Determinants of Low Birth Weight Neonates: A Case Study of Tamale Metropolis in Ghana

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ABSTRACT

Low Birth Weight (LBW), a birth weight less than 2.5kg, is an important public health problem because LBW infants are at greater risk of mortality and morbidity in early infancy (WHO, 2004; UNICEF, 2004). The rate of LBW in the Northern Region consistently ranks high among the ten regions in Ghana, and Tamale metropolis has the highest percentage of LBW births among the twenty districts in the Northern Region, and this is a major concern for health care providers given the high cost of caring for LBW infants. In this study, logistic regression model was used to identify the determining variables in predicting LBW babies in the metropolis. The model was based on the birth records of 500 mothers of singleton neonates resident in the Tamale metropolitan area of the Northern Region of Ghana from November 2010 to January 2011. The significant model coefficients were Gestation (p-value = 0.0008), Household size (p-value = 0.0160), Maternal food intake (p-value = 0.0002), Maternal health (p-value = 0.0000), Passive smoking (p-value = 0.0003) and Type of fuel used for cooking (p-value = 0.0418). A test of predictive ability of the model showed correct classifications of 93% for normal birth weight infants and 76.8% for LBW infants. The likelihood ratio and Nagelkerk R² tests showed positive correlation between the predictors and LBW. Using the Hosmer and Lemeshow test of goodness of fit, a p-value 0.206 was obtained and thus the null hypothesis that the model fits the data well could not be rejected.

Keywords
Birth Weight, Logistic, Predictors, Maternal, neonate

INTRODUCTION
The presumption that women of childbearing age should not possess any special skills in order to give birth to normal and healthy babies may be untrue, especially for women in Tamale metropolis in the Northern Region of Ghana. Available records show that the metropolis consistently records higher rates of LBW infants in the region (Northern Region Reproductive

In informal conversations, many health experts in the region agreed with reports by UNICEF and WHO (2004) and UNICEF (2005) that high rate of LBW is a major problem in developing countries yet the issue and factors influencing it has not received the much-needed attention. The result being that some expectant mothers undermine foetal welfare and thus many births result in LBW babies.

Unavailability of adequate information on the causes of LBW to the general public, especially expectant mothers has compounded the situation. In this evidence-based era, this is a real concern, as no evidence will be available for policy decision-making. This underscores the need to identify and highlight the main risk factors that cause LBW, with the ultimate aim of eliminating it.

LBW prevalence is a major public health issue since it is considered the single most important predictor of infant mortality, particularly in the first month of life (Blanc et al, 2005), and is a significant factor in many adverse child health and development outcomes (WHO, 2004).

Risk factors include maternal age, alcohol abuse, smoking, lack of pre-natal care, gestational age, and maternal ill health (Allen et al, 2001; Steyn et al, 2006; Knopik, 2009; Salmasi et al, 2010).

In this study, logistic regression model was used to investigate the determining factors of LBW neonates and postulating a predictive model of the likelihood of a pregnancy resulting in a LBW neonate in the metropolis.

**MATERIALS AND METHODS**

**Study Design and Data Sources**

The study was a cross-sectional design. Data included all singleton births over a period of three months (November 2010 to January 2011). Five hospitals randomly selected in the metropolis served as study sites. They are the Choggu Clinic, Tamale Central Hospital, Tamale West Hospital, The SDA Hospital and Fulera Maternity Home. The above community-based hospitals provide both antenatal care and counseling services to expectant mothers. The locations of these hospitals in the metropolis portray respondents of variable socio-economic backgrounds.

After obtaining the consent of the women to partake in the study, a structured questionnaire was used to elicit data pertaining to mother’s socio-economic and reproductive-obstetrical information. Maternal and newborn medical history such as number of antenatal visits, gestational age, maternal health, maternal weight gain during pregnancy, neonate’s sex and birth weight recorded in the folders of mothers at the medical facility during the course of pregnancy were all captured by the questionnaire.

**Sampling Techniques**
In order to meet the data requirement for this study, all singleton births to mothers who had medical history recorded at the medical facility during the course of their pregnancy were sampled. Mothers had to be ordinarily resident in the metropolis to be eligible for the study.

**Study Area**
Tamale metropolis

**Study Population**
All mothers who delivered between November 2010 and January 2011 in the metropolis.

**Determination of Sample Size**
Using a guideline provided by Hosmer et al (2000) that the minimum number of cases per independent variable is 10, with a preferred ratio of 20 to 1, a sample of 500 mothers were selected for the study.

