UNIVERSITY FOR DEVELOPMENT STUDIES

TWEEDIE REGRESSION ANALYSIS OF DETERMINANTS OF BIRTH WEIGHT IN NAVRONGO

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TWEEDIE REGRESSION ANALYSIS OF DETERMINANTS OF BIRTH WEIGHT IN NAVRONGO

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SEPTEMBER, 2021

DECLARATION

This thesis is my original work and no part of it has been presented for another degree award in the university or elsewhere.

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We hereby declare that the preparation and presentation of the thesis was supervised in accordance with the guidelines on supervision of the thesis laid down by the University for Development Studies.

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ABSTRACT

This study models infant birth weight and investigate maternal predictors using lifetime data by taking into account the non-zero probability of zero occurrences of the response variable. The birth weights were found to be positively skewed and leptokurtic in nature. The average birth weight was found to be 2.9898kg. In modelling the determinants of infant birth weight, the Tweedie regression model was compared with Gaussian, Gamma and inverse Gaussian regression models. The performance of these models was assessed using the Akaike Information Criterion. Based on the Akaike Information Criterion, the Tweedie regression model showed superiority in modelling the determinants of infant birth weight as compared to the Gaussian, Gamma and inverse Gaussian regression models respectively. This showcases the added advantages of the Tweedie regression models having the capacity of handling non-negative highly right-skewed and continuous data with probability mass at zero. The parameter estimates of the Tweedie regression model revealed that the gender of the child, religion, marital status and educational level of the mother significantly contributes to the infant birth weight. Based on the findings of the study, it was recommended that except for the status of antenatal care, emphasis must be placed on establishing the reasons for the decrease in infant birth weight as a result of the maternal factors; parity, delivery type and the age of the mother.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BW	Birth Weight
CHC	Community Health Centers
EDM	Exponential Dispersion Model
GLM	Generalised Linear Model
LBW	Low Birth Weight
ML	Maximum Likelihood
NHRC	Navrongo Health Research Center
PDF	Probability Density Function
WHO	World Health Organisation
WMH	War Memorial Hospital
IPI	Inter-Pregnancy Interval

CHAPTER ONE

INTRODUCTION

1.0 Background of the Study

Birth weight of babies plays an essential role in the development of the babies and is usually considered as an indicator of health status of a given society. The average birth weight has been found to be associated with good maternal care and healthy living condition (Kramer, 1987). McCormick (1985) reported that birth weight is a key determinant of the likelihood of child survival.

There are many growth challenges that babies with abnormal birth weight face in life. For instance, babies with low birth weight have a high tendency of developing cerebral palsy, mental retardation, visual problem, chronic lung diseases and sudden infant death among others. It has been established by several researchers that the birth weight of babies are related with child mortality and morbidity (Castro et al., 2014; Kader and Perera 2014; MacDorman and Mathew, 2013). According to the World Health Organisation (WHO) (2014), about 15% to 20% of all births globally are low birth weight, constituting more than 20 million births a year. Thus, the birth weight of babies is considered as a primary public health concern.

The birth weight is the first weight of the newborn obtained at birth, which ought to be ideally measured inside the first hour of life, before significant postnatal weight loss occurs (WHO, 1992; UNICEF/WHO, 2000). Owing to the health implications of abnormal birth weight, the WHO and various stakeholders in the health sector have put in several measures to ensure that this problem is reduced to the barest minimum if not eliminated. Some of these measures include; the free maternal health care, access to quality health care, prevention of malaria during pregnancy, adequate birth spacing, peri-conceptual daily folic acid supplementation for reduction of congenital anomalies, promotion of smoking cessation and interventionist care in severe pre-eclampsia before term among others (WHO, 2014).

There are many issues that may influence or determine the birth weight of babies. These comprise: pre-pregnancy weight, marital status, maternal height, birth parity, heredity, placental failure and short maternal stature (Kramer, 1987; Kelly et al., 1996; Kumar and Kumar, 1987). However, these factors may differ from person to person or from country to country. Hence, investigating how some of these factors influence the birth weight of babies could assist in the development of health related policies and stakeholder engagement with parties facing such challenges. This study seeks to investigate the determinant of birth weight of babies in the Navrongo Municipality using Tweedie regression model.

1.1 Problem Statement

The birth weight of a baby is a key factor in the development of the baby. Low birth weight can affect the development of the child in many ways. The risk factors of fetal, child mortality and morbidity and other chronic illnesses such as; type 2 diabetes, hypertension and cardiovascular diseases (Barker et al., 2002;

Godfrey and Barker, 2001; Stottland et al., 2006; Dietz et al., 2009). Srofenyoh et al. (2006) indicated that high birth weight can result in fetal problems such as still birth, Erb's palsy, jaundice in infants and respiratory distress.

Although several studies have been done on modeling the determinants of birth weights, some of these studies use the classical multiple linear regression model which is based on the assumption of normality. However, the birth weight of babies are often skewed which requires that the data on birth weight should be transformed before the multiple linear regression model is fitted (Tweedie, 1984). This leads to the distortion of the data and loss of information. The use of regression models that is capable of handling data that is skewed for modeling the birth weight would be preferable. Thus, this study employs the Tweedie regression model which is capable of handling data with different traits to model the birth weight of the babies.

1.2 General Objective

The goal of the study is to model and investigate the determinants of birth weight of the babies using Tweedie Regression Model.

1.3 Specific Objectives

The study seeks to achieve the following specific objectives.

i. To model the birth weight using Tweedie regression model.

ii. To compare the performance of the Tweedie regression model with the Gaussian, gamma and inverse Gaussian regression models.

iii. To investigate the determinants of the birth weight.

1.4 Significance of the Study

This study unearths some factors that influence the birth weight of babies. This provides key information to stakeholders in the health sector. The information can be used to develop policies for addressing the problem of abnormal birth weights.

1.5 Thesis Organisation

The thesis is organised into five chapters. The first chapter provides some background information on birth weight for the study. The next chapter's talks about the literature review which is composed of works others did regarding birth weight of infants. Methodology explains how the data is obtained, the technique use and the statistical tool. The results and discussion forms the chapter four and the final chapter five comprises of summary, conclusions and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

The chapter presents literature on some determinants of birth weight, consequences of high and low birth weight and related researches on birth weight using Tweedie regression.

2.1 Demographic Characteristics

In certain circumstances, the neighbourhood in which people live defines and shapes their identity. This is followed by a description of their informal organisation, peers, income, education and employment. In several studies, the location of the person's house, whether rural or urban, has been used as a mediator for the person's financial situation. In Ghana, the introduction of industrialisation, along with push and pull dynamics resulted in a hardly discernible difference among urban and rural areas. Furthermore some study has found that rural and urban population have varying levels of well-being, due to disparities in imbalance throughout the social spectrum (Kent et al., 2014). LBW was associated with staying in urban areas of Ghana (Kayode et al., 2014).

Wilkinson and Pickett (2010) tested hypothesis for social gradient of health which states that health disparities go down to social class with the ultimate goal that people in the lowest bar have the most horrendous health outcomes as measured by morbidity and mortality. Communities with a steep social gradient tend to be associated with the worst outcomes in terms of health. In a hygienic inquiry of postmenopausal women, Kaczmarek et al. (2016) investigated some urban differences in the area of quality of health. The study made use of 660 postmenopausal women aged 48 to 60 years in the analysis and it was revealed that women in rural zones have much higher probability of experiencing negative personal satisfaction than women in unrestricted zones. The disparities might relate in terms of birth results.

