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# DETERMINANTS OF BIRTH WEIGHT, MATERNAL WEIGHT, GESTATIONAL AGE AND MATERNAL BODY MASS INDEX AMONG PREGNANT WOMEN IN ETHIOPIA.

KINDU, KEBEDE

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BAHIRDAR UNIVERSITY  
COLLEGE OF SCIENCE  
DEPARTMENT OF STATISTICS

DETERMINANTS OF BIRTH WEIGHT, MATERNAL  
WEIGHT, GESTATIONAL AGE AND MATERNAL BODY  
MASS INDEX AMONG PREGNANT WOMEN IN ETHIOPIA.

BY  
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THE REQUIREMENT FOR THE DEGREE OF MASTER OF SCIENCE IN BIO-  
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## Approval Sheet

We, the undersigned, members of the board of examiners of the final open defense by Kindu Kebede have read and evaluated his thesis entitled “**DETERMINANTS OF BIRTH WEIGHT, MATERNAL WEIGHT, GESTATIONAL AGE AND MATERNAL BODY MASS INDEX AMONG PREGNANT WOMEN IN ETHIOPIA**” and examined the candidate. Therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement for the degree of master of sciences in statistics with specialization of bio statistics.

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## **Abstract**

**Background:** BW, BMI, GA and MW is perhaps the most important indicator for infant survival as well as their physical growth and mental development. The main objective of this research was identify the determinants of BW, BMI, GA and MW simultaneously based on EDHS 2016.

**Methods:** Cross sectional study design was used from Ethiopia demographic health survey 2016. Multivariate linear regression model was used to identify factors of BW, BMI, GA and MW simultaneously which had small standard errors as compare to separate model. Principal components analysis used to reduce response variables where as the determine number of common factors used to factor analysis.

**Results:** The three principal components of BW, BMI, GA and MW with proportion of total population variance of principal components account for 98% and The most variation explain by BW, MW and BMI for PCA<sub>1</sub>, PCA<sub>2</sub> and PCA<sub>3</sub> variation determined by BW and GA response variables. Therefore, the mean of first principal components of BW, BMI, GA and MW were statistically associated with number of tetanus injections before pregnancy, region, frequency of watching television, family size, desire for more children for birth, preferred waiting time for birth and husband educational level. In addition the mean of second principal components of BW, BMI, GA and MW were statistically associated with size of child, number of tetanus injections before pregnancy, region and desire for more children for birth. Moreover, the mean of third principal components of BW, BMI, GA and MW were statistically associated with size of child, preferred waiting time for birth, maternal age group and region. we extract two latent factors from four response variables.

**Conclusion:** From our finding we conclude that maternal number of tetanus injections before pregnancy, region, frequency of watching television, family size, husband educational level, preferred waiting time for birth, desire for more children, age group and size of child were significant predictors of principal components of BW, BMI, GA and MW simultaneously at 5% level of significance. Further more, the two common extract factor also significant predictors for three PCA. Hence, innervation should be given to the pregnant during antenatal care for minimizing the risk of LBW, SGA, under weight and BMI of mothers.

**Keywords:** BMI, BW, MW, GA, Separate Model, Multivariate Model, PCA, FA and EDHS.

# Lists of Acronyms

ANC: Antenatal Care

BMI : Body Mass Index

CSA : Central Statistical Agency

DHS : Demographic Health Survey

EDHS : Ethiopian Demographic Health Survey

HIV : Human Immunodeficiency Virus

MOH : Ministry of Health

SNNP : Southern Nations, Nationalities and Peoples

SSA : Sub-Saharan Africa

UNICEF : United Nations International and Children's Emergency Fund

WHO : World Health Organization

BW : Birth Weight

LBW : Low Birth Weight

GA : Gestational Age

SGA : Small Gestational Age

IUGR : Intrauterine Growth Restriction

PTB : Preterm Birth

FA : Factor Analysis

SES : Socio-Economic Status

RSE: Residual Standard Error

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# 1 Introduction

## 1.1 Background of the Study

Birth weight, maternal body mass index, gestational age and maternal weight is perhaps the most important and reliable indicator for neonatal and infant survival as well as their physical growth and mental development.

Birth weight is an important determinant of an infant's survival and future development. LBW puts a newborn at increased risk of death, illness and limits their growth potential in the adulthood. Globally, LBW contributes 40 up to 60 percent of newborn mortality. But, LBW can be caused by preterm birth or by intrauterine growth restriction [43]. It is the first weight of newborn obtained after birth, preferably measured within the 1<sup>st</sup> hour of life before significant postnatal weight loss has occurred [3, 44]. Globally, out of 139 million live births, about 20 million of them are low birth weight and nearly 95.6 percent of them are in developing countries. A low birth weight carries an increased risk of death on the newborns early in life or exposes to multiple health and development challenges later. The burden of immediate health problems on low birth weight of newborns has been relatively widely documented in many low income countries with national demographic surveys [49, 30]. The estimated of all babies who born LBW found in Sub-Saharan Africa (SSA) each year are 13 percent [30]. The proportion of low birth weight in health facilities has been least documented in south Ethiopia [30].

Birth occurring before 37 completed weeks of gestation comprises nearly 15 million babies each year with a survival chances varying dramatically around the world [21, 7]. South Asia and Sub-Saharan Africa account for almost two-thirds of the world's preterm babies and over three-quarters of the world's new-born deaths are due to preterm birth complications [7].

In developed countries, underweight women may smoke, which may contribute to both PTB and LBW, but women smoke much less often in developing countries. A low maternal BMI and sub optimal weight gain during pregnancy are long recognized risk factors for delivery of infants too small for gestational age, LBW as well as to increase the risk of subsequent obesity and hypertension in the offspring. In the United States of America, it was found that only 2 percent of pregnant women have a BMI less than 18.5 and more than 50 percent have a BMI greater than 25. The most of the work on the effect of maternal BMI on neonatal BW has been done in developed countries. The

anthropometric characteristics of women in the developed world are different from those of the resource-poor nations. Young maternal age, low maternal BMI, and poor weight gain in pregnancy are associated with both increased risk of LBW and poor infant survival [3, 44]. BMI is a fairly reliable indicator of body fatness for most people. BMI does not measure body fat directly, but research has shown that BMI correlates to direct measures of body fat.

Gestational weight gain is also higher than ever before, with approximately 40 percent of pregnant women gaining more weight than its recommended [23]. Obesity during pregnancy may cause adverse outcomes, not only in the mother but also in the child. According to Chernet low body mass index continues to be a major health burden in addition to the emergence of new competing public health priority high BMI in developing countries including Ethiopia [5].

## 1.2 Statement of Problem

Birth weight, maternal body mass index, gestational age and maternal weight are the most sensitive indicator of population health. Based on report of WHO, 16 million adolescent girls gave birth each year, and globally 13 million babies are born before 37 completed weeks of gestation.

According to Zhangbin low maternal BMI and suboptimal weight gain during pregnancy are long recognized risk factors for delivery of infants too small for gestational age, LBW as well as to increase the risk of subsequent obesity and hypertension in the offspring [55]. Globally, more than 20 million infants are born with LBW [51]. The largest number of LBW babies is concentrated in two regions of the developing world which are Asia and Africa.

South Asia and Sub-Saharan Africa account for almost two-thirds of the world's preterm babies and over three-quarters of the world's new-born deaths are due to preterm birth complications [7].

In Ethiopia, 15 percent of babies were reported to be LBW in 2000 [51]. In 2011, the prevalence decreased to 11 percent. In Ethiopia, in 2014, there were 27,243 deaths due to low birth weight accounting 4.53 percent of the total deaths [27]. However, the lack of evidence for a reduction in preterm births, LBW, abnormal weight of pregnant and abnormal pregnant body mass index in intervention of antenatal care visit for certain infections may be due to small sample size or inadequate methodological quality of the

studies. Due to this reason we intended to identify the potential risk factors that affect the birth weight, maternal body mass index,maternal weight during pregnancy and gestational age simultaneously in Ethiopia based on the data gained from EDHS 2016.

According to Abdulai,mccowan,Sharma and goodrich studied the determinants of maternal body mass index[29],the determinants of gestational age [34],the determinants of birth weight [43], and aqualitative study of factors affecting pregnancy weight gain in african american women [20] with some set of predictor variables and statistical methods was multi-nominal logistic regression. But multi-nominal logistic regression not considered linear relationship between dependent and predictor variables.Further more, it not considered multi-col linearity between independent variables.In addition,multi-nominal logistic regression estimated the possibility of an event occurring rather estimated the dependent variable when there is a change in the independent variables.

To solve this problem the present study would be identify determinant factors of birth weight, maternal body mass index,gestational age and maternal weight during pregnancy simultaneously in Ethiopia through multivariate regression model based on EDHS 2016 data.

Multivariate analysis also referred to account the relationships between two or more response variables. Multivariate techniques allow researchers to look at relationships between variables in an overarching way and to quantify the relationship between variables.We can control association between variables by using cross tabulation, partial correlation and multiple regressions, and introduce other variables to determine the links between the independent and dependent variables or to specify the conditions under which the association takes place. Advantages of multivariate analysis include an ability to glean a more realistic picture than looking at a single variable. Further, multivariate techniques provide a powerful test of significance compared to uni variate techniques.

Therefore, the aim of this study tries to address the determinant factors of birth weight, maternal body mass index,gestational age and maternal weight during pregnancy simultaneously taking into consideration various socioeconomic, maternal, infant and health care services factors such as maternal education ,paternal education ,wealth index ,region ,residence, age at first birth,birth interval ,child is twin, sex of child, age of mother, source of water supply, tetanus injection during pregnancy,family size, HIV status of mother and sex of household head. Under this study,we did exploratory factor analysis for explaining the variance between several measured variables as a smaller set of latent variables.Exploratory factor analysis also determine how many factors to extract from the

dependent variables. Factor analysis attempts to identify underlying variables or factors, that explain the pattern of correlations within a set of observed variables. Factor analysis used in data reduction to identify a small number of factors that explain most of the variance observed in a much larger number of manifest variables. Factor analysis can also be used to generate hypotheses regarding causal mechanisms and identify col-linearity prior to performing a linear regression analysis.

## **1.3 Objective of Study**

### **1.3.1 General objective**

The main objective of the study was identify the main factors that affect birth weight, gestational age ,pregnant body mass index and maternal weight during pregnancy simultaneously based on EDHS 2016 data.

### **1.3.2 Specific objective**

- To determine the effect of significant variables on maternal body mass index,gestational age,maternal weight during pregnancy and birth weight separately.
- To explain the number of common factors that are responsible for correlation of response variables by taking together.
- To identify the most important factors which is responsible to determine the most variation of four response variables.
- To provide recommendation for policy maker and source or evidence for other researcher.

## **1.4 Significance of Study**

This study will be assess the worst of factors that affect maternal pregnancy body mass index,gestational age, birth weight and maternal weight during pregnancy simultaneously and provide recommendation for concerned bodies.In addition it will be determine the number of common latent or unobserved factors and its effect for each response variables, and main effects of the independent variables.Furthermore, governmental and non-governmental organizations could take intervention measures and set appropriate plans to reduce abnormal maternal pregnant body mass index,preterm birth, low birth weight

and abnormal maternal weight during pregnancy and giving priority for the areas which mostly affected simultaneously those response variables in the country. Moreover the study will be shown that the net-effects of independent variable on responses. The new information provide may be helpful in designing targeted future interventions intended to prevent abnormal maternal weight during pregnancy, preterm birth, low birth weight and abnormal body mass index. The study will be estimates the multiple and interrelated dependence in a single analysis.



## 2 Literature Review

### 2.1 Factors that affects Birth Weight of Children

By going through the available literature on research relating to birth weight, it is observed that a vast majority of researchers have reported the relationship between very wide spectrums of factors influencing birth weight. Also, there are a number of studies in which information obtained from the ultrasound scan of the pregnant woman has been used for birth weight prediction.

According to Viegas study conducted in Singapore the relationship between birth weight and maternal age are quadratic[14]. The study by Fraser reported that a younger maternal age suitable for increased risk for low birth weight[14]. In study by Feleke and Enquoselassie reported that age of the mother had a significant impact on birth weight[16]. A study by Fernando discovered U-shaped relationship between age and low birth weight[39].

The study by Auger concluded that rural relative to urban area as well as low socio-economic status (represented by maternal education) as having an association with low birth weight. Socio-economic status (SES) mainly comprises of factors relating to education, occupation and income[4].

The study by Nicolaidiset in a retrospective cohort study done in Washington State concluded that paternal education was associated with birth weight[37]. The study by Singhammerrevealed that the family's SES a decade prior to giving birth was not significantly associated with birth weight[45].

A specific finding in a study by Gupta relates to an average reduction of 105 grams in birth weight with smokeless tobacco use[24].

from Siza point of veiw suggested for reducing the prevalence of low birth weight, public health strategy needs to focus attention on better maternal nutrition and education[46].

In study by Zareian also concluded that the superiority of second children over other children is probably because of the existence of older siblings which younger ones follow as models in families[56].

Based on Eide study results shown the positive association between birth length and adult height was stronger than between birth weight and adult weight[15]. From Tadese Ejigu Tafere point of veiw tetanus toxoid vaccination and age were determinants for birth weight [50].

## **2.2 Factors that affects Maternal Body Mass Index**

From Guine study shown some sociodemographic factors associated with BMI classes: age, school year, practicing high competition sport, being federate in a sport or having a vegetarian diet. The educational factors associated with BMI classes included only seminars given at school by a nutritionist. Behavioural factors significantly associated with BMI included: learning in classes, playing in the open air, reading books or use of internet[22].

