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INVESTIGATING THE TREND OF POPULATION GROWTH IN AKWA IBOM STATE USING GENERALIZED LINEAR MODELS

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Abstract
This study investigated the trend of population growth in Akwa Ibom using generalized linear models. Annual population growth data were collected from the National Population Commission for the period of 2006 to 2023. The calculated natural increase revealed a positive trend in the natural increase in akwa ibm from 2006 to 2023. Evidence from summary statistics revealed some degree of over-dispersion (variance > mean). This study explored Poisson and Negative Binomial Regression Models using two links (identity and log). The results revealed a significant positive increase in population growth in the state among the models. Overall, negative binomial regression with identity link for population growth rate was superior among the competing models. Therefore, Data on numbers of population growth are essential if states are to determine priorities, develop and monitor policies for public health care, as well as other government policies that may be based on such data.

INTRODUCTION

Population growth is an increase in the number of people living in a country, state, country, or city. To determine whether population growth has occurred, the following formula is required {birth rate plus immigration} minus {death rate plus emigration}. Birth rate, death rate, and migration are components of population growth in all countries of the world, and the registration of these events is of utmost importance for estimating the population growth, natural increase, and annual change in the size of the structure. Population density is often described as the number of people per square kilometer (or per square mile); it is related to urbanization, migration, and demographics. In Nigeria, birth and death registration started from the colonial era and is currently performed by the national population commission {NPC} which was inaugurated IN 1989 [akande and sekondi 2017].

Akwa Ibom State was created on September 23, 2019, from the former cross River State, and it is currently the highest oil and gas-producing state in the country. It is bordered on the east by the Cross River State, on the west by the Rivers State and Abia State, and on the South by the Atlantic Ocean and the southernmost tip of the Cross River State. The State takes its name from the Qua Iboe River, which bisects the state before it flows into the bright of bonny. It was split from the Cross River and was created by combining the Uyo, Ikot Ekpene,Eket, and

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Abak divisions of old Calabar Province. It has an Estimated population of about 4979418 (2022), projection of 6.858 km2 with area 726.0/km2 population density (2022), and 1.5% annual change.

The population growth in Akwa Ibom State is complex to study, and it is linked to interdisciplinary and multidisciplinary approaches of development that affect both the population and natural resources used for development. Population is the consequence of development, and population and development affect the environment and available resources in a state or country.

Uyo is the state capital with more than 5,000,000 inhabitants. It has an International Airport and two major seaports on the Atlantic Ocean, with the construction of a world class seaport "Ibaka Seaport" at Oron. The State has an ultra-modern sports complex with about 30,000 seaters. The main spoken languages are Ibibio, Annang, Eket, and Oron. The major cities in this region are Uyo, Eket, Ikot Ekpene, Oron, Abak, Ikot Abasi, Ikono, and Etinan. Uyo is currently the richest local government Area in Akwa Ibom State with a Gross Domestic Product (GDP) of $8 billion,with a metro population of about 1.329,000 in 2023, a 5.06% increase from 2022. The metro is population in Uyo in 2022 was 1265000, a 5.42% increase from 2021. The metro area population of myo in 2021 was 1,200,000, representing a 55.63% increase from 2020. Uyo was then established as the capital of Akwa Ibom State. Uyo has rapidly developed into a bustling metropolis. Of the 20 LGAs in Akwa Ibom, Akwa Ibom is the 30th largest in area and 15th most populous, with an estimated population of nearly 4.5 million as of 2016. It is rich and vibrant.

Population growth is a vital event that occurs 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. Population growth registration in a State represents 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 do not have a birth certificate, and in legal terms, they do not exist. Their right to identity, name, and nationality is denied, and their access to basic services is threatened.

