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Modeling Determinants of Low Birth Weight for Under Five- Children in Ethiopia

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MSc Thesis

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DEDICATION

I dedicate this work to my dear parents Mr. Biftu Bekalo and Mrs. Ayantu Bekele for making me who I am today, for their support and for teaching me the value of education. To all my sisters and brothers for their daily encouragement and inspiration.

ABSTRACT

Background: Low birth weight (LBW) is a major determinant of morbidity, mortality and disability in infancy and childhood and has a long-term impact on health outcomes in adult life. It results in substantial costs to the health sector and imposes a significant burden on society as a whole.

Objective: The main objectives of the study was modeling Low birth weight using marginal and generalized linear mixed models as well as identify the determinant factors for the Low birth weight in Ethiopia.

Methods: Data was taken from the 2011 Ethiopian demographic and health survey, which is a nationally representative survey of children in the 0-59 month age groups. Two model families, generalized estimating equation and alternating logistic regression models from marginal model family, and generalized linear mixed model from cluster specific model family were used for the analysis.

Results: The result showed that 34.8% of children were born with Low birth weight. Alternating logistic regression model was best fits the data for population-averaged effects of the given factors on birth weight than generalized estimating equation model and generalized linear mixed model with two random intercepts was the best model to evaluate within and between regional heterogeneity of birth weight. Both the best-fitted models gave the same conclusion that sex, wealth status, age, antenatal care, marital status, vaccination, anemia and mother education level were the most determinant factors of Low birth weight.

Conclusion: More importantly, this study contributes to the understanding of the individual and collective effect of maternal, socio-economic and child related factors influencing infant birth weight in Ethiopia.

***Keywords*:** Low birth weight; Generalized Estimating Equation; Alternating Logistic Regression; Generalized Linear Mixed Model

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LIST OF ACRONYMS

AIC	Akaike's information criterion
ANC	Antenatal care
ALR	Alternating logistic regression
BIC	Bayesian information criterion
BMI	Body mass index
CLID	Cluster level identity number
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
EDHS	Ethiopian Demographic and Health Survey
FDRE	Federal Democratic Republic of Ethiopia
GEE	Generalized Estimating Equation
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
LBW	Low Birth Weight
MDG	Millennium Development Goal
ML	Maximum Likelihood
NBW	Normal Birth Weight
OLS	Ordinary Least Square Estimate
QIC	Quasi information criterion
UN	United Nations
UNICEF	United Nations Children's Fund
WHO	World Health Organization

1. INTRODUCTION

1.1. Background

One of the poor outcomes of pregnancy that has caught the attention of the World Health Organization (WHO) is LBW. LBW has been defined by the World Health Organization (WHO) weight at birth of less than 2,500 grams (WHO Report, 2004). This practical cut-off for international comparison is based on epidemiological observations that infants weighing less than 2,500 grams are approximately 20 times more likely to die than heavier babies (Kramer, 1998). More common in developing than developed countries, a birth weight below 2,500 grams contributes to a range of poor health outcomes (UNICEF/WHO, 2004).

The incidence of LBW is estimated to be 16% worldwide, 19% in the least developed and developing countries and 7% in the developed countries (UNICEF and WHO, 2004). Globally, more than 20 million infants are born with LBW (UNICEF and WHO, 2004). The largest number of LBW babies is concentrated in two regions of the developing world which are Asia and Africa. Seventy-two percent of LBW infants in developing countries are born in Asia, specifically, in South Asia that accounts for half of the LBW, and 22% are born in Africa. The prevalence of LBW in sub-Saharan Africa ranges between 13% and 15%, with little variation across the region as a whole (UNICEF and WHO 2004). In East Africa the prevalence of LBW is 13.5% (UNICEF and WHO, 2004) and in Ethiopia between 2006 and 2010, UNICEF estimated the prevalence of LBW to be 8%.

Low birth weight (LBW) can be caused either by premature delivery (short gestation<37 week) or by foetal growth retardation. Known factors for pre-term delivery and foetal growth retardation which are associated with LBW include low maternal food intake, hard physical work during pregnancy, and illness, especially infections. The studies suggest that cigarette smoking, genetic and environmental factors can cause LBW, short maternal stature, very young age, high parity, close birth spacing is all associated factors (Kramer, 2004).

Many factors affect the duration of gestation and of foetal growth, and thus, the birth weight. They relate to the infant, the mother or the physical environment and play an important role in determining the birth weight and future health of the infant (WHO Technical Consultation, 2004). The studies show that birth weight is affected to a great extent by the mother's own fetal growth and her diet from birth to pregnancy, and her body composition at conception. Mothers in poor socio-economic conditions frequently have LBW infants. In those settings, the infant's low birth weight stems primarily from the mother's poor nutrition and health over a long period of time, including during pregnancy, the high prevalence of specific and nonspecific infections, or from pregnancy complications underpinned by poverty. Physically demanding work during pregnancy also contributes to poor fetal growth (WHO Technical Consultation, 2004).

LBW is one of the critical issues in Ethiopia that causes many babies short- term and long-term health consequences and tend to have higher mortality and morbidity. DHS Ethiopia /2005/ report shows that the percentage of LBW babies has increased in the past five years from 8 percent in 2000 to 14 percent in 2005. LBW is a reasonable well-defined problem caused by factors that are potentially modifiable and the costs of preventing them are well within reach, even in poor countries like Ethiopia. Therefore, it is very important to determine the risk factor of LBW in various communities in the country in order to come up with feasible intervention strategies to minimize the problem.

Certain data will not be continuous like binary and count data, (in this case binary data), and the corresponding outcome variables are categorical and count responses. Such outcome variables will not be normally distributed rather distributed as binomial, Poisson, gamma etc.

In addition, in case of multistage or clustered sampling procedure, responses variables will be correlated within individuals in the same clusters. EDHS data is a two stage stratified sampling where mothers are the second sampling unit in each clustered within regions. There may be also having regional variations that is; heterogeneity within regions as well between regions on birth weight at birth. To handle such types of data, the most flexible and appropriate models should be applied. This includes generalized linear models (GLM) and its extension, which are capable of analyzing correlated and non-normal data (i.e binary in this case).

Marginal models as generalized estimating equations (GEE) and alternating logistic regression (ALR) models are an extension of GLM by considering dependency in the response variables for clustered data and repeated measurement (Molenberghs & Verbeke,2005). Cluster specific models like generalized linear mixed models (GLMM) also are a natural outgrowth of both linear mixed models and generalized linear models (Cosmas, 2011). GLMM can be developed for non-normally distributed responses, allow nonlinear links between the mean of the response and the predictors, and can model over dispersion and correlation by incorporating random effects (McCulloch, 1997). This study applied those models to incorporate the nature of the given data.

1.2. Statement of the Problem

Low birth weight is a worldwide concern, with LBW newborns accounting for 15.5% of all births (Wardlaw *et al*., 2004). This concern exists in both developed and developing countries; however, the burden is more pronounced in developing countries, with 95.6% of all LBW births occurring in these countries (Wardlaw *et al*., 2004). The region of the world with the highest occurrence of LBW newborns is South-central Asia, where 27.1% of infants are born with a LBW. The regions with the next highest proportions of LBW newborns are Western Africa and Western Asia (both 15.4%) (Wardlaw *et al*., 2004). The prevalence of LBW in sub-Saharan Africa ranges between 13% and 15%, with little variation across the region as a whole (UNICEF and WHO 2004). In East Africa the prevalence of LBW is 13.5% (UNICEF and WHO, 2004) and in Ethiopia between 2006 and 2010, UNICEF estimated the prevalence of LBW to be 8%.

Low birth weight can be caused by many factors. Among the factors that were identified by Kraemer, possible determinants of LBW are; maternal factors, socio economic status, calorie intake, urinary tract infection and quality of antenatal care were listed as prominent factors. The influence of some factors are proved beyond doubt, and for others, it is still a matter of controversy.

Previous studies on determinants of LBW in Ethiopia have found that multiple gestations, mother residing in the urban setting, who delivered before 37 weeks of gestation, had weight loss. And who did not receive additional diet during pregnancy (Tema,2006) and first time delivery , lack of antenatal care follow up and being HIV positive(Berihun , 2012) were significantly associated with the incidence of LBW. All those previous study were conducted by using a very small proportion of data sets and have been based on hospital statistics. This is a serious limitation in developing countries where most births do not occur within the health facilities. The results of hospital-based studies in communities where a substantial proportion do not have access or use modern health facilities are subject to selectivity bias and cannot be generalized to the entire population and therefore must be treated with caution. In general ,this approach is prone to limitations; instead, population-based studies (that use DHS survey data) which include women who use modern as well as other (traditional) maternal health care are representative and are expected to identify better, factors responsible for LBW.

(Despite the fact that)Moreover, many studies have been done regarding this, but not so much in Ethiopia in recent times. Because in Ethiopia there is limited information on distribution of birth weight. Especially there is no adequate information on the prevalence and determinants of LBW in the study area. In the context of developing countries where institutional delivery is very low, concentrating only on the children weighed at the health facilities creates some informational gap. Therefore, the current study aims at finding the magnitude and the determinants of low birth weight in Ethiopia based on the 2011 EDHS data by taking into consideration various maternal, socio-economic, demographic and environmental factors. Moreover, previous studies on this area in Ethiopia were considered about modeling only the fixed effects of covariates without including the random effects and with no considering sampling structures of data. Most of the studies previously done are simply using only the ordinary logistic regression model.

Thus, the little magnitude of this service and lack of appropriateness of the model applied for clustered data have generated interest in assessing determinant factors affecting low birth weight by fitting a statistical model that can explain the data in most meaningful manner.

This study, therefore, has tried to fill the gaps in understanding the status of child weight at birth by identifying determinant factors of LBW in Ethiopia and assessing the performance of different models using clustered data from EDHS 2011 by addressing the following research questions:

- Which covariates are the most determinant factors for LBW?
- Which fitted model for the birth weight is statistically plausible?
- Is there a significant within and between regional heterogeneity of weights of child at birth?

1.3. Objectives of the Study

1.3.1. General Objective

The General objective of the study is modeling determinants of low birth weight for under-five children in Ethiopia.

1.3.2. Specific Objectives

The specific objectives of the study are:

- ✓ To formulate models that yield statistically plausible and interpretable estimates of important covariates on LBW for the given data.
- ✓ To identify maternal, child and socio-economic factors associated with low birth weight of children in Ethiopian.
- ✓ To assess between and within regional heterogeneity of weights of child at birth

1.4. Significance of the Study

The results of this study will be very useful in creating awareness on risk factor of LBW and reducing child mortality.

Specifically:

- The results of the study may be upraising the understanding of policymakers by clarifying the main determinant factors that affecting the child weight at birth in Ethiopia.
- The results of this study give information to concerned bodies in setting policies, strategies and further investigation on LBW.
- The results can provide an important input for any possible intervention in this area for the future.
- The international community is committed to MDGs, most of which are closely related to health. In line with this, the results can assist policy makers in the health sector in their effort towards meeting the MDG's related to LBW.
- The study can be used as a stepping-stone for further studies.

2. LITERATURE REVIEW

2.1. Child Weight at Birth

A child's birth weight is an important indicator of its vulnerability to the risk of childhood illnesses and the chances of survival. Children whose birth weight is less than 2.5 kilograms are considered to have a higher risk of early childhood death than children whose birth weight is greater than 2.5 kilograms (Nair N, Rao RS, 2012)

Low birth weight: Low birth weight defines a heterogeneous group of infants. Some are born early, others born growth-restricted and the others born both early and growth–restricted. In the general sense of it, low birth weight is a disadvantage for the baby. Available studies (Bradley, R. H., & Corwyn, R. F. 2011) have revealed variations in birth weights among different populations with different economic, biological, physical and social conditions. There is thus a quest for a standard of reference for birth weight appropriate for developing countries where such data are not readily available.

2.2. Review of Variable that Determine LBW

Low birth weight and antenatal care: The present study showed the positive effect of number of antenatal care visit on birth weight. Those mothers received 4 or more antenatal care gave birth to higher birth weight babies in comparison to mothers who received less than 4 antenatal care visit. The other studies also found similar result (Naher N. *et al*., 2010). Bradley has shown that the strength of association between antenatal care and birth weight varies with different social group and is modified by social situation.

Antenatal care is globally accepted and commonly understood to have a beneficial impact on pregnancy outcome, through either the detesting or treatment of complications or by contributing to the reduction of modifiable maternal risk factors. It is a means of identifying mothers at the risk of delivering a preterm. Alternatively, growth retarded infant and to provide an array of available medical, nutritional and educational interventions intended to reduce the risk of LBW and other adverse pregnancy outcomes (Ahmed and A.M Das, 2009). Early antenatal care initiation has been associated with heavier birth weights (Eisner *et al*., 2013).

Maternal morbidity and quality of antenatal care: The maternal environment is the most important determinant of birth weight and factors such as maternal under-nutrition, malaria, anemia, STDs that prevent normal circulation across the placenta cause shortage of nutrient and oxygen supply to the foetus and restricts the growth of the foetus. Maternal tetanus infection is expected to increase the risk factor for low birth weight and it induces malnutrition by interrupting food intake via anorexia. Rondo, P. H. C., Ferreira, R. F., *et al*. (2011) did show that maternal infection which reflects maternal morbidity status and quality of antenatal care affects fetal growth via: (1) Disruption in maternal nutrition which in turn makes supply of nutrients less available to the foetus. (2) Inability of the placenta to transfer nutrients satisfactorily as a result of several disease conditions and a reduction in blood flows And (3) Foetal infection which causes impaired growth and development.

Several fetal infections transmitted across the placenta are associated with decreased birth weight and high–risk medical care in general may have a higher impact on reducing the incidence of low birth weight than individual-specific interventions but not all of the former may reduce the chances of low birth weight. Strategies that eliminate the incidence of tetanus infections such as Tetanus toxoid vaccines is expected to reduce the incidence of low birth weight and ensure better pregnancy outcomes.

Maternal nutrition: Low maternal weight for height and low birth weight reflect inadequate food intake in women. In developed countries (Pojda and Kelly, 2012) in Kramer AFRO/VPD Data Tables, low birth weights are associated with factors such as preeclampsia and cigarette smoking, while alcohol and the use of drugs may also restrict the growth of the foetus. Kramer (1998) later adds that secular increases in pre- pregnancy Body Mass Index (BMI), gestational weight gain and reduction in maternal smoking are responsible for normal birth weights and the modest decline in LBW and that maternal anthropometry has little or no impact on gestation duration. Poor maternal nutritional status at conception, short maternal stature due to mother's own childhood under-nutrition and/or infection and low weight gain during gestation as a result of inadequate dietary intake have been identified as determinants of LBW in developing countries (Anderson & Bergstrom , 2013).

Maternal smoking and low birth weight: Smoking has been confirmed a high risk factor for LBW. Studies have shown that cessation of smoking by expectant mothers has significant effect on increasing birth weight in most intervention trials (Sexton and Herbel, 2007). Methods applied to bring about smoking cessation include; self-help methods, health education and counseling programs. However, Kramer (1998) has shown that maternal smoking is not a cause of LBW in developing countries.