Study by Ronnenberg reported that maternal nutritional status is important to maternal and fetal well-being, and BMI were influenced by ethnicity and genetics [40].

According to Sattar reported that males are more underweight as compared to females and females are always on higher side of BMI. Married persons were more obese as compared to unmarried. Per month income, background history of diabetes mellitus and family history of obesity found to have a profound effect on BMI[41].

According to Akgun reported that nutrient intake and weight gain during pregnancy are the two main factors affecting maternal and infant outcomes[1].

Using data from a national sample of children in the U.S. and study by Datar examines family size is associated with child BMI and obesity[13].

From study by Gupta shows the frequent television watching was associated with obesity among rural women of reproductive age in Myanmar[25].

## **2.3 Factors affecting Maternal Weight Gain During Pregnancy**

Goodrich stated that women were motivated to exercise for personal health benefits but fear exercise may harm the fetus. In addition, the lack of health care provider advice or advice that is inconsistent with recommendations has been consistently reported as a barrier[20].

Based on national research council and others(2007)report stated that interactions among several biological factors (i.e., pregnancy weight, age, parity, and stature) influence gestational weight gain and the biological influences on gestational weight gain vary widely among women and other potential metabolic factors that may affect gestational weight gain (i.e., placental secretions or metabolic changes in obese women) remain poorly understood[10].

Magalhaes stated that the determinants of excessive weekly weight gain were family income and the prevalence rate of excessive weekly weight gain in pregnant women in the

second and third trimesters was found to be 42 percent[33].

## **2.4 Factors that affects Gestational Age of Children**

Based on study by Anne CC Lee et al.( 2017) said that In low and middle income countries, about one in five infants are born small for gestational age, and one in four neonatal deaths are among such infants[31].

Yoshida et al. (2001) stated that the determination of fetal growth from 20 weeks of gestation onwards seemed to be correlated with birth weight deviation[53, 54].

According to Scanlon risk of preterm birth was increased in women with low hemoglobin level in the first and second trimester[42].

from chu point of veiw fluenza vaccination on birth outcomes, including a potential effect on decreased incidence of small for gestational age (SGA), preterm birth, and low-birthweight infants in pregnant women[8].

## **2.5 Relationship Between Maternal Weight, Birth Weight,Gestational Age and Body Mass Index**

According to Mcdonald the overweight and obese women the risk of induced preterm birth was increased and overweight and obese women had a decreased risk of having an infant of low birth weight[35, 36].

From furlong point of view the correlation between weight-for-length or size of child and BMI-for-age of child was strong ( $r = 0.986$ ,  $P < .0001$ )[19].

Conde-AgudeloMD studies shown that short and long intervals between pregnancies are associated with an increased risk of several adverse pregnancy outcomes such as low birth weight, preterm delivery and small-for-gestational age[9].

Based on study by Zhen the singletons born to underweight women have higher risks of PTB (overall, spontaneous and induced) and LBW than those born to women with normal weight[26].

Infant birth weight to maternal gestational weight gain tends to be lower among adolescents than adults, and higher gestational weight gains do not improve birth weight in infants born to adolescent mothers[10].

According to Sung and Weiss stated that the risks of both total and spontaneous PTB were significantly greater in the overweight/obese group than in the normal BMI

group[48, 52]. It is thought that one of the most important cause of preterm birth balancing BMI pre-pregnancy and during pregnancy contribute positively maternal and neonatal outcomes. Prevention and treatment strategies to optimize pre-gestational BMI and pregnancy weight gain would be useful for promoting maternal/fetal health in Turkey maternal weight gain during pregnancy affects neonatal body weight, higher pre-pregnancy BMI has an adverse effect on recommended weight gain during pregnancy, with increased maternal complications[1].

## 2.6 Review on Statistical Models

The previous study that referred in this study was logistic regression. But, multinomial logistic regression coefficients should be chosen in such a way that it maximizes the probability of Y given X with maximum likelihood, the computer uses different "iterations" in which it tries different solutions until it gets the maximum likelihood estimates. In addition the previous study was not minimize the sum of the squared distances of each observed response to its fitted value. Moreover, most researcher who was used logistic regression, but does not assume residuals to be equal for each level of the predicted dependent variable values. Further more, logistic regression should not be considering the correlation among predictor and dependent variables[47]. The researcher was used code for fit model and the code is completely arbitrary i.e recoding the dependent variable can give very different results. Logistic regression jumps the gap by assuming that the dependent variable is a stochastic event, and the dependent variable describes the outcome of this stochastic event with a density function (a function of cumulative probabilities ranging from 0 to 1). Multinomial regression is robust against multivariate normality then it is better for smaller samples than a multivariate regression model[47].

However this study would be solve those problem listed above by using the following statistical model [47]. Multivariate regression analysis is used to predict the value of one or more responses from a set of predictors. In addition it can also be used to estimate the linear association between the predictors and responses. But it minimizes the sum of the squared distances of each observed response to its fitted value, and residuals to be equal for each level of the predicted dependent variable values. Multivariate regression should be considering the correlation among predictor variable[47]. However, predictors can be continuous or categorical or a mixture of both. In addition this study was used to describe variability among observed, correlated variables in terms of a potentially lower

number of unobserved variables called factors. we would select varimax rotation due to assume the factors are completely uncorrelated. On the other hand, the idea behind factors was that they account for the variation in the sample if the factors are correlated, what accounts for the relationship between the factors. So, this finding did factor analysis with varimax rotation and minimum residual or OLS estimation methods[28]. Principal component analysis was a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables[28].

## **3 Study Design and Methods**

### **3.1 Study Design**

The study was conducted to assess factors that affect birth weight, gestational age, pregnancy body mass index and maternal weight during pregnancy among mother enrolled in the Ethiopia demographic and health survey 2016.

### **3.2 Study Area and Population**

The study would be carried out in Ethiopia based on demographic and health survey 2016. The study included pregnant women who participated on demographic and health survey 2016 in Ethiopia.

### **3.3 Data Collection Procedures**

This research utilized Ethiopian 2016 demographic and health survey as its source of data that is the fourth comprehensive and nationally representative population and health survey. It is an important feature of the data set that avails in-depth information on demographic and health aspects of households. The data would be collected by the central statistical agency (CSA) at the request of the ministry of health (MoH). Data collection took place from January 18, 2016, to June 27, 2016[12].

#### **3.3.1 Inclusion and Exclusion Criteria of the Study**

Mother's who are pregnant and remember her weight during pregnancy, birth weight, gestational age and body mass index during pregnancy which record from January 18, 2016, to June 27, 2016 would be included in the study.

#### **3.3.2 Data Structure, Compilation and Analysis Strategy**

Secondary data would be entered and analyzed by R software.

## **3.4 Variables Included in the Study**

### **3.4.1 Response Variables**

The response variables for the study would be birth weight, gestational age, pregnant body mass index and maternal weight during pregnancy.

### 3.4.2 Explanatory Variables

The predictor variables to be studied as determinants of birth weight, pregnant body mass index, gestational age and maternal weight simultaneously would be grouped in to maternal factor, social-economics factor and infant factors.

#### **Infant factors**

Infant factors would be included sex of child, birth order, child twin, preceding birth interval and size of child at birth.

#### **Maternal factors**

Certain maternal character included under current investigation was maternal education level, family size ,number of tetanus injections before birth,number of tetanus injections before pregnancy, age group, HIV status of mother, mother height, hemoglobin level, anemia level, smokes cigarettes, chews tobacco,timing for first antenatal care ,frequency of reading news paper,frequency of watching television ,total children ever born,antenatal care at private and governmental clinic,toilet facility,distance of delivery,preferred waiting time,desire for more children and live birth between birth , mother drink that contains alcohol and source of water supply.

#### **Socioeconomic factors**

Socio-economic characteristics included in this study were household wealth index , place of residence, region, husband educational level and sex of household head.

### 3.4.3 Operational Definition

**Gestational age** is the common term used during pregnancy to describe how far along the pregnancy is[17].

**Prgenancy weight** can be defined as the amount of weight gained between conception and just before the birth of the infant[11].

**Birth Weight** is the first weight of your baby, taken just after he or she is born[18].

**Body Mass Index** is a measure of body fat based on your weight in relation to your height[18].

## 3.5 Statistical Analysis Methods

We build model in four stages depending on our objectives.First ignore the correlation across birth weight,gestational age,maternal weight and body mass index.Therefore,this study estimate multiple linear regression model separately for each response variables,allowing

for the possibility that variation in BW,MW,GA and BMI might be attributable to difference in socio-economic,maternal health and infant characteristics.Second,recognize the correlation between BW,MW,GA and BMI and identify the correlation effects that load on each responses separately using factor analysis.Third,load the joint variation of BW,MW,GA and BMI by managing the correlation until replace the original responses variables using principal component analysis.Finally, recognizing the joint variation with BW,MW,GA and BMI and joint analysis of the effect of the explanatory variables on the associated response variables are acknowledge and investigate using multivariate regression.

### **3.5.1 Multiple Linear Regression**

Multiple linear regression model is a linear model that describes how one response variable relates to two or more explanatory variables.Multiple regression model may want to know whether a particular explanatory variable is making a useful contribution to the model.To estimates the model parameters then beta coefficients are the values that minimize the sum of squared errors for the sample.

### **3.5.2 Principal Component Analysis**

A principal component analysis concerns with explaining the variance-co variance structure of a set of variables through a few linear combinations of these variables. It is one of a family of techniques for taking high-dimensional data, and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing information.PCA is one of the simplest and most robust ways of doing such dimensional reduction.Principal component analysis (PCA) is a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables. Goals of principal component analysis under this study, we would be used PCA are:-

- To extract the most important information from the data table.
- To compress the size of the data set by keeping only this important information.
- To simplify the description of the data set.
- To analyze the structure of the observations and the variables.



In order to achieve these goals, PCA computes new variables called principal components which are obtained as linear combinations of the original variables. The first principal component is required to have the largest possible variance. The second component is computed under the constraint of being orthogonal to the first component that have the remain largest possible variance. The other components are computed likewise.

### 3.5.2.1 Principal Component Model

If the observed variables are  $y_1, y_2, y_m$ , then PCA are  $PCA_1, PCA_2, \dots, PCA_m$  then the original variables may be expressed as linear functions as follows:-

$$\begin{aligned}
 PCA_1 &= e_{11}y_1 + e_{12}y_2 + e_{13}y_3 + \dots + e_{1m}y_m \\
 PCA_2 &= e_{21}y_1 + e_{22}y_2 + e_{23}y_3 + \dots + e_{2m}y_m \\
 &\vdots \\
 PCA_n &= e_{n1}y_1 + e_{n2}y_2 + e_{n3}y_3 + \dots + e_{nm}y_m
 \end{aligned}
 \tag{3.1}$$

$PCA_i$  are uncorrelated,  $PCA_1$  explain as much as possible more variance in the data set and  $PCA_2$  explain the remaining variance of the original data set etc. The equation (3.1) shows small set of linear combinations of the covariates which are uncorrelated with each other. This would be avoid the multicollinearity problem. However the linear combinations chosen have maximal variance. A good regression design chooses values of the covariates which are spread out.

$$Var(PCA_i) = e_i' \Sigma e_i \quad i = 1, 2, \dots, n \tag{3.2}$$

$$Cov(PCA_i, PCA_k) = e_i' \Sigma e_k \quad i, \text{ and } k = 1, 2, \dots, n \tag{3.3}$$

$$e_i = \begin{pmatrix} e_{1i} \\ e_{2i} \\ \vdots \\ e_{ni} \end{pmatrix}$$

### 3.5.2.2 Estimation of $i^{th}$ Principal Component Coefficients

To estimate the coefficients of principal components from estimate the variance for  $i^{th}$  principal components is equal to  $i^{th}$  eigenvalue.

$$Var(PC A_i) = var(e_{i1}y_1 + e_{i2}y_2 + e_{i3}y_3 + \dots + e_{im}y_m) = \lambda_i \quad (3.4)$$

$$Cov(PC A_i, PC A_k) = 0$$

The eigenvalue of variance covariance matrix  $\Sigma$  explain the variation and the corresponding eigenvectors  $e_1$  through  $e_n$  would be principal component coefficients. However the order of eigenvalue or variance is  $\lambda_1 \geq \lambda_2, \dots, \geq \lambda_n$ . The eigenvalues and eigenvectors of covariance matrix differ from those associated correlation matrix. Therefore PCA of covariance matrix is meaningful only if the variance expressed in the same units, and PCA of correlation matrix to be used when variables on different scales.

### 3.5.2.3 Proportion of Total Population Variance of Principal Components Analysis

Proportion of total variance due to  $k^{th}$  components is equal to

$$\frac{\lambda_k}{\lambda_1 + \lambda_2 + \dots + \lambda_n}, k = 1, 2, \dots, n \quad (3.5)$$

Proportion of total variance due to first  $k^{th}$  components is equal to

$$\frac{\lambda_1 + \lambda_2 + \dots + \lambda_k}{\lambda_1 + \lambda_2 + \dots + \lambda_n}, k = 1, 2, \dots, n \quad (3.6)$$

If total population variance of principal components is between 80 percent to 90 percent then the components replace the original  $n$  variables by first one, two, three components without much loss of information [28].

### 3.5.2.4 The Correlation Between Component and Variables

The correlation between components  $PC A_i$ , and the variable  $Y_k$  are:

$$\rho_{PC A_i, Y_k} = \frac{e_{ik} \sqrt{\lambda_i}}{\delta k k} \quad (3.7)$$

However, the correlation of the variable with principal components often help to interpret the components, they measure only the uni variate contribution of an individual response variables on components. So that not indicate the importance of response variable to its components in the presence of other response variable. Therefore to solve this problem use only coefficients or eigen vectors indicate the importance of response variable to its components in the presence of other response variable [28].

