron pills, folate, vitamin B_{12} and other nutrients (Nestel and Davidsson, 2002).Anemia is a wide range of public health problem related with maximizing the risk of morbidity and mortality, specifically in pregnant women. Anemia can be defined as decrease in Hb levels below the normal range of 13.5 gm/dl (men), 11.5gm/dl (women), and 11.0 gm/dl (children and pregnant women) (WHO, 2018).

Anemia is the major and common of the hematological disorders, hurting about one-third of the overall population. Despite spans of public health interventions, anemia in pregnancy remains a major health problem globally, with a predicted 41.8% of pregnant women being diagnosed with anemia at some point in their pregnancy. Iron deficiency accounts the minimum of half cases of anemia during pregnancy and the other cases are due to folate or vitamin B12 deficiency, chronic inflammatory disorders, parasitic infections like malaria, and inherited disorders. A considerable variation has been observed in the incidence and an etiology of iron deficiency anemia among developed and developing nations, warranting differences in the screening protocols and styles of management applied by clinicians in the countries (Gupta and Gadipudi, 2018).

Anemia during the time of pregnancy, defined as having hemoglobin level below 11g/dl, is the basic adverse health situations that affects pregnant women in both developed and less developing nations (Organization, 2006). Likewise, anemia complicates pregnancy threatens both the life of mother and the fetus (Lone et al., 2004). Anemia affects above 56 million women internationally, two-thirds of them belongs to Asia and it results from the variations in iron uptake that occurs as a response to infectious diseases like malaria and hookworm infections (Crawley, 2004).

There are several causes of anemia in pregnancy. This ranges from micronutrient deficiency (folic acid, riboflavin, vitamin A and B12), acute and chronic infections (malaria, cancer, TB, HIV) to inherited and acquired disorders such as sickle cell that affect hemoglobin synthesis (MacDonald et al., 2002). The main categories of the causes of anemia are: 1) poor, inadequate, or irregular red blood cell production, 2) extreme red blood cell destruction and 3) extra red blood cell loss (Andrew et al., 2015). Sometimes, infections such as peptic ulcers may lead to blood loss and anemia. The communal cause of anemia during pregnancy is iron deficiency. It is a time of significant increase in iron requirement over non-pregnant levels (Al Hassan, 2015). In less developed nations, iron scarcity affects all susceptible groups. Malaria, which can contribute to excessive red blood cell destruction and helminthes infections, a cause of extra red blood cell loss, are geographically specific (Messina et al., 2013).

A Study conducted on Socio-demographic and obstetric risk factors of anemia among pregnant women in rural Tamil Nadu, India using cross sectional study with chi square for significance with a total of 270 pregnant women recorded at rural health training center, from the total pregnant women, 41.5% were anemic. Passive smoking, dietary habits, irregular iron pills and folic acid tablet intake and deworming were significantly related with anemia (Abiselvi et al., 2018). According to (Noronha et al., 2012), a Review of literature, eleven studies considered 1, 93,131 pregnant women to be included in the review, the lower and upper reported percentage of prevalence for anemia at the time of pregnancy were 18 and 80% respectively. The two extremes of severe anemia prevalence affecting pregnant women are 20 and 2.7%. The basic considered factors are like early age, educational level and socioeconomic status, poor birth spacing and insufficient iron supplementation.

Many pregnant women from relatively poor nations embark upon pregnancy with iron deficiency anemia or depleted iron stores. Anemia is the major influential or sole cause in 20–40% of maternal deaths. In developing nations, during the period of pregnancy the case of anemia includes nutritional deficiencies such as iron, folate, vitamin B12 and parasitic diseases, like malaria and hookworm infections (VanderJagt et al., 2007). According to a study conducted in Moshi, Tanzania on anemia in Pregnancy Prevaadamnce, Risk Factors, and Adverse Perinatal Outcomes using cohort study under logistic regression, the clinic of recruitment and educational level for women were factors related with anemia in pregnancy. Anemia in pregnancy was not related with adverse pregnancy outcomes in this setting, and factors like age, marital status, occupation, income, and alcohol intake were assessed but not associated with anemia during pregnancy (Stephen et al., 2018)

According to a study conducted in Turkey, there was a moderate anemia problem both in the second and third trimesters relative to pregnant women in Turkey. The basic factors of anemia were family income, trimester and having four or more living children. Half of the total anemic women were iron deficient, one third were B12 vitamin and two third were folate deficient. Anemia was also related with soil eating (PICA) in the Univarate analysis ($p < 0.05$). From anemic women, 50.0% had transferrin conditions below 10% indicating iron scarcity, 34.5% were deficient in B12 vitamin and 71.7% were lack of folate. Mostly anemia was normocytic-normochromic (56.5%) representing mixed anemia (Karaoglu et al., 2010).

Based on a study at University of Gondar Comprehensive Specialized Hospital, Northwest Ethiopia on anemia among Women Attending antenatal care using cross sectional study some of the cofactors like source of drinking water, parity, gravidity, HIV infection, and household family size were statistically significant (Worku Takele et al., 2018).The research conducted to identify determinants of anemia among pregnant mothers attending antenatal care in Dessie town, Ethiopia, unmatched case-control study using logistic regression model, identified the factors, HIV infection and medication were statistically significant (Tadesse et al., 2017).

2.2 Literature on Common types of Anemia in pregnancy

According to (Sifakis and Pharmakides, 2000), the common types of anemia in pregnancy are Iron-deficiency Anemia, Folic Acid deficiency Anemia and Other deficiency Anemia in Pregnancy.

Iron-Deficiency Anemia

The definition of iron deficiency anemia (IDA) in pregnancy is imprecise as a result of pregnancy-induced changes in plasma volume and hematocrit, differences in hemoglobin (Hb) concentration through the trimesters, differences in diagnostic tests, and ethnic variation. According to the World Health Organization (WHO), a pregnant woman is considered to be anemic if her Hb concentration is <11 g/dl (Organization, 2011)and (Organization, 2015b).

A Study conducted in Pakistan (Zehra et al., 2014) at Tertiary Care Centre from 120 anemic women at delivery, 93 (77%) were iron deficient anemia and also the study indicates that iron deficiency anemia is popular cause of anemia during pregnancy and a chief public health issue in less developed nations. Based on a study conducted on Oxford University Hospitals, Anemia during pregnancy is connected with a range of problems for both the mother and the baby. Iron deficiency anemia can distract the muscle function, ability to exercise and gut function. In pregnancy, iron scarcity also increases the risk of low birth weight baby and a premature delivery and after giving birth iron deficiency anemia can also affect mothers by causing tiredness and affecting milk production and baby may have minimum iron stores at birth (pavord, 2017).

The daily requirement of iron for pregnant women is approximately 20 mg. Given the fact that the reported mean daily intake of iron in Japanese pregnant women is about 11 mg, many women are likely to be gradually developing iron deficiency during pregnancy, resulting in iron deficiency anemia. It is known that iron deficiency anemia accounts for 77–95% of all cases of anemia in pregnancy, existing at a frequency of 20% (Kozuma, 2009). WHO estimates the number of anemic people worldwide to be a staggering two billion and that nearly 50% of anemia can be attributed to iron deficiency. The most dramatic health consequences of anemia, i.e., maximized risk of maternal and child mortality due to severe anemia, have been well acknowledged. additionally, the negative impact of iron deficiency anemia (IDA) on cognitive and physical growth of children, focus on productivity of adults are major concerns (Patience, 2016). In 2011, estimated by WHO iron deficiency anemia was among the top ten leading causes of years lost to disability in different income countries, and the 7th leading cause of years lost to disability in women. According to WHO estimation, about 12.8% of maternal death could be because of anemia.

Folic Acid Deficiency Anemia

Folic acid is a B vitamin that is energetic for the development of red blood cells. The form of folic acid exist naturally in food is termed as ‘folate’. This leaflet will tell us all about folic acid which foods are good sources, how much we need, and who should take supplements. Folic acid together with vitamin B12 needs to form red blood cells. Lack of folic acid cause a type of anemia (minimize oxygen-carrying capacity of red blood cells) called ‘macrocytic’ (large cell) anemia. Both vitamins together also give help the nerves to function correctly. Folic acid is also vital in the creation of DNA/genetic material within body cells, allowing each cell to duplicate accurately (Dietitian., 2016).

Folic acid deficiency causes a megaloblastic type of anemia that is the second in occurrence as a cause for nutritional deficiency anemia in pregnancy after iron deficiency anemia. The absorption happens in the proximal jejunum. Folic acid (folate) is a form of vitamin B that's found in foods. Folic acid is important for the body to make and keep new cells. It also helps pregnant women to avoid anemia and promotes healthy growth of the fetus. Folic acid can be obtained from Bread, pasta, Spinach and other dark green leafy vegetables, Black-eyed peas and dried beans, Beef liver, Eggs, Bananas, oranges, orange juice, and some other , fruits and juices (Grace Stephen et al., 2015).

According to a study conducted in London School of Hygiene and Tropical Medicine, eight of the 184 women tested (4.3%) had red blood/cell folate (RBCF) levels below the normal lower limit (110 ng/ml). Red blood cell folate levels were negatively correlated with hemoglobin level. This negative correlation was found in both parasitaemic and non-parasitaemic primigravidae and multigravida. Parasitaemic women had a higher mean red cell folate level (294 ng/mL) than those without parasitaemia (260 ng/mL) (Shulman et al., 1996).The Ministry of Health, Labor and Welfare (MHLW) in Japan has issued a notice that recommends the administration of folic acid in pregnant women, regardless of whether or not anemia is present. In other countries, basically in Europe and North America, etiological studies indicated that folic acid intake lowers the risk of impairment of neural tube closures such as spinal bifida in fetuses, and it is recommended to increase folic acid intake in women of childbearing age (Mitsuguchi et al., 2017).

Other Deficiency Anemia

Hemic nutrients, trace elements, vitamins, and proteins are important for growth and repairs for various bodily functions, especially for the hematologic system functions of the mother, fetus, and newborn. They are vital in facilitating the metabolism of amino acids, carbohydrates, and fat and are therefore involved in anemia. The increased nutritional requirements during pregnancy commonly result in inadequate dietary intake. Nutritional anemia is not a very common problem in developed countries, except for iron-deficiency or folic acid deficiency anemia. A variety of anemia is associated with chronic ingestion of alcohol. Therefore alcohol related anemia may present with microcytic red cells or normochromic and macrocytic cells with an increased number of ring side oblasts (Oski, 1983).

Except for iron deficiency, which is responsible for the great majority of anemia diagnosed during pregnancy, deficiencies in some other minerals may account for some cases of anemia in rare cases. Severe phosphorus scarcity can cause hemolytic anemia because of adenosine triphosphate depletion in the red cells with successive osmotic fracture (Pryor and Morrison, 1990). Zinc deficiency has been well-known in patients with sickle cell anemia and thalassemia. However, there is lack of evidence that this deficiency causes worsening of anemia (Warth et al., 1981).Other nutrient deficiencies related with anemia were deficiencies of vitamins A, B-6, and B-12, riboflavin, and folic acid, although not all of the causal paths have been clearly recognized. Besides specific nutrient deficiencies, general infections and chronic diseases including HIV/AIDS, as well as blood loss, can cause anemia. For example, there is high risk of anemia in individuals who were exposed to malaria and helminthes infections. There are also many other, rarer causes of anemia, the most common being genetic disorders such as the thalassemia (Penelope et al., 2002).

2.3 Ordinal logistic regression models and determinants of anemia in pregnancy

Ordinal data are mostly available to educational researchers when it is necessary to control various factors. There are different approaches such as mixed or other classes of models, but ordinal logistic regression models are widely applicable in statistical literatures (Lall et al., 2002, Liu, 2010, Abreu et al., 2008). Mostly in clinical and epidemiological studies the dependent variable measured in ordinal scale and the quantitative difference between adjacent categories not known (Kumar et al.).

Several models under the ordinal dependent variable have been conducted to calculate the cumulative probabilities for response variable being beyond specific category. The most commonly and widely used types of ordinal logistic model is proportional odds model assumes that the predictor variables have the same effect on the response across all categories. Multilevel ordinal logistic regression model is the analysis of hierarchical and ordered dependent variable, follow the logistic distribution and nested with higher level units (Khiari and ben Rejeb, 2015).

According to the result obtained from WHO, the prevalence of anemia is high in developing countries due to the socio-economic and health development. Africa and South East Asia countries are highly affected by anemia and it is a pointer of both poor nutrition and lack of health (Patience, 2016). A research conducted in south east Ethiopia on anemia among pregnant women to assess the prevalence and severity showed that moderate anemia among pregnant women and higher prevalence of anemia in rural pregnant women while parity, age of women, marital status and occupation type were not significant factors (Kefiyalew et al., 2014).

A cross-sectional community based study was conducted on 388 pregnant women living in three districts around Gilgel Gibe Dam area, southwestern Ethiopia. Socio-demographic and socio economic data were collected from each participant and using binary logistic regression. This method was applied to control potential factors and to explore associations between the dependent variable (anemia levels) and a wide range of the independent variables. From the total of 388 study participants, 209 (53.9%) were anemic. Pregnant woman who were rural residents, not using insecticide treated nets (ITNs) at the time of the study, those who were Plasmodium malaria infected and those with Soil Transmitted Helminthes (STH) infections had higher odds of being anemic than those who were urban residents, using ITNs, free of Plasmodium malaria and Soil transmitted helminthes infection, respectively (Getachew et al., 2012).

Based on the study conducted on the Prevalence of anemia and associated risk factors among pregnant women attending antenatal care in Azezo Health Center Gondar town, Northwest Ethiopia based on logistic regression analysis, important variables like age of women, residence type, history of malaria attack, hookworm infection and lack of iron supplements were statistically significant and have relation with anemia (Alem et al., 2013) and (Obse et al., 2013).

Facility based cross-sectional study was done on the magnitude of anemia and related risk factors among pregnant women attending antenatal care in Shalla Woreda, West Arsi zone, Oromia region, Ethiopia, pregnant mother who attained ANC visits during the time of the study and who satisfied the inclusion criteria were asked and blood sample was taken. Multiple logistic regression analysis was used to identify the factors like family sizes, trimester, meat consumption less than 1x/wk and pica, number of children, intake of vegetables and fruits less than once per day, intake of tea always after meal, and recurrence of illness during pregnancy had significant relationship with anemia (Obse et al., 2013).

A study done in Jamaica on predictors of anemia among pregnant women in Jamaica, Cross sectional study was conducted by using multiple logistic regression and as indicated by the result antenatal care visits was statistically significant factor for anemia while the factors like age of women and iron taking status were not significant factors (Charles et al., 2010). Another cross sectional study done on burdens and associated risk factors of anemia among pregnant women attending antenatal care in south east Ethiopia showed that ANC visits, menstrual bleeding and residence type were statistically significant variables for anemia (Getahun et al., 2017).

A Study conducted on the Prevalence of Anemia, lack of iron and folic acid with their determinants in Ethiopian Women using logistic regression, the prevalence of anemia was slightly higher among women with no formal education (31.9%), relatively older women (36.6%), married women (30.7%), pregnant women (30.5%), family size of more than five (31.0%), mothers with more than two children (34.6%), narrow birth-spacing (31.6%), who used no family-planning methods (37.4%), and harbored no intestinal parasites (28.6%) (Haidar, 2010).

The fetal consequences of anemia in pregnancy are well established and depend not only on the severity of anemia but also on the duration of the anemic state. A fall in maternal hemoglobin below 11.0 g/d1 is linked with a significant increment in perinatal mortality rates (Oliver and Olufunto, 2012). A study done in Ethiopia for the analysis of determinants of anemia among pregnant women with emphasis on intestinal helminthic infections using logistic regression revealed that the factor iron taking status, malaria infection, gestational age and helminthic infections were significant variables for anemia (Tefera, 2014) and (Mengist et al., 2017).

Based on the study conducted on anemia prevention in pregnancy among antenatal clinic attends in a general Hospital in Lagos, cross-sectional descriptive study using Simple random sampling method was used to select 220 respondents. About 95% of the participants were aware of anemia in pregnancy but the mean knowledge score was 56.5%. Below half (46.3%) of the total respondents believed that contraceptives could help to prevent anemia in pregnancy by reducing closely spaced pregnancies. Only 31.8% were compliant with the importance of iron supplements. About one third (33.2%) didn't combine drinking tea with meals while 47.3% of the respondents didn't use iron supplements with milk products (Yesufu et al., 2013).

The research conducted to identify Magnitude and associated factors of anemia among pregnant women in Dera District: a cross-sectional study in northwest Ethiopia using multivariate logistic regression analysis, the total prevalence of anemia among pregnant women was 30.5% and the result of multivariable analysis discovered that the chance of anemia was higher among pregnant women living in rural areas, had no latrine, low monthly income less than Eth. Birr 1200 (US dollar 52.22), five or above parity and did not prenatal take iron supplementation (Derso et al., 2017). The research conducted on anemic status among pregnant women in Ethiopia and a cross-sectional study design carried out based on the secondary data of the Ethiopian Demographic Health Survey (EDHS, 2011), using Marginal models analysis ,anemia and socio-demographic variables including residence, religion, occupation, marital status, income status, and educational status, smoking status and age categorized showed a statistically significant (Assaye Belay Gelaw and Abiyot Negash Terefe, 2017).

A research conducted in India on the reproductive risk factors assessment for anemia among pregnant women using multinomial logistic regression without considering the order of the categories indicated that number of births in last five years, alcohol consumption, smoking status and wealth index were statistically associated with risk of anemia (Perumal, 2014). Similar study in Bengal on correlates of anemia among pregnant women showed that education level of the mother and wealth index were significantly associated with anemia while age of mother and religion were not significant (Bisoi et al., 2011)

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Data Source

The study used secondary data from EDHS 2016 that is the fourth comprehensive and nationally representative population and health survey conducted by Central Statistical Agency. An important feature of the data set is that it avails in-depth information on demographic and health aspects of households, like family planning behavior, child mortality, nutritional status of children, anemia and others are available from the data set.

Complex sampling design was applied in the EDHS 2016 (i.e. two stage cluster and combined stratified, with selection of unequal probabilities that result in weighted sample to separate the sample components) and was designed in order to obtain typical estimates at the national and regional level.

The EDHS 2016 data used for this research was the national, population-based, cross-sectional survey. In all, a total of 15,683 women from all the 9 regions and 2 city administrations of Ethiopia were selected for the sample, of which 1,122 women were pregnant, of the pregnant women, 1,053were successfully interviewed, yielding a response rate of 94 percent and 37.52% were anemic.

Inclusion-exclusion Criteria of the study

All pregnant women at the reproductive age their anemia level was known were included in this study while pregnant women not completed their anemia level or their anemia level was not known were excluded from this study.