**Study Variables**
We define our outcome variable $Y$ as a binary response corresponding to the risk of a neonate being born LBW. That is, $Y = \begin{cases} 1, & \text{if neonate is LBW} \\ 0, & \text{otherwise} \end{cases}$

Explanatory variables $X$ include maternal age, marital status, parity, cigarettes smoking by the mother during pregnancy, maternal educational attainment, family income, gestational age, passive smoking, type of fuel used by the mother for cooking, type of residence, number of antenatal visits, maternal health, maternal food intake, household size, maternal weight gain during pregnancy, employment status, occupation, history of previous LBW, birth spacing and new-born sex.

Logistic regression model was used to identify risk factors for LBW by estimating the odds ratios (OR) and their 95% confidence interval (CI). A multivariable analysis was conducted to control for confounders. This analysis was carried out by the simultaneous method, where all variables were entered at once. A 0.05 level of significance was used and the data processed and analysed using *Epi info*3.4.1 software.

**Logistic Regression Model for Binary Data**
When we have a binary response variable $Y$, and a vector of associated covariates $X$, the preferred mathematical model to deal with the complex and generally nonlinear interrelationships among the many variables is the binary logistic regression model (Agresti, 2007). Logistic regression combines the independent variables to estimate the probability that an event of interest will occur, that is, a subject will be a member of one of the groups defined by the dichotomous dependent variable.
In our LBW risk application for $Y$ categorical, taking value $Y = \begin{cases} 1, & \text{LBW} \\ 0, & \text{otherwise} \end{cases}$, and the probability of occurrence being a function of covariates $X$, of the form:

$$P(Y = 1 | X = x) = \frac{\exp(\sum \beta x)}{1 + \exp(\sum \beta x)}$$

the binary logistic regression is implied (Subhash, 1996; Agresti, 2007).

If we let $x_i = (1, x_{i1}, ..., x_{ij})^T$ denote the value of predictor $j$ ($j = 1, 2, ..., J$) for subject $i$ ($i = 1, 2, ..., N$), and $y_i = (y_{i1}, ..., y_{ij})^T$ denote setting $i$ of values of $j$ explanatory variables, and $\beta = (\beta_0, ..., \beta_i)^T$, then the logistic regression model (Equation 1) becomes

$$P(Y_i) = \frac{\exp(\sum \beta x_{ij})}{1 + \exp(\sum \beta x_{ij})}.$$ (2)

Within the framework of generalized linear models (GLMs), we assume $Y_i$ are independently and identically distributed Bernoulli random variables with $E(Y_i) = \mu_i$. GLMs linearize the relationship between the mean structure $\mu_i$ and the response variable $Y_i$ via $g(\mu_i) = E(Y_i)$, where $g(.)$ is a monotonic differentiable link function such as the logit (Nelder et al, 1972). The logit link function, which is the log odds, has the linear relationship:

$$\log \frac{P(Y_i)}{1 - P(Y_i)} = \sum \beta x_{ik}$$ (3)

where $X$ represents any collection of exposure variables of interest, whiles $\beta$ are unknown parameters to be estimated.

Like most models, the binary logistic regression uses maximum likelihood (ML) estimation to compute model coefficients (McCulloch, et al, 2001). Under weak regularity conditions, such as the parameter space having fixed dimension with true value falling in its interior, maximum likelihood (ML) estimation has desirable consistency and asymptotic properties (Agresti, 2007; Carlo et al, 2010). The ML method, unlike the least squares, can be used to estimate complex nonlinear as well as linear models, and for this study, because the logistic model is nonlinear, ML estimation is preferred.

The method estimates the parameters by first determining the likelihood function $L(\beta)$, which represents the joint probability of observing the data that have been collected. That is,

$$L(\beta | y_1, y_2, ..., y_n) = f(y_1, y_2, ..., y_n | \beta) = \prod f(y_i | \beta).$$ (4)

Thus the log-likelihood $lnL(\beta | y_1, y_2, ..., y_n) = \sum \ln f(y_i | \beta)$. (5)

In our LBW application, given that our response variable is binary with $n_i$ observations and $y_i$ successes at fixed values of $x_i$, then $\{Y_1, ..., Y_N\}$ are independent binomials having density

$$P(Y = y) = P(y_i)^{y_i}[1 - P(y_i)]^{n_i - y_i},$$ (6)

with $E(Y_i) = n_i P(y_i)$, where $n_1 + \cdots + n_N = n$. 