### 3.5.2.5 Scree Plot

is used to displays the variance explain by each component and recommend the retained all components in the descent before the first one on the line where it levels off.

### 3.5.3 Factor Analysis

Factor analysis is a method for investigating whether a number of variables of interest  $y_1, y_2, y_m$ , are linearly related to a smaller number of unobservable factors  $f_1, f_2, f_k$ . Factor analysis attempts to represent a set of observed variables  $y_1, y_2, y_m$  in terms of a number of 'common' factors plus a factor which is unique to each variable. The common factors (sometimes called latent variables) are hypothetical variables which explain why a number of variables are correlated with each other; it is because they have one or more factors in common[28].

There are a number of different varieties of factor analysis. But under this study ,the observed variables are standardized (mean zero, standard deviation of one) and that the factor analysis is based on the correlation matrix of the observed variables.

#### 3.5.3.1 The Factor Analysis Model

The observed variables  $y_1, y_2, y_m$  relate with common factors are  $f_1, f_2, \dots, f_m$  and the unique factors  $u_1, u_2, \dots, u_n$ .So, variables may be expressed as linear functions of the factors:

$$\begin{aligned}y_1 - \mu_1 &= a_{11}f_1 + a_{12}f_2 + a_{13}f_3 + \dots + a_{1m}f_m + u_1 \\y_2 - \mu_2 &= a_{21}f_1 + a_{22}f_2 + a_{23}f_3 + \dots + a_{2m}f_m + u_2 \\y_n - \mu_n &= a_{n1}f_1 + a_{n2}f_2 + a_{n3}f_3 + \dots + a_{nm}f_m + u_n\end{aligned}\tag{3.8}$$

Each of those equations is a regression equation; factor analysis seeks to find the coefficients  $a_{11}, a_{12}, \dots, a_{nm}$  which best reproduce the observed variables from the factors.

The coefficients  $a_{11}, a_{12}, \dots, a_{nm}$  are weights in the same way as regression coefficients (because the variables are standardized, the mean is zero).

For instance, the coefficient  $a_{11}$  shows the effect on variable  $y_1$  when a one-unit increase in  $f_1$ . In factor analysis, the coefficients are called loading's (a variable is said to 'load' on a factor) and when the factors are uncorrelated, they also show the correlation between each variable and a given factor.

In the model above,  $a_{11}$  is the loading for variable  $y_1$  on  $f_1$ ;  $a_{23}$  is the loading for variable  $y_2$  on  $f_3$ , etc. When the coefficients are correlations, i.e., when the factors are uncorrelated, the sum of the squares of the loading's for variable  $y_1$ , namely  $a_{11}^2 + a_{12}^2 + \dots + a_{13}^2$  shows the proportion of the variance of variable  $y_1$  which is accounted for by the common factors. This is called the commonality.

The larger the commonality for each variable, the more successful a factor analysis solution is. By the same token, the sum of the squares of the coefficients for a factor for  $f_1$  it would be  $[a_{11}^2 + a_{21}^2 + \dots + a_{n1}^2]$  shows the proportion of the variance of all the variables which is accounted for by that factor.

### 3.5.3.2 The Model for Individual Subjects

It used to estimate the value of each factor for each of the subjects in the sample. Factor scores are often used in analyses in order to reduce the number of variables which must be dealt with. However, the coefficients  $a_{11}, a_{12}, \dots, a_{nm}$  are the same for all subjects, and it is these coefficients which are estimated in the factor analysis.

### 3.5.3.3 Extracting Factors and the Rotation of Factors

It is mathematical process used to obtain a factor solution from a correlation matrix such that each successive factor which is uncorrelated with the other factors and accounts the variance of the observed variables as possible. The amount of variance accounted by each factor is shown by a quantity called the eigenvalue which is equal to the sum of the squared loading's for a given factor. This often means that all the variables have substantial loading's on the first factor; i.e., the coefficients  $a_{11}, a_{12} \dots a_{nm}$  are all greater than some arbitrary value such as .3 or .4 while this initial solution is consistent with the aim of accounting for as much as possible of the total variance of the observed variables with as few factors as possible, the initial pattern is often adjusted so that each individual variable has substantial loading's on as few factors as possible (preferably only one). This adjustment is called rotation to simple structure, and seeks to provide a more interpretable outcome.

### 3.5.3.4 Estimating Factor Scores

It used to determine the variables  $y_1 \dots y_n$  in terms of the factors  $f_1 \dots f_m$ , it will be possible to solve the equations for the factor scores, so as to obtain a score on each factor for each subject. In other words, equations of the form:-

$$\begin{aligned}
f_1 &= a_{11}y_1 + a_{12}y_2 + a_{13}y_3 + \dots + a_{1m}y_m \\
f_2 &= a_{21}y_1 + a_{22}y_2 + a_{23}y_3 + \dots + a_{2m}y_m \\
f_n &= a_{n1}y_1 + a_{n2}y_2 + a_{n3}y_3 + \dots + a_{nm}y_m
\end{aligned} \tag{3.9}$$

### 3.5.3.5 Calculating Correlations from Factors

It used to explain correlations among observed variables in terms of a relatively small number of factors. One way of gauging the success of a factor solution is to attempt to reproduce the original correlation matrix by using the loading's on the common factors and seeing how large a discrepancy there is between the original and reproduced correlations the greater the discrepancy, the less successful the factor solution has been in preserving the information in the original correlation matrix. When the factors are uncorrelated, the process is simple. The correlation between variables  $x_1$  and  $x_2$  is obtained by summing the products of the coefficients for the two variables across all common factors; for a three-factor solution, the quantity would be  $(a_{11}xa_{21}) + (a_{12}xa_{22}) + (a_{13}xa_{23})$ .

### 3.5.4 Multivariate Multiple Linear Regression Models

Under this study, we did multivariate multiple linear regression models. The model would be multiple because we have  $p > 1$  predictors, the model would be linear because the response variable is linear function of parameters ( $b_0, b_1, b_2, \dots, b_p$  are parameters), and the model is multivariate because we have  $m > 1$  response variables. The model is linear because  $y_{ik}$  is a linear function of the parameters ( $b_{jk}$  are the parameters for  $j \in (1, \dots, p + 1)$ , and  $k \in (1, \dots, m)$ ). The model is a regression model because we are modeling response variables ( $y_1, \dots, y_m$ ) as a function of predictor variables ( $x_1, \dots, x_p$ ). Each response is assumed to follow its own regression model, so that

$$\begin{aligned}
y_1 &= \beta_{01} + \beta_{11}x_1 + \beta_{r1}x_r + \varepsilon_1 \\
y_2 &= \beta_{02} + \beta_{12}x_1 + \beta_{r2}x_r + \varepsilon_2 \\
&\vdots \\
y_m &= \beta_{0m} + \beta_{1m}x_1 + \beta_{rm}x_r + \varepsilon_m
\end{aligned} \tag{3.10}$$

The another matrix notation to be used for study are:-

$$Y = \beta X + \Sigma \tag{3.11}$$

The error term  $\varepsilon' = \varepsilon_1, \varepsilon_2, \dots, \varepsilon_m$  has  $E(\varepsilon) = 0$  and  $\text{var}(\varepsilon) = \Sigma$ . Thus, the error terms associated with different responses on the same trial are correlated.

### Assumptions

**Normal Distribution:-** The dependent variable should be normally distributed within groups.

**Linearity:-** assumes the linear relationships among all pairs of dependent variables, all pairs of covariates, and all dependent variable-covariate pairs in each cell. Therefore, when the relationship deviates from linearity, the power of the analysis would be compromised.

**Homogeneity of Variances and Covariance:-** In multivariate designs, with multiple dependent measures, the homogeneity of variances assumption described earlier also applies. However, since there are multiple dependent variables, it is also required that their inter-correlations (covariance) are homogeneous across the cells of the design.

#### 3.5.4.1 Parameter Estimation

In a host of scientific research, the basic goal is to assess the simultaneous influence of several covariates on the response variable: the quantity of interest. Multivariate regression models provide an extremely powerful methodology to achieve this task.

The multivariate multiple regression model (MMRM) generalizes the multiple regression model for the prediction of several response variables from the same set of explanatory variables. Multivariate multiple regression model has unknown parameters. Parameters are the characteristic of population. The parameters value is obtained from parameter estimation. According to Nkurunziza and S. Ejaz Ahmed the mostly used estimation methods are the multivariate least squares estimation [38].

##### 3.5.4.1.1 Multivariate Least Squares Estimation

The least squares estimator for  $\beta$  minimizes the sums of squares elements on the diagonal of the residual sum of squares and cross products matrix  $(Y - Z\hat{\beta})'(Y - Z\hat{\beta})$ . Because the matrix  $(Y - Z\hat{\beta})'(Y - Z\hat{\beta})$  has smallest possible trace. Using the least squares estimator for  $\beta$  we can obtain predicted values and compute residuals.

From the theory of the least squares in univariate regression, we can get the estimator of  $\beta$  by minimizing  $\varepsilon'\varepsilon$  Where  $\hat{\varepsilon} = Y - X\hat{\beta}$  is  $n \times q$  error matrix. We can minimize  $\varepsilon'\varepsilon$  by giving constraints to non-negative matrix, the trace, the determinant, and the largest eigenvalue, i.e. estimating  $\hat{\beta}$  to meet the following inequality's for all the possible matrices

of  $\beta$  respectively.  $(Y-Z\hat{\beta})'(Y-Z\hat{\beta}) \leq (Y-Z\beta)'(Y-Z\beta)$ ,  $\text{trace}(Y-Z\hat{\beta})'(Y-Z\hat{\beta}) \leq \text{trace}(Y-Z\beta)'(Y-Z\beta)$ ,  $|(Y-Z\hat{\beta})'(Y-Z\hat{\beta})| \leq |(Y-Z\beta)'(Y-Z\beta)|$  and  $\text{maxeig}(Y-Z\hat{\beta})'(Y-Z\hat{\beta}) \leq (Y-Z\beta)'(Y-Z\beta)$  In fact, the four criteria are equivalent to each other. Under any criteria of the four, we can get the same least square estimator of  $B$ , given by

$$\hat{\beta} = (X'X)^{-1}X'Y \quad (3.12)$$

This is best linear unbiased estimation (BLUE). Therefore the individual coefficients and standard errors produced by multivariate linear regression are identical to those that would be produced by regress each response against the set of independent variable separately. The difference lies in that the multivariate linear regression as joint estimator also estimates the between equation covariance, so we can test the interrelationship between coefficients across equations.

## 3.6 Variable and Model Selection Methods

### 3.6.1 Variable Selection

There are various selection methods for linear regression modeling in order to specify how independent variables are entered into the analysis. By using different methods, a variety of regression models from the same set of variables could be constructed. According to David J and Lilja backward elimination process was prefer because it is usually straightforward to determine which factor we should drop at each step of the process. Determining which factor to try at each step is more difficult with forward selection[32]. Backward elimination has a further advantage, in that several factors together may have better predictive power than any subset of these factors. As a result, the backward elimination process is more likely to include these factors as a group in the final model than is the forward and stepwise selection process. Therefore, under this study we would be used backward elimination.

### 3.6.2 Model Selection

All subset regression tests all possible subsets of the set of potential independent variables. If there are  $K$  potential independent variables (besides the constant), then there are  $2^k$  distinct subsets of them to be tested[2]. Some criteria are:-

1. **The Akaike Information Criterion** is

$$AIC = -2\log(Lmax) + 2k \quad (3.13)$$

$k$  is the number of parameters of the model (number of regression coefficients). Smaller values of AIC correspond to more parsimonious models.

2. **The Bayes Information Criterion (BIC)** is some other commonly used criteria. In general,

$$BIC = -2\log(Lmax) + k\log(n), \quad (3.14)$$

$n$  is the sample size. The complexity penalty is stronger than AIC. Smaller values of BIC correspond to more parsimonious models. BIC tends to be conservative (i.e. it requires quite a bit of evidence before it would be include a predictor).

3. **Adjusted  $R^2$  called  $R_a^2$** . Recall that  $R^2 = 1 - \frac{SSR}{SST}$ . Adding a variable to a model can only decrease the SSR and so only increase the  $R^2$ . So  $R^2$  by itself is not a good criterion because it would always choose the largest possible model.

$$R_a^2 = 1 - \frac{\frac{SSR}{n-p}}{\frac{SST}{n-1}} \quad (3.15)$$

### 3.7 Model Diagnosis Checking

A diagnostic model is a framework for identifying, analyzing and interpreting data in a given context to identify possible needs. Before proceeding to detailed statistical inference, we need to check our modeling assumptions, which mean we need diagnostics. A first step of the regression diagnostic is to inspect the significance of the regression beta coefficients, as well as, the coefficients of determination ( $R^2$ ) that tells us how well the linear regression model fits to the data. The diagnostic plots show residuals in four different ways:-

1. **Residuals vs Fitted**. We would be used to check the linear relationship assumptions. A horizontal line, without distinct patterns is an indication for a linear relationship, what is good.
2. **Normal Q-Q**. We would be used to examine whether the residuals are normally distributed. It's good if residuals points follow the straight dashed line.



3. **Scale Location (or Spread-Location)**. We would be used to check the homogeneity of variance of the residuals (homoscedasticity). Horizontal line with equally spread points is a good indication of homoscedasticity.

4. **Residuals vs Leverage**. We would be used to identify an influential case that is extreme values that might influence the regression results when included or excluded from the analysis.

