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Women Fertility Decision Using the Count Model in Nigeria

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ABSTRACT This study empirically analysed women fertility decision using the count model in Nigeria. Using secondary data from National bureau of statistics and National population commission in Nigeria. This study was carried out using Poisson and Negative binomial regression where the result shows that the Poisson model indicated underdispersion, hence has not violated any assumption. , all criteria for selection methods in Poisson regression model were smaller than their counterparts in Negative binomial model, therefore, Poisson regression model outperformed negative binomial model and revealed that, there were strong positive associations among number of births and the covariates considered and within the covariates themselves which were statistically significant. The prediction of the trend of the women fertility decisions in Nigeria was using Poisson regression model to predict the number of children ever born by every 1000 women based on the religion belief and the wealth index. For every wealth index on this research, 1.230 (95% CI, 1.007 to 1.502) times more children ever born increased, which is statistically significant with p = .042, gives a 23.0% increase in the number of children ever born for each extra wealth index. And that only both religion and wealth index among other predictors considered in this research study were statistically significant. Therefore Poisson regression model should be adopted in modeling and predicting women fertility decision in Nigeria. Religion and wealth index should always be considered as significant factors among others that contribute to the fertility decision making in Nigeria.

Key words: Fertility, children ever born, Poisson Regression, Negative Binomial Regression

I. INTRODUCTION:

Fertility is known as one of the three primary components dynamics that determine the structure, size, and component of the population of any country. (Upadhyay and Bhandari. 2017). Generalized Poisson regression is a useful model for fitting both over-dispersed and under-dispersed count data because it allows for more variability and it is more flexible in analyzing independent variables. In this research work Negative Binomial and Generalized Poisson regression are applied as an alternative for handling over-dispersed and under-dispersed count data considering the number of children ever born in Nigeria.

It is assumed that Nigeria ranks among countries with highest population growth rate. The importance of monitoring the key mechanisms of population dynamics particularly fertility in Nigeria cannot be overemphasized. Sufficient data to track the direction of fertility and other demographic indices are scarce. There is need for mathematical modeling to track the fertility outcomes in Nigeria. Our study which formulates model to predict future fertility in Nigeria was basically conceived to fill the gap. In Nigeria Understanding population, its determinants, growth, dynamics and trends is essential to the government in planning and achieving sustainable development, which include knowing the size of the population, determining the number of taxable adults, forecasting possible economic needs, determining the number of unemployed citizens, formulating economic policies, determining the population density, and providing social amenities which provides data used by the government for policy making planning and administration aimed at enhancing welfare of the people among others. Fertility still remains a key determinant of population pattern, and researchers use fertility patterns to understand the population pattern.

The aim of this study is to fit and identify the effects of some socio demographic and socio economic factors on women fertility decisions in Nigeria.

The above aim will be achieved through the following objectives.

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i. To fit Poisson and Negative binomial regression model on women fertility decisions in Nigeria in terms of socio demographic and socio economic background.
ii. To identify the significant factors in the models which contributes to the fertility decision making.
iii. To identify the association among number of births and the covariates considered.
iv. To predict the trend of the women fertility decisions in Nigeria using the model obtained

II. LITERATURE REVIEW:

The decision about whether to have a child is based on a complex interaction process which includes mutually influential powers of control wielded by both of the partners. According to (Rohana Kamaruddin. 2017) women fertility decision using the count model in Malaysia, The study has developed an empirical model that explains the determinants of household fertility decisions in Malaysia. The empirical results show a negative relationship between the number of children and social status (ownership, education, and socio-economic status), implying that households prefer the quality of children to the quantity of children. On the socio-economic and socio-demographic factors, home ownership, age, and marital status positively affect the number of children. The empirical results presented in the study support the neo-classical theory of fertility and are consistent with fertility studies of many other countries. These findings have important empirical implications for Malaysia, where the declining fertility rate will have an impact on the country's future aspirations of attaining a strong reliable domestic economy and the reallocation of women's time towards work and having a child.

