STATISTICAL ANALYSIS OF REGIONAL HETEROGENEITY OF ADVERSE PREGNANCY OUTCOME IN ETHIOPIA

BY

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STATISTICAL ANALYSIS OF REGIONAL HETEROGENEITY OF ADVERSE PREGNANCY OUTCOME IN ETHIOPIA

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As thesis research advisors, we her by certify that we have read and evaluated the thesis prepared by **BEDANE KITATA** under our guidance, which is entitled **Statistical Analysis of Regional Heterogeneity of adverse pregnancy outcome in Ethiopia.** We recommend that the thesis be submitted as it fulfills the requirements for the degree of Master of Science.

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DECLARATION

I declare that the thesis is my work, has not been submitted to any other university for achieving any academic degree or diploma awards and all source of materials used for the thesis have been duly acknowledged.

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LIST OF ACRONOMY

ANC	Antenatal care
APOs	Adverse pregnancy outcomes
AIC	Bayesian information criteria
BIC	Bayesian information criteria
CSA	Central Statistical Agency
DHS	Demographic Health Survey.
EDHS	Ethiopia Demographic Health Survey
FMOH	Federal Ministry of Health
HLM	Hierarchical linear model
GA	Gestational age
GEE	General estimating equation
OR	Odd Ratio
PM	Prenatal Mortality
SBR	Still Birth Rate
WHO	World Health Organization.

ABSTRACT

Background*: Adverse pregnancy outcome is defined as a pregnancy outcomes other than normal live birth. Adverse pregnancy outcome is still a major public health and socioeconomic status problems in developing countries including Ethiopia. GEE model and multilevel logistic regression models is an extension of GLM model. Multilevel logistic regression models to consider the unexplained variation within groups and between groups as random variability.*

Objectives: *The main objectives of the study were determinants of adverse pregnancy outcomes using Generalized estimating equation model and multilevel logistic regression model as well as identify important determinant factors for the an adverse pregnancy outcomes in Ethiopia.*

Methods: *The data for the study were taken from the 2016 EDHS and women in the age group of 15-49 years. Logistic regression model, GEE model and multilevel logistic regression models is used to explore the major risk factors and regional variations in adverse pregnancy outcome in Ethiopia, by using the STATA 14 software package.*

Results: *Out of the 9694 reproductive age of women, 8412 (86.8%) not an experiencing adverse pregnancy outcome while 1282 (13.2%) of these women experiencing adverse pregnancy outcome of the time of the survey. All the fitted models Multiple logistic regression model, multilevel logistic regression model and generalized estimating equation model gave the same result that, Age of mother, place of residence, antenatal care visits, Parity, Education of mother, Marital status, Occupation of mother and Anemia level were found to be statistically significant at 5% level of significance a factors for an adverse pregnancy outcome among regions. The standard errors from the multilevel logistic regression models are smaller than GEE model. It was found that the random intercept with fixed slope model is an appropriate model for adverse pregnancy outcome.*

Conclusion: *The random intercept with fixed slope multilevel logistic regression model provided the best fit for the data under consideration. There is a variation of adverse pregnancy outcome from region to region and within regions. This study found that not having Antenatal care, residing in rural area, working occupational status, being anemic, increased educational level, never marrieds marital status, being in age group of 15-24 or >35 years are associated with increased risk of adverse pregnancy outcome among reproductive age group women in Ethiopia. Mother's, 35 years or older, should be able to avoid complications that come with age, should visit antenatal care during pregnancy.*

Keywords*: Adverse pregnancy outcome, Abortion, Stillbirth, miscarriage*

CHAPTER ONE

1. INTRODUCTION

1.1 Background of Study

Abortions, stillbirths and miscarriage are common adverse pregnancy outcomes that contribute substantially to poor maternal health. A miscarriage is any pregnancy that ends unintentionally before the fetus is viable. Miscarriage is the most common negative gestational outcome occurring in about 20% of clinically recognized pregnancies (Garcia-Enguidanos *et al.*, 2002). Globally, an estimated 2.6 million stillbirths occur annually, of which 98% occur in low-income and middle-income countries and 75% in sub-Saharan Africa and south Asia. Half of the all stillbirths (1.3 million) occur during labor and birth (Stanton *et al.*, 2006). Worldwide in 2015, 18.4 stillbirths per 1000 total births occurred, compared with 24.7 stillbirths in 2000. Although stillbirth rates have decreased slightly, the average annual rate of reduction of stillbirths (2.0%) has been far slower than that for either maternal (3.0%) or post-neonatal mortality of children younger than 5 years (4.5%) (Lawn et al., 2016).

In South Africa, stillbirth rate was in 2013 with 17 stillbirths per 1000 total births. Furthermore, nearly 258 stillbirths occur every day in Ethiopia (Lawn et al., 2016). According to Ethiopian demographic and health survey EDHS, (2016) the perinatal mortality rate was 33 deaths per 1,000 pregnancies. Induced abortion is an ancient practice, experienced by women of all backgrounds in every part of the world. Abortion are often not registered systematically in many low-income countries and this leads to underestimation of the problem besides its important public health concern. Worldwide an estimated 35 abortions occurred annually per 1000 women aged 15–49 in 1990–94 to 56·3 million in 2010–14 and annual number of abortions worldwide increased by 5·9 million from 50·4 million in 2010–14 (Sedgh *et al.*, 2016). For instance, abortion accounts for about 8% of maternal mortality worldwide (Say et al , 2014). Another hospital based study in Ethiopia revealed 50% unwanted pregnancies and 25.6% induced abortion. Fifty-eight percent of the women who induced abortion terminated the current pregnancy either by seeking the help of untrained personnel or by themselves with no assistance (Tekle-Ab et al., 2007).

The Estimated Incidence of Induced Abortion in Ethiopia reported, about 620,300 cases of induced abortions were accomplished in 2014 and the annual abortion rate was 28 per 1,000 women aged 15–49. Between 2008 and 2014, the proportion of abortions occurring in facilities rose from 27% to 53%, and the number of such abortions increased substantially nonetheless, an estimated 294,100 abortions occurred external of health facilities in 2014 (Moore *et al.*, 2016). A study done, recently, on prenatal outcomes in Addis Ababa in 2010, also indicates that the rate of stillbirth is 3.1% (Tegegne et al., 2010). A survey conducted in Harar, Eastern Ethiopia, showed induced abortion was found to be 14.4% (Worku and Fantahun, 2006). Adverse pregnancy outcome is associated with poor maternal health and heavy burden of economic cost on families and nations.

Moreover, the burden of stillbirth affects women, families, caregivers, public and society. An estimated 4.2 million women are living with depression associated with a previous stillbirth (Lawn et al, 2016). Adverse pregnancy outcomes are influenced by a myriad of biologic, social, economic and ecological factors. Many of the 3 million deaths of babies each year in the first week of life and 2.7 million stillbirths are related to poor health of the mother and to inadequate care during pregnancy, childbirth and the period directly after birth. It is estimated that nearly two thirds of the 8 million infant deaths that occur each year result largely from poor maternal health and hygiene, inadequate care, inefficient organization of delivery, and lack of essential care of the newborn (Gebremeskel *et al.*, 2017).

GEE allows for non-linear relationships between independent variables and the dependent variable, and accommodate the dependent variable has non-normal distribution (Ward and Myers, 2007). The widespread availability of the Generalized Estimating Equation (GEE) method is the usability on data that consist of clustered or repeated observations (Hammill and Preisser, 2006). GEE is useful to analyze the data that are collected in clusters where observations within a cluster may be correlated, but observations in separate clusters are independent. Estimation of the standard logistic model is equivalent to GEE estimation with an independent working correlation structure. With repeated binary outcomes, the standard logistic model yields the same population averaged estimates as the GEE. However, the standard errors from the standard logistic models are biased because the independence assumption is violated (Fitzmaurice et al., 1993).

Logistic regression is widely used to model the outcomes of a categorical dependent variable. For categorical variable, it is inappropriate to use linear regression because the response values are not measured on a ratio scale and the error terms are not normally distributed. In addition, the linear regression model can generate as predicted values any real number ranging from negative to positive infinity, whereas a categorical variable can only take on a limited number of discrete values within a specified range. In multilevel model, the data structure in the population is hierarchical, and the sample data are a sample from this hierarchical population (Gelman and Hill, 2007).

However, one should keep firmly in mind that the central statistical model in multilevel analysis is one of successive sampling from each level of a hierarchical population. Pupils are nested within schools. Other examples are cross national studies where the individuals are nested within their national units, organizational research with individuals nested within departments within organizations, family research with family members within families, and methodological research into interviewer effects with respondents nested within interviewers. For multistage clustered samples, the dependence among observations often comes from several levels of the hierarchy (Khan and Shaw, 2011). Therefore, multilevel analysis is used in several fields of data examination existing between and within the occurrence of experienced adverse pregnancy outcome.

1.2. Statement of the problem

Adverse pregnancy outcomes (abortion, stillbirth and miscarriage) represent significant problems of both developing and developed countries. It accounts for a large proportion of perinatal loss and the victims suffer from lifelong physical, nervous, or educational ill health, often at great cost of families and societies. More than any other region, sub-Saharan Africa is home to the highest number adverse pregnancy outcome (World health organization, 2015). In Ethiopia, adverse outcomes of pregnancy is still major public health difficulties. Although expanding health facilities and availing essential supplies is vital to reduce adverse pregnancy outcomes. Stillbirth rate for developed countries is estimated to be much less, that is, 4.2–6.8 per 1000 births whereas form developing world, the estimate ranges from 20 to 32 per 1000 live births and there is a wide gap of the Still birth rate between developed and developing countries (Froen *et al.*, 2016).

Different studies were conducted to identify factors affecting adverse pregnancy outcome but almost all of them used multiple logistic regression model, although they weren't accounted for adverse pregnancy outcome of country level and didn't explored if there is heterogeneity (variation) between regions of Ethiopia (Berhie and Habtamu, 2016; Yeshialem *et al.*, 2016; Gebremeskel *et al.*, 2017). This study aimed at filling the gap by considering the random effects of multilevel logistic regression model. This study tries to identify risk factors of adverse pregnancy outcome of the individual and region level; by using multilevel logistic regression models in order to see the variation between and within regions of adverse pregnancy outcome. The Generalized estimating equation model provided information about the association with individual observations within the same cluster (Liang and Zeger, 1986).

This study tries to answer the following basic research questions:

1. Which factors significantly affect the adverse pregnancy outcome?

2. Is there variation in adverse pregnancy outcomes of different National Regional States of Ethiopia?

3. Which model Generalized estimating equation model and multilevel logistic regression model describes well adverse pregnancy outcome in Ethiopia?

1.3. Objective of the Study

1.3.1. General Objective

The general objective of this study is to assess the determinants of adverse pregnancy outcome in Ethiopia using EDHS2016 data.

1.3.2. The Specific Objectives

1. Identify factors associated with adverse pregnancy outcomes in Ethiopia.
2. To estimate the within-regional and between-regional variation in the rate of adverse pregnancy Outcome in Ethiopia.
3. To compare generalized estimating equation and multilevel logistic regression model in adverse Pregnancy outcome in Ethiopia.

1.4. Significances of the study

This study is useful to understand how important it is to consider the hierarchical structure of the adverse of pregnancy outcome data, whether the magnitude of the random effects is small or large. It is specifically helpful for those who want to deal with the variation between and within the clusters or groups for cross sectional data set of the factors that affect adverse pregnancy outcome. This research is expected to give ideas of those focuses on this area:

1. It helps the governmental and non-governmental organizations to take interference measures and set appropriate plans to reduce adverse on pregnancy outcome and giving import in the areas which mostly affected in adverse pregnancy outcome in the country.
2. To give emphases on the factors that had a strong association with adverse of pregnancy outcome; so that policy makers acts on accordingly.
3. This study also helps in reducing the adverse of pregnancy outcome by giving essential recommendations to the policy makers and other stakeholders on the factors that increase the probability of adverse of pregnancy outcomes.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Overview of adverse pregnancy outcome

The burden of adverse pregnancy outcomes (APOs), which includes both stillbirth and abortions, is substantial in both developed and developing countries. Globally, out of an estimated 210 million pregnancies, 75 million end in abortions or stillbirths. Every day more than 7200 babies are stillborn, and 2.6 million stillbirths occurred worldwide in 2009 and majority of all stillbirths occur in low-income countries. Study revealed that, a high correlation between stillbirths and maternal mortality; 28 countries reporting the highest stillbirth rate contributed the highest maternal mortality rate worldwide (Löfwander, 2012). The world health statistics revealed that the rate of stillbirth globally was 19 per 1000 deliveries, in the African region it was 28 per 1000 deliveries, 26/1000 for low income countries, 21/1000 for low middle income countries and less than 1% for the high income countries.

More than any other region, sub-Saharan Africa is home to the highest number of child deaths roughly 3 million in 2015 (World health organization, 2015). In Ethiopia, the world health statistics revealed a stillbirth rate of 26/1000 deliveries which is third highest in the east African countries next to Djibouti and Somalia (with stillbirth rates of 34 & 30 per 1000 births, respectively (Engmann *et al.*, 2012).

The number is a small decline of 1.1% per year over the previous years (Löfwander, 2012). In addition, study conducted Uganda reported an adverse pregnancy outcome (abortion or stillbirth) was accounted for 10.8 % pregnancies (Gershim *et al.*, 2015). The rate of experiencing stillbirth among women of childbearing age was about 25.5 per 1000 deliveries in Ethiopia (Analizi et al 2017). Complications or problems associated with adverse pregnancy outcome can lead to severe maternal morbidity and mortality. Furthermore, over 830 women died due to preventable causes related to pregnancy and childbirth each day in 2015, largely from preventable or treatable causes.

2.2. Factors affecting adverse pregnancy outcome

2.2.1. Demographic and socioeconomic factors.

2.2.1.1. Maternal age and adverse pregnancy outcome.

Women in higher age group, especially those above 35 years, are more likely to experience adverse pregnancy than those at a lower age group. Review of researches done on five clinical sites in America stated that the adverse pregnancy rates is increased twofold for women 35–39 years of age, and 3- to 4-fold for women aged forty or older. While any age-associated risk is due to higher rates of maternal complications, in uncomplicated pregnancies there may be a 50% increased risk associated only with maternal age ≥35 (Kenny *et al.*, 2013). Analizi et al, (2017) in their study, investigated stillbirth in Ethiopia also using the multilevel logistic regression analysis, age group, was found to be statistically significant factors for experiencing stillbirth among regions. Another study also reported on older mothers was at increased risk of adverse pregnancy outcome compared to their younger peers. This risk is evident in women as young as 30–34 years of age and increases with age (Ayemigbara, 2012). Adverse pregnancy outcomes in rural Uganda, trends and associated factors from serial cross sectional surveys, reports that teenage pregnancies have a significant association with risk of adverse pregnancy outcome is increased with age of mother (Gershim *et al.*, 2015).

2.2.1.2. Education level of mother and adverse pregnancy outcome.

Berhie & Habtamu, (2016) using logistic regression analysis models, investigated factors influencing stillbirth to Ethiopia suggested that women have only primary education had no significant difference in experiencing stillbirth with those having no educational attainment, women with secondary and higher education were less likely to experience stillbirth than those with no educational attainment .The study therefore concluded that there was a possible major reduction of stillbirth by elevating education levels from none to primary level (Jansen *et al.*, 2009). Furthermore, conducted Kenya showed achieving secondary and higher education reduces the probability of a mother experiencing a miscarriage, stillbirth, or an abortion (Patricia, 2014). Study conducted in Ghana using logistic regression analysis have reported that educated urban women are more likely to seek an abortion than their less educated rural counterparts (Ahiadeke, 2001).

2.2.1.3. Marital status and adverse pregnancy outcome.

Studies have shown adverse pregnancy outcome also associated with marital status. Facility-based studies conducted in Malawi using the multivariate logistic regression model observed that there is a higher prevalence of married women (78.7% - 81.0%) of all women presenting for post abortion care than single, separated, widowed or divorced women (Kalilani-Phiri *et al.*, 2015). Other study also showed a 4% reduction in the odds of induced abortion in married women compared with women who were single (ELlen et al., 2014). Furthermore, studies report that never-married are more likely to seek abortion (Schwandt *et al.*, 2011). Others have found the highest proportion of abortion seekers among single ever-marrieds (divorced, separated, and widowed) compared with marrieds (ELlen et al., 2014). In addition Ahiadeke et reported evidence of a reduction in the odds of induced abortion among married women compared with women who had never married or were divorced. More than three quarters of the women who sought induced abortion were unmarried (Ahiadeke, 2001).