### 3.8 Goodness of Fit Test

The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question. No one has come up with a perfect measure of goodness of fit for statistical models, although there has been and continues to be much research in the area. We would be look at a variety of concepts that fall into the general category of goodness of fit including:-

- Examining residuals from the model
- Outlier detection
- A global measure of “variance explained”,  $R^2$
- A global measure of “variance explained” that is adjusted for the number of parameters in a model, adjusted  $R^2$

**Examining Residuals from the Model:-** We will discuss at residuals from a model, Residuals can be used descriptively, usually by looking at histograms or scatter plots of residuals, and also form the basis for several other methods we will check it.

**Outlier Detection:-** One other thing we can glean from residual plots or residual histograms are whether there are any “outliers” from the model. An outlier is an extreme observation, different from other observations in the dataset. We will check from the residual plots.

**A Global Measure of “Variance Explained”:-**  $R^2$  gives the “proportion of variance explained by adding the variables  $X_1, X_2, \dots, X_p$  if there are  $p$  independent variables in the model. Overall,  $R^2$  provides a useful measure of how well a model fits, in terms of (squared) distance from points to the best fitting line. However, as one adds more regression coefficients,  $R^2$  never goes down, even if the additional  $X$  variable is not useful.

In other words, there is no adjustment for the number of parameters in the model.

**Adjusted  $R^2$** :- In a simple linear regression, where  $p$ , the number of independent variables is one, then Adjusted  $R^2 = R^2$ . As the number of parameters increases, Adjusted  $R^2 \leq R^2$ , with this definition:-

$$R_a^2 = 1 - \frac{\frac{SSR}{n-p}}{\frac{SST}{n-1}} \quad (3.16)$$

So, there is some attempt to adjust for the number of parameters. SSE is the residual sum of squares; this is a goodness of fit measure.

## 4 Result and Discussion

In this section we discussed the descriptive statistics, fitted and adequacy checking for separate and multivariate models.

### 4.1 Descriptive Statistics

A total of 1996 pregnant were included in the study. The descriptive statistics of continues variables are summarized in Table 4.1. Out of the total 1996 pregnant were included in the study, the mean of maternal BMI is 22.5 kg per m<sup>2</sup> with standard deviation 4.38 kg per m<sup>2</sup>,and the average family size were 5 with standard deviation 2 approximately.In addition the average time that mother who start first antenatal care were 3.57 months with standard deviation 1.47 months.Moreover,the average weight of mother were 56.52 kg with standard deviation 11.84 kg,and the average birth weight were 3.27 kg with standard deviation 0.83 kg.Furthermore,the average duration of pregnancy were 35.87 weeks with standard deviation 1.01 weeks.From total children ever born point of view the average total child ever born were 3 with standard deviation 2 approximately,and the average proceeding birth interval were 48.40 months with standard deviation 29.72 months.Finally,the average height of mothers were 1.58 meter with standard deviation 0.67 meter.

Table 4.1: Summary Statistics of Continues Variables

Variables	Minimum	Maximum	Mean	Standard Deviation
Body mass index	13.58	43.13	22.5	4.38
Timing first antenatal care	0	9	3.57	1.47
Birth weight	0.5	6	3.27	0.83
Family size	1	19	5.39	2.26
Height of mother	1.36	1.89	1.58	0.67
Maternal weight	30.5	113.6	56.52	11.84
Total children ever born	1	13	2.96	2.15
Preceding birth interval	9	213	48.40	29.72
Gestational Age	28	40	35.87	1.01

Table 4.2: Summary Statistics of Categorical Variables

Variables		Variables		Variables		Variables	
<b>Size of child</b>	%	<b>Sex of child</b>	%	<b>ntetanus</b>	%	<b>anemia</b>	%
Very large	22.7	male	51.9	0	15.8	severe	0.4
Larger than average	17.7	female	48.1	1-3	56.6	moderate	5.4
average	42.5	<b>Lbirth</b>		4-6	7.2	mild	18.7
smaller than average	6.3	no	63.6	> 7	0.2	not	72.9
very small	10.8	yes	0.5	<b>ntetanusb.</b>		<b>Hfacility</b>	
Don't know	0.1			0	14.7	problem	30.2
<b>Region</b>		<b>alcohol</b>		1-3	7.6	noproblem	69.8
Tigray	13.8	yes	35.3	4-6	5.2	<b>tfacility</b>	
Afar	1.9	no	64.7	> 7	0.5	unimproved	52.4
Amhara	4.2	<b>W.index</b>		don'tknown	2	improved	45.6
Oromia	6.6	Poorest	9.1	<b>desirechild</b>		<b>waitT</b>	
Somali	7.3	Poorer	9.7	2year	13.8	<12month	9.1
Benishangul	7.5	Middle	9.0	after 2years	48.1	1year	4.8
SNNPR	9.2	Richer	11.5	unsure time	4	2years	10.2
Gambela	8.4	Richest	60.6	undecided	3.9	3year	11.9
Harari	10.3	<b>M.educl</b>		nomore	29.5	4year	7.2
Addis Ababa	19.3	No education	26.4	sterilized	0.4	5year	11.2
Dire Dawa	11.1	Primary	38.1	d.infecud	0.3	>6year	7.6
<b>w.TV</b>		Secondary	20.2	<b>age</b>		nonnumeric	1.8
Not at all	42.2	Higher	15.3	15-19	4.1	don'tknown	2.3
<once a week	13.1	<b>h.educl</b>		20-24	23.3		
≥ once a week	44.7	No education	16.8	25-29	32.3		
<b>R.newspaper</b>		Primary	28.5	>30	40.3		
Not at all	75.8	Secondary	22.5				
Less than once a week	18.5	Higher	21.9				
At least once a week	5.7	Don't know	0.9				

From summarized in Table 4.2 shows that child's with average size were 42.5% ,22.7% very large,17.7% larger than average,10.8% very small and 6.3% smaller than average size. The infant were 51.9% male child and 48.1% female child.From live birth between births point of view 63.6% were not live birth between births.

In addition,the highest and a lowest participants(19.3%)and(1.9%) who was found Addis Ababa and Afar respectively. In this study 44.7% mothers who watch tv at least once a week.Regarding the reading news paper 75.8% mothers were not read,18% mothers read news paper for less than once a week and 5.7% mothers was read for at least once a week.From educational level point of view,38.1% of mother and 28.5% her husband were primary.Under this study 64.7% of mother were no drink alcohol and 60.6% mother were richest wealth index status in this study.

Moreover,there were 56.6% mothers who received tetanus injunction before birth between 1 and 3 times ,and 14.7% mothers who were not received tetanus injunction before pregnancy.Regarding the anemia level,72.9% were mild,and 0.4% were severe.From the health facility point of view,69.8% were not found problem and 52.4% mothers used uni-improved toilet facility.Moreover,32.3% mothers were between 25 and 29 age group and 48.1% wants to born after more 2 years.

## 4.2 Inferential Statistics

### 4.2.1 Uni-variate Analysis

For infants to survive, grow and develop properly they require the right proportion of nutrients during pregnancy.Therefore,this study discussed the effect of explanatory variables when birth weight,maternal weight,maternal body mass index and gestational age were fitted separately. Before going to further analysis ,first assess uni-variate normality of data through normality tests. Under this study used breusch pagan test of normality of data sets followed uni-variate normality at shown on Table 4.3.

Table 4.3: Breusch-Pagan Test of Univariate Normality

Response variables	Data	BP	Df	P-value
maternal weight	model1	83.257	69	0.1161
birth weight	model4	57.142	69	0.8452
body mass index	model3	83.506	69	0.1125
gestational age	model2	84.62	69	0.1662

$H_0$  data sets comes from uni-variate normality and  $H_1$  not  $H_0$ . Therefore, Table 4.3 shows that the birth weight, maternal pregnancy weight, body mass index and gestational age was uni-variate normality at 5% level of significance because the p value is larger than the significant level the fail to reject  $H_0$ .

#### 4.2.1.1 Variable Selection Method

In order to select variables to be included in the analysis, backward elimination process was used. According to David J and Lilja backward elimination process was prefer. Because it is usually straightforward to determine which factor drop at each step of the process [32]. The first step fit the model which include all variables then seen the p value of each variables and remove the variable that had large p value equal to 0.3.

Backward method of variable selection was employed to potentially significant variables in the final model. The result recognized were sex of child, preceding birth interval, size of child at birth, maternal education level, family size, number of tetanus injections before birth, number of tetanus injections before pregnancy, age group, mother height, anemia level, mother drink that contains alcohol, source of water, household wealth index, region, husband educational level, timing for first antenatal care, frequency of reading news paper, frequency of watching television, total children ever born, antenatal care at private clinic, toilet facility, distance of delivery, preferred waiting time, desire for more children and live birth between birth are statistically significant and other variables are found to be non-significant and thus excluded from analysis.

#### 4.2.1.2 Multiple Linear Regression

From the result of uni-variate models use for four different response variables such as birth weight, maternal pregnancy weight, body mass index and gestational age to determine the effect predictors separately shown given in Table 4.4.

Therefore, Table 4.4 results shows region, family size, frequency of watching television, husband educational level, maternal height, desire for more children, preferred waiting time for birth and number of tetanus injections before pregnancy are statistically significant at 5% level of significance for maternal pregnancy weight in Ethiopia.

In addition, preferred waiting time for birth, size of child and number of tetanus injections before pregnancy are statistically significant at 5% level of significance for birth weight in Ethiopia. Moreover, educational level of husband, preferred waiting time for birth, region, family size, desire for more children, frequency of watching television, and num-

ber of tetanus injections before pregnancy are statistically significant at 5% level of significance for maternal pregnancy body mass index in Ethiopia.

Further more,number of tetanus injections before pregnancy,educational level of husband,desire for more children,drink alcohol, and region are statistically significant at 5% level of significance for gestational age in Ethiopia.

From separate analysis of birth weight,maternal pregnancy weight,body mass index and gestational age shows husband educational level and preferred waiting time for birth, region,family size,frequency of watching television,maternal height ,desire for more children and number of tetanus injections before pregnancy were statistically associated with maternal pregnancy weight at  $\alpha$  equal to 5%.

Similarly,size of child ,preferred waiting time for birth , number of tetanus injections before pregnancy were statistically associated with birth weight at  $\alpha$  equal to 5%.

In addition number of tetanus injections before pregnancy,region ,desire for more children drinking alcohol and husband educational level were statistically associated with gestational age at  $\alpha$  equal to 5%.

Finally, region,family size,frequency of watching television,desire for more children and number of tetanus injections before pregnancy were positively associated with pregnancy body mass index at  $\alpha$  equal to 5%.

Table 4.4: Multiple Linear Regression

<b>MW</b>	coef	p values	<b>GA</b>	coef	p values
no tetanus inj	<b>reference</b>				
nbpre(1-3)	9.93	0.022*	intercept	9.59	$2e^{-16}$ ***
nbpre(4-6)	13.75	0.005**	nbpre(4)	-0.16	0.041 *
nbpre(>7)	10.62	0.043*	Region(4)	-0.56	$1.75e^{-05}$ ***
Region(Tigray)	<b>reference</b>		d.alcohol(no)	<b>reference</b>	
SNNP	11.29	0.034*	yes	0.11	0.029 *
no watch	<b>reference</b>				
watchtv(>1)	13.97	0.005**	heducl(3)	0.17	0.032 *
family sizes	1.65	0.042*	desire(4)	-0.69	0.0002***
noeduc	<b>reference</b>				
hasband(secondary)	-9.43	0.02941 *	desire(6)	-0.70	0.021*
mheight	48.00	0.048 *	R <sup>2</sup> =0.86	AdjR <sup>2</sup> =0.84	BIC=100.72
Preferred< 1 year	<b>reference</b>				
Preferred(3year)	-14.49	0.009 **	AIC=93.55		
Preferred(5year)	-11.88	0.020*	<b>BMI</b>	coef	pvalue
Preferred(6year)	-17.04	0.002**	nbpre(2)	3.99	0.02114 *
d.with 2 years	<b>reference</b>				
desire(5)	10.36759	0.034*	nbpre(5)	5.45	0.005 **
R <sup>2</sup> =0.82	AdjR <sup>2</sup> =0.80	BIC=1049.09	nbpre(8)	4.35	0.038*
AIC=854.82			Region(7)	4.53	0.034*
<b>BW</b>	coef	pvalue	watchtv(2)	5.38	0.007 **
sizechild(3)	-0.61	0.015*	familysize	0.69	0.033*
sizechild(4)	-1.22	0.001**	heducl(2)	-3.76	0.030 *
sizechild(5)	-0.98	0.012 *	Preferred(3)	-5.69	0.0098 **
nbpre(6)	3.31	0.006**	Preferred(5)	-4.81	0.019 *
Preferred(3)	-0.79	0.034*	Preferred(6)	-6.93	0.002 **
Preferred(4)	-0.88	0.035*	desire(5)	3.94	0.043 *
R <sup>2</sup> =0.77	AdjR <sup>2</sup> =0.75	BIC=437.65	R <sup>2</sup> =0.79	AdjR <sup>2</sup> =0.77	BIC=840.01
AIC=243.38			AIC=645.74		



\*, \*\* and \*\*\* shown on Table 4.4 implies that the variables was significant if the level of categories not had \*, \*\* and \*\*\* then the level of categories was not included in the Table Table 4.4 like region.