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The joint likelihood function of (Equation 6) (after some manipulation of the terms) is
\[
\prod_{i=1}^{N} P(y_i)^{y_i} [1 - P(y_i)]^{n_i-y_i} = \left\{ \prod_{i=1}^{N} \exp \left[ \log \left( \frac{P(y_i)}{1-P(y_i)} \right)^{y_i} \right] \right\} \left\{ \prod_{i=1}^{N} [1 - P(y_i)]^{n_i} \right\} \exp \left[ \sum_i y_i \log \left( \frac{P(y_i)}{1-P(y_i)} \right) \right] \left\{ \prod_{i=1}^{N} [1 - P(y_i)]^{n_i} \right\}. \tag{7}
\]

Thus, for the logistic regression model \( P(y_i) = \frac{\exp(\sum_k \beta_k x_{ik})}{1+\exp(\sum_k \beta_k x_{ik})} \), the \( i \)-th logit is \( \sum_j \beta_j x_{ij} \) (see Equation 3), so the exponential term in (Equation 7),
\[
\exp \left[ \sum_j y_i (\sum_j \beta_j x_{ij} \beta_j) \right] = \exp \left[ \sum_j (\sum_j y_i x_{ij} \beta_j) \right]. \tag{8}
\]

Also, since \([1 - P(y_i)] = [1 + \exp(\sum_j \beta_j x_{ij})]^{-1}\), the log likelihood
\[
\mathcal{L}(\beta) = \sum_j (\sum_j y_i x_{ij} \beta_j) - \sum_j n_i \log [1 + \exp(\sum_j \beta_j x_{ij})]. \tag{9}
\]

The ML process then chooses that estimator, \( \hat{\beta} \) of the set of unknown parameters, \( \beta \) which maximizes \( L(\beta) \) (McCulloch, et al, 2001; Lance et al, 2004).

Like many models, the curve of \( L(\beta) \) is concave (Kleinbaum et al, 1994) and \( \hat{\beta} \) is the point at which \( \frac{\partial \ln L(\beta)}{\partial \beta_j} = 0, j = 1, 2, ..., k \). \tag{10}

The ML estimate is then the solution of (Equation 10).

For our model, since \( \frac{\partial L(\beta)}{\partial (\beta_j)} = \sum_j y_i x_{ij} - \sum_j n_i x_{ij} \frac{\exp(\sum_k \beta_k x_{ik})}{1+\exp(\sum_k \beta_k x_{ik})} \),
\[
\sum_j y_i x_{ij} - \sum_j n_i \hat{\beta}_i x_{ij} = 0, j = 1, ..., k, \tag{11}
\]
where \( \hat{\beta}_i = \exp(\sum_k \hat{\beta}_k x_{ik})/[1 + \exp(\sum_k \hat{\beta}_k x_{ik})] \) is the ML estimate of \( P(x_i) \).

If \( X \) denotes the \( N \times k \) matrix \( x_{ij} \), then the likelihood equations have form
\[
X \hat{\beta} = X \hat{\mu}, \tag{13}
\]
where \( \hat{\mu} = n_i \hat{\beta}_i \).

Maximum-likelihood estimation is an iterative procedure that successively tries to work to get closer and closer to the correct answer using the likelihood equations (Kleinbaum et al, 1994).

Often, the Newton Raphson iterative method is used to solve the nonlinear equations, by generating a sequence of guesses that converge to the location of the maximum (Agresti, 2007).

The overall measure of how well the model fits is given by the likelihood value, which is similar to the residual sum of squares value for multiple regression (McCulloch, et al, 2001). A model that fits the data well will have a small likelihood value. If the P-value for the overall model fit
statistic is less than the conventional 0.05 then there is evidence that at least one of the independent variables contributes to the prediction of the outcome.

RESULTS
This study covered 500 mothers, and the mean age was 27.2 (±6.2) years. Results of Table 1 show that a large proportion of mothers (60%) were between 20 and 30 years old, reflecting a relatively young age structure among mothers in the metropolis. Teenage mothers constituted 11.2%, whiles mothers above 40 years old constituted only 1.0% of the 500 mothers sampled. About half of the mothers (44%) were illiterate, and only 4.4% attained tertiary education status, suggesting low literacy levels among mothers in the metropolis. A little over three-quarters of the respondents were married.