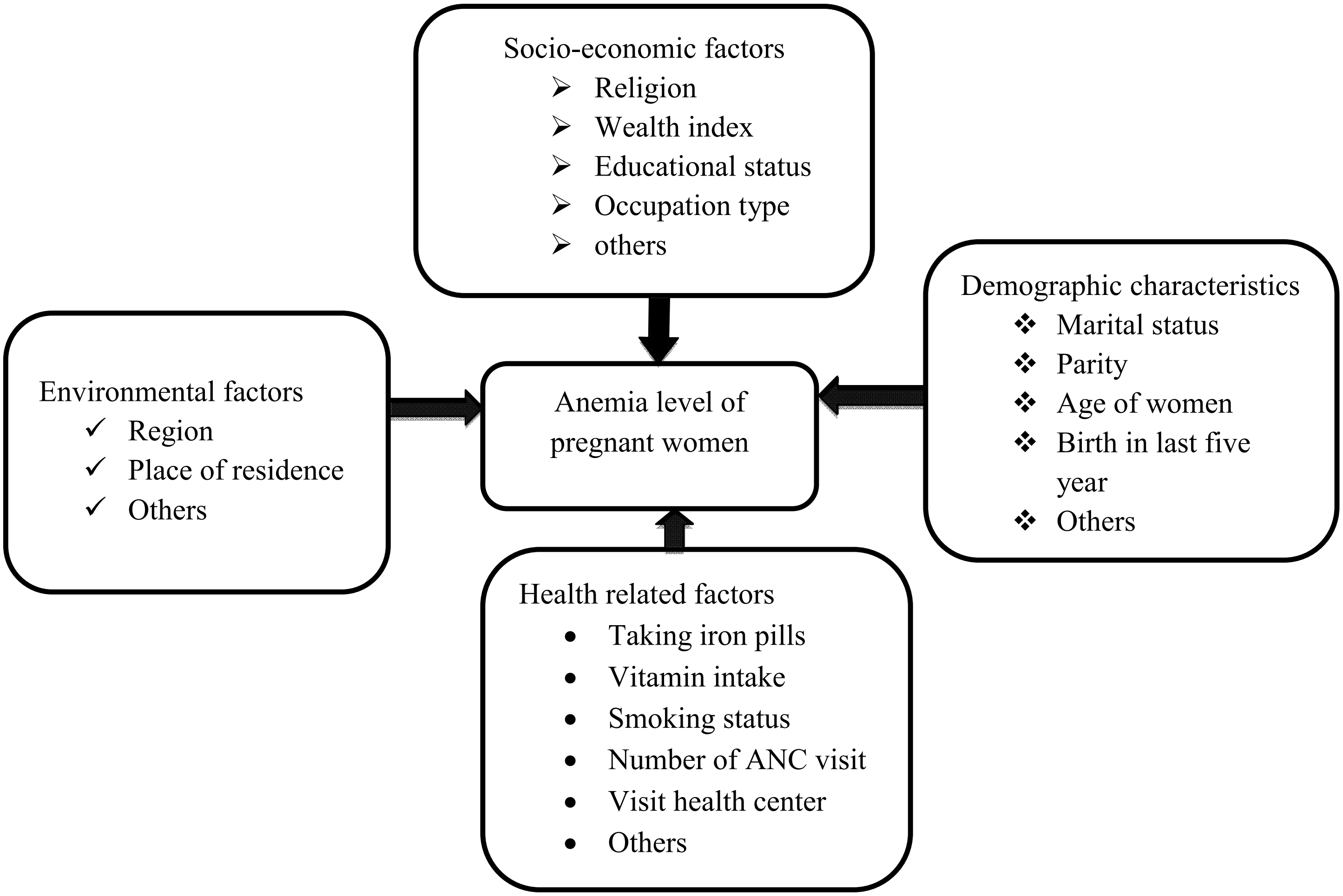
3.2 Variables of the study

3.2.1 Dependent variable

Response variable denoted by (Y_i) is the anemia level of pregnant women aged from 15 to 49, coded as (1=severe, 2= moderate, 3=mild, 4= not anemic).

3.2.2Independent variables

Independent variables include socioeconomic, demographic, health and environmental related factors. The detailed coding and description of independent variables presented in Table A1.



Source: Adapted from (Patience, 2016), *Knowledge and Perception of Risk of Anaemia During Pregnancy.*

Figure 3. 1: Conceptual Framework for the determinants of anemia level among pregnant women

3.3 Method of Statistical Analysis

Logistic regression is the basic and popular modeling approach when the dependent variable is dichotomous or polytomous. This model allows one to predict the log odds of outcomes of a dependent variable from a set of independent variables that may be continuous, discrete, categorical, or a mix of any of these (Hosmer and Lemeshow, 2000). The logistic regression model does not assume linearity in the relationship between the cofactors and the response variable, and does not require normally distributed variables (AGRESTI, 2007b).

Logistic Regression models can be classified according to the types of categories of response variable as: binary, multinomial and ordinal logistic regression models (Hosmer and Lemeshow, 2000). 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 (McCullagh and Nelder, 1989).

3.3.1 Ordinal logistic regression model

The application of the ordinal logistic regression model is dependent, in large part, on the measurement scale of the variables and the underlying assumptions. Ordinal logistic regression model is a type of logistic regression model that used to analyze ordinal dependent variables having more than two categories. For instance, if the dependent variable (outcome variable) is in ordinal scale (ordered anemia level in pregnant women as non-anemic, mild anemic, moderate anemic and severe anemic in our case), the ordinal logistic regression model is preferred (McCullagh and Nelder, 1989).There are different types of ordinal logistic regression models, the most commonly used are: proportional odds models, partial-proportional odds model, adjacent-category, continuation-ratio (Hosmer and Lemeshow, 2000).

3.3.1.1 Proportional odds model (ordered logit model)

The proportional odds model (POM), also known as the cumulative logit model, is indicated when an originally continuous response variable is later grouped and parallel lines assumption holds tested by parallel lines test. Proportional Odds Model is used for modeling the response variable that has more than two levels with K set of explanatory variables by defining the cumulative probabilities, cumulative odds and cumulative logit for the J-1 categories of the response, this model simultaneously use all cumulative logits (McCullagh, 1980) and (Hosmer and Lemeshow, 2000).

Consider the response variable *Y* with *J* categories coded in j= *1,2... J* and X=(x1, x2... xk) the vector of explanatory variables (co-variables). The *J* categories of *Y* conditionally to the values of co-variables occur with probabilities $p_1, p_2, \dots, p_J$, that is $pr(Y = 1) = p_1, pr(Y = 2) = p_2, \dots, (Y = j) = p_j$.For Y, the response with the J ordinal categories given that of K explanatory variables the cumulative probability at or below category j can be defined as the sum of the category probabilities;

$$pr(Y \le j|X) = \pi_j(X) = p_1 + p_2 + \cdots + p_j \; for \; j = 1,2 \ldots, J-1 \tag{3.1}$$

Then the odds of the first $J-1$ cumulative probabilities are,

$$odds\big(pr(Y \le j)\big) = \frac{pr(Y\le j)}{1-pr(Y\le j)} = \frac{\pi_j}{1-\pi_j} \text{Where j} = 1, 2, \ldots, \text{J} - 1 \tag{3.2}$$

Given that the categories of the dependent variable appear to be ordered in terms of the level of anemia, a typical approach is to use the standard ordered logit model which is also called proportional odds model. The cumulative probabilities reflect the ordering, with $pr(Y \le 1) \le pr(Y \le 2) \le \cdots \le pr(Y \le J) = 1$. Models for cumulative probabilities do not use the final one, $pr(Y \le J)$, since it necessarily equals 1.

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

$$logit\big(pr(Y \le j)\big) = \log\left(\frac{pr(Y\le j)}{1-pr(Y\le j)}\right) = log\left(\frac{\pi_j}{1-\pi_j}\right), \text{j} = 1,2, \ldots, \text{J} - 1, \tag{3.3}$$

And then the relationship between the cumulative logits of Y is:

$$log\left(\frac{\pi_j}{1-\pi_j}\right) = log\left(\frac{\pi_j}{\pi_{j+1} + \pi_{j+2} \ldots + \pi_J}\right), j = 1,2, \ldots, J-1$$

Each cumulative logit uses all the response categories.

The relationship between the predictors and response variable is not a linear function in logistic regression instead; the logistic regression function is used, which is the logit transformation of π.

Where $\pi_j = \frac{\exp\big(\alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K)\big)}{1+\exp(\alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K))}$

The log-odds/logit of the cumulative probability (π_j), which is the probability of response Y less than or equal to category j is modeled as a linear function of the predictor variables as:

$$logit\big(pr(Y \le j)\big) = \log\left(\frac{pr(Y \le j)}{1-pr(Y \le j)}\right) = log\left(\frac{\pi_j}{1-\pi_j}\right) = \alpha_j - (\beta_1 X_1 + \cdots + \beta_K X_K), 0 \le \pi_j$$

$$\le 1, j = 1,2, \ldots, J-1 \tag{3.4}$$

Where $\alpha_j =$ threshold value

$X_i =$ sets of factors or predictors

The above equation (3.4) is called proportional odds model and this model has *(J - 1 + K)* parameters. In proportional odds model, every single cumulative logit has its own threshold value, coefficients of the equality are independent from dependent variable categories, which are shown as “J” ($j = 1,2, \dots, J - 1$). Thus coefficients of the independent variable will be equal to each other in every cumulative logit model (Ananth and Kleinbaum, 1997, McCullagh and Nelder, 1989). This model assumes a linear relationship for each logit and parallel regression lines and it estimates simultaneously multiple equations of cumulative probability. Logistic regression coefficients indicate the direction and strength of the relationship between independent variables and the log odds of the dependent variable. However, the regression coefficients $\beta_i{}'s$ interpretations are different from the usual regression coefficients and the interpretation for categorical explanatory variable is the effect (more likely and less likely) of the estimated category of the independent variables relative to the reference category on the log odds being in higher levels of the categories of the dependent variable. In this model the effect of the independent variable is the same for different logit functions, that’s also the reason why the model is called the proportional odds model.

Testing parallel lines

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

To fit an ordinal logistic regression using the proportional odds model the assumption is that the relationship between independent variables and dependent variable does not change for dependent variable’s categories. That means this results are test of parallel lines or planes one for each category of the response outcome. The test of parallelism contains: minus 2 log-likelihood for the constrained model (proportional odds), the model that assume the planes or surfaces are parallel across the category of the response variable and minus 2 log-likelihood for the general model that assumes planes or surfaces are separated across the category.

The chi-square statistic is the log-likelihood difference (LRT) between the two models. If the lines or planes are parallel, the observed significance level for the change should be large, since the general model doesn’t improve the fit very much and the parallel model is adequate that the odds ratio can be interpreted as constant across all possible cut point of the response. Likelihood Ratio Test, score test, Wald Chi-Square test, and the other related tests are used to test parallel lines assumption (Agresti, 2002).

In a way, this assumption states that the dependent variable's categories are parallel to each other. When the assumption does not hold, it means that there are no parallelity between categories then an alternatives may be used such as Partial Proportional Odds Model (Fullerton and Xu, 2012).

3.3.1.2 Partial proportional odds model (PPOM)

It is rare for all the explanatory variables included in the model to display the proportional odds property. Suggested by (Peterson and Harrell Jr, 1990), Partial Proportional Odds Model can be used when parallel lines assumption holds or not. Partial Proportional Odds Model bears the same characteristics with Proportional Odds Model but now the coefficients are associated with each category of the response variable (Ananth and Kleinbaum, 1997).

To contemplate a more accurate situation, the PPOM allows for some the explanatory variables to be modeled with the parallel line assumption, and for the other variables in which this assumption is violated specific parameters are included in the model that vary with different category comparisons. The PPOM is an extension of the proportional odds model. There are two types of partial proportional odds models, unrestricted and restricted (Peterson and Harrell Jr, 1990).

Unrestricted partial proportional odds model (PPOM-UR)

According to this model, among the predictive K variables $X = (x_1, x_2, \dots, x_k)$, only some have proportional odds. Without losing generality, let us assume that for the first explanatory variables, the proportional odds assumption does not hold true. For a variable in which the proportional odds property does not hold, increased by the coefficient γ_{j1}, which is the effect associated with each cumulative logit, adjusted for the other explanatory variables.

The unrestricted partial proportional odds model used when proportional chance assumption is not valid and the coefficients are associated with each category of the response variable (in this case both parallel and linear assumptions are not fulfilled). In this model, for the first q cofactors, the coefficient depends on j, means that the relationship between X and Y is dependent on the response categories. Consequently, ORs are estimated for all the comparisons between response variable categories. Where x is a (px1) vector holding the parallel line assumption and t is (qx1)scaled vector not holding the parallel line assumption (Peterson and Harrell Jr, 1990):

$$\lambda_j(x) = log\left\{\frac{pr(Y = 1|x) + \cdots + pr(Y = j|x)}{pr(Y = j + 1|x) + \cdots + pr(Y = J|x)}\right\}$$

$$\lambda_j(x) = -\alpha_j - x'\beta - t'\gamma_j, j = 1,2,..J - 1, \tag{3.5}$$

Restricted partial proportional odds model (PPOM-R)

When the relationship between independent and the dependent variable is not proportional, a kind of tendency is frequently expected. Peterson & Harrell proposed a model that is applicable when there is a linear relationship between the logit for an independent variable and the response variable. In this case, restrictions (represented by the gamma parameters and which are fixed scalars) can be inserted as parameters in the model in order to incorporate this linearity.$\emptyset_j$is the defined scalar constant and γ vector is q scaled not depend on J.

The model becomes (Peterson and Harrell Jr, 1990):

$$\lambda_j(x) = log\left\{\frac{pr(Y = 1|x) + \cdots + pr(Y = j|x)}{pr(Y = j + 1|x) + \cdots + pr(Y = J|x)}\right\}$$

$$\lambda_j(x) = -\alpha_j - x'\beta - t'\gamma\emptyset_j, \;\; j = 1,2, \ldots, J - 1 \tag{3.6}$$

3.3.1.3The Generalized ordered logit model (GOM)

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 (Williams, 2006a).

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

$$logit\big(pr(Y > j|X)\big) = ln\left(\frac{pr(Y > j|X)}{pr(Y \leq j|X)}\right) = \alpha_j + \beta_{1j}X_1 + \cdots + \beta_{Kj}X_K,$$
$$j = 1,2,..J-1 \qquad (3.7)$$

Where,$\alpha_j$are the intercept or cut points and $\beta_{1j}, \dots, \beta_{Kj}$ are logit coefficients. This model estimates the odds of being beyond a certain category relative to being at/below that category.

A positive logit coefficient indicated that an individual is less likely to be at or below the category as opposed to beyond the category of the outcome variable. Generalized ordered logit model estimates the regression parameters for each explanatory variable on J-1 logit of the probability being at or below j^{th}category in every logit to have different estimated values. The generalized ordered logit model that relaxes the proportionality assumption for all explanatory variables, which is less parsimonious model so, another model that allows some variables to have proportional across all logits and the other variables to vary across logits this model is called Partial proportional odds model.

3.3.1.4 Continuous ratio model (CRM)

(Fienberg, 2007), Proposed the continuation ratio logistic model (CRM), which compares the probability of a response equal to a given category, say $Y = j$, to the probability of a higher response, $Y > j$. This model has different intercepts and coefficients for each category of response comparison and can be adjusted for J binary logistic regression models(Lall et al., 2002).It is more suitable when there is an intrinsic attention in a specific category of the response variable, and not merely an arbitrary grouping of a continuous variable (Ananth and Kleinbaum, 1997).

The continuation ratio model is affected by the direction chosen to model the response, i.e. the property of coding invariance does not hold for this model (Greenland, 1994). The OR obtained from modeling increasing severity is not equivalent to the reciprocal. Thus, one cannot merely invert the coefficient's sign to change directions in the comparison, as occurs with binary logistic regression models and the proportional odds model (Scott et al., 1997).
The model proposed by (Fienberg, 2007)can be written as:

$$\lambda_j(x) = log\left\{\frac{pr(Y=j|x)}{pr(Y=j+1|x)+\cdots+pr(Y=J|x)}\right\} = \alpha_j - (\beta_{j1}X_1 + \cdots + \beta_{jk}X_k),\ j = 1,2,\dots,J \qquad (3.8)$$

The intercept α_j and the coefficients βs are different for each category j.

3.3.1.5 Adjacent-Categories Logit model

The construction of the adjacent-categories logits recognizes the ordering of *Y* categories. To benefit from this in model parsimony requires appropriate specification of the linear predictor. For instance, if an explanatory variable has similar effect for each logit; advantages accrue from having a single parameter instead of $(j-1)$parameters describing that effect (Agresti, 2002).

One approach form logits for all pairs of adjacent categories. The *adjacent-category logits* are:

$$log\left(\frac{\pi_{j+1}}{\pi_j}\right), \qquad\qquad j = 1, 2, \dots, j-1$$

The adjacent-categories logit model with common effect β(Agresti, 2002) is:

$$log\frac{\pi_{j+1}(x)}{\pi_j(x)} = \alpha_j + \boldsymbol{\beta}'\boldsymbol{X},\ j = 1, 2, \dots, j-1 \qquad (3.9)$$

The adjacent-categories logits, like the baseline-category logits, determine the logits for all pairs of response categories (Agresti, 2007a).

3.3.1.6 Likelihood function and parameter estimation

For logistic regression, the model parameters 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 (McCullagh, 1980).

A model for $logit(pr(Y \leq j))$alone is ordinary logit model for binary response in which categories 1 to $j$form one outcome and categories $j+1$to J form a second outcome. Again let $(Y_{i1}, \dots, Y_{iJ})$ be binary indicators of the response for subject i.The likelihood function *L,* defined as follows and the parameters were estimated by maximizing the likelihood, or more usually, by maximizing the logarithm of the likelihood. The likelihood function is given by the equation (Agresti, 2002):

$$L = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \pi_j(x_i)^{y_{ji}} \right] = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left(pr\,(Y \le j | x_i) - pr\,(Y \le j-1 | x_i) \right)^{Y_{ji}} \right]$$

$$L\left(\beta^*\right) = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left(\frac{\exp(\alpha_j + \beta' x_i)}{1+\exp(\alpha_j + \beta' x_i)} - \frac{\exp(\alpha_{j-1} + \beta' x_i)}{1+\exp(\alpha_{j-1} + \beta' x_i)} \right)^{Y_{ji}} \right]$$

$$L\left(\beta^*\right) = \prod_{i=1}^{n} \left[\pi_1(X_i)^{Y_{1i}} \pi_2(X_i)^{Y_{2i}} \cdots \pi_J(X_i)^{Y_{Ji}} \right]$$

β^* is used to denote both slope and intercept coefficients then the log likelihood function is:

$$\ell\left(\beta^*\right) = \sum_{i=1}^{n} \left[Y_{1i} \ln(\pi_1(X_i)) + Y_{2i} \ln(\pi_2(X_i)) + \dots + Y_{Ji} \ln(\pi_J(X_i)) \right]$$

The maximum possible value of the likelihood for a given data set occurs if the model fits the data exactly.