Socio-economic risk factors on low birth weight*:* Number of researchers stated that maternal socio- economic factors (education, marital status, and income and employment status) are associated with particular health behavior peculiarities and health status that can further directly influence the newborns' health. Low educated mothers with low income and without permanent employment are more frequently malnourished, have unhealthy habits (smoking, alcohol consumption and drug abuse), chronic diseases and inadequate prenatal care (Dičkutė, J. and Padaiga, Ž. *et al.*, 2012). However, some investigators concluded that maternal education remains a significant factor increasing the risk to deliver LBW baby even after adjustment for possible confounding factors such as maternal age, parity, obstetrical anamnesis and pre-natal care level (Tuntiseranee P, *et al* 2013). Hirve SS., *et al*. found that the risk of LBW is directly correlated with mother's education and the etiological fraction in exposed to the risk factor accounted for 41.4% of LBW cases (Hirve SS, Ganatra BR, 2008). Researchers from California University (USA) found the association between LBW and family income as well as the direct correlation between the income and employment (Cogswell M.E, 2011). According to the literature review from 1990–2000 years, women who were employed during pregnancy had the higher risk of LBW, stillbirth and prenatal death, if compared to unemployed. However, later studies from 2007 showed the different tendencies of the higher incidence of LBW among unemployed pregnant women. Moreover, the differences in the proportions of LBW between various occupational groups were observed during last few decades (Saurel-Cubizolles, *et al*. 2013). There are several possible reasons explaining the importance of maternal employment. Firstly, modern occupational devices and environment of workplace guarantee the better working conditions. With the improvement of industrial and manufacturing technologies the hard manual work became less popular, which is accounted for the higher risk of complicated pregnancy. Secondly, employment is also associated with other socio-economic factors, such as education, income, social class and marital status. According to results from different studies, employed expectant mothers are more likely to be married, nonsmoking and to have better prenatal care (Jolly, M., *et al.*, 2011). The results from different studies showed the association between unstable marital status and the higher risk of LBW (Dičkutė, J., Padaiga, Ž., 2012). This status affects the maternal economic, social and psychological welfare. It is apparent that mothers with unstable marital status during pregnancy suffer more economic deprivation, feel less in control of their life, are more dependent on state support, look after themselves less well, are more emotionally distressed and experience more serious life events than married or cohabiting women (Andersson SW, *et al*., 2013). Also, unstable marital status is related to the delivery in young age, unemployment, low education and low income (Andersson SW, *et al.*, 2013).

Women of low economic status have been associated with a high-risk of having low weight babies (Halbreich, U. 2011). Tuntiseranee *et al*., (2013) examined the effect of socioeconomic determinants of pregnancy outcomes for Thailand to find that mean birth weight correlated with family income even after adjusting for maternal characteristics and number of antenatal visits. In his view, socioeconomic status of the household is a major determinant of the weight of a baby at birth.

Maternal risk factors: From an individual point of view, maternal risk factors tend to impact birth weight smaller than would medical condition effects. These risk factors affect larger numbers of women and altering it is quite difficult. However, the higher incidence of low birth weight among teenage mothers may be an indication that some maternal risk factors are partly amendable by population-based comprehensive and prenatal interventions. There is a consistent relationship between some of the maternal risk factors such as age, birth order and birth intervals and LBW. Several authors Magadi *et al*., (2013) have found birth order as an important factor influencing birth weight and first order births are on average more likely to be small babies than higher order births. Although it is expected that short birth intervals will increase the risk of adverse outcomes, some studies (Ester, W. A.,*et al*., 2008) have showed a reverse relationship. Channon, A. A. (2011) and Olowonyo *et al.*, (2006), found that in Nigeria, LBW was common with some ethnic groups, female infants, teenage and educationally disadvantaged mothers.

2.3. Empirical Literature Review

Numerous studies have investigated LBW in various regions of the world. The results of those studies outlined here in order to illustrate the situation from both a developed and developing countries.

Khatun, S., & Rahman, M. (2008) conducted a study in Bangladesh to analyze socio-economic determinants of low birth weight using logistic regression analysis. A total of 1,467 births occurred during the study period, of which 465 met the study criteria. Among which one hundred and eight LBW babies were compared with 357 normal birth weight babies. Out of 20 possible risk variables analyzed, nine were found significant when studied separately. Mother's age, education, occupation, yearly income, gravid status, gestational age at first visit, number of antenatal care visit attended, quality of antenatal care received and pre-delivery body mass index had significantly associated with the incidence of LBW. Using the stepwise logistic regression, mother's age ($p<0.001$), education ($p<0.02$), number of antenatal care visit attended ($p<0.001$, OR=29.386) and yearly income ($p<0.001$, OR=3.379) created the best model, which predicted 86.1% and 94.4% of the LBW babies and normal birth weight babies respectively. Maternal age, educational level and economic status play an important role in the incidence of low birth weight.

Dharmalingam,*et al*., (2010) conducted a study from India using national survey data investigated the association between the mother's nutritional status and birth weight of her newborn. The authors concluded that nutritional status, as measured by the mother's body mass index, was the most important determinant of LBW. Other important determinants included safe drinking water, antenatal care utilization, and anemia. Another study examined the association between social factors and newborn birth weight in a population in Québec, Canada (Dubois, L., & Girard, M. 2006). Results demonstrated that birth weight increased with higher levels of family socioeconomic status and with higher maternal body mass indices. Newborn birth weight was lower among mothers who smoked. Body mass index was the most important indicator of LBW among mothers of higher socioeconomic status; however, maternal smoking was the most important indicator among mothers of lower socioeconomic status. Findings from these two studies may suggest that while many of the determinants of LBW may be similar in developed and developing countries, there are disparities reflective of local genetic, cultural, and environmental contexts.

Brawarsky, P., *et al*., (2012) carried out a case-control study investigating risk factors for LBW in Sancti Spiritus, Cuba. Cases consisted of 764 singleton live births of less than 2,500 grams while controls consisted of 1,437 singleton live births of at least 2,500 grams, selected from the same hospital. Data were obtained from clinical histories, birth registries, and personal interviews with the mothers. Multivariate analyses revealed an increased likelihood of LBW for mothers with anemia, with a gestational weight gain of less than eight kilograms, and for mothers who smoked during pregnancy. There was no association found between LBW and low educational attainment (incomplete primary school or less) or late attendance at first antenatal care visit.

Barbieri, M. A., Silva, A. A., *et al*., (2014) conducted a study from Brazil examined maternal smoking and its association with LBW using a historical cohort design. All 5,166 live births delivered in 2012 in Pelotas, Brazil, were included in the cohort. Data were obtained from personal interviews with the mothers soon after the birth of their child. Smoking was found to be statistically significantly associated with LBW such that those who smoked during pregnancy had increased odds of delivering a LBW newborn compared to those who did not smoke during pregnancy, even after adjusting for several potential confounders (socioeconomic status, education, parity, pregnancy interval, previous LBW newborns, maternal height, and antenatal care). Further, newborns of mothers who smoked during pregnancy weighed less, on average, than newborns of mothers who did not smoke during pregnancy.

Barbieri, M. A., *et al*., (2014) conducted a study from Ribeirao Preto , Brazil examined trends in LBW by comparing two birth cohorts from 2006-2007(n = 6,750, a population survey (n = 2,990, a sample survey). Multivariate logistic regression adjusted for newborn sex, maternal age (< 20 years, 20-34 years, = 35 years). Marital status (cohabiting, non-cohabiting), parity (1 birth, 2-4 births, = 5 births), preterm birth (yes, no), antenatal care (< 4 visits, = 4 visits), type of delivery (vaginal, cesarean), health care (public, private), smoking (yes, no), maternal education (< 4 years, 4-11 years, = 12 years), and occupational group (lower managers, executives, academics; skilled and semi-skilled; unskilled/unemployed). In the 2006-2007 cohort, the following variables statistically significantly increased the likelihood of LBW: female sex, maternal age = 35 years, preterm delivery, less than four antenatal care visits, maternal smoking, 4-11 years of education, skilled or semi-skilled occupational status, and unskilled/unemployed. In the 2008 cohort, the following variables statistically significantly increased the likelihood of LBW.

Siega-Riz, *et al.,* (2013) carried out case-control study investigated risk factors for LBW in Natal, Brazil, while taking into account preterm delivery and intrauterine growth restriction. Cases consisted of 429 preterm newborns and 422 intrauterine growth-retarded (IUGR) singleton newborns. Controls consisted of 2,555 newborns of NBW and gestational age. Adjusted odds ratios were estimated using logistic regression, and the proportion of LBW that may have been prevented was estimated using attributable risk percent (AR %). Preventable determinants of preterm birth were maternal age < 20 years (AR = 7.1%), maternal weight < 50 kilograms (AR = 20.5%), smoking during pregnancy (AR = 14.6%), < 5 antenatal care visits (AR = 28.1%), history of LBW (AR = 12.2%), gestational illness (AR = 15.5%), and vaginal bleeding in the first trimester (AR = 13.4%). Preventable determinants of IUGR were maternal weight < 50 kilograms (AR = 17.8%), maternal education < 4 years (AR = 11.6%), smoking during pregnancy (AR = 14.8%), < 5 antenatal care visits (AR = 11.6%), history of LBW (AR = 14.1%), gestational illness (AR = 6.0%), and prim parity (AR = 25.6%).

Mwabu, G (2011) investigated the determinants of birth weight in Kenya in the year 2009 using data from welfare monitoring surveys collected by the Central Bureau of Statistics, Ministry of Planning and National Development. Structural equation model was used for analysis. It is shown that immunization of the mother against tetanus during pregnancy has a strong positive effect on birth weight. Other determinants of birth weight include age of the mother at first birth and birth orders of siblings. It is further shown that birth weight is positively associated with mother's age at first birth and with higher birth orders, with the first-born child being significantly lighter than subsequent children. Moreover, birth weights are lower in rural than in urban areas and females are born lighter than males. There is tentative evidence that babies born at the clinics are heavier than babies from the general population.

Siza J.E. (2008) carried out a descriptive retrospective cross - sectional study investigating the risk factor associated with LBW using existing data from a one-year (2006) block of birth registers of 3464 pregnant women was done at Kilimanjaro Christian Medical Centre in Moshi, Tanzania. HIV positive women were twice more likely to give birth to LBW infants than HIV negative ones ($\chi 2 = 6.7$; $P<0.01$; OR = 2.4; 1.1, 5.1). Mothers without formal education were 4 times more likely to give birth to LBW neonates than those who had attained higher education (OR= 3.6; 2.2, 5.9). There was a linear decrease in low birth weights of newborns as maternal educational level increased ($\chi 2$ for linear trend = 42.7; $P< 0.01$). There was no statistically significant difference among parents' occupations regarding LBW of their newborns. Unmarried mothers were more likely to give birth to LBW neonates as compared to their married counterparts (OR = 1.65; 1.2, 2.2) and the difference was statistically significant ($\chi 2=13.0$, $P< 0.01$). Hypertension, pre-eclampsia and eclampsia disease complex had the highest prevalence (46.67%) and population attributable fraction of low birth weight (PAF = 25.2%; CI= 22.0-27.6). Bleeding and schistosomiasis had the same prevalence (33.33%) of LBW babies. Other complications and diseases that contributed to high prevalence of LBW included anemia (25%), thromboembolic diseases (20%), tuberculosis (17%) and malaria (14.8%). LBW was strongly associated with gestational age below 37 weeks (OR = 2; CI=1.5, 2.8) contributing to 42% of LBW deliveries in the study population (PAF = 42.4%: 25, 55). Pregnant women with malnutrition (BMI<18) gave the highest proportions 17% of LBW children followed by underweight (BMI; 18-22) who gave 15.5% of LBW neonates. There was statistically significant difference between the proportions of LBW infants from mothers who did not receive antenatal care (28.6%) and those who attended for the services (13.8%) ($\chi 2 = 8.8$; $P= 0.01$).

Ipadeola, O. B., *et al*., (2013) examine the influence of household poverty levels and maternal nutritional status on child's weight at birth using 2008 Nigeria Demographic Health Survey (NDHS) measures weight at birth on an ordinal scale. Ordinal logistic regression technique was employed for all analyses. Quintiles of wealth index were used as a measure of assets owned by households while body mass index was used to assess maternal nutritional status. Other demographic characteristics such as mother's age at birth of the child, educational attainment, locality (urban/rural) and geo-political zones were controlled for in the models. The sample size for survey was 5138. Wealth index and maternal nutritional status were positively associated with child's weight at birth, while mother's educational attainment was not statistically significant. Significant and positive association of wealth index was evident with middle (OR=1.38, $p<0.0001$), higher (OR=1.48, p= $p<0.0001$), and highest (OR=1.37, p=0.009) when compared with those in the poorest category of wealth index. Mothers that were too thin or underweight based on their BMI, were more likely to give birth to children with low birth weight. (OR=0.80, p=0.008); while those that weighed more than they should (overweight: OR=1.35, $p<0.0001$; or obese: OR=1.29, p=0.065) were more likely to give birth to children with large weights when compared with mothers with normal BMI. Significant gender differentials were also found. Males were about 1.4 times ($p<0.0001$) more likely to have weights larger than their female counterparts at birth. Age of mother at the birth of a child has also been shown to be of risk to pregnancy outcomes. Teenage mothers were more likely to give birth to children with low birth weight. Here, positive significant association was observed for mothers' age at birth and child's weight at birth. Children from mothers in the age range 25 to 39 years were about 1.26 times more likely to weigh more at birth compared with children from teenage mothers ($p<0.05$). Significant spatial pattern was observed at the level of geopolitical zones with $p<0.05$. This spatial variation, however, needs to be investigated further at a highly disaggregated level of states as information at this level could be masked. Multiple births are significantly associated with low birth weight compared with singleton births (OR=0.59, $p<0.0001$).

Tema(2006). Conducted A cross-sectional descriptive study to assess the Prevalence and determinants of low birth weight in Jimma Zone, Southwest Ethiopia. Mothers with newborns delivered in the four health centers (Jimma, Agaro, Asendabo and Shebe) and jimma university hospital from September 1, 2002 to march 30, 2003, and those delivered at home and received care within the first 24 hours after delivery in these health care settings. A total of 145 (22.5%) of the newborns were LBW. Mothers residing in the urban setting had higher risk of delivering LBW babies and the difference was statistically significant (p = 0.000). Analysis of maternal obstetric history revealed that those mothers who delivered before 37 weeks of gestation, had weight loss, and who did not receive additional diet during pregnancy had higher risk of delivering LBW babies and the difference was statistically significant (p = 0.01, 0.00, 0.00) respectively. Similarly, those who had multiple gestations had a higher risk of delivering LBW babies and the difference was statistically significant (p = 0.00).

In general, therefore, the literature investigating LBW from the above studies have found several determinants that increase the likelihood of delivering a LBW infant. These include smoking during pregnancy, low gestational weight gain, inadequate antenatal care, low educational attainment, low socioeconomic status , less skilled occupation, maternal pre-pregnancy weight, low gestational weight gain, anemia, history of LBW, gestational illness, vaginal bleeding in the first trimester, prim parity, smoking, preterm birth, caesarean delivery and female sex of the newborn. Few studies have found that higher calorie and protein reserves (i.e. the mother's nutritional status) had a positive effect on infant birth weight, concluding that the mother's nutritional status is a key determinant of newborn birth weight (Karim E, Mascie-Taylor 2012).

2.4. Overview of Model Families

Proper analysis of data is required in modeling the association between the response variable and the given set of covariates. Molenberghs & Verbeke broadly classified models in to two main model families (Molenberghs & Verbeke, 2005). Marginal model and cluster specific model.

Marginal models: in which responses are modeled, marginalized overall other responses; the association structure is then typically captured using a set of association parameters, such as correlations, odds ratios, etc. Generalized estimating equation (GEE) and alternating logistic regression (ALR) are among marginal model family.

Cluster-specific models: the responses are assumed independent, given a collection of cluster-specific parameters. Generalized linear mixed model is one of subject specific family (Molenberghs & Verbeke, 2005). Based on the nature of sampling design and nature of data, some of the model families would be appropriate for this study is discussed as follow.

2.4.1. Generalized Estimating Equation (GEE)

According to Agresti, computationally simple alternative to maximum likelihood (ML) for clustered categorical data is a multivariate generalization of quasi likelihood. Rather than assuming a particular type of distribution for the response variable, this method only links each marginal mean to a linear predictor and provides a guess for the variance covariance structure of the response. The method uses the observed variability to help generate appropriate standard errors and called the GEE method because the estimates are solutions of generalized estimating equations. These equations are multivariate generalizations of the equations solved to find ML estimates for generalized linear models (Agresti, 2007). 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 vector of binary responses and phrase the working assumptions about the association between pairs of outcomes in terms of marginal correlations (Molenberghs & Verbeke, 2005).

