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ON THE TRENDS OF REGISTERED BIRTH AND DEATH RATES IN NIGERIA: EVIDENCE FROM GENERALIZED LINEAR MODELS

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ABSTRACT

This study investigated the trends of registered Death and Birth in Nigeria using Generalized Linear Models. Annual data on Death and Birth was collected from National Population Commission for the period of 2004 to 2017. The Natural increase calculated revealed a positive trend in the natural increase in Nigeria from 2004 to 2017. Evidence from summary statistics revealed some level of over dispersion (variance > mean). This study explored Poisson Regression Models and Negative Binomial Regression Models using two links (identity and log). The results revealed a positive increase in registration of birth and death rates in Nigeria and among the competing the models, Negative Binomial regression model with identity link emerged as the best model for modeling birth and death rates registration in Nigeria. Data on numbers of deaths and causes of death are essential if countries are to determine priorities, formulate and monitor policies for public health care as well as other government policies that may be based on such data.

Keywords: Birth, Death, Trends, Generalized Linear Models (GLMs), Poisson, Negative Binomial.

1.0 Introduction

Birth and death are vital events that occur in all countries of the world and the registration of these events is of utmost importance for estimating the natural increase (or decrease) and the annual change in the size and structure of the population. In Nigeria, birth and death registration started from the colonial era and is currently carried out by the National Population Commission (NPC), which was inaugurated in 1989 (Akande & Sekoni, 2005). The level of birth and death registration in a country represents to a large extent the level of recognition of the significance of vital statistics as an essential input for the planning of human development. In developed countries, vital registration is done well enough to be useful for determining population changes and socioeconomic planning, but such is not the case in developing countries where adequate attention is not paid to such registration.

According to statistics from the United Nations Children's Fund (UNICEF) about 70 percent of five million children born annually in Nigeria are not registered at birth. They have no birth certificate and in legal terms, they do not exist. Their right to an identity, name and nationality is denied and their access to basic services threatened. More worrisome is the general apathy towards registering deaths and the lack of awareness among the public (Bequele, 2005).

A vital registration system is a system that is concerned with the continuous, permanent, and compulsory recording of the occurrence and characteristics of vital events such as birth, marriage, divorce, migration, and death (Ayeni & Olayinka, 1979). By this definition, vital statistics, which are derived from civil registration records, are compiled from local registers and their coverage should be nationwide and comprehensive if both the registration and statistics systems are adequate and well maintained. Unfortunately, most of the vital registration systems in Nigeria and other parts of Africa are far from yielding the accurate and complete data needed for the direct estimation of basic demographic and socioeconomic variables. According to Momodou (2012), there are, at present only 2,370 registration centres in the 774 Local Governments Areas of Nigeria and this number is said to be insignificant considering the country's population.

Timely data on births and deaths is a cornerstone and a prerequisite for rational planning in the health sector and beyond. Particularly, reliable birth and death statistics from vital registration system have been scanty for the last several decades and the demand for accurate data on fertility and mortality has also grown immensely over the same period in Nigeria and other developing countries (Adekolu-John, 1988).

To fill these gaps, population censuses and nationally representative household sample surveys have been widely used as two principal methods of data collection. These two data sources have contributed significantly to providing data required for the estimation of the vital rates (crude birth and death rates, general, age-specific and total fertility rates, gross and net reproduction rates, life expectancy, etc). These approaches have brought to light the much needed information on levels, patterns, and trends in fertility and mortality (NPopC , 2010).

When numbers of births and deaths are derived from civil registration, for example, corresponding numbers of persons required for the calculation of rates and summary measures are usually estimated from population census data. When population censuses are used to collect data on numbers of births and deaths, they are often supplemented by surveys of various kinds, which may provide more detailed and timely data (Eguda, 2006).

Most literature revealed that a country with low life expectancy can lead to high levels of mortality (Chukwu and Oladipupo, 2012). Estimates of life expectancy revealed that adult mortality is higher in Nigeria than some other African countries such as Ghana and Cote d'Ivore (WHS, 2009). Tobin et al (2013) found out that considerable number of respondents in their survey has heard about birth and death registration but birth rate registration is higher than death rate.