2.2 Determinants of Birth Weight

Identifying the factors of birth weight is critical, because of the health hazards connected with birth weight. Low birth weight infants are more likely to die during the neonatal period and the first year of life (Oechsli, 1990). According to McCornick (1985), low birth weight is most frequent in developing nations where the encumbrance of malnutrition and infectious illnesses are weighty (Michele et al., 2001). WHO (1995) acknowledged that a variety of factors influence the birth weight of a newborn during gestation and fetal growth.

These elements which are connected to the newborn, the mother or the physical surroundings, have a significant impact in determining the newborn’s birth weight in terms of future health (UNICEF, 2004a). Beaten et al. (1990) considered that during delivery, maternal variables such as nutrition and gestational age impact newborn weight and length thus, whether the newborn is full term or not, birth weight analysis must take these aspects into consideration. Andersson and Bergstrom (1997) discovered that maternal pre-pregnancy weight is a result of the woman's long-term nutritional health. Weight growth throughout pregnancy was the most important factor of birth weight. According to Onis et al. (1998), hereditary variables as well as alcohol and drug use during pregnancy contribute to the high likelihood of low birth weight.

Low birth weight infants according to Tay (2000) are more likely to have growth anomalies, developmental delays and chronic disease. Low birth weight is defined in a country as the proportion of live births weighing less than 2500g out of all live births over the same time period. The child development and growth occur in the womb, where maternal factors influence development. Maternal nourishment increases development and growth of infants during and after pregnancy which is shown to benefit the newborn (Leung et al., 2016). As a result, actions at this level of the system can only benefit the mother and guarantee that the child is born safely.

Amegah et al. (2012) conducted research using a sample of 592 women and weight of babies was taken at the Korle Bu Teaching Hospital of Ghana. Maternal features, indoor location and birth weight were all stated. The study discovered that maternal exposure to charcoal during pregnancy, as well as the burning of garbage in the household environment was linked to low birth weight.

Growth retardation and low birth weight may also be caused by the infant mother's age, malaria during pregnancy, gastro-intestinal, colonic parasitic or other diseases and cigarette smoking all of which are more common in developing countries (Kramer, 1998). According to Kramer (1987), the aforementioned disorders and practices were linked to poor fetal development. Also, McGregor et al. (1983) posited that infants born to women with placental malaria have a mean deficit in birth weight.

2.2.1 Maternal Age

The mother's age during pregnancy is an important factor to reflect since it aids in identifying whether the infant mother is at risk of having malnourished baby or not. Goisis et al. (2017), Kaur et al. (2014) and Yi et al. (2013) in their respective studies examined the association between maternal age and low birth weight. The studies found early maternal age at delivery to relate with low birth weight. In other study, Kaur et al. (2014) proved that low birth weight found in both women under the age of 20 and those over the age of 30 are 87.5 and 78.8 percent respectively. Similarly, lots of research has been conducted on maternal age in other jurisdictions such as Pelotas, Brazil, and Avon basically to find the effect of maternal age on birth outcome (Restrepo-Méndez et al., 2015). The study made use of three birth observational studies for 1982, 1993 and 2004 to ascertain the relationship between maternal age and low birth weight. The Hosmer–Lemeshow goodness-of-fit test was used in investigating the relationships among the variables. The maternal age below 20 and above 34 years was shown to be highly linked with low birth weight in 1982 and 1993 cohorts. However, when the connection was adjusted for socioeconomic position, it was reduced to nothing.

Borah and Agarwalla (2016) assessed the impact of old mother age on low birth weight. Multivariate logistic regression analysis was used to evaluate data from 450 mothers. According to the findings, mothers under the age of 20 were almost four times more likely than mothers between the ages of 20 and 30 to give birth to infants of low birth weight. Furthermore, the connection was not significant when compared to mothers above the age of 30. In a similar study, Chen et al. (2013) discovered that mothers under the age of 20 were more likely to have low birth weight infants than mothers over the age of 20.

2.2.2 Educational Level

According to the notion of health demand, the health production effectiveness is as a result of education. The argument that educated individuals are informed about the production of health care, Wagstaff (1986) investigated whether schooling enhances health knowledge using the allocated efficiency theory. The study revealed there are several additional causes that have an influence on health outcomes, whereas low maternal training was shown to be connected to low birth weight in Malawi (Muula et al., 2011).

Greece et al. (2011) performed a countrywide survey of migrants and locals to determine the maternal socioeconomic and demographic predictors of low birth weight. The use of 103,266 women was subjected to a multinomial logistic regression analysis. According to the study findings, when compared to educational achievement up to the secondary level, the relative risk ratios for low birth weight among tertiary educated mothers were 0.724 ($p > 0.05$).

Avachat et al. (2014) conducted a cross-sectional research in which they analysed data with random sample of 652 children under the age of five through the utilisation of birth weight records. According to the study's descriptive analysis, a large proportion of mothers with lower educational status related to low birth weight. These tendencies were also visible in another cross-sectional research done at Kinaye Prime Health Care in Karnataka's rural community (Metgud et al., 2012). According to findings of the multiple logistic regression analysis, low education women were almost three times more likely than women with higher education to have low birth weight infants.

Silvestrin et al. (2013) used a meta-analysis to examine the link between mother educational level and low birth weight. Nine of the 729 papers assessed were of sufficient quality to be included in the review. The study found mothers education to reveal a 33% helpful impact on low birth weight as compared to no education mothers. Comparing no education and a middle education revealed that there are no statistical differences. Also, in reference to no education, high maternal education had a 33 percent helpful impact against low birth weight. There was no degree of correlation observed in the middle or low motherly education groups. Based on this discussion, one might infer that there is credible association among educational gradient and health outcomes. Also lower level of education showed in the study to be related with low birth weight.

2.2.3 Birth Spacing

According to researches, infants born within 18-month birth spacing intervals are at an elevated risk of ill health (Kaur et al., 2014), including low birth weight (Partington et al., 2009). The study by Firdous et al. (2014), who performed a cross-sectional research in Lalla Ded Hospital in the Valley of Kashmir from August 2010 to August 2011, demonstrates how birth spacing translates to low birth weight. A total of 1,000 mother-baby paired data were gathered and examined in order to determine the relationship between birth spacing and low birth weight. The data was subjected to multiple logistic multivariate analyses. In the study, it was discovered that child spacing intervals of 48 months raised the risk of low birth weight considerably after adjusting for other socio-demographic characteristics.

In Zimbabwe, the average birth duration is 47.1 months, with about 9% of children born within a 24-month period (Zimbabew, 2014). The findings were also verified in Tampa, Florida and Sweden (Salihu et al., 2012; Class et al., 2017). Short inter-pregnancy intervals of 0 to 5 months, for example, were observed by scientists in a Swedish study. Also, long inter-pregnancy intervals of at least 60 months were connected with low birth weight. An earlier study by Klerk and Stanley (2014) reached a unique outcome, whereas Chen et al. (2015) discovered that the inter-pregnancy gap was connected to low birth weight. Ball et al. (2014) employed matched analysis to estimate the incidence of bad birth outcomes in a retrospective cohort study of 40,441 women. The researchers ended by calling into query the causal effect of a short inter-pregnancy interval (IPI) and speculating that there might be latent factors contributing to the apparent link established by earlier studies.

Chen et al. (2015) investigated the link between birth interval and low birth weight using a retrospective cohort research methodology. Data collected between 1989 and 2000 were examined. According to the findings of the preceding review, excessive birth spacing will be connected with low birth weight. Mothers in their early twenties and thirties appear to have better birth outcomes. Outside of those age ranges, research seems to indicate that a rise in birth spacing will increase the likelihood of low birth weight.