Odds Ratio: It measures the strength effect of each independent variable in the model on the log odds of the dependent variable. According to the common definition, OR is the ratio of two odds, but in this case odds can be defined in terms of cumulative probabilities. For its interpretation, the response has been dichotomized, and the event is to be classified until the category j. If A and B represent, respectively, exposure and non-exposure to a risk factor, OR quantifies the odds of an individual in the exposed group being classified up to a given category, compared to the odds of the unexposed group (Abreu et al., 2008).

Marginal effects: In ordinal logistic regression the average marginal probability effects of predictors on single level of response variable is not possible. The average marginal probability effects used to measure types of association and magnitude between levels of explanatory variables and probability of response level. Marginal effects are computed at the representative value that is at the mean value of the continuous variable and the mode value for categorical dummy variables (Soon, 2010, Washington et al., 2010).

3.3.1.7 Model Selection Criteria

In logistic regression, the methods like forward, backward, and stepwise selection gives incorrect estimates of the standard errors and p-values (Harrell, 2001). In the case of logistic regression the model selection criteria based on their results, reasonableness, and fit as measured, will be taken as AIC/ BIC. R^2 and Adjusted R^2 criterion does not apply to logistic regression models, as we do not have the same kind of residuals as in linear models.

The AIC computation is based on the likelihood of the fit and the number of parameters in the model is considered. Therefore, if the model contains many variables there will be many parameters to be estimated, this may penalize the AIC criteria and the model with small value of this criterion is the optimal model. The optimal model is the one that tends to have its fitted values closest to the true outcome probabilities (Agresti, 2007a):

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

3.3.1.8 Test of overall model fit

Likelihood ratio test

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. To keep use of the selected model the null hypothesis must be rejected and possibility for examining the significance for the individual parameters. The overall model fit in ordinal logistic regression can be based on the change in minus2 log-likelihood when the variables are added to a model that contains only the intercept.

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

$$G^2 = -2Log\Lambda = -2(LL_0 - LL_1),$$

Where, G^2 $is\ distrbuted\ as\ \ chi - square\ with\ degree\ of\ freedom = k - (J - 1)$

k = the number of parameters, J = number of category of the response variable.

LL_0 =the maximized log-likelihood functions of the null model and,

LL_1 =the maximized log-likelihood functions of the selected model.

Pseudo R^2measures

In logistic regression model, McFadden's pseudo R-squared statistic used to compute based on the log likelihood for the model with predictors compared to the log likelihood for the model without predictors. It is defined as one minus the ratio of the log likelihood with in intercepts only and the log likelihood with all predictors (McFadden, 1974).

3.3.1.9 Test for individual predictors

Wald test

The significance of individual explanatory variables in the model was checked by using Wald test. Its test statistic is obtained by the squaring the ratio of the estimated coefficient to its standard error.

$W = \left(\frac{\widehat{\beta}_i}{SE(\widehat{\beta}_i)}\right)^2$, the statistic is distributed as chi-square distribution at one degree of freedom under the null hypothesis that β_i equals to zero.

3.3.1.10 Goodness-of-Fit Test

The measure of goodness of fit in logistic regression is done by testing whether a model fits is to compare observed and expected values. The Pearson goodness-of-fit test and deviance goodness-of-fit test will used to measure goodness of fit for the model. Both deviance and Pearson chi-square for a model with f degrees of freedom, has chi-square distribution with $(n - f)$ degree of freedom.

Pearson goodness-of-fit test

The Pearson goodness-of-fit test assesses the inconsistency between the current model and the full model. The Pearson chi-square statistic also compares the model fit to the actual data, defined by:

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

Deviance goodness-of-fit test

It is also used to construct a goodness-of-fit test for the model and goodness of fit statistic for ordinal logistic regression has a form:

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

Where $O_{ij} and\ E_{ij}$ are the observed and expected frequencies from i^{th}row and j^{th} columns of the cross tabulation. The observed frequency is obtained from the data on the response but the expected frequency is obtained from the estimated probabilities of the response.

3.3.1.11 Model Adequacy checking

In logistic regression analysis after fitting the model the adequacy of the model should be checked and it can measure based on diagnosing residuals and measure of influence. Basically in ordinal and multinomial logistic regression this is difficult to perform. The categories of response variable are changed in to binary categories by overlapping two/more categories together to minimize the difficulties.

Model Evaluation- Residuals

In logistic regression diagnostics Residuals are the basic building blocks and used to identify potential outliers (not well fitted by the model). The residuals for logistic regression model are typically defined as the difference between observed response, and the estimated probability of the response, conditional on the covariates. Pearson residual values fluctuate around zero, following approximately a normal distribution when n_i *is* large (Agresti, 2002).

For a GLM with binomial random component, the Pearson residual (r_i) comparing y_i to its fit is (AGRESTI, 2007b).

$$r_i = \frac{Y_i - n_i\hat{\pi}_i}{\sqrt{n_i\hat{\pi}_i(1-\hat{\pi}_i)}}$$

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 leverage value is called standardized Pearson residual.

The Standardized Pearson residual is similar with Pearson residual that it only 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 et al., 2001). The standardized Pearson residual is given (Agresti, 2002).

The standardized residual divides $(y_i - n_i\hat{\pi}_i)$by itsSE

Standardized residual= $\frac{y_i - n_i\hat{\pi}_i}{SE} = \frac{Y_i - n_i\hat{\pi}_i}{\sqrt{n_i\hat{\pi}_i(1-\hat{\pi}_i)(1-h_i)}}$

The term h_i in this formula is the observation's leverage, the greater an observation's leverage, the greater its potential influence on the model fit. The standardized residual equals$\frac{r_i}{\sqrt{(1-h_i)}}$, so it is larger in absolute value than the Pearson residual r_i. An absolute value larger than roughly 2 or 3 provides evidence of lack of fit (AGRESTI, 2007b).

Deviance residuals are useful to determining individual points that are not well fitted by the model. The deviance residual for the i^{th}observation is the signed square root of the contribution of the i^{th}case to the sum for the modeldeviance, for the i^{th}observation, and is given by

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

When $Y_i \geq \hat{\pi}_i, D_i$ becomes positive otherwise it is negative. An observation with a residual greater than two or three in either direction is an indication of poor fit.

Influence Measures

As in ordinary regression, some observations may have too much influence in determining the parameter estimates. However, a single observation can have a more inflated influence in ordinary regression than in logistic regression, since ordinary regression has no bound on the distance of $y_i$from its expected value (AGRESTI, 2007b).

Influence measure shows the effect that removing 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.

Leverage values are a measure of how far an observation is from the others in terms of the levels of the independent variables (not the dependent variable). These leverage points can have an effect on the estimate of regression coefficients and its value measures the influence of a point on the fit of the model (Cook, 2009). A leverage value greater than 2 or 3 times of average leverage is considered as large (Agresti, 2002).In logistic regression, an observation identified as influential if its Cook's distance is greater than one (Hosmer and Lemeshow, 2000).

DFBETA (s) is a diagnostic that measure the effect of the i^{th}observation on the estimates of the logistic regression coefficients. These are computed by dropping the i^{th}observation. If DFBETAs are less than unity, this implies no specific impact of an observation on the coefficient of a particular predictor variable, while $DFBETA$ of i^{th}observation greater than 1, implies the observation is an outlier (Cook and Weisberg, 1982).

3.3.2 Multilevel logistic regression model

Reflecting the usefulness of multilevel analysis and the importance of categorical outcomes in many areas of research, generalization of multilevel models for categorical outcomes has been an active area of statistical research. For dichotomous response data, several approaches adopting either a logistic or probit regression model or various methods for incorporating and estimating the influence of the random effects have been developed (Busing et al., 1995).The developments have been mainly in terms of logistic and probit regression models. Because the proportional odds model, which is based on the logistic regression formulation, is a common choice for analysis of ordinal data, many of the multilevel models for ordinal data are generalizations of this model (De Leeuw et al., 2008).

A multilevel logistic regression model also referred as a hierarchical model in the literature. It can account for lack of independence across levels of nested data. Hierarchical models are statistical models that can be used to analyze nested sources of variability in hierarchical data, taking account of the variability associated with each level of the hierarchy. These models have also been referred to as multilevel models, mixed models, random coefficient models, and covariance component models (Breslow and Clayton, 1993, Goldstein and Noden, 2003).

3.3.2.1 Two level model

The basic multilevel ordinal model based on generalized linear models uses the cumulative probabilities of response categories as the dependent variables (De Silva and Sooriyarachchi, 2012). In this study two level models are used that accounts women level and regional level effects. In the structure of the data, women are level-1 while regions are level-2. There are n_r pregnant women within each level-2 unit in the r^{th}region.

The two-level proportional odds model with a logit link is the most frequently used model for multilevel ordinal categorical data and for this case the model can be expressed as follows (Fielding et al. 2013).

$$logit(\pi_{ir(j)}) = \log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\beta x_{ir} + U_{0r}), j = 1,2,\dots,J-1 \qquad (3.10)$$

Where $\alpha_j$corresponds to the intercept of the model for the j^{th} cumulative logit andx_{ir} is the value of the explanatory variable X for thei^{th}observationinther^{th} cluster (Epasinghe and Sooriyarachchi, 2017).

The parallel formulation modeling for anemia levels directly without reference to explicit measurement scales. The four categories of response are denoted by integer labels j=1, 2, 3, 4. Following the single level model method (McCullagh, 1989), we use generalized linear models with cumulative probabilities associated with responses as dependent. For the i^{th} women from the r^{th}region the probability of anemia level lower than that represented by j is denoted by $\pi_{ir(j)}$. We have $0 < \pi_{ir(1)} < \pi_{ir(2)} < \pi_{ir(3)<}\pi_{ir(4)} = 1$.

The two level representation of the ordinal model follows the same logic as the dichotomous model. When the multilevel model is expressed in terms of the observed response variable y, the level-1 model is written in terms of the cumulative logits, as shown below.

Level-1 model:

$$\log\left(\frac{\mathrm{pr}(y_{ir}\le j)}{1-\mathrm{pr}(y_{ir\le j})}\right) = \alpha_j - X'_{ir}b_r, \text{ j=1, 2… J-1}$$

Where X_{ir} represent the values of the covariates corresponding to level-1 unit i nested within level-2 unit r.

Level-2 model:

If all the elements of the coefficient vector $\boldsymbol{b_r}$ are allowed to vary randomly across level-2 units, then

$b_r = \beta + V_r,$

which models the level-2 effects as a function of an overall mean $\boldsymbol{\beta}$ and a unique random component $\boldsymbol{V_r} \sim NID(\boldsymbol{0}, \boldsymbol{\Sigma_v})$. The latter is also referred to as the level-2 residuals and indicates the extent to which a given level-2 unit differs from the average, as estimated by the first part of the level-2 model.

Note that the level-2 model does not depend on the response variable. As the regression coefficients $\boldsymbol{\beta}$ are without subscript, it is assumed that they do not vary across the categories and hence that the relationship between the predictor variables and the cumulative logits is not dependent on j . (McCullagh, 1980) referred this as the assumption of identical odds ratios across the J-1categories (ordinal_final.pdf).

3.3.2.2 Heterogonous Proportion

For the proper application of multilevel analysis, testing heterogeneity of proportions between groups is the basic and the first step. The most commonly used test statistic to check for heterogeneity of proportions between groups is the chi-square. To test whether there are indeed systematic differences between the groups, the well-known chi-square test can be used. The decision will be based on the chi-square distribution with (J-1) (g-1) degrees of freedom.

3.3.2.3The Empty Two-Level Model

The empty two-level model for ordinal outcome variable refers to a population of groups (level-two units) and specifies the probability distribution for group-dependent probabilities without taking any explanatory variables into account. This model only contains random groups and random variation within groups. It can be expressed with cumulative logit link function as follows (Fielding et al., 2003).

$$logit(\pi_{ir(j)}) = \log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - u_{0r}, j = 1,2, \dots, J-1 \quad (3.11)$$

Where $\alpha_j$the population average of the transformed cumulative probabilities andu_{0r} is the random deviation (single random effect) from this average for the r^{th} group (region), which is assumed ~ $N(0, {\sigma_{u0}}^2)$.

3.3.2.4 Intra-class Correlation Coefficient (ICC)

ICC is the degree of alikeness between level one units belonging to the same group or randomly selected from the same cluster. It is an indication of the proportion of variance at the second level (region) and it can also be interpreted as the expected (population) correlation between two randomly chosen individuals within the same group (Joop, 2010).

For a multilevel model, it is often of interest to express the cluster variance in terms of an Intra-class correlation (ICC). The ICC indicates the proportion of unexplained variance that is at the cluster level, and is given by $\boldsymbol{ICC} = \frac{\boldsymbol{\sigma_c}^2}{\boldsymbol{\sigma_c}^2+\boldsymbol{\sigma}^2}$, where${\sigma_c}^2$ is the cluster or level-2 variance and $\sigma^2$is the level-1 variance. For a logistic regression model (either binary or ordinal), the level-1 variance, which is not estimated, equals the variance of the standard logistic distribution $\pi^2/3$ (Agresti, 2002).

3.3.2.5 The Random Intercept ordinal Logistic Regression Model

In this model, the intercept is the only random effect meaning that the groups differ with respect to the average value of the response variable. It represents the heterogeneity between groups in the overall response.

The ordinal logistic random intercept model expresses the cumulative logit of$\pi_{ir(j)}$, as a sum of a linear function of the explanatory variables and a random group-dependent deviation U_{0r}. That is:

$$logit(\pi_{ir(j)}) = log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\beta_{0r} + \beta_1 X_{1ir} + \beta_2 X_{2ir} + \cdots + \beta_k X_{kir})$$

Where: - The intercept term β_{0r} is assumed to vary randomly and is given by the sum of an average intercept and group- dependent deviations U_{0r}(Liu, 2015). That is:

$\beta_{0r} = U_{0r}$and $\beta_{hr} = \beta_{h0}$, thenextend the basic model by adding to the model appropriate fixed effect covariates(Fielding et al., 2003), then

$$logit(\pi_{ir(j)}) = \log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\beta_{1o}x_{1ir} + \cdots + \beta_{ko}x_{kir} + U_{0r}), j = 1,2,\ldots,J-1, \quad (3.12)$$

This model possesses the proportional odds property(McCullagh, 1980). For all j the fixed or random effects operate on cumulative odds by a constant multiplicative factors and solving for $\pi_{ir(j)}$, and this model is the two-level proportional odds model

$$\pi_{ir(j)} = \frac{e^{\alpha_j - (\beta_{10}x_{1ir} + \ldots + \beta_{k0}x_{kir} + U_{0r})}}{1 + e^{\alpha_j - (\beta_{10}x_{1ir} + \ldots + \beta_{k0}x_{kir} + U_{0r})}}$$

$U_{0r} \sim IID(0, {\sigma_{u0}}^2)$, and assumed independent of x variable.

The above equation (3.12) does not include a level one residual because it is an equation for the cumulative probability $\pi_{ir(j)}$ rather than for the outcome Y_{ir}.

3.3.2.6 The Random intercept and slope (Random Coefficients) Model

The multilevel analogue, random coefficient logistic regression, is based on linear models for the log-odds that include random effects for the groups or other higher level units. In the random coefficient model, both the intercepts and slopes are allowed to differ across regions. Suppose that there are k level one predictors $X_1, X_2, \ldots, X_k$, and consider the model where all X-variables have varying slopes and random intercept (Liu, 2015). That is,

$$logit(\pi_{ir(j)}) = log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\beta_{or} + \beta_{1r}X_{1ir} + \cdots + \beta_{kr}X_{kir})$$

Letting

$$\beta_{0r} = U_{0r} \; and \; \beta_{hr} = \beta_h + U_{hr}, \qquad for \; h = 1,2,\ldots,k, j = 1,2,\ldots,J-1$$

$$logit(\pi_{ir(j)}) = log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\sum_{h=1}^{k} \beta_{hr}X_{hir} + U_{0r} + \sum_{h=1}^{k} U_{hr}X_{hir}) \quad (3.13)$$

$$\pi_{ir(j)} = \frac{e^{\alpha_j - (\sum_{h=1}^{k}\beta_{hr}x_{hir} + U_{0r} + \sum_{h=1}^{k}U_{hr}x_{hir})}}{1 + e^{\alpha_j - (\sum_{h=1}^{k}\beta_{hr}x_{hir} + U_{0r} + \sum_{h=1}^{k}U_{hr}x_{hir})}}$$

The first part of this model, $\alpha_j - \sum_{h=1}^{k} \beta_{hr} X_{hir}$is the fixed part and the second part,$-U_{0r} - \sum_{h=1}^{k} U_{hr}\, X_{hir}$is the random part of the model (Snijders and Roel, 1999).

For different groups, the pairs of random effects (u_{0r}, u_{hr}) are independent and identically distributed. The random intercept variance, $var(u_{0r}) = {\sigma_0}^2$ the random slope variance, $var(u_{hr}) = {\sigma_h}^2$, and the covariance between the two random effects $cov(u_{0r}, u_{hr}) = \sigma_{0h}$ are called variance components (Snijders and Roel, 1999).

An important extension of multilevel proportional odds model is ordinal multilevel non-proportional odds model, commonly used in conditions when there is noticeable doubt to suggest that the effect of some variables different across response categories (De Silva and Sooriyarachchi, 2012). As a result the cumulative proportion can be modeled as:

$$logit(\pi_{ir(j)}) = log\left(\frac{\pi_{ir(j)}}{1-\pi_{ir(j)}}\right) = \alpha_j - (\omega_j t_{ir} + X_{ir}\beta + Z_{ir}U_r) \qquad (3.14)$$

Where, t_{ir}= refers to variables having different effect across logits, ω_j = coefficients vary across logits, Z_{ir} = subset of X and T variables.

The Generalized linear latent and mixed model (GLLAMM) command of stata15 (Rabe-Hesketh and Skrondal, 2008) was used with the "thresh" option in order to relax the proportional odds assumption for one or more explanatory variables within the model and the "adapt" option helps to estimate the model by using adaptive quadrature (Rabe-Hesketh et al., 2004b).The GLLAMM stata command also used to fit the partial proportional random coefficients model by specifying the "*eqs slope"* option to include random slopes for one or more predictors (Skrondal, 2012). GLLAMM uses stata's maximum likelihood to maximize the likelihood (Rabe-Hesketh et al., 2004a).

3.3.2.7 Parameter Estimation for multilevel logistic regression

The most common methods for estimating multilevel logistic regression models are based on likelihood. Marginal Quasi likelihood (MQL) and Penalized Quasi likelihood (PQL) are approximate methods. For two Taylor series expansions, first and second order there are first and second order version for both methods (Rabe-Hesketh, 2003, Laird, 1978). After applying quasi likelihood methods, the model estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) (Snijders and Roel, 1999).