2.2.1.4. Place of residence and adverse pregnancy outcome.

Different studies showed that women's place of residence also associated with adverse pregnancy outcome. Study done on Nigeria Predictors of Poor Pregnancy Outcomes among Antenatal Care Attendees in Primary Health Care Facilities in Cross River State, using Multilevel Model studies revealed that the likelihood of experiencing adverse pregnancy outcome for those women residing in urban area is higher for those women residing in rural area when compared to those in the rural areas (Ameh *et al.*, 2016). Another study conducted in Ethiopia using logistic regression analysis showed women residing in rural areas were found to be more likely to experience stillbirth than those in urban areas (Berhie and Habtamu, 2016). Another study conducted in Nepal identified that the rate of abortion is more among the women of rural areas (Tamang *et al.*, 2012). On the other hand, mothers who had lived in rural area were found to be five times more likely to have adverse pregnancy outcomes than urban and this was consistent with the study conducted in Ethiopia (Siza J.E., 2008).

2.2.1.5. Income and adverse pregnancy outcome.

Numerous studies have found that income inequality are correlate with adverse outcomes. Investigating the socioeconomic position and the risk factors for preterm birth using a multivariate logistic models (Morgen *et al.*, 2008). It was pointed out that several studies on the socioeconomic status impact on pregnancy outcomes produced conflicting results. For Self-employment among the partners of the respondents was associated with poor pregnancy outcomes compared with employed partners. Furthermore, it was shown that women in the poor wealth index were more likely to experience poor pregnancy outcome than rich wealth index (Padhi *et al.*, 2012) .Other study revealed that if a mother is working her risk of experiencing stillbirth, abortion or miscarriage is higher compared to women who are not working. This may suggest that having an occupation can be detrimental to maternal health. Furthermore, study done by Ziyo *et al.,* (2009) found out that as regards to women's occupation, professional and semiprofessional women had better fetal outcome as compared to others. Other study conducted in New York, NY, USA by Mundigo, (2006) Determinants of unsafe induced abortion in developing countries women who were unemployed were less likely to seek induced abortion than those who were employed.

2.2.2. Health related factor and adverse pregnancy outcome

2.2.2.1. Antenatal care utilization and adverse pregnancy outcome.

During pregnancy antenatal care visits (ANC) play an important role. Opportune and adequate antenatal care is generally acknowledged to be an effective method of preventing adverse outcomes in pregnant women and their babies (Joyce Jebet, 2012)**.** Survey in Kenya showed that respondents who never received antenatal care during their pregnancy were associated with poor pregnancy outcomes. Study conducted on binary logistic in assessing and identifying factor affecting the adverse pregnancy outcome in selected health facilities of North Wollo Zone in Ethiopia show that level of ANC having significant effect on adverse pregnancy outcomes, Mothers who didn't attend ANC were more than 3 times to have adverse pregnancy outcome, than mothers who attended ANC follow up, OR = 3.4 (EsheteA., 2013).

In study done in Hawassa University Hospital, southern Ethiopia, both the crude and adjusted analysis showed that the stillbirth rate was highest among mothers who had no ANC follow up (Bayou and Berhan, 2012). Other study also women who have made antenatal care visit for at least once during their pregnancy times were less likely (OR = 0.482) to experience stillbirth than those who haven't visited antenatal care (Analizi et al., 2017).

2.2.2.2. Anemia level and adverse pregnancy outcome.

World health organization (WHO) defines anemia as a low blood hemoglobin responsiveness. Anemia during pregnancy is one of the most mutual indirect obstetric cause of adverse pregnancy outcome in developing countries. It is responsible for poor maternal and fetal outcomes. A limited number of studies were conducted on anemia during pregnancy in Ethiopia, and they present inconsistent findings. Anemia is a global health problem for women (Benoist *et al.,* 2008). Women with severe anemia are particularly at risk and have a 3.5 times greater chance of dying than women without anemia (Lule *et al.*, 2005). Anemia during pregnancy and birth outcome done by a meta-analysis suggested that anemia in pregnancy is associated with an increased risk of adverse pregnancy outcomes, such as abortion, still birth, and miscarriage (Xiong *et al.*, 2000). Analysis of EDHS 2011 data showed women who were anemic are 2.499 times more than likely to experience stillbirth than those who were not anemic (Analizi et al., 2017).

2.2.2.3. Parity and adverse pregnancy outcome.

Number of pregnancy (parity) is also associated with pregnancy outcome. For instance study publicized that multipara women, those having at least one child, were more likely vulnerable to experience stillbirth than the nulliparous women, those having no children (Analizi et al, 2017). It was also observed that women with their second pregnancies were 3.8 times more likely to seek induced abortion and women with more than two pregnancies were 6.6 times more likely to do so (OR 3.81, CI 1.94–7.49 and OR 6.58, CI 2.58–16.79, respectively) (ELlen et al., 2014). Determinants of unsafe induced abortion in developing countries compared women with a single pregnancy, women with a second pregnancy were 3.8 times more likely to seek induced abortion, and women with more than two previous pregnancies were 6.6 times at risk (Mundigo, 2006). Other study also showed multipara had 2.6 times higher proportion of stillbirths compared to null paras (Lawn et al., 2009).

2.2.2.4. Body mass index (BMI) and adverse pregnancy outcome.

A study done on weight gain during pregnancy reexamining the guidelines by Rasmussen and Yaktine AL, (2009) the Institute of Medicine classified body weight based on body mass index (BMI) as underweight (BMI <18.5 kg/m2), normal (BMI = 18.5–24.9 kg/m2), overweight (BMI = 24.9–29.9 kg/m2), and obese (BMI ≧30 kg/m2), and then published suggested guidelines for gestational weight gain according to these BMI categories. Reduction in cesarean delivery rate, even when the body weight was kept within the suggested range. These findings also specified that weight reduction prior to pregnancy is important in refining pregnancy outcomes in obese women with BMI ≥30 in pregnancy (Poston *et al.*, 2015).

2.2.2.5. Place of delivery and adverse pregnancy outcome.

Women who delivered their babies at any health center were 75.8 % (0.242-1, OR = 0.242) less likely to experience stillbirth than those who preferred to deliver at home (Analizi et al., 2017).

Predictors of Poor Pregnancy Outcomes Among Antenatal Care Attendees in Primary Health Care Facilities in Cross River State, Nigeria by Multilevel Model study also shows delivering at health center associated with decreased probability experiencing still birth when compared to delivering at home (Ameh *et al*., 2016).

2.2.2.6. Smoking cigarette and adverse pregnancy outcome.

In the review of the criteria of causation, the study found that the relative risk of spontaneous abortions are increased by one-third in women who smoke during pregnancy compared to those who do not smoke. Also a strong gradient for smoking during pregnancy was reported in relation to spontaneous abortions Ayemigbara, (2012) found that the women with low education levels were more likely than others to smoke and this doubled their risk of delivering a stillbirth infant. Whereas smoking increases risk of abortion and stillbirths, women of lower socioeconomic status with lower level of education were reported to be at a higher risk of smoking during pregnancy.

2.3. Hierarchal liner model

Multilevel or clustered data consist of units of study at a women nested within units of analysis at a region. The levels in the multilevel analysis are another name for the different types of unit of analysis. Multilevel logistic regression is allowance of generalized linear models. The multilevel model contains numerous different residual variances, and no single number can be interpreted as the amount of explained variance (Hox, 2010). The modern approach to the problem of non-normally distributed variables is to include the necessary change and the choice of the appropriate error distribution (not necessarily a normal distribution) explicitly in the statistical model. These classes of statistical models are called generalized linear models (McCullagh and Nelder, 1989).

Modeling the association between explanatory and response variables is a fundamental activity encountered in statistics. Simple linear regression is often used to examine the relationship between a single explanatory (predictor) variable and a single response variable. In multilevel logistic regression problems, decisions about group membership and operationalization's involve a wide range of theoretical assumptions, and an equally wide range of requirement problems for the auxiliary (Blalock, 1990; Klein and Kozlowski, 2000). If there are effects of the social context on individuals, these effects must be facilitated by intervening procedures that depend on characteristics of the social context. When the number of variables at the different levels is large, there are an enormous number of possible cross-level exchanges. Ideally, a multilevel theory should specify which variables belong to which level, and which direct effects and cross-level interaction effects can be expected. Cross-level interaction effects between the individual and the context level require the specification of processes within individuals that cause those individuals to be differentially inclined by certain aspects of the context.

2.4. Generalized Estimating Equation

Over the past 2 decade, the GEE approach has proven to be an very useful method for the analysis of longitudinal data, especially when the response variable is discrete (e.g., binary, ordinal, or a count). Correlated data are modeled using the same link function and linear predictor setup (systematic component) as the independence case. As estimators, those standard errors can also show more variability than parametric estimators (Kauermann and Carroll, 2001). GEE estimates are the same as those made by logistic regression analysis when the dependent variable is normally distributed and no correlation within response is assumed.

Generalized estimating equations (GEE) models are a direct extension of basic quasi likelihood theory from cross-sectional to repeated or otherwise correlated measurements. They estimate the parameters associated with the expected value of an individual's (women's) vector of binary responses and phrase the working assumptions about the association between pairs of outcomes in terms of marginal correlations (Molenberghs and Verbeke, 2005).

When interest is in the first-order marginal parameters, McCullagh and Nelder, (1989) have shown that a full likelihood procedure can be replaced by quasi-likelihood based methods. In any generalized linear model, even for choices of link and variance functions that do not correspond to exponential families. Consequently Liang and Zeger,(1986) proposed the method of generalized estimating equations (GEE) as an extension of GLM to accommodate correlated data using quasi-likelihood approach. Rather than assuming a particular distribution for the response, One of the desirable properties of the GEE method is that it yields consistent and asymptotically normal solutions even with the misspecification of the covariance structure(Liang and Zeger, 1986).

CHAPTER THREE

3. Methodology

3.1 Source of data

For the analysis, the data has been obtained from the Demographic and Health Survey showed in Ethiopia in 2016. The 2016 (EDHS) is the fourth Demographic and Health Survey conducted in Ethiopia. It was applied by the (CSA) at the request of the Federal Ministry of health (FMoH). The 2016 EDHS used three questionnaires: the Household Questionnaire, the Woman's Questionnaire, and the Man's Questionnaire. The Woman's Questionnaire was used to collect information from all women age 15-49 from the selected households. The primary purpose of the EDHS is to furnish policymakers and planners with detailed information on fertility, sexual activity, family planning, breast feeding practices, nutrition, child hood, maternal mortality, maternal and child health, nutrition and knowledge of HIV/AIDS and other sexually transmitted contaminations. A nationally representative sample of 15,683 women aged 15−49 and 12,688 men age 15-59 in 16,650 selected households were interviewed.

3.2. Sampling Design

The 2007 Population and Housing Census, conducted by the CSA, provided the sampling frame from which the 2016 EDHS sample was drawn. Administratively, regions in Ethiopia are divided into zones, and zones, into administrative units called wereda. Each wereda is further subdivided into the lowest administrative unit, called kebele. During the 2007 Census, each kebele was subdivided into census enumeration areas (EAs) or clusters, which were convenient for the implementation of the census. The 2016 EDHS sample was selected using two stage cluster sampling design and census enumeration areas (EAs) were the sampling units for the first stage. The sample included 645 EAs (202 in urban areas and 443 in rural areas). Households included the second stage of sampling. A complete listing of households was carried out in each of the 645 selected EAs from January 18, 2016, to June 27, 2016. Households comprised the second stage of sampling. A complete listing of households was carried out in each of the 645 selected EAs from January 18, 2016, to June 27, 2016. A total of 18,008 households and all women age 15-49 and all men age 15-59 in these households were selected for the sample, of which 16,650 households were successfully interviewed. In the interviewed households, 16,583 eligible women were recognized for individual interviews, of which 15,683 women were successfully completed.

3.3. Inclusion and Exclusion Criteria

A woman was eligible if she was resident in Ethiopia and lies between 15 and 49 years of age (Reproductive age group of women). The women were considered as experienced adverse pregnancy outcome at least one of Miscarriage, abortion or still birth and women were considered as not experienced adverse pregnancy outcome at least one of Miscarriage, abortion or still birth is Inclusion Criteria. When these data is obtained, a women‘s of Ethiopia not exist in Ethiopia is although excluded from the survey.

3.4. Study Variables

3.4.1 Response variable.

The 2016 EDHS asked women to report any pregnancy loss that occurred in the five years preceding the survey. The response was binary: presence or absence. The response (dependent) variable for the i^{th} women (15-49) is represented by a random variable Y_i with two possible values coded as 1 and 0. So, the response variable of the i^{th} women Y_i was measured as a dichotomous variable with possible values Y_i = 1, if i^{th} women have experienced adverse pregnancy outcome and Y_i = 0 otherwise.

$$Y_i = \begin{cases} 1, if the\ i^{th}\ \ experienced\ adverse\ pregnancy\ outcome \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases}$$

3.4.2 Independent variables.

Many explanatory variables are used as predictors of adverse pregnancy outcome. Since based on the reviewed literatures, some of the common predictors that are expected to influence on determinants of adverse pregnancy outcome in Ethiopia were recorded as given below for the purpose of the analysis. These include education level of women, place of residence, region, marital status, Antenatal care utilization, Place of Delivery, Body mass index (BMI), Smokes cigarettes, Anemia level, Occupation of women, Maternal age, Wealth Index, Parity.

Table 3. 1 Description Explanatory Variables

No	Variables name	Categories	No	Variables name	Categories
1	Education level of mother	1=No education 2=Primary 3=Secondary 4= Higher	8	Place of delivery	0=Home 1=Health facility
2	Place of residence	1= Urban 2=Rural	9	Body mass index (BMI)	0=Under weight 1=Normal 2=Overweight 3=Obesity
3	Region	1=Tigray 2=Affar 3=Amhara 4=Oromiya 5=Somali 6=Benishangul-Gumuz 7=SNNP 8=Gambela 9=Harari 10=Addis Ababa 11=Dire Dawa	10	Parity	0=Nulliparous 1=Single para 2=Multipara
4	Marital status	0=Never in union 1=Living with partner 2=Divorced 3=Married 4=Widowed 5=Separated	11	Anemia level	0=Not anemic 1=Anemic
5	Antenatal care utilization	0=No antenatal visits 1=Visited at least once	12	Maternal age	0=15-24 1=25-34 2=35 above
6	Occupation of women	0=Not working 1=Working	13	Wealth Index	0=Poor 1=Middle 2=Rich
7	Smokes cigarettes	0=Yes 1=No			

3.5. Methodology

3.5.1. Statistical methodology

In this study Descriptive statistics, logistic regression model, Generalized estimating equation and multilevel logistic regressions model were employed to identify determinant risk factors of an adverse pregnancy outcome in Ethiopia. The response variable of the study is experiencing adverse pregnancy outcome prior to the survey. Using multilevel logistic regression model by assuming the occurrence of adverse pregnancy outcome and assessed the effect of determinant factors and regional difference of an adverse pregnancy outcome.

3.5.2. Binary Logistic Regression Model

Binary regression models are very common in statistical applications. When the response variables has two categories, binary Logistic regression is used. Binary data are the most common form of categorical data and the most popular model for binary data is logistic regression (Agresti, 2000). Logistic regression is based on the $\log it$ transformation of the response variable. In instances where the independent variables are categorical or a mix of continuous and categorical, logistic analysis is preferred to discriminant analysis (Gelman and Hill, 2007). Another issue with dichotomous data is that the error terms are not normally distributed, (distributed binomially) thus ordinary sum of squares regression and all normality tests are invalid. The assumptions required for statistical tests in logistic regression are far less restrictive than those for ordinary least squares regression. There is no formal requirement for multivariate normality, homoscedasticity, or linearity of the independent variables within each category of the response variable.