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Therefore, the aim of this paper investigates the trend of birth and death registration in Nigeria using Generalized Linear Models (Poisson and Negative Binomial regression models of Identity and log links).

2.0 Model Specification

a. Poisson Regression Model of Identity and Log Links

A generalized linear model is made up of a linear predictor

$$\eta_i = \beta_0 + \beta_{1x1i} + \ldots + \beta_p x_{pi} \qquad 2.1$$

having two functions (Turner, 2008)

A link function that describes how the mean, $E(Y_i) = \mu_{i,}$ depends on the linear predictor

$$g(\mu_i) = \eta_i \qquad 2.1$$

A variance function that describes how the variance, var(Y_i) depends on the mean

$$\text{var}(Y_i) = \varphi V(\mu) \qquad 2.3$$

Where the dispersion parameter φ is a constant.

b. Modelling Poisson Data

Suppose $Y_i \sim$ Poisson (λ_i) 2.4

Then,

$$E(Y_i) = \lambda_i \qquad var(Y_i) = \lambda_i \qquad 2.5$$

Meaning that the mean = variance from equation 2.5

So the variance function is

$$V(\mu_i) = \mu_i \qquad 2.6$$

The link function must map from $(0,\infty) \rightarrow (-\infty,\infty)$.

Then, $g(\mu_i) = log(\mu_i)$ 2.7

Modelling the logarithm of the mean as a linear function of observed covariates then result to a generalized linear model with Poisson response and link log.

While $g(\mu_i) = \mu_i$ is called identity link.

c. Maximum Likelihood Estimation

The log likelihood function is given as

$$Log\ L(\beta) = \sum\{yi\ log(\mu i) - \mu i\} \quad 2.8$$

Where μ_i depends on the covariates X_i and a vector of P parameters β through the log link in equation (2.6).

The log-linear Poisson models satisfy the estimating equation

$$X'Y = X'\dot{\mu} \quad 2.9$$

Where X is the model matrix, with one row each observation and one column for each predictor, including the constant.

And $\dot{\mu}$ is the vector of fitted values, calculated from the mle's β by exponentiating the linear predictor $\eta = X'\beta$. (Fox. 2014)

d. Negative Binomial Regression Model of Identity and Log Links

$$f(y_i U_i \Psi) = \frac{\Gamma(y_i + \Psi)}{\Gamma(y_i+1)\Gamma(\Psi)} \left(\frac{\Psi}{u_i + \Psi}\right)^{\Psi} \left(\frac{\Psi}{u_i + \Psi}\right)^{y_i} \quad 2.10$$

Which it can also be define as

$$f(y_i \Psi, U_i) = \binom{y_i + \Psi - 1}{\Psi - 1} \left(\frac{\Psi}{u_i + \Psi}\right)^{\Psi} \left(\frac{\Psi}{u_i + \Psi}\right)^{y_i} \quad 2.11$$

The first moment of negative binomial is as follow

$$E[y_i; U_i \Psi] = U_i \quad 2.12$$

$$E[y_i; U_i \Psi] = U_i + \frac{U_i^2}{\Psi} \quad 2.13$$

The next step consists of defining the log-likelihood function of the negative binomial 2

$$ln\left(\frac{y}{1}\right) = \sum_{j=0}^{y-1} ln\,(J + \Psi) \qquad 2.14$$

By substituting equation (2.14) above into equation (2.10) the log-likelihood can be computed using the following

$$lnL(\Psi,\beta) = \sum_{j=1}^{n}\{\left(\sum_{j=0}^{y-1} ln\,(J + \Psi)\right) - ln\,y_i! - (y_i + \Psi)\ln(1 + \Psi^{-1}\,U_i) + ln\Psi^{-1} + y_i\,lnU_i\}$$

y_i 2.15

The log-likelihood has been expressed as

$$lnL(\Psi,\beta) = \sum_{j=1}^{n}\{\,y_i\,ln\left(\frac{\Psi U_i}{1+\Psi U_i}\right) - \Psi^{-1}\ln(1 + \Psi U_i) + ln\,\Gamma(y_i + \Psi^{-1}) - ln\Gamma(y_i + 1) - ln\Gamma(\Psi^{-1})\}$$

2.16

Recall that $U_i = \exp(x';\beta)$

$$g(\mu_i) = \log(\mu_i) \qquad 2.17$$

(Tobias and Roland, 2017).

d. Criterion for Model Solution (AIC and BIC)

Akiake Information Criterion (AIC)

The AIC is a measure of fit that penalizes for the number of parameters p

$$AIC = -2l_{mod} + 2p \qquad 2.18$$

Where l_{mod} is the log-likelihood of the fitted models. Smaller values indicate better fit and thus the AIC can be used to compare models. (Turner, 2008).