There are also other estimation methods like Maximum Likelihood Method (several simulation based) (McCulloch, 1997), Bayesian methods using Markov Chain Monte Carlo (MCMC). In general, PQL performs best when there are many observations per cluster (Rabe-Hesketh and Skrondal, 2004, Bellamy et al., 2005, Ten Have and Localio, 1999).

3.3.2.8 Significance Testing in Multilevel logistic Regression

As with logistic regression, we can consider significance tests for individual estimates, such as intercepts, slopes, and their variances, as well as whether the full model accounts for a significant amount of variance in the dependent variable (BAYKO, 2014).

Significance Testing for Fixed Effects

The fixed effects in multilevel regression are typically tested in a familiar way, by using a ratio of the intercept or slope estimate to the estimate of the standard error. The usual null hypothesis test is whether the coefficient, either intercept or slope, is significantly different from zero (i.e., is the population value zero or not). This kind of ratio, usually assumed to be distributed as a *z* or *t*, is used in many statistical tests (referred to as a "Wald" ratio) (Raudenbush and Bryk, 2002).

$$t = \frac{\hat{\beta}_h}{SE(\hat{\beta}_h)}$$

Where $\hat{\beta}_h$ is either the intercept or slope coefficient and SE ($\hat{\beta}_h$) is the standard error estimate.
In SPSS and STATA fixed effect tests involve the same ratio of the estimate to the standard error estimate, but significance is determined by the normal curve, so it is considered a z-test.
The z-test is often referred to as a "Wald" test.

Significance Testing for Random Effects

Individual random effects tests examine hypotheses about whether the variance for each random intercept or slope (and their covariance) are significantly different from zero. Software packages print these estimates under the "random effects" or "covariance tests" portion of the output.

The tests of variances and covariance are made using a Wald z-test and chi-square test. The Wald test for variances is simply a ratio of the variance estimate divided by the standard error estimate. one important precaution is that the significance tests for the intercept or slope variances (but not the covariance) should be interpreted after dividing the *p*-value from the output in half i.e., as a one-tailed test (Snijders and Roel, 1999).

3.3.2.9 Goodness of Fit Test for multilevel model

A goodness of fit test is a vital technique which is used to check the adequacy of a fitted model. It measures how well the fitted model describes the set of observations (Epasinghe and Sooriyarachchi, 2017).

The test compares the deviance (-2 log likelihood) from maximum likelihood procedure of two models by subtracting the smaller deviance (model with more parameters) from the larger deviance (model with lower parameters). The difference is a chi-square test with the number of degrees of freedom equal to the number of different parameters in the two models. Similarly, the overall model evaluation is also examined using Akaike Information Criteria (AIC) (Akaike, 1973) and Schwartz Information Criteria (BIC). The smaller the value, the better of the model will be fitted.

$$AIC = -2\ln(likelihood) + 2 \times k,\ BIC = -2\ln(likelihood) + \ln(N) \times k$$

Where k is model df (rank of variance–covariance matrix) and N is the number of observations used in estimation or, more precisely, the number of independent terms in the likelihood.

3.3.3 Statistical Software Packages

In this study, data were analyzed using STATA 15 with OLOGIT, MARGINS and GOLOGIT2 add-on command, SAS 9.2 and SPSS 20 then decision was made based on 0.05 level of significance.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Descriptive Statistics

This research was based on Ethiopian demographic and health survey (EDHS, 2016) data. A total sample of 1,053 pregnant women at the reproductive age (15-49) was included in this study from those 32 (3.04%) were severe anemic, 214(20.32%) were severe or moderate anemic and 395 (37.51%) were sever, moderate or mild anemic while among all pregnant women 658(62.49%) were non-anemic (Table 4.1, figure 4.1).

Table 4.1: proportions of anemia levels for pregnant women

Anemia levels	**Freq.**	**percent**	**Com. Percent**
Severe	32	3.04	3.04
Moderate	182	17.28	20.32
Mild	181	17.19	37.51
Non anemic	658	62.49	100

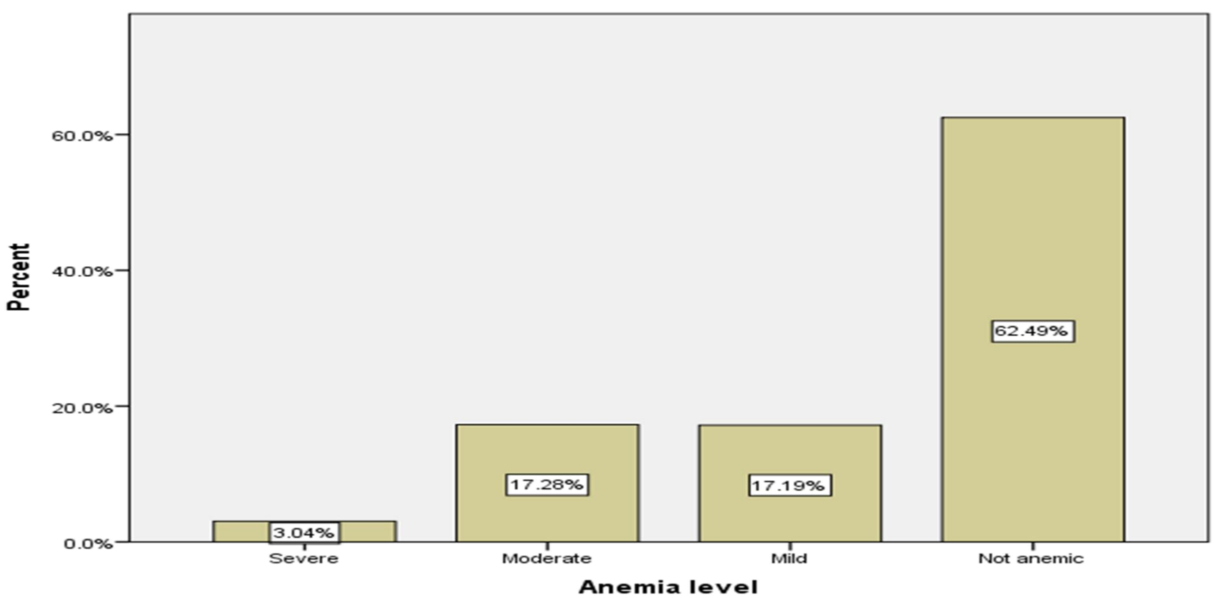


Figure 4.1: Bar graph of anemia levels of pregnant women using EDHS 2016 data

The prevalence of anemia levels of pregnant women among regions indicated that the proportions of severe anemia were 10.98%, 4.08%, 3.51% and 3.40% in pregnant women from Somali, Dire Dawa, Afar and Oromia respectively and in Tigray, Amhara, SNNPR, Gambela and Addis Ababa the proportion of severe anemia was lower than other regions (Table 4.2). The proportions of moderate anemia were indicated to be low in pregnant women from Addis Ababa (0.00%), Amhara (4.9%) and Tigray (7.59%) while these proportions were higher in Somali (38.73%), Afar (26.32%), Dire Dawa (22.45%) and Harari (20.55%) as compared with other regions. The percentages of mild anemia level for pregnant women from Harari (26.03%), Afar (24.56%) and Addis Ababa (20.00%) were found to be higher than other regions. Pregnant women from Amhara, Addis Ababa and Tigray had highest percentages of non-anemia by 84.31%, 80.00% and 78.48% respectively (Table 4.2).

Table 4.2: The distribution of anemia levels of pregnant women by regions

	Anemia level for pregnant women				
Variable	**Severe** Count (%)	**Moderate** Count (%)	**Mild** Count (%)	**Non anemic** Count (%)	**Total**
Region					
Tigray	0(0.00)	6(7.59)	11(13.92)	62(78.48)	79
Afar	4(3.51)	30(26.32)	28(24.56)	52(45.61)	114
Amhara	0(0.00)	5(4.90)	11(10.78)	86(84.31)	102
Oromia	5(3.40)	13(8.84)	29(19.73)	100(68.03)	147
Somali	19(10.98)	67(38.73)	28(16.18)	59(34.10)	173
Ben. Gumz	1(1.33)	11(14.67)	11(14.67)	52(69.33)	75
SNNPR	0(0.00)	15(11.03)	21(15.44)	100(73.53)	136
Gambela	0(0.00)	9(15.00)	8(13.33)	43(71.67)	60
Harari	1(1.37)	15(20.55)	19(26.03)	38(52.05)	73
Addis Ababa	0(0.00)	0(0.00)	9(20.00)	36(80.00)	45
Dire Dawa	2(4.08)	11(22.45)	6(12.24)	30(61.22)	49

The distribution of anemia levels among pregnant women by demographic and socio-economic characteristic is presented in table 4.3. Among a total of 1053 sampled pregnant women 705(66.9%) were from rural and the remaining were from urban area. The proportions of sever, moderate, mild and non-anemia among pregnant women who were from rural area are 4.4%, 21.42%, 20.71% and53.48% respectively. The proportions of sever, moderate and mild anemia were increased from urban pregnant women to rural pregnant women. About 80.75 percent of pregnant women from urban area were non-anemic while about 53.48 percent were from rural area. The proportions of both sever and moderate anemia levels for pregnant women were higher in the age group of above 40 but non-anemia proportion was higher in the age group 15-24. The proportion of severe anemia decreases when education level of pregnant women increases. Women who attained higher education were more non-anemic while the proportion of non-anemia was small for pregnant women who attained primary education. Pregnant women from poorest household were developed higher proportions of severe, moderate and mild anemia.

Anemia levels of pregnant women were varied according to number of antenatal care visits, the proportion of severe, moderate and mild anemia for pregnant women who didn't visit/don't know were higher than visiting women. The proportions of severe and moderate anemia levels were decreased as the number of antenatal care visits of pregnant women increased while the proportion of non-anemic increased with the number of antenatal care visit. The proportion of anemia levels among pregnant women were varied according to total number of children ever born (parity), pregnant women who had no child were developed lower proportion of severe, moderate and mild anemia levels than pregnant women who had one/ more children. The proportions of severe, moderate and mild anemia levels were increased with total number of children ever born but the proportion of non-anemia decreased. Pregnant women who had more number of births in last five years were developed higher proportions of sever, moderate and mild anemia. As the number of births within last five years for pregnant women increased, the proportion of non-anemia decreased from 90.83% in no birth to 28.31% in above two births.

The proportion of moderate anemia was higher in smoker pregnant women than nonsmokers and from smoker pregnant women 61.54% were non-anemic while it is about 62.5% in nonsmokers. Anemia distributions were varied according to occupation type of pregnant women; higher proportions of severe, moderate and mild anemia were observed in nonworking pregnant women but had lower proportion of non-anemia than pregnant women who had occupation agricultural and non-agricultural. Pregnant women don't know/didn't visit health facility in last 12 months had higher proportions of severe and moderate anemia but had lower proportion of non-anemia than pregnant women who visited health facility in last 12 months. Among unmarried pregnant women 70.73% were non- anemic and the percentage of non-anemia in married pregnant women was 62.15%.The percentages of severe, moderate and mild anemia were higher in pregnant women who didn't take iron but had lower proportion of non-anemia than pregnant women who took iron pills (Table 4.3).

Table 4.3: Distribution of anemia levels by socioeconomic and demographic variables

Variables	Severe Count (%)	Moderate Count (%)	Mild Count (%)	Non anemic Count (%)	Total
Age groups					
15-24	14(3.64)	64(16.62)	62(16.10)	245(63.64)	385
25-34	12(2.40)	92(18.12)	84(16.7)	315(62.62)	503
35-39	4(3.45)	17(14.66)	26(22.41)	69(59.48)	116
Above 40	2(4.08)	9(18.37)	9(18.37)	29(59.18)	49
Residence					
Urban	1(0.29)	31(8.91)	35(10.06)	281(80.75)	348
Rural	31(4.40)	151(21.42)	146(20.71)	377(53.48)	705
Educ. Level					
No education	25(5.06)	124(25.10)	88(17.81)	257(52.02)	494
Primary	7(3.80)	42(22.83)	56(30.43)	79(42.93)	184
Secondary	0(0.00)	8(3.52)	30(13.22)	189(83.26)	227
Higher	0(0.00)	8(5.41)	7(4.73)	133(89.86)	148
Wealth index					
poorest	24(6.33)	94(24.8)	72(19.00)	189(49.87)	379
Poorer	3(1.68)	34(18.99)	25(13.97)	117(65.36)	179
Middle	1(0.71)	17(12.06)	23(16.31)	100(70.92)	141
Richer	2(1.54)	15(11.54)	24(18.46)	89(68.46)	130
Richest	2(0.89)	22(9.82)	37(16.52)	163(72.77)	224
Antenatal visit					
No /don't know	23(5.09)	106(23.45)	73(16.15)	250(55.31)	452
1-3	8(2.50)	48(15.00)	64(20.00)	200(62.5)	320
Above 4	1(0.36)	28(9.96)	44(15.66)	208(74.02)	281
Religion					
Orthodox	1(0.36)	20(7.22)	37(13.36)	219(79.06)	277
Muslim	28(4.84)	140(24.22)	111(19.20)	299(51.73)	578
Others	3(1.52)	22(11.11)	33(16.67)	140(70.71)	198
Parity					
No child	1(0.38)	11(4.23)	13(5.00)	235(90.38)	260
1-2	3(1.06)	26(9.19)	44(15.55)	210(74.20)	283
3-5	6(2.29)	49(18.70)	42(16.03)	165(62.98)	262
Above 6	22(8.87)	96(38.71)	82(33.06)	48(19.35)	248
Birth in 5 years					
No birth	1(0.29)	10(2.87)	21(6.02)	317(90.83)	349
One birth	5(1.32)	54(14.25)	71(18.73)	249(65.70)	379
Above 2 birth	26(8.00)	118(36.31)	89(27.38)	92(28.31)	325

Smoking status					
No	32(3.08)	179(17.21)	179(17.21)	650(62.50)	1040
Yes	0(0.00)	3(23.08)	2(15.38)	8(61.54)	13
Occupation					
Not working	28(4.40)	121(19.00)	115(18.05)	373(58.56)	637
Agricultural	1(0.51)	26(13.33)	33(16.92)	135(69.23)	195
Non agricultural	3(1.36)	35(15.84)	33(14.93)	150(67.87)	221
Visithealthfac12mo					
No /don't know	22(4.64)	92(19.41)	76(16.03)	284(59.92)	474
Yes	10(1.73)	90(15.54)	105(18.13)	374(64.59)	579
Marital status					
Unmarried	3(7.32)	4(9.76)	5(12.20)	29(70.73)	41
Married	29(2.87)	178(17.59)	176(17.39)	629(62.15)	1012
Iron taking status					
No /don't know	31(4.37)	168(23.66)	146(20.56)	365(51.41)	710
Yes	1(0.29)	14(4.08)	32(10.20)	293(85.42)	343

Depending on vitamin A taking status of pregnant women the proportion of anemia levels were found to be different; 256(24.3%)were don't know/didn't take vitamin A, 205(19.47%) were took vitamin A but 592(56.22%) were missing as their vitamin A taking status was incomplete. The proportion of non-anemia for pregnant women who took vitamin A were 60.49% and for those didn't took vitamin A were 56.25% while from pregnant women with missing vitamin A taking status, 65.88% were non-anemic. Because of this missingness issue this variable was excluded from the analysis in this study (table 4.4).

Table 4.4: The distribution of anemia levels by vitamin A taking status

Variable	**Anemia level of pregnant women** Severe Count (%)	Moderate count (%)	Mild count (%)	Non anemic count (%)	Total
Receive vitamin A					
No/don't know	9(3.52)	58(22.66)	45(17.58)	144(56.25)	256
Yes	9(4.39)	35(17.07)	37(18.05)	124(60.49)	205
Missing	14(2.36)	89(15.03)	99(16.72)	390(65.88)	592

4.2 Results of Ordinal Logistic Regression Model

As indicated by different number of literatures (Abiselvi et al., 2018, Worku Takele et al., 2018, Derso et al., 2017, Perumal, 2014),the predictors like educational level of women, taking iron pills, place of residence, region, parity (total number of children ever born), age groups of women, number of birth in last 5 years, occupation type, visit health center, wealth index, smoking status, antenatal care visits and marital status have relationship with anemia levels. Before running logistic regression model to analyze the data the association of anemia level with all explanatory variables was checked by using chi-square test of association. As a result all predictors were found to be significantly associated with anemia levels at 0.15 significant (Table A2), then all explanatory variables are entered to the analysis.

The proportional odds model was fitted using OLOGIT add-on command in STATA 15 from 1053 pregnant women who fulfill the inclusion criterion. Among different factors considered in this study educational level, region, residence type, parity, birth in last five years, antenatal visit, wealth index, iron take and visit health facility in last 12 months were found to be significantly associated factors for anemia level (Table A3).The goodness of fit tests supported that the model well fit the data as indicated by insignificant p values for both tests. Fitting POM perform test of proportionality assumption by using score test which indicated that the violation of the assumption. In addition, the model proportionality assumption can be tested using parallel line test also confirmed that the violation of this assumption (Table A3).

As the POM assumption was violated, the PPOM and GOM relax the some and all of predictors respectively. Therefore, in order to overcome this problem the PPOM was used (Williams, 2006b) and it provided a good alternative model. The continuation ratio model (CRM) and adjacent category logit model (ACM) also conducted and compared with POM and PPOM.

4.3 Results of Test of Overall Model Fit

Table 4.5 below depicted the statistic of the goodness-of-fit for five models

Table 4.5: AIC, BIC and Pseudo R2 for all five ordinal models

Model	**Obs**	**DF**	**AIC**	**BIC**	**Pseudo R^2**
POM	1,053	39	1462.679	1656.095	0.3465
PPOM	1,053	51	1426.994	1619.924	0.3746
GOM	1,053	110	1479.272	2024.805	0.4057
CRM	1,053	63	1562.733	1875.176	0.3432
ACM	1,053	84	1478.135	1894.725	0.3817

Key: Prob > chi2 = 0.0000 for all models

All models were significant in the final fit relative to their intercept only model as indicated by significant deviance LR test. A model with small value of AIC/BIC was considered as good model and preferable. PPOM has smallest AIC and BIC values those are 1426.994 and 1619.924 respectively than the others. The pseudoR^2value for PPOM is 0.3746, suggesting that there is 37.46% relationship between, anemia level for pregnant women and predictors (Table 4.5).

PPOM is a series of binary logit models estimated simultaneously and to conduct the model goodness of fit test all logits separately fitted for each binary model. For ordinal dependent variable with J categories there are J-1 binary models to conduct series of comparisons. In this study the response variable has four categories and there are three possible binary comparisons: severe anemia Vs moderate, mild or non-anemic denoted by (Bin (1)), severe anemia or moderate anemia Vs mild anemia or non-anemic denoted by (Bin (2)) and severe, moderate or mild anemia Vs non-anemic denoted by (Bin (3)).

The Hosmer- Lemeshow goodness of fit test used after fitting the above three separate binary models (Bin (1), Bin (2) and Bin (3)). Insignificant Hosmer-Lemeshow test results indicated that all binary models were fitted well (Table 4.6). As a result the partial proportional odds model also well fitted the data.

