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On Comparison Among Poisson And Negative Binomial For Modeling Count Data With Application To Road Accident Data In Nigeria

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***Abstract:** Road accident has claimed many lives in Nigeria, left some with serious injuries, and resulted in a huge loss of properties. Many researchers reported in the literature used the conventional regression models to model the road accidents, which is inappropriate. In this research, we compare two suitable regression models for the count data, Poisson and Negative Binomial regression models. The aim is to find a model that better fits the quarterly count accident data.*

The findings of this research indicated that the explanatory variables, Driver Error, Road Condition, and Faulty Vehicle, significantly contributed to the expected number of deaths per quarter due to road accidents. So also, the Negative binomial model was found to be the appropriate model based on the goodness of fit test results using AIC, BIC, and Deviance statistic.

***Keywords:** Poisson Regression Model; Negative Binomial Regression Model; Count Data; Road Accident; Generalized Linear Model (GLM).*

I. INTRODUCTION

The World Health Organization (WHO) describes a road traffic accident as a collision involving at least one vehicle in motion on a public or private road, resulting in injury or killing of at least one person.

When science and technology became more influential, people changed their inclination toward modernity and expediency. That has led to increased motor vehicle numbers.

The number of registered vehicles in the world rose by 15 percent (WHO 2010) from 2007 to 2010, and had a direct impact on road traffic injuries and fatalities. The rapid growth of modernized cities risks the health of non-motorized road users, including cyclists and pedestrians in particular. Road traffic incidents have a huge impact not only on human lives but on economies as well. The global loss due to traffic accidents is measured at USD 518 billion and is roughly equivalent to 1 to 4 percent of total national products (Integrated Good Air Quality Conference 2014).

About 50 million people worldwide each year suffer serious road accident injuries, and about 1.2 million people suffer fatal injuries (Chin and Quddus, 2003; Tay, 2003; Anwaar et al., 2012; Rosenbloom and Eldror, 2013).

The causes of Nigeria's fatal car accidents were divided into psychological, mechanical, and environmental factors (Umar, 2003).

The human factor accounts for up to 90% of injuries, while the technological and environmental factors contribute to the other 10%. Human factors include visual acuteness, driver fatigue, poor knowledge of road signs and rules, analphabetism, health problems, excessive speed, drug abuse, and over-confidence while on the steering wheel. Poor maintenance of cars, tyre blowouts, bad lighting, unroad worthy vehicles and broken-down vehicles on the road without adequate warning are among the technical factors that lead to fatal car accidents. The environmental factors include heavy rainfall, winds from harmattan, reflection from the sun, heavy wind, potholes, and untarred paths. Such factors have contributed individually and/or collectively to the high rate of fatal road accidents in Nigeria.

In recent times researchers have been modeling road accidents in different parts of the world with crash prevention models. It is, however, extremely tedious to apply only models that function in other areas to data obtained from different countries due to differences in the different factors in different countries (Fletcher et al., 2006).

A lot of educational research has studied the link between different factors and number of people killed in road accidents. The most widely used statistical models fall under the "general linear model" category (Kutner, Nachtsheim, Neter, & Li, 2005), such as simple linear regression analysis, multiple linear regression analysis, and variance analysis (ANOVA).

As a developing country Nigeria has increased traffic density resulting in the loss of many lives and properties. Therefore, the aim of this work is to determine the appropriate count regression model, between the Poisson and negative Binomial models, that better fits the accident data with respect to the estimated number of people who will be killed by road accidents in Nigeria and, in addition, to use the appropriate count regression model to examine main accident predictors resulting in the death of victims.

II. LITERATURE REVIEW

It is important to explain precisely what count data is used when describing the modeling of count data, as well as "count data" and "count variable." Typically, the term "count" is used as a verb meaning to enumerate units, objects or events.

We might count the number of road deaths observed on a stretch of the highway, how many patients died in a particular hospital within 48 hours of myocardial infarction, or how many different sunspots were found in March 2013. "Count data," on the other hand, is a plural noun referring to the observations made about the enumerated events or objects.

Count data in statistics refers to results that have only non-negative integer values ranging from zero to some broader undetermined value. Theoretically, counts can range from zero to infinity, but they are always limited to some smaller, distinct value, usually the maximum value of the count data being modeled. When the data being analyzed is made up of a large number of distinct numbers, even though they are positive integers, many statisticians tend to model the counts as if they were continuous.

A "count variable" is a given list or count data array. These results can only presume non-negative integer values, once again. However, an answer variable is known as a random variable in a statistical model, meaning that at any given time the particular set of enumerated values or counts could be different than they are.