When we are mainly interested in first-order marginal mean parameters and pair wise interactions, a full likelihood procedure can be replaced by quasi-likelihood based methods

(McCullagh and Nelder, 1989). In quasi-likelihood, the mean response is expressed as a parametric function of covariates, and the variance is assumed function of the mean up to possibly unknown scale parameters.

Wedderburn first noted that likelihood and quasi-likelihood theories coincide for exponential families and that the quasi-likelihood estimating equations provide consistent estimates of the regression parameters in any generalized linear model, even for choices of link and variance functions that do not correspond to exponential families (Wedderburn 1974). Consequently, Liang and Zeger 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, GEE method requires a correct specification of the mean as well as how the variance depends on the mean. 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).

In the methodology of generalized estimating equations, the user may impart a correlation structure that is often called a working correlation matrix. One often does not know what the true correlation is, hence, the term working correlation. Common correlation structures include; **Exchangeable:** all correlations within subjects are equal, **Independent:** all correlations are assumed to be zero (Myers *et al.*, 2010). Because GEE does not have likelihood function, likelihood-ratio methods are not available for checking fit, comparing models, and conducting inference about parameters.

2.4.2. Alternating Logistic Regression (ALR)

Generalized estimating equation (GEE), allows estimation of first and second moment parameters in regression models for multivariate binary data. When association among the observation is importance and is measured using marginal odds ratios, the computations required will exclude the applications in studies with large clusters. An alternative approach that overcomes the computational limitations encountered in many problems is proposed what is called alternative logistic regression (Zeger *et al.*, 1993). As explained by Zeger *et al.*, alternating logistic regression is reasonably efficient relative to GEE. In ALR, we estimate the association parameters by modeling the conditional distribution of one response given another.

Molenberghs & Verbeke also expressed ALR as extension of classical GEE, in the sense that precision estimates follow for both the parameters. However, unlike with GEE, no working assumptions about the third- and fourth-order odds ratios are required. The clever combination of a marginal and a conditional specification, addressing the third and fourth moments is avoided all together, which is strictly different from setting them equal to zero. This combination of marginal and conditional specification can be advantageous of ALR (Molenberghs & Verbeke, 2005).

2.4.3. Generalized Linear Mixed Model (GLMM)

Agresti explained that, generalized linear model (GLM) extend ordinary regression by allowing non-normal responses and a link function of the mean. The generalized linear mixed model is a further extension that permits random effects as well as fixed effects in the linear predictor (Agresti, 2007). Antonio & Beirlant defined GLMM as extend of GLM by allowing for random or cluster-specific effects in the linear predictor. These models are useful when the interest of the analyst lies in the individual response profiles rather than the marginal mean. The inclusion of random effects in the linear predictor reflects the idea that there is natural heterogeneity across subjects or clusters in some of their regression coefficients (Antonio & Beirlant, 2006). According to McCulloch clarification, GLMM is very versatile in that they can handle non-normal data, nonlinear models, and a random effects covariance structure. This can be used to incorporate correlations in models, model the correlation structure, identify sensitive subjects and can be used to handle heterogeneous variances. The modeling process is relatively straightforward, requiring the following decisions: what is the distribution of the data, what is to be modeled, what are the factors, and are the factors fixed or random? This all makes GLMM attractive for use in modeling. Unfortunately, computing methods for much of the class of GLMM is an area of active research. No general-purpose software exists and, tests and confidence intervals are asymptotic and approximate (McCulloch, 1997).

Generalized the above explanation, GLMM is an extension to generalized linear model (GLM) that includes random effects in the linear predictor, giving an explicit probability model that explains the origin of the correlations. The resulting cluster-specific parameter estimates are suitable when the focus is on estimating the effect of changing one or more components of the predictor on a given individual.

The key problem in GLMM is maximization of the marginal likelihood, obtained by integrating out the random effects. In general, no analytic expressions are available for the integrals and numerical approximations are needed. There are large statistical literatures on various methods like approximation of the data, approximation of the Integral (Molenberghs & Verbeke, 2005).

To summarize, this brief literature review has shown the importance of a range of characteristics in determining LBW. Some determinant covariates such as mother's education level, mother's age at birth, birth order and wealth status are assessed, which are assumed to have positive or negative associations with the LBW. Some important model families like marginal models (GEE & ALR), cluster specific model (GLMM) which are appropriate for analysis to the nature of the given data would have assessed.

3. DATA AND METHODOLOGY

3.1. Source of Data

The source of data for this study was the 2011 Ethiopia Demographic and Health Survey (EDHS), which is obtained from Central Statistical Agency (CSA). It was the third survey conducted in Ethiopia as part of the worldwide Demographic and Health Surveys project. The 2011 Ethiopian Demographic and Health Survey, was designed to provide estimates for the health and demographic variables of interest for the following domains. Ethiopia as a whole; urban and rural areas (each as a separate domain); and 11 geographic administrative regions (9 regions and 2 city administrations), namely: Tigray, Affar, Amhara, Oromiya, Somali, Benishangul-Gumuz, Southern Nations, Nationalities and Peoples (SNNP), Gambela and Harari regional states and two city administrations, that is, Addis Ababa and Dire Dawa. The principal objective of the 2011 EDHS is to provide current and reliable data on fertility and family planning behavior, child mortality, adult and maternal mortality, children's nutritional status, use of maternal and child health services, knowledge of HIV/AIDS, and prevalence of HIV/AIDS and anemia.

3.1.1. Study Population

The 2007 Population and Housing Census, conducted by the CSA, provided the sampling frame from which the 2011 EDHS sample was drawn. Administratively, regions in Ethiopia are divided into zones, and zones, into administrative units called weredas. Each wereda was 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 2011 EDHS sample was selected using a stratified, two-stage cluster sampling design.

Clusters were the sampling units for the first stage. The sample included 624 clusters, 187 in urban areas and 437 in rural areas. Households comprised the second stage of sampling. In the second stage, a fixed number of 30 households were selected for each cluster. A complete listing of households was carried out in each of the selected clusters from September 2010 through January 2011 (CSA, 2011).

The 2011 EDHS used three questionnaires: the Household Questionnaire, the Woman's Questionnaire, and the Man's Questionnaire. These questionnaires were adapted from model survey instruments developed for the measure DHS project to reflect the population and health issues relevant to Ethiopia. In addition to English, the questionnaires were translated into three major local languages-Amharigna, Oromiffa, and Tigrigna.

A representative sample of 17,817 households was selected for the 2011 EDHS. A total of 11,654 children (0 – 59 months) were surveyed. The 2011 EDHS questionnaire recorded birth weight, if available from written records or mother's recall, for all births in the five years preceding the survey. Because birth weight may not be known for many babies, and particularly for babies delivered at home and not weighed at birth, the mother's estimate of the baby's weight at birth was also obtained. Although subjective, mothers' estimates can be a useful proxy for the weight of the child. A total of 11,654 children less than 59 months were identified in the households of selected clusters. There were cases in which information on the relevant variables was missing and these cases were excluded from the analysis. Thus, the analysis presented in this study on the risk factors of LBW was based on the 3,225 children aged less than 59 months.

3.2. Variables in the Study

3.2.1. Response Variable

Birth weight information for the majority of births in Ethiopia are not available because in practical situation; only 5 percent of children in Ethiopia are weighed at birth ((WHO & UNICEF 2004). This is not surprising because the majority of births do not take place in a health facility, and children are less likely to be weighed at birth in a non-institutional setting, the mother's estimate of the baby's weight at birth has been chosen for these analyses. This is because; scientific evidences support the idea that even if subjective, mothers' estimates are useful proxy indicators for the weight of a child. Magadi *et al.*, (2013) assessed the issue of the reliability of mothers' reporting of weight at birth against the available birth weight information using 2003 Kenya DHS and found it to be reliable. Also, DaVanzo *et al.*, (2005) showed evidence from the Malaysian Family Life Survey that mothers' recall of birth weight, including that of 'un weighted babies' are approximately same as the reported weight at birth, and can be used to examine biological and socioeconomic determinants of birth weight.

Often in many epidemiologic, biomedical and related fields of studies, the outcome of interest is a binary variable such as small birth weight versus large birth weight. In such circumstances, it is possible to employ plausible statistical tools for estimating the magnitude of the association between the response variable of interest as a function of independent predictor variables. The association provides information about the risk of developing an outcome. In practical, advantage of using statistical methods for binary response over statistical methods for continuous response variable in epidemiologic research is that parameter estimates of the possible risk factors can be directly converted to an odds ratio, which is interpretable. Additionally, the use of binary outcome for defining LBW and its severity at the population level, as well as the chronology of their founding allows the identification of populations at greatest risk of LBW and priority areas for action, especially when resources are inadequate. In view of the above, the child weight was first dichotomized based on the cut-off points as described in literature review leading to the binary response.

Table 3.1: Coding and explanation of response variable

Variable	Presentation of variable	Factor coding
Child Weight at Birth	Child Weight	1=Small Birth Weight (<2500gm) 0=Large Birth Weight ($\geq$2500gm)

3.2.2. Predictor (Explanatory Variables)

The explanatory variables that would be included were explained as follow. The variables that were considered in the research and expected to be the risk factors of LBW, were grouped in to maternal, socio-economic, demographic, and health and environmental factors.The choice of these variables was guided by different literatures as the determinant factors of LBW.

Table 3.2: Coding and explanation of explanatory variables

Attributes	Description		Categories	
Sex	Sex of child	**0**=Female	**1**=Male	
Residence	Place of residence	**0**=Rural	**1**= Urban	
Wealth Status	Wealth of mothers during birth	**1**=Poor	**2**=Middle	**3**=Rich
Age	Age of mother during birth	**1**=15-19	**2**=20-39	**3**=40-49
Terminated Pregnancies	Pregnancy terminated before the last birth	**0**=No	**1**=Yes	
Antenatal Visits	Number of antenatal visit during pregnancy	**1**=No Visit	**2**=1-4	**3**= ≥5
Marital Status	Marital status of mother	**1**=Married	**2**=Widowed	**3**=Divorced
Vaccination	Vaccination status	**0**=No	**1**=Yes	
Anemia	Maternal Anemia	**1**=Not Anemic	**2**=Moderate	**3**=Sever
Education	Mother education level	**1**=No Education	**2**=Primary	**3**=Sec. and above
Birth Order	Numbers of pregnancy including this birth	**1**=1-4	**2**=5-9	**3**= ≥10(year)
Preceding Birth Interval	Period(gap) of birth between current birth	**1**=1-5	**2**=6-10	**3**= ≥11(year)

3.3. Method of Data Analysis

A range of techniques has been developed for analyzing data with categorical and clustered response variables. For this study, some extension of generalized linear models such as marginal models and cluster specific modes would be applied.

3.3.1. Generalized Linear Models (GLM)

Generalized linear models (GLMs) extend ordinary regression models to encompass non-normal response distributions and modeling functions of the mean (Agresti, 2002). Three components that specify a generalized linear model are random component, which identifies the response variable Y and its probability distribution; a systematic component specifies explanatory variables used in a linear predictor function; and a link function specifies the function of expected value of the response variable that the model equates to the systematic component. In general, GLM is a linear model for a transformed mean of a response variable that has distribution in the natural exponential family.

The Exponential Family: A random variable Y follows a distribution that belongs to the exponential family, if the density function is of the form

$$f(y/\theta,\phi) = exp\{\phi^{-1}[y\theta - \psi(\theta)] + c(y,\phi)\} \qquad (3.1)$$

For a specific set of unknown parameters θ and ϕ, and for known functions $\psi(\cdot)$ and $c(\cdot,\cdot)$.The parameter θ is called the canonical parameter and represents the location while, ϕ is called the dispersion parameter and represents the scale parameter and for the Poisson and binomial distribution it is fixed to be one (Faraway, 2006). An important property of the GLM is the functional relation between mean and variance.

Generalized linear model assumes that the response variables are independent. In clustered data however, observations are usually taken from the same unit, and thus this information forms a cluster of correlated observations. For instance, in the EDHS the dependent variable (low birth weight) was measured once for representative of samples nested within clusters from each region.

3.3.2. Marginal Models

In clustered data, observations are usually taken from the same unit, and thus this information forms a cluster of correlated observations. Proper analysis of clustered data is required in modeling the association between the response variable and the given set of covariates. Marginal models are among the statistical models widely used to model clustered or repeated data. The primary objective of marginal model is to analyze the population-averaged effects of the given factors in the study on the binary response variable of interest. This means that the covariates are directly related to the marginal expectations (Molenberghs & Verbeke, 2005). The marginal models fitted in this study that would be included are Generalized Estimating Equations (GEE) and Alternating Logistic Regression (ALR).

3.3.3. Generalized Estimating Equations (GEE)

For binary data, a GEE approach is used to account for the correlation between responses of interest for subjects from the same cluster (Zorn, C. J. 2001). GEE is non-likelihood method that uses correlation to capture the association within clusters or subjects in terms of marginal correlations (Molenberghs & Verbeke, 2005). For clustered as well as repeated measured data, (Liang & 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 Zeger, included independence, unstructured, exchangeable and autoregressive 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 or sequences with differing lengths (Molenberghs and Verbeke, 2005).

Let $y_j = \left(y_{j1}, \dots \dots y_{jnj}\right)'$ be the response values of observations from j^{th}cluster,

for $j = 1,2, \dots \dots \dots m$ follows a binomial distribution i.e $y_j = Bin(n_j, \pi_j)$that belongs to the exponential family with the density function of the form (3.1). Then, to model the relation between the response and covariates, one can use a regression model similar to the generalized linear models given by:

$$g(\pi_j) = logit(\pi_j) = X_j'\beta \qquad 3.2$$

Where $g(\pi_j)$ is logit link function, $X_j\ is\ (n_j \times P)$dimensional vector of covariates,

$\beta = (1 \times P)$ dimensional vector of unknown fixed regression parameter to be estimated and $E(Y_j) = \pi_j$ is expected values of the j^{th} response variable from cluster.

3.3.3.1. Parameter Estimation for GEE

As previously expressed GEE is not likelihood approach, rather it is quasi-likelihood based and estimates $\hat{\beta}$ by solving estimating equations which consist of the working covariance matrix V_j. The score equation used to estimate the marginal regression parameters while accounting for the correlation structure is given by:

$$S(\beta) = \sum_{j=1}^{m} \frac{\partial \pi_j}{\partial \beta'} \left[A_j^{1/2} R_j A_j^{1/2}\right]^{-1} (Y_j = \pi_j) = 0 \qquad (3.3)$$

Where R_j is working correlation matrix, and the covariance matrix of Y_j is decomposed in to $A_j^{1/2} R_j A_j^{1/2}$ With A_j the matrix with the marginal variances on the main diagonal and zeros elsewhere and Y_j is multivariate vector of asymptotically normal response variables with mean vector π_j i.e $Y_j \cong N(X_j\beta, V_j)$. An advantage of the GEE approach is that it yields a consistent estimator of $\hat{\beta}$, even when the working correlation matrix R_j is misspecified. However, severe misspecification of working correlation may seriously affect the efficiency of the GEE estimators (Molenberghs & Verbeke, 2005).

3.3.4. Alternating Logistic Regression (ALR) Model

This method is very similar to that of GEE, in that they are both quasi-likelihood based and they account for dependency in the data. However, unlike GEE which measures the association among the observed data through the correlation structure; Alternating logistic regression (ALR) measures this association using the odds ratio, which is interpretable and more applicable for binary data. ALR extends beyond classical GEE in the sense that precision estimates follow for both the regression parameters β and the association parameters α. Moreover, with ALR inferences can be made, not only about marginal parameters but also about pair wise associations between subjects as well (Molenberghs & Verbeke, 2005).