Bayesian information criteria (BIC)

Similar to AIC, the BIC also imploys a penalty term associated with the number of parameter (*P*) and the sample size (*M*). This measure is also known as schwanze information criterion. It is computed the following ways

$$AIC = -2lnL + pln\, n \qquad 2.19$$

Equation 2.19 is then the BIC. Again smaller values are better.

e. Goodness of Fit

A measure of discrepancy between observed and fitted values is the deviance. It takes the form

$$D = 2\sum\{y_i \log(\frac{y_i}{\hat{\mu}_i}) - (y_i - \hat{\mu}_i)\}. \qquad 2.20$$

The first term is identical to the binomial deviance, representing ‘twice a sum of observed times log of observed over fitted’. The second term, a sum of differences between observed and fitted values, is usually zero, because m.l.e.’s in Poisson models have the property of reproducing marginal totals. Thus, the deviance can be used directly to test the goodness of fit of the models.

3.0 Materials and Methods

This research focused on vital registration of birth and death in Nigeria for the period of 2004 to 2017. The Data was collected from National Population Commission, Abuja. Natural increase was computed from the data collected while Generalized Linear Models (Poisson and negative Binomial Models) of identity and log links were used to investigate the trends in Birth and Death in Nigeria.

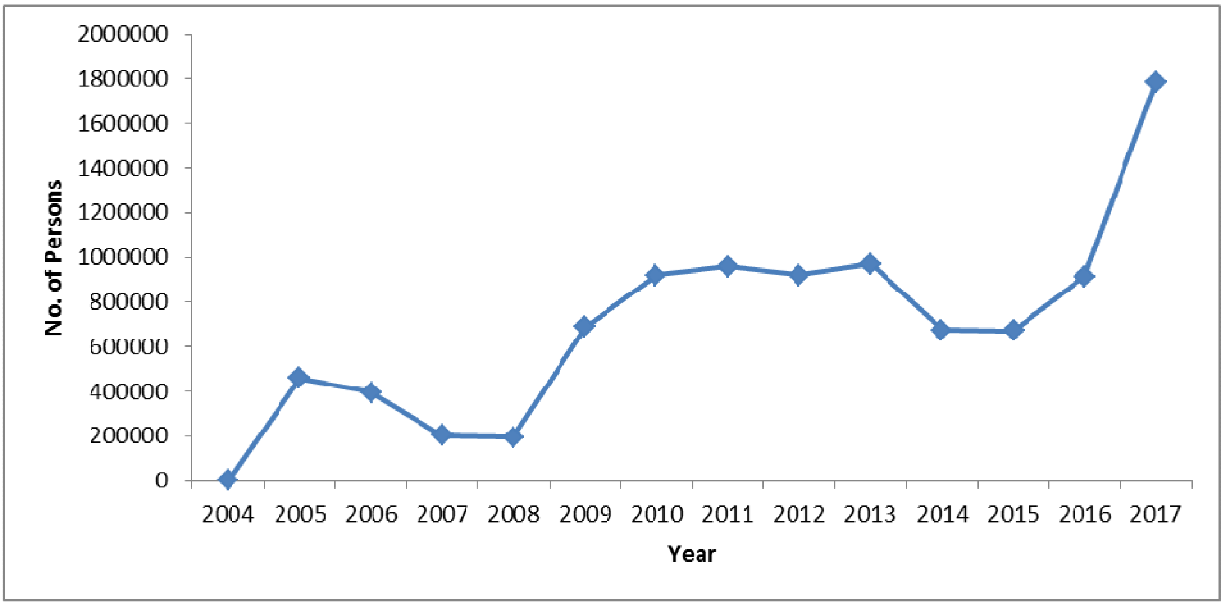

Fig. 1: Plot of natural Increase in Nigeria from 2004 to 2017

Fig 1 above shows some fluctuations while there is a positive growth from 2015 to 2017.