Table 4.6: Hosmer and Lemeshow goodness- of- fit test for the three binary models

	Hosmer-Lemeshow test		
	Chi-square	**Df**	**Sig**.
Bin(1)	2.115	8	0.977
Bin(2)	14.256	8	0.076
Bin(3)	6.901	8	0.547

4.4. Results of Partial Proportional Odds Model (PPOM)

The STATA user written command GOLOGIT2 with AUTOFIT option was fitted the partial proportional odds model. In this model constraints of parallel line impose for some variables to meet the assumption while others like residence, education and parity were not. PPOM used a series of Wald tests to check the assumption of proportionality for the categories of all explanatory variables.

For the final model with the unconstrained model versus constrained a global Wald test is performed. According to this global Wald test the final model does meet the proportional odds assumption as its chi-square statistic equal to 45.63 with 60 df and p-value of 0.915.

Table 4.7 revealed results of the parameter estimates for the PPOM model

Table 4.7: Parameter estimates of PPOM

Predictors		Severe				Moderate				Mild			
		Coef.	p-value	OR	95%CI	Coef.	P-value	OR	95%CI	Coef.	P-value	OR	95%CI
Region (Ref:Tigray)	Afar	-0.805	0.004	0.447	0.208-0.961	-0.805	0.004	0.447	0.208-0.961	-0.805	0.004	0.447	0.208-0.961
	Amhara	0.3003	0.526	1.351	0.534-3.415	0.3003	0.526	1.350	0.534- 3.414	0.3003	0.526	1.350	0.534- 3.415
	Oromia	-1.4192	0.030	0.242	0.067- 0.875	0.2764	0.58	1.318	0.496- 3.508	-0.0231	0.961	0.977	0.387 -2.465
	Somali	-1.5677	0.001	0.209	0.080- 0.544	-1.5677	0.001	0.209	0.080-0.543	-1.5677	0.001	0.209	0.080- 0.544
	Benishangul	-0.2498	0.611	0.779	0.297- 2.040	-0.2498	0.611	0.779	0.297- 2.04	-0.2498	0.611	0.779	0.297- 2.040
	SNNP	0.3715	0.434	1.450	0.572- 3.674	0.3715	0.434	1.449	0.572-3.674	0.3715	0.434	1.449	0.572- 3.674
	Gambela	-0.3953	0.466	0.673	0.233- 1.949	-0.3953	0.466	0.673	0.233- 1.949	-0.3953	0.466	0.673	0.233-1.949
	Harari	-0.7337	0.158	0.480	0.174- 1.329	-0.7337	0.158	0.480	0.174-1.329	-0.7337	0.158	0.480	0.174-1.33
	Addis Ababa	-0.6742	0.268	0.510	0.155- 1.679	-0.6742	0.268	0.510	0.155- 1.679	-0.6742	0.268	0.510	0.155-1.679
	Dire Dawa	-1.4482	0.011	0.235	0.077-0.713	-1.4482	0.011	0.235	0.077- 0.713	-1.4482	0.011	0.235	0.077-0.713
Educational Level (Ref:no education)	Primary	-0.1539	0.746	0.857	0.338 -2.174	-0.1566	0.531	0.855	0.524- 1.40	-1.0698	0.000	0.343	0.208-0.567
	Secondary	0.594	0.243	1.81	0.668 -4.898	1.901	0.000	6.692	2.85-15.69	0.6843	0.013	1.982	1.15-3.407
	Higher	1.56	0.000	4.746	2.288- 9.847	1.56	0.000	4.75	2.28- 9.847	1.5574	0.000	4.746	2.288- 9.847
Iron take(ref: no)	Yes	1.304	0.000	3.685	2.407- 5.642	1.304	0.000	3.685	2.406- 5.64	1.304	0.000	3.685	2.407- 5.64
Residence (ref: urban)	Rural	-2.401	0.021	0.091	0.012-0.701	-0.9105	0.003	0.402	0.220-0.736	-1.5574	0.000	0.211	0.121-0.368
Parity (TNCEB) (Ref: no)	1-2	-0.7459	0.013	0.474	0.264- 0.852	-0.7459	0.013	0.474	0.264-0.852	-0.7459	0.013	0.474	0.264-0.852
	3-5	-1.1764	0.000	0.308	0.172- 0.553	-1.1764	0.000	0.308	0.172-0.553	-1.1764	0.000	0.308	0.172-0 .553
	Above 6	-1.9852	0.000	0.137	0.055-0.345	-2.1059	0.000	0.122	0.066-0.225	-3.2486	0.000	0.039	0.020-0.074
Age group (Ref:15-24)	25-34	0.1075	0.541	1.113	0.789-1.57	0.1075	0.541	1.113	0.789-1.57	0.1075	0.541	1.113	0.789-1.57
	35-39	-0.4709	0.080	0.624	0.368-1.058	-0.4709	0.080	0.624	0.368-1.058	-0.4709	0.080	0.624	0.368-1.058
	Above 40	-0.0146	0.968	0.986	0.479-2.026	-0.0146	0.968	0.986	0.479-2.026	-0.0146	0.968	0.986	0.479-2.026
Births in last5 years Ref:No birth	1 Birth	-1.523	0.000	0.218	0.129- 0.370	-1.523	0.000	0.218	0.128-0.370	-1.523	0.000	0.218	0.129-0.370
	Above	-2.391	0.000	0.092	0.054-0.155	-2.391	0.000	0.092	0.054-0.155	-2.391	0.000	0.092	0.054-0.155

	2birth												
Occupation (Ref:notworking)	Agricultural	0.171	0.475	1.187	0.742-1.899	0.1712	0.475	1.187	0.742-1.899	0.1712	0.475	1.187	0.742-1.899
	Non Agricultural	-0.089	0.689	0.915	0.591-1.415	-0.0891	0.689	0.915	0.591-1.415	-0.0891	0.689	0.915	0.591-1.415
Wealth Index (Ref:poorest)	Poorer	1.003	0.133	2.727	0.735-10.11	-0.2648	0.375	0.767	0.428-1.378	0.2438	0.397	1.276	0.726- 2.242
	Middle	0.232	0.421	1.261	0.717-2.220	0.2321	0.421	1.261	0.717-2.219	0.2321	0.421	1.261	0.717- 2.220
	Richer	0.0551	0.853	1.057	0.590-1.892	0.0551	0.853	1.057	0.590-1.892	0.0551	0.853	1.057	0.590-1.892
	Richest	0.7331	0.033	2.08	1.061-4.084	0.7331	0.033	2.08	1.061-4.084	0.7331	0.033	2.08	1.061-4.084
Smoking (Ref:No)	Yes	-0.4244	0.551	0.654	0.162-2.638	-0.4244	0.551	0.654	0.162-2.638	-0.4244	0.551	0.654	0.162-2.638
Antenatal Visits (Ref:no)	1-3	0.1477	0.458	1.160	0.785-1.712	0.1477	0.458	1.159	0.784- 1.711	0.1477	0.458	1.159	0.785- 1.712
	Above 4	0.4582	0.036	1.581	1.029 -2.429	0.4582	0.036	1.581	1.029- 2.429	0.4582	0.036	1.581	1.029-2.429
Marital sta. (Ref:unmarried)	Married	0.4181	0.369	1.519	0.610-3.783	0.4181	0.369	1.519	0.610-3.783	0.4181	0.369	1.519	0.610-3.783
Visit health Facility in 12 months	Yes	0.3998	0.022	1.49	1.059-2.102	0.3998	0.022	1.49	1.059-2.102	0.3998	0.022	1.49	1.059-2.102
Religion (Ref:orthodox)	Muslim	0.084	0.792	1.088	0.582-2.032	0.084	0.792	1.088	0.582-2.032	0.084	0.792	1.088	0.582-2.032
	Others	0.064	0.849	1.066	0.553-2.053	0.064	0.849	1.066	0.553-2.053	0.064	0.849	1.066	0.553-2.053
	-cons	8.8723	0.000			4.6828	0.000			4.188	0.000		

Key: LR chi2 (48) = 793.78 Prob > chi2 = 0.0000 Pseudo R2 = 0.3746

4.5 Marginal Effects

Average marginal probability effect indicated the effect of explanatory variables on single level of anemia. The coefficients sign does not always determine the direction of the effect of intermediate outcomes in PPOM (Washington et al., 2003). Table 4.8 presents the average marginal probability effects of predictors on anemia levels.

Table 4.8: Average marginal probability effects (AMPE) of predictors on anemia levels

Predictors		Severe		Moderate		Mild		Non anemic	
		MPE1	P-value	MPE2	P-value	MPE3	P-value	MPE4	P-value
Region	Afar	0.0133	0.015	0.0678	0.000	0.0102	0.020	-0.0913	0.038
	Amhara	-0.0031	0.539	-0.0224	0.526	-0.0064	0.531	0.0319	0.526
	Oromia	0.031	0.079	-0.0544	0.155	0.0259	0.390	-0.0025	0.961
	Somali	0.0366	0.001	0.135	0.001	0.0109	0.000	-0.1825	0.001
	Benishangul	0.0032	0.607	0.0200	0.609	0.0043	0.627	-0.0275	0.610
	SNNPE	-0.0036	0.473	-0.0273	0.440	-0.008	0.421	0.0393	0.436
	Gambela	0.0054	0.479	0.0322	0.467	0.0063	0.486	-0.0439	0.466
	Harari	0.117	0.157	0.0616	0.154	-0.095	0.278	-0.0836	0.157
	AddisAbaba	0.0105	0.345	0.056	0.273	0.0092	0.293	-0.076	0.271
	Dire Dawa	0.0320	0.037	0.125	0.010	0.0112	0.004	-0.168	0.010
Educational Level	Primary	.0048	0.753	0.013	0.645	-0.014	0.000	0.0316	0.000
	Secondary	-0.0346	0.000	-0.1236	0.000	-0.081	0.009	0.0773	0.012
	Higher	-0.0262	0.000	-0.1114	0.000	-0.0254	0.020	0.1630	0.000
Iron take	Yes	-0.0234	0.000	-0.093	0.000	-0.026	0.001	0.143	0.000
Residence	Rural	0.0345	0.000	0.0486	0.059	0.0832	0.000	-0.1663	0.000
Parity (TNCEB)	1-2	0.0082	0.034	0.0503	0.009	0.03	0.020	-0.0885	0.010
	3-5	0.0159	0.004	0.0846	0.000	0.044	0.001	-0.1445	0.000
	Above 6	0.0401	0.000	0.1695	0.000	0.2165	0.000	-0.4261	0.000
Births in last 5 years	1 Birth	0.0151	0.000	0.1008	0.000	0.054	0.000	-0.1699	0.000
	Above2birth	0.0376	0.000	0.1800	0.000	0.0682	0.000	-0.2858	0.000

Wealth Index	Poorer	-0.0203	0.053	0.0450	0.097	-0.0500	0.045	0.0253	0.397
	Middle	-0.0062	0.402	-0.0144	0.428	-0.0036	0.444	0.0241	0.421
	Richer	-0.0015	0.851	-0.0034	0.854	-0.0008	0.854	0.0058	0.853
	Richest	0.0266	0.074	-0.045	0.021	-0.0075	0.064	0.0789	0.029
Antenatal Visits	1-3	-0.0039	0.451	-0.0104	0.461	-0.002	0.482	0.0164	0.458
	Above 4	-0.011	0.029	-0.0322	0.041	-0.006	0.101	0.049	0.037
Visit health Facility in last12month	Yes	-0.0107	0.032	-0.0268	0.020	0.0044	0.070	0.0419	0.020

Pregnant women from Somali and Dire Dawa were more likely to be moderate anemic by 13.5 and 12.5 percent and they were also more likely to be severe anemic by 3.66 and 3.2 percent respectively as compared to pregnant women from Tigray. The estimated average marginal probability effect to be non-anemic for pregnant women from Somali and Dire Dawa are significantly negative indicated that they were 18.25 and 16.8 percent less likely to be non-anemic respectively as compared to pregnant women from Tigray. There were 1.09 and 1.12 percent more likely to be mild anemic for pregnant women from Somali and Dire Dawa respectively as compared to pregnant women from Tigray. Pregnant women from Afar were 1.33, 6.78 and 1.02 percent more likely to be severe, moderate and mild anemic respectively as compared with pregnant women from Tigray (Table 4.8).

Pregnant Women who completed secondary and higher education were 12.36 and 11.14 percent less likely to be moderate anemic respectively as compared to non-educated pregnant women. Pregnant women who completed primary, secondary and higher education were3.16, 7.73 and 16.3 percent more likely to be non-anemic respectively relative to non-educated women. Completing primary school have no any effect to be sever anemic but women who completed secondary and higher education were 3.46 and 2.62 percent less likely to be severe anemic respectively as compared to non-educated pregnant women. Being mild anemic was 2.54, 8.1 and 1.4 percentage points less likely in pregnant women who completed higher, secondary and primary education respectively relative to non-educated pregnant women. Taking iron pills in pregnant women approximately decreased the estimated probability of being severe, moderate and mild anemic by 2.4, 9.3, and 2.6 percentage points respectively relative to pregnant women who didn’t take iron. Being non-anemic in pregnant women who took iron was increased by 14.3

percent than pregnant women who didn't take iron. Rural pregnant women were 3.45, 4.86 and 8.32 percentage points more likely to be severe, moderate and mild anemic respectively and 16.6% less likely to be non-anemic as compared to pregnant women from urban area.

Pregnant women who had 1-2, 3-5 and 6 or above children were 5.03, 8.46 and 16.95 percentage points more likely to be moderate anemic respectively as compared with pregnant women who had no child. Severe anemia in pregnant women who had 1-2, 3-5 and above 6 children was 0.82%, 1.59% and 4.01% more likely than pregnant women who had no child. The marginal probability effects to be non-anemic for pregnant women who had total number of children 1-2, 3-5 and above 6 are negative, indicated that pregnant women who had 1-2, 3-5 and above 6 children were 8.85, 14.45 and 42.61 percentage points less likely to be non-anemic respectively as compared to pregnant women who had no child. Pregnant women from richest household were 4.5% less likely to be moderate anemic and 7.89% more likely to be non-anemic than pregnant women from poorest household.

Pregnant women who had one birth and two or more births in last five years were 10.08% and 18.00% more likely to be moderate anemic respectively as compared with pregnant women who had no birth. Pregnant women who had one and two or more births within last five years were 1.51% and 3.76% more likely to be severe anemic and also they were 16.99% and 28.58% less likely to be non-anemic respectively as compared to pregnant women who had no birth. Pregnant women who visited antenatal care 4 or more times were 1.1%, 3.22% and 0.6% less likely to be severe, moderate and mild anemic respectively when compared with pregnant women who were not visit antenatal care. Visiting antenatal care 4 or more times increased the average marginal probability of being non-anemic by 4.9% as compared to pregnant women didn't visit antenatal care.

Pregnant women who visited health facility in last 12 months were 1.07 and 2.68 percentage points less likely to be severe and moderate anemic respectively as compared to pregnant women who were not visit health facility. Being non- anemic was more likely in pregnant women who visited health facility by 4.19% as compared with pregnant women who were not visit health facility (Table 4.8).

4.6 Model Adequacy Checking

As stated in model diagnostics section the binary response predicted probability value versus other statistic was used to model adequacy checking and each plot depicted the adequacy of the model assumptions.

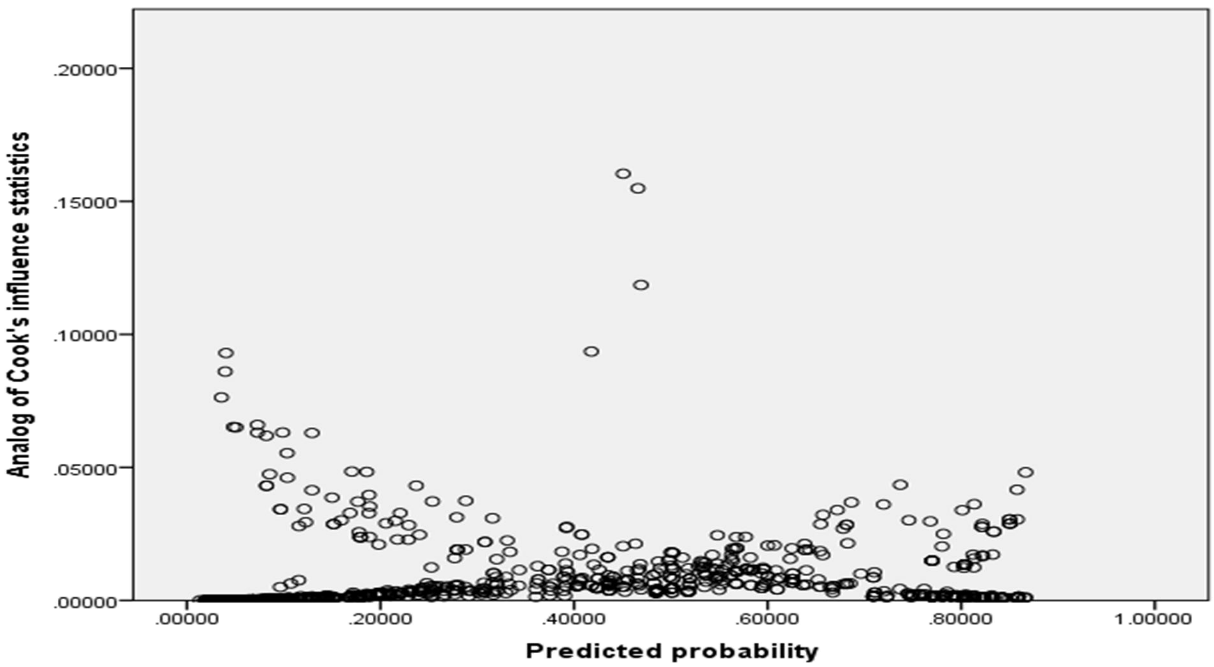


Figure 4.2: Plots of Analog of Cook's influence statistics Vs predicted probabilities

Figure 4.2 is a plot for all observations of analog of cook's influence Vs predicted probabilities and there are observations a little far away from the anthers. The model is adequate as all influence statistics are less than one (on the Y-axis).