2.3 Consequences of Low Birth Weight (LBW)

There are several models of global health, each of which gives a unique perspective on health. Devinder et al. (2002) discovered that improvements in the healthcare system, increased knowledge of the need of prenatal care among the general public, and improved maternal health at the start of reproductive life all contributed to higher birth weights and lower perinatal mortality. Such interventions must create a variety of supporting nutrition communication messages and activities that are tailored to the needs and interests of the target population (Winichagoon et al., 1992).

According to WHO (2016), one of the primary reasons of birth weight might be dietary deficiencies. Iron is in charge of transporting oxygen to fulfill the body's other complicated physiologic demands. Diet that gives a variety of nutrients to the pregnancy's growth therefore plays a significant role during the infant's development. According to the World Health Organisation, the long-term effects of preterm delivery include neurological issues such as periventricular, cerebral palsy, seizures, delayed development and learning impairments, and pulmonary consequences such as retinopathy and blindness. Adults born with low birth weight have an increased risk of high blood pressure, obstructive lung disease, high blood cholesterol, and kidney impairment (Barker and Osmond, 1986). According to Barker (1998), adaptations for fetal survival in an insufficient nutritional environment lead to adult chronic illness due to the abundance of resources. Low birth weight has long-term physiological effects, such as a mother having problems forming a placenta that will deliver appropriate sustenance to the child (Andersson and Bergstrom, 1997).

According to Mi et al. (2000), an undernourished fetus conserves or diverts blood flow to the head while decreasing blood flow to the liver, pancreas, and kidneys, resulting in decreased secretion of growth hormones, insulin, and other endocrine changes that lead to childhood health problems and non-insulin diabetes mellitus (NIDDM) in adulthood. Hales et al. (1991) discovered that more than 20% of males with birth weights less than 2500g had impaired glucose tolerance compared to those with birth weights greater than 4000g.

Mi et al. (2000) in a study indicated that Type 2 diabetes mellitus and hypertension have a shared beginning in suboptimal fetal development, and that syndrome X–Type 2 diabetes mellitus, hypertension, and tiny baby syndrome–all have a common origin in suboptimal fetal development. In general, birth weight is connected with greater morbidity and death (Bukenya et al., 1991). Ashworth (1998) reported that the risk of neonatal mortality is four times higher for preterm newborns weighing 2000–2500g at birth than for newborns weighing 2500–3000g, and ten times greater for newborns weighing 3000–3500g. Birth weight babies have a significant death rate throughout the post-neonatal era (> 28 days of age). It was also shown that the risks of low birth weight infants in the post neonatal era were higher than those of low birth weight infants in the neonatal era. Furthermore, low birth weight infants have neonatal and postnatal mortality risks that are roughly comparable to preterm infants of the same birth weight. According to James et al. (2001), such fatality rates are quite high for the male infant than the female. Acute Lower Respiratory Infections (ALRI) was caused by low birth weight in 69 percent of cases (Dutta et al., 1987). According to Arifeen (1997), eliminating low birth weight might avoid almost half of all baby fatalities from pneumonia, ALRI and diarrhea. Lemons et al. (2001) identified chronic lung illness as a significant morbidity in low birth weight infants. Low birth weight is related with an increased risk of death from respiratory infections and hospitalisation for pneumonia (Victora et al., 1990; Victora et al., 1994; Lira et al., 1996) observed a high relationship between low birth weight and prevalence of cough.

According to Barros et al. (1992), low birth weight is a major predictor of diarrhea, mortality and hospitalisation due to dehydration (Victora et al., 1992). Lira et al. (1996) discovered that term low birth weight infants aged 0-6 months have 33 percent more diarrhea than typical birth weight newborns. Bukenya et al.

(1991) found that low birth weight babies aged 0 to 59 months were more likely to die due to a reported 60% increase in the number of days with diarrhea.

2.4 Interventions to Prevent Low Birth Weight (LBW)

Intra Uterine Growth Retardation (IUGR) is a complex condition that is difficult to prevent with a single intervention. WHO (2002) listed dietary, health-related behavior and infection management as potential interventions to prevent low birth weight. Judith and Laura (2000) indicated that interventions to prevent low birth weight should be seen to have the capacity to disrupt the intergenerational cycle of under nutrition that leads to low birth weight. According to Hack et al. (2002), efforts to prevent prematurity and low birth weight necessitate long-term systemic interventions addressing issues of women's health, nutrition, literacy, and overall lifestyle, which would necessitate significant engagement from the public.

According to WHO (2002), endocrine mechanisms regulate fetal growth, which may or may not be altered by interventions because some of the systems are genetically controlled. Thus, therapies aimed at modifiable pre-pregnancy characteristics such as maternal stature, BMI, age, and birth interval as well as modifiable pregnancy factors such as maternal weight gain, micronutrient status, calorie and protein consumption, malaria, smoking/polluting, violence and stress was mostly efficient. Also, WHO (2002) indicated that the most effective therapies for IUGR prevention include macronutrient meal supplements, smoking cessation counseling, malaria treatment in pregnant mothers and low-dose diclofenac in high-risk mothers. Partington et al. (2009) proposed that lowering workload and using pelvic ultrasound in women with cervix insufficiency can help reduce premature birth. Protein/energy and multivitamin supplements during pregnancy dramatically reduced preterm births, stillbirths and miscarriage rates (Fawsi et al., 1998). Mario et al. (2003) indicated that balanced protein energy supplement can lower the total risk by 30 percent.

Improving prenatal weight and gaining weight during pregnancy are helpful techniques for reducing and preventing low birth weight (Andersson and Bergstrom, 1997). Breastfeeding, suitable supplementary feeding and proper nutrition are all important nutritional status required during infancy, early childhood, puberty, and pregnancy to minimise and avoid low birth weight (Lucas et al., 1997; Judith and Laura, 2000). Even while the requirement for continuous health care throughout the prenatal, antenatal and early childhood periods support optimum fetal development, it is becoming more well acknowledged, the translation of this into the delivery of suitable intervention packages remains a challenge (WHO, 2006).

2.5 Review on Tweedie Regression

Statistical modeling is the most important issue in applied statistics, and it is used in a wide range of research projects, including agronomy, economics, sociology, insurance, ecology and medication, to name a few. Tweedie regression models are a versatile family of distribution that can handle non-negative extremely right-skewed, heavy-tailed and symmetric data as well as continuous data with probability mass at zero. The maximum likelihood technique was backed by

Tweedie regression models, which were restricted in the occurrence of an infinite sum within the non-trivial and probability function limits on the parameter space.

Tweedie regression has the statistical trait of being substantially right-skewed, and as a result, it has been widely used to model lifetime data such as birth weight with certain explanatory factors such as the mother's present age, birth order, age at marriage, religion and gender. Other studies in literature have utilised the Generalised Linear Model (GLM) as well as a hybrid GLM based on log Gaussian and Gamma distributions (McCullagh and Nelder, 1989).

Rice and Thapar (2010) used the Gamma distribution to identify the risk variables related with newborn weight. The Tweedie distribution can simulate life time data and can handle both discrete and continuous data. The Tweedie model is better suited for models that combine non-zero, discrete and continuous data. Tweedie regression families have been used in a variety of sectors including actuarial science, economics, telecommunications, medicine and ecology (Dunn, 2004; Dunn and Smyth, 2005; Gilchrist 2007; Hiroshi and Shono, 2008). Many studies in the literature suggest that the Tweedie regression model fits rainfall data the best (Hasan and Dunn, 2010; 2011).