4.0 Data Analysis and Results

```
summarize death birth

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       death |         14     12690.5    5549.882         24      23882
       birth |         14    709730.1    451664.5       1124    1807025
```

The above output shows over dispersion in the data set on birth and death rate (variance > mean). With this result one will expect negative binomial regression to outperform the Poisson regression.

Table 4.0: Poisson Generalized Linear Model of death rate using identity link

```
. glm death time, family(poisson) link(identity)

Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =  36307.01776                    (1/df) Deviance =   3025.585
Pearson          =  28298.35055                    (1/df) Pearson  =   2358.196

Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =   2604.508
Log likelihood   = -18229.55872                    BIC             =   36275.35

------------------------------------------------------------------------------
             |                 OIM
       death |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   598.9221   7.785369    76.93   0.000     583.6631    614.1812
       _cons |   8797.506   53.95534   163.05   0.000     8691.756    8903.257
------------------------------------------------------------------------------
```

The table 4.0 above presented the Poisson GLM for death rate using the identity link. The result revealed a significant increase in death rate as time increases (time = 598.9221, P-value = 0.000)

Table 4.1: Poisson Generalized Linear Model of death rate using log link

```
. glm death time, family(poisson) link(log)
Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =  36706.10509                    (1/df) Deviance =   3058.842
Pearson          =  27992.05883                    (1/df) Pearson  =   2332.672

Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =   2633.015
Log likelihood   = -18429.10238                    BIC             =   36674.44

------------------------------------------------------------------------------
             |                 OIM
       death |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .0440896   .0005942    74.20   0.000     .0429251    .0452541
       _cons |   9.146282    .004898  1867.36   0.000     9.136683    9.155882
------------------------------------------------------------------------------
```

The table 4.1 above presented the Poisson GLM for death rate using the log link. The result revealed a significant increase in death rate as time increases (time = .0440896, P-value = 0.000).

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Table 4.2: Negative Binomial Generalized Linear Model of death rate using identity link

```
. glm death time, family(nbinomial 1) link(identity)

Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =  11.26296829                    (1/df) Deviance =   .9385807
Pearson          =  2.713906125                    (1/df) Pearson  =   .2261588

Variance function: V(u) = u+(1)u^2                 [Neg. Binomial]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =   21.14498
Log likelihood   = -146.0148401                    BIC             =  -20.40572

------------------------------------------------------------------------------
             |                 OIM
       death |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |    687.509   980.9227     0.70   0.483    -1235.064    2610.082
       _cons |   8293.297    5824.16     1.42   0.154    -3121.846    19708.44
------------------------------------------------------------------------------
```

The Table 4.2 above presented the Negative Binomial GLM for death rate using the identity link. The result revealed an insignificant increase in death rate as time increases (time = 687.509, P-value = 0.483).

Table 4.3: Negative Binomial Generalized Linear Model of death rate using log link

```
. glm death time, family(nbinomial 1) link(log)
Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =   11.3253381                    (1/df) Deviance =   .9437782
Pearson          =  2.523265816                    (1/df) Pearson  =   .2102722

Variance function: V(u) = u+(1)u^2                 [Neg. Binomial]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =   21.14943
Log likelihood   =  -146.046025                    BIC             =  -20.34335

------------------------------------------------------------------------------
             |                 OIM
       death |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .0473031   .0692988     0.68   0.495      -.08852    .1831262
       _cons |   9.124348   .5237709    17.42   0.000     8.097776    10.15092
------------------------------------------------------------------------------
```

The Table 4.3 above presented the Negative Binomial GLM for death rate using the log link. The result revealed an insignificant increase in death rate as time increases (time = .0473031, P-value = 0.495)

Table 4.4: Model Selection for Death rate using AIC and BIC

Model	Link	AIC	BIC
Poisson	Identity	2604.508	36275.35
Poisson	Log	2633.015	3667.44
Negative Binomial	Identity	21.14498	-20.40572
Negative Binomial	Log	21.14943	-20.34335

From the Table 4.4 above, the best model is the model having the lowest values of AIC and BIC which are 21.14498 and -20.40572 respectively. This result is associated with Negative Binomial Regression Model with Identity Link.