Table 1: Mothers’ Socio-Demographic Characteristics

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Observation</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age of Respondent</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>56</td>
<td>11.2</td>
</tr>
<tr>
<td>20-30</td>
<td>300</td>
<td>60.0</td>
</tr>
<tr>
<td>31-40</td>
<td>139</td>
<td>27.8</td>
</tr>
<tr>
<td>&gt;40</td>
<td>5</td>
<td>1.0</td>
</tr>
<tr>
<td>Total</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td><strong>Educational Level of Respondent</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Education</td>
<td>220</td>
<td>44.0</td>
</tr>
<tr>
<td>Basic</td>
<td>162</td>
<td>32.4</td>
</tr>
<tr>
<td>Sec/Vocational</td>
<td>96</td>
<td>19.2</td>
</tr>
<tr>
<td>Tertiary</td>
<td>22</td>
<td>4.4</td>
</tr>
<tr>
<td>Total</td>
<td>500</td>
<td>100</td>
</tr>
</tbody>
</table>

In general, cases of LBW were recorded across the age spectrum. However, babies born to mothers below age 20 were the most affected by the LBW anomaly; close to half (41.1%) of mothers below age 20 gave birth to low weight babies, compared with 28.0%, 24.5% and 20.0% of mothers 20-30, 31-40 and those above 40 years respectively. Surprisingly, only 20% of mothers above 40 years gave birth to low weight babies, contrary to findings of similar work on birth-weight, suggesting higher rates of LBW among older mothers (Kelly et al, 1996). These analyses are shown in Table 2.
The results of Table 2 also show that women with no formal education ranked highest (30.9%) in pregnancies that resulted in LBW babies. Mothers with basic, Sec/Vocational and tertiary level education followed in that order (29%, 26%, and 9.1% respectively). As educational level advanced, the percentage of mothers who gave birth to LBW babies showed substantial declines. About half (44.2%) of mothers who used firewood for cooking were shown in this study to have given birth to LBW babies compared with the 14.7% mothers who used Liquefied Petroleum Gas (LPG), which generates virtually no smoke (Table 2).

Gestational Age and Intra Uterine Growth Retardation
Results of our study show that the mean duration of pregnancy was 36.7015(±1.82) weeks whiles the mean birth-weight was 2.7144kg (± 0.54970). About 85.8% of all the LBW babies were born at 37 weeks, with only 0.7% of them being 40 weeks old. The overall proportion of small for gestational age (SGA) therefore stood at 86.5%. Other research findings concluded that most LBW infants in developing countries were born at term but were affected by IUGR (Doctor et al, 2001).

RELATIONSHIP BETWEEN SEX OF BABY AND BIRTH-WEIGHT
Results of the chi-square test of independence (Table 3) showed no significant dependence between neonate sex and birth-weight (\( p = 0.257 \geq \alpha = 0.05 \)).

Table 3: Chi-Square Test of Independence

<table>
<thead>
<tr>
<th>Value</th>
<th>df</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.719</td>
<td>2</td>
<td>.257</td>
</tr>
</tbody>
</table>

Table 3: Chi-Square Test of Independence

<table>
<thead>
<tr>
<th>Pearson ( \chi^2 )</th>
<th>Value</th>
<th>df</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.719</td>
<td>2</td>
<td>.257</td>
</tr>
<tr>
<td>No of Valid Cases</td>
<td>500</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
PREVALENCE OF LOW BIRTH WEIGHT IN THE TAMALE METROPOLIS
The prevalence of low birth weight in a population is defined as the percentage of live births that weigh less than 2.5kg out of the total of live births during the same period. In this study, Number of live births with birthweight less than 2.5kg = 142
Total number of live births = 500

Hence
\[
\frac{142 \times 100}{500} = 28.4\% 
\]

The overall low birth weight rate of 28.4% is much higher than the overall low birth weight rate for the metropolis (15.3%) as reported by the 2009 Northern Region RCH annual report.

FITTING THE LOGISTIC REGRESSION MODEL
Results of Table 4 show that gestation was a significant factor for LBW (p-value = 0.0008). The odds ratio 0.1828 is the statistical evidence supporting the relationship that a one-unit increase in gestation decreased the odds that a mother would give birth to a LBW baby by 81.72%. Similar findings from international studies have shown shorter gestational age for giving birth to LBW infants (Steyn et al, 2006; Salmasi et al, 2010).

Household size also showed significance (p-value = 0.0160, OR = 1.2009), and a one unit increase in household size increased the odds that a mother would give birth to a LBW baby by 20.09%. This finding is not surprising because the communal system of living is typical of people of the Northern Region of Ghana.