For cluster$j = 1,2, \dots \dots \dots m$, let $y_j = (y_{j1}, \dots \dots y_{jnj})'$ be a $n_j \times 1$ response vector with mean $E(Y_j) = \pi_j$ and let ψ_{ijk} be the odds ratio between responses $Y_{jk}$and Y_{jl} $(1 \leq k \leq l \leq n_j)$ defined by:

$$\psi_{ijk} = \frac{P\big(Y_{jk} = 1, Y_{jl} = 1\big)P(Y_{jk} = 0, Y_{jl} = 0)}{P\big(Y_{jk} = 1, Y_{jl} = 0\big)P(Y_{jk} = 0, Y_{jl} = 1)} \qquad (3.4)$$

$j = 1,2, \dots \dots m \quad k, l = 1,2, \dots \dots n_j$, where Y_{jk} and Y_{jl} represents the response values for child k and l respectively from the same cluster. Let γ_{jkl} be the log odds ratio between outcomes Y_{jk} and Y_{jl} , $\pi_{jk} = P(Y_{jk} = 1)$ and $v_{jkl} = P(Y_{jk} = 1, Y_{jl} = 1)$ then the association of the two responses (Zeger *et al*, 1993) is defined as:

$$logit\big(Y_{jk} = 1/Y_{jl} = y_{jl}\big) = \gamma_{jkl} y_{jl} + \log\left(\frac{\pi_{jk} - v_{jkl}}{1 - \pi_{jk} - \pi_{jl} + v_{jkl}}\right) \qquad (3.5)$$

Assume$\gamma_{jkl} = \alpha$. Then the pair wise log odds ratio α is the regression coefficient in logistic regression of Y_{jk} on Y_{jl} as long as the second term on the right-hand side in (3.5) is used as an offset. Generally $log\ (\psi_{jkl}) = \gamma_{jkl} = Z'_{jkl}\alpha$ where Z_{jkl} is a $q \times 1$ vector of covariates which specifies the form of the association between Y_{jk} andY_{jl}.

3.3.4.1. Parameter Estimation for ALR

Since ALR also not maximum likelihood approach like GEE, parameter estimation is based on the score equation of the approximate likelihood that is based on quasi likelihood approximation. Let ξ_j be vector with elements

$\xi_{jkl} = E(Y_{jk}/Y_{jl} = y_{jl})$ and let R_j be the vector of residual with elements

$R_{jkl} = Y_{jk} - E(Y_{jk}/Y_{jl} = y_{jl}) = Y_{jk} - \xi_{jkl}$

Let S_j a vector of diagonal matrix with diagonal element $\xi_{jkl}(1 - \xi_{jkl})$and let W_j denote matrix $\frac{\partial \xi_j}{\partial \alpha}$. Finally, let $A_j = Y_j - \pi_j,\ B_j = cov\left(Y_j\right), C_j = \frac{\partial \pi_j}{\partial \beta}$

Then the alternating logistic regression parameter $\delta = (\beta, \alpha)$is the simultaneous solution of the following unbiased estimating equations (Zeger *et al* 1993).

$$U_\beta = \sum_{j=1}^{m} C_j' B_j^{-1} A_j = 0 \qquad (3.6)$$

$$U_\alpha = \sum_{j=1}^{m} W_j' S_j^{-1} R_j = 0 \qquad (3.7)$$

Estimating equation 3.6 and 3.7 are solving for β and α by using Gauss-Seidel procedure algorithm. ALR is computationally feasible for very large cluster.

3.3.5. 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. With this, we mean selecting the best subset of the covariates from the available covariates in the data.

3.3.6. Variable Selection Technique

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. Finally, the two models were compared using model comparison techniques. Additionally, using the same procedures, an ALR model, which provides information about pair wise association of observations between two different individuals within the same cluster, was fitted. It turned out that the model with selected covariates is found to be the most parsimonious model.

3.3.7. Model Comparison Technique

Quasi-Information Criterion (QIC): In a condition, when the likelihood function cannot be fully specified, such as in the GEE case, the Akaike's 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's 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 quasi-likelihood function takes the following form (McCullagh &Nelder, 1989)

$$Q(\pi) = \int_{y}^{\pi} \frac{y-t}{\phi_v(t)} dt$$

Where $\pi = E(y), v(y) = \phi_v(\pi)\ and\ \phi$ is the dispersion parameter. An equation for the QIC is $QIC = -2Q(\hat{\pi}, I) + 2trace\left[(\Omega_I^{-1}\hat{V}_R)\right]$ where I represen the independent correlation structure (diagonal matrix) and R is the specified working correlation structure.

The p-dimensional matrices Ω_I^{-1} and $\hat{V}_R$ are variance estimators of the regression coefficients under the correlation structure I and R respectively. The QIC value will be computed based on the quasi-likelihood estimate $\hat{\pi}$ and will be used to select the candidate explanatory variables. The model with the smallest QIC value for all correlation structures will be considered as the best candidate model.

3.3.8. Model checking technique

Preisser and Qaqish (1996) further generalize regression diagnostics to apply to models for correlated data fitted by generalized estimating equations (GEEs) and alternating logistic regression (ALR), where the influence of entire clusters of correlated observations is measured. The diagnostic measures proposed for marginal models were similar to those that exist for generalized linear models: DFBETAC, Cluster Cooks '*D*, Cluster leverage and Cluster DFFIT. The diagnostic purpose of each measure is similar as well. DFBETAC is a measure of the influence that any cluster has on each $\hat{\beta}$ (Belsley et al., 1980); Cluster Cooks' *D* is a measure of the influence of any cluster on the overall fit of the model (Cook, 1977); Cluster leverage is a measure of how extreme cluster is with respect to the predictors (Belsley *et al*., 1980). Cluster DFFIT represents the studentized Cook distance type statistic to measure the influence of deleting cluster on the overall model fit. DFBETAC, Cluster Cooks 'D and Cluster DFFIT are referred to as deletion diagnostics because the magnitude of each is related to changes in the fit of the model after a particular cluster is removed compared to the fit of the model on the full data. Let $n_i$be the number of responses for cluster i, and $N = \sum_{i=1}^{k} n_i$ the total number of observations. A_i is n_i x n_i diagonal matrix Let B NxNdiagonal matrix and let B_i the n_i x n_i diagonal matrix corresponding to cluster i. Let $Q_i = X_i(X'X)^{-1}X_i'$ where X_i is the n_i x p design matrix corresponding to cluster i. The adjusted residual vector is defined as $E = B(Y - \hat{\pi})$ and $E_i = B_i(Y_i - \hat{\pi}_i)$ the estimated residual for the i^{th} cluster.

CLEVERAGE

The leverage of cluster i is contained in the matrix $H_i = Q_i$and is summarized by the trace of H_i, where H_i is the hat matrix of cluster i.

$\text{CLEVERAGE}_i = tr(H_i)$

The leverage value greater than one for the i^{th} cluster indicates that cluster is influential (Belsley et al., 1980).

DFBETAC

The effect of deleting cluster i on the estimated parameter vector is given by the following one-step approximation for $\hat{\beta} - \hat{\beta}_{[i]}$:

$\text{DFBETAC}_i = (X'X)^{-1}X_i'(I - Q_i)^{-1}E_i$

If DFBETAC_i is less than unity, this implies no specific impact of cluster on the coefficient of a particular predictor variable, while DFBETAC_i of i^{th}cluster greater than 1.0, implies the cluster is an outlier (Cook and Weisberg, 1982).

DFBETACS

DFBETAS is the standardized DFBETAC. The cluster deletion statistic DFBETAC can be standardized by dividing the components of DFBETAC by its standard error.

CLUSTERCOOKSD

Let DCLS_i be the cluster-level Cook's D for cluster i, which can be calculated as

$\text{DCLS}_i = E_i'(I - Q_i)^{-1})Q_i(I - Q_i)^{-1})E_i/p\hat{\phi}$ where p is the number of predictors in the model and $\hat{\phi}$ is dispersion parameter. The suggested cut off values for i^{th} cluster to be influential is, if DCLS_i is greater than "one" (Preisser and Qaqish ,1996).

CLUSTERDFFIT

Let MCLS_i be the cluster-level DFFIT for cluster i which can be calculated as

$\text{MCLS}_i = E_i'(I - Q_i)^{-1}H_iE_i/p\hat{\phi}$ The suggested cut off values for i^{th} cluster to be influential is, if MCLS_i is greater than "one" (Preisser and Qaqish,1996).

PEARSON RESIDUAL

Another model diagnostic tool for marginal model is Pearson residual. Raw residuals and Pearson residuals are available for models fit with generalized estimating equations (GEEs) and alternating logistic regression (ALR). The raw residual is defined as

$r_i = y_i - n\hat{\pi}_i$ Where y_i is the i^{th} response and $n\hat{\pi}_i$ corresponding predicted mean.

The Pearson residual is defined by the difference between observed and fitted values and divides by an estimate of the standard deviation of the observed value. Observations with a Pearson residual exceeding three in absolute value may shows lack of fit (Davison and Snell, 1991). Pearson residual is given by: $r_{pi} = \frac{y_i - n\hat{\pi}}{[var(y_i)]^{1/2}}$

3.3.9. Subject Specific Models

When interest is in the marginal or population-averaged models to analysis the relationships of the covariates to the dependent variable for an entire population, marginal models as discussed in previous section are preferred. However, in most biomedical and biological data problems, interest often lies in understanding the response of individual patient characteristics and how this response is influenced by a given set of possible covariates (Myers et al.,2010). This proves even to be essential when individual interventions may be necessary. Cluster specific models are useful in such cases. Cluster specific models differ from the marginal models by inclusion of parameters that are specific to clusters or subjects within a population. Consequently, random effects will directly used in modeling the random variation in the dependent variable at different levels of the data.

3.3.10. Generalized Linear Mixed Model (GLMM)

Generalized linear models (GLM) is one parts of subject specific models which extends ordinary regression by allowing non-normal responses and a link function of the mean. The generalized linear mixed model is a further extension that permits random effects as well as fixed effects in the linear predictor (Agresti, 2002).

Let y_{ij}denote the birth weight of i^{th} individual child from j^{th} cluster where $i = 1,2, \dots \dots n_j$ and y_j the n_j dimensional vector of all measurements available for cluster$j$. Let $f(b_j/D)$ be the density of the $N(0, D)$distribution for the random effect b_j. Assumed conditionally on q-dimensional random effects b_j to be drawn independently from $N(0, D)$, the outcomes y_{ij} of Y_j are independent with the density of the form

$$f_j\left(y_{ij}/b_j,\beta,\phi\right) = exp\{\phi^{-1}\left[y_{ij}\theta_{ij} - \psi\left(\theta_{ij}\right)\right] + c\left(y_{ij},\phi\right)\} \quad (3.8)$$

Then the generalized linear mixed model (Molenberghs and Verbeke, 2005); with logit link is defined as

$$logit\left(\pi_{ij}\right) = X'_{ij}\beta + Z'_{ij}b_j\ , \qquad j = 1,2,\dots\ \dots\ \dots m \quad (3.9)$$

Where $E\left(Y_{ij}/b_j\right) = \pi_{ij}$, is the mean response vector conditional on the random effects b_j , for child in cluster j and, X_{ij} and Z_{ij} are *p*-dimensional and *q*-dimensional vectors of known covariate values. The random effects b_j are assumed to follow a multivariate normal distribution with mean 0 and covariance matrix D.

3.3.10.1. Parameter Estimation for GLMM

Random-effects models were fitted by maximization of the marginal likelihood, obtained by integrating out the random effects. Such likelihood may involve high-dimensional integrals that cannot be evaluated analytically. The likelihood of the data expressed as a function of unknown parameters is

$$L(\beta, D, \phi) = \prod_{j=1}^{m} f_j\left(Y_j/\beta, D, \phi\right) = \prod_{j=1}^{m} \int \prod_{j=1}^{n_j} f_{ij}\left(Y_{ij}/b_j, D, \phi\right) f\left(b_j/D\right) db_j \quad 3.10$$

It is the integral over the unobserved random effects of the joint distribution of the data and random effects. The problem in maximizing (3.10) is the presence of m integrals over the q-dimensional random effects b_jWith Gaussian data, the integral has a closed form solution and relatively simple methods exist for maximizing the likelihood or restricted likelihood. With non-linear models, numerical techniques are needed. The Laplace method (Molenberghs and Verbeke, 2005) has been designed to approximate integrals of the form:

$$I = \int e^{Q(b)}\, db \quad 3.11$$

Where $Q(b)$ is a known, unimodal, and bounded function of a q-dimensional variable $\boldsymbol{b}$. Let $\hat{b}$ be the value of b for which Q is maximized. Then the second order Taylor expansion of $Q(b)$ is the form

$$Q(b) \approx Q(\hat{b}) + \frac{1}{2}(b-\hat{b})' Q''(\hat{b})(b-\hat{b}) \qquad 3.12$$

Where, $Q''(\hat{b})$ is the matrix of second-order derivative of Q, evaluated at $\hat{b}$.Replacing $Q(b)$ in (3.11) by its approximation in (3.12) we obtain

$$I \approx (2\pi)^{q/2} \left| -Q(\hat{b}) \right|^{-1/2} e^{Q(\hat{b})}$$

Clearly, each integral (3.10) is proportional to an integral of the form (3.11) for functions $Q(b)$ given by

$$Q(b) = \phi^{-1} \sum_{i=1}^{n_j} \left[y_{ij}(x'_{ij}\beta + Z'_{ij}b) - \psi(x'_{ij}\beta + Z'_{ij}b) \right] - \frac{1}{2} b' D^{-1}$$

This is called the Laplace's method or approximation of integrands. Note that the mode $\hat{b}$ of Q depends on the unknown parameters $\beta, \phi,$ and D, such that in each iteration of the numerical maximization of the likelihood, will be recalculated conditionally on the current values for the estimates for these parameter.

3.3.11. Model Building for GLMM

A different approach to account for clustering is by using random components such as random intercepts. Under the GLMM, model building will begin by adoption of the marginal model covariates. Additionally, the model also included the random effects, in this case, random intercepts to address the between and within-regional heterogeneity. These were introduced in the generalized linear mixed model due to the fact that, the probability of having low birth weight baby possibly varies for individuals within the same regions as well as individuals in different regions. Variable selection procedure for GLMM is similar with marginal model previously explained.

3.3.12. Model Comparison in GLMM

This study has been used Likelihood ratio test and Information criteria to select the best model based on the values of asymptotic estimations.

Likelihood Ratio Test: In order to decide on the better of the two random effects models, two models were fitted, one with the two random intercepts (between and within regional variations) and another with one random intercept (within regional variation). One can use the approximate restricted maximum likelihood ratio test (LRT) to compare these two models (Myers et al., 2010).

Let $LR_{full} = -2\log likelihood$ value for full model and

$LR_{redu} = -2\, log\ likelihood$ value for reduced model. Then, the likelihood ratio test statistic, is given by $\lambda = LR_{full} - LR_{redu}$

The asymptotic null distribution of the likelihood ratio test statistic λ, is a chi-square distribution with degrees of freedom equal to the difference between the numbers of parameters in the two models.

Akaike's information criterion (AIC): AIC is a measure of goodness of fit of an estimated statistical model. It is not a test on the model in the sense of hypothesis testing; rather it is a tool for model selection. The AIC penalizes the likelihood by the number of covariance parameters in the model, therefore

$$AIC = -2\log(L) + 2P$$

Where, L is the maximized value likelihood function for the estimated model and p is the number of parameters in the model. The model with the lowest AIC value is preferable.

3.3.13. Model Checking Technique

In GLMM, it is assumed that the random effects are normally distributed and uncorrelated with the error term. Normality of the random effects is assessed using normal plot of each random effect. Normal Q-Q plot of estimated random effects is an important method for checking the normality (Myers et al., 2010).

4. ANALYSIS AND DISCUSSION

4.1. Summary of Descriptive Statistics

Before any statistical analysis, it is better to examine the overall picture of the data. Table 4.1 presents basic descriptive information that summarizes the associations between the determinant factors and LBW of children.