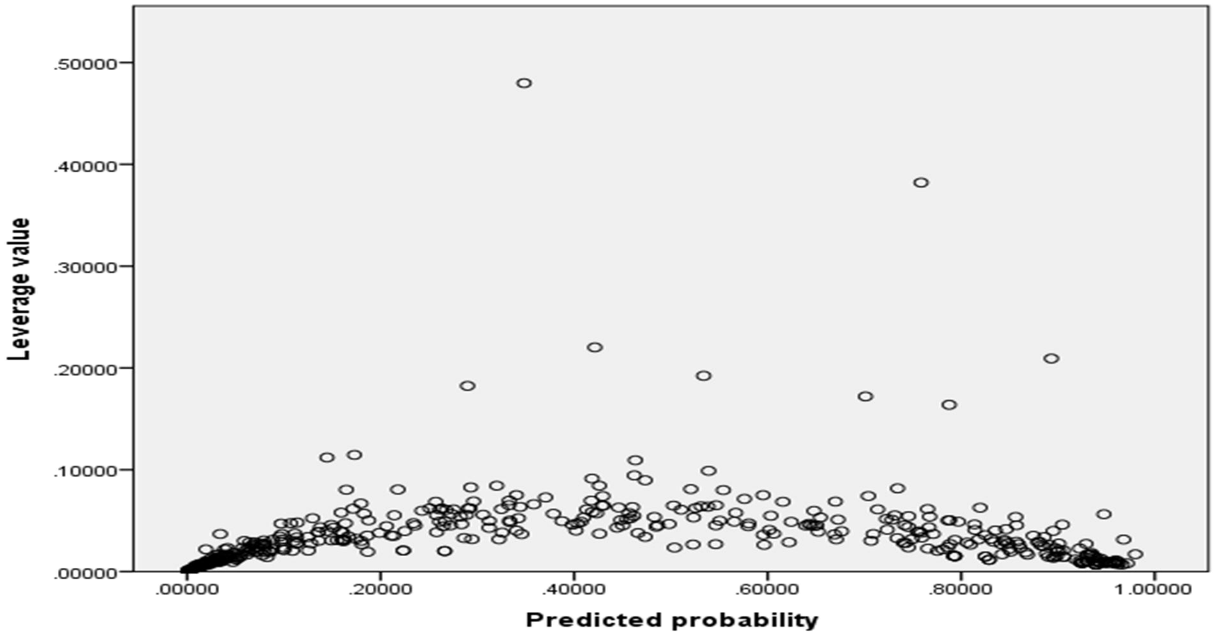


Figure 4.3: plot of leverage value versus predicted probability

The plot of all observation leverage values versus probabilities presented by figure 4.3. In the plot all leverage values are below one indicated that the adequacy of the model (on the Y-axis).

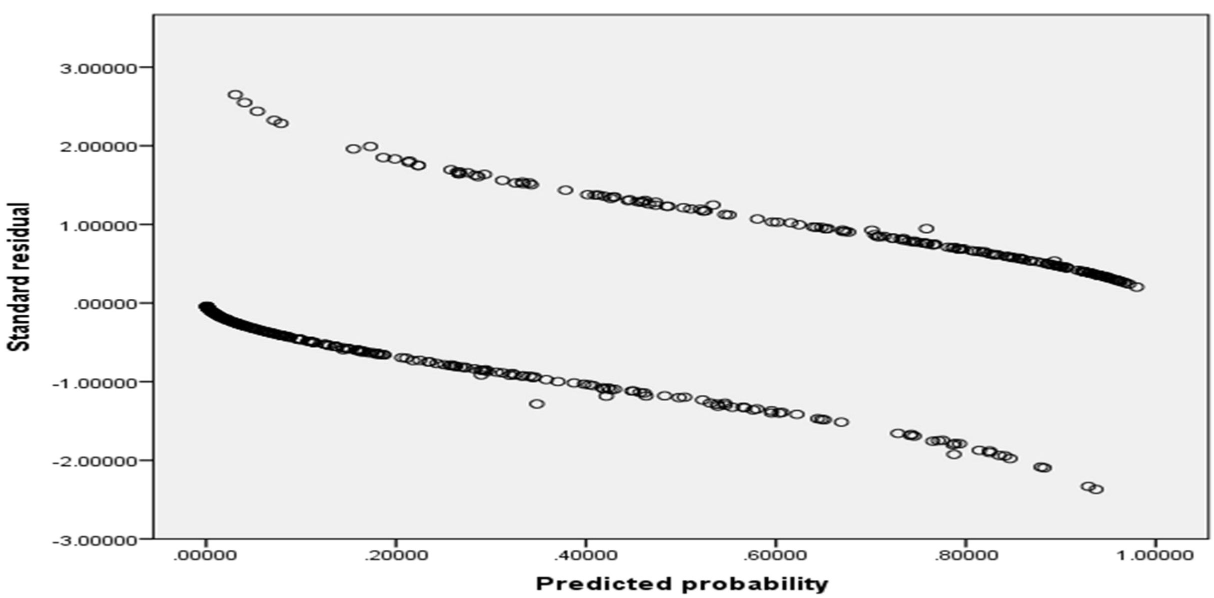


Figure 4.4: Plot of standard residual versus predicted probability

Figure 4.4 indicated the plot of standard residual versus predicted probabilities of all observations and few of them are far from the others. As all standard residuals are less than three in absolute value they do not influence the model and there is no lack of fit (on Y-axis).

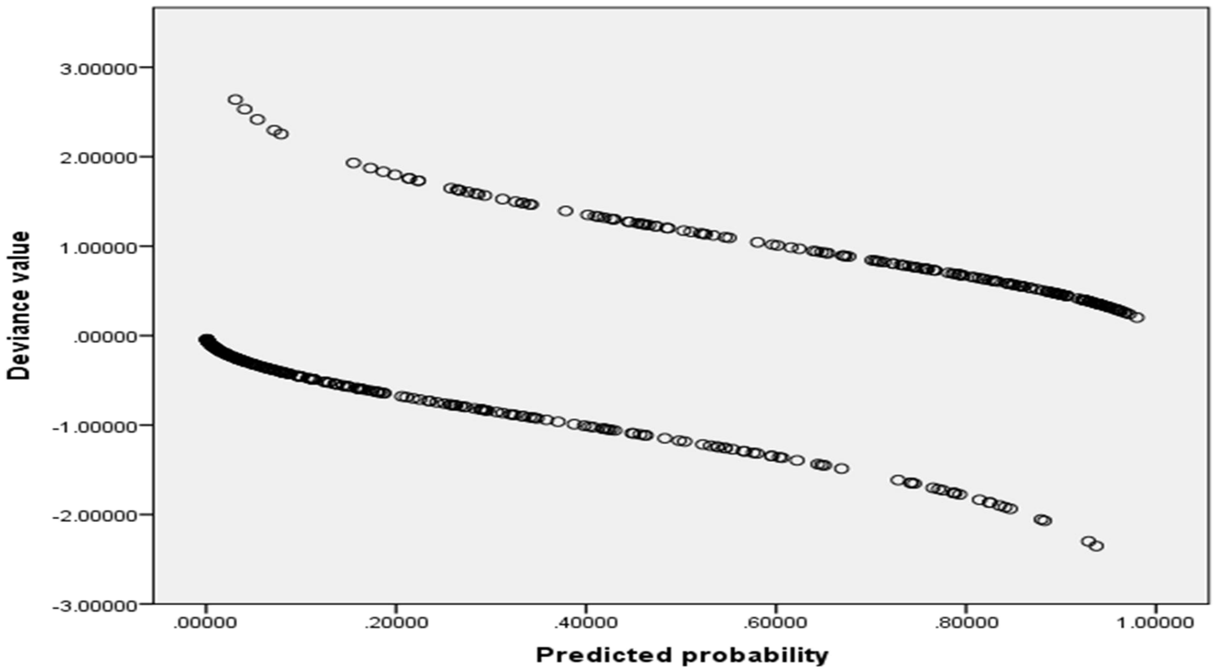


Figure 4.5: plot of deviance value versus predicted probability

From figure 4.5 there were few observations away from the others but all absolute deviance residuals were below three, indicated that there is no luck of fit.

DFBETA(S) plots of explanatory variables with predicted probabilities shows that the DFBETA(S) of the variables are all bellow one indicated that no stern problem in the final model (figures A1-A9).

4.7 Results of Multilevel Ordered Logistic Regression Models

The (EDHS, 2016) data used in this study have hierarchical structure. Pregnant women are nested within regions of Ethiopia. In this study, two level structures used regions as second level units and individual pregnant women were first level units. Multilevel models were used in order to explore between regions variation (variance) of anemia levels of pregnant women, in a set of 11 regions there are a total of 1,053 pregnant women.

4.7.1 Test of Heterogeneity

The heterogeneity proportion between regions was tested to conduct a meaningful multilevel analysis. The chi-square value used to test this heterogeneity between regions was$x^2 = 192.99$ with d.f =30 and p = 0.000.Thus, there is evidence of heterogeneity in anemia levels of pregnant women among regions.

4.7.2 Null Model

The null model/ intercept only model was fitted without any predictors and used to estimate the overall cumulative probabilities at/below a particular category of the variability between groups. Thus, here in this study regions were used as a second group to estimate the variability between them.

Table 4.9: Results of null model for anemia levels

	Coef	Std. error	z-value	p-value	95% CI
Fixed part					
Cons-1(S)	-3.888	0.281	-13.84	<0.0001	(-4.451,-3.33)
Cons-2(S+M)	-1.64	0.232	-7.06	<0.0001	(-2.093, -1.186)
Cons-3(S+M+Mi)	-0.672	0.223	-3.013	<0.0001	(-1.115, -.2298)
Random part					
Region Var(cons)	0.531	0.232			(0.199, 1.249)

LRchibar2 (01) = 123.26 p < 0.0001 Log likelihood = -997.7598 ICC = 0.1364

S= Severe M= Moderate Mi= Mild

As indicated in Table 4.9 above, the estimation contains two parts those are the fixed effect part and the variance components of random effects of the model. From the table we can see that the fixed part estimates (constants) of the model are -3.888, -1.640 and -0.672 with p-values of <0.0001, implies that the average log odds of anemia levels for pregnant women are significantly different from zero. The fixed part of the model can be interpreted as the overall means of the log odds of severe anemic, severe or moderate anemic and severe or moderate or mild anemic with the odds of exp (-3.888), exp (-1.640) and exp (-0.672) respectively and the corresponding average probabilities are $\frac{e^{-3.888}}{1+e^{-3.888}} = 0.0218$, $\frac{e^{-1.64}}{1+e^{-1.64}} = 0.1625$ *and* $\frac{e^{-0.672}}{1+e^{-0.672}} = 0.3381$, which means that on average the chance of being severe anemic, sever or moderate anemic and sever, moderate or mild anemic were 2.18%, 16.25% and 33.81% respectively. The random effect variance component separated from the constants. As a result of no random variables included in to the model only the between region variance is reported. The between region variance var (cons) is 0.531, which is the intercept variance across all regions. The ratio of intercept variance to its standard error is 2.52, larger than two which indicates that the between region variance is differ from zero. The significant log likelihood ratio test ($p < 0.0001$) suggested that the between region variance is significant or there is evidence of heterogeneity of anemia level across regions for pregnant women and it also indicates that the empty model with random effect for anemia levels is better than the empty model without random effect for anemia levels of pregnant women.

The null model with random effect helps to obtain variation between regions using intra class correlation coefficient (ICC). For this model ICC is equal to 0.1364 showed that 13.64% of the total variation in anemia levels explained or accounted by level two units (regions) reveals that multilevel ordinal logistic regression is appropriate model and the remaining 86.36% of the variation in anemia levels for pregnant women is explained by lower level units within regions.

4.7.3 Goodness of Fit and Model Selection Criteria

In multilevel logistic regression the overall goodness of fit test was done using the deviance. AIC and BIC also used to assessed the model. Based on Table 4.9random intercept partial proportional odds model have significant deviance and the values of AIC and BIC are less than the values obtained from null, random intercept PO, random coefficient PO and random coefficient PPO Model. Finally we conclude that the model is good fit.

As the proportionality/parallel line assumption was not satisfied there is a difference between the coefficients in dichotomization of the dependent variable. Violation of this assumption was indicated by the significant test result using score test(χ^2: $472.61, p$: $< .0001$). Following the finding of the proportional odds assumption test, multilevel partial proportional odds models were carried out(Kern, 2014). The intercept only model in multilevel proportional odds and multilevel partial proportional odds is the same because there are no predictors vary their coefficients across cut point equations.

Table 4.10: Model selection criteria and LR test

	Null model	Random inter. POM	Random Coef. POM	Random intr. PPOM	Random Coef. PPOM
AIC	2003.5	1462.7	1464.89	1448.7	1459.3
BIC	2023.4	1656.1	1573.998	1566.9	1677.5
LL	-997.8	-692.4	-710.4	-680.4	-685.6
Deviance	1995.6	1384.8	1420.8	1360.8	1371.2

In table 4.10 the null model, random intercept proportional odds model, random coefficient proportional odds model, random intercept partial proportional odds model and random coefficient partial proportional odds model are compered by using deviance and IC values. The random intercept partial proportional odds model has the smallest deviance value(1360.8) indicated that the smaller the deviance the better the model.

Additionally, both AIC/BIC values were 1448.7 and 1566.9 for random intercept partial proportional odds model were smaller than the others, supported that the model better fit the data.

4.7.4 Results of random Intercept Partial Proportional Odds Model

In random intercept partial proportional odds model, predictors are included but none of them have region specific effect on the response and the effect of each covariate is the same in all regions. Predictors in level one are fixed across regions but the probabilities of anemia level are allowed to vary across regions. Table 4.11 present the results of random intercept partial proportional odds model.

Table 4.11: Results of Parameter estimate of Random Intercept PPO Model

Variables satisfying proportional odds assumption					
Predictors	Categories	Coef.	p-value	OR	95%CI
Iron take (Ref: No)	Yes	1.311	0.000	3.71	(2.431-5.657)
Age group (Ref:15-24)	25-34	0.089	0.605	1.093	(0.778,1.538)
	35-39	-0.445	0.094	0.641	(0.380,1.079)
	Above 40	-0.061	0.867	0.941	(0.458,1.930)
Birth in 5 years (Ref:nobirth)	One birth	-1.508	0.000	0.221	(0.131,0.374)
	Above 2 birth	-2.410	0.000	0.089	(0.053,0 .152)
Occupation(Ref: no working)	Agricultural	0.265	0.260	1.303	(0.822,2.065)
	Nonagricultural	-0.086	0.694	0.917	(0.596,1.411)
Wealth index(Ref:poorest)	Poorer	0.213	0.395	1.237	(0.757,2.022)
	Middle	0.352	0.212	1.422	(0.818,2.471)
	Richer	0.212	0.474	1.237	(0.692,2.210)
	Richest	0.752	0.022	2.121	(1.113,4.043)
Smoking status (Ref:No)	Yes	-0.421	0.531	0.657	(0.176,2.450)
Antenatal visits(Ref:No)	1-3	0.191	0.329	1.210	(0.825,1.776)
	Above 4	0.487	0.025	1.628	(1.064,2.491)
Marital status(Ref:unmarried)	Married	0.444	0.331	1.559	(0.636,3.821)
Visit health facility in 12months (Ref:No)	Yes	0.382	0.026	1.470	(1.047-2.052)
Religion (Ref:orthodox)	Muslim	-0.320	0.280	0.726	(0.406-1.298)
	Others	-0.012	0.970	0.988	(0.544-1.796)
Independent variables violating PO assumption for the categories					
Severe	**Residence (Ref:rural)**				
	Urban	2.304	0.027	10.01	(1.290,77.7)
	Education (Ref:higher)				
	No education	0.045	0.925	1.05	(0.407,2.69)
	Primary	-2.037	0.000	0.13	(0.037,0.457)
	Secondary	-0.061	0.867	0.94	(0.459,1.931)
	Parity (Ref:above 6)				
	No child	0.425	0.009	1.529	(1.080,2.172)
	Between 1 & 2	0.608	0.587	1.837	(0.205,16.49)
	Between 3 & 5	1.552	0.143	4.711	(0.593,37.337)
	Cons	-10.16	0.000		
	Residence (Ref:rural)				
	Urban	0.859	0.005	2.360	(1.295,4.305)
	Education (Ref:higher)				
	No education	0.135	0.592	1.144	(0.699,1.873)

Moderate	Primary	-1.818	0.000	0.162	(0.069,0.378)
	Secondary	-1.378	0.004	0.252	(0.099,0.638)
	Parity (Ref: above 6)				
	No child	0.306	0.439	1.358	(0.625,2.953)
	Between 1 & 2	0.857	0.025	2.356	(1.115,5.003)
	Between 3 & 5	1.752	0.000	5.766	(2.804,11.84)
	Cons	-4.79	0.000		
Mild	**Residence (Ref:rural)**				
	Urban	1.417	0.000	4.124	(2.389,7.106)
	Education (Ref:higher)				
	No education	-1.073	0.000	0.342	(0.207,0.565)
	Primary	-0.682	0.013	0.505	(0.296,0.865)
	Secondary	-1.549	0.000	0.212	(0.10-0,450)
	Parity (Ref:above 6)				
	No child	0.806	0.008	2.239	(1.229,4.075)
	Between 1 &2	1.208	0.000	3.347	(1.839,6.092)
	Between 3 & 5	0.684	0.019	1.980	(1.036,3.792)
	Cons	-5.19	0.000		
Level 2 Region var (1)= 0.165					

The variance component in the random effect represents the variation between regions has changed from 0.531 in the null model to 0.165 in multilevel random intercept partial proportional odds model (table 4.11). The decrement of random effect of the variance component was due to the inclusion of fixed predictors and considering the fixed explanatory variables extra predictive value for anemia levels in each region. This was the basic indication of significant variation in anemia levels of pregnant women between regions.

The estimated parameters of the variables can be interpreted in a very similar way as those in standard ordinal logistic regression model. As a result everything else is being approximately the same except difference in the random part of the model. The predictors like taking iron pills, number of births in last five years, wealth index, antenatal care visits during pregnancy and visit health facility in last 12 months are significant and have the same effect on the binary comparisons of each categories of anemia level (Table 4.11).

The odds of being less anemic in pregnant women who took iron pills was 3.71 times than pregnant women who didn’t take iron pills controlling other variables in the model and random effect at level two (OR = 3.71; 94% CI: 2.431-5.657). The odds of pregnant women who had one birth in last five years developing lower risk of anemia was 0.221 times than pregnant women who had no any birth within last five years or the odds of higher risk of anemia in pregnant women who had one birth in last five years was 4.52 (1/0.221) times than pregnant women who had no birth in last five years keeping other variables constant and random effect at level two (OR = 0.221; 95% CI: 0.131-0.374), while the odds of higher risk of anemia in pregnant women who had above two births in last five years was 11.24 (1/0.089) times than pregnant women who had no birth in last five years controlling other variables and random effect at level two (OR = 0.089; 95% CI; 0.053, 0 .152).

As indicated by the result, the odds of developing lower risk of anemia in pregnant women from richest household was 2.12 times than poorest pregnant women keeping all other variables constant and random effect in level two (OR = 2.12; 95% CI: 1.113,4.043). The odds of developing lower risk of anemia in pregnant women who visited antenatal care above four times during pregnancy was 1.63 times than pregnant women who didn't visit antenatal care during pregnancy controlling all variables constant and random effect in level two (OR = 1.63; 95% CI : 1.064,2.491). On the other hand the odds of developing lower risk of anemia in pregnant women who visited health facility in last 12 months was 1.47 times than pregnant women who were not visit health facility in last 12 months keeping all variables and random effect at level two (OR = 1.470; 95% CI: 1.047-2.052).