As stated in Olayinka (2024), "a statistical report from the National Population commission shows that only 2,011,303 male, female, 1,951,944 Total 3,963,247 population growth in Akwa Ibom state in the year 2007. In 2008; female 2,040,865 and male 1,986,248 amount to 4,027,113 population growth. In 2009 the growth of female in Akwa Ibom State increase to 2,021,295 and Male 2,071,438 with Total 4092733.Also, in 2010 male was 2,102,874 and female 2,056,997,and in 2011 male was 2,135,022 with female 2,093,215, In 2011 it was 2,135,022 Male and Female 2,093,215, then in 2012 it was 2,167,600 and Female 2,129,821, moreover in 2013 it was 2,200,611 Male and Female 2,166,595, in 2014 it increased to 2,233,739 Male and Female 2,203,461, the male also increased in 2015 to 2,266,860 and Female 2240184, and in 2016 the male also increased to 2,299,729 and Female 2,276,565, in 2017 the male was 2,332,315 and female was 2,312,552, in 2018 the male increased to 2,364,714 and female 2,348,253,, then in 2020 the population growth has slight increase with male 2,428,692 and female 2,418,850, then in 2021 the population growth increased rapidly to male 2,460,224 and female 2,453,585, then in 2022, the make was 2,491,436 and female 2,487,982 and finally in 2023 we have male 2,563,738 and female 2,480,548.." These figures clearly point to the low levels of female and male population growth. Especially the 16 -30 years is associated with high risks, especially among the male population. The growth of the youth population imposes supply pressures on education systems and labor markets. This also means that a growing proportion of the overall population is made up of those considered to be of working age and thus not dependent on the economic activity of others. In turn, this declining dependency ratio can have a positive impact on overall economic growth, creating a demographic dividend. However, it is dependent on its ability to ensure the deployment of this working-age population toward productive economic activity and to create the jobs necessary for the growing labor force in Akwa Ibom State. When available population figures for the same period are considered, this shows that the Akwa Ibom vital registration system is being taken cognisante of.

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, 2023). By this definition, vital statistics, which are derived from civil registration records, are compiled from local registers from the 31 Local Government Areas in Akwa Ibom State. The largest local government area is Oruk Anam, which is made up of the Annang people, a minority tribe in the State.

1. Conceptual Framework

The conceptual framework for analyzing the trend of population growth in the akwa ibom state using Generalized Linear Models (GLMs) identified birth and death rates as dependent variables influenced by several independent variables. Generalized linear models provide a unified approach to many of the most common statistical procedures used in applied statistics. They have applications in disciplines as widely varied as agriculture, demography, ecology, economics, education, engineering, environmental studies and pollution, geography, geology, history, medicine, political science, psychology, and sociology. Models are abstract, simplified representations of reality that are often used in science and technology. No one should believe that a model could be true although much theoretical statistical inference is based on this assumption alone. Models can be deterministic or probabilistic. In the former case, outcomes are precisely defined, whereas in the latter case, they involve variability due to unknown random factors. Models with probabilistic components are called statistical models. The most important class with which we are concerned contains generalized linear models. They are so called because they generalize classical linear models based on a normal distribution. In addition to the linear regression part of the classical models, these models can involve a variety of distributions selected from a special family, exponential dispersion models, and they involve transformations of the mean through what is called a “link function” linking the regression part to the mean of one of these distributions (Lindsey, 2019). In addition, generalized linear models (GLMs) represent a class of regression models that allow us to generalize the linear regression approach to accommodate many types of response variables, including count, binary, proportions, and positive-valued continuous distributions. Given its flexibility in addressing a variety of statistical problems and the availability of software to fit the models, it is considered a valuable statistical tool and is widely used. In fact, the generalized linear model has been referred to as the most significant advance in regression analysis in the past 20 years. Generalized linear models include three components which are; a random component, which is the response and an associated probability distribution; a systematic component, which includes explanatory variables and relationships among them; and a link function, which specifies the relationship between the systematic component or linear predictor and the mean of the response. The link function allows generalization of the linear models for count, binomial, and percent data, thus ensuring linearity and constraining the predictions to be within a range of possible values (Tony et al, 2023)

2. Population Growth

Population growth in Akwa Ibom is driven at high birth rate, declining mortality, and migration trends. The country’s fertility rate, —veraging 5.2 children per woman, —s among the highest globally, while improved health care has significantly reduced death rates, increasing life expectancy. However, despite offering opportunities for a youthful labor force, rapid population growth presents challenges such as resource strain, unemployment, and poverty. Statistical models like Generalized Linear Models (GLMs) are crucial for analyzing population growth, helping policymakers project trends and address associated challenges. Effective strategies, such as family planning and improved infrastructure, are essential for sustainable development in the state.

Akwa Ibom State, located in Nigeria's South-South region, has experienced steady population growth over the years. The 2006 national census recorded a population of approximately 3.9 million, with projections indicating consistent increases since then. By 2016, the population had been estimated at nearly 5.5 million, and by 2023, it had risen to approximately 5.78 million, with an annual growth rate of around 3.4%. Akwa Ibom State, located in Nigeria's South-South geopolitical zone, has experienced significant population growth over the past few decades. According to the 2006 national census, the state's population was recorded at approximately 3.9 million. In the years following the 2006 census, projections indicated a continued increase in the population. For instance, the National Bureau of Statistics provided projected population figures for Akwa Ibom State from 2007 to 2015, reflecting a consistent upward trend during that period. By 2016, estimates suggested that the population had grown to nearly 5.5 million, making Akwa Ibom the 15th most populous state in Nigeria at that time. More recent estimates, as of 2023, place the population at approximately 5.78 million. The state's annual population growth rate has been projected to be around 3.4%. This growth has been accompanied by increased urbanization, with a significant portion of the population migrating from rural to urban areas, particularly to cities like Uyo, the state capital, as well as to Ikot Ekpene and Eket.