Table 4.1: Summary of descriptive statistics for weight of child at birth

Factors	Child Weight (%)		
Maternal Factors	**Large**	**Small**	**Total**
Mother's Age at Pregnancy	**Weight(≥2500g)**	**Weight(<2500g)**	
15-19	36(26.7)	99(73.3)	135
20-39	1795(67.5)	866(32.5)	2661
40-49	271(63.2)	158(36.8)	429
Mother's Education			
No Education	1567(62.9)	923(37.1)	2490
Primary	484(72.0)	188(28.0)	672
Secondary and Above	51(81.0)	12(19.0)	63
Mother's Marital Status			
Married	1924(66.6)	963(33.4)	2887
Widowed	52(65.0)	28(35.0)	80
Divorced	126(48.8)	132(51.2)	258
Number of ANC Visits			
No ANC visit	1331(62.2)	809(37.8)	2140
1-4	575(69.6)	251(30.4)	826
≥5	196(75.7)	63(24.3)	259
Ever had Vaccination			
Yes	1681(68.8)	764(31.2)	2445
No	421(54.0)	359(46.0)	780

Ever had Terminated Pregnancy			
Yes	411(59.5)	280(40.5)	691
No	1691(66.7)	843(33.3)	2534
Maternal Anemia			
Not anemic	1011(71.1)	411(28.9)	1422
Moderate	997(63.7)	567(36.3)	1564
Sever	94(39.3)	145(60.7)	239
Child Related Factors			
Sex of Child			
Female	972(60.9)	625(39.2)	1597
Male	1130(69.4)	498(30.6)	1628
Birth Order			
1-4	1071(66.9)	585(33.1)	1656
5-9	912(65.6)	479(34.4)	1391
≥10	119(64.7)	59(35.3)	178
Preceding Birth Interval			
1-5	1835(65.3)	975(34.7)	2810
6-10	193(64.3)	107(35.7)	300
≥11	74(64.3)	41(35.7)	115
Socio-economic Factors			
Wealth Status			
Poor	1127(61.2)	714(38.8)	1841
Middle	349(64.7)	190(35.3)	539
Rich	626(74.1)	219(25.9)	845
Residence			
Rural	1875(64.7)	1025(35.3)	2900
Urban	227(69.8)	98(30.2)	325
Total	2102(65.2)	1123(34.8)	3225

The total of 3225 children (0-59 months old) from nine regional states and two city administrations in Ethiopia were eligible for this study. Among these eligible children, 2102 (65.2%) children were born with large weight whereas 1123 (34.8%) were born with small weight. The proportion of LBW is slightly larger (39.2%) for female child than the male child (30.6%). LBW is higher (38.8%) for poor mothers when compared to mothers with middle wealth status (35.3%) and rich mothers (25.9%). There is also a variation of LBW due to place of residence of mothers. The proportion of bearing child with LBW for rural mothers is (35.3%) and who living in urban area is (30.2%). The proportion of bearing child with LBW is higher for young mothers (73.3%) than adult mothers (36.8%). The proportion that adolescent mothers (32.5%) bear child with LBW is less when compared to young mothers (73.3%) and adult mothers (36.8%). The proportion of bearing child with LBW is slightly higher for mothers who had terminated pregnancy (40.5%) than mothers who had not (33.3%). Proportion of bearing child with LBW is higher for those mothers who do not follow antenatal care (37.8%) when compared to mothers who follow antenatal care at least one time(30.4%) and at most four times. Mothers who follow antenatal care for more than four times (24.3%) have small proportion of bearing child with LBW when compared to the others. The proportion of LBW is lower for mothers who are married (33.5%) when compared to widowed (35.0%) and divorced mothers (51.2%). The mothers who are vaccinated (31.2%) have less proportion of bearing child with LBW than mothers who are not vaccinated (46.0%). Mothers who are not anemic (28.9%) have less proportion of bearing child with LBW than mothers who are moderately anemic (36.3%) and severely anemic (60.7%).
Educational level of mothers has decreasing proportion to LBW. The proportion of LBW is (37.0%) for non-educated mothers, (28.0%) for primary educated mothers and (19.0%) for mothers whose education level is secondary and above.

Children whose their birth order is from 1-4 (33.1%) have less proportion of LBW when compared to the children whose their birth order is from 6-9 (34.4%) and ten and above (35.3%).Preceding birth intervals have decreasing effect on LBW.

As preceding birth interval increase the proportion of children with LBW decrease. Children whose their preceding birth interval is from 1-5 year (34.7%) have relatively less proportion of LBW when compared to those children whose their preceding birth interval is from 6-10 year(35.7%) and 11 and above(35.7%).

4.2. Statistical Analysis of Marginal Models

In this section, LBW has been analyzed using marginal models including generalized estimating equation and alternating logistic regression models.

4.2.1. Analysis of Generalized Estimating Equations (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. 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 LBW, the backward elimination procedure was used. The full model for the probability of getting LBW of i^{th} child from j^{th} cluster, (π_{ij}) was fitted as

$$\begin{aligned} logit(\pi_{ij}) = {} & \beta_0 + \beta_1 Sex_M + \beta_2 WealthS_{Mi} + \beta_3 WealthS_{Ri} + \beta_4 Residence_U + \beta_5 Age_1 \\ & + \beta_5 Age_2 + \beta_6 termpregnancy_Y + \beta_7 Antenatalcare_{1+} + \beta_8 antenatalcare_{5+} \\ & + \beta_9 Maritalst_W + \beta_{10} Maritalst_D + \beta_{11} Vaccination_Y + \beta_{12} Anemia_{Mo} \\ & + \beta_{13} Anemia_{Se} + \beta_{14} Educationle_{Pr} + \beta_{15} Educationle_{Sec} + \beta_{16} Birthorder_{5-9} \\ & + \beta_{17} Birthorder_{10+} + \beta_{18} Prebirthinterval_{5-10} + \beta_{19} Prebirthinterval_{11+} \end{aligned}$$

The subscripts in each covariate is defined as,

M=Male, Mi=middle, Ri=Rich, U=Urban, 1=20-39, 2=40-49, Y=Yes,1+=1-4,5+=five and above,W=Widowed,D=divorced,Mo=Moderate,Se=severe,Pr=Primary,Sec=Secondary,10+=ten and above,11+=eleven and above

After fitting the model, covariates with the largest p-value are removed and the model was refitted with the rest of the covariates sequentially. Then, residence, ever had terminated pregnancy, birth order and preceding birth interval are the covariates excluded from the model: p-value for the given covariates are large (*P-value > 0.05*) which is found in the appendix.

The QIC values of full model and reduced models are 4011.6165 (which is found in appendix) and 3986.4033 respectively. Then it turned out that the model with sex, wealth status, age of mother, number of antenatal care, marital status, vaccination, anemia level and mothers' education level was the most parsimonious model.

Table 4.2: Empirical and model based standard errors for two proposed working correlation

	Exchangeable			Independent		
Coeff.	Estimates	Model based (S.E)	Empirical (S.E)	Estimates	Model based (S.E)	Empirical (S.E)
β_0	0.6468	0.2481	0.2523	0.7185	0.2300	0.2820
β_1	-0.3449	0.0756	0.0779	-0.3536	0.0769	0.0801
β_2	0.0249	0.1064	0.1045	-0.3536	0.1065	0.1114
β_3	-0.3505	0.1037	0.1013	-0.3887	0.0994	0.1039
β_4	-0.9798	0.2359	0.2532	-1.0449	0.2190	0.2780
β_5	-0.8337	0.2542	0.2677	-0.8565	0.2395	0.2914
β_6	-0.1361	0.0929	0.0985	-0.1307	0.0933	0.0996
β_7	-0.2818	0.1635	0.1538	-0.2426	0.1633	0.1554
β_8	0.3448	0.1480	0.1674	0.4387	0.1451	0.1908
β_9	0.0198	0.2403	0.2411	0.0698	0.2423	0.2320
β_{10}	-0.2584	0.0962	0.1020	-0.2930	0.0931	0.1088
β_{11}	0.2262	0.0811	0.0854	0.2322	0.0814	0.0872
β_{12}	0.6872	0.1671	0.1910	0.8098	0.1620	0.2226
β_{13}	-0.1951	0.1026	0.1059	-0.1783	0.1015	0.1111
β_{14}	-0.3240	0.3351	0.3337	-0.3595	0.3402	0.3461

Finally, as a customary, 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.

Moreover, since no dramatic differences among the correlations, using the exchangeable working correlation structure is recommended. In addition, the empirically corrected standard errors for exchangeable correlation structure are somewhat smaller than their counterpart under the independence assumptions.

Then, from table 4.2, exchangeable working correlation assumption was found to be plausible since the two standard errors were closer to each other with correlation parameter (α =0.0857). Therefore, the final proposed generalized estimating equation model for low birth weight is given as:

$$\begin{aligned} logit(\pi_{ij}) = \beta_0 + \beta_1 Sex_M + \beta_2 WealthS_{Mi} + \beta_3 WealthS_{Ri} + \beta_4 Age_1 + \beta_5 Age_2 \\ + \beta_6 Antenatalcare_{1+} + \beta_7 Antenatalcare_{5+} + \beta_8 Maritalst_W + \beta_9 Maritalst_D \\ + \beta_{10} Vaccination_Y + \beta_{11} Anemia_{Mo} + \beta_{12} Anemia_{Se} + \beta_{13} Educationle_{Pr} \\ + \beta_{14} Educationle_{Sec} \end{aligned}$$

Parameter estimates and their corresponding empirically corrected standard errors alongside the p-values from the final GEE model are presented in table 4.3.

Table 4.3: Parameter estimates (empirically corrected standard errors) for GEE

Analysis Of GEE Parameter Estimates

Empirical Standard Error Estimates

Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept		0.6468	0.2523	0.1523	1.1414	2.56	0.0104*
SEX	male	-0.3449	0.0779	-0.4976	-0.1923	-4.43	<.0001*
WEALTH	middle	0.0249	0.1045	-0.1800	0.2298	0.24	0.8118
WEALTH	rich	-0.3505	0.1013	-0.5491	-0.1520	-3.46	0.0005*
AGE	20-39	-0.9798	0.2532	-1.4761	-0.4835	-3.87	0.0001*
AGE	40-49	-0.8337	0.2677	-1.3585	-0.3090	-3.11	0.0018*
ANTENATALCARE	1-4	-0.1361	0.0985	-0.3292	0.0571	-1.38	0.1674
ANTENATALCARE	five and above	-0.2818	0.1538	-0.5831	-0.1196	-3.83	0.0069*
MARITALST	divorced	0.3448	0.1674	0.0167	0.6728	2.06	0.0394*
MARITALST	widowed	0.0198	0.2411	-0.4526	0.4923	0.08	0.9345
VACCINATION	yes	-0.2584	0.1020	-0.4584	-0.0584	-2.53	0.0113*
ANEMIA	moderate	0.2262	0.0854	0.0588	0.3936	2.65	0.0081*
ANEMIA	sever	0.6872	0.1910	0.3129	1.0614	3.60	0.0003*
EDUCATIONLE	primary	-0.1951	0.1059	-0.4027	-0.1126	-3.84	0.0056*
EDUCATIONLE	secondary and above	-0.3240	0.3337	-0.9780	0.3299	-0.97	0.3314
	QIC=3986.4033						
	α =0.0857						

4.2.2. Analysis of Alternating Logistic Regression Model (ALR)

Model building for ALR is follows the same procedure in GEE model building strategy. First ALR model is fitted using all proposed covariates. Then the covariate with the large p-value is removed. Residence, ever had terminated pregnancy, birth order and preceding birth interval are removed covariates with (p-value > 0.05). The QIC values of both saturated and reduced models, which are found in the appendix, are 4011.8139 and 3986.1527 respectively.

Therefore, the reduced model with the rest of eight covariates was considered as the best candidate model. Using the selected covariates and the association parameter α, alternating logistic regression (ALR) model that provides information about pair wise association of observations between two different individuals within the same cluster was fitted. Therefore, the final proposed ALR model included the association parameter for low birth weight is given as:

$$\begin{aligned} logit(\pi_{ij}) = \alpha + \beta_0 + \beta_1 Sex_M + \beta_2 WealthS_{Mi} + \beta_3 WealthS_{Ri} + \beta_4 Age_1 + \beta_5 Age_2 \\ + \beta_6 Antenatalcare_{1+} + \beta_7 Antenatalcare_{5+} + \beta_8 Maritalst_W + \beta_9 Maritalst_D \\ + \beta_{10} Vaccination_Y + \beta_{11} Anemia_{Mo} + \beta_{12} Anemia_{Se} + \beta_{13} Educationle_{Pr} \\ + \beta_{14} Educationle_{Sec} \end{aligned}$$

Parameter estimates and their corresponding empirically corrected standard errors alongside the p-values from the final ALR model are presented in table 4.4.

4.2.3. Comparison of GEE and ALR Models

Since the likelihood function does not fully specified in marginal models, model comparison is based on quasi likelihood criteria (QIC) which is the modified AIC criteria. From table 4.3 and table 4.4, we found that the QIC values are 3986.4033 and 3986.1527 for the GEE and ALR respectively which is almost equal. However, the empirically corrected standard errors for ALR model are somewhat smaller than their counterpart under the GEE model. This implies that the ALR fits the data with small disturbance than GEE. Moreover, ALR extends beyond classical GEE in the sense that precision estimates follow for both the regression parameters β and the association parameters α. We were also in a position to emphasize that the association is strongly significant ($P < 0.0001$), provided it has been correctly specified, a declaration we could not make in the corresponding exchangeable GEE analysis. Therefore, we can conclude that ALR is the better model for explaining the marginal association between low birth weight and the selected predictor variables. Thus, the interpretation of parameters is based on the final proposed ALR model. Overall, parameter estimates under ALR are slightly less than those of GEE. This difference in parameter estimates from the two models might be due to the fact that ALR takes the associations into account, whereas GEE not consider the association parameter in the model.

Table 4.4 Parameter estimates (empirically corrected standard errors) from ALR

Analysis Of ALR Parameter Estimates

Empirical Standard Error Estimates

Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept		0.6689	0.2510	0.1770	1.1608	2.67	0.0077*
SEX	male	-0.3461	0.0778	-0.4985	-0.1936	-4.45	<.0001*
WEALTH	middle	0.0291	0.1044	-0.1755	0.2337	0.28	0.7805
WEALTH	rich	-0.3522	0.1012	-0.5505	-0.1540	-3.48	0.0005*
AGE	20-39	-1.0008	0.2520	-1.4947	-0.5068	-3.97	<.0001*
AGE	40-49	-0.8581	0.2670	-1.3815	-0.3348	-3.21	0.0013*
ANTENATALCARE	1-4	-0.1375	0.0986	-0.3308	0.0557	-1.39	0.1630
ANTENATALCARE	five and above	-0.2832	0.1537	-0.5845	-0.1181	-1.84	0.0055*
MARITALST	divorced	0.3402	0.1659	0.0152	0.6653	2.05	0.0402*
MARITALST	widowed	0.0213	0.2419	-0.4528	0.4955	0.09	0.9297
VACCINATION	yes	-0.2582	0.1019	-0.4580	-0.0585	-2.53	0.0113*
ANEMIA	moderate	0.2293	0.0853	0.0622	0.3965	2.69	0.0072*
ANEMIA	sever	0.6874	0.1887	0.3176	1.0573	3.64	0.0003*
EDUCATIONLE	primary	-0.1962	0.1056	-0.4031	-0.1107	-1.86	0.0031*
EDUCATIONLE	secondary and above	-0.3351	0.3350	-0.9916	0.3215	-1.00	0.3172
Alpha1		0.4107	0.0879	0.2385	0.5829	4.67	<.0001*

QIC=3986.1527

4.2.4. Parameter Interpretation of Marginal Models

Table 4.4 presents parameter estimates and their corresponding empirically corrected standard errors alongside the p-values from ALR model. Each parameter β_j reflects the effect of factor X_j on the log odds of the probability of being born with LBW, statistically controlling all the other covariates in the model. Then, the odds ratio of variables is calculated as the exponent of β_j i.e odds ratio=e^{β_j}

The ALR analysis from table 4.4 suggests that, sex of child is significantly related to birth weight of child. After controlling all other variables in the model the odds that a male child born with LBW is exp(β_1)=exp(-0.3461)=0.7074 (95% CI: 0.6074,0.8239) times lower than the female child. This means the probability that male child born with LBW is 29% lower than that of female.