#### 4.2.1.3 Model Selection Criteria

The most commonly model selection methods in linear regression was standard error of residuals and information criteria. Standard error of residuals and information criteria tests for each model are presented in Table 4.5. The separate regression model had the largest standard error of residuals and information criteria that demonstrating a poor fit to the data. But, multivariate model had minimum standard error of residuals that demonstrating good fit to the data for significant predictors. Table 4.5 shows the multivariate model were better fit that has small total residual standard error which was 5 times lower than separate regression model due to manage the correlation between the response variables. Furthermore, based on information criteria test results also support multivariate model were statistically good fit to the data for significant predictors.

Table 4.5: Comparison of Separate and Multivariate Models

Uni-variate	RSE	AIC	BIC	Multivariate	RSE	AIC	BIC
W	8.854	854.82	1049.09	PCA <sub>1</sub>	1.118	384.4283	567.7536
BMI	3.558	645.74	840.01	PCA <sub>2</sub>	0.7641	297.5523	480.8776
BW	0.6697	243.38	437.65	PCA <sub>3</sub>	0.584	236.2734	419.5987
GA	0.1426	93.55	100.72				
Total	13.2243	Total	2.4661				

Now multivariate model is better than separate model then diagnosis checking of multivariate model shown the distribution of residuals that shows on appendix.

#### 4.2.1.4 Model Diagnosis

This section was dedicated to studying the appropriateness of multivariate model. The residuals plot shown on appendix (figure 5, appendix D) seems to indicate that the residuals and the fitted values confirm linearity without distinct patterns and the profile plot (figure 3, appendix C) shows constant variance and also quantile-normal plot (figure 7, appendix E) confirms normality of errors which was residual points follow the straight dashed line. In addition, figure 6 and figure 7 found on appendix D and E shows that the data sets come from populations with a common distribution which is normal. Similarly, figure

8 shown the most observation has small cook's distance mean that the data set has not more influential observation.

#### **4.2.1.5 Goodness of Fit Test**

A goodness of fit test refers to measuring how well do the observed data correspond to the fitted model. Linear regression calculates an equation that minimizes the distance between fitted line and all of the data points. Technically, ordinary least squares (OLS) regression minimizes the sum of the squared residuals. The residual standard error, R squared and adj R-squared was statistical measure of how close the data to the fitted regression line that shown Table 4.5 had small residual standard error of model implies it has higher values of R squared and adj R-squared. In general, model has small residual standard error of model when model higher values of R squared and adj R-squared then better model fits to the data.

#### **4.2.2 Multivariate Analysis**

Now extended the regression model to multivariate when measured four responses such as birth weight, body mass index, maternal weight and gestational age with the same set of predictors in the uni variate case. In addition the correlation between body mass index and maternal weight, body mass index and birth weight, body mass index and gestational age, birth weight and gestational age, birth weight and maternal weight and maternal weight and gestational age was 0.92, 0.69, 0.58, 0.68, 0.67 and 0.59 respectively.

This study assessed multivariate normality of data through multivariate normality tests. Under this study would be used E-statistic or energy test of multivariate normality that was show multivariate normality with P.value equal to 0.0825. Before going to further analysis reduce the response variables using orthogonal transformation or principal component.

##### **4.2.2.1 Factor Analysis**

Factor analysis is a measurement model of a latent variable. The primary approaches in factor analysis methods are common factor analysis and component analysis. In this study discussed the common factor model. The purpose of multivariate determine common factor that extract from the response variables which answered why those responses were correlated.

Therefore, factor analysis were determine the number of unobserved factors that ex-

tract from four response variables. In this study determined the number of factor using hypothesis. The hypothesis that used to determine the number of common unobserved factors as follows:-

$H_o$ :test of the hypothesis that 2 factors are sufficient vs  $H_1$ :not  $H_o$ .

The chi square statistic is 12.94 on 12 degrees of freedom with the p-value is 0.373.

From the results of hypothesis shown that two unobserved factors load or extract from four response variables at significant level  $\alpha$  equal to 5%. Therefore, the significance level p value is 0.373 and chi square statistic is 12.94 indicates that the hypothesis of perfect fit cannot be rejected. This study estimate standard loading or parameters based upon correlation matrix shown on Table 4.6.

Table 4.6: Standardized loading or parameters based upon correlation matrix

Variables	f <sub>1</sub>	f <sub>2</sub>	Communality	Specific Variance	Variance of Variable
W	0.96	-0.04	0.851	0.15	1.0
GA	0.00	0.82	0.672	0.328	1.0
BMI	0.92	0.02	0.847	0.154	1.0
BW	0.07	0.70	0.495	0.505	1.0
Eigenvalue	1.773	1.164			
Total proportion	0.604	0.306			

From Table 4.6 results shown that the communalities (0.96,0.92,0.82,0.70) indicate that the two factors account for a large percentage of the sample variance of maternal pregnancy body mass index ,pregnancy weight,gestational age and birth weight.

In addition,maternal pregnancy weight and body mass index load highly on factor one and have negligible loading's on factor two. The first factor might be called pregnancy weight gain of mother. Similarly,gestational age and birth weight have high loading's on factor two as compare to pregnancy weight and body mass index. The second factor might be labeled as pregnancy weight gain of child .In this results, only factors with eigenvalue greater than 1.0 are retained.

An eigenvalue represents the amount of variance associated with the factor. Hence, only factors with a variance greater than 1.0 are included. Factors with variance less than 1.0 are no better than a single variable, since, due to standardization, each variable has a variance of 1.0. Finally, the latent or unobserved two factor pregnancy weight gain of mother factor and pregnancy weight gain of child factor causing the four measured variables which account the variation of 60% and 30.6% respectively. we can interpret

this model as a set of regression equations:-

$$MW = 0.96 * \text{pregenancyweightgainofmother} - 0.04 * \text{pregenancyweightgainofchild} + u_1$$

$$BMI = 0.92 * \text{Pregenancyweightgainofmother} + 0.02 * \text{pregenancyweightgainofchild} + u_2 \quad (4.1)$$

$$GA = 0.82 * \text{pregenancyweightgainofchild} + u_3$$

$$BW = 0.07 * \text{Pregenancyweightgainofmother} + 0.7 * \text{pregenancyweightgainofchild} + u_4$$

From equation(4.1) obtained two unobserved explanatory variables that used to explain multivariate response. However the two unobserved explanatory variables is uncorrelated each other that was 0.003. Therefore, pregnancy weight gain of mother or first latent variable change by one unit then birth weight, pregnancy weight and body mass index is change by 0.07, 0.96 and 0.92 units respectively. Similarly, pregnancy weight gain of child due to duration is change by one unit then gestational age, birth weight, pregnancy maternal weight and body mass index is change 0.82, 0.7, (-0.04) and 0.02 units respectively. The next this study discussed about reduction of response variables in our analysis with out loss of information.

#### 4.2.2.2 Principal Component Analysis

This technique is widely used to reduce the number of dimensions in a data set, in order to use only the components that most contribute for replace the original four variables without much loss of information. However, the four response variable measure diferent uints of measurements that must be standardized with correlation matrix. This study reduce the response variables by the new variables which has 80 percent to 90 percent of total population variance of the components. So, total population variance of the components and scree plot of variation is determine the number of retained components [28].

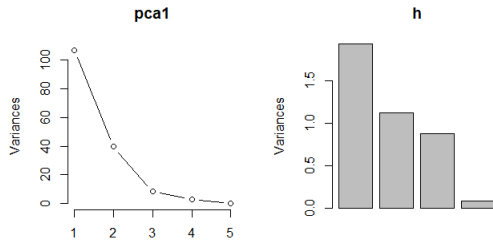


Figure 1: Scree Plot

Figure 1 shown that explain how the first three components dominate and it explain original variables with out loss of information. The principal components of birth weight, body mass index, maternal weight and gestational age with proportion of total population variance of principal components are given in Table 4.7. Based on the Table 4.7 the first three components account 98% variation of original variables.

Table 4.7: Importance of Components

Statistic	PCA1	PCA2	PCA3	PCA4
variance	1.9	1.1	0.9	0.08
Proportion of Variance	0.46	0.28	0.21	0.03
Cumulative Proportion	0.46	0.76	0.98	1.00

The estimated coefficients of principal components obtained after estimate the variance of  $i^{th}$  principal components. In order to achieve the goals of PCA computes new variables which obtained as linear combinations of original variables. Therefore, the principal component coefficient or eigen vectors estimation of birth weight, body mass index, maternal weight and gestational age were given in Table 4.8.

Table 4.8: Parameter Estimation of Principal Components

Variables	PCA1	PCA2	PCA3
Maternal Weight	0.7021495	-0.08002346	0.02856975
Gestational Age	0.0385409	0.71886539	0.69391688
Body Mass Index	0.7026260	-0.06581253	0.04449042
Birth Weight	0.1087082	0.68738454	-0.71811123

Based on Table 4.8 the new variables might be expressed as linear functions of the original variables:-

$$PCA_1 = 0.70mw + 0.04ga + 0.70bmi + 0.11bw$$

$$PCA_2 = -0.08mw + 0.72ga - 0.07bmi + 0.69bw \quad (4.2)$$

$$PCA_3 = 0.03mw + 0.69ga + 0.04bmi - 0.72bw$$

From equation(4.2) shown that maternal weight,birth weight and maternal body mass index competitions receive the highest weight of explained ,but gestational age is less important for the first principal components.However,birth weight and gestational age competitions receive more important to determine second and third principal components where as maternal weight,and body mass index result is less important.

The result also revealed that weight of mother increased by one standardized unit, the mean of first and third principal components was increased by 0.7 and 0.03 standardized unit respectively,but the mean of second principal components decreased by 0.08 standardized units when other variable remain constant.Similarly, body mass index of mother increased by one standardized unit, the mean of first and third principal components was increased by 0.7 and 0.04 standardized unit respectively ,but the mean of second principal component decreased by 0.07 standardized unit when other variable remain constant.

In addition gestational age of mother increased by one standardized unit then the mean of first,second and third principal components increased by 0.04,0.72 and 0.69 standardized units respectively, when other variable remain constant.

Moreover,birth weight of child increased by one standardized unit, the mean of first and second principal components increased by 0.11 and 0.69 units respectively,but the mean of third principal components decreased by 0.72 standardized units ,when other variable remain constant.

Furthermore,the three principal components would be replace four original variables without much loss of information and the original variables would be contributed for each principal components even if the contribution differ.For instance,the factors that affect first principal components implies that factors also affect birth weight,pregnancy weight and body mass index due to linear combination properties.In addition,the factors that affect second principal components implies that factors also affect birth weight and gestational age.Further,the factors that affect third principal components implies that factors also affect birth weight and gestational age as compare to pregnancy weight and body mass index.

### 4.2.2.3 Multivariate Multiple Linear Regression

The model would be multiple because we have  $p > 1$  predictors, the model would be linear because the response variable is linear function of parameters  $(b_0, b_1, b_2 \dots b_p)$ , and the model were multivariate because we have three response variables which was  $PCA_1$ ,  $PCA_2$  and  $PCA_3$ .

#### 4.2.2.3.1 Parameter Estimation of Multivariate Multiple Linear Regression

From Table 4.9 result shows region, family size, frequency of watching television, number of tetanus injections before pregnancy, desire for more children, husband educational level and preferred waiting time for birth are statistically associated with first principal components of maternal pregnancy weight, birth weight, body mass index and gestational age in Ethiopia at 5% level of significance.

Therefore, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who received injections of tetanus between 1-3 times before birth decreased by a factor of 1.27 as compared with mothers who was not received injections of tetanus before birth when the effect of other variable remain constant.

Similarly, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who received injections of tetanus between 4-6 times before birth decreased by a factor of 1.06 as compared with mothers who was not received injections of tetanus before birth when the effect of other variable remain constant.

In addition, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who is don't know number of received injections of tetanus before birth decreased by a factor 1.44 as compared with mothers who was not received injections of tetanus before birth when the effect of other variable remain constant.

The finding of this study also revealed that the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who waiting three year for birth of another child increased by a factor 1.63 as compared to those waiting less than one year for birth of another child . Likewise, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who waiting five and six year for birth of another child increased by

factor 1.56 and 1.96 as compared to those waiting less than one year for birth of another child respectively, when the effect of other variable remain constant.

According to the results, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who watching television at least once a week decreased by factor 1.82 as compared to those not watching at all when the effect of other variable remain constant.

This study also showed the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers who lived SNNP decreased by factor 1.33 as compared to those who lived Tigray when the effect of other variable remain constant. However, the remain 8 region and two administration town was insignificant at alpha equal to 5%.

As family size increased by one units, the mean of first principal components of birth weight, body mass index, maternal weight and gestational age during pregnancy decreased by 0.21 units when the effect of other variable remain constant.

The mean of first principal components of birth weight, body mass index, maternal weight and gestational age for fathers with secondary education increased by factor 1.18 as compared to those with non-educated when the effect of other variable remain constant.

The result also revealed that the mean of first principal components of birth weight, body mass index, maternal weight and gestational age for mothers wants no more time interval to birth decreased by factor 1.22 as compared to those wants within 2 years when the effect of other variable remain constant.

From results on Table 4.9, region, desire for more children and size of child are statistically associated with second principal components of maternal pregnancy weight, birth weight, body mass index and gestational age in Ethiopia.

Region had significant factor on the second principal components of birth weight, body mass index, maternal weight and gestational age. So, the mean of second principal components of birth weight, body mass index, maternal weight and gestational age for mothers who lived Oromia increased by factor 1.99 as compared to those who lived Tigray when the effect of other variable remain constant. But, the remain 8 region and two administration town was insignificant at alpha equal to 5%.

Similarity, the mean of second principal components of birth weight, body mass index, maternal weight and gestational age for mothers wants to be sterilized or block birth increased by factor 3.51 as compared to those wants within 2 years when the effect of other variable remain constant.