The rising population has implications for various sectors, including housing, infrastructure, and social services. For example, studies have examined the impact of population growth on land costs in urban centers like Uyo, highlighting challenges related to urban planning and development. Overall, Akwa Ibom State’s population dynamics reflect broader national trends of rapid growth and urbanization, necessitating strategic planning to accommodate the increasing number of residents and ensure sustainable development.

Urbanization has significantly impacted this growth, with migration to urban centers such as Uyo, Ikot Ekpene, and Eket. The growing population poses challenges for housing, infrastructure, and social services, highlighting the need for effective urban planning and sustainable development strategies.

3. Generalized Linear Models (GLMs)

Generalized Linear Models (GLMs) extend traditional linear regression by accommodating response variables that follow non-normal distributions, such as Poisson for count data or binomial for proportions. GLMs consist of three components: a random component (distribution of the response variable), a systematic component (linear combination of predictors), and a link function (connecting predictors to the response mean).

In the analysis of state population growth rates, GLMs are invaluable for modeling trends and identifying significant predictors like healthcare, education, and socioeconomic factors. They offer flexibility, interpretability, and robustness, making them a critical tool for demographic and policy-related studies.

According to Fahrmeir and Tutz (2021), the density (or probability mass function, respectively) of the response Y_i in a GLM (for i ∈ {1,, n}) is a member of the exponential family. This is a very useful class of distributions, which they now define.

4. Exponential family

A random variable Y follows a distribution function of the exponential family if its density (or probability mass function, respectively) can be written as follows:

$$f(y|\theta, \emptyset, w) = \exp\left\{\frac{y\theta - b(\theta)}{\emptyset}\ w + c(y, \emptyset, w)\right\} \qquad (1)$$

Where;

$b(.)$ and $c(.)$ are specified functions determined by the distribution.

φ ∈R^+ is the so-called scale or dispersion parameter.

θ ∈R is called canonical or natural parameter.

ω is the weight.

A generalized linear model is described by the following three components:

(i) **The random component:** for each observation i ∈{1,⋯ ,n} the corresponding random response Y_i is independent of the other responses and follows a distribution belonging to the exponential family, i.e., its density (or probability mass function, respectively) is of the form:

$$f(y|\theta_i, \emptyset) = \exp\left\{\frac{y_i\theta_i - b(\theta_i)}{\emptyset} + c(y_i, \emptyset)\right\} \quad (2)$$

(ii) **The systematic component:** for each observation i ∈{1,⋯ ,n} we define the linear predictor.

$$\cap i = \cap i(\beta) := x_i^T \beta_{Eq}^{Eq} = \beta_0 + \beta_{1xi1} + \ldots + \beta_k x_{ik} \quad (3)$$

where β_0 ∈R is called intercept and β ∈Rp is the vector of the regression parameters.

(iii) **The parametric link component**: it relates the random component to the systematic component. The mean μ_i = E[Y_i] for each observation i ∈{1,⋯ ,n}. The difference is that we do not assume that the mean is exactly equal to the linear predictor. Instead, we assume a relationship according to the so-called link function g : G→H (with G,H⊂R):

$$g(u_i) = \cap i(\beta) = x_i^T \beta \quad (4)$$

Link Function:

For poisson

$$log(\mu_i) = \beta_0 + \beta_1 X_{1i} + \cdots$$

For Binomial:

$$logit(p_i) = \beta_0 + \beta_1 X_{1i} + \cdots$$

Where;

$$logit(p_i) = log\left(\frac{p_i}{1 - p_i}\right).$$

Y_i = observed birth counts for each region i.

μ_i = expected birth counts for region i.

$$X_1, X_2, \ldots, X_p = predictoris\ healthcare\ expenditure$$

$$\beta_0, \beta_1, \ldots, \beta_p = model\ coefficients.$$

This model identifies significant factors influencing birth rates and informs policy decisions on population growth and public health in Akwa Ibom State.

5. Data Analysis and Model Specification Techniques

The statistical methods of analysis employed in this dissertation are as follows:

i Basic Equation of Population Dynamics

ii Poisson Regression Model of Identity and Log Links

iii Negative Binomial Regression Model of Identity and Log Links

iv Criterion for model solutions: AIC and BIC

6. Basic Equation of population Dynamics

Natural increase from time *t* to *t* + 1

Naturalincrease = Births$_t$ Deathst (5)

This basic equation can also be applied to subpopulations. For example, the population size of ethnic groups or nationalities within a given society or country can be subject to the same sources of change. However, when dealing with ethnic groups, "net migration" might have to be subdivided into physical migration and ethnic re-identification (assimilation). Individuals who change their ethnic self-labels or whose ethnic classification in government statistics changes over time may be considered migrating or moving from one population subcategory to another.