Independent variables such as residence type, educational level and parity were significant variables and they have different effect on binary comparisons of anemia level categories. As severe anemia compared with moderate, mild and non- anemia; the odds of urban pregnant women having moderate, mild or non-anemic (opposed to severe anemia) was 10.01 times than pregnant women from rural area keeping other variables and random effect at level two (OR = 10.01; 95% CI: 1.290-77.7). The odds of being moderate, mild or non-anemic (opposed to severe anemia) for pregnant women who attained primary education was 0.13 times than pregnant women who completed higher education keeping other variables constant and random effect at level two (OR = 0.13; 95% CI: 0.037-0.457).

The odds of being moderate, mild or non-anemic (opposed to sever anemia) for pregnant women who had no child was 1.53 times than pregnant women who had above six children controlling all variables and random effect at level two (OR = 1.53; 95% CI:1.08, 2.172). The odds of having mild or non-anemic (opposed to severe or moderate anemic) in pregnant women from urban area was 2.36 times than pregnant women from rural area controlling all variables and random effect at level two (OR = 2.36; 95% CI: 1.295-4.305). Under the comparison of severe and moderate anemia with mild and non-anemic, the odds of having mild or non-anemic in pregnant women who attained primary and secondary education were 0.162 and 0.252 times respectively than pregnant women who attained higher education controlling all variables in the model and random effect at level two, on the other hand the odds of having mild or non-anemic (opposed to severe or moderate anemic) in pregnant women who had number of children between 1 and 2 and number of children between 3 and 5 were 2.36 times (OR = 2.36; 95% CI :1.115-5.003) and 5.71 times (OR = 5.77; 95% CI: 2.804-11.84) than pregnant women who had above six births keeping all variables and random effect at level two.

The odds of being non-anemic (opposed to severe or moderate or mild anemia) for pregnant women from urban area was 4.124 times than rural pregnant women controlling all other variables and random effect at level two (OR = 4.124; 95% CI: 2.389-7.106). The odds of pregnant women who were not attained education having non-anemic was 0.34 times than pregnant women who attained higher education keeping all variables constant and random effect (OR = 0.34; 95% CI: 0.207-0.565). The odds of being non-anemic for pregnant women who attained primary and secondary education were 0.505 and 0.212 times than pregnant women who attained higher education respectively keeping all other variables constant and random effect. The estimated odds of being non-anemic in pregnant women who had no child was 2.24 times than pregnant women who had above six children (OR = 2.24; 95%CI: 1.229-4.075). The odds of being non-anemic for pregnant women who had number of children between 1 and 2 and between 3 and 5 were 3.35 and 1.98 times than women who had above 6 children other variables keep constant and random effect at level two.

4.8 Discussion of the Results

The main purpose of this study was to investigate variations of anemia levels for pregnant women among regions of Ethiopia by using EDHS 2016 data. In this study ordinal logistic regression and multilevel ordinal logistic regression was used to model the anemia levels among pregnant women. Factors/variables included in this study were education level, iron take, marital status, occupation type, wealth index, number of antenatal visits, parity, visit health facility in last 12 months, smoking status, age groups, region, religion, residence and number of births in last 5 years.

The prevalence of anemia levels for pregnant women varied among regions. The Highest proportion of severe anemia was observed at Somali followed by Dire Dawa, moderate anemia at Somali followed by Afar and mild anemia at Harari followed by Afar. Pregnant women from Amhara followed by Addis Ababa had highest proportions of non-anemia. The lowest proportions of severe and moderate anemia were observed at Addis Ababa followed by Amhara. Demographic and socio-economic characteristics applied in each region might be a cause of this discrepancy. The highest proportion of non-anemia was observed in urban pregnant women than pregnant women from rural area.

In the uni-variable analysis, all predictors used in this study had significant association with anemia levels at 0.15 significant values and hence the multi-variable analysis contains all predictors. The comparison of ordinal logistic regression models was done by using AIC/BIC criterion. A model with smallest AIC/BIC values was considered to be the best and most appropriate. As a result, partial proportional odds model was appropriate model to describe the anemia levels of pregnant women data.

Under multilevel ordinal logistic regression analysis the variables like iron taking status, number of births in last five years, wealth index, number of antenatal care visits during pregnancy, visit health facility in last 12 months, residence type, educational level and parity were statistically significant. A significant log likelihood ratio test and chi2 test of heterogeneity were indicated the appropriateness of multilevel model meaning that the anemia level of pregnant women vary among regions. As a result, multilevel ordinal logistic regression model was better than single level ordinal logistic regression model for pregnant women data.

Iron taking status for pregnant women was one of statistically significant predictors of anemia levels among pregnant women in this study. As indicated by this study pregnant women who took iron were more non-anemic than pregnant women who didn’t take iron pills. This result is consistent with the past studies that, the severity of anemia decrease as pregnant women takes iron pills (Noronha et al., 2012, Worku Takele et al., 2018, Abiselvi et al., 2018, Derso et al., 2017, Alem et al., 2013, Mengist et al., 2017, Tefera, 2014).This research also believes that iron helps to form and oxygenate the blood cells and hemoglobin then decrease the risk of anemia.

The finding of this study revealed that number of births in last five years had a significant effect on the anemia levels of pregnant women. This showed that pregnant women who had one or more birth were more anemic which is similar with previous studies conducted by (Perumal, 2014) and inconsistent with a study conducted by (Haidar, 2010). This might be due to higher bleeding during birth and related with problems of more family size.

The analysis showed that wealth index was another important factor for anemia level of pregnant women, indicated that pregnant women from richest household were develop lower risk of anemia than poorest household pregnant women. Similar study by (Mbule et al., 2013a, Perumal, 2014, Bisoi et al., 2011),concluded that the risk of anemia decrease as wealth index increases.

This study also found out that number of antenatal visit during pregnancy was an important factor for anemia levels of pregnant women. When the number of antenatal visits were above 4 the risk of anemia decreased. The study conducted by (Charles et al., 2010) in Westmoreland, Jamaica shows that number of antenatal care visits was significantly associated with anemia for pregnant women. Pregnant women who had four or more antenatal care visits were 30% less likely to be anemic than pregnant women had bellow four visits. Similar result was found in the study conducted by (Getahun et al., 2017), pregnant women who didn't follow antenatal care were more anemic.

Type of place of residence was found as a significant variable for anemia levels of pregnant women. In this study urban pregnant women were more likely to be non-anemic than rural pregnant women and the risk of anemia increase in pregnant women who were from rural area. This result in lined with the previous studies that, high prevalence of anemia in pregnant women from rural area and rural residents were more anemic (Kefiyalew et al., 2014, Getachew et al., 2012, Alem et al., 2013), urban pregnant women were 55% less likely to be anemic than rural pregnant women (Getahun et al., 2017). This might be due to lack of infrastructures, anticipate long waiting times and lack of information about adequate nutrition during pregnancy.

The current study identified that educational level of pregnant women was significant factor for anemia levels. In this finding pregnant women who were illiterate, attained primary and attained secondary education were more likely to be anemic (sever, moderate or mild anemia) as compared with pregnant women who attained higher education. This is consistent with the result obtained by (Noronha et al., 2012) concluded that low educational level increase risk of anemia, (Terfe, 2017), concluded that non-educated pregnant women were more anemic than pregnant women who attained higher education and (Bisoi et al., 2011), indicated that illiterate, primary and secondary educated pregnant women were more anemic than higher educated pregnant women. This might be the fact that educated pregnant women can be aware of anemia during pregnancy then take any preventive measures.

The results of this study also suggested that parity (number of children ever born) was significant factor for anemia levels of Ethiopian pregnant women. Pregnant women who had no child, between 1 and 2 and between 3 and 5 were more likely to be non- anemic than pregnant women had above six children. The study conducted by (Noronha et al., 2012) in Oman reported that the risk of anemia is highest in pregnant women with high number of children (high parity) and conducted by (Obse et al., 2013) in Ethiopia reported that pregnant women who had parity above four were five times more likely to develop higher risk of anemia as compared to pregnant women with 2-4 births. Similar result was noted from the study by (Worku Takele et al., 2018) and (Derso et al., 2017). Visiting health facility was another important predictor for anemia levels; pregnant women who visited health facility were less anemic than women didn't visit any health center this is consistent with (Asres et al., 2014), concluded that pregnant women who didn't visit health institution were 2.99 times more anemic than visited pregnant women.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 conclusions

The basic purpose of this study was to identify demographic, socio economic, environmental and health related factors and to assess the regional variation of anemia levels of pregnant women based on EDHS 2016 data.

In this study both single level and multilevel ordinal logistic regression models were applied. From the results of ordinal logistic regression models, partial proportional odds model was better fitted the data characterized by violating the parallel line assumption and considered as best model to predict anemia levels of pregnant women. The results of partial proportional odds model showed that region, educational level, iron taking status, wealth index, parity, number of antenatal care visits during pregnancy, number of births in last five years, visit health facility in last 12 months and residence were found to be significantly associated with anemia levels of pregnant women.

In multilevel ordinal logistic regression analysis, individual pregnant women are first level and regions are next higher level units. In this multilevel approach, the significant log likelihood ratio test, the ratio of intercepts variance to its standard error, chi2 test of heterogeneity and ICC were indicated that the anemia levels of pregnant women varied among regions (heterogeneity of anemia level among regions) and multilevel model was appropriate. From multilevel partial proportional odds model the random intercept model provided the best fit for anemia levels of pregnant women. The random effects variance decreased in multilevel partial proportional odds model than the null model because of added fixed predictors. In the fixed part of random intercepts PPOM the predictors like iron taking status, number of birth in last five years, wealth index, visit health facility in last 12 months and number of antenatal care visits during pregnancy were statistically significant and have the same effect on the binary comparisons of anemia level categories while the variables like residence type, parity and educational level were also significant and have different effect on the categories of anemia level. As anemia level for pregnant women varies among regions the study proposes that there is a need to have independent estimates of PPOM for regions of Ethiopia.

5.2 Recommendations

Based on the findings of this study, the researcher suggested the following recommendations:

- ✓ As the anemia levels of pregnant women vary among regions, it is advisable that the implementation of maternal health related programs, polices and strategies established by the government will give special attention for regions like Somali, Afar and Dire Dawa.
- ✓ It is better to expand health extensions and other health programs aimed to improve mother's awareness on the importance of antenatal care visits, taking iron pills, number of births in last five years and total number of children ever born (parity) in order to minimize the risk of anemia.
- ✓ Ethiopian ministry of health in the collaboration of other stakeholders built infrastructures like sophisticated health centers and hospitals with qualified personnel to improve the health of mothers and the government increase investment on education especially, female education by considering one part of the policy for reducing the risk of anemia.
- ✓ Further studies are recommended to identify additional factors of anemia level by including variables those are not considered in this study like HIV status of the mother and gestational age may important factors of anemia level using three or more level ordinal logistic regression model to assess anemia levels across regions.

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Appendix

Table A 1: Description and coding of variables of the study

Variable's name	**Description**	**Code/ Value**
Age	Age of women	1=15-24,2=25-34,3=35-39, 4= above 40
Region	Region of respondents	1=Tigray,2=Affar,3=Amhara,4=Oromia,5=Somali,6=Benishangul,7=SNNPR,8=Gamebela,9=Harari,10=Addis Ababa,11=Dire Dawa
Place of residence	Types of place of residence	1= Urban, 2= Rural
Educational level	Women educational level	0=Noeducation,1=primary,2=secondary,3=higher
Wealth index	Household wealth index	1=poorest,2=poorer,3=middle,4=richer,5=richest
Marital status	Women marital status	0 =unmarried,1= married
Visit health fl12	Visit health facility in last 12 months	0 = no, 1 = yes
Taking iron pills	Women taking iron pills	0 =No/Don't know ,1= yes
Smoking status	Smoking status of women	0= No, 1=Yes
Number of antenatal visits	Total number antenatal visit by women during pregnancy	0 = no visit/don't know, 1=1-3, 2= above 4
Occupation type	Women occupation type	0 = Not working, 1= Agricultural sector, 2=nonagricultural sector
vitamin intake	Vitamin intake of women	0 =No/Don't know ,1= yes
Religion	Religion of women	1=orthodox, 2 = Muslim,3 = others
Parity(TCEB)	Total children ever born	0 =no child, 1 = 1-2,2= 3-5, 3 = above 6
Birth in last 5 years	Total number of birth within last 5 years	0= No births, 1= single birth, 2= above 2 births

Table A 2: chi-square test of association between anemia levels and predictors

Predictors	chi-square	(p-value)
Educational level	163.762	0.000
Iron taking status	121.195	0.000
Residence type	77.158	0.000
Region	192.99	0.000
Parity	312.382	0.000
Age groups	10.902	0.091
Number of Birth in last 5 years	302.536	0.000
Occupation	18.077	0.006
Wealth index	64.204	0.000
Smoking status	26.147	0.004
Number of antenatal visits	44.68	0.000
Marital status	5.91	0.118
Visit health facility in last 12 months	11.119	0.011
Religion	79.724	0.000

Table A 3: Parallel lines test, Goodness of fit test and parameter estimates for POM

Goodness-of-fit test				
	Chi-square	**Df**	**sig**	
Person	751.987	1302	1.000	
Deviance	573.037	1302	1.000	
Test of parallel lines				
Model	**-2LL**	**chi-square**	**df**	**Sig**
Null hypothesis	583.002	100.546	72	0.015
General	482.455^{b}			
Score Test for the proportional odds assumption				
Chi-square	**Df**	**p-value**		
472.61	28	<.0001		

Results of Parameter estimates of POM		
Predictor	**coef.**	**P-value**
Education (ref: no education)		
Primary	-0.604	0.003
Secondary	1.01	0.000
Higher	1.66	0.000
Taking iron (ref: no)		
Yes	1.29	0.000
Residence (ref: urban)		
Rural	-1.29	0.000
Region (ref: Tigray)		
Afar	-0.85	0.081
Amhara	0.337	0.466
Oromia	0.007	0.987
Somali	-1.54	0.001
Benishangul	-0.225	0.639
SNNPR	0.364	0.430
Gambela	-0.263	0.621
Harari	-0.742	0.145
Addis Ababa	-0.757	0.197
Dire Dawa	-1.499	0.007
Parity (ref: no child)		
1-2	-0.82	0.006
3-5	-1.31	0.000
Above 6	-2.64	0.000
Age group (ref: 15-24)		
25-34	0.111	0.517
35-39	-0.43	0.104
Above 40	-0.095	0.793

Num. birth in 5 yrs.(ref:no birth)		
1 birth	-1.38	0.000
Above 2 births	-2.24	0.000
Occupation(ref: notworking)		
Agricultural	0.184	0.435
Nonagricultural	-0.079	0.713
Wealth index(ref: poorest)		
Poorer	0.122	0.629
Middle	0.174	0.535
Richer	0.028	0.923
Richest	-0.69	0.036
Smoking status(ref: no)		
Yes	-0.417	0.549
Num.antenatal visits(ref: novisit)		
1-3	0.118	0.542
Above 4	0.45	0.036
Maritalstatus(ref: un married)		
Married	0.45	0.329
Visit health facility in last		
12months (ref:no)	-0.360	0.036
Yes		
Religion (Ref:orthodox)		
Muslim	0.064	0.836
Others	0.163	0.960
Cons-1	-8.24	
Cons-2	-5.30	
Cons-3	-3.66	