However, the assumptions that apply to logistic regression model include: meaningful coding, inclusion of all relevant and exclusion of all irrelevant variables in the regression model and low error in the explanatory variables, no outliers and sampling adequacy. Multiple logistic regressions were used to analyze the effect of each of the independent variables on adverse pregnancy outcome of women, while controlling for the other independent variables. The statistical significance of the individual regression coefficients is tested using the Wald and score chi-square statistic. A Multiple Logistic Regression analysis was achieved to assess the possible association between the covariates and dependent variable and it allows a precise exploration of the association between the various covariates, while controlling for other variables.

3.5.2.1. Goodness of Fit of the Model

After fitting the logistic regression model or once a model has been developed through the various steps in estimating the coefficients, there are several techniques involved in assessing the appropriateness, adequacy and helpfulness of the model. First, the importance of each of the explanatory variables would be assessed by carrying out statistical tests of significance of the coefficients. Then the overall goodness of fit of the model would be tested (Agresti, 1996). The goodness of fit measures how well the model describes the response variable. Assessing goodness of fit involves studying how close values are predicted by the model with that of observed values

(Bewick and Jonathan, 2005). Finally, if possible, the model is validated by checking the goodness of fit and discrimination on a different set of data from that which will be used to develop the model (Bewick and Jonathan, 2005). The Pearson's Chi-square, the likelihood ratio tests, Hosmer and Lemeshow Goodness of fit Test are the most commonly used to measures of goodness of fit for categorical data (Hosmer and Lemeshow, 1989).

3.5.2.2. Diagnostic checking

Regression model building is often an iterative and interactive process. The first model we try may prove to be inadequate. Regression diagnostics are used to detect problems with the model and suggest developments. In logistic regression, observations whose values deviate from the expected range, produce extremely large residuals, and may indicate a sample individuality called outliers. These outliers can unduly influence the results of the analysis and lead to incorrect inferences. An observation said to be influential if removing the observation substantially changes the estimate of coefficients. Influence can be thought of as the product of leverage and outliers.

Leverage is a measure of how far an independent variable departs from its mean. DFBETA diagnostic can be used to assess the effect of an individual observation on each estimated parameter of the fitted model. If DFBETA of a case is greater than 1, then it is potential outlier. Cases for which Cook's distance is large have substantial influence on both the estimate of β and on fitted values and deletion of these cases may result in significant changes. If Cook's distance of a case is greater Than 1, then it is potential outlier (Hosmer and Lemeshow, 2000).

3.6. Multilevel logistic regression model

Multilevel models can be fitted for dependent variables that are categorical outcomes as well as allowing the relationship between the explanatory and dependent variables to be estimated, having taken into account the population structure. Linear and logistic regressions, generalized linear models can be fit to multilevel structures by including coefficients for group indicators and then adding group-level models. A multilevel logistic regression model also referred to in the literature as a hierarchical model, can account for lack of independence across levels of nested data (i.e., women nested within regions). Standards logistic regression assumes that all experimental units (in this case, women) are independent in the sense that any variables affecting the dependent variable have the same effect in all regions. Multilevel analysis is a methodology for the analysis of data with complex patterns of variability, with a focus on nested sources of variability. When the data structure is hierarchical with elementary units at women nested in clusters at region. The latent variables, or random effects, are interpreted as unobserved heterogeneity at the different levels which induce dependence among all women units belonging to a region unit. The best way to the analysis of multilevel data is an approach that represents within group as well as between groups relations within a single analysis, where group refers to the units at the higher levels of the nesting hierarchy. Very often, it makes sense to use possibility models to represent the Variability within and between groups.

The most important methods of multilevel analysis are variants of regression analysis designed for hierarchically nested data sets. The main model is the hierarchical linear model (HLM), an extension of the general linear model in which the probability model for the errors, or residuals, has a structure reflecting the hierarchical structure of the data. The standard assumptions for the HLM are the linear model expressed by the model equation, normal distributions for all residuals, and independence of the residuals for different levels and for different units in the same level.

3.6.1. Two level models

Multilevel models are statistical models which allow not only independent variable at any level of hierarchical structure but also at least one random effect of level one group. Conventional logistic regression assumes that all experimental units are independent in the sense that any variable which affects occurrence of adverse pregnancy outcome has the same effect in all regions, but multilevel logistic regression models are used to assess whether the effect of predictors vary from region to region. The binary multilevel logistic regression model has a binary outcome (experiencing or not experiencing of adverse pregnancy outcome). In this study the basic data structure of the two-level logistic regression is for women-level and regional -level effects.

We further simplify the presentation by assuming there is a women level predictor and regional level factor. To provide a familiar starting point, we first consider a two-level model for binary outcomes with a single explanatory variable. Let Y_{ij} be the binary response for women i in region j and X_{ij} an explanatory variable at the women level. We define the probability of the response equal to one as.

π_{ij} =Pr$(Y_{ij} = 1)$, then the two -level model can be written as:-

$log\ (\frac{\pi_{ij}}{1-\pi_{ij}}) = \beta_0 + \beta_1 X_{ij} + U_{0j}$

Where $U_{0j} \sim iid\ (0,\ \delta^2)$, $U_{0j,}$ is the random effect at level two. Without U_{0j} , the above equation becomes a standard logistic regression model. Conditional on U_{0j}, the Y_{ij} is assumed to be independent.

$$\text{logit}(\pi_{ij}) = log\ (\frac{\pi_{ij}}{1-\pi_{ij}}) = \beta_{0j} + \beta_1 X_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\text{level [1]}.$$

$$\beta_0 + \beta_1 X_{ij} + U_{0j} \ldots\ldots\ldots\ldots\ldots\text{level [2]}.$$

Where β_1 is the difference between the log-odds of the outcome for women in the same cluster in the same division who have observed x values that differ by one unit.

3.6.2. The Empty multilevel logistic Model

The empty two-level model for a dichotomous outcome variable in which there are no explanatory variable at all. This model only contains random groups and random variation within groups. The empty two-level model for a binary outcome variable refers to a population of groups (Level-two units, i.e. regions) and specifies the probability distribution for group-dependent Probabilities. We focus on the model that specifies the transformed probabilities $f\ (P_j)$ to have a normal distribution. This is expressed, for a general link function $f\ (P_j)$, by the formula:

$$f\ (P_j) = \beta_0 + U_{0j}$$

Where β_0 is the population average of the transformed probabilities and U_{0j} the random deviation from this average for group j.

3.6.3. The Random Intercept and fixed effect multilevel Model

A random intercept model is a model in which intercepts allow varying, and therefore the scores on the dependent variables for each individual observation was predicted by the intercept that varies across groups. Random intercept models are models where only the intercept of the level-1 dependent variable is modeled as an effect of the level-2 grouping variable and possibly other level-1or level 2. It represents the heterogeneity between groups in the overall response. Random intercept regression models are also called outcome regression models. In this model the intercept vary between groups and slope was fixed. The random intercept model expresses the,

$\log it$ Of P_{ij} *as* a sum of a linear function of the explanatory variables. These formula is:

$$\log it(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = \beta_{oj} + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots\ldots + \beta_k X_{kij}$$

$$= \beta_{0j} + \sum_{h=1}^{k} \beta_{hX_{hij}}$$

$$= \beta_0 + \sum_{h=1}^{k} \beta_{hX_{hij}} + U_{oj}$$

Where the intercept term β_{0j} is assumed to vary randomly and is given by the sum of an average intercept β_0 and group-dependent deviations, U_{0j}

Where $\beta_{0j} = \beta_0 + U_{0j}$

$\beta_{0j} + \sum_{h=1}^{k} \beta_{hX_{hij}}$ *, is the fixed part of regression model. b/c the Coefficients are fixed.*

U_{0j}, is the random part of the model.

Where Residual U_{0j} *is* residual are mutually independent and normally distributed with Mean zero and variance δ_0^2.

Random intercept models have many applications, for instance estimating the regional effects on adverse pregnancy outcome, adjusting for individual women's level factors, and within the model, evaluate and compare the performance of the region's adverse pregnancy outcome. This can be done by obtaining the odds ratio for each region. This regional effect is a measure of the performance of adverse pregnancy outcome due to the region relative to the average of all regions.

3.6.4. The Random Coefficient multilevel Model

Random coefficient model represents heterogeneity in relationship between the response and explanatory variables. The response variable in this study, adverse pregnancy outcome was binary. Therefore the statistical model used in this analysis was the two-level random coefficient regression model or multilevel regression models. The level 1 dependent is predicted by at least one level 1 covariate. The slope of this covariate and the intercept are predicted by the random effect of the grouping variable at level 2. That is, each group at the higher level is assumed to have a different regression slope as well as a different intercept for purposes of predicting a level 1 dependent variable. In logistic regression analysis, linear models are constructed for the log-odds. 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. Consider explanatory variables which are potential explanations for the observed outcomes.

Denotes these variables by $X_1, X_{2,} X_3 \ldots . X_K$, the values of X_h (h=1, 2, 3…….k) are indicated in the usual way by X_{hij} ,since some or all of these variables could be level one variables, the success probability is not necessarily the same for all individuals in a given group (region). Therefore, the success probability depends on the individual as well as the group, and is denoted by P_{ij} Now consider a model with group specific regression of

$\log it(P_{ij})$ Of the success probability $\log it(P_{ij})$, on a single level -one explanatory variables X_1.

$$\log it(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = \beta_{0j} + \beta_1 X_{ij}$$

The intercept β_{0j} as well as the regression coefficients, or slopes, β_{1j} are group dependent. These group dependent coefficients can be split into an average coefficient and the group dependent deviation. $\beta_{0j} = \beta_0 + U_{0j}$, $\beta_{1j} = \beta_1 + U_{1j}$

$$\log it(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = (\beta_0 + U_{0j}) + (\beta_1 + U_{1j})X_{ij} = \beta_0 + \beta_1 X_{1ij} + U_{0j} + U_{1j} X_{1ij}$$

There are two random group effects, the random intercept U_{oj} the random slope U_{1j}. It is assumed that the level two residuals U_{0j} and U_{1j} have means zero given the values of the explanatory variable X. Thus β_1 is the average regression coefficients like β_0 is the average intercept. $\beta_0 + \beta_1 X_{1ij}$ Called is the fixed part of the model and the second part $U_{oj} + U_{1j} X_{1ij}$ is called the random part. The term $U_1 X_{1ij}$ can be regarded as a random interaction between group and predictors (X). This model implies that the groups are characterized by the two random effects: their intercepts and their slope. These two group effects U_{0j} and U_{1j} will not be independent, but correlated.

But further it assumed that, for different groups, the pairs of random effects (U_{oj}, U_{1j}) are independent and identically distributed. The random intercept variance, $var(U_{0j}) = \delta_0^2$ the random slope variance, $var(U_{1j}) = \delta_1^2$ and the covariance between the random effects, $cov(U_{0j}, U_{1j}) = \delta_{01}$ are called variance components. The model for a single explanatory variable discussed above can be extended by including more variables that have random effects. Suppose that there are k level-one explanatory variables $X_1, X_2, \ldots \ldots X_k$ and consider the model where all X-variables have varying slopes and random intercept. That is,

$$\log it(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots + \beta_{kj}X_{kij}$$

Where $\beta_{0j} = \beta_0 + U_{0j}$ *and* $\beta_{hj} = \beta_h + U_{hj}$, *h=1, 2….k*

$$\log it(P_{ij}) = log(\frac{P_{ij}}{1-P_{ij}}) = \beta_o + \sum_{h=1}^{k} \beta_{hXh_{ij}} + U_{oj} + U_{hj}Xh_{ij}$$

Thus, β_1 is the average regression coefficient like β_o is the average intercept. There are two random group effects, the random intercept U_0 and the random slope U_1 . The first part of this model $\beta_{oj} + \sum_{h=1}^{k} \beta_{hXh_{ij}}$ is the fixed part and the second part $U_{0j} + U_{hj}X_{hij}$ is the random part of the model.

Intra-class Correlation Coefficient (ICC)

The other fundamental reason for applying multilevel analysis is the existence of intra-class (intraregional) correlation arising from similarity of adverse pregnancy outcome in the same region compared to those of different regions. The intra-class correlation coefficient (ICC) measures the proportion of variance in the outcome explained by the grouping structure. ICC can be calculated using an intercept only model. $\log it(P_{ij}) = \beta_o + U_{oj}$, the ICC is then calculated based on the following formula:

$$ICC = \frac{\delta_{uo}^2}{\delta_{uo}^2 + \delta_e^2}$$

Where δ^2_e variance of individual (lower) level units.

In multilevel log it model level one residual variance $\sigma_e^2 = \frac{\pi^2}{3} \approx 3.29$ (Snijders and Bosker, 1999).

3.6.5. Heterogonous Proportion

For the proper application of multilevel analysis, the first logical step is to test heterogeneity of proportions between groups. 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.

3.6.6. Estimation of Multilevel Logistic Regression Model

The statistical theory behind the multilevel regression model is complex. On the basis of the observed data, we want to estimate the parameters of the multilevel regression model such as the regression coefficients and the variance components. The estimators now used in multilevel regression analysis are maximum likelihood (ML) estimators. ML estimators estimate the parameters of a model by providing estimates for the population values that maximize the so called likelihood. Parameter estimation for a multilevel logistic model is not straightforward like the methods for logistic regression. Parameter estimation in hierarchical generalized linear models is more difficult than the hierarchical linear models. The most frequently used kind of approximation method used is based on a first-order or second-order Taylor series expansion of the link function.

3.6.6.1. Multilevel model selection criteria:

There are several methods of model selection. Two most commonly used model selection criteria is Information Criterion (AIC) and Bayesian information criteria (BIC). The model with the smallest AIC and BIC value is considered a better fit. When fitting several models to the same data set, it can be helpful to compare those using summary measures of fit.

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

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

where $\ln L$ is the maximized log-likelihood of the model and k is the number of parameters estimated and N is the number of observations used in estimation or, more precisely, the number of independent terms in the likelihood.

3.6.6.2. Goodness of Fit Test

It is useful to be able to justice whether a model is a good fit to the data. For this study, test of goodness of fit is using the deviance. The maximum likelihood procedure produces a statistic called the deviance, which indicates how well the model fits the data. The test associates the deviance (-2log $likelihood$) 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 observed using Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The smaller the value, the better of the model will be.

3.7. Marginal Model

The primary scientific objective of marginal models is to analyze the population-averaged effects of the given factors in the study on the binary response variable of interest for clustered data. In which responses are modeled, marginalized overall other responses; the association structure is then typically captured using a set of association parameters. In clustered data, observations are usually taken from the same unit, and thus this information forms a cluster of correlated observations. As with independent observations, with clustered observations models focus on how the probability of a particular outcome (e.g., "success") depends on explanatory variables (Agresti, 2002). The marginal model for the mean response depends only on the covariates of interest, not on any random effects or previous responses. This means that the covariates are directly related to the marginal expectations (Molenberghs and Verbeke, 2005).

3.7.1 Generalized Estimating Equation

Generalized estimating equations are extension of GLMs to accommodate correlated data. Generalized Estimating Equations models known function of the marginal expectation of dependent variable as linear function of one or more explanatory variables. The GEE methodology provides consistent estimators of the regression coefficients and their variances under weak assumptions about the actual correlation among a subject's observations (Molenberghs and Verbeke, 2005).

The purpose of GEE model was to measures that provided information about the association between individual observations within the same cluster. The GEE analysis is to explore the relationship between the expected value of the outcome variable and covariates measured on each of the subjects, while adjusting for the correlation within the measurements on each cluster. This approach avoids a need for multivariate distributions by assuming only a functional form for marginal distribution at each time point or condition. It relies on independence across subjects to consistently estimate the variance of proposed estimators even when the assumed working correlation structure is incorrect. For binary data, a GEE approach is used to account for the correlation between responses of interest for subjects from the same cluster (Liang, Scott and Zeger, 1986).