More generally, while the basic demographic equation holds true by definition, in practice, the recording and counting of events (births and deaths) and the enumeration of the total population size are subject to error. Therefore, allowances need to be made for errors in the underlying statistics when any accounting of population size or change is made.

7. Poisson Regression Model of Identity and Log Links

A generalized linear model is composed of a linear predictor:

$$\eta_i = \beta_0 + \beta_{1x1i} + \ldots + \beta_p x_{pi} \quad (6)$$

Having two functions (Turner, 2008)

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

$$g(\mu_i) = \eta_i \quad (7)$$

A variance function that describes how the variance, $\mathrm{var}(Y_i)$ depends on the mean

$$\mathrm{var}(Y_i) = \varphi V(\mu) \quad (8)$$

Here, the dispersion parameter φ is a constant.

8. Modeling Poisson Data

Suppose $Y_i \sim \text{Poisson}\ (\lambda_i)$ (9)

Then,

$$E(Y_i) = \lambda_i \qquad var(Y_i) = \lambda_i \quad (10)$$

The mean = variance from equation 5

Thus, the variance function is given by

$$V(\mu_i) = \mu_i \quad (11)$$

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

Then, $g(\mu_i) = log(\mu_i)$ (12)

Modeling the logarithm of the mean as a linear function of observed covariates then results in a generalized linear model with Poisson's response and link log.

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

9. Maximum Likelihood Estimation

The log-likelihood function is given by

$$Log\ L(\beta) = \sum\{yi\ log(\mu i) - \mu i\} \quad (13)$$

Where μ_i depends on the covariates X_i and a vector of P parameters β through the log link In equation (12).

The log-linear Poisson model satisfies the estimating equation

$$X'Y = X'\dot{\mu} \quad (14)$$

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

Furthermore, $\dot{\mu}$ is the vector of fitted values, calculated from the mle's β by exponentiating the linear predictor $\eta = X'\beta$. (Fox. 2023)

10. Negative Binomial Regression Model of Identity and Log Links

$$f(y_i U_i \Psi) = \frac{\Gamma(y_i + \Psi)}{\Gamma(y_i+1)\Gamma(\Psi)} \left(\frac{\Psi}{u_i + \Psi}\right)^{\Psi} \left(\frac{\Psi}{u_i + \Psi}\right)^{y_i} \quad (15)$$

It can also be defined as follows:

$$f(y_i\Psi, U_i) = \binom{y_i + \Psi - 1}{\Psi - 1}\left(\frac{\Psi}{u_i + \Psi}\right)^{\Psi}\left(\frac{\Psi}{u_i + \Psi}\right)^{y_i} \quad (16)$$

The first moment of a negative binomial is

$$E[y_i; U_i\Psi] = U_i \quad (17)$$

$$E[y_i; U_i\Psi] = U_i + \frac{{U_i}^2}{\Psi} \quad (18)$$

The next step is to define the log-likelihood function of the negative binomial 2

$$ln\left(\frac{y}{1}\right) = \sum_{j=0}^{y-1} ln\,(J + \Psi) \quad (19)$$

By substituting equation (19) above into equation (15), the log likelihood can be computed as follows:

$$lnL(\Psi, \beta) = \sum_{j=1}^{n}\{\left(\sum_{j=0}^{y-1} ln\,(J + \Psi)\right) - ln\, y_i! - (y_i + \Psi)\ln(1 + \Psi^{-1}\, U_i) + ln\Psi^{-1} + y_i\, lnU_i\}\, y_i \quad (20)$$

The log likelihood is expressed as follows:

$$lnL(\Psi, \beta) = \sum_{j=1}^{n}\{\, y_i\, ln\left(\frac{\Psi U_i}{1 + \Psi U_i}\right) - \Psi^{-1}\ln(1 + \Psi U_i) + ln\,\Gamma(y_i + \Psi^{-1}) - ln\Gamma(y_i + 1) - ln\Gamma(\Psi^{-1})\} \quad (21)$$

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

$$g(\mu_i) = \log(\mu_i) \quad (22)$$

11. Criterion for Model Solution (AIC and BIC)

12. Akiake Information Criterion (AIC)

The AIC is a measure of fit that penalizes the number of parameters p *as follows:*

$$AIC = -2l_{mod} + 2p \quad (23)$$

Here, l_{mod} is the log-likelihood of the fitted models, and p is the number of unknown parameters included in the model. Smaller values indicate better fitting; thus, the AIC can be used to compare models. (Turner, 2008).