CHAPTER THREE

METHODOLOGY

3.0 Introduction

The chapter presents the data and its source, the study area, the statistical tool used for analysis, Tweedie, Gaussian, Gamma and inverse Gaussian regression models and its application. Furthermore, the study highlighted the method of estimating the model parameters and model selection criteria's used to determine the best model that fit the empirical data.

3.1 Data and Source

This study is based on secondary data obtained from the Navrongo Health Research Center (NHRC). In this study, the data were collected from women who gave birth at the War Memorial Hospital (WMH) of the Navrongo Municipality and other Community Health Centers (CHC). The data collected at the health center is on a monthly basis. We extracted data from multiple women in Navrongo and modelled the birth weight of the baby based on the Tweedie, Gaussian, Gamma and inverse Gaussian distributions.

3.2 Research Area

The municipality has Navrongo as its political and administrative capital. The municipality is located between latitude 11 ° 10` to 10 ° 3` north and longitude 10 ° 1` west. This municipality shares the northern border with the Kassena-Nankana West (KNW) District and Burkina Faso. It shares border with the West Mamprusi (WM), the KNW district to the East, Bolgatanga City, the Builsa district to the West, and the Northeastern (NE) region to the South. The climatic conditions of the Kassena-Nankana (KN) region are mainly characterised by dry season humidity affected by two (2) platforms that is Northeastern Trade (NET) Winds and Southwestern (Tropical Oceans). Daytime temperatures record 42 degrees Celsius (especially between February and March) and night temperatures can drop to 18 degrees Celsius. The landscape is generally undulating and the Western part of the municipality has isolated hills about 300 meters above sea level.

The municipality is mainly covered in Sahel and Sudan Savannah types of vegetation. Commonly observed trees are dawadawa, baobab, cyanats, and mango (GSS, 2010).

3.3 Exponential Dispersion (ED) and Tweedie Model

Tweedie distribution is a special case of the Exponential Dispersion Model (EDM) and is utilised as distributions for the Generalised Linear Model (GLM). It can also consist of several families of distributions in probability such as the continuous normal, gamma and inverse Gaussian (Tweedie, 1984).

In this study, we focused on three EDMs that are, the Gaussian, Gamma, and inverse Gaussian distributions by following Jorgensen (1997). These classes of EDMs for the continuous distributions are summarised in Table 3.1.

Table 3.1 Summary of some Absolute Continuous EDMs

	Gaussian	*Gamma*	*Inverse Gaussian*
$c(y,\lambda)$	$\frac{\sqrt{\lambda}}{\sqrt{2\pi}}e^{\frac{-\lambda y^2}{2}}$	$\frac{\lambda^{\lambda}x^{\lambda-1}}{\Gamma(\lambda)}$	$\frac{\sqrt{\lambda}}{\sqrt{2\pi}}y^{\frac{-3}{2}}e^{\frac{-\lambda}{2y}}$
$k(\theta)$	$\frac{\theta^2}{2}$	$-\log(-\theta)$	$-\sqrt{-2\theta}$
$k'(\theta)$	θ	$-\frac{1}{\theta}$	$(-2\theta)^{-1/2}$
$\psi(\mu)$	μ	$-\frac{1}{\mu}$	$-\frac{1}{2\mu^2}$
$V(\mu)$	1	μ^2	μ^3

3.3.1 The Gaussian Distribution

The Gaussian distribution (Normal or Laplace-Gauss distribution) is continuous and also seen as an EDM. Consider that $X \sim N(\mu,\sigma^2)$ such that the mean (location) parameter, $\mu \in \mathbb{R}$, the variance, $\sigma^2 > 0$ and with support $x \in \mathbb{R}$ then the probability density function (PDF) of the Gaussian distribution is given as:

$$f(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\}. \tag{3.1}$$

This distribution through the approach of integration gives the expected value and variance as: $E(X) = \mu$ and $Var(X) = \sigma^2$.

3.3.2 The Inverse Gaussian Distribution

This is a two-parameter continuous probability distribution that belongs to a class of EDM family of distribution and it is also known as Wald distribution. The parameters are such that $\mu > 0$ and $\lambda > 0$ with $X \sim IG(\mu, \lambda)$ then the PDF associating the inverse Gaussian distribution is given as:

$$f(x;\mu,\lambda) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left[-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right]. \tag{3.2}$$

The distribution of the inverse Gaussian through the integration approach is also accompanied with mean and variance respectively given as: $E(X) = \mu$ and $Var(X) = \frac{\mu^3}{\lambda}$.

3.3.3 The Gamma Distribution

The Gamma distribution is seen as an EDM. The mean μ of the distribution depends on the independent variable X, with $E(Y) = \mu = g^{-1}(X\beta)$, where $E(Y)$ is the expected value of Y, $X\beta$ is the predictor variable and g is the link function. Consider that gamma distribution with a random variable Y having shape parameter α and rate parameter β, then the density function is given as:

$$f(y;\alpha,\beta) = \frac{\beta^\alpha y^{\alpha-1} e^{-\beta y}}{\Gamma(\alpha)}, \tag{3.3}$$

where the denominator $\Gamma(\alpha)$ in equation (3.3) is the gamma function defined as $\Gamma(x)=\int_0^{\infty} y^{x-1}e^{-y}dy$. From equation (3.3), through computations using the approach of integration, we obtain the mean and variance of the Gamma distribution respectively as $E(X)=\dfrac{\alpha}{\theta}$ and $Var(X)=\dfrac{\alpha}{\theta^2}$.

3.4 The Tweedie Regression Model

The Tweedie distribution is part of the EDM (Jorgensen, 1987; 1997). The density function of any random variable that follows an EDM can be written as:

$$f_Y(y;\mu,\varphi,p) \;=a(y,\varphi,p)\exp\{(y\psi-k(\psi))/\varphi\}, \tag{3.4}$$

where the mean is given as $\mu=E(Y)=k'(\psi)$, the dispersion parameter is strictly positive that is $\varphi>0$, the canonical parameter is ψ, and the cumulant function is given as $k(\psi)$. The parameter function $a(y,\varphi,p)$ cannot be described in a closed-form unless the different case is named. The variance is given as: $Var(Y) \;=\varphi V(\mu)$, where $V(\mu)=k''(\psi)$ is seen as the variance function.

