***Review Article***

# MULTINOMIAL LOGISTIC REGRESSION MODELING OF SOME FACTORS AFFECTING WEIGHT OF CHILD AT BIRTH

# IMPACT OF MATERNAL EDUCATION ON WEIGHT OF CHILD AT BIRTH: USE OF MULTINOMIAL LOGISTIC REGRESSION MODELING

**OR**

# EFFECT OF MATERNAL EDUCATION AND CHILD WEIGHT AT BIRTH: IN MULTINOMIAL LOGISTIC REGRESSION MODEL




## ABSTRACT

Childbirth weight can be defined as the baby's weight at birth. World Health Organization (WHO) gave the range of normal birth weight as 2.5 – 4.2 kilograms and every child whose birth weight is below this lowest bound is regarded as low birth weight (LBW) and is 40 times more likely to die when compared to a normal weighted baby. Then, to reduce these overwhelming death records due to LBW in developing countries, urgent research about the causes of LBW is very necessary. The Multinomial Logistic Regression model was applied to data from the 2018 Nigerian Demographic and Health Survey report to predict the probability of giving birth to LBW (less than 2.5kg), normal birthweight (between 2.5kg and 4.2kg), and overweight (over 4.2kg) babies using the maternal education level and age variables. The data collection was naturally stratified by maternal education level (1 = Higher Education, 2 = Secondary Education, 3 = Primary Education, and 4 = No Education). The equal sample allocation technique was used, which assigns equal stratum sample sizes ($n_i$ = 200 for the $i^{th}$ maternal education level in this case). The 800 sample size was reduced to 735 after screening for outliers in the maternal age data. Out of a total of 54 low birth weights, 57% (0.5741) were from mothers with no education. The results showed mother's education level and age have a causal effect on childbirth weight in Nigeria. Younger mothers (less than 28years) are 96.5% likely to have LBW babies at birth while mothers who attained a minimum of primary, secondary, and higher education are 88.00%, 82.00%, and 57.90% likely to have normal birth weight babies at birth respectively when compared to those with no formal education. The results, therefore, suggested that mothers should acquire at least primary school education and early child marriage (less than 28years) of the girl child discouraged.

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*Keywords:* Multinomial Logistic Regression; World Health Organization; Demographic and Health Survey; Low Birth Weight, Maternal education level

## 1. INTRODUCTION

The weight at birth of a baby usually serves as a good measure of intrauterine growth; a reliable predictor of a baby's survival probability and psychosocial development. On average, European babies weigh 3.5kg, but the normal weight at term delivery as prescribed by the World Health Organization (2014)[14] is 2.5 – 4.2 kg. Every child's birthweight below the lower bound of the WHO standard is regarded as having low birth weight (Park, 2007)[9]. Low birth weight (LBW) may result in high medication costs to the individual and society at large. There are many determinants of LBW but the most important is maternal social status, which can be measured as maternal education level (Shi, 2004)[10]. Maternal education is a measure of a mother's education level. (Here, maternal education is educational status or educational level of a pregnant woman) It affects birthweight by enhancing the productivity of health investments. This simply justifies that the impact of maternal education level is worthy of research. Ganchimeg, *et al.* (2014)[5] found that there is an increased risk of adverse birth outcomes in younger mothers (10 – 19 years) when compared with adult mothers (20 – 24 years) after controlling for covariates. Currie and Moretti (2003)[3], opined that maternal education has a causal effect on the use of prenatal care, improves the choice of life partner, reduces smoking, and also reduces the incidence of low birth weight by 1%. Luis *et al.* (2017)[6] used Multinomial Logistics Regression (MLR) to estimate the probability of each category of General Health Perception among some selected independent variables (stress, burnout, sleeping troubles, and depressive symptoms). The dependent variable had 5 levels (deficient, reasonable, good, very good, and excellent). The findings from the MLR analyses revealed that moving from the reference category (deficient level) to other categories of the dependent variable is not significantly caused by stress but by burnout and some levels of depressive and sleeping troubles. Mengasha *et al. (*2017)[8], investigated predictors of low birth weight and macrosomia (overweight) in Tigray, Northern Ethiopia. The dependent variable in the multinomial logistic regression had three nominal categories (low, normal, and macrosomia). The result showed that 10.5% and 6.68% incidence were recorded for low birth weight and macrosomia respectively. Fayehun and Asa (2020)[4], recently examined factors causing abnormal birth weights in urban areas of Nigeria. The findings from the paper suggested that the significant predictors of low birth weight are: geographical region, child characteristics (the type of birth), and household (wealth index) while the significant predictors of high birth weight were: geographical region, child characteristics, maternal education, and health utilization. The work of Fayehun and Asa (2020)[4] was conducted for people in urban areas of Nigeria, but this paper has extended the research to include both rural and urban residents and estimated the probabilities of each category of birth weight (low, normal, and overweight) in Nigeria.