13. Bayesian information criteria (BIC)

Similar to AIC, BIC also employs a penalty term associated with the number of parameters (p) and sample size (n). This measure is also known as the schwanze information criterion. The function is computed as follows:

$$BIC = -2ln\, L + pln\, n \quad (24)$$

Again, smaller values are better.

14. Goodness of Fit

Deviance is a measure of discrepancy between observed and fitted values. It takes the following form:

$$D = 2\sum\{y_i \log(\frac{y_i}{\hat{\mu}_i}) - (y_i - \hat{\mu}_i)\}. \quad (25)$$

The first term is identical to the binomial deviance, representing 'twice a sum of observed time 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 model goodness-of-fit.

15. Justification of Methods

The Basic estimation of Population Dynamics (Natural Increase) is applicable to determine whether a population is increasing or decreasing over time. Also, the data for this dissertation are secondary data and a frequencies data which made Generalized Linear Models (Poisson and Negative Binomial Models) appropriate for modeling such. Another problem with the count data is over-dispersion (variance is greater than mean), and this problem is corrected by the negative binomial model.

16. Data Presentation

The data used in this project are presented in the table 4.1 below:

Table 4.1: Total population growth in Akwa Ibom State by year and geo political zones 2006-2023.

Year	North-central	North-east	North-west	South-east	South-south	South-west	**Total**
2006	20	15	5	1	15	3	**59**
2007	1557	1946	5957	2183	1886	2062	**15591**
2008	1104	1614	8221	1869	1151	1051	**15010**
2009	1409	1110	1821	1708	1297	373	**7718**
2010	1484	465	3945	2542	1122	888	**10446**
2011	3459	662	3555	2772	1656	747	**12851**
2012	2495	3169	3896	2457	1182	3521	**16720**
2013	2291	2551	3594	1818	2866	4316	**17436**
2014	2516	1627	1738	1323	2017	4788	**14009**
2015	2863	1383	905	1044	2102	3606	**11903**
2016	1354	1159	683	2299	2464	3586	**11545**
2017	1279	493	157	1290	1350	2785	**7354**
2018	2079	994	615	2839	2720	3931	**13178**
2019	3833	2446	4552	4650	4567	3834	**23882**
2020	4321	2356	4327	3263	2423	3634	**20324**
2021	2356	3263	2356	3263	4321	2368	**18827**
2022	2341	3422	2321	3452	3421	2356	**17313**
2023	2302	3204	3426	3472	3423	3205	**19032**
Total	**39063**	**31879**	**52074**	**42245**	**39983**	**47054**	**253198**

Source: National Population Commission, Abuja, Nigeria

Table 4.1 shows the population growth for each geopolitical zone from 2006 to 2023

Table 4.2: Total population growth in akwa ibm state (2006-2023)

Years	Population growths
2006	1124
2007	474822
2008	410412
2009	210055
2010	205983
2011	700911
2012	936590
2013	978222
2014	935496
2015	982043
2016	686929
2017	679137
2018	927472
2019	1807025
2020	7638023
2021	3542328
2022	2354562
2023	5422986

Source: National Population Commission, Abuja, Nigeria

Table 4.2 shows the population growth by years from 2006 to 2023.

Table 4.3: Total population growth by sex and geo political zones (2006-2023).

S/N	GEO POLITICAL ZONES	SEX		TOTAL
		FEMALE	MALE	
1.	North-central	8630	19093	**27723**
2.	North-east	6046	13588	**19634**
3.	North-west	14723	24921	**39644**
4.	South-east	9379	19416	**28795**
5.	South-south	7920	18460	**26380**
6.	South-west	12120	23371	**35491**
	TOTAL	**58818**	**118849**	**177667**

SOURCE: National Population Commission, Abuja, Nigeria

Table 4.3 shows the total population growth in Akwa Ibom State by sex and geopolitical zone from 2006 to 2023.

Table 4.4: Total population growth by sex and geo political zones (2006-2023).

S/N	GEO POLITICAL ZONES	SEX		TOTAL
		FEMALE	MALE	
1.	North-central	703596	816480	**1520076**
2.	North-east	447613	556400	**1004013**
3.	North-west	799639	1035161	**1834800**
4.	South-east	533619	583309	**11169928**
5.	South-south	641501	707449	**1348950**
6.	South-west	1475121	1636333	**3111454**
	TOTAL	**4601089**	**5335132**	**9936221**

Source: National Population Commission, Abuja.

Table 4.4 shows total population growth by sex and geographic location from 2006 to 2023.

Table 4.5 presents the natural increase in population growth.