Table 4.5: Poisson Generalized Linear Model of birth rate using identity link

```
. glm birth time, family(poisson) link(identity)

Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =    1582497.2                    (1/df) Deviance =   131874.8
Pearson          =  1474787.945                    (1/df) Pearson  =     122899

Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =   113050.6
Log likelihood   = -791352.0036                    BIC             =    1582466

------------------------------------------------------------------------------
             |                 OIM
       birth |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   89209.23   52.49574  1699.36   0.000     89106.34    89312.12
       _cons |   129870.1   290.3283   447.32   0.000       129301    130439.1
------------------------------------------------------------------------------
```

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The table 4.5 above presented the Poisson GLM for birth rate using the identity link. The result revealed a significant increase in birth rate as time increases (time = 89209.23, P-value = 0.000)

Table 4.6: Poisson Generalized Linear Model of birth rate using log link

```
. glm birth time, family(poisson) link(log)

Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =  1792640.902                    (1/df) Deviance =   149386.7
Pearson          =  1512362.373                    (1/df) Pearson  =   126030.2

Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =   128060.8
Log likelihood   = -896423.8544                    BIC             =    1792609

------------------------------------------------------------------------------
             |                 OIM
       birth |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |    .126448   .0000849  1490.17   0.000     .1262817    .1266144
       _cons |   12.52407   .0007844  1.6e+04   0.000     12.52253     12.5256
------------------------------------------------------------------------------
```

The Table 4.6 above presented the Poisson GLM for birth rate using the log link. The result revealed an insignificant increase in birth rate as time increases (time = .126448, P-value = 0.000).

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Table 4.7: Negative Binomial Generalized Linear Model of birth rate using identity link

```
. glm birth time, family(nbinomial 1) link(identity)


Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =   4.91105528                    (1/df) Deviance =   .4092546
Pearson          =  7.461677127                    (1/df) Pearson  =   .6218064

Variance function: V(u) = u+(1)u^2                 [Neg. Binomial]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =   28.50468
Log likelihood   = -197.5327454                    BIC             =  -26.75763

------------------------------------------------------------------------------
             |                 OIM
       birth |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   138599.7    38575.9     3.59   0.000     62992.28     214207
       _cons |   1144.186   1165.336     0.98   0.326    -1139.832   3428.203
------------------------------------------------------------------------------
```

The Table 4.7 above present the Negative Binomial GLM for birth rate using the identity link. The result revealed a significant increase in birth rate as time increases (time = 138599.7, P-value = 0.000).

Table 4.8: Negative Binomial Generalized Linear Model of birth rate using log link

```
. glm birth time, family(nbinomial 1) link(log)
Generalized linear models                          No. of obs      =         14
Optimization     : ML                              Residual df     =         12
                                                   Scale parameter =          1
Deviance         =  11.04598545                    (1/df) Deviance =   .9204988
Pearson          =  3.336296782                    (1/df) Pearson  =   .2780247

Variance function: V(u) = u+(1)u^2                 [Neg. Binomial]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =   28.94289
Log likelihood   = -200.6002105                    BIC             =   -20.6227

------------------------------------------------------------------------------
             |                 OIM
       birth |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .1456096   .0724485     2.01   0.044     .0036131    .2876061
       _cons |   12.38212   .5414705    22.87   0.000     11.32086    13.44339
------------------------------------------------------------------------------
```

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The table 4.8 above presented the Negative Binomial GLM for birth rate using the log link. The result revealed a significant increase in birth rate as time increases (time = .1456096, P-value = 0.044).

Table 4.9: Model Selection for Birth rate using AIC and BIC

Model	**Link**	**AIC**	**BIC**
Poisson	Identity	113050.6	1582466
Poisson	Log	128060.8	1792609
Negative Binomial	Identity	28.50468	-26.75763
Negative Binomial	Log	28.94289	-20.6227

From the table 4.9 above, the best model is the model having the lowest values of AIC and BIC which are 28.50468 and -26.75763 respectively. This result is associated with Negative Binomial Regression Model with Identity Link.