**Statement of the Problem**

WHO (2014)[14] revealed that, out of 139 million live births in the world, more than 20 million LBW babies are delivered yearly, consisting of 15.5% of all live births, about 95.6% of them come from developing countries. Park (2007)[9] opines that 50% of all perinatal and 75% of all infant deaths occur in babies with LBW. It is very crucial to study the factors that cause low birth weight, identify these factors and recommend ways to cushion their effects to reduce deaths amongst newborn babies in Nigeria.

**Aim and Objectives of the study**

This paper aims to build a Multinomial Logistic Regression model to predict the probabilities of low, normal, and overweight babies from Nigerians. The specific objectives are to:

i) estimate the relative risk in mother's age for giving birth to low birth weight versus normal birth weight baby and overweight versus normal birth weight baby,
ii) estimate the relative risk in the mother's education level on the weight of the child,
iii) generate the predicted probabilities for the observations,
iv) investigate the changes in the predicted probability associated with maternal education level, and
v) plot the predicted probabilities against the maternal age score.

## 2. MATERIAL AND METHODS

### Logistic Regression

Logistic regression is a statistical model that employs a function other than the usual least-squares approach to model a binary dependent variable. The function is called the logistic function and it models the probability of a certain dependent variable, class, or event existing such as on or off, pass or fail, win or lose, healthy or sick. Logit regression is important in the area of machine learning, medical sciences, and social sciences. Boyd *et al*. (1987)[2], developed Trauma and Injury Severity Score (TRISS) widely used to predict mortality (death or alive) using the logistic regression function.

**Binary Logistic Model**

Consider a model with two independent variables say, $x_1$ and $x_2$ , and one binary (Bernoulli) response variable $\mathrm{Y}$, denoted as $\pi = \mathrm{P}(\mathrm{Y}=1)$. If it is assumed that there is a linear relationship between the independent variables and the log-odds (logit) of the response, then this linear relationship is represented mathematically in the following form

$$\xi = \log_b \frac{\pi}{1-\pi} = \beta_0 + \sum_{i=1}^{2} \beta_i x_i \qquad (1)$$

where $\xi$ is the log-odds, *b* is the base of the logarithm, and $\beta_i$ are parameters of the model: Exponentiating the logit gives the odds as expressed in equation (2)

$$\frac{\pi}{1-\pi} = b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)} \qquad (2)$$

Dividing the numerator and denominator of (2) by $b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)}$, the probability that $Y=1$ is

$$\pi = \frac{b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)}}{b^{\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right)} + 1} = \frac{1}{1 + b^{-(\beta_0 + \sum_{i=1}^{2} \beta_i x_i)}} = S_b\left(\beta_0 + \sum_{i=1}^{2} \beta_i x_i\right) \qquad (3)$$

where $S_b$ is the sigmoid function with base $b$ fixed.

Equation (3) states that, if $\beta_i$ is fixed, then either the log-odds $Y=1$ for a given observation or the probability that $Y=1$ can be calculated.

**Multinomial Logistic Regression (MLR)**

Multinomial logistic regression generalizes the logistic regression to more than two categories of problems. The multinomial logistic regression is simply a logit model with more than two possible discrete outcomes for the outcome variable. The model was used in this study to predict the probabilities of the different possible outcomes of childbirth weight (low, normal, and overweight) that has a nominal scale using some set of independent variables (maternal education level and age).

**Model of MLR**

Multinomial logistic regression uses a linear predictor function say $f(k,l)$ to predict the probability that an observation say *i* has outcome *k*, of the following form:

$$f(k,l) = \beta_{0,k} + \sum_{m=1}^{k} \beta_{1,k} x_{m,i} + \beta_{2,k} x_{2,i} + e_i \qquad i = 1, 2, . . . ., n; \quad l = 1, 2, ...., m; \qquad (4)$$

Where

$k = Categories\ of$ birth weight

$f(k,l)$ is a linear prediction function that predicts the likelihood of observation $x_{m,i}$ that has an outcome as $k$

$\beta_{0,k}$ is the intercept term of the linear prediction function

$\beta_{1,k}$ is the regression parameter of the maternal education level at the kth outcome.