In addition, the values are assumed to be independent of each other (i.e., they do not provide any strong evidence of association). For count test, the Poisson regression model is used, with large count results being rare events (Kutner et al., 2005). In addition, the Poisson regression model is particularly attractive for modeling count results, since the model has been expanded into a regression system, has a simple structure, and can be easily estimated (Lee, 1986).

This simplicity, however, is the product of some limiting assumptions: the variance should be equal to the mean of the count data for the response. Violations of this principle can have significant effects on the model coefficients ' reliability and efficiency (Sturman, 1999). In fact, in most cases, the mean and the variance of a dependent variable are not the same, such as the number of accident deaths. Instead the model's variance sometimes exceeds the mean value, a phenomenon called dispersion (Hilbe, 2007). In addition, count data characteristics that give rise to further assumption breaches, which may lead to flaws in the Poisson regression model. Consequently, this condition may lead the Poisson regression model being replaced by negative binomial regression because the negative binomial regression has an extra parameter that counts for over dispersion (Hilbe, 2007).

Road traffic accidents place a heavy burden on household finances as well as regional and foreign economies. The loss of breadwinners and the added burden of caring for members handicapped by road traffic accidents push many families deep into poverty. Motor vehicle accidents are also the third most important cause of death in developing countries among males of the economically active age group (Soderland et al., 1995). The literature hardly considers reliable epidemiological data from many of the developing countries (Van et al., 2006). Hospital archives or police records from which data on injuries and incidents could be collected underestimate the overall injury burden (Balogun, 1992; Asogwa, 1992). In addition, given the significance of injury as a public health issue, few studies have examined the economic and social impacts. This is because of several factors mainly linked to the quality of reliable data. (Afukaar et al., 2003).

Nader, (1997) noted that vehicles play a dominant role on the road, mechanical vehicle deficiencies are the main source of most traffic accidents. The truth is that no vehicles on our roads are free, in addition to second-hand vehicles imported as "Tokumbo". Various vehicle manufacturers emphasized maintenance in encouraging the minimal effect of road accidents caused by vehicle failure. Stringent regulations are placed on vehicles with faulty brakes, poor lighting, bad tires and the entire body structure as they serve as the essential structural components for vehicle control when in service. Similarly, the existence and condition of the roads that depends largely on road design provides smooth traffic flow or otherwise. Traffic output pavements and public spaces affect the cause of accidents or their avoidance. Slippery pavement with skidding can cause vehicle accidents. Specific paving design requires strong tire adhesion and adequate control skills (Kadiyali,2010).

Hardly a day goes by in Nigeria today without the occurrence of a road traffic accident leading to a progressively rising incidence of morbidity and mortality rates as well as financial costs for both society and the individual involved. News about some of these traffic accidents gets to media houses ' news rooms and is broadcast while the majority goes unreported. Nigeria has the highest rate of road accidents and the highest death toll per 10,000 vehicles (Sheriff, 2009). One might be tempted to think the level of awareness among Nigerians about the causes of road traffic accidents is very small. In other words, Nigerian roads have become vulnerable killing grounds for their users.

Contrary to the general belief that Nigerians have very low awareness of the causes of road traffic accidents, earlier research has shown that Nigerians know a great deal about what could cause road traffic accidents (Asalor, 2010).

III. METHODOLOGY

Poisson distribution serves as the basis for the creation of models for count data. Most of the count data models belong to the family of Generalized Linear Models.

Generalized linear (GLM) models are commonly used in the study of road accidents. We consider two types of GLMs in this research; Poisson regression model, and models of negative binomial regression model. The Poisson distribution is generally appropriate for representing count data like traffic accidents, since accidents occur only rarely.

Almost all of count models have a basic structure as described by (Hilbe, 2014) as the equation given as

$$\mathrm{Ln}(\mu) = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots \alpha_p X_p \quad (1)$$

To isolate the predicted mean count on the left side of equation (1), we take exponential of both sides of the equation, we obtain

$$\mu = e^{\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots \alpha_p X_p} \quad (2)$$

Both Equations (1) and (2) are important in defining the terms in the count data models as it shall be discussed later. Hilbe (2014) claimed that significant feature of using the natural log link in the count data linear relationship model is that it assures that the predicted values will be positive, that is, $\mu > 0$. The common models for handling count data which are the Poisson and negative binomial models are discussed as follows:

POISSON REGRESSION MODEL

The Poisson distribution is often used as a standard model for count observations. The distribution was derived by Poisson as a limiting case of the binomial distribution. It was the first model specifically used to model counts and it still stands at the base of many types of count models available to analysts. Since the mean and variance of Poisson distribution coincide, in the Poisson regression model, the mean and the variance are assumed to be equal. This makes it unsatisfactory to use Poisson model on real study data. The Poisson probability distribution function (pdf) is given by

$$\mathrm{P}(y_i/x_i) = \frac{\pi_i^{y_i}\exp(-\pi_i)}{y_i!}, \qquad y_i = 0,1,2,\cdots \quad (3)$$

Where y_i is the number of counts (persons killed in accidents) for a particular period of time i, π_i is the expected number or mean number of counts per period, which can be modeled as;

$$\pi_i = \exp(x_i\alpha_i) \quad (4)$$

Where x_i the vector of the explanatory or independent variables and α is the vector of unknown regression parameters.

Equation (4) implies that a unit increase in x_i leads to an increase in π_i by a multiplicative factor of $\exp(\alpha_i)$. The main drawback of the Poisson regression model is that, the mean and the variance are approximately equal, that is

$$\mathrm{E}\,(y_i/x_i) = \mathrm{Var}\,(y_i/x_i) = \pi \quad (5)$$

Therefore, when there is heterogeneity or over-dispersion, the variance increases faster, the Poisson regression model does not work well. Therefore, there is the need to fit a parametric model that is more dispersed than the Poisson model and a natural choice is to use the negative binomial regression model.

The Log-likelihood function of the Poisson regression model is defined as;

$$\ell = \sum_{i=1}^{n}(-\pi_i + y_i ln\pi_i - lny_i!) \quad (6)$$

By substituting equation (4) into equation (6), the Log-likelihood function is obtained as;

$$\ell = \sum(-e^{x_i\alpha_i} + y_i x_i \alpha - lny_i!) \quad (7)$$

Moreover, to estimate the regression coefficients using the Maximum Likelihood Estimation (MLE) criteria, the partial derivatives of the Log-likelihood function with respect to the β_s are set to zero as;

$$\frac{\partial \ell}{\partial \alpha} = \sum_{i=0}^{n}(y_i - e^{x_i\alpha_i})\,x_i = 0 \quad (8)$$

The Poisson regression model parameter estimates the cannot be obtained directly from Equation (8), the iterative numerical procedure, the Newton Raphson method, is often employed to get the estimates the parameters (Anseline, 2002).

THE NEGATIVE BINOMIAL MODEL

The Negative Binomial model can be obtained from the mixture of Poisson and Gamma distributions, and it is given as

$$\mathrm{P}(y_i/x_i) = \frac{\Gamma(y_i+\gamma^{-1})}{y_i!\Gamma(\gamma^{-1})}\left[\frac{1}{1+\gamma\pi_i}\right]^{\gamma^{-1}}\left[\frac{\gamma\pi_i}{1+\gamma\pi_i}\right]^{y_i}$$

for $i = 0,1,2,\ldots$ (9)

Where y_i is the number of counts (persons killed in accidents) for a particular period of time i, π_i is the expected number of persons killed due to road accidents per period, and it is given as; $\pi_i = \exp(x_i'\beta)$.

The conditional mean and variance of NB model are given BY

$\mathrm{E}(y_i/x_i) = \pi_i$ and $\mathrm{Var}(y_i/x_i) = \pi_i(1+\gamma\pi_i) > \mathrm{E}(y_i/x_i)$

Thus, the Negative Binomial model is over-dispersed and allows extra variation compared with the Poisson model, and it has more desirable properties than the Poisson model (Chin and Quddus, 2003).

The variance of the Negative Binomial model is greater than the mean. In the model, γ represents the variability parameter which indicates the degree of over-dispersion. For example, if γ =0, the Negative Binomial model is the equal to the Poisson model. The Log-likelihood function of the model can be derived as

$$\ell = \sum_{i=1}^{n}\{[\sum_{i=1}^{y-1}\ln(y_i+\gamma^{-1}) - lny_i! + \gamma^{-1}[\ln(\gamma^{-1}) - \ln(\gamma^{-1}+e^{x_i\alpha})] + y_i[x_i\alpha - \ln(\gamma^{-1}+e^{x_i\alpha})]]\}$$

Meanwhile, to parameters of the model, α and γ, can be estimated using the Newton Raphson method (Lee and Mannering, 2002).