Moreover, mean of second principal components of birth weight, body mass index, maternal weight and gestational age for child who has smaller than average size at birth increased by factor 2.67 as compared to child who has very large size at birth when the effect of other variable remain constant.

Finally, preferred waiting time for birth, region, size of child and age group are statistically associated with third principal components of maternal pregnancy weight, birth weight, body mass index and gestational age in Ethiopia at 5% level of significance. So, the mean of third principal components of birth weight, body mass index, maternal weight and gestational age for child who has larger than average at birth, average size at birth, smaller than average size at birth and very small size at birth increased by factor 0.63, 0.63, 1.19 and 1.03 as compared to child who has very large at birth respectively.

Region had significant factor on the third principal components of birth weight, body mass index, maternal weight and gestational age. The mean of third principal components of birth weight, body mass index, maternal weight and gestational age for mothers who lived Oromia decreased by factor 1.25 as compared to those who lived Tigray when the effect of other variable remain constant. However, the remain 8 region and two administration town was insignificant at alpha equal to 5%.

The finding of this study also revealed that the mean of third principal components of birth weight, body mass index, maternal weight and gestational age for mothers who waiting three and four year for birth of another child increased by 0.73 and 1.09 as compared to those waiting less than one year for birth of another child respectively when the effect of other variable remain constant.

Finally, mothers who have age between 20-24 has significant impact on third principal components then the mean of third principal components of birth weight, body mass index, maternal weight and gestational age for mothers who has age between 20-24 increased by factor 2.14 as compared to mothers who has age between 15-19 when the effect of other variable remain constant.

From factor analysis we determined two unobserved variables such that pregnancy weight gain of mother and child was significant effect for three principal components of birth weight, body mass index, maternal weight and gestational age.

For instance, the mean of first principal components increased by 1.23 and 0.92 units when pregnancy weight gain of mother and child increased by one units respectively. In addition, the mean of second principal components increased by 1.03 and 0.73 units when pregnancy weight gain of mother and child increased by one units. Moreover, the pregnancy

wight gain of mother and child increased by one units then the mean of third principal components increased by 1.32 and 1.72 units respectively.

Table 4.9: Multivariate Multiple Linear Regression Model Parameters

<b>PCA1</b>	coef	p.value	<b>PCA3</b>	coef	p.value
no t.injection	<-ref		very large size	<-ref	
1-3 times	-1.27	0.004**	larger than .ave	0.63	0.027 *
4-6	-1.06	0.025*	Average	0.63	0.006 **
don't know number	-1.44	0.022 *	smaller than .ave	1.19	0.0007****
pw.time < 1year	<-ref		Very small	1.03	0.005**
3 years	1.63	0.016 *	Tigray	<-ref	
5 years	1.56	0.015 *	Oromia	-1.25	0.012 *
6 years	1.96	0.003 **	pwtime < 1 year	<-ref	
Reigion(Tigray)	<-ref		3 years	0.73	0.036 *
SNNPR	-1.33	0.046 *	4 years	1.09	0.006**
not watch tv	<-ref		age b 15-19	<-ref	
At least 1 week	-1.82	0.003 **	20-24	2.14	0.019 *
family size	-0.21	0.037*	pwgm	1.03	0.005**
hasbandeduc(no)	<-ref		pwgm	0.73	0.015*
Primary	0.98	0.045 *	<b>Variation</b>	R <sup>2</sup> =0.89	AdjR <sup>2</sup> =0.81
secondary	1.13	0.036 *	<b>PCA2</b>	coef	p.value
size.child(very large)	<-ref		Tigray	<-ref	
very small s.child	-1.19	0.035	oromia	1.99	0.003 **
pwgm	1.23	0.004**	very large size	<-ref	
pwgm	0.92	0.012*	smallerthan.ave	2.67	0.007 **
<b>Variation</b>	R <sup>2</sup> =0.88	AdjR <sup>2</sup> =0.82	wants with2 years	<-ref	
			Sterilized	3.51	0.019 *
	<b>unobserved</b>	- >	pwgchild	1.72	0.0042*
			Intercept	-7.21	0.041 *
			<b>Variation</b>	R <sup>2</sup> =0.75	AdjR <sup>2</sup> =0.72

\*,\*\* and \*\*\* shown on Table 4.9 implies that the variables was significant if the level of categories not had \*,\*\* and \*\*\* then the level of categories was not included in the Table 4.9 like region.

However, mothers who was drink alcohol,maternal educational level,frequency of reading news and toilet facility are found to be statistically significant factors for principal components of birth weight,maternal weight,maternal body mass index and gestational age simultaneously at 10% level of significance.But,this study focused on the effect of factors at 5% level of significance rather than at 10% level of significance.

### 4.3 Discussion of the Results

Pregnancy outcomes determined by potential socioeconomic,maternal and infant factors in this study.This study shows that 63.6% were not live birth between births, 75.8% mothers were not read,56.6% mothers who received tetanus injuncion before birth and 32.3% mothers has age group between 25 and 29 . Therefore, this study has been attempted to identify socioeconomic , maternal and infant related determinants of birth weight,gestational age,maternal weight and body mass index based on EDHS 2016. The obtained results are discussed as follows:-

#### 4.3.1 Multivariate Multiple Linear Regression Models

$$\begin{aligned}
 PCA_1 &= \left\| \begin{aligned} &-1.27ntbp(1)-1.06ntbp(2)-1.44ntbp(4)-1.33Reg(7)-1.82wtv(2)-0.21(fs) \\ &+0.98heducl(1)+1.13heducl(2)+1.63pwt(3)+1.56pwt(5)+1.96pwt(6)+ \\ &1.23pwg+0.92pwg \text{ of child} \end{aligned} \right\| \\
 PCA_2 &= \left\| -7.21+3.51desire(6)+1.99Reg(4)+2.67 \text{ size child}(4)+1.32pwg+1.72pwg \text{ ofchild} \right\| \\
 PCA_3 &= \left\| \begin{aligned} &0.63\text{size child}(2)+0.63\text{size child}(3)+1.19\text{size child}(4)+ 1.03 \text{ size child}(5) \\ &+2.14\text{age group}(2)-1.25Reg(4)+0.73pwt(3) \\ &+1.09pwt(4)+1.63pwgfactor+0.63pwg \text{ of child} \end{aligned} \right\|
 \end{aligned}$$

According to the results, nummber of tetanus injection before birth is an important predictor of frist principal components.Thefore,the study showed that mother who recieved tetanus injection before birth has higher risk of small birth weight,under weight

and under body mass index than mother who was not received tetanus injection before birth. This result is lined with the previous study by chu(2014) and tafere(2018) [8, 50].

This study showed that mother who live SNNP has less variation of first principal components as compare to mother who live Tigray. But, the remain 8 region and two administration town was insignificant at alpha equal to 5%. Therefore, the study showed that mother who live SNNP has higher risk of small birth weight, under pregnancy weight and under body mass index than as compare to mother who live Tigray. But mothers who lived Oromia is less risk of small gestational age, under body mass index, low birth weight and under pregnancy weight as compared to those who lived Tigray which is similar with the previous studies conducted by different scholars [40].

Similarly, mother who was watch television at least one a week had lower variation of first principal components of birth weight, gestational age, body mass index and maternal weight as compare mother who was not watch television. The study also revealed that mother who was watch television at least one a week had higher risk of small birth weight, under pregnancy weight and under body mass index than mother who was not watch television which result was observed in another study done by [25].

Family size are negatively correlated with first principal components. So, family size increase by one unit then the risk of small birth weight, under pregnancy weight and under body mass index significantly decreased. Similar result was observed in another study done by [13].

This study found that parental education level is an important socio-economic predictor of first principal components. More educated parents had less the risk of having under body mass index, under weight of mother and low weight of child as compare to no educate. This result is lined with the previous study by nicolaidis [37].

This finding also revealed that mother who preferred more waiting time for birth of another child had less the risk of under body mass index, under weight of mother and low weight of child as compare mother who preferred less waiting time for birth of another child. This has been confirmed by different studies that refereed by Conde-Agudelo MD and studies by him also show it [9].

The study also revealed that desire more children is significant predictor for second principal components. So, mother who desire for more children that wants with in more number of years had less risk small gestational age and low weight of child.

The result shows the size of child had significant factor on the second and third principal components implies child has large size had less risk of low birth weight, under

weight of mother, under body mass index and small gestational age. This finding is consistent with the literature [19, 15].

Finally, mothers age group was statistically associated with third principal components of birth weight, body mass index, maternal weight and gestational age. Therefore, a mother who has higher age than the risk of low birth weight, small gestational age, underweight and under body mass index decrease. This study is similar with the previous studies Dennis, Restrepo and Fessler that association between maternal age at child-birth and child outcomes in the offspring [39, 14, 16, 6]. But, contradict with Viegas and Fernando study shown the relationship between birth weight and maternal age are quadratic [14] and discovered U-shaped relationship between age and low birth weight [16] respectively, but this finding shown linear relationship between birth weight and maternal age.

From factor analysis we determined two unobserved variables such that pregnancy weight gain of mother and child was significant effect for three principal components of birth weight, body mass index, maternal weight and gestational age. Therefore, the mean principal components of birth weight, body mass index, maternal weight and gestational age had higher correlation with pregnancy weight gain of mother and pregnancy weight gain of child.

## 5 Conclusion and Recommendation

### 5.1 Conclusion

The purpose of this study was to identify the socioeconomic, maternal and infant factors and assess the effect of those variables with best model.

From the exploratory results we could identify the adequate model to fit birth weight,maternal weight,body mass index and gestational age was multivariate models which has small standard error for all significant predictors as compared to separate model.In this study multiple liner regression,factor analysis, principal component analysis and multivariate multiple regression model were used.

From application of principal components the observed variables birth weight,body mass index, maternal weight and gestational age were transformed to the new variable  $PCA_1$ ,  $PCA_2$  and  $PCA_3$  which was linear and uncorrelated or independent. Therefore,the maternal weight,birth weight and maternal body mass index competitions receive the highest weight of explained ,but gestational age is less important for the first principal components.However,birth weight and gestational age competitions receive more important to determine second principal components where as maternal weight,and body mass index result is less important. Finally, four responses variables competitions receive the highest weight of explained to third principal components.

Under multivariate multiple regression model analysis this study found that region,family size,frequency of watching television,husband educational level ,desire for more children,preferred waiting time for birth,size of child and number of tetanus injections before pregnancy had their own influence on the principal components of four responses.The risk of low birth weight,small gestational age,abnormal pregnancy weight and body mass index in Ethiopia increase when mother received more tetanus injection during pregnancy and who live in oromia and SNNP, mothe who had more family size and more the number of watch TV. Furthermore,the risk of low birth weight,small gestational age,abnormal pregnancy weight and body mass index in Ethiopia increase when parent was not educated,small number of prefer waiting time,desire more child wants with more than 2 years expectancy,small size of child and young mother.

This review may help policy-makers and program officers to design low birth weight,small gestational age,abnormal pregnancy weight and body mass index preventive intervention.

From factor analysis we determined two unobserved variables such that pregnancy

wight gain of mother and child was significant effect for three principal components of birth weight,body mass index, maternal weight and gestational age. Therefore, the mean of principal components of birth weight,body mass index, maternal weight and gestational age had positively correlation with pregnancy wight gain of mother and pregnancy wight gain of child.

## **5.2 Recommendation**

Starting from our finding we recommended for concerned bodies that should create awareness in the society about factors of birth weight, gestational age, pregnancy weight and body mass index during antenatal care .Intervention should be given to the pregnant during antenatal care for minimize the risk of low birth weight,small gestational age,abnormal pregnancy weight and body mass index. Our recommendation going to policy maker that create awareness about reduction of tetanus injection and family size for prevent low birth weight,preterm birth,abnormal pregnancy of weight and body mass index as well as infant mortality during antenatal care.

Similarly,our finding recommend to minimize the risk of low birth weight,small gestational age,abnormal pregnancy weight and body mass index ,they must be increased waiting time to birth of other child and age of mother who wants to birth.Mother should be extend educational level by read or watch related to pregnancy for reduce the problem of low birth weight,small gestational age,abnormal pregnancy weight and body mass index.

Health works should be provide interventions to enhanced the knowledge of parents for desire children properly and guide to parents to waiting more than 2 years for birth of another child. Finally,our recommendation going to the researcher who works on multivariate analysis must be consider the latent or unobserved predictors which has answer why the response variable is correlated to each other.

### **5.2.1 Limitation of the Study**

In this study there are some challenges that we faced. This study was based on secondary data,but some potentially important predictors were not available such as level of income and food type.Some variables are not included because of large number of missing values.We recommended that Ethiopia demographic health survey data collector should register other predictor variables of LBW,SGA,abnormal weight and BMI of mothers.