GEE is non-likelihood method that uses correlation to capture the association within the clusters or subjects in terms of marginal correlations (Molenberghs and Verbeke, 2005). For clustered as well as repeated data, Liang and Zeger, (1986) proposed GEE which require only the correct specification of the univariate marginal distributions provided one is willing to adopt "working" assumptions about the correlation structure. The "working" assumptions as proposed by Liang and Scott L . Zeger, (1986) include independence, unstructured, exchangeable and auto-regressive AR (1). Independence and exchangeable working assumptions can be used in virtually all applications, whether longitudinal, clustered, multivariate, or otherwise correlated. Auto regressive AR (1) and unstructured correlation structures are less relevant for clustered data, studies with unequally spaced measurements and/or sequences with differing lengths (Molenberghs and Verbeke, 2005).

Independent: all correlations are assumed to be zero or measurements are independent to each other within individuals in the given cluster (Myers *et al.*, 2010). Note that the independence structure brings about no additional parameters α and hence, when there is no over dispersion, parameter estimates $\hat{\beta}$ will not differ from those obtained from logistic regression.

Exchangeable: All correlations within subjects are equal. The exchangeable structure assumes that there is a common correlation within observations. This structure has homogenous correlations between elements.

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

Then to model the relation between the response and covariates, one can use a regression model similar to the generalized linear model.

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

Where, $\text{logit}(\mu_j)$ = log it link

X_j= (n_jx P) dimensional vector of known covariates.

β = ($\beta_1, \beta_2 \ldots \beta_p$)' (Px1) dimensional vector of unknown fixed regression parameter to be estimated

$E(Y_j) = \mu_j$ is expected value of responses. Assume that you have chosen a model that relates a marginal mean to the linear predictor $X'_j\beta$

Through a link function. The generalized estimating equations for estimating β, is given by:

$$U(\beta, \hat{\alpha}) = \sum_{j=1}^{n} \frac{\partial \mu_j}{\partial \beta}^{T} V_j^{-1}(y_j - \mu_j) = 0$$

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

$\hat{\alpha}$ = an estimate of the 'nuisance' parameter vector

$$V_j = \varphi A_j^{\frac{1}{2}} Rj\,(\alpha)\, A_j^{\frac{1}{2}}$$

Where A_j = is n_j xn_j diagonal matrix with $v(\mu_{ij})$ as i^{th} diagonal element ($A_j = diag(v(\mu_{ij}))$

$R_j(\alpha)$ is n_jxn_j working correlation matrix of within cluster responses that is fully specified by the vector of parameter α. This working correlation matrix may depend on the vector of unknown parameters α, which is the same for all subjects. If $R_j(\alpha)$ is the true correlation matrix of Y_j, then V_j is the true covariance matrix of Y_j. φ is dispersion parameter and is estimated by

$$\hat{\varphi} = \frac{1}{N-p} \sum_{j=1}^{m} \sum_{j=1}^{nj} e_{ji}{}^{2}$$

Where $N = \sum_{j=1}^{m} n_j$ is the total number of measurements and P is the number of regression parameters and e_{ji} is the Pearson residual given by $e_{ji} = \frac{yji - \mu ji}{\sqrt{V(\mu_{ji})}}$.

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

$$S(\beta) = \sum_{j=1}^{m} \frac{\partial \mu j^{T}}{\partial \beta} \left[A_j^{\frac{1}{2}} Rj\, A_j^{\frac{1}{2}} \right]^{-1} \left(y_{j-\,\mu_j} \right) = 0$$

The model-based estimator of $cov\ (\hat{\beta})$ is given by $\sum_{m} \hat{\beta}\ I_0{}^{-1}$

Where $I_0 = \sum_{j=1}^{m} \frac{\partial \mu j^T}{\partial \beta} V_j^{-1} \frac{\partial \mu j}{\partial \beta}$ the estimator $\sum_e = I_0{}^{-1} I_1 I_0{}^{-1}$ is called the empirical, or robust, estimator of the covariance matrix of $\hat{\beta}$, where $I_1 = \sum_{j=1}^{m} \frac{\partial \mu j^T}{\partial \beta} V_j^{-1} \mathrm{cov}\left(y_j^{-1}\right) \frac{\partial \mu j}{\partial \beta}$.

GEE describes changes in the population mean and is used to estimate population average models or marginal models. An advantage of the GEE approach is that it yields a consistent estimator of coefficients, even when the working correlation matrix R_j is mis-specified. However, severe misspecification of working correlation may seriously affect the efficiency of the GEE estimators (Molenberghs and Verbeke, 2005).

3.9.2. Parameter Estimation of GEE

Parameter estimates from the GEE are consistent even when the covariance structure is mis-specified, under mild regularity conditions. The generalized estimating equations are estimates of quasi-likelihood equations which is quasi-likelihood estimators (Liang, Scott and Zeger, 1986).
A quasi-likelihood estimate of β arises from maximization of normality-based log likelihood without assuming that the response is normally distributed. In general, there are no closed-form solutions, so the GEE estimates are obtained by using an iterative algorithm, that is iterative quasi-scoring procedure. GEE estimates of model parameters are valid even if the covariance is mis-specified (because they depend on the first moment, e.g., mean). However, if the correlation structure is mis-specified, the standard errors are not good, and some adjustments based on the data (empirical adjustment) are needed to get more appropriate standard errors.
Wald statistics based confidence intervals and hypothesis testing for parameters; recall they rely on asymptotic normality of estimator and their estimated covariance matrix. Points out that a chosen model in practice is never exactly correct, but choosing carefully a working correlation (covariance structure) can help with efficiency of the estimates (Barnhart and Williamson, 1998).

3.7.2. Model Building for Marginal Models

Model selection is an important issue in almost any practical data analysis. A common problem is variable selection in regression given a large group of covariates (including some higher order terms) one needs to select a subset to be included in the regression model. Model selection is data analysis strategy, which leads to a search of best model

3.7.2.1. Variable Selection Technique

Variable selection is an essential part of any statistical analysis. To select significant variables, firstly under the GEE, model building strategy started by fitting a model containing all possible covariates in the data. This is done by considering two working correlation assumptions (exchangeable and independence). In order to select the important factors related to the response variable, the backward selection procedure was used. The strategy is called backward because we were working backward from our largest starting model to a smaller final model. In this case, the procedure is used to remove covariates with non-significant p-values. This means that variables that did not contribute to the model based on the highest p-value would be eliminated sequentially and each time a new model with the remaining covariates were refitted, until we remained with covariates necessary for answering our research question.

3.7.2.2. Model Comparison Technique

Quasi-Information Criterion (QIC): is used to select a correlation structure. The QIC is called the quasi-likelihood information criterion. In a condition, when the likelihood function cannot be fully specified, such as in the GEE case, the Akaike Information Criterion (AIC) cannot be directly applied to select either the optimal set of explanatory variables or correlation matrix. As an alternative, one can use the modified Akaike Information Criterion called Quasi Information Criteria (QIC), which is based on the quasi-likelihood function (Pan, 2001). QIC is derived from the AIC and conceptually similar. The QIC can then be used to choose between several correlations structures, with the best structure being the one which has the lowest QIC value. The QICu could be potentially useful in variable selections; however, QICu cannot be used to select the working correlation matrix. A model with a smaller QICu value contains more suitable variables than a model with a bigger QICu value (Hardin and Hibbe, 2003).

3.7.2.3. Goodness of Fit of the Model

The goodness of fit of a model measures how well the model describes the data. Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values. Although methods exist for assessing the adequacy of the fitted models for uncorrelated data with likelihood methods, it is not appropriate to use these methods for models fitted with correlated (clustered) data, GEE method is quasi-likelihood. We propose model-based and robust (empirically corrected) goodness-of-fit tests for GEE modeling with binary responses data. Similarly, it was also assessed by using QIC (Hardin and Hibbe, 2003).

3.7.2.4. Significance Test

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. GEE model parameters are estimated using quasi likelihood procedures, there is no associated likelihood underlying the model. To determine the significance of the predictor variables we can use Wald statistic from empirical (robust) estimates. To compare the GEE models; however, one can construct a multi-parameter Wald test to test the null hypothesis that a set of βs equal 0.

Wald test then equals

$X^2 = \hat{\beta}' C' (CV(\hat{\beta}')C')' C\hat{\beta}.$

Which is distributed as X^2 with q degrees of freedom under the null hypothesis. The prime symbol indicates the transpose of the matrix or vector. Where C is a 1 x p vector selecting a single regression coefficient β (Liang, Scott and Zeger, 2002).

This will help test the hypothesis:

$H_0 = \beta_1 = \beta_2 = \beta_3 = ... = \beta_q$ versus the alternative that

$H_1 = \beta_q \neq \beta_p$

3.7.2.5. Diagnostics Checking

The fitted model may be inadequate because of particular observations, outliers, influential, Cook's distance and DFBTA values. These observations may affect the conclusions to be drawn from the study. It is of interest to obtain the residual values from the estimated multilevel logistic regression model. Plots are a good way to examine the residuals. But in multilevel logistic regression, many different residual plots can be used. For this study, the fitted model was checked for possible presence of outliers and influential values in a similar way with standard logistic model. But additionally, the presence of outliers and influential observation were examined for level two. The value of standardized residuals greater than 3 in absolute value is considered as an outlier for both level one and level two (Agresti, 2007). Leverage and influence value greater than one is considered as an influential observation for both level one and level two.

DFBETA diagnostic can be used to assess the effect of an individual observation on each estimated parameter of the fitted model. If DFBETA of a case is greater than 1, then it is potential outlier. Cases for which Cook's distance is large have substantial influence on both the estimate of β and on fitted values and deletion of these cases may result in significant changes. If Cook's distance of a case is greater Than 1, then it is potential outlier (Hosmer and Lemeshow, 2000).

Preisser and Qaqish, (1996) further generalize regression diagnostics to apply to models for correlated data fitted by generalized estimating equations (GEEs) where the influence of entire clusters of correlated observations is measured. The diagnostic measures proposed for marginal models were alike to those that exist for generalized linear models. In marginal model building is to perform an analysis of residuals and diagnostics to study influence of observations.

3.8. Handling Missing Data

3.8.1. Deletion methods

Missing data are also discussed to as non-response or unobserved data and occur in most types of studies. Missing data is loss of information, impact on precision and power. It is important to handle the problem of missing data in a suitable way to obtain unbiased results that can be used in research and should have good statistical power. Deletion techniques are the most basic techniques to handle missing data. Deletion will result in a reduced sample size and less power to identify statistical effects (Allison, 2002). The advantage of this method is that the remaining data set is complete. However, if the assumption of MCAR is fulfilled, deletion is known to produce unbiased estimates and conservative results. When the data do not satisfied the assumption of MCAR, deletion may cause bias in the estimates of the parameters (Donner, 1982). Thus, the data for this study has full fill the assumption of MCAR that we have used the deletion method.

Definition of Some Basic Terms

Adverse pregnancy outcome: This refers to pregnancy results of a non-viable baby or a Pregnancy that did not result in a live birth.

Stillbirth: birth of child but who shows no sign of life at delivery or defined as fetal death after 28 weeks of gestation.

Abortion: defined the termination of a pregnancy before 28 weeks of gestational age.

Gestational age: fetal age or duration of pregnancy measured from the first days of the last Normal menstrual period and expressed in completed days or weeks.

Miscarriage: A miscarriage, also known as a spontaneous abortion (SAB), is a term used for Pregnancy that ends at a stage where the fetus is incapable of surviving on its own Or if the pregnancy ends in the first 20 weeks of gestation.

CHAPTER FOUR

4. RESULT AND DISCUSSION

The purpose of this chapter is to analyze different factors that heterogeneity of adverse pregnancy outcome in Ethiopia using data from 2016 Ethiopian Demographic and Health Survey (EDHS). The results of the analysis are divided into the following sections: descriptive analysis, binary logistic regression analysis, multilevel logistic regression analysis and GEE model analysis. To identify determinant factors of experiencing adverse pregnancy outcomes and variation in experiencing adverse pregnancy outcome across regions using multilevel logistic regressions model. To identify the association within the clusters or subjects in terms of marginal correlations using generalized estimating equation.

4.1. Descriptive Analysis

Table 4.1. Present basic descriptive information that summarizes the associations between the determinant factors and adverse pregnancy outcome of mothers. The initial population consisted of 15683 women of reproductive age. Out of this 9694(61.8%) of women with complete information were selected and studied in the analysis. From the sampled women, the proportion of experiencing adverse pregnancy outcomes was about 1282 (13.2%) and 8412 (86.8%) not experiencing adverse pregnancy outcome.

The proportion of the experienced adverse pregnancy outcome varied from one region to the other in Ethiopia. The highest percentage of experienced adverse pregnancy outcomes was observed in Somalia (21.4%) while the lowest percentage of experienced adverse pregnancy outcomes was recorded in Addis Ababa (8.5%). Hence, there appears to be some variation in the proportion of experienced adverse pregnancy outcomes among women in different regions. The proportion of experienced adverse pregnancy outcome, observed in type of place of residence: urban and rural. Accordingly, higher numbers of experienced adverse pregnancy outcome (14.2%) resided in rural areas, and relatively small number of experienced adverse pregnancy (10.9%) resided in urban areas. The proportion of adverse pregnancy outcome is (13.81%) for no educated women, (13.6%) for primary educated women and (13.1%) for women whose education level is secondary and 9% for women whose education level is higher education.

The proportion of experienced adverse pregnancy outcome among women who are underweight, normal, overweight and Obesity were 12.4%, 13.2%, 15.1% and 14.9% respectively. Similarly, the highest proportions of experienced adverse pregnancy outcome were observed among women who do not antenatal visit (15.4%) and visit at least once (11.6%). The proportion of experienced adverse pregnancy outcome, observed in Table 4.1 shows differs with their age groups. For instance, higher proportion of experienced adverse pregnancy outcome was observed for women 35 and above years of age (22.7%) and the lowest proportion of experienced adverse pregnancy outcome of women was found in the age group between 15-24 years (6.1%). The proportion of experienced adverse pregnancy outcome vary by wealth index (households economic status).The highest percentage of experienced adverse pregnancy outcome that was observed among women from poor households (14.6%) as opposed to women residing among middle households (12.7%). 12.7% of women were delivered at home, 14.16% had delivered at any health center. 16.9% of the women were anemic and with less proportion of experiencing adverse pregnancy outcome than those (11.1%) with not anemic.

The proportion of experienced adverse pregnancy outcome, observed in type of parity: Null parity, single parity and multi parity. Accordingly, higher numbers of experienced adverse pregnancy outcome (14%) single parity, and relatively small number of experienced adverse pregnancy (8.2%) null parity. The experienced adverse pregnancy outcome of women varies by their marital status. The highest percentage of women experienced adverse pregnancy outcome was observed in women Widowed (24.3%) as opposed to the lowest percentage of experienced adverse pregnancy outcome of women which was recorded for women never in union (3.4%). The proportion of experienced adverse pregnancy out come as observed in table 4.1 show differs with the occupation of their women. For instance, proportion of experienced adverse pregnancy outcome was observed for women had working (16.1%) and the proportion of experienced adverse pregnancy outcome was women no had working (10.75%). The number of experienced adverse pregnancy outcome differs between smoking cigarette and nonsmoking cigarette. Accordingly, a higher percentage of experienced adverse pregnancy outcome happened to women coming from nonsmoking cigarette households (13.3%) as opposed to women coming from smoking cigarette households (9.4%).

Table 4. 1 Distribution of experiencing adverse pregnancy outcome among women of Ethiopia.