IV. MODEL SPECIFICATION

In this research, the models considered have the expected number of persons killed in road accidents within a particular period of time as a function of the explanatory variables; driver error, road condition and faulty vehicle, each of the models parameterizes

$$\pi_i = \exp(\alpha_0 + \alpha_1 \text{ DE} + \alpha_2 \text{ RC} + \alpha_3 \text{ FV }) \quad (10)$$

Where DE, RC, and FV respectively denote the Driver Errors, Road Condition, and Faulty Vehicle.

PARAMETER ESTIMATION

To estimate the parameters of the two models, The Maximum Likelihood Estimation (MLE) procedure is used. It is because both the two models involved in this research can be estimated using the MLE method. To evaluate the models, it is necessary to examine the significance of the variables included in the model. For a better model, the estimated regression coefficients have to be statistically significant.

MODEL SELECTION METHODS

After fitting the various models to the data obtained, it is necessary to check the overall fit as well as the adequacy of the fit of the respective models. The quality of the fit between the observed values (y) and the predicted values ($\hat{\theta}$) can be measured by the various test statistics, but in this research we used a statistic called the deviance goodness of fit test which is defined as;

$$D(y:\hat{\pi}) = -2\sum_{i=1}^{n} y_i \ln\left(\frac{y_i}{\hat{\pi}_i}\right) - (y_i - \hat{\pi}_i) \quad (11)$$

Where y_i is the number of observed counts, n is the number of observations and $\hat{\pi}_i$ represents the fitted means of the models.

Thus, the smaller the value of the deviance of the fitted model the better the model or the more statistically significant the model becomes.

AKAIKE'S INFORMATION CRITERION (AIC)

Akaike's Information Criterion (AIC) (Akaike, 1973) is a measure of the relative quality of a statistical model for a given data. That is, given a collection of models for a data, AIC shows the quality of each model, relative to other models. Hence, AIC provides a means for model selection. For any statistical model, the AIC value is computed using the relation;

$$AIC = -2L + 2k$$

Where L is the maximized value of the likelihood function and k is the number of parameters in the model. The best model is always the model with the smallest AIC.

BAYESIAN INFORMATION CRITERION (BIC)

The Bayesian Information Criterion (BIC) is a criterion for selecting a model among a finite set of models considered in a research. It is based on the likelihood function and is closely related to the Akaike's Information Criterion (AIC). Mathematically the BIC is an asymptotic result obtained under the assumption that, the distribution of the data is in the exponential family. Let;

$x =$ the observed data

$n =$ sample size

$k =$ the number of unknown parameters to be estimated. For example, for a linear regression model, k is the number of independent variables, including the intercept.

P(x/M) is the marginal likelihood of the data given the model, and $\hat{L}$ is the maximized value of the model's likelihood function. Thus,

$\hat{L}$= P($x/\hat{\pi}$, M), $\hat{\pi}$ is the value of the parameter that maximizes the model's likelihood function

Therefore, the Bayesian Information Criterion (BIC) is given as

-2ln P(x/M) $\approx$ BIC = -2ln $\hat{L}$ + k(ln(n)-2ln(2β))

The best model is always the model with the smallest BIC value.

The general analysis is performed using R package version 3.5.1

V. RESULTS AND DISCUSSION

Table 1 presents the quarterly recorded deaths due to road accidents on Nigerian roads for the year 2017 and 2018.

QUARTER	PERSONS KILLED (Y)	DRIVER ERROR (X_1)	ROAD CONDITION (X_2)	FAULTY VEHICLE (X_3)
Q1 2017	1466	1308	28	400
Q2 2017	1279	1307	32	401
Q3 2017	1070	1103	27	312
Q4 2017	1306	1331	26	111
Q1 2018	1292	1261	41	401
Q2 2018	1331	1321	38	398
Q3 2018	1538	1323	25	378

Table 1: Quarterly Distribution of Person Killed by Road Accidents for 2017 and 2018 in Nigeria

The interesting feature of the above table is that, the number of deaths seem to be decreasing in the year 2017 .In the first quarter, there were 1466 deaths but it dropped down to 1279 deaths in the second quarter. However, it rose to 1306 in the third quarter and dropped down again in the first quarter of the year 2018.It turned out to be increasing in the year 2018.On average ,there are 1326 deaths quarterly in Nigeria due to road accidents.

VARIABLES	PARAMETER ESTIMATE	STANDARD ERROR	RATE (exp(β))	P-VALUE
Intercept	6.253725	0.262428	519.95	0.000
Driver Error	0.000829	0.0001759	1.00	0.000

(DE)				
Road Condition (RC)	-0.008967	0.002249	0.99	0.000
Faulty Vehicle (FV)	0.000473	0.0001160	1.00	0.000

Table 2: Parameter Estimates of Poisson Regression Model

The table 2 displays the estimates of the parameters in the Poisson regression model for the number of person killed in road accidents. The table gives the parameter estimates, standard errors, rate and the corresponding p-value for the various variables used in the model.