## References

- [1] Nilufer Akgun, Huseyin L Keskin, Isik Ustuner, Gulden Pekcan, and Ayse F Avsar. Factors affecting pregnancy weight gain and relationships with maternal/fetal outcomes in turkey. *Saudi medical journal*, 38(5):503, 2017.
- [2] DR Anderson and K Burnham. Model selection and multi-model inference. *Second. NY: Springer-Verlag*, 2004.
- [3] Radha Y Aras et al. Is maternal age risk factor for low birth weight? *Archives of medicine and health sciences*, 1(1):33, 2013.
- [4] Nathalie Auger, Marie-Andrée Authier, Jérôme Martinez, and Mark Daniel. The association between rural-urban continuum, maternal education and adverse birth outcomes in quebec, canada. *The Journal of Rural Health*, 25(4):342–351, 2009.
- [5] Yolán Banda, Victoria Chapman, Robert L Goldenberg, Benjamin H Chi, Sten H Vermund, and Jeffrey SA Stringer. Influence of body mass index on pregnancy outcomes among hiv-infected and hiv-uninfected zambian women. *Tropical Medicine & International Health*, 12(7):856–861, 2007.
- [6] Samiran Bisai, Amitava Sen, Dilip Mahalanabis, Nandini Datta, and Kaushik Bose. The effect of maternal age and parity on birth weight among bengalees of kolkata, india. *Human Ecology*, 14:139–143, 2006.
- [7] Hannah Blencowe, Simon Cousens, Mikkel Z Oestergaard, Doris Chou, Ann-Beth Moller, Rajesh Narwal, Alma Adler, Claudia Vera Garcia, Sarah Rohde, Lale Say, et al. National, regional, and worldwide estimates of preterm birth rates in the year 2010 with time trends since 1990 for selected countries: a systematic analysis and implications. *The Lancet*, 379(9832):2162–2172, 2012.
- [8] Helen Y Chu and Janet A Englund. Maternal immunization. *Clinical Infectious Diseases*, 59(4):560–568, 2014.
- [9] Agustin Conde-Agudelo, Anyeli Rosas-Bermúdez, and Ana C Kafury-Goeta. Effects of birth spacing on maternal health: a systematic review. *American journal of obstetrics and gynecology*, 196(4):297–308, 2007.
- [10] National Research Council et al. *Influence of pregnancy weight on maternal and child health: workshop report*. National Academies Press, 2007.

- [11] National Research Council et al. *Weight gain during pregnancy: reexamining the guidelines*. National Academies Press, 2010.
- [12] ICFInternational CSA. Ethiopia demographic and health survey 2011. *Addis Ababa, Ethiopia and Calverton, Maryland, USA: Central Statistical Agency and ICF International*, 430, 2012.
- [13] Ashlesha Datar. The more the heavier? family size and childhood obesity in the us. *Social Science & Medicine*, 180:143–151, 2017.
- [14] Jeff A Dennis and Stefanie Mollborn. Young maternal age and low birth weight risk: an exploration of racial/ethnic disparities in the birth outcomes of mothers in the united states. *The Social science journal*, 50(4):625–634, 2013.
- [15] Martha G Eide, Nina Øyen, Rolv Skjøerven, Stein Tore Nilsen, Tor Bjerkedal, and Grethe S Tell. Size at birth and gestational age as predictors of adult height and weight. *Epidemiology*, pages 175–181, 2005.
- [16] Daniel MT Fessler, C David Navarrete, William Hopkins, and M Kay Izard. Examining the terminal investment hypothesis in humans and chimpanzees: associations among maternal age, parity, and birth weight. *American Journal of Physical Anthropology: The Official Publication of the American Association of Physical Anthropologists*, 127(1):95–104, 2005.
- [17] Marcelo Fiszman, Thomas C Rindflesch, and Halil Kilicoglu. Summarization of an online medical encyclopedia. *Medinfo*, 2004:506–510, 2004.
- [18] Susannah Fox. *The social life of health information 2011*. Pew Internet & American Life Project Washington, DC, 2011.
- [19] Kayla R Furlong, Laura N Anderson, Huiying Kang, Gerald Lebovic, Patricia C Parkin, Jonathon L Maguire, Deborah L O’Connor, Catherine S Birken, TAR-Get Kids! Collaboration, et al. Bmi-for-age and weight-for-length in children 0 to 2 years. *Pediatrics*, 138(1):e20153809, 2016.
- [20] Kara Goodrich, Mary Cregger, Sara Wilcox, and Jihong Liu. A qualitative study of factors affecting pregnancy weight gain in african american women. *Maternal and child health journal*, 17(3):432–440, 2013.

- [21] James M Greenberg. 18 noncardiac problems of the neonatal period. *Pediatric Cardiovascular Medicine*, 2011.
- [22] Raquel PF Guiné, Sofia R Fernandes, José Luís Abrantes, Ana Paula Cardoso, and Manuela Ferreira. Factors affecting the body mass index in adolescents in portuguese schools. *Hrvatski časopis za prehrambenu tehnologiju, biotehnologiju i nutricionizam*, 11(1-2):58–64, 2016.
- [23] Erica P Gunderson. Childbearing and obesity in women: weight before, during, and after pregnancy. *Obstetrics and Gynecology Clinics*, 36(2):317–332, 2009.
- [24] Prakash C Gupta and S Sreevidya. Smokeless tobacco use, birth weight, and gestational age: population based, prospective cohort study of 1217 women in mumbai, india. *Bmj*, 328(7455):1538, 2004.
- [25] Rajat Das Gupta, Ibrahim Hossain Sajal, Mehedi Hasan, Ipsita Sutradhar, Mohamad Rifat Haider, and Malabika Sarker. Frequency of television viewing and association with overweight and obesity among women of the reproductive age group in myanmar: results from a nationwide cross-sectional survey. *BMJ open*, 9(3):e024680, 2019.
- [26] Zhen Han, Sohail Mulla, Joseph Beyene, Grace Liao, and Sarah D McDonald. Maternal underweight and the risk of preterm birth and low birth weight: a systematic review and meta-analyses. *International journal of epidemiology*, 40(1):65–101, 2010.
- [27] Yenework Acham Jemberu, Ahmed Esmael, and Kedir Y Ahmed. Knowledge, attitude and practice towards blood donation and associated factors among adults in debre markos town, northwest ethiopia. *BMC hematology*, 16(1):23, 2016.
- [28] Richard Arnold Johnson, Dean W Wichern, et al. *Applied multivariate statistical analysis*, volume 5. Prentice hall Upper Saddle River, NJ, 2002.
- [29] Abukari Kadiri. *Determinants Of Maternal Weights During Pregnancy And Birth Weight In The Northern Region Of Ghana*. PhD thesis, 2015.
- [30] Samson Kastro, Tsegaye Demissie, and Bereket Yohannes. Low birth weight among term newborns in wolaita sodo town, south ethiopia: a facility based cross-sectional study. *BMC pregnancy and childbirth*, 18(1):160, 2018.

- [31] Anne CC Lee, Pratik Panchal, Lian Folger, Hilary Whelan, Rachel Whelan, Bernard Rosner, Hannah Blencowe, and Joy E Lawn. Diagnostic accuracy of neonatal assessment for gestational age determination: a systematic review. *Pediatrics*, 140(6):e20171423, 2017.
- [32] David J Lilja. *Linear Regression Using R: An Introduction to Data Modeling*. University of Minnesota Libraries Publishing, 2016.
- [33] Elma Izze da Silva Magalhães, Daniela Santana Maia, Carla Fabrícia Araújo Bonfim, Michele Pereira Netto, Joel Alves Lamounier, and Daniela da Silva Rocha. Prevalence and factors associated with excessive weight gain in pregnancy in health units in the southwest of bahia. *Revista Brasileira de Epidemiologia*, 18(4):858–869, 2015.
- [34] LME McCowan, CT Roberts, GA Dekker, RS Taylor, EHY Chan, LC Kenny, PN Baker, R Moss-Morris, LC Chappell, and RA North. Risk factors for small-for-gestational-age infants by customised birthweight centiles: data from an international prospective cohort study. *BJOG: An International Journal of Obstetrics & Gynaecology*, 117(13):1599–1607, 2010.
- [35] Sarah D McDonald, Zhen Han, Sohail Mulla, and Joseph Beyene. Overweight and obesity in mothers and risk of preterm birth and low birth weight infants: systematic review and meta-analyses. *Bmj*, 341:c3428, 2010.
- [36] SD McDonald, Z Han, S Mulla, J Beyene, et al. Overweight and obesity in mothers and risk of preterm birth and low birth weight infants: systematic review and meta-analyses. *Obstetric Anesthesia Digest*, 31(3):158–159, 2011.
- [37] Christina Nicolaidis, Cynthia W Ko, Somnath Saha, and Thomas D Koepsell. Racial discrepancies in the association between paternal vs. maternal educational level and risk of low birthweight in washington state. *BMC pregnancy and childbirth*, 4(1):10, 2004.
- [38] Sévérien Nkurunziza and S Ejaz Ahmed. Estimation strategies for the regression coefficient parameter matrix in multivariate multiple regression. *Statistica Neerlandica*, 65(4):387–406, 2011.
- [39] María Clara Restrepo-Méndez, Debbie A Lawlor, Bernardo L Horta, Alicia Matijasevich, Iná S Santos, Ana MB Menezes, Fernando C Barros, and Cesar G Victora.

- The association of maternal age with birthweight and gestational age: a cross-cohort comparison. *Paediatric and perinatal epidemiology*, 29(1):31–40, 2015.
- [40] Alayne G Ronnenberg, Xiaobin Wang, Houxun Xing, Chanzhong Chen, Dafang Chen, Wenwei Guang, Aiqun Guang, Lihua Wang, Louise Ryan, and Xiping Xu. Low preconception body mass index is associated with birth outcome in a prospective cohort of chinese women. *The Journal of nutrition*, 133(11):3449–3455, 2003.
- [41] Abdul Sattar, Shahbaz Baig, Naveed UR Rehman, and Muhammad Badar Bashir. Factors affecting bmi. *The Professional Medical Journal*, 20(06):956–964, 2013.
- [42] Kelley S Scanlon, Ray Yip, Laura A Schieve, and Mary E Cogswell. High and low hemoglobin levels during pregnancy: differential risks for preterm birth and small for gestational age. *Obstetrics & Gynecology*, 96(5):741–748, 2000.
- [43] Sudesh Raj Sharma, Smith Giri, Utsav Timalsina, Sanjiv Sudarshan Bhandari, Bikash Basyal, Kusum Wagle, and Laxman Shrestha. Low birth weight at term and its determinants in a tertiary hospital of nepal: A case-control study. *PloS one*, 10(4):e0123962, 2015.
- [44] Swati Singh, Constance E Shehu, Daniel C Nnadi, et al. The relationship between maternal body mass index and the birth weight of neonates in north-west nigeria. *Sahel Medical Journal*, 19(4):185, 2016.
- [45] John Singhammer, Maurice B Mittelmark, Anne-Kjersti Daltveit, and Grethe S Tell. The influence on birthweight of maternal living conditions a decade prior to giving birth. *Norsk epidemiologi*, 15(1), 2005.
- [46] JE Siza. 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, 2008.
- [47] Statistics Solutions. Conduct and interpret a multinomial logistic regression. *Statistic Solutions*, 2015.
- [48] Su Jin Sung, Seung Mi Lee, Sunmin Kim, Byoung Jae Kim, Chan-Wook Park, Joong Shin Park, and Jong Kwan Jun. The risk of spontaneous preterm birth according to maternal pre-pregnancy body mass index in twin gestations. *Journal of Korean medical science*, 33(13), 2018.

- [49] Rosnah Sutan, Mazlina Mohtar, Aimi Nazri Mahat, and Azmi Mohd Tamil. Determinant of low birth weight infants: A matched case control study. *Open Journal of Preventive Medicine*, 4(03):91, 2014.
- [50] Tadese Ejigu Tafere, Mesganaw Fanthahun Afework, and Alemayehu Woreku Yalew. Providers adherence to essential contents of antenatal care services increases birth weight in bahir dar city administration, north west ethiopia: a prospective follow up study. *Reproductive health*, 15(1):163, 2018.
- [51] Tessa M Wardlaw. *Low birthweight: country, regional and global estimates*. Unicef, 2004.
- [52] Joshua L Weiss, Fergal D Malone, John Vidaver, Robert H Ball, David A Nyberg, Christine H Comstock, Gary D Hankins, Richard L Berkowitz, Susan J Gross, Lorraine Dugoff, et al. Threatened abortion: a risk factor for poor pregnancy outcome, a population-based screening study. *American journal of obstetrics and gynecology*, 190(3):745–750, 2004.
- [53] Sho-hei Yoshida, Nobuya Unno, Hideyuki Kagawa, Norio Shinozuka, Shiro Kozuma, and Yuji Taketani. Sonographic determination of fetal size from 20 weeks of gestation onward correlates with birth weight. *Journal of Obstetrics and Gynaecology Research*, 27(4):205–211, 2001.
- [54] Sho-hei Yoshida, Nobuya Unno, Hideyuki Kagawa, Norio Shinozuka, Shiro Kozuma, and Yuji Taketani. Sonographic determination of fetal size from 20 weeks of gestation onward correlates with birth weight. *Journal of Obstetrics and Gynaecology Research*, 28(4):231–232, 2002.
- [55] Zhangbin Yu, Shuping Han, Jingai Zhu, Xiaofan Sun, Chenbo Ji, and Xirong Guo. Pre-pregnancy body mass index in relation to infant birth weight and offspring overweight/obesity: a systematic review and meta-analysis. *PloS one*, 8(4):e61627, 2013.
- [56] Ehsan Zareian, Farhad Saeedi, and Vahid Rabbani. The role of birth order and birth weight in the balance of boys aged 9-11 years old. *Annals of Applied Sport Science*, 2(2):51–64, 2014.