$\beta_{2,k}$ is the regression parameter of maternal age at the kth outcome

$x_{m,i}$ is the $i^{th}$ observation of the $m^{th}$ level of maternal education level variable

$e_i$ is the $i^{th}$ random error component associated with observation $i$

In this paper,

$x_{1,i}$ is Higher Education

$x_{2,i}$ is Secondary School

$x_{3,i}$ is Primary School

$x_{4,i}$ is No Education

This paper uses 735 data points and each data point consists of a set of 2 independent variables (maternal education level and age) and an associated categorical outcome variable $Y_i$ (weight of child). The $Y_i$ was coded into three groups using the WHO (2014)[14] recommendation. The Normal birthweight was chosen as the reference level in the dependent variable while No education level was chosen as a reference level in the categorical predictor variable. To arrive at the multinomial logit model, for K possible outcomes of the outcome variable (childbirth weight), running K-1 independent binary logistic regression models, in which one outcome is chosen as a "reference level" (Normal birthweight) and then the other K-1 outcomes are separately regressed against the reference level outcome.

If outcome K (Normal birthweight) is chosen as the pivot:

$$Ln\left(\frac{P_r(Y_i=1)}{P_r(Y_i=K)}\right)=\beta_1 X_{m,i} \tag{5}$$

$$Ln\left(\frac{P_r(Y_i=2)}{P_r(Y_i=K)}\right)=\beta_2 X_{m,i}$$

$$\vdots \tag{6}$$

$$Ln\left(\frac{P_r(Y_i=k-1)}{P_r(Y_i=K)}\right)=\beta_{k-1} X_{m,i}$$

Exponentiating both sides and solving for the probabilities in equations (5) and (6), we get:

$$P_r(Y_i=1)=P_r(Y_i=K)\exp(\beta_1 X_{m,i})$$

$$P_r(Y_i=2)=P_r(Y_i=K)\exp(\beta_2 X_{m,i})$$

$$\vdots \tag{7}$$

$$P_r(Y_i=K-1)=P_r(Y_i=K)\exp(\beta_{k-1} X_{m,i})$$

The probability of any K possible childbirth weight can be expressed as:

$$P_r(Y_i = K) = 1 - \sum_{k=1}^{k-1} P_r(Y_i = k)$$
$$= 1 - \sum_{k=1}^{k-1} P_r(Y_i = k)\exp(\beta_k X_{m,i})$$
$$= \frac{1}{\sum_{k=1}^{k-1} \exp(\beta_k X_{m,i}) + 1} \quad (8)$$

Other probabilities can be computed:

$$P_r(Y_i = 1) = \frac{\exp(\beta_1 X_{m,i})}{\sum_{k=1}^{k-1} \exp(\beta_k X_{m,i}) + 1}$$
$$P_r(Y_i = 3) = \frac{\exp(\beta_3 X_{m,i})}{\sum_{k=1}^{k-1} \exp(\beta_k X_{m,i}) + 1}$$

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$$P_r(Y_i = K-1) = \frac{\exp(\beta_{K-1} X_{m,i})}{\sum_{k=1}^{k-1} \exp(\beta_k X_{m,i}) + 1} \quad (9)$$

The unknown parameters in each regression parameter vector $\beta_k$ are typically jointly estimated by an extension of maximum likelihood using regularization of the weights. The solution is typically found using any of the following: iteratively reweighted least squares (IRLS), (Bishop, 2006)[1], gradient-based optimization algorithms such as L-BFGS (Malouf, 2002)[7], or specialized coordinate descent algorithms (Yu and Huang 2011)[15]. The iteratively reweighted least squares by Bishop (2006)[1], were implemented in this paper using the R statistical programming software, version 4.10.

## 3. RESULTS AND DISCUSSION

**Data Source and Nature**

Secondary data extracted from the 2018 Nigeria Demographic and Health Survey data was used for this study. The independent (predictor) variables of interest are maternal age and education levels while the dependent (response) variable was childbirth weight. The dependent variable was recoded into a different variable (nominal scaling) using the recommended WHO standards, where birth weights less than 2.5kg are classified as Low Birth Weight, between 2.5kg to 4.2kg, is classified as Normal Birth Weight, and above 4.2kg is classified as Overweight. The data collection was naturally stratified by maternal education levels (1 = Higher Education, 2 = Secondary Education, 3 = Primary Education, and 4 = No Education). The equal sample allocation technique was used and assigns equal sample sizes ($n_i$ = 200 for the ith maternal education level in this case) to all strata irrespective of the stratum population size, stratum variability, or cost per unit. However, after removing the rows with possible outliers (in maternal age), as shown in Figure 1, the following stratum sample sizes were used (Higher Education level = 193, Secondary Education = 180, Primary Education = 169, and No Education = 193).The outlier test using the box and whisker's plot in Figure 1 showed that the maternal age data does not contain an outlier which may influence the proportion of observations in each child's birth weight level.