Table 4.5: Natural increase of population growth.

TOTAL BIRTH	TOTAL DEATH	NATURAL INCREASE
1124	24	1100
474822	15591	459231
410412	15010	395402
210055	7718	202337
205983	10446	195537
700911	12851	688060
936590	16720	919870
978222	17436	960786
935496	14009	921487
982043	11903	970140
686929	11545	675384
679137	7354	671783
927472	13178	914294
1807025	23882	1783143

From table 5 above, there is a natural increase in the population growth rate.

17. **Data Analysis and Results**

Summarizing population growth

Variable	Observation	Mean	Std. Dev.	Min	Max
Death	14	13690.5	5449.882	24	23982
Birth	14	609730.1	431664.5	1124	1707025

The above output shows over-dispersion in population growth in Akwa Ibom State (variance > mean). With this result, we expect negative binomial regression to outperform Poisson regression because of the problem of over-dispersion.

Table 4.2.1: Poisson Generalized Linear Model of population growth in Akwa Ibom State Using Identity Link Data

```
. gm death time, family(poisson) link(identity)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 37307.01776 (1/df) = 3125.585
Pearson = 29298.35055 (1/df) Pearson's = 2458.196
Variance function: V(u) = u [Poisson]
Link function: g(u) = u [Identity]
 AIC = 2704.508
Log likelihood = 19229.55872 BIC = 36275.35
 | OIM
 death | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | 597.9221 7.795369 77.93 0.000 593.6631 624.1812
 _cons | 8797.506 54.95534 164.05 0.000 8791.756 8904.257
```

The table 4.2.1 above present the Poisson GLM for population growth using the identity link. The results revealed a significant increase in population growth as time increases (time = 597.9221, P-value = 0.000)

Table 4.2.2: Poisson Generalized Linear Model of population growth in Akwa Ibom State Using Log Link Data

```
. gm death time, family(poisson) link(log)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 37706.10509 (1/df) Deviance = 3158.842
Pearson = 27892.05883 (1/df) = 2342.672
Variance function: V(u) = u [Poisson]
Link function: g(u) = ln(u) [Log]
 AIC = 2653.015.
Log likelihood = 18529.10238 BIC = 37674.44
 | OIM
 death | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | .0550896 .0005842 75.20 0.000 .0439251 .0462541
 _cons | 9.156282 .004998 1967.36 0.000 9.146683 9.165882
```

The table 4.2.2 above present the Poisson GLM for population growth in Akwa Ibom using the log link. The results revealed a significant increase population growth as time increases (time = .0550896, P-value = 0.000).

Table 4.2.3: Negative Binomial Generalized Linear Model of population growth in Akwa Ibom State Using Identity Link Data

. gm death time, family (nbinomial 1) link(identity)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
Scale parameter = 1
Deviance = 12.26296829 (1/df) Deviance =.9585807
Pearson's correlation coefficient = 2.733906125 (1/df) Pearson's correlation coefficient =.2361588
Variance function: V(u) = u+(1)u^2 [Neg. Binomial]
Link function: g(u) = u [Identity]
AIC = 23.14498
Log likelihood = 146.0148401 BIC = 21.40572
| OIM
death | Coef Std. Err z P>|z| [95% Conf. Interval]
time | 688.509 990.9227 0.71 0.484 -1335.064 2620.082
_cons | 8294.297 5834.16 1.43 0.154 3221.846 19808.44

The table 4.2.3 above present the Negative Binomial GLM for death rate using the identity link. The results revealed an insignificant increase in population growth as time increases (time = 688.509, P-value = 0.483).

Table 4.2.4: Negative Binomial Generalized Linear Model of death rate using log link

. gm death time, family (nbinomial 1) link(log)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
Scale parameter = 1
Deviance = 12.325,3381 (1/df) Deviance =.953,37782
Pearson = 2.533265816 (1/df) Pearson = .2202722
Variance function: V(u) = u+(1)u^2 [Neg. Binomial]
Link function: g(u) = ln(u) [Log]
AIC = 22.14943
Log likelihood = 146.04605; BIC = 21.3435
| OIM
death | Coef Std. Err z P>|z| [95% Conf. Interval]
time | .0476031 .0692988 0.68 0.495 -.08852 .1831262
_cons | 9.134348 .5238709 17.45 0.000 8.098776 11.15092

The table 4.2.4 above present the Negative Binomial GLM for population growth using the log link. The result revealed an insignificant increase in the mortality rate as time increased (time = .0476031, P-value = 0.495)

Table 4.2.5: Model Selection for population growth using AIC and BIC

Model	**Link**	**AIC**	**BIC**
Poisson	Identity	2644.518	36376.45
Poisson	Log	2655.015	3657.55
Negative Binomial	Identity	22.14498	-21.40572
Negative Binomial	Log	22.14943	-21.34335

From the table 4.2.5 above, the best model has the lowest values of AIC and BIC, which are 22.14498 and 21.40572, respectively. This result is associated with a Negative Binomial Regression Model with an Identity Link.