The Tweedie density function is characterised by the variance function power of the form $V(\mu) \;=\mu^p$, and the index determining the distribution that is $p\in\;(-\infty,0]\;\cup\;[1,\infty)$. Although the Tweedie density function is unknown in its closed form, the cumulant generation function is quite simple to find. The cumulant generation function can be stated as:

$$K(t) = \{k(\psi + \varphi t) - k(\psi)\}/\varphi, \tag{3.5}$$

where the cumulant function is $k(\psi)$,

$$\psi = \begin{cases} \dfrac{\mu^{1-p}}{1-p}, & p \neq 1 \\ \log\mu, & p = 1 \end{cases} \text{ and } k(\psi) = \begin{cases} \dfrac{\mu^{2-p}}{2-p}, & p \neq 2 \\ \log\mu, & p = 2 \end{cases}.$$

The density function $a(y,\varphi,p)$ is estimated statistically. Jorgensen (1997) presented two expansions to evaluate the density function, for $1 < p < 2$ and for $p > 2$. The case one can be given as:

$$P(Y = 0) = \exp\left\{-\frac{\mu^{2-p}}{\varphi(2-p)}\right\}, \tag{3.6}$$

and for $y > 0$ that is;

$$a(y,\varphi,p) = \frac{1}{y}W(y,\varphi,p). \tag{3.7}$$

Define $W(y,\varphi,p) = \sum_{k=1}^{\infty} W_k$ from equation (3.4), then

$$W_k = \frac{y^{-k\alpha}(p-1)^{\alpha k}}{\varphi^{k(1-\alpha)}(2-p)^k k!\Gamma(-k\alpha)},$$

where we denote $\alpha = (2-p)/(1-p)$. For $p > 2$, the expression is given by:

$$a(y,\varphi,p) = \frac{1}{\pi y}V(y,\varphi,p), \tag{3.8}$$

where $V=\sum_{K=1}^{\infty}V_k$ and

$$V_k=\frac{\Gamma(1+\alpha k)\varphi^{k(\alpha-1)}(p-1)^{\alpha k}}{\Gamma(1+k)(p-2)^k y^{\alpha k}}(-1)^k\sin(-k\pi\alpha).$$

Dunn and Smyth (2005) employed series and a technique to assess the Tweedie density function based on sample sizes in their experiments. The approach was implemented using the function dtweedie.series in the tweedie package (Dunn, 2013) for the statistical R software (R Core Team, 2016). Dunn and Smyth (2008) also suggested two approaches for assessing the Tweedie distributions density function, one focused on the Fourier inverse of the cumulant generating function and other on the saddle point estimate (Dunn, 2013).

3.5 Estimation and Inference

To estimate and make inferences on the Twedie regression models, we consider Maximum Likelihood Estimation (MLE) and some model selection criteria such as Akaike Information Criterion (AIC).

3.5.1 Maximum Likelihood Estimation

The parameter vector θ of the Maximum Likelihood (ML) estimator denoted by $\hat{\theta}_M$ can be found by maximising the log-likelihood ratio function given as:

$$L(\theta)=\sum_{i=1}^{n}\log\{a(y_i;\lambda)\}+\frac{1}{\exp(\delta)}(y_i\psi_i-k(\psi_i)). \tag{3.9}$$

We consider when two vectors β and λ are orthogonal then the score function associating the regression parameters $\beta=(\beta_0,\cdots,\beta_Q)$ function is given as;

$$U_b(\beta,\lambda)=\left(\frac{\partial L(\theta)^T}{\partial\beta_1},\cdots,\frac{\partial L(\theta)^T}{\partial\beta_Q}\right)^T, \text{ with}$$

$$\begin{aligned}\frac{\partial L(\theta)}{\partial\beta_j}&=\sum_{i=1}^{n}\frac{\partial L(\theta)}{\partial\psi_i}\frac{\partial\psi_i}{\partial\mu_i}\frac{\partial\mu_i}{\partial\eta_i}\frac{\partial\eta_i}{\partial\beta_j}\\&=\sum_{i=1}^{n}\mu_i x_{ij}\left[\frac{1}{\exp(\delta)\mu_i^p}\right](y_i-\mu_i),\ for\ j=1,\cdots,Q.\end{aligned}$$

The entry (j,k) of the $Q\times Q$ regression coefficient for the Fisher information matrix F_β is given by:

$$F_{\beta_{jk}}=-E\left\{\frac{\partial^2L(\theta)}{\partial\beta_j\partial\beta_k}\right\}=\sum_{i=1}^{n}\mu_i x_{ij}\left[\frac{1}{\exp(\delta)\mu_i^p}\right]\mu_i x_{ik}. \tag{3.10}$$

Hence, the dispersion parameter for the score function $\lambda=(\exp(\delta),p)$ is given by $U_\lambda(\lambda,\beta)=\left(\frac{\partial L(\theta)^T}{\partial\delta},\frac{\partial L(\theta)^T}{\partial p}\right)^T$ with its components given as:

$$\frac{\partial L(\theta)}{\partial\delta}=\sum_{i=1}^{n}\frac{\partial}{\partial\delta}\log a(y_i;\lambda)-\frac{1}{\exp(\delta)}(y_i\psi_i-k(\psi_i)), \tag{3.11}$$

and

$$\frac{\partial L(\theta)}{\partial p}=\sum_{i=1}^{n}\frac{\partial}{\partial p}\log a(y_i;\lambda)+\frac{1}{\exp(\delta)}\left[y_i\frac{\partial\psi_i}{\partial p}-\frac{\partial k(\psi_i)}{\partial p}\right]. \tag{3.12}$$

The entry (j,k) of the 2×2 Fisher information parameter dispersion function F_λ is given by:

$$F_{\lambda_{jk}}=-E\left\{\frac{\partial^2 L(\theta)}{\partial\lambda_j\partial\lambda_k}\right\}. \tag{3.13}$$

The derivatives of equations (3.11), (3.12) and (3.13) are dependent on infinite sum of derivative $a(y_i;\lambda)$, by expressing it in closed system is not possible. In this respect, numerical techniques are required to perform the approximation of this derivative. Consider $\tilde{U}_\lambda$ and $\tilde{F}_\lambda$ to be approximate total function and observed statistic for the dispersion parameters matrix respectively. Also, the Fisher information matrices cross entries is defined to be:

$$F_{\beta_j\delta}=-E\left\{\frac{\partial U_{\beta_j}(\beta,\lambda)}{\partial\delta}\right\}=-E\left\{\mu_i x_{ij}\left[-\frac{1}{\exp(\delta)\mu_i^p}\right](y_i-\mu_i)\right\}=0$$

and

$$F_{\beta_j p}=-E\left\{\frac{\partial U_{\beta_j}(\beta,\lambda)}{\partial p}\right\}=-E\left\{\mu_i x_{ij}\left[\frac{\partial}{\partial p}\frac{1}{\exp(\delta)\mu_i^p}\right](y_i-\mu_i)\right\}=0.$$

Hence, β and λ are orthogonal vectors. Fisher information matrix for the joint parameter θ is given by $F_\theta = \begin{pmatrix} F_\beta & 0 \\ 0 & F_\lambda \end{pmatrix}$ with its entries defined by equation (3.10) and (3.13). Furthermore, the asymptotic distribution $\hat{\theta}_M$ can be defined as $\hat{\theta}_M \sim \mathrm{N}\left(\theta, F_\theta^{-1}\right)$ where the inverse of the Fisher information matrix is F_θ^{-1}. Also, practically in some instances F_λ can be replaced with the approximation that is $\tilde{F}_\lambda$. The system of equations can be solved by letting $U_\beta = 0$ and $\tilde{U}_\lambda = 0$, then utilising the two steps Newton scoring algorithm defined in this study as:

$$\begin{aligned} \beta^{(i+1)} &= \beta^{(i)} - F_\beta^{-1} U_\beta\left(\beta^{(i)}, \lambda^{(i)}\right) \\ \lambda^{(i+1)} &= \lambda^{(i)} - \tilde{F}_\lambda^{-1} \tilde{U}_\lambda\left(\beta^{(i+1)}, \lambda^{(i)}\right), \end{aligned} \tag{3.14}$$

which utilises the orthogonality between β and λ.

3.5.2 Model Selection Criteria

The study employed the Akaike Information Criterion (AIC) to make a decision based on the best model. Akaike (1974) defined AIC as:

$$AIC = 2k - 2\log\ell. \tag{3.15}$$

From equation (3.15), k is the number of parameters and ℓ is the likelihood function value.