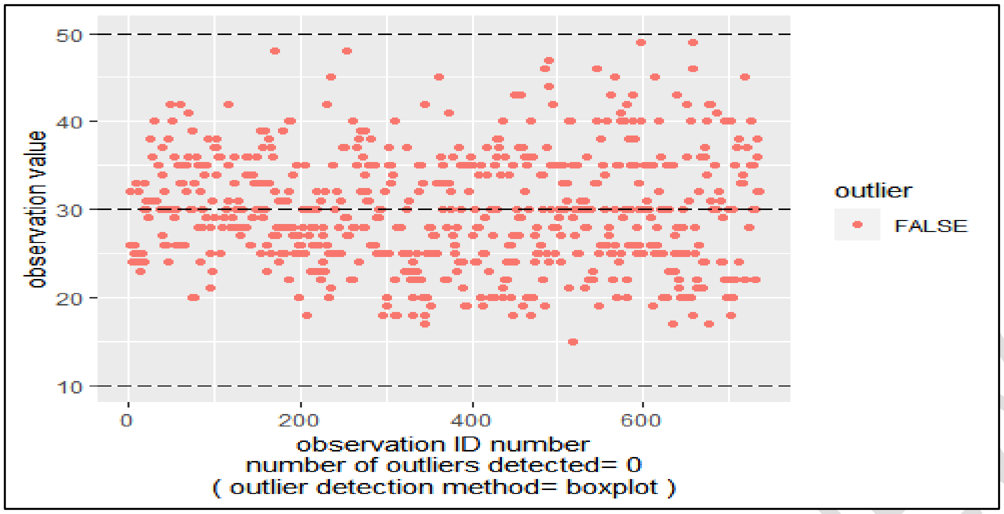


**Figure 1**: The maternal age Box and Whisker's distribution.

Table 1 below shows that the mean weight of the sampled 735 child weights was 3.2kg with a corresponding 0.59 standard deviation. The standard deviation values show that the individual observations are not very far from the mean value. The mean age of the mothers considered for this seminar work is approximately 30 years.

## Table 1: Descriptive Statistics

| | Mean | Std. Deviation | Skewness | | Kurtosis | | N |
|---|---|---|---|---|---|---|---|
| | | | Statistic | Std. Error | Statistic | Std. Error | |
| Weight of Child at Birth | 3.1971 | .58667 | .202 | .090 | -.019 | .180 | 735 |
| Highest Education Level | 2.4925 | 1.14108 | - | - | - | - | 735 |
| Mother's Age | 29.91 | 6.261 | .290 | .090 | -.263 | .180 | 735 |

The correlation values between Maternal Education Level and mother's age with the weight of the child at Birth are -0.247 and 0.136 respectively. They are significant at the alpha level (0.05) but very small. This satisfies the assumption of the multinomial logistic regression because the correlations do not necessarily need to be high.

**Table 2: Correlation Matrix**

| | | Weight of Child at Birth | Maternal Education Level | Mother's Age |
|---|---|---|---|---|
| Pearson Correlation | Weight of Child at Birth | 1.000 | -.247 | .136 |
| | Maternal Education Level | -.247 | 1.000 | -.035 |
| | Mother's Age | .136 | -.035 | 1.000 |
| Sig. (1-tailed) | Weight of Child at Birth | . | **.000**** | **.000**** |
| | Highest Education Level | **.000**** | . | .172 |
| | Mother's Age | .000** | .172 | . |

Table 3 shows that about 57% (0.5741) of the Low Birth Weight babies among the proportion of LBW set were from mothers with No Education. This proportion is too high and needs to be investigated

**Table 3: Proportion of Birth weight by Mother's Education Level**

| Maternal Education | Low Birth Weight | Proportion | Normal Birth Weight | Proportion | Overweight | Proportion | Total |
|---|---|---|---|---|---|---|---|
| Higher Education | 13 | 0.24 | 164 | 0.253 | 16 | 0.471 | 193 |
| Secondary School | 6 | 0.12 | 159 | 0.246 | 15 | 0.441 | 180 |
| Primary School | 4 | 0.07 | 165 | 0.255 | 0 | 0.000 | 169 |
| No Education | 31 | 0.57 | 159 | 0.246 | 3 | 0.088 | 193 |
| Total (%) | 54 (7.34%) | 1.000 | 647 (88.03%) | 1.000 | 34 (4.63%) | 1.000 | **735** |

. Table 4 shows that Maternal Age and Education influence Childbirth Weight in Nigeria.