As it has been seen from the result of the ALR model, mothers wealth status is statistically significant on birth weight of child. The estimated odds that child born to a mother who are from highest wealth status is exp(-0.3522) =0.7031 (95% CI:0.5766,0.8572) times less likely to have low birth weight compared to the reference group.

This implies that the probability of LBW is reduced by 29% for children whose their mother are from highest wealth status when compared with children whose their mothers are from lowest wealth status. In this study, middle wealth status has no significant effect on LBW of children.

There is also a strong association between age of mother and birth weight of child. This implies that, after adjusting all other predictor variables in the model, the estimated odds that child born to a mother who are from age group 20-39 is exp(-1.0008)=0.3675 (95% CI:0.2242,0.6024) times lower to have low birth weight compared to reference age group(15-19). This means percentage of low birth weight is decreased by 63% for children whose their mothers are in age group 20-39 when compared to children whose their mothers are in early age group.

The estimated odds that child born to a mother who are from age group 40-49 is exp(0.8581)=0.4239 (95% CI:0.2512,0.7154) times lower to have low birth weight when compared to reference age group. This means percentage of low birth weight is decreased by 57% for children whose their mothers are in age group 40-49 when compared to children whose their mothers are in early age group.

The results also indicate a negative association between LBW and the number of antenatal care visits. The results suggest that the higher the number of antenatal visits, the lower the odds of LBW. The odds that a child born to mother who follow antenatal care for more than five times is exp(-0.2832)=0.7533 (95%CI:0.5573,0.8886) times lower to have low birth weight compared to one whose mother do not follow antenatal care. This implies that low birth weight is reduced by 25% for children whose their mothers follow antenatal care for more than five times. As we can see from the analysis, following antenatal care for less than five times has no significant effect on LBW of child.

Another significant ingredient of LBW is marital status of mother. Mothers who are divorced are more likely to deliver child with LBW than mothers who are married. The odds of LBW for divorced mother is exp(0.3402)=1.4052 (95% CI:1.0153,1.9450) times higher as compared to reference group. This implies LBW of baby increased by 40% for divorced mothers when compared to married mothers.

Statistically significant association has been seen between vaccination and LBW of child. The odds that a child born to vaccinated mother is exp(-0.2582) =0.7724 (95% CI:0.6325,0.9431) times lower to have low birth weight compared to one whose mother is not vaccinated. This implies LBW is decreased by 22% for children whose their mothers are vaccinated.

Statistically significant association has been seen between LBW and anemia level. The odds that a child born to mother who moderately suffered from anemia is exp(0.2293)=1.2577 (95% CI:1.0641,1.4866) times higher to have low birth weight. And the odds that a child born to mother who severely suffered from anemia is exp(0.6874)=1.9885 (95% CI:1.3738,2.8785) times higher to have low birth weight compared to one whose mother is not suffered from anemia. This implies that the percentage of delivering child with LBW is increased by 26% and 99% respectively for moderately anemic and severely anemic mothers compared to not anemic mothers.

The analysis from table 4.4 suggests that, education is significantly related to LBW of children. After controlling all other variables in the model, the odds that mother whose her education level is primary deliver a child with LBW is exp(-0.1962)=0.8218 (95% CI:0.6682,0.8952) times lower when compared to the reference group. This shows LBW is reduced by 18% for children whose their mothers education level is primary compared to children whose their mothers are not educated.

The ALR model also presents the estimated constant log odds ratio (alpha) which, provide information about the association between individual observations within the same cluster. The estimated pair wise odds ratio relating two responses from the same cluster is exp(0.4107) =1.5078 (95% CI: 1.2693, 1.7912). Thus, the value of alpha which is greater than one indicates that, the associations is found to be significant (p-value <.0001) and this means that there is a strong positive association between individual children regarding LBW in the same cluster.

4.2.5. Model diagnostic for Marginal Models

Plots of DFBETA, Cook's distance, leverage and cluster DFFIT value as a function of ordered cluster can then be used to see the pattern of all cases.

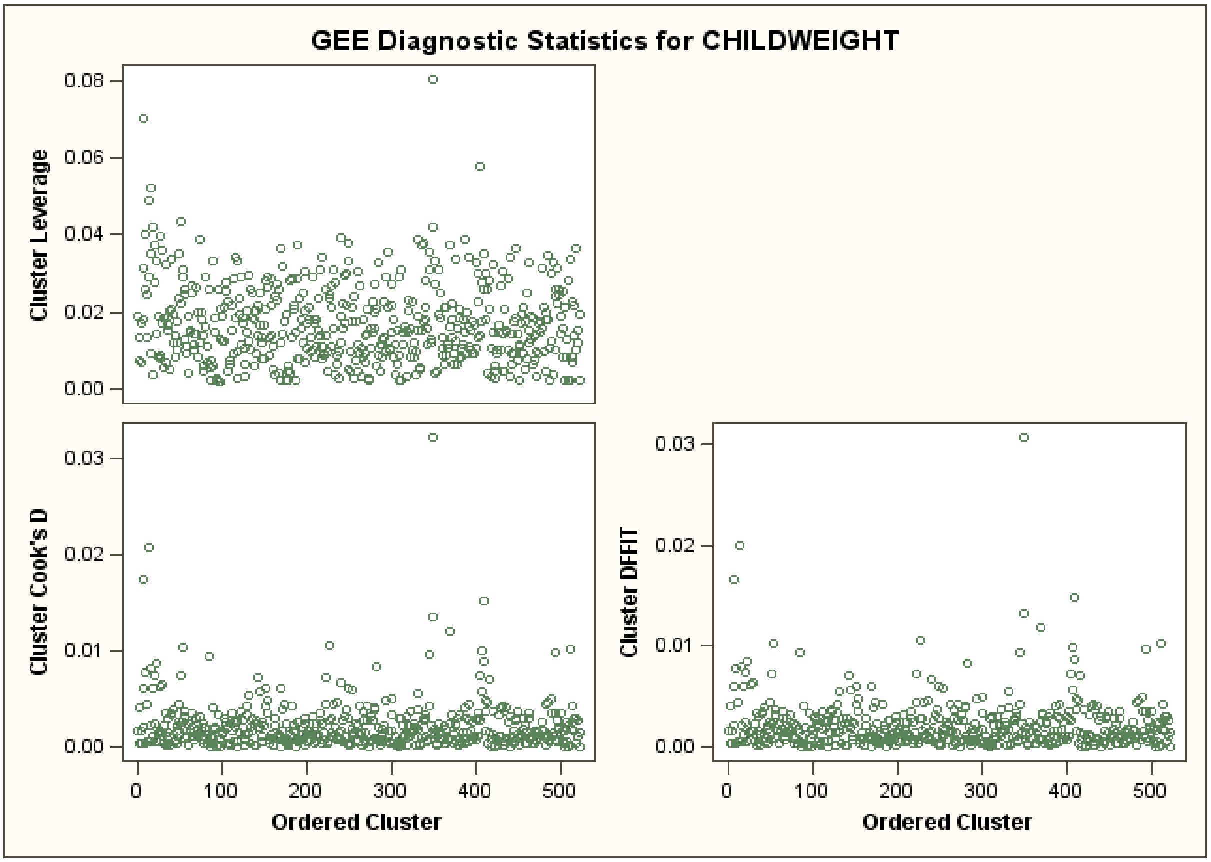

Figure 4.1: Plots of cluster leverage, cluster cook's *D* and cluster DFFIT versus ordered cluster.

Figure 4.1 the plots of leverage value versus the ordered cluster of all cluster. It was observed that leverage values of the above plots are less than one. Therefore, there are no outliers.

The above figure also shows plot of Cook's *D* statistic versus the ordered cluster of all cluster. There are clusters a little far away from the others but these are not influential clusters since all Cook's *D* statistic are less than one.

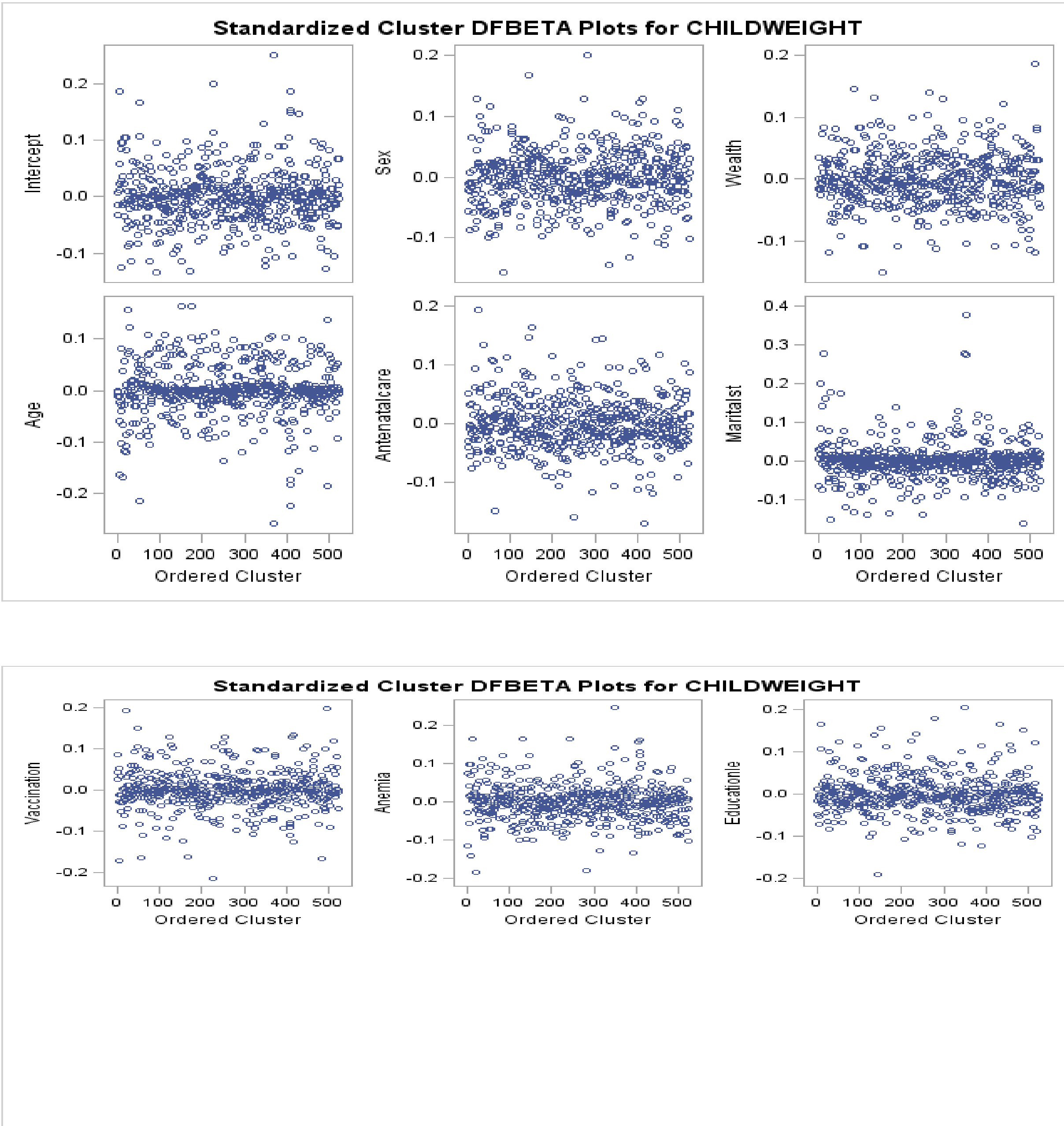

Figure 4.2: Plots of DFBETACS versus orderd cluster for all predictors in the fitted model.

Plots of DFBETACS of all explanatory variables vs order cluster are given in Figures 4.2 where it is shown that all the DFBETACS of all explanatory variables are less than one. This is an indication that there is no serious problem with the fitted model.

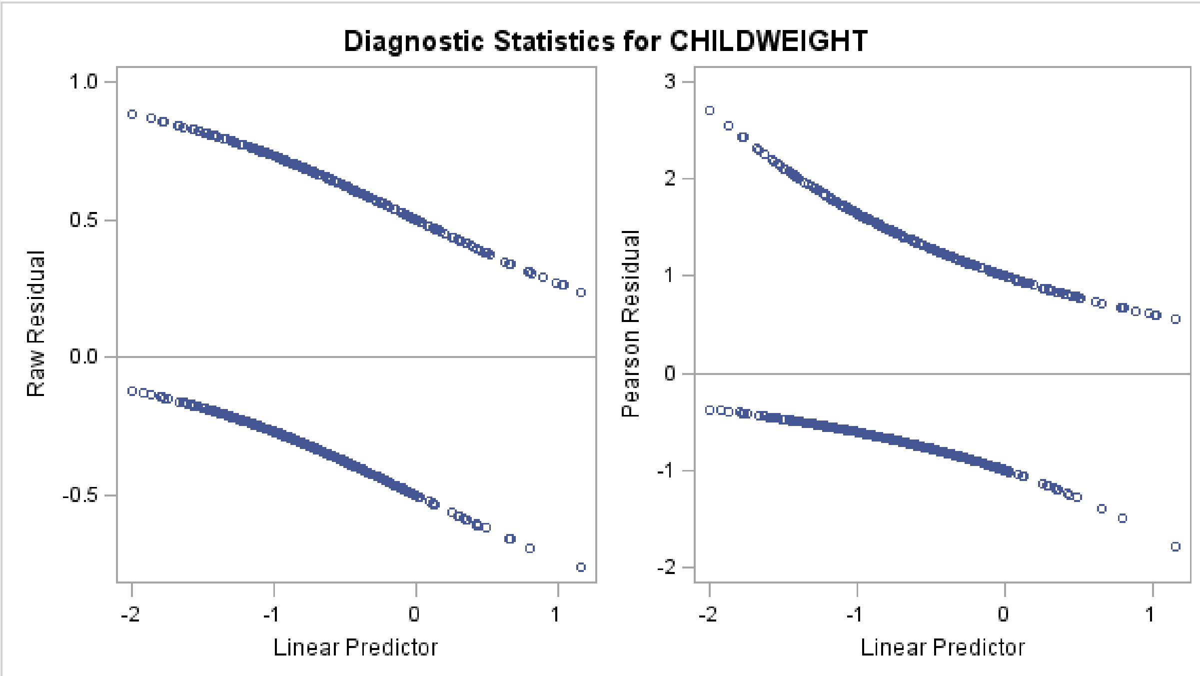

Figure 4.3: Plots of raw and pearson residual versus linear predictors.

Figure 4.3 is the plot of raw residuals and pearson residual versus linear predictors of all observations. There are few observations far from the others. However, the computed pearson residuals do not influencing the model that means all pearson residuals are less than three (see from Y- axis).