Table 4.2.6: Poisson Generalized Linear Model of population growth using identity link

```
. gm birth time, family(poisson) link(identity)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 1583497.2 (1/df) Deviance = 132874.8
Pearson = 1574787.945 (1/df) Pearson's = 133899
Variance function: V(u) = u [Poisson]
Link function: g(u) = u [Identity]
 AIC = 113250.6
Log likelihood = 791452.0036, BIC = 1583466
 | OIM
 birth | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | 899219.23 53.49574 1688.36 0.000 89126.34 89322.12
 _cons | 139870.1 290.3383 448.32 0.000 139301 131439.1
```

The table 4.2.6 above present the Poisson GLM for population growth using the identity link. The results revealed a significant increase in population growth as time increased (time = 89219.23, P-value = 0.000)

Table 4.2.7: Poisson Generalized Linear Model of population growth using log link

```
. gm birth time, family(poisson) link(log)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 1892640.902 (1/df) Deviance = 159386.7
Pearson = 1612362.373 (1/df) Pearson's = 136030.2

Variance function: V(u) = u [Poisson]
Link function: g(u) = ln(u) [Log]
 AIC = 138060.8
Log likelihood = 897523.8544, BIC = 1892609
 | OIM
 birth | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | .136448 .0000859 1590.17 0.000 .1362817 .1366144
 _cons | 13.52407 .0007855 1.6e+05 0.000 13.52253 13.5256
```

The table 4.2.7 above present the Poisson GLM for population growth in Akwa Ibom using the log link. The results revealed a significant increase in population growth as time increases (time = .136448, P-value = 0.000).

Table 4.2.8: Negative Binomial Generalized Linear Model of population growth using identity link

```
. gm birth time, family (nbinomial 1) link(identity)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 5.91105528 (1/df) Deviance =.5092546
Pearson's alpha = 8.461677127 (1/df) Pearson = .7218064
Variance function: V(u) = u+(1)u^2 [Neg. Binomial]
Link function: g(u) = u [Identity]
 AIC = 29.50468
Log likelihood = 198.5327454 BIC = 27.75763
 | OIM
 birth | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | 148599.7 48575.9 4.59 0.000 63992.28 224207
 _cons | 1155.186 1265.336 0.98 0.426 -1149.832 3528.203
```

Table 4.2.8 above present the Negative Binomial GLM for population growth in Akwa Ibom using the identity link. The results revealed a significant increase in the birth rate as time increased (time = 148599.7, P-value = 0.000).

Table 4.2.9: Negative Binomial Generalized Linear Model of population growth in Akwa Ibom State Using Log Link Data

```
. gm birth time, family (nbinomial 1) link(log)
Generalized linear models No. of obs = 14
Optimization: ML Residual df = 12
 Scale parameter = 1
Deviance = 12.04598545 (1/df) Deviance = .9304988
Pearson = 4.336296782 (1/df) Pearson = .3780247
Variance function: V(u) = u+(1)u^2 [Neg. Binomial]
Link function: g(u) = ln(u) [Log]
 AIC = 29.94289
Log likelihood = 211.6002105 BIC = 21.6227
 | OIM
 birth | Coef Std. Err z P>|z| [95% Conf. Interval]
 time | .1566096 .0734485 3.01 0.055 .0036231 .2877061
 _cons | 13.38212 .5424705 33.87 0.000 12.32086 14.44339
```

The table 4.2.9 above present the Negative Binomial GLM for birth rate using the log link. The results revealed a significant increase in birth rate as time increases (time = .1566096, P-value = 0.055).

Table 4.2.10: Model Selection for population growth in Akwa Ibom using AIC and BIC

Model	**Link**	**AIC**	**BIC**
Poisson	Identity	114050.6	1682466
Poisson	Log	138060.8	1793609
Negative Binomial	Identity	29.50468	-27.75763
Negative Binomial	Log	29.94289	-21.6227

From the table 4.2.10 above, the best model has the lowest values of AIC and BIC, which are 29.50468 and 27.75763, respectively. This result is associated with a Negative Binomial Regression Model with an Identity Link.

18. Conclusions

The table 4.2.1 above present the Poisson GLM for the death rate using the identity link. The results revealed a significant increase in the mortality rate as time increased (time = 597.9221, P-value = 0.000). The implication of this result is that the death rate in Akwa Ibom State increases over time. This result is in line with the findings of Chukwu and Oladipupo, (2022) and WHS, (2019), which stated that adult mortality is higher in population growth in Akwa Ibom State than in other countries.