**Table 4: Mean Maternal Age at different Birth Weight and Maternal Education Levels**

| | Birth Weight Levels for mean age | | | |
|---|---|---|---|---|
| **Maternal Education** | **Low Birth Weight** | **Normal Birth Weight** | **Over Weight** | **Grand Total** |
| Higher Education | 29.54 | 31.23 | 32.44 | 31.22 |
| Secondary School | 27.50 | 28.16 | 32.87 | 28.53 |
| Primary School | 32.75 | 29.35 | | 29.43 |
| No Education | 28.42 | 30.51 | 38.33 | 30.30 |
| **Grand Total** | **28.91** | **29.82** | **33.15** | **29.91** |

**Table 5: Iteratively reweighted least squares by Bishop (2006) output**

```
# weights:  18 (10 variable)
initial  value 807.480032
iter  10 value 294.120938
iter  20 value 291.199334
final  value 291.190994
converged
```

A diagnostic examination is conducted on the multinomial logistic regression model with two predictor variables. The standard errors of the predictor variables are between 0 and 2 (Table 6) suggesting no multicollinearity among the predictor variables.

**Table 6: Multinomial Logistic Regression Output**

**Coefficients:**

| | (Intercept) | Higher Educ. | Pri. Sch | Sec. Sch | Maternal Age |
|---|---|---|---|---|---|
| LBW | -0.626 | -0.865 | -2.120 | -1.712 | -0.034 |
| OW | -7.300 | 1.732 | -6.568 | 1.917 | 0.100 |

**Std. Errors**:

| | (Intercept) | Higher Educ. | Pri. Sch | Sec. Sch | Maternal Age |
|---|---|---|---|---|---|
| LBW | 0.704 | 0.350 | 0.544 | 0.463 | 0.023 |
| OW | 1.247 | 0.646 | 1.640 | 0.659 | 0.030 |

**Table 7: Wald Statistic and Coefficient Significance Test Output**

| | (Intercept) | Higher Educ. | Pri. Sch | Sec. Sch | Maternal Age |
|---|---|---|---|---|---|
| LBW | 0.790 | 6.088 | 15.135 | 13.683 | 2.137 |
| OW | 34.251 | 7.174 | 0.160 | 8.460 | 10.632 |

**p-values**

| | (Intercept) | Higher Educ. | Pri. School | Sec. School | Age |
|---|---|---|---|---|---|
| LBW | **3.74e-01**** | **0.013**** | **0.0001**** | **0.0002**** | 0.1438 |
| OW | **4.84e-09**** | **0.007**** | 0.688 | **0.0036**** | **0.0011**** |

Footnote: LBW- Low Birth Weight; OW- Over Weight

The model fitting information (Table 8) shows that the multinomial logistic regression model with two predictor variables is better at predicting childbirth weight in Nigeria than the multinomial logistic regression model without the two predictor variables (p-value = 0.000).

**Table 8: Model Fitting Information**

| Model | Model Fitting Criteria | Likelihood Ratio Tests | | |
|---|---|---|---|---|
| | -2 Log Likelihood | Chi-Square | df | Sig. |
| Intercept Only | 336.637 | | | |
| Final | 263.020 | 73.617 | 8 | **0.000**** |

Pearson chi-square (p-value = 0.994) and Deviance (p-value = 1.000) in Table 9 show that the multinomial regression model with two predictor variables indicates a good fit to the data.

**Table 9: Goodness-of-Fit**

| | Chi-Square | df | Sig. |
|---|---|---|---|
| Pearson | 160.552 | 208 | .994 |
| Deviance | 145.699 | 208 | 1.000 |

The Nagelkerke R-square indicates that 16.1% of the total variations in a child's birth weight occurred due to the variations among the two predictor variables (Table 10).

**Table 10: Pseudo R-Square**

| | |
|---|---|
| Cox and Snell | 0.095 |
| Nagelkerke | 0.161 |
| McFadden | 0.112 |

The two predictor variables are statistically significant in predicting a child's birth weight in Nigeria (Table 11, p-value = 0.001 and p-value = 0.000 respectively).