4.3. Analysis of Generalized Linear Mixed Model (GLMM)

4.3.1. Model Building in GLMM

Under the GLMM, model fitting began by adoption of the marginal model covariates. Additionally, the model also included the random effects in this case, random intercepts to address the between and within-regional variations. First, main effect covariates and the two random intercepts model were fitted and as usual, non-significant covariates were removed sequentially starting from variables with highest p-value for fixed effect covariates. The saturated models for GLMM were fitted as follows where, b_j and b_{ij} two random intercepts

$$logit(\pi_{ij}) = \beta_0 + \beta_1 Sex_M + \beta_2 WealthS_M + \beta_3 WealthS_{Ri} + \beta_4 Residence_U + \beta_5 Age_1 + \beta_5 Age_2 + \beta_6 termpregnancy_Y + \beta_7 Antenatalcare_{1+} + \beta_8 antenatalcare_{5+} + \beta_9 Maritalst_W + \beta_{10} Maritalst_D + \beta_{11} Vaccination_Y + \beta_{12} Anemia_{Mo} + \beta_{13} Anemia_{Se} + \beta_{14} Educationle_{Pr} + \beta_{15} Educationle_{Sec} + \beta_{16} Birthorder_{5-9} + \beta_{17} Birthorder_{10+} + \beta_{18} Prebirthinterval_{5-10} + \beta_{19} Prebirthinterval_{11+} + \boldsymbol{b_j} + \boldsymbol{b_{ij}}$$

In order to decide on the better of the two random effects models, two models were fitted, one the saturated model above with two random intercepts to estimate between and within regional variations and the other with one random intercept model to estimate within regional variation. AIC and Likelihood ratio test (LRT) were used to compare the two models to select an appropriate models.

Table 4.5: Information criteria for comparison of one and two random intercept models

Models	AIC	BIC	LogLik	Deviance	σ_W	σ_B	P
Model with one Random intercept	3933.1	4066.8	-1944.5	3889.1	0.6032		
Model with two Random intercept	3919.7	4059.5	-1936.9	3873.8	0.5392	0.2411	0.000

Where, σ_W and σ_B are within and between regional standard deviation respectively. As we have seen from table 4.5, the AIC of model with two random intercept is reduced from 3933.1 to 3919.7 and the deviance is reduced from 3889.1 to 3873.8.The small p-value of the log likelihood ratio test (P < 0.001) also indicates that the model with two random intercept is parsimonious model. P is the p-value of the log likelihood ratio test of the two models. Also when considered a model without random effects (i.e simply the generalized linear model), it gives AIC value of 3980.1 which is large as compared to the above two models with random effects.

Next, the covariates for the fixed effect were assessed and the candidate covariates were selected by removing covariates starting from with highest p-value sequentially. Then the first removable covariate is preceding birth interval with the highest p-value 0.8391 and refitted the reduced model with the remaining covariates. The AIC is reduced from 3919.7 to 3916.0 and the p-value of log likelihood ratio test (p=0.8556) supports the reduced model is preferable one. The next removable variable is ever had terminated pregnancy with p-value (p=0.2345) and refitted the reduced model . The AIC is reduced from 3916.0 to 3915.4 and

the p-value of log likelihood ratio test (p=0.2359) supports the reduced model is preferable. The next removable variable is birth order with p-value (p=0.1734) and refitted the reduced model. The AIC is reduced from 3915.4 to 3914.3 and the p-value of log likelihood ration test (p= 0.2345) support the reduced model is preferable.

The next removable variable is place of residence with p-value (p=0.1342) and refitted the reduced model. For this model AIC is similar with the previously reduced model but still the log likelihood ratio test indicates that the reduced model is better with p-value(p=0.1096). In addition, the model with small number of covariates is considered to be preferable. Therefore, the final proposed GLMM for low birth weight of children is given as:

$$logit(\pi_{ij}) = \beta_0 + \beta_1 Sex_M + \beta_2 WealthI_{Mi} + \beta_3 Wealth_{Ri} + \beta_4 Age_1 + \beta_5 Age_2 + \beta_6 Antenatalcare_{1+} + \beta_7 Antenatalcare_{5+} + \beta_8 Maritalst_W + \beta_9 Maritalst_D + \beta_{10} Vaccination_Y + \beta_{11} Anemia_{Mo} + \beta_{12} Anemia_{Se} + \beta_{13} Educationle_{Pr} + \beta_{14} Educationle_{Sec} + \boldsymbol{b_i} + \boldsymbol{b_{ij}}$$

The parameter estimate and standard error of GLMM are presented in table 4.6 of below.

Table 4.6: Parameter estimates (standard errors) and corresponding P value for GLMM.

Effects	Level	Para.	Estimates(S.E)	95% conf.int	p-value
Intercept		β_0	0.7062(0.2757)	(0.1657,1.2468)	0.0104
Sex	Female(ref)	..	..	..	..
	Male	β_1	-0.3815(0.0819)	(-0.5420,-0.2209)	0.0079
WealthS.	Poor(ref)	..	..	..	..
	Middle	β_2	0.0650(0.1165)	(-0.1633,0.2934)	0.5768
	Rich	β_3	-0.3304(0.1113)	(-0.5485,-0.1122)	0.0029
Age	15-19(ref)	..	..	..	..
	20-39	β_4	-1.1031(0.2502)	(-1.5937,-0.6126)	0.0070
	40-49	β_5	-0.9378(0.2706)	(-1.4682,-0.4074)	0.0005
Antecare	No visit(ref)	..	..	..	..
	1-4	β_6	-0.1557(0.1002)	(-0.3522,0.0406)	0.1201
	$\geq$5	β_7	-0.2956(0.1744)	(-0.6376,-0.0463)	0.0002
Maritalst	Married(ref)	..	..	..	..
	Widowed	β_8	0.0817(0.2570)	(-0.4221,0.5855)	0.7506
	Divorced	β_9	0.3587(0.1591)	(0.0467,0.6707)	0.0242
Vaccinate	No(ref)	..	..	..	..
	Yes	β_{10}	-0.2640(0.1063)	(-0.4724,-0.0555)	0.0130
Anemia	Notanemic(ref)	..	..	..	..
	Moderate	β_{11}	0.2459(0.0885)	(0.0725, 0.4194)	0.0054
	Sever	β_{12}	0.7822(0.1820)	(0.4255,1.1390)	0.0016
Education	No educ.(ref)	..	..	..	..
	Primary	β_{13}	0.7822(0.1820)	(-0.3767,-0.0112)	0.0030
	Sec. and above	β_{14}	-0.4141(0.3591)	(-1.1180,0.2897)	0.2488

Ref=reference category

4.3.2. Parameter Interpretation of GLMM

Unlike in the marginal models, (GEE and ALR) where parameters are treated as population averages, in the GLMM analysis, parameter interpretation is based on specific subjects or cluster. The parameter interpretation is conditional on the random effects, which is common for all individual children in the same cluster.

Given the same random intercept $b_{j,}$ the estimated odds of LBW of child is exp(-0.3815) =0.6828 (95% CI: 0.5815,0.8017) times lower for male child when compared to female child in the same j^{th}cluster keeping constant the other fixed effect variable in the model. This implies the probability of low birth weight is 32% less likely for male child than female child in the same cluster at the given random effect.

In the same way, the estimated odds that a child born to a mother who are from highest wealth status is exp(-0.3304)=0.7186 (95% CI: 0.5778,0.8939) times lower to have low birth weight compared to the reference group in the same cluster. This shows that the probability of LBW is reduced by 28% for children whose their mother are from highest wealth status when compared with children whose their mothers are from lowest wealth status.

The estimated odds that child born to a mother who are from age group 20-39 is exp(-1.1031)=0.3318 (95% CI: 0.2031,0.5419) times lower to have low birth weight compared to reference age group (15-19). This means percentage of low birth weight is decreased by 67% for children whose their mothers are in age group 20-39 when compared to children whose their mothers are in early age group in the same cluster. The estimated odds that child born to a mother who are from age group 40-49 is exp(-0.9378)=0.3914 (95%CI: 0.2303,0.6653 times lower to have low birth weight when compared to reference age group. This means percentage of low birth weight is decreased by 61% for children whose their mothers are in age group 40-49 when compared to children whose their mothers are in early age group in the same cluster.

At the given constant random effect, The odds that a child born to mother who moderately suffered from anemia is exp(0.2459) = 1.2787 (95% CI: 1.0751,1.5210) times higher to have low birth weight. And the odds that a child born to mother who severely suffered from anemia is exp(0.7822) = 2.1862 (95% CI: 1.5303,3.1236) times higher to have low birth weight compared to one whose mother is not suffered from anemia. This shows that the probability that mothers deliver child with LBW for mothers who are moderately anemic is 28% more likely than mothers who are not anemic and the probability that mothers deliver child with LBW for severely anemic mothers is two folds more likely than mothers who are not anemic. The interpretation of other predictor variables can be done in a similar manner.

4.3.3. Model diagnostic for GLMM

Residuals versus observation CLID number plot panel one, suggested that the residuals are symmetric around zero (i.e. positive and negative residuals are almost equal). Q-Q plots for normality of random effects at regional and cluster levels are also given in the figure at panel two and three, and illustrates that the random effects are normally distributed with mean zero and variance covariance matrix D. Thus, the fitted GLMM model is fine for the given data.

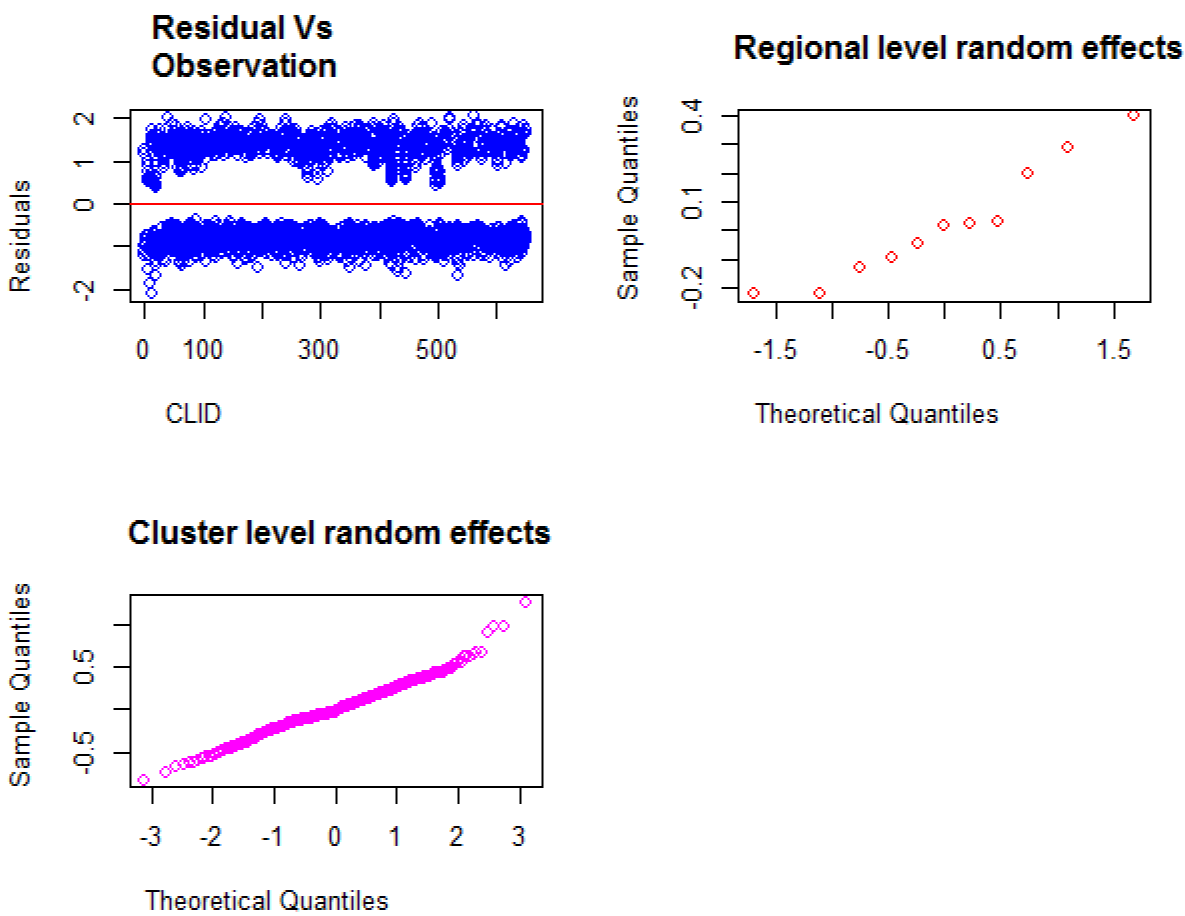

Figure 4.4: Diagnosis plots for the generalized linear mixed model

4.4. Discussion

This study was aimed at modeling the determinants of low birth weight in Ethiopia. As a preliminary analysis, assortments of summary statistics were employed to explore the association between the response variable of interest and available covariates. It should be well-known that there is inconsistency in the conclusion from the analysis of various summary statistics, which might be due to the fact that they make use of varying amount of information, which determines the power of their inferences. Thus, the analysis was extended to other statistical methods to account for the clustered nature of correlated observations. The data were then analyzed using two model families one with marginal models (GEE and ALR), and the other is random effects model (Generalized linear mixed model).

Two proposed working correlation structures, exchangeable and independence correlation assumptions were taken for the comparison, in GEE model-building strategy. The model with exchangeable working correlation structure was found to be better fits the data than independence. This supports that considered the clustering nature of the data was essential for the analysis and the dependency of individuals for the given data. In addition, ALR was fitted for simultaneously regress the response variable on explanatory variables as well as association among responses in terms of pair wise odds ratio.

Two models from marginal model families were compared in order to assess which model is efficiently explain the relations between response and explanatory variables as well as to evaluate that whether considering pair wise association is important. After then, ALR model was selected as best model and the model shows that there is a positive pair wise association between responses. This is supported the idea explained by Zeger *et al*, alternating logistic regression is reasonably efficient relative to GEE (Zeger *et al*, 1993).

The purpose of GLMM was to evaluate within and between regional variations of LBW in Ethiopia. Two models was fitted one with only one random intercept model to assess only within regional variation and other with two random intercepts model, in order to account within and between regional variations. Additionally, generalized linear model was fitted as the sake of comparison whether including random effects in the analysis is important or not. The three models were compared using the AIC value followed by likelihood ratio test and we got a model with two random intercept was favorable. This demonstrates that, accounting within and between regional variations for the analysis of LBW should be vital and, indicates within and between regional heterogeneity in LBW. This finding is supported by the explanation or suggestion of Antonio & Beirlant (2011). Even though the two model families are different and their comparability may not be meaningful as they have different parameter interpretations and estimations, parameter estimates obtained from GLMM are generally bigger in absolute values than those from marginal models (GEE and ALR) similar with Agresti (2007).

All the fitted models were leads to the same conclusion that sex of child, wealth status, age of mother, number of antenatal care visit, marital status, vaccination, maternal anemia and mother education level were found to be significantly associated with LBW. This study found that male gender has a protective effect against LBW. Male child is less likely to be born with LBW than female child. Which agree with study of Amory JH, *et al* (2013).

This study finding shows the negative association between wealth status of mothers and LBW which agree with study done in England by Smith, G. C., *et al* (2010) and in Ghana Charles *et al* (2011). The study shows that the odds of mother bearing child with LBW is consistently decreased as the mother wealth status increased. One of the most predominant causes of low birth weight is the mother's age. The chance of having LBW baby is higher among young mothers of age 15-19. This is similar with finding of Kamaladoss *et al*, 2013.

There was also a significant association between LBW and maternal anemia. According to this study, maternal anemia increased the risk of having a LBW baby. The findings of this study are similar to a study done in Turkey by Chuku, S. N., 2013.

In agreement with previous studies, maternal education emerged as a strong determinant for LBW. Women with ‘no education’ had the greatest odds of giving birth to an infant with LBW. This finding is similar with some other studies such as, Karim E, *et al.*2012

This study showed the negative effect of number of antenatal care visit on LBW. Those mothers received antenatal care gave birth to higher birth weight babies in comparison to mothers who do not received antenatal care visit. The other studies also found similar result. Naher N, *et al*,. 2012.

In agreement with previous studies, maternal vaccination emerged as a strong determinant for LBW. Women with 'no vaccination' had the greatest odds of giving birth to an infant with LBW. Som S. *et al* 2012.