3.6 Variables of the Study

The study made use of the following variables and the corresponding coding as captured in Table 3.2 in modeling the birth weights of infants in the Navrongo Municipality.

Table 3.2 Categorisation of the Variables in the Analysis

Domain/ Variable Name		Description
	Child gender	0= Female and 1= Male
Household /Community Factors	Religion	1= Christian 2= Traditional 3= Islamic
	Educational level	1=No formal education, 2=Primary, 3=JSS/JHS, 4=SSS/SHS and 5=Tertiary
	Status of ANC	1=Poor and 2= Good
	Mothers age	In Years
Maternal Factors	Parity	1=One child, 2=Two children and 3=Three children and above
	Marital status	1=Single and 2= Married
	Delivery type	1=Normal vaginal delivery, 2=Caesarian section, 3=Vacuum extraction, 4=Vaginal cutting and 5=Others
Dependent variable	Birth weight	In Kilograms

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

This chapter is put into two sections namely preliminary and further analysis. The preliminary analysis involved exploring the data using descriptive statistics while the further analysis involved using Tweedie, Gaussian, Gamma and inverse Gaussian regression models.

4.1 Preliminary Analysis

Descriptive statistics were used to summarise the data by describing the relationship between variables in the sample. Tables 4.1 indicate that the total of 1972 birth weight of infants was recorded at the Navrongo Health Research Centre for the study period (November 2016 to December 2020). It was evident that infants' birth weights recorded were largely normal birth weights (85.1%). This was followed by low birth weights (13.5%) and finally by overweight (1.3%).

Table 4.1 Status of Infant Birth Weight

	Frequency	**Percent**
Low Birth Weight	267	13.5
Normal Birth Weight	1679	85.1
Overweight	26	1.3
Total	1972	100.0

The birth weight of infants and that of the age of the mother were examined to better under the characteristics of the data as found in Table 4.2. It can be deduced from Table 4.2 that the minimum and maximum age of the mother is 17 and 60 years respectively while that of the birth weight of infants can be seen to have a minimum value of 1.5kg and a maximum value of 6.0kg. The mean for the period under review indicates that the birth weight of the child averages around 3kg and with the age of the mother averaging around 34 years. The birth weight of infants had a standard deviation of 0.4304 while the age of the mothers in the study recorded a standard deviation of 43.3120. Also, skewness which is a measure of symmetry or lack of symmetry confirmed that the infant's birth weight was positively skewed with coefficient of skewness of 0.3892 and the mother's age was also positively skewed with a coefficient of skewness of 0.3170. This implies that the distributional tails on the right side are found to be longer or fatter for the birth weight and age of the mothers.

Also, the nature of distribution relative to the normal distribution (excess kurtosis) indicate that the birth weight of the infants was positive suggesting a leptokurtic distribution while that of the mother's age was found to be negative confirming a platykurtic distribution.

Table 4.2 Descriptive Statistics of Child Birth Weight and Mother's Age

Statistic	Birth Weight	Mother's Age
Minimum	1.5000	17.0000
Maximum	6.0000	60.0000
Mean	2.9898	33.2900
Standard deviation	0.4304	43.3120
Skewness	0.3892	0.3170
Kurtosis	2.6243	-0.1300

The Pearson Chi-square test of independence was used to test for association among the categorised variables as found in Table 4.3. It can be observed from Table 4.3 that the birth weight of the child versus each of these independent variables (mother's age, antenatal care (ANC), marital status, parity and gender of the child) were significant (p-value less than 0.05). This indicates that there is enough evidence to reject the null hypothesis and hence conclude that there is an association between the dependent variable (birth weight) and independent variables (mother's age, ANC and marital status, parity and gender of the child) whiles birth weight versus the each of these independent variables (religion and birth type) are not significant hence there is no association between birth weight and the aforementioned independent variables.

Table 4.3 Chi-Square Analysis of Birth Weight and Maternal Information

Variables	Chi-Square	p-value
Birth Weight *Mother Age	10.0000	**0.040**
Birth Weight *Religion	6.7100	0.152
Birth Weight *ANC	11.3500	**0.003**
Birth Weight * Birth Type	12.2700	0.139
Birth Weight * Marital Status	12.1000	**0.002**
Birth Weight *Parity	15.6570	**0.000**
Birth Weight *Child Gender	15.5690	**0.000**

4.3 Further Analysis

This part of the study is a buildup on the preliminary analysis purposely to develop and determine the appropriate model that best predicts the birth weight of infants in the Navrongo Municipality.

The maximum likelihood approach was used to determine the highest value of the index parameter, Xi (ξ) and the dispersion parameter, Phi (ϕ) as captured in Table 4.4 and Figure 4.1. It can be observed that Figure 4.1 and Table 4.4 came into a consensus that the maximum value of the index parameter stands at 1.5 and that of the dispersion parameter from Table 4.4 stands at 0.0343 and hence in modelling the birth weight of the child, consideration must be given to these parameter values and incorporated into the Tweedie Regression model.

Table 4.4 Estimates of the Tweedie Regression Parameters

Parameter	Estimate
ξ	1.5000
ϕ	0.0343

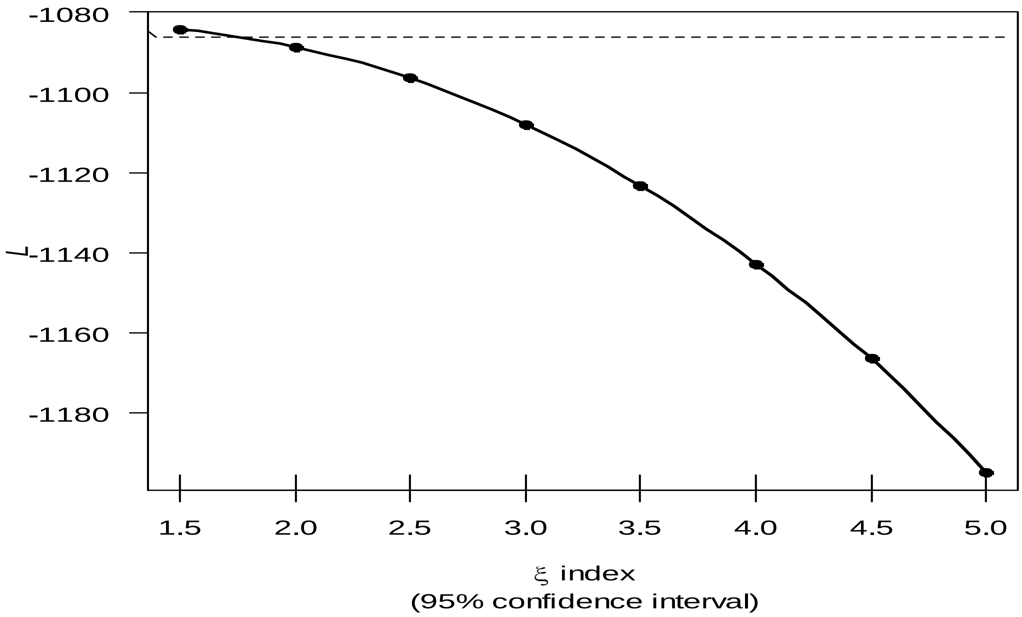

Figure 4.1 Profile Log Likelihood of the Index Parameter of Tweedie Regression

It is imperative to always check to see how well the model fits the actual data before utilising it for predictions. In this study, traditional Tweedie regression with an index parameter of 1.5 and other forms of Tweedie with different specification of the variance and link functions were developed. The developed models adopted the use of the model selection criteria approach in determining the appropriate model. According to Akaike (1974), smallest value of AIC is an indication of a good model. Following the view of Akaike (1974), with the least AIC of 2204.713 then it can be concluded that the Tweedie regression model with an index parameter of 1.5 can best predict the birth weight of children in the Navrongo Municipality as shown in Table 4.5.