**Table 11: Likelihood Ratio Tests**

| Effect | Model Fitting Criteria | Likelihood Ratio Tests | | |
|---|---|---|---|---|
| | -2 Log Likelihood of Reduced Model | Chi-Square | df | Sig. |
| Intercept | 263.020 | .000 | 0 | . |
| Age | 276.529 | 13.509 | 2 | **0.001**** |
| Education | 326.290 | 63.270 | 6 | **0.000**** |

Following equation (5) and (6), the logit models are as follow:

$$Ln\left(\frac{weight=Low}{weight=normal}\right)=\beta_{10}+\beta_{11_1}\ (\text{maternal edu.}=\text{Highe }r)$$
$$+\beta_{11_3}(\text{maternal edu.}=\text{Primary})$$
$$+\beta_{11_2}(\text{maternal edu.}=\text{Secondary})$$
$$+\beta_{12}(\text{maternal A}ge.) \quad (10)$$

$$Ln\left(\frac{\text{weight}=\text{Overweight}}{\text{weight}=\text{normal}}\right)=\beta_{20}+\beta_{21_1}\ (\text{maternal edu.}=\text{Higher})$$
$$+\beta_{21_3}(\text{maternal edu.}=\text{P}rimary)$$
$$+\beta_{21_2}(\text{maternal edu.}=\text{Secondary})$$
$$+\beta_{22}(\text{maternal A}ge.) \quad (11)$$

Following equation (10), we have that:

$$Ln\left(\frac{weight=Low}{weight=normal}\right)=-0.63-0.86(\text{maternal edu.}=\text{Higher})$$
$$-2.12(\text{maternal edu.}=\text{Primary})$$
$$-1.71(\text{maternal edu.}=\text{Secondary})$$
$$-0.034(\text{maternal Age}) \quad (12)$$

Following equation (11), we have that:

$$Ln\left(\frac{\text{weight}=\text{Overweight}}{\text{weight}=\text{normal}}\right)=-7.3+1.73(\text{maternal edu.}=\text{Higher})$$
$$-6.57(\text{maternal edu.}=\text{P}rimary)$$
$$-1.92(\text{maternal edu.}=\text{Secondary})$$
$$+0.101(\text{maternal A}ge.) \quad (13)$$

The exponent of the regression coefficients in equations (11) and (12) is shown in Table 12

**Table 12: Exponents of the Multinomial Regression Parameters**

| | (Intercept) | Higher Educ. | Pri. Sch | Sec. Sch | Age |
|---|---|---|---|---|---|
| LBW | 0.5348 | 0.4211 | 0.1200 | 0.1803 | 0.9665 |
| OW | 0.0007 | 5.6536 | 0.0014 | 6.800 | 1.105 |

Refer to equations (10), (11), (12), and (13), following Ugwuanyim *et al*. (2020)[12], the interpretation follows:

**Interpretation of the regression coefficients for Low Birth Weight vs. Normal Birth Weight**

$\beta_{12}$ = A one-unit increase in maternal age is associated with the decrease in the log odds of giving birth to a low-weight baby vs. a normal-weight baby in the amount of -0.034, this coefficient is not significant as the p-value is 0.1438 (Tables 6 and 7 respectively). The relative risk (exp(-0.034) = 0.9665)) implies that a one-unit increase in maternal age reduces the odds for low birth weight by (1 – 0.9665 = 0.0335)*100 = 3.35%.

$\beta_{11_1}$ = The log odds of giving birth to a low-weight baby vs normal birth weight will decrease by -0.866 when a mother with no education attains higher education (Table 6). This coefficient is significant in predicting childbirth weight (p-value is 0.014) at 5%. The relative risk (exp (-0.866) = 0.421), also implies that mothers who move from no education to higher education are (1.000 – 0.421 = 0.579)*100 = 57.9% more likely to give birth to a normal birth weight baby.

$\beta_{11_2}$ = The log odds of giving birth to a low-weight baby vs a normal-weight baby will decrease by -1.71 when a mother moves from no education to secondary school level. This decrease is significant at 5% (p-value = 0.0002). The relative risk (exp (-1.71) = 0.18), also implies that mothers who move from no education to secondary education are (1.000 – 0.18 = 0.82)*100 = 82% more likely to give birth to normal weight babies.