Another important risk factor for LBW in this study is marital status of mothers. The odds of having infants with low birth weight were higher among mothers who were divorced. However, from the previous studies, residence, terminated pregnancy, birth order and preceding birth interval were significantly associated with LBW; these covariates are not significant determinant factors on this study.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

For this study two marginal models, GEE and ALR, have been compared for the analysis of marginal or average effects of covariates on the response variable and, we conclude that, ALR model with measure of association exhibited the best fit for this data than GEE models. For this study also GLMM, with two random intercept model was found to be appropriate for the analysis of within and between regional variations for LBW baby in Ethiopia. This concluded that there is heterogeneity of LBW between and within regions.

This study suggests that maternal age, educational level, wealth status, vaccination, child sex and wealth status have negative effect on LBW. Whereas, maternal anemia and marital status have positive effect on LBW. However, in this study, residence, terminated pregnancy, birth order and preceding birth interval were not significantly associated with LBW.More importantly, this study contributes to the understanding of the individual and collective effect of maternal, socio-economic and child related factors influencing infant birth weight in Ethiopia.

5.2. Recommendation

This study has identified a number of important factors that influence LBW of baby in Ethiopia. Strategy to reduce LBW in Ethiopia focus has to be given on nutrition education, iron and vitamins supplementation during pregnancy along with discouraging teenage pregnancy. It is suggested that programs that work to reduce the rate of LBW infants should focus on improving maternal lifestyle choices by increasing access, utilization and quality of care, while addressing the intractable socio-economic disparities that continue to indirectly contribute to the incidence of LBW. Socio-economic factors influenced the growth of fetus and outcomes of pregnancies. Most women lacked knowledge of the pregnancy risk factors that adversely affect infant birth weight, and the exact mechanisms by which the risk factors act to cause the adverse effects. Intervention programs and behavior change communication during pregnancy should focus on significant risk factors associated with LBW, and target pregnant women at risk. Health education for pregnant women should be strengthened to promote care seeking and demand for skilled care at all stages of maternity. This way healthy infants are produced who have a better chance of surviving and becoming tomorrow’s wealth.

REFERENCES

Agresti, A., (2002).Categorical Data Analysis, Second Edition

Agresti, A., (2007).An Introduction to Categorical Data Analysis, 2nd Ed, Wiley Inc

Ahmed, F. U., & Das, A. M. (2009). Beneficial effects of Three ANC visits might be the divergent point in lowering low birth weight babies. Bangladesh. *Integration*, (33), 50-3.

Amory JH, Adams KM, Lin MT, Hansen JA, Eschenbach DA, Hitti J. (2013) anemia and prenatal outcome. *Prenatal Journal*, 15(3): 127-130.

Anderson R. and Bergstrom S. (2013) 'Maternal nutrition and socioeconomic status as determinants of birth weight in chronically-malnourished African women', *Tropical Medicine and International Health* 2(11): 1080-87

Andersson SW, Niklasson A, Lapidus L, (2013) Sociodemo- graphic characteristics influencing birth outcome in Sweden,. J Epidemiology Community Health 2000; 54:269-78.

Antonio, K. & Beirlant, J., (2011).Actuarial Statistics with Generalized Linear Mixed Models, University Center for Statistics, Belgium.

Barbieri, M. A., Silva, A. A., Bettiol, H., & Gomes, U. A. (2014) Risk factors for the increasing trend in low birth weight among live births born by vaginal delivery, Brazil. *Revista de Saúde Pública, 34*(6), 596-602.

Belsley D. A., E. Kuh and R. E. Welsch. (1980) Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. Wiley, New York.

Berihun, Zeleke, Megabiaw, Meseret Zelalem, and Nuru Mohammed. (2012) "Incidence and correlates of low birth weight at a referral hospital in Northwest Ethiopia." *Pan African Medical Journal* 12(1)

Bradley, R. H., & Corwyn, R. F. (2011). Socioeconomic status and child development. *Annual review of psychology*, *53*(1), 371-399.

Brawarsky, P., Stotland, N. E., Jackson, R. A., Fuentes-Afflick, E., Escobar, G. J., Rubashkin, N., & Haas, J. S. (2012). Pre-pregnancy and pregnancy-related factors and the risk of excessive or inadequate gestational weight gain. *International Journal of Gynecology & Obstetrics, 91*(2), 125-131.

Central Statistical Agency, (2011). Ethiopian Demographic and Health Survey Addis Ababa Ethiopia.

Channon, A. A. (2011). Can mothers judge the size of their newborn? Assessing the determinants of a mother's perception of a baby's size at birth. *Journal of biosocial science*, *43*(05), 555-573.

Chuku, S. N. (2013). *Low Birth Weight in Nigeria: Does Antenatal Care Matter?*

Cogswell, M. E., & Yip, R. (2011, June). The influence of fetal and maternal factors on the distribution of birthweight. In *Seminars in perinatology* (Vol. 19, No. 3, pp. 222-240).

Cook R. D. and Weisberg S. (1982). Residuals and influence in regression. New York: Chapman and Hall.

Cosmas, G., (2011).Socio-Demographic determinants of anemia among children aged 0-59 months in mainland Tanzania.

DaVanzo, J., J.P Habcht and W.P. Butz (2005) 'Assessing socioeconomic correlates of birth weight in Peninsular Malaysia: Ethnic differences and changes over time', *Social Science and Medicine* 18(5):387-404.

Davidson, A. C. and Snell, E. J. (1991). Residuals and diagnostics.

Dharmalingam, A., Navaneetham, K., & Krishnakumar, C. S. (2010). Nutritional status of mothers and low birth weight in India. *Maternal and child health journal*, *14*(2), 290-298.

Dičkutė, J., Padaiga, Ž., Grabauskas, V., Gaižauskienė, A., Basys, V., & Obelenis, V. (2012). Do maternal social factors, health behavior and working conditions during pregnancy increase the risk of low birth weight in Lithuania?. *Medicina*, *38*(3), 321-332.

Dubois, L., & Girard, M. (2006). Determinants of birthweight inequalities: Population-based study. *Pediatrics International*, *48*(5), 470-478.

Eisner, V, J.V. Brasie, M.W Pratt and A.C Hexter (2013) 'The risk of low birth weight', *American Journal of Public Health* 69(9):887-93.

Ester, W. A., & Hokken-Koelega, A. C. S. (2008). Polymorphisms in the IGF1 and IGF1R genes and children born small for gestational age: results of large population studies. *Best Practice & Research Clinical Endocrinology & Metabolism*, *22*(3), 415-431.

Ethiopia Demographic and Health Survey 2005 report Central Statistical Agency Addis Ababa, Ethiopia

Faraway, J., (2006).Extending the Linear Model with R, Generalized Linear, Mixed Effects, and Nonparametric Regression Models, *Boca Raton London New York,*

Halbreich, U. (2011). The association between pregnancy processes, preterm delivery, low birth weight, and postpartum depressions—the need for interdisciplinary integration. *American journal of obstetrics and gynecology*, *193*(4), 1312-1322.

Hirve SS, Ganatra BR. (2008) Determinants of low birth weight: a community based prospective cohort study.

Hosmer DW. And Lemeshow S. (2000). Applied logistic regression (2nd ed.). New York: Wiley & Sons.

Ipadeola, O. B., Adebayo, S. B., Anyanti, J., & Jolayemi, E. T. (2013). Poverty levels and maternal nutritional status as determinants of weight at birth: An ordinal logistic regression approach. *International Journal of Statistics and Applications*, *3*(3), 50-58.

Jolly, M., Sebire, N., Harris, J., Robinson, S., & Regan, L. (2011). The risks associated with low birth weight. *Human reproduction*, *15*(11), 2433-2437.

Kamaladoss T, Abel R, Sampathkumar V. (2013). Epidemiologicalcorrelates of low birth weight in rural Tamil Nadu. *Ind J Paed*; 59:209-304.

Karim E, Mascie-Taylor CG. (2012) The association between birth weight, socio-demographic variables and maternal anthropometry in an urban sample from Dhaka, Bangladesh. Ann Hum Biol. 1997; 24: 387- 401.

Khatun, S., & Rahman, M. (2008). Socio-economic determinants of low birth weight in Bangladesh: a multivariate approach. *Bangladesh Medical Research Council Bulletin*, *34*(3), 81-86.

Kramer, M (2004) ‘Socioeconomic determinants of intrauterine growth retardation’ *European of Clinical Nutrition* 52(S1):S21-S28

Kramer, M. (1998) 'Determinants of Low birth Weight: methodological assessment and meta-analysis', *Bulletin of the World Health Organization* 65:663-73.

Magadi, M., I. Diamond, N. Madise (2013) 'Individual and community-level factors associated with premature births, size of baby at birth and caesarean section.

McCullagh, P., & Nelder, J. (1989).Generalized Linear Models, 2ndedition, London, Chapman, and Hall 120-125

McCulloch, E., (1997).An Introduction to Generalized Linear Mixed Models, Biometrics Unit, and Statistics Center Cornell University.

Molenberghs, G., & Verbeke, G., (2005).Models for Discrete Longitudinal Data. Library of Congress

Mwabu, G. (2011) determinants of birth weight in Kenya.

Myers, H., Montgomery, C., Vining, G. &Robinson, J., (2010).Generalized Linear Models, With Applications in Engineering and the Sciences, Second Edition.

Naher N, Afroza S, Hossain M. (2010). Incidence of LBW in three selected communities of Bangladesh. Bangladesh Med Res Counc Bull. 24(2): 49-54.

Nair N, Rao RS, Chandrashekar S, Acharya D, Bhat HB.,(2012). Socio-demographic and maternal determinants of low birth weight: A multivariate approach. Indian J Pediatr. 67(1): 914.

Olowonyo, T., S. Oshin, I. Obasanjo-Bello (2006) 'Some factors associated with low birth weight in Nigeria', *Nigerian Medical Practitioner* 49(6):154-7

Pan, W., (2001).Akaike's information criterion in generalized estimating equations, Biometrics, 57, 120-127

Pojda J. and Kelly L. (2000) 'Low Birth Weight' ACC/SCN Nutrition Policy Paper. A report based on the International Low Birth Symposium and Workshop held on 14-17 June 1999 at The International Centre for Diarrhoeal Disease Research in Dhaka, Bangladesh.

Preisser, J.S., Qaqish, B.F., (1996). Deletion diagnostics for generalised estimating equations. Biometrika 83, 551–562.

Rondo, P. H. C., Ferreira, R. F., Nogueira, F., Ribeiro, M. C. N., Lobert, H., & Artes, R. (2011). Maternal psychological stress and distress as predictors of low birth weight, prematurity and intrauterine growth retardation. *European Journal of Clinical Nutrition*, *57*(2), 266-272.

Saurel-Cubizolles, M. J., Subtil, D., & Kaminski, M. (2013). Is preterm delivery still related to physical working conditions in pregnancy?. *Journal of epidemiology and community health*, *45*(1), 29-34.

Sexton, M and J.R. Hebel (2007) ‘A clinical trial of change in maternal smoking and its effect on birth weight’, *Journal of the American Medical Association* 251:911-15

Siega-Riz, A. M., Adair, L. S., & Hobel, C. J. (2013). Maternal underweight status and inadequate rate of weight gain during the third trimester of pregnancy increases the risk of preterm delivery. *Journal of Nutrition*, *126*(1), 146-153.

Silva, A. A., Barbieri, M. A., Gomes, U. A., & Bettiol, H. (2014). Trends in low birth weight: a comparison of two birth cohorts separated by a 15-year interval in Ribeirao Preto, Brazil. *Bulletin of the World Health Organization*, *76*(1), 73.

Siza, J. E. (2008). Risk factors associated with low birth weight of neonates among pregnant women attending a referral hospital in northern Tanzania. *Tanzania journal of health research*, *10*(1), 1-8.

Smith, G. C., Smith, M. F., McNay, M. B., & Fleming, J. E. (2010). First-trimester growth and the risk of low birth weight. *New England Journal of Medicine*, *339*(25), 1817-1822.

Som S Jr, Pal M, Adak DK, Gharami AK, Bharati S, Bharati P. (2012) Effect of socio-economic and biological variables on birth weight in Madhya Pradesh. Malays J Nutr 10:159-71.

Tema T. (2006). Prevalence and Determinants of Low Birth Weight in Jimma Zone, Southwest Ethiopia. East African Medical Journal. Volume 83, pp.45-51

Tuntiseranee P, Olsen J, Chongsuvivatwong V, Limbutara S. (2013). Socioeconomic and work related determinants of pregnancy outcome in Southern Thailand. J Epidemiol Community He- alth; Vol.53, pp.624-9

UNICEF and WHO (2004) ‘Low birth weights: Country, Regional and Global estimates. UNICEF, Editorial and publication section, NY, USA.

Wardlaw, Tessa M., ed. (2004). Low Birthweight: Country, regional and global estimates.

Wedderburn, R.W.M. (1974).Quasi-Likelihood Functions, Generalized Linear Models and the Gauss Newton Method," Biometrika, Vol. 61, pp.439-447.

Zeger, S. & Liang K., (1986). Longitudinal data analysis using generalized linear models. *Biometrics, Vol.73, pp.13-22*

Zorn, C. J. (2001). Generalized estimating equation models for correlated data: A review with applications. *American Journal of Political Science*, 470-490.

APPENDIX

The full model test for variable selection in GEE

Analysis Of GEE Parameter Estimates

Empirical Standard Error Estimates

Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept	-0.1711	0.1717	-0.5076	0.1654	-1.00	0.3190
SEX	-0.3528	0.0776	-0.5050	-0.2006	-4.54	<.0001
WEALTH	-0.1763	0.0526	-0.2795	-0.0731	-3.35	0.0008
RESIDENCE	0.1911	0.1490	-0.1009	0.4830	1.28	0.1996
AGE	-0.0641	0.1236	-0.3063	-0.0581	-0.52	0.0038
TERMPREGNANCY	0.1346	0.1035	-0.0683	0.3374	1.30	0.1935
ANTENATALCARE	-0.1573	0.0695	-0.2935	-0.0211	-2.26	0.0236
MARITALST	0.1833	0.0781	0.0302	0.3364	2.35	0.0190
VACCINATION	-0.3077	0.1013	-0.5062	-0.1091	-3.04	0.0024
ANEMIA	0.3176	0.0726	0.1753	0.4600	4.37	<.0001
EDUCATIONLE	-0.2389	0.0945	-0.4241	-0.0537	-2.53	0.0115
BIRTHORDER	-0.0788	0.0736	-0.2231	0.0654	-1.07	0.2841
PREBIRTHINTERVAL	0.0309	0.0789	-0.1238	0.1857	0.39	0.6950

GEE Fit Criteria	
QIC	4011.6165

The full model test for variable selection in ALR

Analysis Of ALR Parameter Estimates

Empirical Standard Error Estimates

Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept	-0.1719	0.1705	-0.5061	0.1623	-1.01	0.3135
SEX	-0.3536	0.0775	-0.5055	-0.2016	-4.56	<.0001
WEALTH	-0.1766	0.0525	-0.2795	-0.0736	-3.36	0.0008
RESIDENCE	0.1863	0.1492	-0.1061	0.4787	1.25	0.2118
AGE	-0.0609	0.1230	-0.3019	-0.0401	-4.50	0.0201
TERMPREGNANCY	0.1291	0.1032	-0.0732	0.3313	1.25	0.2110
ANTENATALCARE	-0.1586	0.0695	-0.2949	-0.0223	-2.28	0.0226
MARITALST	0.1802	0.0776	0.0281	0.3323	2.32	0.0202
VACCINATION	-0.3043	0.1012	-0.5026	-0.1060	-3.01	0.0026
ANEMIA	0.3167	0.0722	0.1753	0.4582	4.39	<.0001
EDUCATIONLE	-0.2383	0.0943	-0.4232	-0.0535	-2.53	0.0115
BIRTHORDER	-0.0801	0.0734	-0.2239	0.0637	-1.09	0.2748
PREBIRTHINTERVAL	0.0306	0.0791	-0.1245	0.1857	0.39	0.6991
Alpha1	0.4344	0.0874	0.2630	0.6057	4.97	<.0001

GEE Fit Criteria	
QIC	4011.8139