Variables	Categories	Experienced of adverse pregnancy outcome		Total	Chi-square	df	p-valu
		Yes	No				
Region	Tigray	129 (13%)	822(86.4%)	951	111.7	10	0.001
	Amhara	134 (14.8%)	772(85.2%)	906			
	Afar	82 (9.63%)	769(90.4%)	851			
	Oromia	195 (15.8%)	1046(84.2%)	1241			
	Somali	148 (21.4%)	543(78.6%)	691			
	Benishangul	88 (13.9%)	544(86.1%)	632			
	SNNPR	178 (16.4%)	906(83.6%)	1084			
	Dire Dawa	85 (10.3%)	742(89.7%)	827			
	Harari	66 (12.1%)	480(87.9%)	546			
	AddisAdaba	112 (8.5%)	1207(91.5%)	1319			
	Gambela	65 (10.1%)	581(89.9%)	646			
Type of place of residence	Urban	311(10.9%)	2536(89.1%)	2847	18.59	1	0.001
	Rural	971(14.2)	5876(85.8%)	6847			
Education attainment	No educ	540(13.8%)	3371(86.1%)	3911	15.99	3	0.001
	Primary	497(13.6%)	3135(86.4%)	3632			
	Secondary	163(13.1%)	1077(86.9%)	1240			
	Higher	82(9%)	829(91%)	911			
Wealth index	Poor	178(14.6%)	1044(85.4%)	1222	3.635	2	0.162
	Middle	630(12.7%)	4346(87.3%)	4976			
	Rich	474(13.6%)	3022(86.4%)	3496			
Current marital status	Never in un	36(3.4%)	1032(96.6%)	1068	124.5	5	<0.0001
	Married	1064(13.9%)	6606(86.1%)	7670			
	Living withp	19(15.7%)	102(84.3%)	121			
	Widowed	42(24.3%)	173(75.7%)	215			
	Divorced	88(18.5%)	388(81.5%)	476			
	Separated	33(22.9%)	111(77.1%)	144			
Number of antenatal visits during pregnancy	No antenatal visi	631(15.4%)	3461(84.6%)	4092	29.74	1	<0.0001
	Visit at least onc	651(11.6%)	4951(88.4%)	5602			
Smokes cigarettes	No	1268(13.3%)	8277(86.7%)	9545	1.9	1	0.164
	Yes	14(9.4%)	135(90.6%)	149			
Anemia level	Not anemic	681(11.1%)	5463(88.9%)	6144	66.99	1	<0.0001
	Anemic	601(16.9%)	2949(83.1%)	3550			
Place of delivery	Home	806(12.7%)	5527(87.3%)	6333	3.94		
	Health facility	476(14.16%)	2885(85.84%)	3361		1	0.260
Age groups	15-24	178(6.1%)	2762(93.9%)	2940	341.5	2	<0.0001
	25-34	504(12.3%)	3606(87.7%)	4110			
	35 above	600(22.7%)	2044(78%)	2644			
Body Mass Index	Underweight	277(12.4%)	1963(87.6%)	2240	4.694	3	0.196
	Normal	826(13.2%)	5434(86.6%)	6260			
	Over weight	145(15.1%)	821(84.9%)	966			
	Obesity	34(14.9%)	194(85.1%)	228			
Total children ever born	Null parity	28(8.2%)	314(91.8%)	342	8.791	2	0.012
	Single parity	426(14%)	2617(86%)	3043			
	Multi parity	828(13.2%)	5481(86.8%)	6309			
Occupation	Not Working	558(10.75%)	4629(89.29%)	5187	59.1	1	<0.0001
	Working	724(16.1%)	3783(83.9%)	4507			

4.2. Logistic Regression Analysis of Adverse pregnancy outcome.

According to Table 4.2 Age of women, place of residence, Occupation of women, Anemia level, Parity, marital status of women, antenatal care of women and Education of women were found to be significant predictors of adverse pregnancy outcome at 5% level of significance. But delivery place, smoking cigarette, wealth index, Body mass index are not significant. The odds of adverse pregnancy outcome in Tigiray was found to be 2.1 times more likely than the odds of adverse pregnancy outcomes in Addis Ababa controlling for the other variables in the model. The odds of adverse pregnancy outcome in Hariri was found to be 1.5 times more likely than the odds of adverse pregnancy outcome in Addis Ababa controlling for the other variables in the model. The odds of adverse pregnancy outcome in Afar, Oromia, Somali and Benishal, SNNPR were 2.03, 2.12, 3.44, 1.87 and 2.32 times more than the odds of adverse pregnancy out come in Addis Ababa respectively; controlling for other variables in the model.

The odds of adverse pregnancy outcome of women that were from primary educated women was 1.493 more likely than those no educated women. While women from secondary educated women were 1.572 times more likely than those no educated women controlling for other variables in the model. The odd of adverse pregnancy outcome of women higher education are not significant when compared to no education. Place of residence to be significantly associated with adverse pregnancy outcome women that resided in the urban areas was 0.697 times less likely than those from the rural areas.

The model revealed that the odds of adverse pregnancy outcome of women in reproductive age of group who don't antenatal visits had 1.371 times more likely than those women who visited at least once. The odds of adverse pregnancy outcome for employed women is 1.5 times more likely than those unemployed. The odds of adverse pregnancy outcome of reproductive age of women who are age group 15-24 is 2.278 times more likely than those age group 24-34(reference categories). While the odds of adverse pregnancy outcome of reproductive age of women who Age above 35 is 4.63 times more likely than those age group 24-34.

Women who were never in a union were 3.139 times more likely than those married. In contrast women who are living with partner were 3.71 times more likely than those married and those women who are widowed were 2.79 times more likely than adverse pregnancy outcome compared to those women who were married. Similarly the odd of adverse pregnancy outcome of women divorced is 3.69 times more likely than those married and separated women is 4.65 times more likely than married (reference categories). Total children ever born (parity) was also found to be significantly associated with adverse pregnancy outcome. The odds of adverse pregnancy outcome for Single parity women is 1.91 times more likely than those multi parity.

Table 4. 2: Parameter estimates, and 95% CI for Odds Ratio for confounders

Confounders	Estimate	Standard error	P-value	|OR|	[95% C. Interval of OR]	
Intercept	-5.31	0.323				
Region						
Addis Ababa (ref)						
Tigiray	0.717	0.152	<.0001*	2.05	1.519	2.761
Afar	0.707	0.151	<.0001*	2.03	1.511	2.725
Amhara	0.251	0.162	0.118	1.28	0.938	1.757
Oromia	0.749	0.135	<.0001*	2.12	1.621	2.761
Somali	1.236	0.147	<.0001*	3.44	2.581	4.596
Benishalgum	0.628	0.162	<.0001*	1.87	1.367	2.572
SNNPR	0.843	0.137	<.0001*	2.32	1.774	3.046
Gambella	0.304	0.161	0.058	1.35	0.989	1.855
Harar	0.464	0.171	0.006*	1.59	1.139	2.223
Dire Dawa	0.271	0.169	0.109	1.31	0.941	1.827
Parity						
Multi par(ref)						
Single para	0.647	0.224	0.004*	1.911	1.233	2.961
Null parity	0.133	0.219	0.543	1.143	0.742	1.758
Body mass index						
Normal(ref)						
Underweight	0 .118	0.077	0.155	1.118	0 .965	1.312
Over weight	0.242	0.117	0.213	1.265	0.998	1.573
Obesity	0.221	0 .262	0.272	1.248	0.836	1.889
Occupation of mother						
Not work(ref)						
Working	0.418	0.064	<.0001*	1.519	1.338	1.725
Age of mother						
24-34(ref)						
15-24	0.823	0.102	<.0001*	2.278	1.872	2.772
35 above	1.533	0.103	<.0001*	4.632	3.779	5.681
Antenatal visit						
Visit at least once (ref)						
No antenat visit	0.315	0.066	<.0001*	1.371	1.198	1.552
Marital status						
Married(ref)						
Never in union	1.144	0.185	<.0001*	3.139	2.183	4.515
Living with	1.310	0.314	<.0001*	3.707	2.001	6.865
Widowed	1.011	0.258	<.0001*	2.791	1.657	4.563
Divorced	1.306	0.218	<.0001*	3.692	2.401	5.661
Separated	1.536	0.274	<.0001*	4.647	2.712	7.960
Wealth index						
Rich(ref)						
poor	0.616	0.104	0.543	1.063	0.868	1.307
Middle	0.144	0.076	0.057	1.154	0.995	1.346
Education of mother						
No educ(ref)						
Primary	0.401	0.072	<.0001*	1.493	1.294	1.724
Secondary	0.453	0.107	<.0001*	1.572	1.273	1.941
Higher	-0.233	0.132	0.078	0.791	0.610	1.026
Residence						

Rural(ref)						
Urban	-0.359	0.079	<0.0001*	0.697	0.596	0.816
Smoking						
No(ref)						
Yes	-0.574	0.295	0.056	0.562	0.315	1.005
Anemia						
Not anemic(ref)						
Anemic	0.513	0.063	<.0001*	1.671	1.475	1.893
Delivery place						
Home(ref)						
health facility	0.105	0.069	0.132	1.109	0.969	1.269

*=significant at 5% level of significance.

4.2.1. Goodness of Fit of the Model

For categorical data, after a logistic regression model has been fitted, a global test of goodness of fit of the resulting model should be achieved. It is necessary to see the suitability, adequacy and usefulness of the fitted model. The most commonly used techniques are Likelihood-Ratio test, Hosmer-Lemeshow test.

Likelihood-Ratio Test

Likelihood ratio test is the chi-square difference between the null model with the constant only and the model containing a set of predictors. Under model summary (See Appendix A; Table 4.9).-2log =. This statistics 6818.794 show us how much improvement is needed before predictors provide the best possible prediction of the response variable, the smaller the statistics the better the model.

The statistics for only intercept model is –LL0= 754.846+6818.794 =6063.948, the inclusion of the parameters reduced the -2log likelihood statistics by (6818.794- 6063.948)=754.846, which is reflected chi-square for omnibus test. The result X^2 =754.846, df =33, P- value =<.0001, shows that the model is adequate, meaning that at least one of the predictors is significantly related to the dependent variable. That is, the null hypothesis is that there is no difference between the model with only a constant and the model with independent variables was rejected.

Hosmer and Lemeshow test

Table 4. 3 Test of Significance of Hosmer-Lemeshow Goodness of Fit Statistics.

Hosmer and Lemeshow Test			
Step	Chi-square	Df	Sig.
1	7.635	8	0.470

The Hosmer-Lemeshow Goodness-of-fit test tests the hypotheses:

H_0: the model is a good fit, vs.

H_1: the model is not a good fit

A non-significant chi-square implies that there is no significant difference between the observed and the model predicted values and hence the estimated model adequately fit the data. Since the p-value is 0.47, we do not reject the null hypothesis that there is no difference between observed and model-predicted values, implying that the estimated model fits the data at an acceptable level.

4.2.2. Diagnostic checking

After model fitting, the next important step in logistic regression is model building to perform the study of residuals and diagnostics to study the influence of observations and taking appropriate remedial measure. A failure to detect outliers and hence influential cases can have simple distortion on the validity of the inferences drawn from the model. The diagnostic test results for detection of outliers and influential cases are displayed in (Appendix A Table 4.9) shows that the maximum values of analog of Cook's influence statistics and DFBETA for each predictor variables, which were less than 1. Hence there is no potential influential observation. Therefore, from the above goodness of fit tests and diagnostic checking the models are adequate.

4.3. Multilevel Logistic Analysis of Adverse pregnancy out come in Ethiopia

Multilevel models were developed to examine hierarchically structured data. The advantages of using a multilevel model include the ability to fully explore the variability at all levels of the data hierarchy, and estimation of correct standard errors in the presence of clustered data. Stepwise regression was used to fit the multilevel model.

The first step examined the null model of overall probability of experiencing adverse pregnancy outcome without adjustment for predictors. Secondly, multilevel model for random intercept and fixed slope multilevel analysis was done. Third step considered a model for two level random intercept and random slope (random coefficient) multilevel logistic regression analysis adopted. The chi-square test was applied to assess heterogeneity between regions mean. The test yields X^2 = 111.787 with d.f = 10 (P<0.0001). Thus, there is evidence of heterogeneity with respect to adverse pregnancy outcome among the regions of Ethiopia.

4.3.1. Empty model with random intercept or intercept only model

The empty two-level model also called the null two-level model for a dichotomous outcome variable refers to a population of groups (level-two unit, i.e. regions) and an intercept-only model that predicts the probability of adverse pregnancy outcome.

$log\,it\ (\pi_j) = \beta_0 + U_{0j}$, *where* U_{0j} *~IID* $(0,\delta_0^2)$.

The intercept β_0 also known as the grand mean is shared by all regions while the random effect U_{0j}, also known as level two residual is specific to region j. It shows how the mea in a particular region deviates from the grand mean. δ_0^2 is the between regions variance. The random effect is not directly estimated but is summarized in terms of their estimated variances.

Table 4. 4 Result of Parameter Estimate of Intercept-Only Model with Random Effect.

	Fixed effect estimated					
Covariates	Estimate	Std. Err.	Z	P>|z|	[95% Conf. Interval]	
Intercept	-1.906356	0 .094311	-20.21	<0.001	-2.091202	-1.72151
	Random effects Parameters estimated					
Parameters		Estimate		Std. Err.	[95% Conf. Interval]	
Region (Intercept) $Var(U_{0j}) = \delta_o^2$		0.086767		0.0413	0.0342	0.2205

LR test vs. logistic model: chibar2 (01) = 58.63 Prob >= chibar2 = <0.001

AIC	BIC	log Lik	deviance
7502.49	7516.848	-3749.245	7498.49

Table 4.4 are the estimates of fixed effects and random effects. The estimate of the fixed part of the model is -1.90677 with a p- value of <0.001 implying that the average log odds of women is

significantly different from zero. The intercept β_0 = -1.90677 is reflects as the average overall log odds of adverse pregnancy outcome.

The variance of the regional level residuals errors, symbolized by δ_0^2 is estimated to be 0.086767. This parameter estimate is larger than the corresponding standard errors and the 95% confidence interval of the estimate shows that it is significant since the lower bounder of confidence interval is does not close to zero. The fixed part of the model is interpreted as the grand mean of log odds of women with odds $\exp(-1.906356)$ = 0.148621. The average probability of the occurrence of women is $\frac{\exp(-1.906356)}{1+\exp(-1.906356)}$ = 0.1294 which means that the chance for the women to experienced adverse pregnancy outcome is 0.1293 on average. Which is somewhat similar with the descriptive result (0.132). The table 4.4 also contains the variance estimate of the random effects at regional level, δ_0^2 = 0.086767 which implies that the between region variance of women is 0.086767.

The model for the j^{th} region as log $it(\pi_j)$ = -1.90677+U_{0j}.

The value of the test statistics and the corresponding p-value for testing the hypothesis H_0: δ_o^2 =0 that there is no cross-regional variation in adverse pregnancy outcome are presented. Since the value of the test statistic is 58.63 with p= <0.001, the null hypothesis is rejected, and we conclude that there is strong evidence of heterogeneity or cross-regional variation in adverse pregnancy outcome.

Table 4.4. The intra-class correlation coefficient, which is a measure of the correlation between two individuals who are in the same higher level unit (region). A low ICC indicates a relatively small between region variations. In other words regions tend to perform at comparable levels to reduce the adverse pregnancy outcome. As ICC increases, regions tend to perform with ever increasing variations to the adverse pregnancy outcome.

Intra-class correlation coefficient is 0.02487, meaning that 2.49% of variation in the experienced adverse pregnancy outcome can be explained by difference between regions (higher level units). The remaining 97.51% of the variation is explained by variation among individuals within region (lower level units).

4.3.2. The Random Intercept and Fixed Effect Multilevel Model

In a random intercept and fixed effect multilevel logistic regression model, we allow the probability of adverse pregnancy outcome to vary across regions assuming that the effects of the explanatory variables are the same for each region. That is, the random intercept varies across Regions, but women level explanatory variables are fixed across regions.

Table 4. 5 Result of Parameter Estimate of random intercept and fixed slope multilevel logistic Model.