The feeding habits of mothers during pregnancy also played an important role in explaining reasons for variation in birth weight outcomes (p-value = 0.0002, OR = 0.4477), and a one unit increase in maternal food intake decreased the odds of LBW by 55.23%. This finding is similar to a review published more than a decade ago by Kramer (Gortmaker et al, 1997) who concluded that maternal nutritional factors both before and during pregnancy account for >50% of cases of LBW in many developing countries.

We also observe from Table 4 that maternal history of ill health including anaemia, nausea, malaria and other pregnancy-related medical complications increased the risk of giving birth to a LBW infant by 19.8192 folds (p-value < 0.0001).

Maternal exposure to passive smoking was also found as a risk factor for LBW (p-value = 0.0003, OR = 7.2226), although it was self-reported.

Finally, associated with LBW in this study, is the variable ‘Type of Fuel Used for Cooking’ (p-value = 0.0418). The odds ratio of 0.2411 indicates that we have more success in group two. That is, a mother who used charcoal for cooking was more likely to give birth to a normal weight baby than a mother who used firewood.
However, since the p-values for the remaining independent variables were greater than $\alpha = 0.05$ level of significance, we concluded that they were not statistically significant, and were therefore excluded from the model.

### Table 4: Epi Info Analysis Output of the Logistic Regression Model

<table>
<thead>
<tr>
<th>Term</th>
<th>O.R.</th>
<th>95% C.I.</th>
<th>Coefficient</th>
<th>S. E.</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gestation</td>
<td>0.1828</td>
<td>0.0680</td>
<td>0.4915</td>
<td>1.6995</td>
<td>0.5047</td>
</tr>
<tr>
<td>HouseholdSize</td>
<td>1.2009</td>
<td>1.0347</td>
<td>1.3938</td>
<td>0.1830</td>
<td>0.0760</td>
</tr>
<tr>
<td>MaternalFoodIntake</td>
<td>0.4477</td>
<td>0.2925</td>
<td>0.6853</td>
<td>-0.8035</td>
<td>0.2171</td>
</tr>
<tr>
<td>MaternalHealth</td>
<td>19.8192</td>
<td>8.7893</td>
<td>44.6905</td>
<td>2.9866</td>
<td>0.4149</td>
</tr>
<tr>
<td>PassiveSmoking</td>
<td>7.2226</td>
<td>2.4807</td>
<td>21.0285</td>
<td>1.9772</td>
<td>0.5452</td>
</tr>
<tr>
<td>TypeOfFuel</td>
<td>0.2411</td>
<td>0.0613</td>
<td>0.9485</td>
<td>-1.4225</td>
<td>0.6988</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>63.7645</td>
<td>18.6637</td>
</tr>
</tbody>
</table>

**Fitted Model**

In this analysis, the p-value of the model chi-square (64.929) was <0.0001, which is less than 0.05. Further, the Nagelkerke R square 0.706 gives an indication that about 71% of the variation in LBW is explained by the predictor variables. The model is therefore useful in predicting LBW.

Hence, the best-fit logistic regression model, for individual characteristics, of the likelihood of a pregnancy resulting in a LBW neonate in the metropolis is presented below:

$$logitP(LBW = 1) = 63.76 - 1.70G + 0.18_{HS} - 0.80_{MFI} + 2.99_{MH} + 1.98_{PS} - 1.42_{TF}$$

**DISCUSSION**

This study evaluated the contributions of various risk factors to the prevalence of LBW in the Tamale metropolis of the Northern Region of Ghana. Most of the risk factors, especially alcohol and substance abuse, were scored negative by higher proportions of mothers. However, using logistic regression analysis to construct a predictive model, the outcome reaffirms well established findings which concluded that shorter gestation, large household size, maternal malnutrition, poor health, Passive Smoking and use of firewood for cooking were detrimental to neonatal weight-gain and so predisposes babies to LBW (Jamal and Khan, 2003, Valero et al, 2004; Knopik, 2009; Salmasi et al, 2010).

The most powerful predictor for LBW in the metropolis was maternal health, especially among mothers who suffered chronic malaria or anaemia during pregnancy. This was considered even more important than preterm birth (or shorter gestation). Documented research has confirmed that maternal diseases increase the risk of delivering LBW infants (Jamal et al, 2003; Berghella, 2007; ACOG, 2007). Improving the health of a mother is said to enhance foetal well-being and consequently eliminates or minimizes the prevalence of LBW (WHO, 2004; Knopik, 2009).
Maternal food intake has been shown to be a key dimension in birth-weight studies. Obstetricians value quality and regular diets because it might lead to better pregnancy outcomes and allay fears and concerns of anaemia and subsequently LBW. A balanced diet on its own is not a function of maternal health improvement, but it is a dimension of birth-weight outcomes (WHO, 2003). In our study, the median number of meals eaten by a mother a day was less than four. Fewer meals a day was found to be significantly associated with LBW in this study (Table 4).