$\beta_{11_3}$ = The log odds of giving birth to a low weight baby vs a normal weight baby will decrease by -2.12 when a mother moves from no education to primary school level of education. This coefficient is significant at 5% (p-value = 0.001). The relative risk (exp (-2.12) = 0.12), also implies that mothers who move from no education to primary education are (1.000 – 0.120 = 0.88)*100 = 88.0% more likely to give birth to normal weight baby.

**Interpretation of the regression coefficients for Overweight vs. Normal Birth Weight**

$\beta_{22}$ = A one-unit increase in maternal age is associated with the increase in the log odds of giving birth to an overweight baby vs. a normal-weight baby in the amount of 0.100 (Table 6). The increase is significant at 5% (p-value = 0.001). This simply means that one unit increase in maternal age increases the relative risk (exp (0.100) = 1.106)) of giving birth to overweight baby by (1.105- 1.000 = 0.106)*100 = 10.6%.

$\beta_{21_1}$ = The log odds of giving birth to an overweight baby vs normal weight increases by 1.73 when a mother with no education attains Higher Education. The increase is significant at 5% (p-value = 0.00740). The relative risk (exp (1.73) = 5.65)), also implies that mothers who move from no education to higher education are (5.65 – 1.000 = 4.65)*100 = 465% more likely to give birth to overweight babies.

$\beta_{21_2}$ = The log odds of giving birth to an overweight baby vs a normal weight baby will increase by 1.92 when a mother with no education attains secondary school level of education. The increase is significant at 5% (p-value = 0.0036). The relative risk (exp (1.92) = 6.820)), also implies that mothers with no education that attains secondary education are (6.82 - 1.000 = 5.82)*100 = 582% more likely to give birth to overweight babies.

$\beta_{21_3}$ = The log odds of giving birth to an overweight baby vs a normal weight baby will decrease by -6.57 when a mother with no education attains primary school level of education. The decrease is not statistically significant at 5% (p-value = 0.688). The relative risk (exp (-6.57) = 0.00140)), also implies that mothers with no education that attains primary education are (1.000 – 0.00140 = 0.999)*100 = 99.9% more likely to give birth to normal weight babies.

**Predicted Probabilities (or Relative Risk) and Interpretation**

The computed predicted probabilities for each of the outcome levels (childbirth weight) and the first six rows of the 735 rows are shown in Table 13

**Table 13: Predicted Probabilities for each level of childbirth weight**

| | Normal Weight | Low Weight | Over Weight |
|---|---|---|---|
| 1 | 0.8542138 | 0.06475142 | 0.08103480 |
| 2 | 0.8734275 | 0.08120511 | 0.04536743 |
| 3 | 0.8756458 | 0.08714508 | 0.03720917 |
| 4 | 0.8756458 | 0.08714508 | 0.03720917 |
| 5 | 0.8734275 | 0.08120511 | 0.04536743 |
| 6 | 0.8734275 | 0.08120511 | 0.04536743 |

To examine the changes in predicted probability associated with one of the two independent variables, small datasets varying one variable while holding the other constant can be created. When maternal age and its mean (29 years) are held constant, the changes in the predicted probabilities for each level of maternal education are displayed in Table14. Table 14 shows that the probability of a normal birth weight baby increases but decreases for a low birth weight baby as the maternal education levels move from higher to no education while holding maternal age at the average.

**Table 14: Changes in predicted probabilities at mean maternal age**

| | Normal Birth Weight | Low Birth Weight | Over Weight |
|---|---|---|---|
| 1 | 0.86 | 0.07 | 0.07 |
| 2 | 0.89 | 0.03 | 0.08 |
| 3 | 0.98 | 0.02 | 0.00 |
| 4 | 0.83 | 0.16 | 0.01 |

**Footnote:** 1 = Higher, 2 = Secondary, 3 = Primary and 4 = No education

Table 15 showed the mean probability of the three categories of the outcome variable at each level of maternal education. It was observed that the probability was smaller for low birth weight for those mothers with higher education and highest for those with no education. However, higher educated mothers had a high mean predicted probability for overweight classification more than others**.**

**Table 15: The Mean probabilities of child birth weight within each levels of education**

| | Normal Birth Weight | Low Birth Weight | Over Weight |
|---|---|---|---|
| Higher Education | 0.58 | 0.03 | 0.39 |
| Secondary School | 0.56 | 0.01 | 0.43 |
| Primary School | 0.99 | 0.01 | 0.00 |
| No Education | 0.78 | 0.09 | 0.13 |