Covariates	Estimate	Std. Err.	P>|z|	OR	[95% Conf. Interval OR]	
Intercept	-5.039	0.315	<0.001			
Residence						
Rural(ref)						
Urban	-0.3542	0.0784	<0.001	0.7018	0.6001	0.8206
Anemia						
Not anemic(ref)						
Anemic	0.5241	0.0658	<0.001	1.6889	1.4767	1.9316
Education of mother						
No education(ref)						
Primary	0.3996	0.0726	<0.001	1.4912	1.2933	1.7194
Secondary	0.4532	0.1074	<0.001	1.5734	1.2745	1.9424
Higher	-0.2319	0.1301	0.078	0.7930	0.6117	1.0279
Marital status						
Married(ref)						
Never in union	1.1415	0.1852	<0.001	3.1315	2.1777	4.5031
Living with partner	1.3054	0.3142	<0.001	3.6893	1.9927	6.8306
Widowed	1.0235	0.2545	<0.001	2.7829	1.6799	4.6099
Divorced	1.3044	0.2170	<0.001	3.6857	2.4039	5.6511
Separated	1.5388	0.2744	<0.001	4.6592	2.7207	7.9791
Age of mother						
25-34(ref)						
15-24	0.8226	0.0997	<0.001	2.2765	1.8715	2.7692
35 above	1.5310	0.1037	<0.001	4.6228	3.7718	5.6658
Occupation of mother						
Not working(ref)						
Working	0.4170	0.0647	<0.001	1.5174	1.3365	1.3365
Parity						
Multi parity(ref)						
Single para	0.6541	0.2232	0.003	1.9233	1.2412	2.9790
Null parity	0.1396	0.2196	0.525	1.1499	0.7476	1.7685
Antenatal care						
Visit at least once(re)						
No antenatal visit	0.3150	0.0662	<0.001	1.3702	1.2033	1.560333

Random-effects Parameters estimated

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Region: var(_cons)				
$Var(U_{0j})=\delta_o^2$	0.0967	0 .0488	0 .0401	0.2604

ref = Reference Category

LR test vs. logistic model: chibar2 (01) = 75.15 Prob >= chibar2 = 0.0000

AIC	BIC	$\log Lik$	deviance
6904.991	7084.473	-3427.496	6854.99

The 95% confidence interval of the estimate shows that it is significant since the lower bounder of confidence interval is does not close to zero. The deviance-based Chi-square (deviance = 643.5) is the difference in deviance between the empty model with random intercept (deviance = 7498.49) and fixed slope model with random intercept (deviance = 6854.99).

This value is compared to chi-square distribution with 10 degree of freedom. The significant of it (X^2= 643.5, df = 10, P-value = 0.000) implies that fixed slope model with random intercept model is better than empty model with random intercept. Therefore, this model is a better fit as compared to the empty model with random intercept. The AIC and Deviance value for fixed slope model with random intercept (AIC= 6904.991, and Deviance = 6854.99) are less than the empty model with random intercept (AIC = 7502.49, and Deviance =7498.49). This indicates that fixed slope model with random intercept is a better fit as compared to the empty model with random intercept model.

Moreover, the values of chibar2 (01) = 75.15 and P=<0.001 (see Table 4.5) lead to the rejection of the null hypothesis that the random effect is zero as in the assumption of ordinary logistic regression. From this we can conclude that the random effect at regional level is significantly different from zero. We have a between regions variance of 0.0967. Intra-class correlation coefficient is 0.0285, meaning that 2.85% of variation in the experienced adverse pregnancy outcome can be explained by grouping in regions (higher level units). The remaining 97.15% of the variation is explained within region (lower level units).

4.3.3. The Random Coefficient Model

In this model, both intercept and slopes are allowed to vary across regions, meaning that they are different in different regions. Example, in experiencing adverse pregnancy outcome (nesting structure: women within regions) it is possible that the effect of Antenatal care of a woman and anemia level of women on experiencing adverse pregnancy outcome is stronger in some regions than in others. The effect of Antenatal care of women and anemia level of women (allowing it to randomly vary between regions) with other fixed effects (by setting the variance of other coefficients zero) on experienced adverse pregnancy outcome.

According to (Appendix A table 4.10), the values of AIC and BIC for the random coefficient model (AIC = 6908.909 and BIC = 7124.287) are more than the AIC and BIC values for the random intercept model (AIC= 6904.991, and BIC= 7084.473). This indicates that the random intercept and fixed effect model is a better fit compared to the random coefficient model.

4.3.3.1. Comparison of Multilevel Logistic Models

The model which has small AIC is best model for the data set of adverse pregnancy outcome in Ethiopia.

	AIC	BIC	$\log Lik$	Deviance
Only random intercept	7502.49	7516.848	-3749.245	7498.49
Random intercept and fixed slope	6904.991	7084.473	-3427.496	6854.99
Random coefficient (Anemia level and ANC)	6908.909	7124.287	-3428.454	6856.91

The random intercept and fixed slope model with small AIC =6904.991 was an improved fit as compared to the rest models. According to table 4.5 the result of parameters of observed variables can be interpreted much the same way as those from the standard log it model. Thus, everything else being equal except slight difference on random effect in the model, the result of the random intercept model, the fixed part showed that place of residence, educational status, Parity, Occupation status, Anemia level , antenatal care, Marital status and Age of women were found to be significant variation in the adverse pregnancy outcome among regions.

The odds of adverse pregnancy outcome of women who have primary education were 1.49 times more likely than adverse pregnancy outcome compared to women with no education controlling for other variables in the model. While women with secondary education were 1.57 times more likely to be adverse pregnancy outcome when compared to women with no education. However there is no statistically significant difference in the odds of experiencing adverse pregnancy outcome between women who attended higher education when compared no education. The odds of adverse pregnancy outcome of women who had working were 1.52 times more likely to be adverse pregnancy outcome than women not had working controlling for other variables in the model. The odds of adverse pregnancy outcome of women who had age 15-24 years were 2.28 times higher than the odds of adverse pregnancy outcome of women age 24- 34 years controlling for other variables in the model. Similarly the odds of adverse pregnancy outcome of women who were age 35 above years were 4.62 times higher than the odds of adverse pregnancy outcome of women age 24- 34 years controlling for other variables in the model. Women who live in urban were 0.71 times less likely to with adverse pregnancy outcome than women who reside in rural controlling for other variables in the model. Conversely, the odd of adverse pregnancy outcome of never in union women were about 3.13 times more likely to be adverse pregnancy outcome than married women. In addition, women who are living with partner were 3.69 times more likely to experienced adverse pregnancy outcome than married women. Widowed women were 2.78 times more likely to be adverse pregnancy outcome than married women or reference categories. Furthermore, the odd of adverse pregnancy outcome of among Divorced women were about 3.68 times more likely to be adverse pregnancy outcome than married women.

Similarly, separated women were 4.65 times more likely to experienced adverse pregnancy outcome than married women. Regarding to place of delivery (place of termination pregnancy), were no statistically significant difference in the odds of experiencing adverse pregnancy outcome among women who delivered at home and those whose delivered at health facilities. The odds of adverse pregnancy outcome among women who had anemia were 1.674 times more likely than the odds among women not anemia. Total children ever born (parity) also another influential factor in adverse pregnancy outcome the odds of adverse pregnancy outcome single parity were 1.92 times more likely to be adverse pregnancy outcome than the women multi parity. Furthermore, utilization is also important factor that predict the occurrence of adverse pregnancy outcome. Accordingly, to women’s who did not visit antenatal care, were 1.37 times more likely to experienced adverse pregnancy outcome than those who visit ANC at least once.

4.3.3.2. Goodness of Fit Test

An overall evaluation of the multilevel logistic model was assessed using the deviance. The test is done by comparing the deviance of two models by subtracting the smaller deviance from the larger deviance. The difference is a chi-square with the number of degrees of freedom equal to the Number of different parameters in the two models. The significance of this chi square indicates that the model is a good fit. Similarly, it was also assessed by using AIC and BIC. Based on

Table 4.4 random intercept with fixed slope model have a significant deviance chi-square and the value of AIC and BIC are less than from the random coefficient model and Random Intercept Only Model So, we conclude that the random intercept with fixed slope model is a good fit.

4.4. Analysis of data using Generalized Estimating Equation (GEE)

In the methodology that is termed generalized estimating equations, the user may impart a correlation structure that is often called a working correlation matrix. The categorized adverse pregnancy outcome are classified under experienced adverse pregnancy outcome and not experienced adverse pregnancy outcome data has been analyzed using the generalized estimating equation. With this analysis, GEE has considered different correlation structures such as independence and exchangeable correlation structures and compared with their QIC values. Before selecting the correct correlation structure, consider the model building strategy (variable selection).

Under the GEE, model building strategy is started by fitting a model containing all possible covariates in the data. This was done by considering two different working correlation assumptions (exchangeable and independence). In order to select the important factors related to adverse pregnancy outcome, the backward elimination procedure was used. The full model for the probability of getting adverse pregnancy outcome of i^{th} women from j^{th} cluster (region) was fitted as:

$$\begin{aligned}
\log it(\pi_{ij}) \ = \ & \beta_o + \beta_1 Deliv_{healthfacility} + \beta_2 Anemia_{anim} \\
& + \beta_3 Residence_{Urb} + \beta_4 Education_{prim} + \beta_5 Education_{secand} \\
& + \beta_6 Education_{Higher} + \beta_7 Marital_{Never\ uni} + \beta_8 Marital_{Livepart} + \beta_9 Marital_{widow} \\
& + \beta_{10} Marital_{Divorsed} + \beta_{11} Marital_{Separete} + \beta_{12} Antenatal_{No} + \beta_{13} Age_{15-24} \\
& + \beta_{14} Age_{above35} + \beta_{15} Occupation_{Working} + \beta_{16} Parity_{Singlepar} + \beta_{17} Parity_{Nullparity} \\
& + \beta_{18} WID_{Poor} + \beta_{19} WID_{Rich} + \beta_{20} Smokes_{Yes} \\
& + \beta_{21} BMI_{Undeweght} + \beta_{22} BMI_{pOverweght} + \beta_{23} BMI_{Obsity}
\end{aligned}$$

In this case the procedure was used to remove non-significant p-values that improve overall fit (i.e. minimize QIC and QICu). After fitting the full model, covariates with the largest p-value are removed and the model was refitted with the rest of the covariates sequentially. Then, Wealth index, Smoking cigarette, delivery place and Body mass index are the covariates excluded from the model: p-value for the given covariates are large (P-value > 0.05).

The QIC values of full model and reduced models are 7151.1564 (which is found in appendix C) and 6993.8033 respectively. Then it turned out that the model with Place of residence, Occupation of women, Age of women, number of antenatal care, marital status, anemia level women, education level of women and total children ever born (parity) was the most parsimonious model. Therefore, the reduced model with the rest of eight covariates was considered as the best candidate model. Independent and exchangeable correlation structures were considered and compared to select best correlation structure depending on the QIC and standard error value.

Table 4. 6 Independent and Exchangeable correlation structures with its QIC for GEE.

Correlation structure	QIC value	QICu value
Independent	6993.8033	6978.45
Exchangeable	6994.1171	6978.5287

Table 4.6, show that the QIC value of the model with independent was less than that of exchangeable correlation structure. However, the best correlation with smaller standard error has been selected by comparing the standard error for both of the model based and empirical standard error of fitting the model. Thus the independent correlation structure was regarded as better to fit the given model. Then now let’s compare the empirical and model based standard error of independent correlation structure to fit the appropriate model.

Table 4.7.The standard error of the model based Estimates is relatively less as compared to empirical (robust) Standard Error Estimate. Therefore, the parameter estimates and their corresponding model based standard errors with the p values from the final GEE model for parameter estimate was parsimonious.

Table 4. 7 Empirical and model based standard errors for two proposed working correlation.

	Exchangeable			Independent		
Coeff.	Estimate	Empirical (SE)	Model based(SE)	Estimate	Empirical (SE)	Model based (SE)
$\boldsymbol{\beta_0}$	-4.6694	0.2678	0.3399	-4.7446	0.3187	0.2797
$\boldsymbol{\beta_1}$	0.49867	0.0626	0.0637	0.5268	0.0527	0.0631
$\boldsymbol{\beta_2}$	-0.3369	0.0827	0.0789	-0.3011	0.0871	0.0782
$\boldsymbol{\beta_3}$	0.3863	0.1237	0.0717	0.3645	0.1322	0.0727
$\boldsymbol{\beta_4}$	0.4335	0.1323	0.1061	0.4442	0.1351	0.1073
$\boldsymbol{\beta_5}$	-0.2466	0.2003	0.1291	-0.2651	0.2083	0.1311
$\boldsymbol{\beta_6}$	1.1117	0.2438	0.1915	1.0987	0.2647	0.1853
$\boldsymbol{\beta_7}$	1.2580	0.3872	0.3150	1.2340	0.4128	0.3122
$\boldsymbol{\beta_8}$	0.9978	0.4110	0.2587	0.9720	0.4333	0.2555
$\boldsymbol{\beta_9}$	1.2943	0.2245	0.2235	1.2918	0.2432	0.2176
$\boldsymbol{\beta_{10}}$	1.5216	0.2615	0.2793	1.5491	0.2743	0.2745
$\boldsymbol{\beta_{11}}$	0.3224	0.0989	0.0646	0.3288	0.0998	0.0648
$\boldsymbol{\beta_{12}}$	0.8121	0.1269	0.1021	0.8274	0.1213	0.0998
$\boldsymbol{\beta_{13}}$	1.5147	0.1553	0.1120	1.5511	0.1516	0.1038
$\boldsymbol{\beta_{14}}$	0.4086	0.0628	0.0643	0.4042	0.0661	0.0649
$\boldsymbol{\beta_{15}}$	0.5645	0.2362	0.2129	0.6047	0.2597	0.2168
$\boldsymbol{\beta_{16}}$	0.0665	0.2713	0.2094	0.0953	0.2936	0.2142

Comparison of empirical and model based standard errors for the parameter estimates obtained based on the given working correlation assumptions (in this study exchangeable and independence) was performed using selected covariates. The correlation structure that the model based and empirical standard errors are closest to each other is referred to be the best assumption correlation structure. The model based and empirical based standard errors estimates are almost equal, this occurs only if the true correlation structure is correctly modeled.

Therefore, the final proposed generalized estimating equation model for adverse pregnancy outcome of women is given as:

$$\log it(\pi_{ij}) = \beta_o + \beta_1 Anemia_{anim} + \beta_2 Residence_{Urb} + \beta_3 Education_{prim} + \beta_4 Education_{secand} + \beta_5 Education_{Higher} + \beta_6 Marital_{Never\ uni} + \beta_7 Marital_{Livepart} + \beta_8 Marital_{widow} + \beta_9 Marital_{Divorsed} + \beta_{10} Marital_{Separete} + \beta_{11} Antenatal_{No} + \beta_{12} Age_{15-24} + \beta_{13} Age_{above35} + \beta_{14} Occupation_{Working} + \beta_{15} Parity_{Singlepar} + \beta_{16} Parity_{Null\ parity}$$

Table 4. 8 Parameter estimates of model based standard errors for GEE model using independent correlation structure.

Parameter		Estimate	Standard Error	OR	95%Confidence interval(OR)		Z	Pr > |Z|
Intercept	β_0	-4.7446	0.2797	0.0086	0.0050	0.0150	-16.96	0.001
Anemic	β_1	0.5268	0.0631	1.6936	1.4973	1.9156	8.38	<0.0001
Resi-Urban	β_2	-0.3011	0.0785	0.7400	0.6345	0.8631	-3.84	0.002
Educ- Primary	β_3	0.3645	0.0727	1.4398	1.2508	1.6573	5.08	0.005
Educ-Second	β_4	0.4442	0.1075	1.5593	1.2672	1.9188	4.20	<0.0001
Educ- Higher	β_5	-0.2376	0.1311	0.7885	0.6097	1.0197	-1.81	0.070
Marit-Nevunio	β_6	1.0987	0.1853	2.999	2.0903	4.3065	5.96	<0.0001
Mart-LivParet	β_7	1.2340	0.3152	3.4349	1.8611	6.339	3.96	0.002
Mart-Widow	β_8	0.9720	0.2555	2.6432	1.6019	4.3615	3.78	0.017
Mart-Divorce	β_9	1.2918	0.2176	3.6396	2.3801	5.5658	5.93	<0.0001
Mart-Separate	β_{10}	1.5491	0.2745	4.7073	2.7602	8.0278	5.75	<0.0001
Antenatal-No	β_{11}	0.3288	0.0668	1.3893	1.2235	1.5775	5.07	<0.0001
Age 15-24	β_{12}	0.8274	0.0998	2.2874	1.8821	2.7798	8.31	<0.0001
35 above	β_{13}	1.5511	0.1038	4.7168	3.8531	5.7741	15.03	<0.0001
Occup-Workin	β_{14}	0.4042	0.0649	1.4981	1.3214	1.6983	6.36	<0.0001
Parity-Single	β_{15}	0.6047	0.2168	1.8307	1.1967	2.8004	2.79	0.005
Parity Null	β_{16}	0.0953	0.2142	1.100	0.7228	1.6742	0.45	0.656

From table 4.6, the QIC value of the model with independent was less than that of exchangeable correlation structure. Thus the independent correlation structure was regarded as better to fit the given model. The parameter estimates for GEE stand for the effect of the predictors averaged across all individuals with the same predictor values. Like standard normal logistic regression, the interpretation of the parameters in the marginal (population average) model would be interpreted in terms of odd ratio. Table 4.8 stands for the parameter estimates and their corresponding model based standard errors estimate and the p-values for GEE model. Each parameter β_j reflects the effect of factor X_j on the log odds of the probability of women in reproductive age being adverse pregnancy outcome, statistically controlling all the other covariates in the model. Then, the odds ratio of variables were calculated as the exponent of β_ji.e. odds ratio = exp (β_j). The GEE analysis from table 4.8 shows that, anemia is significantly related to adverse pregnancy outcome of women in reproductive age. Statistically significant association has been seen between adverse pregnancy outcome and anemia level in the same j^{th}cluster. Thus, the odds ratio of adverse pregnancy outcome women whose anemic had $\exp(\beta_3)$=$\exp(0.5268)$= 1.69(95%CI: 1.497, 1.915) times more than women whose not anemic. Equivalently, the probability of reproductive women being adverse pregnancy outcome is around 69% times more likely than reproductive women being adverse pregnancy outcome compared to not anemic women.