Figure (A1-A9): Plots of DFBETA(S) with each explanatory variable

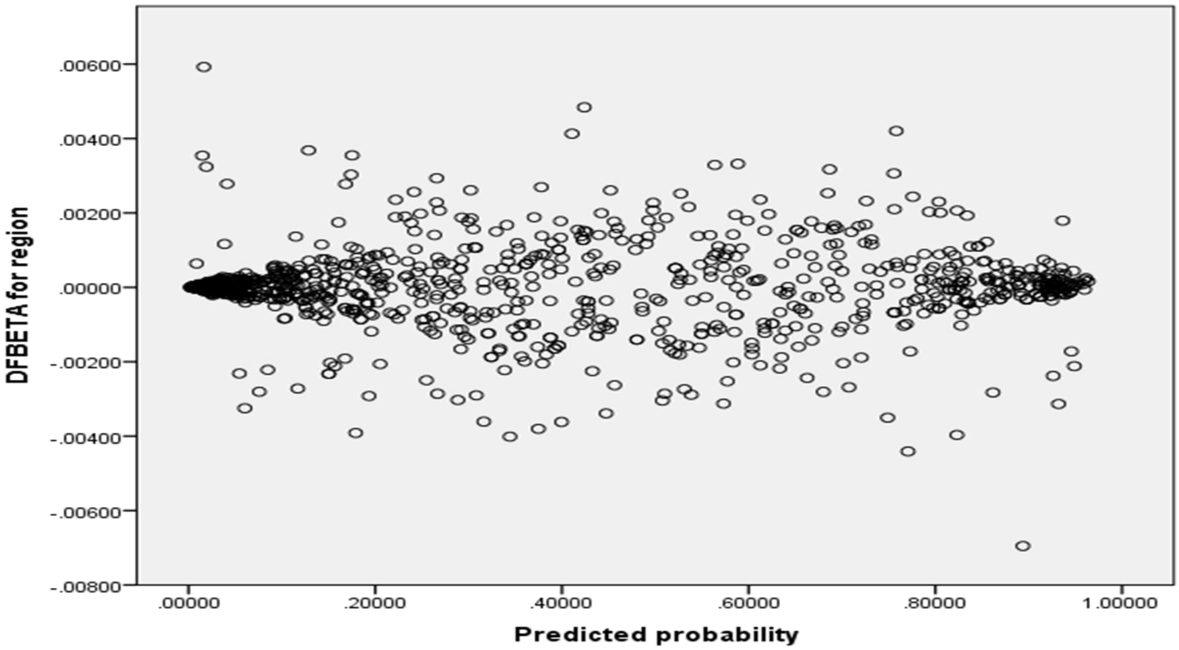

Figure A 1: plots of DFBETA(S) for regions Vs predicted probability

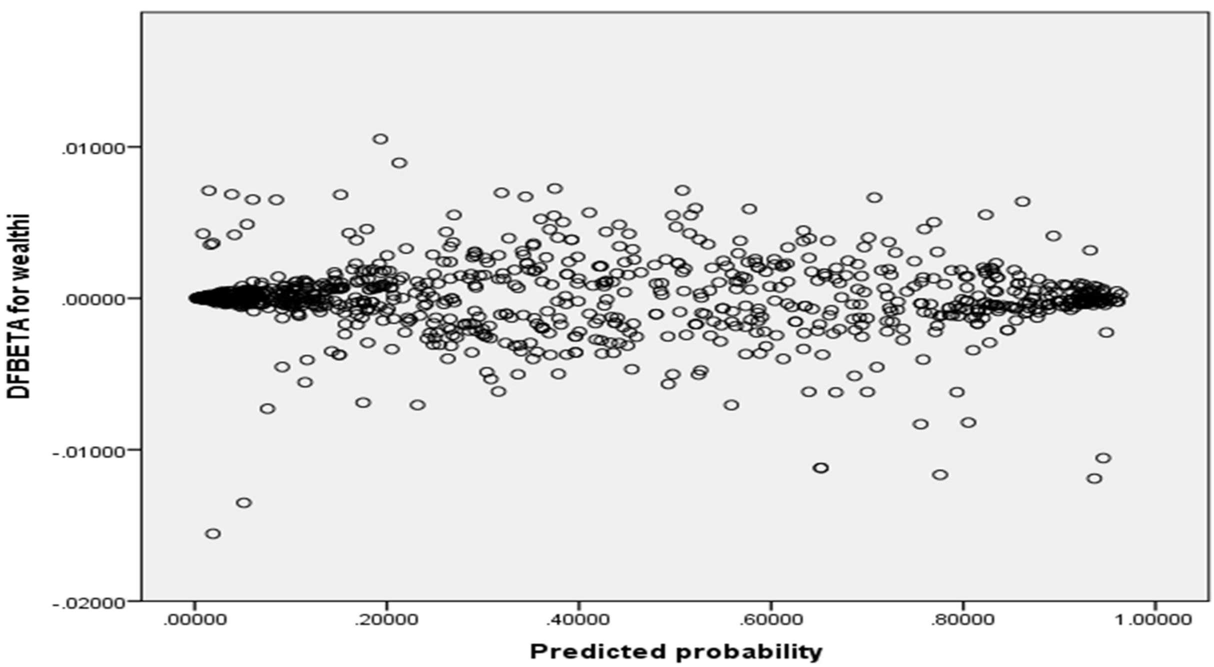

Figure A 2: plots of DFBETA(S) for wealth index Vs predicted probability

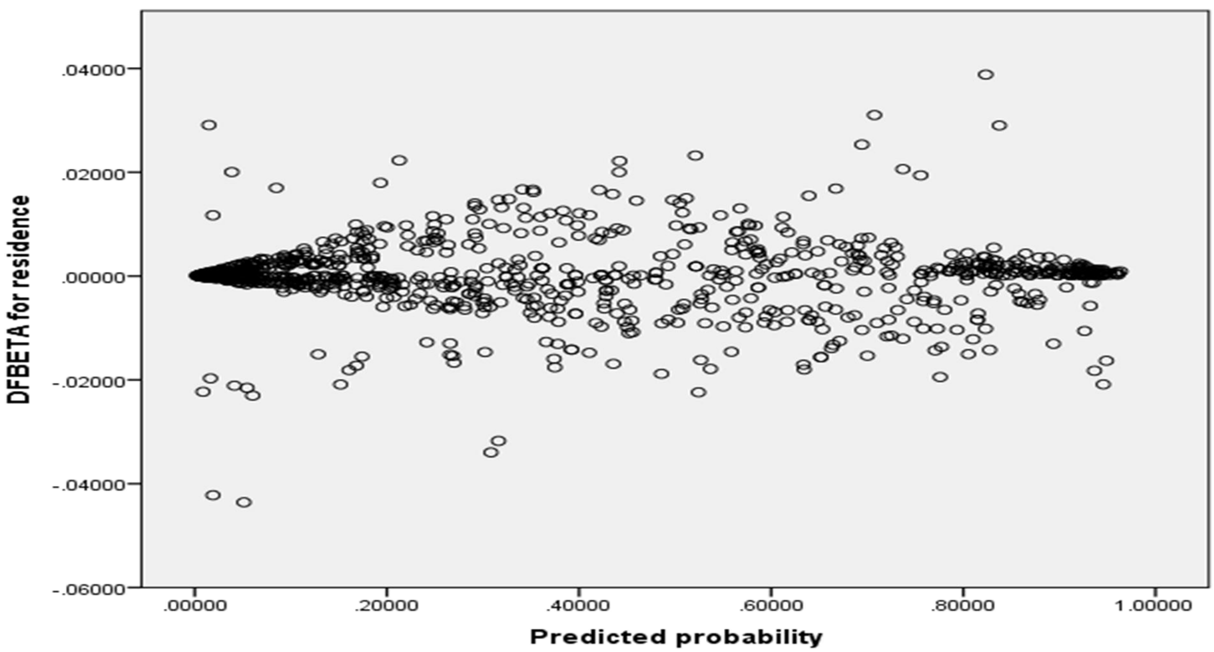

Figure A 3: plots of DFBETA(S) for residence Vs predicted probability

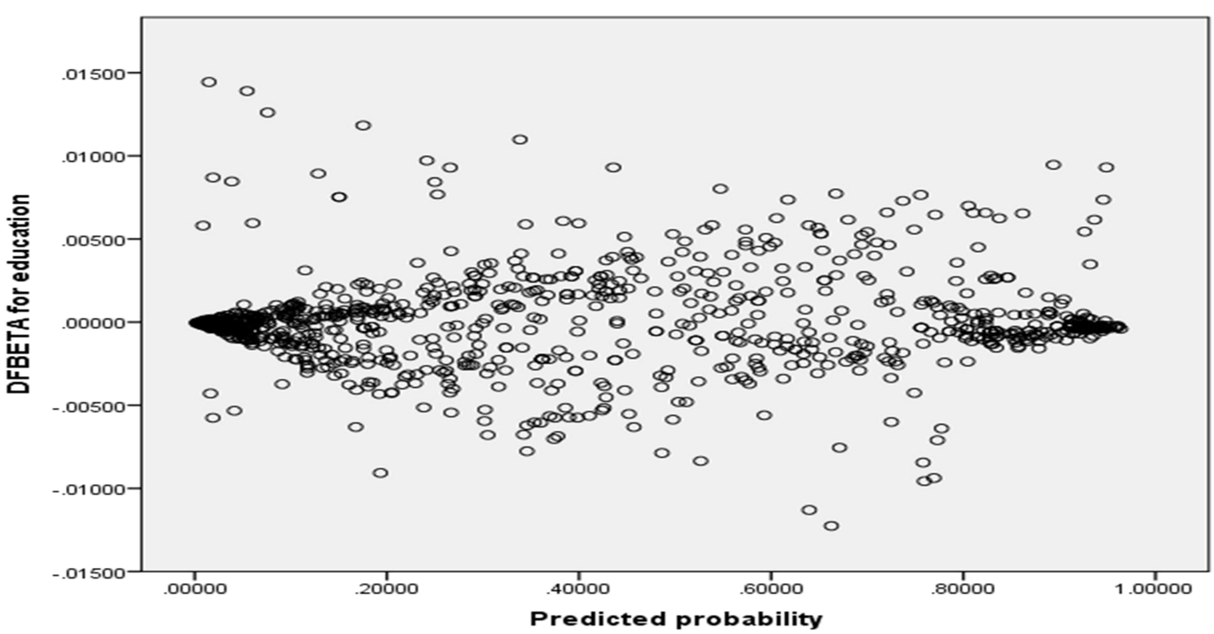

Figure A 4: plots of DFBETA(S) for educational level Vs predicted probability

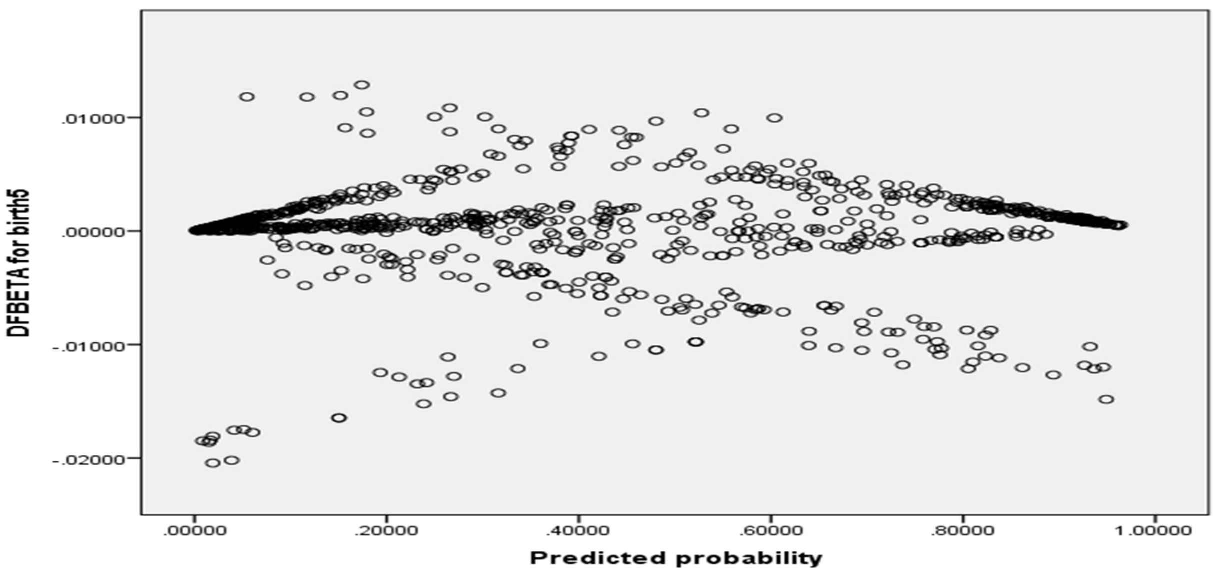

Figure A 5: plots of DFBETA(S) for birth in last five years Vs predicted probability

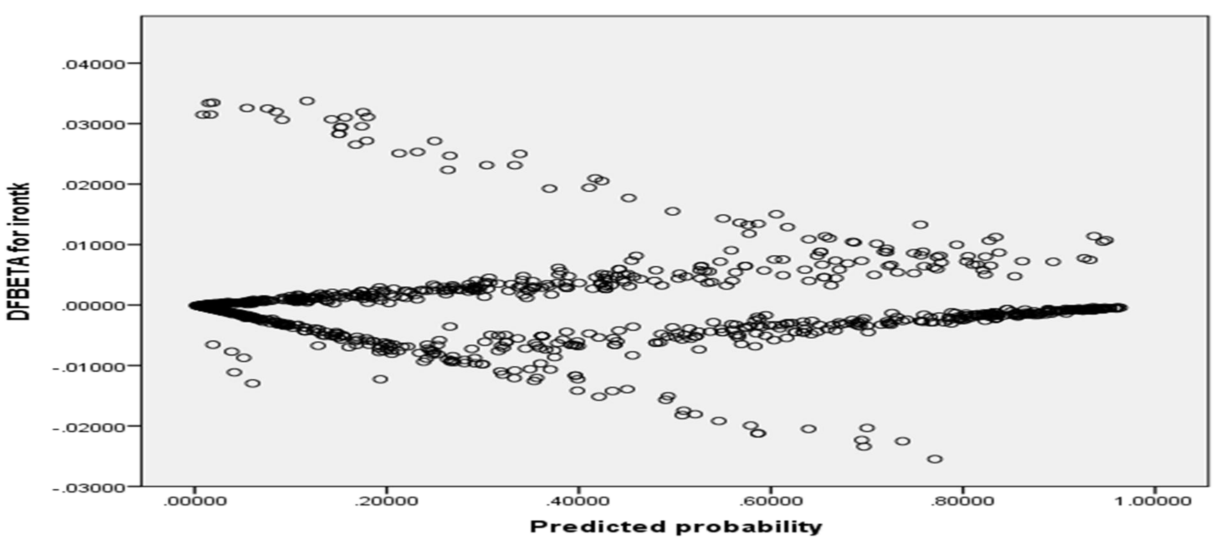

Figure A 6: plots of DFBETA(S) for iron taking status Vs predicted probability

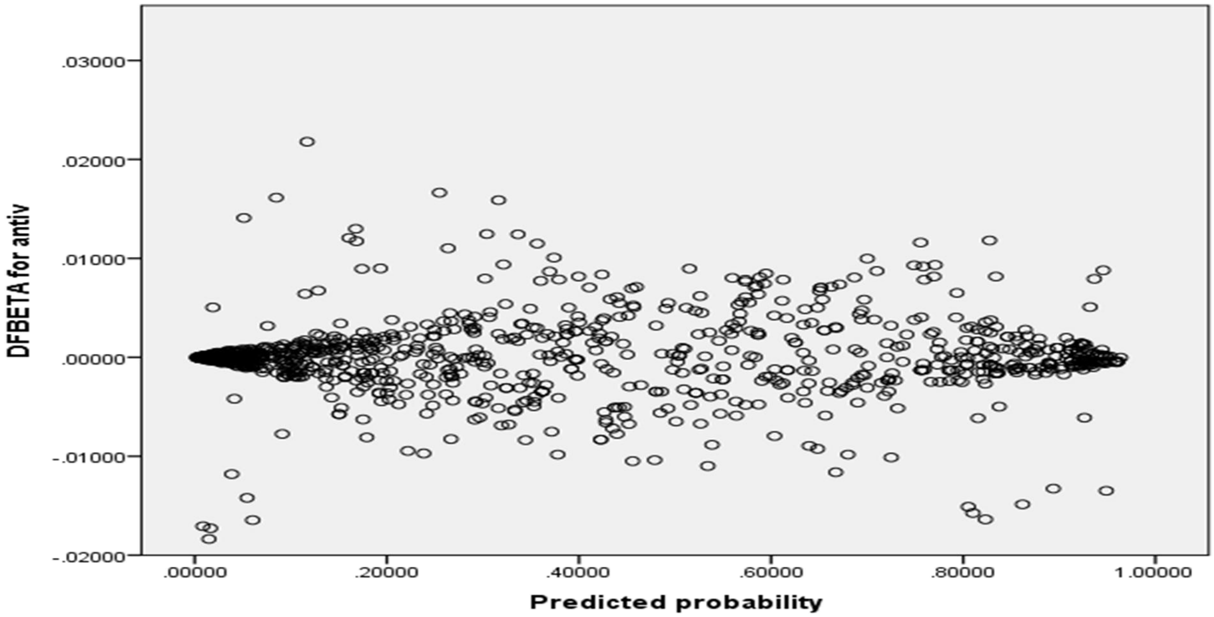

Figure A 7: plots of DFBETA(S) for number of antenatal care visits Vs predicted probability

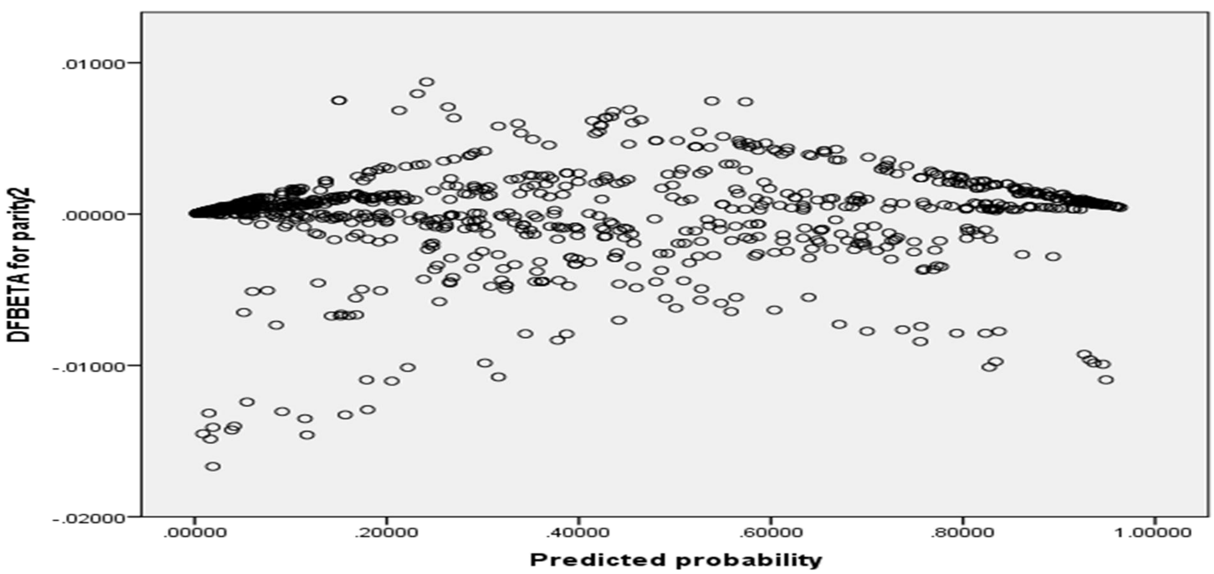

Figure A 8: plots of DFBETA(S) for parity Vs predicted probability

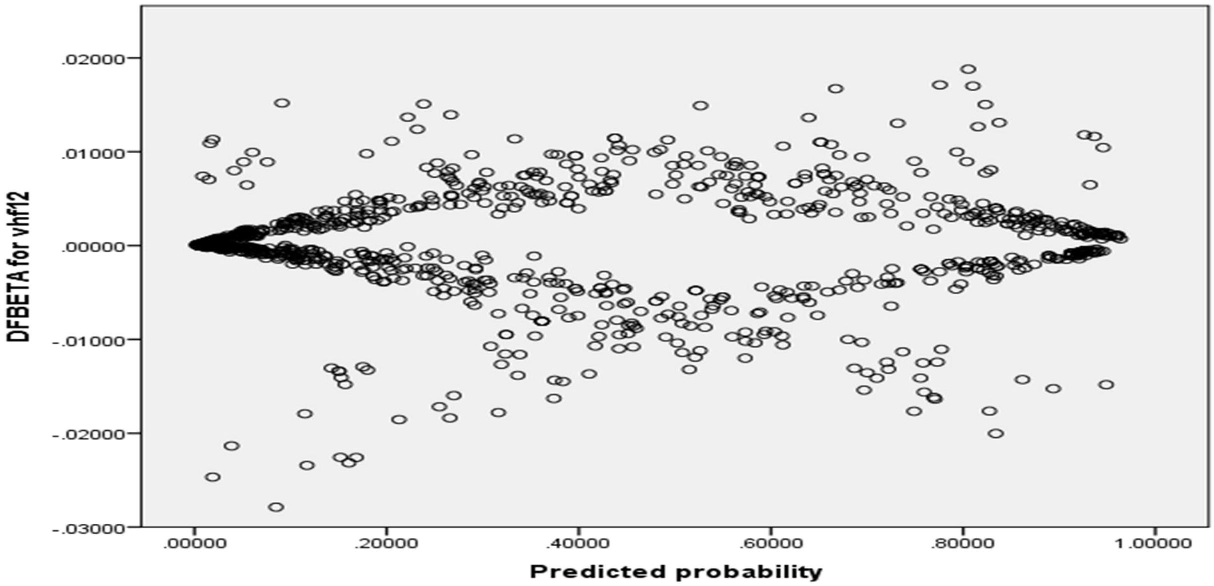

Figure A 9: plots of DFBETA(S) for visit health facility in last 12 months Vs predicted probability