4.1 Discussion of Findings

The Table 4.0 above presented the Poisson GLM for death rate using the identity link. The result revealed a significant increase in death rate as time increases (time = 598.9221, P-value = 0.000). The implication of this result is that the death rate in Nigeria increases over time. This result is in line with the works of Chukwu and Oladipupo, (2012) and WHS, (2009) which stated that Adult mortality is higher in Nigeria than some other countries.

The Table 4.1 above presented the Poisson GLM for death rate using the log link. The result revealed a significant increase in death rate as time increases (time = .0440896, P-value = 0.000) which is similar to the above Poisson GLM for death rate using identity link. The increase in death rate over time using Poisson GLM for death rate with log link is similar to the works of

Chukwu and Oladipupo, (2012) and WHS, (2009) which stated that Adult mortality is higher in Nigeria than some other countries.

The Table 4.2 above shows the Negative Binomial GLM for death rate using the identity link. The result revealed a non-significant increase in death rate as time increases (time = 687.509, P-value = 0.483). Although there is increase in death rate using Negative Binomial GLM which is in line with the works of Chukwu and Oladipupo, (2012) and WHS, (2009) but in this work, the increase in death rate over time is not significant.

The table 4.3 above presented the Negative Binomial GLM for death rate using the log link. The result revealed an insignificant increase in death rate as time increases (time = .0473031, P-value = 0.495). This result is similar to the Negative Binomial GLM for death rate using the identified link. Although there is increase in death rate using Negative Binomial GLM which is in line with the works of Chukwu and Oladipupo, (2012) and WHS, (2009).

From the table 4.4 above, the best model is the model having the lowest values of AIC and BIC which are 21.14498 and -20.40572 respectively. This result is associated with Negative Binomial Regression Model with Identity Link as the best model.

The Table 4.5 above presented the Poisson GLM for birth rate using the identity link. The result revealed a significant increase in birth rate as time increases (time = 89209.23, P-value = 0.000). The result is in line with Tobin et al (2013) that found out that birth registration was higher than death registration in south-south Nigeria.

The Table 4.6 above presented the Poisson GLM for birth rate using the log link. The result revealed a significant increase in birth rate as time increases (time = .126448, P-value = 0.000). This result is similar to Poisson GLM for birth rate using the identity link. The result is in line with Tobin et al (2013) that found out that birth registration was higher than death registration in south-south Nigeria.

The Table 4.7 above present the Negative Binomial GLM for birth rate using the identity link. The result revealed a significant increase in birth rate as time increases (time = 138599.7, P-value = 0.000). The result is in line with Tobin et al (2013) that found out that birth registration was higher than death registration in south-south Nigeria.

The Table 4.8 above presented the Negative Binomial GLM for birth rate using the log link. The result revealed significant increase in birth rate as time increases (time = .1456096, P-value = 0.044). This result is similar to Negative Binomial GLM for birth rate using the identity link.

From the table 4.9 above, the best model is the model having the lowest values of AIC and BIC which are 28.50468 and -26.75763 respectively. This result is associated with Negative Binomial Regression Model with Identity Link.

5.0 Conclusion and recommendations

This study was designed to investigate the trends of birth and death rates registration in Nigeria. The natural increase was used to analyses the data and discovered that birth registration was higher than death registration in the country.

Comparing Poisson Regression Models and Negative Binomial Regression models with Identity and Log links, the study concluded that there is positive increase in the registration of birth and death in Nigeria, but for the models, Negative Binomial Regression models with Identity Link outperformed the other models.

In view of the findings of this research, this study therefore recommends the following:

(i) The urgent strengthening of the country's civil registration systems by the federal government not only to ensure legal protection for all citizens but also to contribute to the economic, social and health development of the nation through creation of a functional demographic database.

(ii) Data on numbers of deaths and causes of death are essential if countries are to determine priorities and formulate and monitor policies for public health care as well as other government policies that may be based on such data.

(iii)It is therefore strongly recommended that the federal and state governments bring to the front-burner the importance, significance, encouragement and enforcement of vital event registration in the country.

(iv)The country's six geo-political zones should be sensitized well enough to register every vital event in their domains.

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