Table 4.9 shows that, residence is significantly related adverse pregnancy outcome of women in reproductive age. The odds ratio of adverse pregnancy outcome women whose residence living in Urban had $\exp(\beta_4)$ = $\exp(-0.3011)$= 0.74 (95%CI: 0.634, 0.863) times less than those women who seen live in rural, which means that the probability that the women being adverse pregnancy outcome who live in urban is 26% times less exposed to be adverse pregnancy outcome than those adverse pregnancy outcome women in reproductive age who live in rural. Likewise, Education is one of factors that related to adverse pregnancy outcome of women, which means that the reproductive women who primary educated had $\exp(\beta_5)$=exp(0.3645) =1.439(95%CI:1.25 ,1.657) times more than those reproductive women being adverse pregnancy outcome who no education level, which means that the probability that the reproductive women who primary educated and being adverse pregnancy outcome is 43.9% more likely than those who not educated and being adverse pregnancy outcome.

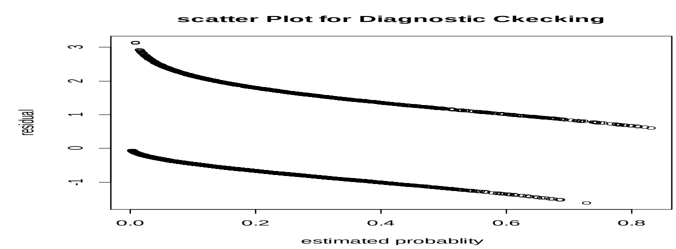
For secondary educated similarly $\exp(\beta_6)$= $\exp(0.442)$ = 1.559(95%CI: 1.267, 1.918) times more than those reproductive women being adverse pregnancy outcome who no education level, which means that the probability that the reproductive women who secondary educated and being adverse pregnancy outcome is 55.9% more likely than those who not educated. Marital status also has significantly associated with adverse pregnancy outcome women in reproductive age. The odds ratio of reproductive women being adverse pregnancy outcome who never in union is $\exp(\beta_8)$= $\exp(1.098)$ = 2.998 (95%CI: 2.09, 4.31) times higher than those reproductive women being adverse pregnancy outcome who married. Equivalently, the probability of reproductive women who are never in union and being adverse pregnancy outcome is 99% times more likely than those women who married. The odds ratio of reproductive women being adverse pregnancy outcome who were living with partner is $\exp(\beta_9)$= $\exp(1.234)$ =3.453(95%CI: 1.86, 6.339) times higher than those reproductive women being adverse pregnancy outcome who married. Equivalently, the probability of reproductive women who are living with partner and being adverse pregnancy outcome is 45.3% times more likely than those women who married. The odds ratio of reproductive women being adverse pregnancy outcome who were widowed is $\exp(\beta_{10})$ $= \exp(0.972)$ = 2.64(95%CI: 1.61, 4.36) times higher than those reproductive women being adverse pregnancy outcome who married. The probability of reproductive women; who are windowed and being adverse pregnancy outcome is 64% times more likely than those women who did married.

The odds ratio of reproductive women being adverse pregnancy outcome who were divorced is $\exp(\beta_{11})$ $= \exp(1.29)$= 3.63(95%CI: 2.38, 5.56) times higher than those reproductive women being adverse pregnancy outcome who married. Additionally, the odds ratio of reproductive women being adverse pregnancy outcome who no longer living together (separated) is $\exp(\beta_{12})$= $\exp(1.549)$= 4.71(95%CI: 2.76, 8.03) times more than those reproductive women being adverse pregnancy outcome who married. The odd of the adverse pregnancy outcome among pregnant women who had no antenatal visit is $\exp(\beta_{13})$ = $\exp(0.3285)$ = 1.389 (95%CI: 1.22, 1.577) times higher than women those who visit at least once. There is also a strong association between age of mother and adverse pregnancy outcome. Adverse pregnancy outcome among women was significantly associated with the age group of mother. The odd ratio of adverse pregnancy outcome of women age between group (15-24) is $\exp(\beta_{14})$= $\exp(0.8277)$ = 2.287 (95%CI: 1.88, 2.778) times higher than age group 24-34(reference group). The odd ratio of reproductive women being adverse pregnancy outcome who age of above 35 above is $\exp(\beta_{15})$= $\exp(1.55)$ = 4.72 (95%CI: 3.85, 5.77) times higher than those reproductive women being adverse pregnancy outcome of women age group between 24-34. Similarly, Occupation status of women in reproductive age is statistically significant on adverse pregnancy outcome of women. Thus, the odds ratio of adverse pregnancy outcome women whose is working had $\exp(\beta_{16})$ = $\exp(0.404)$ = 1.49(95%CI: 1.32, 1.698) times more than women whose not working. Total children ever born (parity) also has significant effect on adverse pregnancy outcome of reproductive women, that is the odds ratio that the women being adverse pregnancy outcome single parity is $\exp(\beta_{17})$ $= \exp(0.6047)$ = 1.83(95%CI: 1.196, 2.81) times more than multi parity.

4.5. Diagnostic Checking

The diagnostic test results for detection of outliers of leverage, influential values are presented in Appendix B. The value of DFBET and Cook's distance observation is less than one. The Cook's distance less than one showed each observation had no impact on the group of regression coefficients. A value of the leverage statistic show's that no observation is far apart from the others in terms of the levels of the independent variables (not the dependent variable). Similarly, the value of residuals are less than 3 in absolute value for both level one and level two. Thus, from the goodness of fit test above and diagnostic test results presented in the Appendix B. we can say that the fitted model is adequate.

Figure 4. 1 plot of residual versus fitted values of experienced adverse pregnancy outcome in Ethiopia.



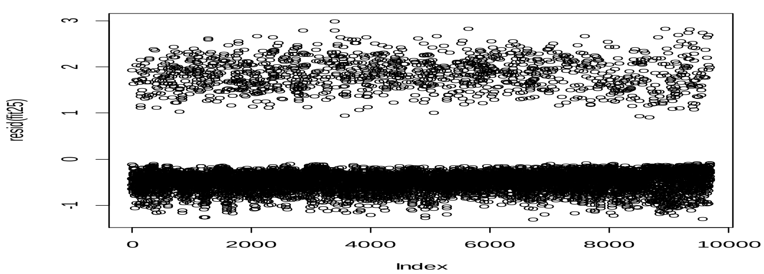


Figure show that Residual versus fitted value plot for final multilevel model. It does not show any systematic pattern. This points out that the model fits the data well.

4.6. Comparison of Multilevel logistic regression model and GEE model

The parameter estimates in multilevel logistic regression model and GEE model have different interpretations, multilevel provides subject-specific (individual) parameter estimates whereas GEE only estimate population average regression coefficients), we can compare the two models using their respective standard error estimates. For the sake of comparison, the study did not use the outputs of respective final models directly. This is because non-significant covariates were removed from GEE final model and multilevel logistic regression final model so that it is impossible to compare two models having different number of covariates. Thus, we considered all covariates for both models and the result from random intercept with fixed slope model (Table 4.5) and GEE model (Table 4.8) is presented. The standard error estimates of multilevel logistic regression model are smaller than that of GEE, except three covariates.

GEE model and multilevel (hierarchical) models as basically the same thing, with the main difference being that GEEs focus on estimating a non-varying (or average) coefficient in the presence of clustering, whereas multilevel logistic regression model (HLMs) focus on estimating the aspects of the model that vary by group. GEE model takes into account the averaged relationship, but the multilevel logistic regression models to express the relationships of inter-individual via random effects. In our study, although the results were similar, the estimates from the two models were different. The differences between parameter estimates at the two models largely depend on the between-individual heterogeneity. This heterogeneity can be described by random effect. This is due to the fact that the target of marginal models is the population (Liang and Zeger, 1988) , while the target of multilevel logistic regression model is the subject specific (Neuhaus.et al, 1991).

The marginal model, GEE, does not measure the association between the change within-subject covariate and the change in the outcome. For this reason, multilevel model appears to be more suitable for the analysis of experienced adverse pregnancy outcome in Ethiopia. What's more, the GEE model does not allow for assessing the suitability of fit (Odueyungbo *et al.*, 2008). Whereas the multilevel logistic regression model does (Moscatelli et al., 2012). For such type of study, therefore, multilevel logistic regression model is more appropriate than generalized estimating equation model.

4.7. Discussion

The study has intended to model predictors of adverse pregnancy outcomes of women in reproductive age group of Ethiopia using the Ethiopian demographic and health Survey data. Accordingly, different models are fitted to the data to identify potential experiencing adverse pregnancy outcomes of women in reproductive age group. First, using binary logistic regression model, multilevel logistic regression model and generalized estimating equation. Two proposed working correlation structures, exchangeable and independence correlation assumptions were taken for the comparison, in GEE model-building strategy. The model with independence working correlation structure was found to be better fits the data than exchangeable. The multilevel logistic model provided interesting relationships that give more evidence than standard logistic model. We showed that there is variation in adverse pregnancy outcome between regions.

The purpose of multilevel model was to evaluate within and between regional variations in adverse pregnancy outcome of women in Ethiopia. In the multilevel analysis, women are considering as nested within the various regions in Ethiopia. First the intercept only or the empty model was fitted to check whether multilevel effects or heterogeneity exists among the hierarchies. The next step was fitting random intercept and fixed slope model, usually called random intercept model, and finally the random intercept and random slope (random coefficient model) is fitted.

All the fitted models leads to the same result that place of residence, Age of mother, marital status, Antenatal care, Occupation of mother, Anemia level of mother, Educational level of mother, Parity were found to be important determinants of adverse pregnancy outcome among reproductive age women (15-49 years). Furthermore, in binary logistic regression Region was significantly associated with experiencing adverse pregnancy outcome. The experiencing adverse pregnancy outcome in Amara, Gambele and Dire Dawa were not significantly differing from that in Addis Ababa. However, women who live in Afar, Somali and Benishangul Gumuz, Tigray. SNNPR and Oromia, Harar regions were significantly more likely to experience adverse pregnancy outcome than those women living in Addis Ababa.

The study also revealed that odds of experiencing adverse pregnancy outcome was significantly associated with the women's age. Women whose age range between 15-24 years was 6.1% more likely to experiencing adverse pregnancy outcome than women whose age range between 25-34 years. On the same way, women whose age range 35 above years were 22.7% more likely to experiencing adverse pregnancy outcome than women whose age range between 15-24 years. Women in higher age group, especially those above 35 years, are more likely to experience adverse pregnancy outcome than those at 24-34 age group. These might be both age extremity is risky for adverse pregnancy of outcome due to it associated with higher rate maternal complications. This finding is consistent with pervious study (Kenny *et al.*, 2013). Similarly (Gershim *et al.*, 2015) suggested that risk of adverse pregnancy outcome is increased with age of mother.

Women's place of residence was found to be significantly associed with experiencing adverse pregnancy outcome. The study showed that the women's who reside in urban areas was 0.7038 times less likely to affect experiencing adverse pregnancy outcome than that of women who reside in rural areas. This result is consistent with (Berhie and Habtamu, 2016; Tamang et al., 2012). They argued that this may be due to fact that women residing in rural areas have a high shadow value of home production activities. Similarly, other studies revealed that (Ameh *et al.*, 2016) those women residing in rural areas were found to be more likely to experience adverse pregnancy outcome than those in urban areas which might be for the reason that in rural areas there is lack of education, lack of full information on health services and access to health facility. This study finding shows the significant association between Antenatal care (ANC) of women and adverse pregnancy outcome. The odd of adverse pregnancy outcome of women no antenatal visit had 1.373 times more likely than women visit at least once. Visiting antenatal care for at least once is found to decrease the probability of experiencing adverse pregnancy outcome. Similarly, the finding is correspondence with (Analizi et al., 2017). Study done in Wollo showed that, Mothers who didn't attend ANC were more than 3 times to have adverse pregnancy outcome, than mothers who attended ANC follow up, OR = 3.4. (EsheteA., 2013).

Another important risk factor for adverse pregnancy outcome in this study is marital status of women. Women's who had Never in union, Living with partner, Divorced, Widowed, separated were more likely to experienced adverse pregnancy outcome than married women. These findings agree with the findings of a study which revealed out that with respect to pregnancy, marital status seems to be the significant factor (Magadi et al., 2004; Kalilani-Phiri *et al.*, 2015). This is similar to findings from other studies in Ghana (Oliveras *et al.*, 2008) which reported that the risk of abortion were higher among unmarried (never marrieds, divorced, or separated).

There was also a significant association between adverse pregnancy outcome and anemia level of women. According to this study, anemia level of women increased the risk of having adverse pregnancy outcome of reproductive age of women. This finding similar to (Xiong *et al.*, 2000; Analizi et al., 2017).They suggested that anemia in pregnancy is associated with an increased risk of adverse pregnancy outcomes, such as abortion, still birth, and miscarriage. Women's level of education was found associated with risk of experiencing adverse pregnancy outcome. The risk of adverse pregnancy outcome was significantly higher for women had primary education level and secondary education level than women had no education. This finding is consistent with a study done in Kenya by (Patricia, 2014; Berhie and Habtamu, 2016). Occupation of women is significantly associated with experienced adverse outcome. The adverse pregnancy outcome of women who had working were 1.52 times more likely to be adverse pregnancy outcome than women not working. This finding similarly done to study (Magadi et al., 2001). This finding confirms other studies in Ghana (Mundigo, 2006) and Nigeria (Oye-Adeniran *et al.*, 2004) supports the observation that employed women are more likely to seek induced abortion than their counterparts who are not employed. But research done on still birth found occupation is not significantly associated to still birth (Analizi et al., 2017). The result of this study showed that single parity were more likely to adverse pregnancy outcome than women who had multi parity. This result is in agreement with (ELlen et al., 2014; Analizi et al., 2017).

Smoking cigarette, wealth index, delivery place or place of termination of pregnancy, Body mass index of women is not significant factor for experiencing adverse pregnancy outcome. These inconsistencies between researches might be due to difference in sample size, data analysis and population across studies.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The purpose of this study was to assess socioeconomic, demographic, and medical factors associated with experiencing adverse pregnancy outcome and to estimate within regions and between-regional level of difference in the experienced adverse pregnancy outcome in Ethiopia. The proportion of pregnant women that experienced adverse pregnancy was below quarter of all women under study. Additionally, the study identified that place of residence, age of a woman, educational level of women, occupation of women, marital status, and antenatal care of women, Parity and Anemia level were significant predictors in adverse pregnancy outcome among women in Ethiopia. From the results of multilevel logistic regression analysis among all the three models compare using AIC, BIC and Deviance, the random intercept with fixed slope multilevel model provided the best fit for the data under consideration for the analysis of within and between regional variations in adverse pregnancy outcome of women in Ethiopia.

Women are considered as nested with in the regions. The study conclude that, using standard error multilevel logistic regression models is better fitted for the analysis of adverse pregnancy outcomes than Generalized estimation equation model. It showed that there is heterogeneity in experiencing of adverse pregnancy outcomes between and within regions. This heterogeneity might be due socio cultural variations and difference in accessibility of reproductive health services between these regions of Ethiopia.