The parameter estimates are interpreted in terms of the rate of the number of persons killed in road accidents. The rates reflect the multiplicative effect of the various variables on the number of persons killed in road accidents.

The results obtained gave an intercept estimate of 6.254 and an estimated death rate of 519.95 was significant at 5 % level of significance. Also, the variables, Road Condition, and Faulty vehicle were also significant.

The Intercept has a rate of 519.95, while Driver Errors, Road Condition and Faulty Vehicle have the rates of 1.00, 0.99, and 1.00 respectively.

Therefore, the average of the Poisson regression model with significant factors for estimating the average number of persons killed in road accident is

$$\pi_i = \exp(6.25373 + 0.00083DE - 0.00897RC + 0.00047FV) \quad (12)$$

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	RATE ($\exp(\beta)$)	P-VALUE
Intercept	6.23815	0.362724	511.93	0.0000
Driver Error (DE)	0.00084	0.000242	1.00	0.0005
Road Condition (RC)	-0.0088	0.003221	0.99	0.0064
Faulty Vehicle (FV)	0.00047	0.000166	1.00	0.0045

Table 3: Parameter Estimates of Negative Binomial Regression Model

Table 3 shows the parameter estimates, standard errors, rates, and the corresponding p-values for the variables used in the Negative Binomial Regression Model. The Intercept, Driver Error, Road Condition and Faulty Vehicle were found to be significant at 5% level of significance.

The mean regression of the Negative Binomial model for estimating the expected number of persons killed in road accidents within a specific year with significant variables is therefore formulated as;

$$\pi_i = \exp(6.23815 + 0.00084DE - 0.00880RC + 0.00047FV) \quad (13)$$

The Intercept has a rate of 511.93, while Driver Errors, Road Condition and Faulty Vehicle have the rates of 1.00, 0.99 and 1.00 respectively.

VI. GOODNESS OF FIT TEST FOR POISSON VERSUS NEGATIVE BINOMIAL REGRESSION MODELS

The goodness of fit test is to assess the quality of the model compared to other fitted models as provided in table 4;

CRITERION	POISSON	NEGATIVE BINOMIAL
AIC	85.305	84.994
BIC	85.08882	84.72322
NULL DEVIANCE	102.347 on 6 degrees of freedom	50.9512 on 6 degrees of freedom
RESIDUAL DEVIANCE	14.109 on 3 degrees of freedom	6.9075 on 3 degrees of freedom

Table 4: Goodness of Fit Test

From Table 4, It can be observed that Poisson model has AIC=85.305 which is higher than that of Negative Binomial (AIC=84.994). Similarly, the larger BIC value of 85.08882 is for Poisson Model, while Negative Binomial has 84. 72322.With respect to Null and Residual deviances obtained, Poisson has 102.347 and 14.109, while Negative Binomial has 50.9512 and 6.9075 respectively.

VII. COMPARISON AND ASSESSMENT OF THE MODELS

From Tables 2 and 3, it can be observed that both models have similar parameter estimates and rates with varying standard errors, yet both models proved that the factors are significant at 5% level of significance.

Furthermore, table 4 provides the goodness of fit for both models with respect to AIC, BIC and Deviance. The Negative Binomial model produced smaller values of AIC = 84.994, BIC = 84.72322 and Deviance = 6.9075, these indicate that Negative Binomial fits accident data better with respect to the expected number of persons killed in road accident as compared to Poisson regression model.

We therefore conclude that the negative binomial regression model is the suitable model in fitting accident data with respect to the expected number of persons killed in road accident in Nigeria. Hence, the mean of the Negative Binomial model with significant variable; Driver Errors, Road Condition and faulty Vehicle for predicting the expected number of person killed in road accident in Nigeria per quarter is given as

$$\pi_i = \exp(6.23815 + 0.000840DE - 0.0088RC + 0.00047FV)$$

We discovered that the two fitted models produced significant factors at 5% level of significance. The factors are the Driver Errors (DE), Road Condition (RC) and finally Faulty Vehicle (FV) ,this is in accord with the results obtained by Abdurrar'uf et al.(2017) which stated that driver's behavior, vehicle's fault and the road environment are the major causes of road accident .However, the goodness of fit test revealed that Negative Binomial regression performs better than the Poisson model; as such the Negative Binomial is referred as the appropriate count regression model with respect to the expected number of persons killed in road accident in Nigeria.

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