The table 4.2.2 above present the Poisson GLM for the death rate using the log link. The result revealed a significant increase in death rate as time increases (time = .0550896, 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's GLM for death rate with log link is similar to the works of Chukwu and Oladipupo, (2022) and WHS, (2019), which stated that adult mortality is higher in Akwa Ibom State than in other states.

The table 4.2.3 above present the Negative Binomial GLM for death rate using the identity link. The result revealed a non-significant increase in the mortality rate as time increased (time = 688.509, 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, (2022) and WHS, (2019), in this work, the increase in death rate over time is not significant.

The table 4.2.4 above present the Negative Binomial GLM for death rate using the log link. The result revealed an insignificant increase in death rate as time increases (time = .0476031, P-value = 0.495). This result is similar to the Negative Binomial GLM for death rate using the identified link. There is an increase in death rate using negative binomial GLM, which agrees with the works of Chukwu and Oladipupo, (2022) and WHS, (2019).

From the table 4.2.4.1 above, the best model has the lowest values of AIC and BIC, which are 22.14498 and 21.40572, respectively. This result is associated with the Negative Binomial Regression Model with the Identity Link as the best model.

The table 4.2.5 above present the Poisson GLM for birth rates using the identity link. The results revealed a significant increase in birth rate as time increases (time = 89309.34, P-value = 0.000). The result agrees with Tobin et al. (2023), who found that birth registration was higher than death registration in south-south population growth in Akwa Ibom State.

The table 4.2.6 above present the Poisson GLM for birth rates using the log link. The results revealed a significant increase in birth rate as time increased (time = 89219.23, P-value = 0.000). This result is similar to Poisson's GLM for birth rate using the identity link. The result agrees with Tobin et al; (2023), who found that birth registration was higher than death registration in south-south population growth in Akwa Ibom State.

The table 4.2.7 above present the Negative Binomial GLM for birth rate using the identity link. The results revealed a significant increase in birth rate as time increased (time = .136448, P-value = 0.000). The result agrees with Tobin et al; (2023), who found that birth registration was higher than death registration in south-south population growth in Akwa Ibom State.

table 4.2.8 above present the Negative Binomial GLM for birth rate using the log link. The results revealed a significant increase in birth rate as time increases (time = 148599.7, P-value = 0.000). This result is similar to a negative binomial GLM for birth rate using the identity link.

From the table 4.2.8.1 above, the best model has the lowest values of AIC and BIC, which are 29.50468 and 27.75763, respectively. This result is associated with a Negative Binomial Regression Model with an Identity Link.

19. Conclusion

TThisstudy underscores the dynamic nature of population growth in Akwa Ibom State. driven by regional disparities, urbanization, and improvements in health care. The findings highlight the need for data-driven planning to address regional inequalities, support population growth, and ensure sustainable development. Effective statistical modeling is crucial for understanding and managing population dynamics.

Comparing Poisson Regression Models and Negative Binomial Regression models with Identity and Log Links, this study concluded that there is a positive increase in the registration of birth and death in Akwa Ibom State, but for the models, Negative Binomial Regression models with Identity Link outperformed the other models.

20. Recommendations

In view of the outcomes of this research, this dissertation recommends the following:

i Regional Policy Development: Allocate resources to address population growth disparities, particularly in underdeveloped zones.

Enhance health care and education infrastructure in high-growth areas to effectively sustain the population.

ii Gender-sensitive interventions: policies should be implemented to support gender equality in access to education, healthcare, and employment.

iii Use of Advanced Statistical Tools: Encourage the use of appropriate statistical models, like the Negative Binomial model, for accurate population projections and analysis.

iv Improved Data Collection Systems: Invest in robust population data collection and management systems for precise monitoring and decision-making.

v Focus on Mortality Reduction: Strengthen health care interventions to further reduce mortality rates, especially in vulnerable regions.

21. Limitations of the study

This research work is solely based on data collected from the National Population Commission Abuja and covers only data obtained from vital registration in Akwa Ibom State. The findings and conclusions are for use in Akwa Ibom State.

i Data Quality: Population data may be subject to inconsistencies or underreporting, thereby affecting accuracy.

ii Model Assumptions: The assumption of over-dispersion in the Negative Binomial model may not fully capture other complexities of population growth.

iii Exclusion of External Factors: Factors such as migration, economic conditions, and conflict were not incorporated into the analysis but may significantly impact population dynamics.

iv Temporal Scope: The analysis was limited to 2006–2023, which may not capture long-term trends or future shifts in population dynamics.

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