The plot of the predicted probabilities is shown in figure 2, the likelihood that a mother will give birth to low weight baby decreases as the age of the mother increases, and the curve is almost flattened for all levels of education other than no education. The plot also shows that as the age of the mother increases, the likelihood of such a mother giving birth to an overweight child increases for all levels of education but remains constant for mothers with only primary school education

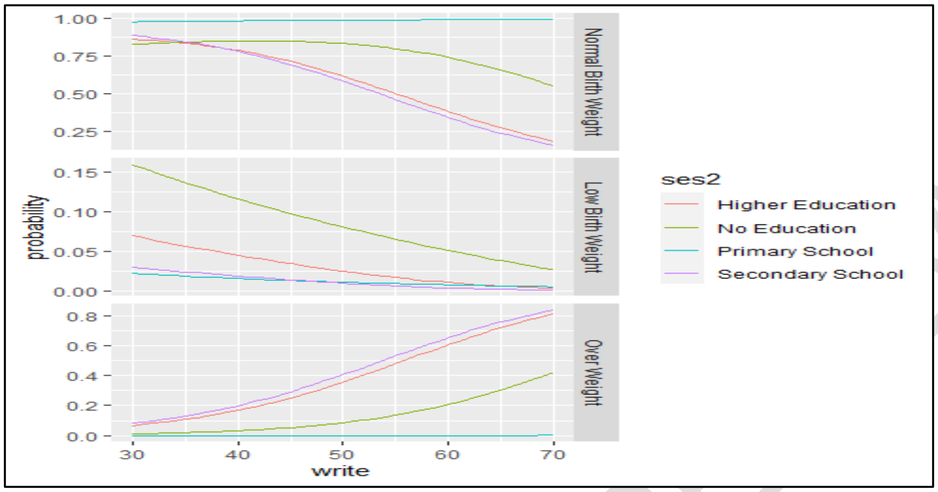

Figure 2: Plot of the predicted probabilities

## 4. CONCLUSION

**Table 16: Summary of findings**

| Variable | Relative Risk | Interpretation |
|---|---|---|
| Maternal Age | Low Birth Weight vs. Normal Birth Weight = 0.9665 | Older mothers are **3.35%** likely to have low-weight babies at birth. This implies that younger mothers are at risk. |
| | Overweight vs. Normal Birth Weight = 1.10596 | Younger mothers are **10.6%** likely to have overweight babies at birth. This implies that older mothers are at risk. |
| Higher Education | Low Birth Weight vs. Normal Birth Weight = 0.4211. | Mothers who move from no education to higher education are **57.9%** likely to give birth to a normal-weight baby at birth. |
| | Overweight vs. Normal Birth Weight = 5.65 | Mothers that switch from no education to higher education are **46.5%** likely to give birth to overweight babies at birth. |
| Primary School | Low Birth Weight vs. Normal Birth Weight = 0.12 | Mothers that move from no education to primary school level of education are **88%** likely to have normal birth weight babies at birth. |
| | Overweight vs. Normal Birth Weight = 0.0014 | Mothers who move from no education and attain primary school level of education are **99%** likely to have normal-weight babies at birth. |
| Secondary School | Low Birth Weight vs. Normal Birth Weight = 0.18 | Mothers that move from no education to secondary school level of education are **82%** likely to have normal-weight babies at birth. |
| | Overweight vs. Normal Birth Weight = 6.8 | Mothers that move from no education to secondary school level of education are **82%** likely to have overweight babies at birth. |

i) The weight of a child at birth is positively correlated with the mother's age. This finding is in agreement with Welcher and Mellits (1971)[13] that had also reported positive relationships between maternal age and infant birth weight.

ii) From Table 14, as we go up from no education to Higher education, the likelihood to give birth to low weight baby decreases. This means that maternal education increases the weight of a child at birth. This finding is in agreement with the findings of (Shi, 2004)[10] and Fayehun and Asa (2020)[4].

iii) (Figure 2 showed that) low birth weight babies are associated more with no educated mothers and this likelihood decreases as maternal age increases (Figure 2).

Based on the findings of this work, the following recommendations follow:
Recommendations based on study findings are;

i) That early marriage of the girl child should be discouraged in Nigeria since low child birth weight is associated with younger mothers (less than 28years) and children with low birth weight are more likely to die than those with normal weight.

ii) The girl child should at least acquire primary school education before marriage since maternal education has been shown in this paper to significantly affect child birth weight and the causal effect of education is identified for individuals with a low level of education rather than at the upper end of the education distribution.



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