Table 4.5 Tentative Regression Models

	AIC
Gaussian	2220.317
Gamma	2213.454
Inverse Gaussian	2252.136
TEDM with Index parameter($\xi = 1.5$)	2204.713

In other to make use of any model for prediction, it is imperative to subject it to model diagnostics. The diagnostic plot serves as a check to ensure that the model adequately fits the data. The various diagnostics plots were observed to help check the appropriateness of the assumed distribution of the birth weight, detect any isolated and systematic discrepancies and assess the predictive ability of the selected model.

For GLMs, the Pearson residuals are the most commonly used for diagnostic analysis. To check whether the Tweedie model is suitable for the actual data, the Q-Q plot of the deviance, Pearson and Quantile residuals were examined to see if there is some discrepancy with that of the normal line. The Q-Q plot of the Pearson and Quantile residuals as shown in Figure 4.2 revealed that except for a few extreme values, the normal line does not deviate from plotted points. Also, quantile residuals were replicated twice (set 1 and set 2) which also confirm the plotted points does not in any way deviate from the normal line. Also, the fitted values as shown in Figure 4.2 point to some form of a uniform scattering or randomness. The Cook's Distance (D) also revealed that with few upticks of some observations, these observations do not in any way influence the substantive

Tweedie regression model. Thus, the Tweedie model with index parameter estimate given as 1.5 and the dispersion parameter 0.0343 best fits birth weight data appropriately from the model diagnostics as shown in Figure 4.2.

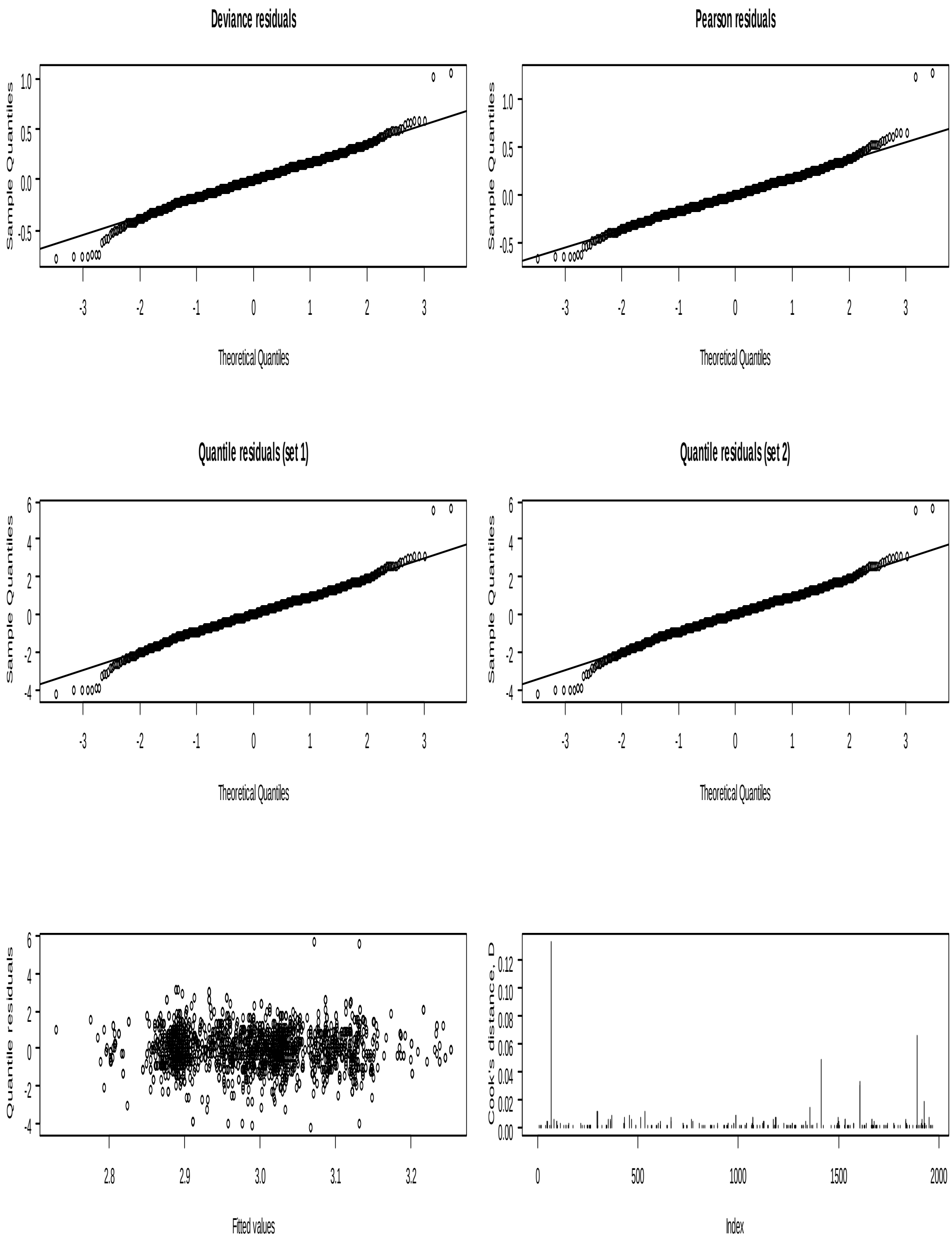

Figure 4.2 Diagnostic Plots of the Substantive Tweedie Regression Model

Table 4.6 presents the estimates of the substantive Tweedie regression model for the birth weight. In interpreting the estimates of the parameters in Table 4.6, a positive parameter estimate of a predictor indicates that such a predictor increases the birth weight of infants while a negative parameter estimate of a predictor is an indication of the predictor contributing to a decrease in the birth weight of the infants.

From Table 4.6, the average birth weight of infants is expected to be 1.1591kg considering that the explanatory variables were not included in the Tweedie regression model. Also results from Table 4.6 indicate that male infants on the average increases birth weight by 2.7502kg units as compared to that of female infants. However, such an increase in birth weight for male infants was significant at the 5% level. Based on Parity, mothers with two children and three children and above decreases the average birth weight by 0.0229kg and 0.0174kg units respectively as compared to those with one child but the decreases in birth weight recorded were not significant for both categories of Parity. Moreover, on the issue of Religion, a decrease but a significant relationship was established with that of the birth weight. For instance; Traditional and Muslim mothers were accompanied by a decrease in the average birth weight of infants by 0.0213kg and 0.0280kg units respectively as compared to the Christian mothers. Besides Religion, mothers with a good ANC attendance contributed to an increase in the birth weight of infants as compared to those with a poor ANC attendance. In addition, these increments were found not significant for the status of ANC at the 5% level. With regards to the level of education of the mothers, except for SSS/SHS leavers, all the other categories (Primary, JSS/JHS and Tertiary) contributed to an increase in the birth weight of the infants as compared to those with no formal education respectively. Further results from Table 4.6 confirm the existence of a significant relationship at the 5% level between JSS/JHS leavers and that of the no formal education. On the delivery type of infants by the mothers, except for other types of delivery that was associated to a decrease in birth weight, all the remaining categories (caesarean section, vacuum extraction and vaginal cutting) were found to increase the infant's birth weight as compared to the normal vaginal delivery respectively. Again, none of the categories showcased significance at the 5% level for the type of delivery of infants by mothers. Lastly, the age of the mother was not found to be significant. However, an additional age of the mother was seen to decrease the birth weight of the infant by 0.0005kg units.