In the final model (the random intercept with fixed slope multilevel model), it is found that not having Antenatal care, residing in rural areas, working occupational status, being anemic, increased educational level, never marrieds, divorced, or separated marital status, being in the age group of 15-24 or >35 years are associated with increased risk of adverse pregnancy outcome among reproductive age group women in Ethiopia.

5.2. Recommendations

Based on our findings, we recommend the following:

1. Any intervention by governmental and non-governmental organizations that aims at preventing adverse pregnancy should take consider factors such as regions, educational status of mother, place of residence, Age of mother, marital status, Antenatal care, Occupation of mother, Anemia level of mother, and Parity during planning and policy making.
2. All mothers should take care of their health condition when they become pregnant, during Pregnancy and when approaching to labor. This can be made by use of antenatal care. Those older ages and young women, should be more careful with difficulties that come with age that could result adverse pregnancy and they should visit antenatal cares during pregnancy.
3. The administration should give more support and emphasis on those regions with high rates of experienced adverse pregnancy outcome. Experienced adverse pregnancy outcome differentials among regions are significant. This is an indication that the severity of adverse pregnancy outcomes varies from one region to another.
4. The multilevel logistic regression model give better results for experienced adverse pregnancy outcomes in Ethiopia. The results from the study suggested that there are variations within groups and between groups. Since the findings from the study suggested that there are some unobserved characteristics which were accounted for heterogeneity across regions. So, future studies should have to take by using multilevel logistic regression model.

5.3. Limitations of the Study

The study has different limitations. The major limitations of the study are:-

The study was based on the 2016 Ethiopia Demographic and Health Survey (EDHS) which are secondary data and for this reason the aim of some variables is not clear. The study is conducted based on secondary data which might have incomplete and biased information. Similarly, there are also some predictor variables not included in the analysis due to missing values and non-responses. This may make the study somewhat incomplete.

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APPENDEX A

Table 4. 9 Model Summary of Binary Logistic Regression Model.

Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	754.846	33	.000
	Block	754.846	33	.000
	Model	754.846	33	.000

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Analog of Cook's influence statistics	9694	.00000	.12338	.0035423	.00896637
Leverage value	9694	.00026	.02986	.0035073	.00288461
DFBETA for constant	9694	-.03814	.09697	-.0000004	.00475895
DFBETA for delivery(1)	9694	-.00440	.00267	.0000000	.00070154
DFBETA for Anim(1)	9694	-.00257	.00227	.0000000	.00064845
DFBETA for Smokes(1)	9694	-.08254	.03206	.0000003	.00310781
DFBETA for Region(1)	9694	-.01876	.01563	.0000000	.00186271
DFBETA for Region(2)	9694	-.01965	.01098	-.0000001	.00175459
DFBETA for Region(3)	9694	-.01960	.00974	-.0000001	.00167805
DFBETA for Region(4)	9694	-.01872	.01528	-.0000001	.00185229
DFBETA for Region(5)	9694	-.01948	.01189	.0000000	.00178710
DFBETA for Region(6)	9694	-.01947	.00986	-.0000001	.00174833
DFBETA for Region(7)	9694	-.01919	.00740	.0000000	.00161759
DFBETA for Region(8)	9694	-.01889	.01484	-.0000001	.00187007
DFBETA for Region(9)	9694	-.01815	.01840	.0000000	.00194830
DFBETA for Region(10)	9694	-.01785	.01049	.0000000	.00172320
DFBETA for Residence(1)	9694	-.00667	.00484	.0000001	.00084662
DFBETA for Educ(1)	9694	-.01465	.00565	-.0000002	.00130738
DFBETA for Educ(2)	9694	-.01491	.00514	-.0000001	.00130143
DFBETA for Educ(3)	9694	-.01601	.00826	-.0000001	.00149055
DFBETA for WID(1)	9694	-.00469	.00457	.0000001	.00078887
DFBETA for WID(2)	9694	-.00385	.00877	.0000000	.00102453
DFBETA for Marital(1)	9694	-.04266	.03197	.0000001	.00286727
DFBETA for Marital(2)	9694	-.04153	.02297	.0000001	.00223419
DFBETA for Marital(3)	9694	-.04042	.06263	.0000003	.00340660
DFBETA for Marital(4)	9694	-.04019	.03083	.0000001	.00287012
DFBETA for Marital(5)	9694	-.04033	.02391	.0000001	.00252484
DFBETA for ANC(1)	9694	-.00354	.00337	.0000000	.00069508
DFBETA for Age(1)	9694	-.00876	.01044	-.0000001	.00111752
DFBETA for Age(2)	9694	-.00327	.00432	.0000000	.00072683
DFBETA for BMI(1)	9694	-.03695	.02237	.0000001	.00216463
DFBETA for BMI(2)	9694	-.03683	.02241	.0000001	.00208901
DFBETA for BMI(3)	9694	-.03670	.02245	.0000001	.00225861
DFBETA for Occupation(1)	9694	-.00278	.00329	.0000000	.00066156
DFBETA for Parity(1)	9694	-.02044	.04171	.0000001	.00224654
DFBETA for Parity(2)	9694	-.00494	.00397	.0000000	.00076099
Valid N (listwise)	9694				

Table 4. 10 Result of Parameter Estimate of Random Coefficient Multilevel Model for Anemia and Antenatal care level of women.

Covariates	Estimate	Std. Err.	P>|z|	OR	[95% OR]	Conf. Interval
Intercept	-5.039	0.315	<.00001			
Anemia						
Not anemic(ref)						
Anemic	0.5241	0.0658	<.00001	1.6889	1.4767	1.9316
Smoking						
No (ref)						
Yes	-0.5593	0.2961	0.059	0.5715	0.3199	1.0213
Residence						
Rural(ref)						
Urban	*-0.3556*	*0.0783*	*<.00001*	*0.7007*	*0.5992*	*0.8194*
Education of mother						
No education(ref)						
Primary	*0.4003*	*0.0727*	*<.00001*	*1.4922*	*1.2938*	*1.7209*
Secondary	*0.4542*	*0.1076*	*<.00001*	*1.5750*	*1.2754*	*1.9448*
Higher	*-0.2266*	*0.1306*	*0.087*	*0.7971*	*0.6146*	*1.0338*
Marital status						
Married(ref)						
Never in union	*1.1498*	*0.1854*	*<.00001*	*3.1576*	*2.1945*	*4.5433*
Living with partner	*1.3183*	*0.3151*	*<.00001*	*3.7373*	*2.0151*	*6.9311*
Widowed	*1.0333*	*0.2581*	*<.00001*	*2.8103*	*1.6943*	*4.6616*
Divorced	*1.3064*	*0.2185*	*<.00001*	*3.6929*	*2.4063*	*2.4063*
Separated	*1.5444*	*0.2752*	*<.00001*	*4.6854*	*2.7319*	*8.0355*
Age of mother						
25-34(ref)						
15-24	*0.8246*	*0.0993*	*<.00001*	*2.2810*	*1.8750*	*2.7749*
35 above	*1.5333*	*0.1037*	*<.00001*	*4.6338*	*3.7802*	*5.6803*
Body mass index						
Normal(ref)						
Underweight	*0.1068*	*0.0777*	*0.169*	*1.1127*	*0.9554*	*1.2958*
Over weight	*0. 1816*	*0.1166*	*0.116*	*1.1448*	*0.956*	*1.5037*
Obesity	*0.2165*	*0.2078*	*0.297*	*1.2417*	*0.8262*	*1.8661*
Occupation of mother						
Not working(ref)						
Working	*0.4142*	*0.0648*	*<.00001*	*1.513*	*1.3324*	*1.7183*
Parity						
Multi parity(ref)						
Single para	*0.6489*	*0.2244*	*0.004*	*1.9135*	*1.2325*	*2.9709*
Null parity	*0.1303*	*0.2107*	*0.555*	*1.1392*	*0.7391*	*1.7558*
Delivery place						
Home(ref)						
Health facility	*0.1057*	*0.0690*	*0.125*	*1.1115*	*0.9709*	*1.2725*
Antenatal care						
Visit at least once(re)						
No antenatal visit	*0.3077*	*0.0927*	*0.001*	*1.3603*	*1.1343*	*1.6313*

Random-effects Parameters	Estimate	Std. Err	[95% Conf. Interval]	
Region: Unstructured				
$\boldsymbol{Var}(\boldsymbol{Anemia})$	0.0049	0.0989	0.0001	0.2431
$\boldsymbol{Var}(\boldsymbol{ANC})$	0.0404	0.0350	0.0073	0.2213
$\boldsymbol{Var}$ (_cons)	0.1739	0.0880	0.0644	0.4693
$\boldsymbol{cov}(\boldsymbol{Anemia}, \boldsymbol{ANC})$	-0.0131	0.0168	-0.0200	0.0461
$\boldsymbol{Cov}(\boldsymbol{Anemia}, \boldsymbol{\_cons})$	-0.0277	0.0319	-0.0903	0.0347
$\boldsymbol{Cov}(\boldsymbol{ANC}, \boldsymbol{\_cons})$	-0.0616	0.0467	-0.1533	0.0301

LR test vs. logistic model: chi2 (6) = 77.79 Prob > chi2 = 0.0000

AIC	BIC	$\log Lik$	deviance
6908.909	7124.287	-3428.454	6856.91

APPENDEX B

Figure 4. 2 Scatter Plots for Diagnostic Checking for multilevel Model for Leverage and influence.

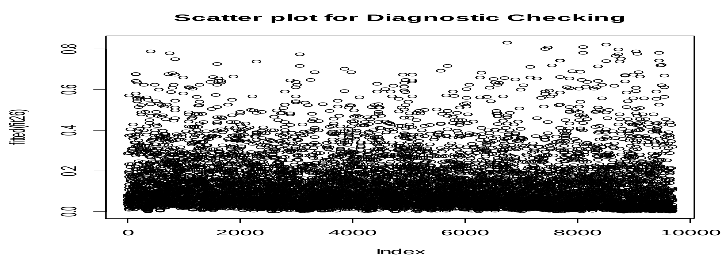
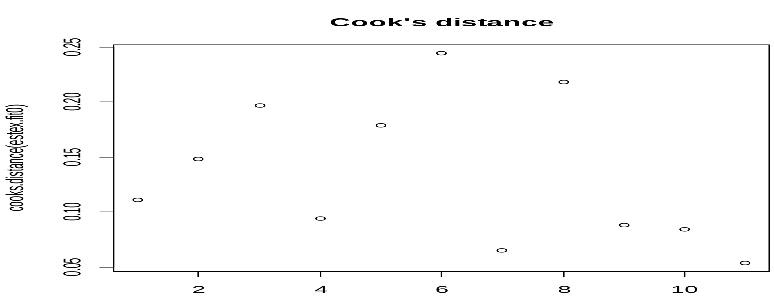
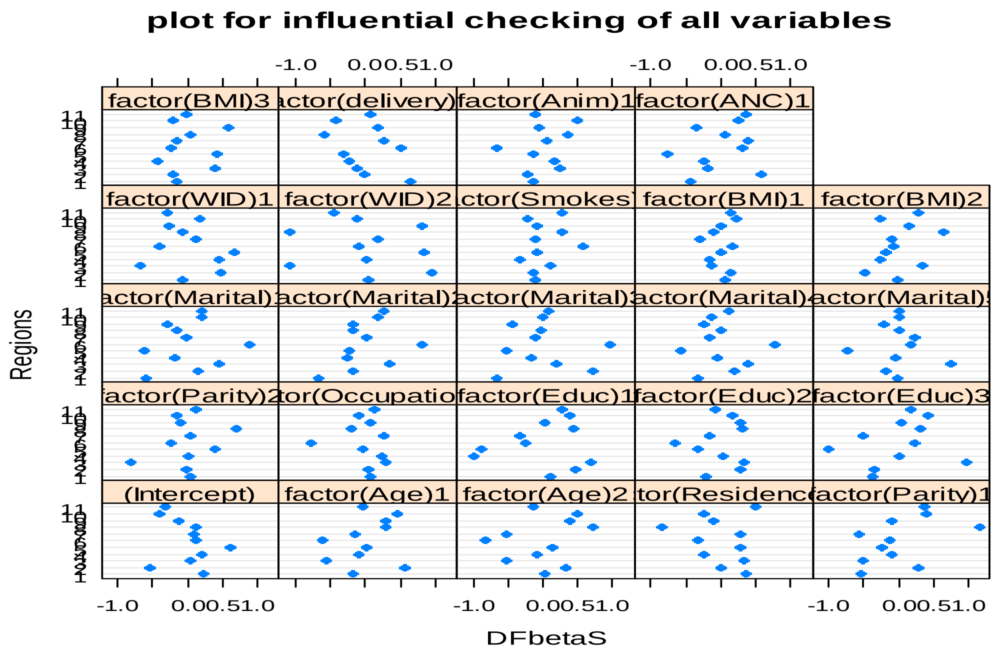


Figure 4. 3 Scatter Plots for Diagnostic Checking for multilevel Model for Cook's distance and DFBETA.





APPENDIX C

Table 4. 11 Full model General estimating equation Results analysis.

xtgee exp i.delivery i.Anim i.Residence i.Educ i.Marital i.BMI i.WID i.Smokes i.ANC i.Age i.Occupation i.Parity, i(Region) family(bin) link(logit) corr(independent)

GEE population-averaged model Number of ob s = 9,694
Group variable: Region Number of groups = 11
Link: logit Obs per group:
Family: binomial min = 546
Correlation: independent avg = 881.3
max = 1,343
Wald chi2(24) = 556.33
Scale parameter: 1 Prob > chi2 = 0.0000
Pearson chi2(9694): 9630.93 Deviance = 6917.32
Dispersion (Pearson): .9934942 Dispersion = .713567

Parameter	Estimate	Standard error	Z	P-value	[95% C. Interval]	
Age of mother						
24-34(ref)						
15-24	0.8213	0.0996	8.24	0.000	0.62597	1.0167
35 above	1.5491	0.1034	14.97	0.000	1.34642	1.7519
Body mass index						
Normal(ref)						
Underweight	0.0965	0.0771	1.25	0.211	-0.05467	0.0461
Over weight	0.1805	0.1156	1.57	0.118	-0.05467	0.2205
Obesity	0.1814	0.2051	0.88	0.376	-.220573	0.58341
Occupation of mother						

Not working(ref)						
Working	.40908	.06420	6.37	0.000	.28325	.53491
Parity						
Multi parity(ref)						
Single para	0.69224	.22085	3.13	0.002	.25938	1.1251
Null parity	0.17338	.217502	0.80	0.425	-.25290	.5996
Antenatal care						
Antenatal visity(ref)						
No antenat visit	.31041	.06588	4.71	0.000	.18128	.43955
Marital status						
Married(ref)						
Never in un	1.1136	.18492	6.02	0.000	.75123	1.4761
Living with	1.2414	.31341	3.96	0.000	.62712	1.8556
Widowed	.97320	.25660	3.79	0.000	.47028	1.4761
Divorced	1.2822	.21732	5.90	0.000	.85675	1.7086
Separated	1.5544	.27292	5.70	0.000	1.0195	2.0893
Wealth index						
Rich(ref)						
poor	.06435	.09898	0.65	0.516	-.12965	.2583
Middle	-.0720	.06791	-1.06	0.289	-.20515	.0610
Education of mother						
No education(ref)						
Primary	0.3720	0 .07206	5.16	0.000	.23077	.51326
Secondary	0.4444	0.10660	4.17	0.000	.23548	.65335
Higher	-0.2324	0.13132	-1.78	0.077	-.48997	.0251
Residence						
Rural(ref)						
Urban	-0.2996	.07882	-3.80	0.000	. -.45411	-.1451
Smoking						
No smoking(ref)						
Yes	-.44832	.29193	-1.54	0.125	-1.0205	.12385
Anemic						
Not anemic(re)						
Anemic	0.5340	.06308	8.47	0.000	.41041	.65770
Delivery place						
health facility	*0.1068*	*0.0689*	*1.53*	*0.122*	*-0.297*	*0.2412*
cons	-6.212	.53335	-11.65	0.000	-7.2582	-5.1675
QIC =7151.5164						