Another risk factor is the proportion that reported having partners or people close to them that smoked cigarettes. Results of Table 2 show that 65.3% of all mothers exposed to secondary smoking delivered low weight babies. Table 4 also shows that mothers who were passive smokers during pregnancy were nearly eight times as likely to give birth to a LBW neonate compared with non-passive smoking mothers. Evidence suggests the strong effect of passive smoking during pregnancy on LBW even after controlling for other variables (Steyn et al, 2006).

A further risk factor of LBW was proportion of respondents who used firewood for cooking. The firewood when used for cooking generates smoke; the mothers then inadvertently inhale this smoke. The etiology of LBW is complex such that even environmental factors such as indoor air pollution due to cooking smoke from firewood and poor housing quality are known determinants (Steyn et al, 2006). Moreover, the energy expended by the women in gathering firewood could put extra stress on a pregnancy, possibly interfering with foetal growth and full-term delivery (Vinod et al, 2004).

We used maternal household size (family size) also as a risk factor. We found the median family size to be quite large, and significantly associated with LBW (Table 4). The large and extended family system, practiced largely by people in the Northern Region of Ghana, enjoins all members of the family to eat from the same bowl. This often affects the dietary needs of women who need special menus, especially during pregnancy.

Concerning family income, findings from this research indicate that a greater number of mothers (65.8%) lived on less than one dollar a day. Since poverty acts to limit access to care and the choice and quantity of foods available to pregnant women, maternal malnutrition occurs, a fact that might explain this variable’s association with LBW (Gomes et al, 1999). Although family income remained in the univariate and multivariable analyses as a risk factor for LBW, it was not statistically significant in predicting LBW (p-value = 0.3799).

No significant relationship between LBW and maternal age was found (p-value = 0.2648) in this study.

Although maternal educational level was not significant even for the univariate analysis, it showed a strong inverse relation with LBW, where more women with little or no education gave birth to LBW babies than those with vocational or tertiary level education. Well established studies have indicated that mothers with lower educational level have a higher likelihood of giving birth to LBW neonates (Finch, 2003, Grjibovski et al, 2002).

Maternal residence type did not show a statistically significant relationship with LBW, but an increased risk (OR = 2.1621) was observed for pregnant women who lived in thatch houses.
Studies on LBW have suggested significant associations with socioeconomic indicators and area deprivation. Women with lower socio-economic status and those living in deprived areas give birth more to LBW infants (Dibben et al, 2006).

CONCLUSION AND RECOMMENDATIONS

Overall, the prevalence of LBW in the Tamale metropolis is 28.4%, implying that about one in every three births resulted in a LBW neonate.

The latent determinants of the prevalence of LBW neonates in the metropolis are gestation, household size, maternal food intake, maternal health, Passive Smoking and Type of Fuel used for cooking. From this study, the weight of an infant at birth does not depend on its sex.

Although the overall LBW prevalence of 28.4% in the metropolis was high, the mean birth weight of 2.7144kg is commendable. Results of this study also show that pregnant women were apparently awake to the risks and consequences of their health related decisions, such as smoking, dietary needs and how these decisions affect their unborn children. This was evident when most of the risk factors, especially alcohol and substance abuse, were scored negative by higher proportions of mothers. The findings are consistent with other international research work, which indicated that risky maternal behaviour during pregnancy adversely affect birth-weight.

Given the findings of this study, detailing the relationship between maternal socioeconomic and anthropometric variables and the prevalence of LBW in the metropolitan area of Tamale, a follow-up research that investigates the nature of the existing relationship between these causal factors and prevalence of LBW is recommended.

Educational programs and a wide array of prenatal services need to be readily available and accessible to all expectant mothers. Pregnant women need to be educated on the risks and consequences of their health related decisions, such as smoking and dietary needs, and how it affects their unborn children in order to prevent premature births and low birth weight. Efforts to improve pregnancy outcomes may also be more effective if they are combined with strategies that address underlying factors such as poverty and illiteracy. Policies focused on smoking in public places should be properly emphasized to eliminate or minimize the effect of passive smoking on birth-weight.

The ability to predict who is at risk for low birth weight and preterm birth makes prevention easier.

REFERENCES