Table 4.6 Parameter Estimates of the Substantive Tweedie Regression Model

	Tweedie Model for ($\xi = \mathbf{1.5}$)			
Variables	Estimate	Std. Error	t value	p-value
Intercept	1.1591	0.0380	30.4761	**0.0000**
Child Gender				
*Female**				
Male	0.0448	0.0064	7.0168	**0.0000**
Parity				
*One Child**				
Two Children	-0.0229	0.0296	-0.7739	0.4391
Three Children and above	-0.0174	0.0294	-0.5902	0.5551
Religion				
*Christian**				
Traditional	-0.0213	0.0081	-2.6233	**0.0088**
Muslim	-0.0280	0.0128	-2.1858	**0.0289**
Status of ANC				
*Poor**				
Good	0.0446	0.0346	1.2884	0.1977
Marital Status				
*Single**				
Married	-0.0402	0.0132	-3.0578	**0.0023**
Educational level				
*No Formal Education**				
Primary	0.0074	0.0099	0.7498	0.4535
JSS/JHS	0.0325	0.0123	2.6437	**0.0083**
SSS/SHS	-0.0260	0.0201	-1.2916	0.1967
Tertiary	0.0274	0.0257	1.0658	0.2866
Delivery Type				
*Normal Vaginal Delivery**				
Cesarean Section	0.0067	0.0154	0.4387	0.6609
Vacuum Extraction	0.0277	0.0627	0.4417	0.6588
Vaginal Cutting	0.0025	0.0242	0.1022	0.9186
Others	-0.0301	0.0212	-1.4210	0.1555
Mothers age	-0.0005	0.0005	-0.9470	0.3437

Footnote: * means reference outcome

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter of the study presents summary, conclusions and possible recommendations based on the findings of the study.

5.1 Summary

The study primarily focuses on modelling and investigating the determinants of birth weight in the Navrongo Municipality. To this effect, secondary data of 1,972 infant birth weight alongside some demographic and other pertinent health characteristics of the mother were sought from the Navrongo Health Research Center for the period under study (November 2016 to December 2020).

The preliminary analysis in Table 4.2 revealed that the average birth weight of infants is 2.9898kg with 85.1% of these birth weights of infants found to be normal as indicated in Table 4.1. Also, infant birth weight was positively skewed and leptokurtic. Further exploration of the data as captured in Table 4.3 for the adoption of the Chi-square analysis of infant birth weight with the explanatory variables (mothers age, religion, status of ANC, birth type, marital status, parity and child gender) indicated the existence of an association between infant birth weight and each of the explanatory variables (mothers age, the status of ANC, marital status, parity and child gender) at the 5% level of significance.

The performance of the Tweedie regression was compared with that of the Gamma, Gaussian and inverse Gaussian regression models are shown in Table 4.5. The AIC was used in making the comparisons for these fitted models of birth weight. Following the principle of the least AIC accompanying a model as the best out of the lot, then the choice of a substantive model to this effect is the Tweedie regression model with an AIC of 2204.713. Also subjecting the substantive Tweedie regression model to the diagnostics approach as found from Figure 4.2 confirmed that the residuals of the model tend to follow the linearity assumption, randomness and non-evidence of outliers with the Cooks Distance (D) plot.

In investigating the determinants of birth weight, it was evident from Table 4.6 that the gender of the child, religion, marital status and educational level of the mother contribute significantly to the prediction of the birth weight of infants in the Navrongo Municipality.

5.2 Conclusions

The study modelled and investigated the determinants of birth weights of infants. Based on this summary of the findings, the followings conclusions can be drawn:

The birth weight of infants is positively skewed and therefore exhibits a leptokurtic distributional shape confirming that the tails on the right side are longer or fatter.

Based on the findings, it can be concluded from the Chi-square analysis that infant birth weight associate with each of the explanatory variables (mother’s age, the status of ANC, marital status, parity and child gender).

Tweedie regression model is much more efficient than the Gaussian, Gamma and inverse-Gaussian regression models based on the AIC value. This research demonstrates the efficiency of the Tweedie distribution in modelling the determinants of infant birth weight.

Based on the estimations of the parameters using Tweedie regression model, gender of the child, religion, marital status and educational level of the mother are the predictors of infant birth weight in the Navrongo Municipality.

5.3 Recommendations

i. Health experts and stakeholders should consider using Tweedie regression model in modelling lifetime data such as birth weight among others since the study finds such a model to perform best as compared to other EDMs (Gaussian, Gamma and inverse-Gaussian).

ii. Based on the findings, it can be suggested that maternal mothers with SSS/SHS level of education should be given more maternal health training by the Ghana Health Service in other to improve the birth weight of babies.

iii. Government and stakeholders in the health sector should put measures in place to ensure birth spacing, avoid early child bearing and provide adequate ANC for mothers since the study finds these factors as crucial towards reducing low birth weight in babies.

iv. Further studies should also consider variables such as; maternal health status, lifestyle, and alcohol addiction of the mother since at the inception of this study, such variables were not available at the NHRC.

v. Further studies using data from all regions of Ghana to be carried out and identify the associated risk factors and the possible lifetime of children born with low birth weight.

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APPENDIX

Table A1: Cross Tabulation of Birth Weight and Age of Mother

	Mother Age			
Birth Weight	15-25	26-35	36+	Total
1.5-2.5	67	128	76	267
2.6-4.0	433	881	365	1679
4.1+	11	10	5	26
Total	**511**	**1015**	**446**	**1972**

Table A2: Cross Tabulation of Birth Weight and Status of ANC

	Status of ANC		
Birth Weight	Poor	Good	Total
1.5-2.5	86	181	267
2.6-4.0	439	1240	1679
4.1+	1	25	26
Total	**526**	**1446**	**1972**

Table A3: Cross Tabulation of Birth Weight and Religion

	Religion			
Birth Weight	Christian	Traditional	Muslim	Total
1.5-2.5	63	147	57	267
2.6-4.0	360	960	359	1679
4.1+	7	9	10	26
Total	**430**	**1116**	**426**	**1972**

Table A4: Cross Tabulation of Birth Weight and Delivery Type

	Delivery Type					
Birth Weight	Normal Vagina Delivery	Caesarean Section	Vacuum Extraction	Vaginal Cutting	Others	Total
1.5-2.5	236	17	0	3	11	267
2.6-4.0	1536	69	5	32	36	1678
4.1+	23	3	0	0	0	26
Total	**1795**	**89**	**5**	**35**	**47**	**1971**

Table A5: Cross Tabulation of Birth Weight and Marital Status

	Marital Status		
Birth Weight	Single	Married	Total
1.5-2.5	25	242	267
2.6-4.0	260	1419	1679
4.1+	8	18	26
Total	**293**	**1679**	**1972**

Table A6: Cross Tabulation of Birth Weight and Parity

	Parity			
Birth Weight	One Child	Two Children	Three Children and above	Total
1.5-2.5	5	127	135	267
2.6-4.0	18	848	813	1679
4.1+	1	11	14	26
Total	**24**	**986**	**962**	**1972**

Table A7: Cross Tabulation of Birth Weight and Child Gender

	Child Gender		
Birth Weight	Female	Male	Total
1.5-2.5	169	98	267
2.6-4.0	845	834	1679
4.1+	13	13	26
Total	**1027**	**945**	**1972**