# A Appendix

A<sub>1</sub>

Table A.1: Description of Variable in Study and Coding one

Variables	Factor Categories
Child Twin	0=single ,1=multiple
Preceding Birth Interval(in months)	continues
Mother Education	0=Noeducation,1=Primary ,2=Secondary,and higher
Husband education level	0=Noeducation,1=Primary ,2=Secondary,and higher
Birth Weight	Continues)
Family Size	Continues)
Sex of the child	0=male ,1=female
Source of Water Supply	0=unimproved ,1= improved
Maternal BMI	Continues
Sex of Household Head	0=male ,1=female
No. of Antenatal Visits	Continues
HIV Status of Mother	0=no ,1=yes
Region	1=Tigray,2=Afar ,3=Amhara ,4= oromo....,10
Gestational Age at Birth	Continues
Tetanus Injection before birth	0=no,1=1-3,2=4-6,3=>7,4=did not known
Tetanus Injection before pregnancy	0=no,1=1-3,2=4-6,3=>7,4=did not known
Live birth between births	0=no,1=yes
Desire for more children	1=Wants within 2 years,....,8=never had sex
Wealth index	1=Poorest,2=Poorer,3=Middle,4=Richer,5=Richest
Household has: electricity	0=no,1=yes
Total children ever born	count

Table A.2: Description of Variable in Study and Coding two

Age of respondent at 1st birth	continues
Number of living children	count
Contraceptive use and intention	0=no,1=modern,2=tradition
Size of Child at Birth	1= Large,2= medium,3=small
Height of Mother	Continues
Smokes Cigarettes	0=no,1=yes
Chews Tobacco	0=no,1=yes
Hemoglobin Level	Continues
Anemia Level	1=severe,2=moderate,3=mild,4=not
Mother Drink Alcohol	0=no,1=yes
Weight of Maternal	Continues
Place of Residence	1=urban ,2=rural
Birth Weight	Continues
Distance to Health Facility	0=no,1=yes
Age groups	1=15-19,2=20-24,3=25-29,4= > 30
Preferred waiting time for birth	0=<1,1=1,2=2,3=3,4=4,5=5,6=6,7=7,8=8
Timing of 1st antenatal check (months)	continuous
Antenatal care: government hospital	0=no,1=yes
Antenatal care: private hospital	0=no,1=yes
Antenatal care: private hospital	0=no,1=yes
Frequency of reading newspaper or magazine	0=no,1=<1,2=1,3=always
Frequency of listening to radio	0=no,1=j1,2=1,3=always
Frequency of watching television	0=no,1=1,2=1,3=always
Age at first sex	continues



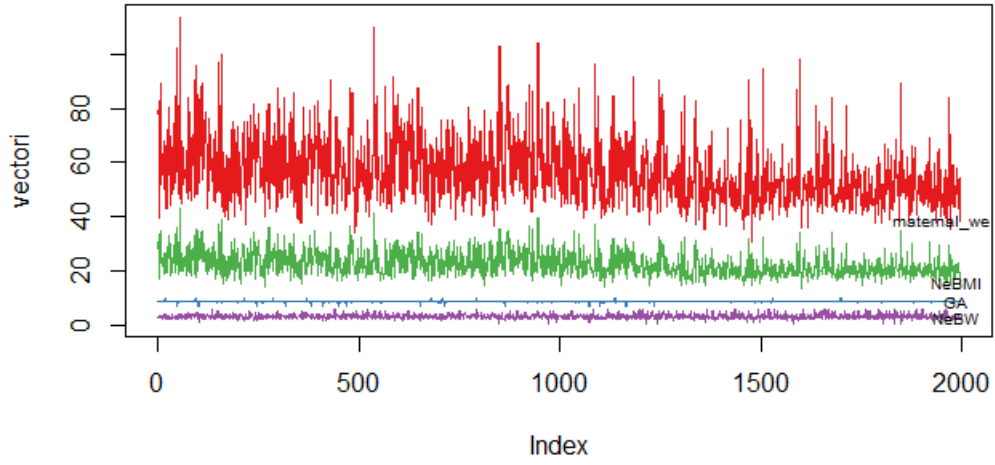


Figure 2: Profile Plot of Original Response Variables

*C*

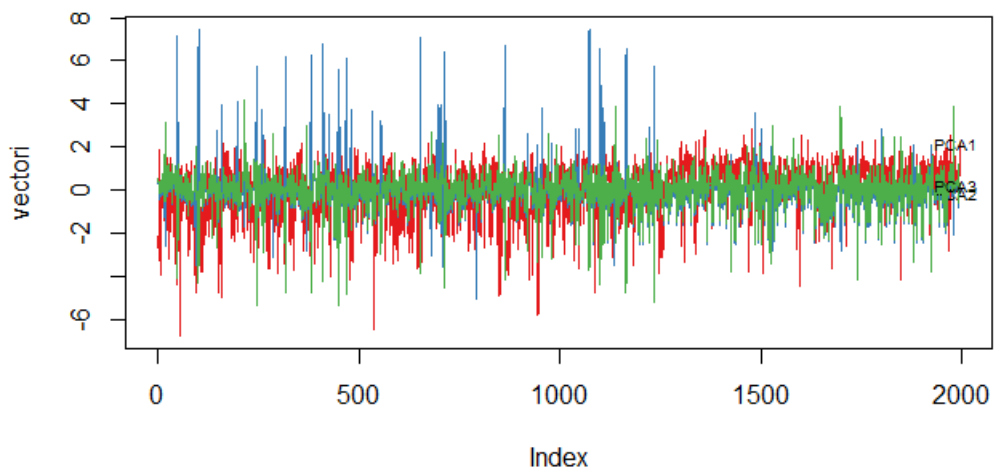


Figure 3: Profile Plot of Principal Components

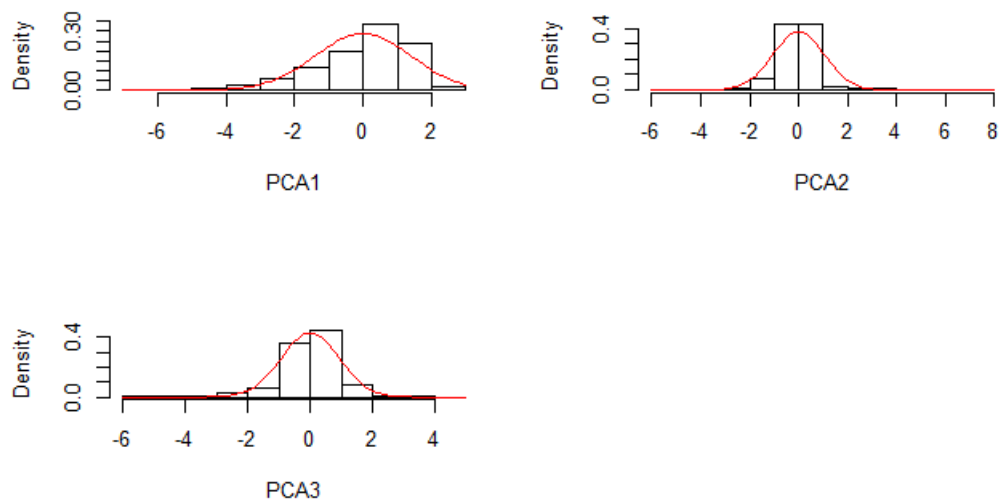


Figure 4: Distribution of Residuals

*D*

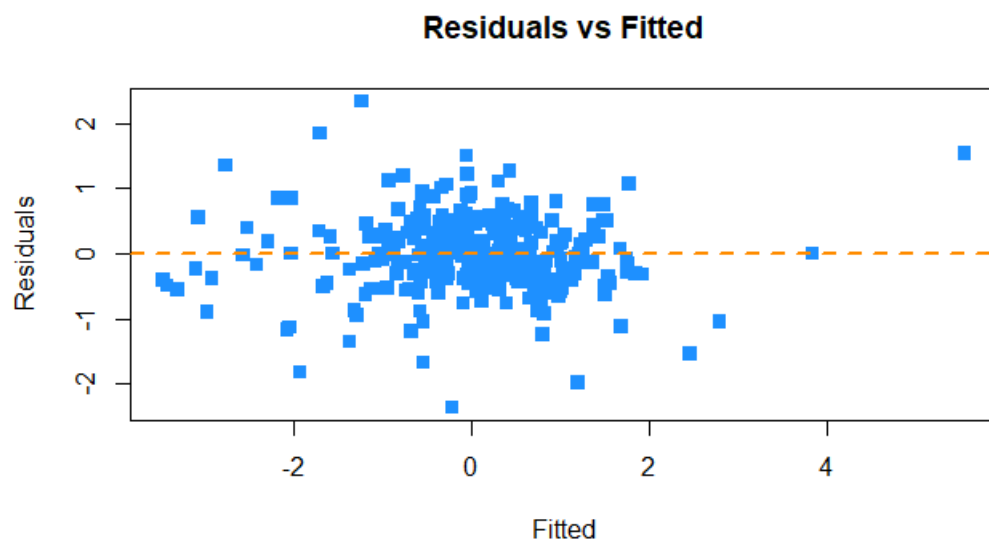


Figure 5: Residual Plot

### Multivariate Distribution of Studentized Residuals

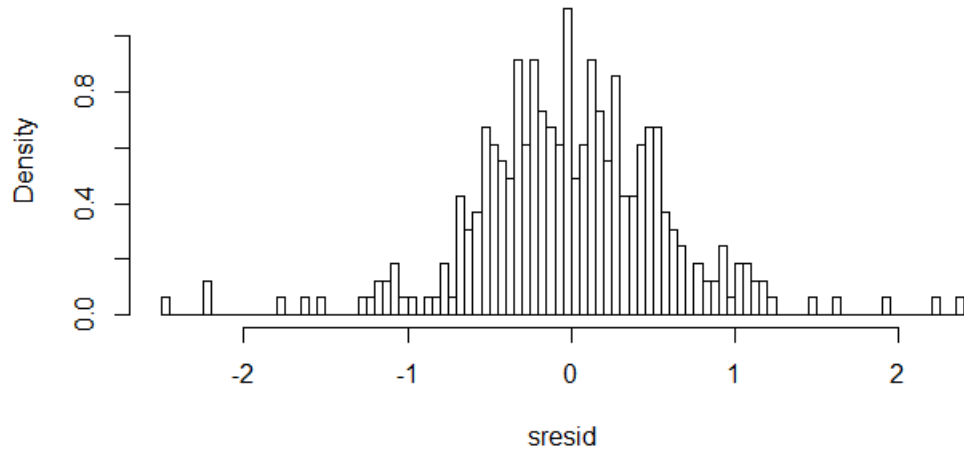


Figure 6: Histogram

*E*

### Normal Q-Q Plot after transformation

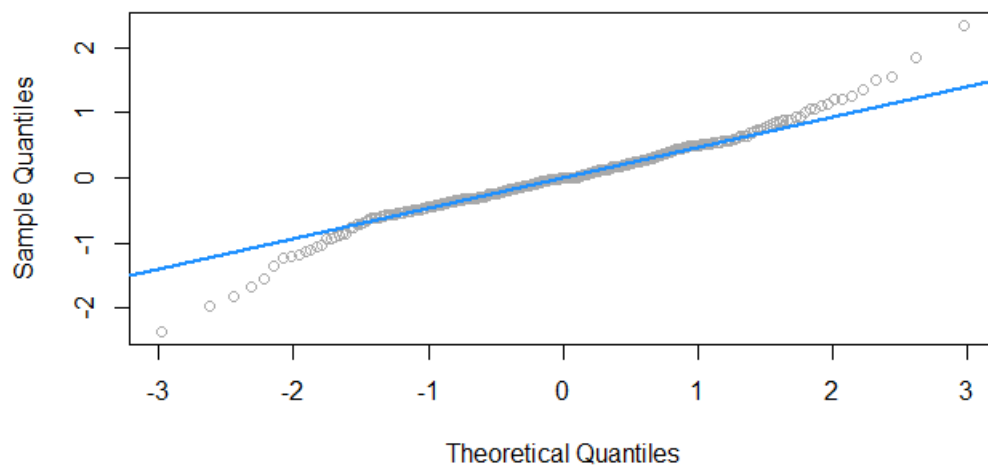


Figure 7: QQplot

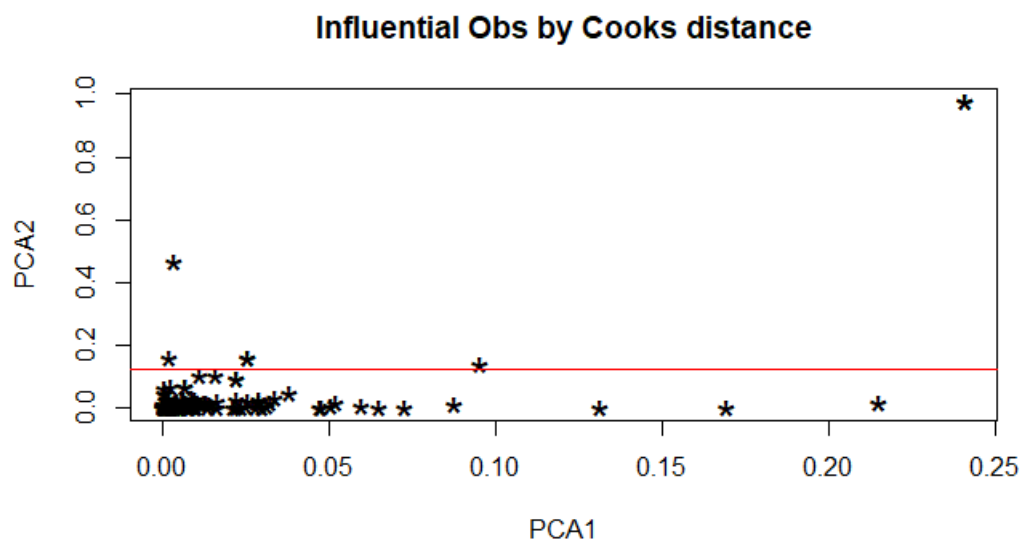


Figure 8: Cook Distance