An increase in women's economic activity, women's high educational attainment, late marriage, childcare and education expenses, changing valuation of children, household income and the instability of employment status and residence are important factors contributing to the declining fertility rate (Ermisch, 1988, Caldwell and McDonald, 2002). Many studies have indicated that as women become more socially active, they are less inclined to have a baby directly after marriage (Shapiro and Mott, 1994). However, other studies in European countries have indicated that countries with relatively high levels of women's social participation have correspondingly higher level of fertility (Del Boca etal, 2003). In the empirical estimation, household fertility decisions, intergenerational relationships, socio-economic factors and demographic behaviours all contribute to fertility decisions. The study's result has the potential to reveal pattern in household's preferences for deciding fertility. This may allow practitioners and policymakers to prioritize the benefits of child care allowances and preparations for the upcoming generations.

III. METHODOLOGY:

Children ever born was our dependent variable while the independent variable include respondents' residence, age group, geopolitical zone, educational background, wealth index, ethnicity, modern contraceptive use, gender and religion. Children ever born in the context of this study refers to the number of children a woman previously born as at the time of the study. This study used secondary data from the individual's questionnaire of the Nigerian Demographic and Health survey 2018. And the Nigerian Multiple Indicator Cluster Survey 2018. Which covers all regions in the country. In reality, the mean and the variance of a dependent variable in most educational data are not the same. Instead, the variance of the model often exceeds the value of the mean, a phenomenon called over dispersion (Hilbe, 2007). Moreover, characteristics of count data may yield further violations of assumptions, which may produce flaws in the Poisson regression mode. Therefore, the negative binomial regression may substitute for this situation because the negative binomial regression has an extra parameter which counts for the over dispersion (Hilbe, 2007).

Poisson regression

As (Kutner etal. 2005) stated, the Poisson regression model can be expressed as follows:

$$\mu_i=\mu(X_i,\beta)=\exp \quad (X_i'\beta) \qquad (1)$$

Models for Count Data

Where $X_i'\beta$ is equivalent to the expression of $\mu_i=\sum_j\beta_j x_{ij}$, $\sum$ in (Gardner etal. 1995). μ_i are the dependent mean for the ith case, and they are assumed to be a function of the set of independent variables X_i. In other words, $\mu(X_i,\beta)$is the value of the predictor variables for case i from the function that relates the mean dependent μ_i to X_i, β are the values of the regression coefficients.

The explanation for the formula (1) is that a one-unit change in the predictor variable X_i multiplies the expected values by a factor of

$\exp^{(\beta_i)}$ and a one-unit decrease divides the expected incidents by the same amount (Gardner etal., 1995). In other words, “Poisson models are typically used to either summarize predicted counts based on a set of explanatory predictors, or are used for interpretation of exponentiated estimated slopes, indicating the expected change or difference in the incidence rate ratio of the outcome based on changes in one or more explanatory predictors” (Hilbe, 2007,). The Poisson probability density function below directly follows the derivation

$$f(x|\lambda)=\begin{cases}\dfrac{e^{-\lambda}\lambda^{x}}{x!} & \text{for } x = 0,1,2 \\ = 0 & \text{otherwise.}\end{cases} \quad (2)$$

where:

- x is a random variable with a discrete distribution, and it is supposed to be a nonnegative integer.
- λ is a mean under the probability function of X following the Poisson probability function.

Therefore, it is important to consider alternative regression models.

Negative binomial regression

The negative binomial regression model is more flexible than the Poisson model and is frequently used to study count data with overdispersion (Hoffman, 2004). In fact, the negative binomial regression model is in many ways equivalent to the Poisson regression model because the negative binomial model could be viewed as a Poisson-gamma mixture model. However, the difference is that the negative binomial regression model has a free dispersion parameter. In other words, the Poisson regression model can be considered as a negative binomial regression model with an ancillary or heterogeneity parameter value of zero (Hilbe, 2007). In the negative binomial regression model, a random term reflecting unexplained between-subject differences is included (Gardner et al., 1995), that is, the negative binomial regression adds an overdispersion parameter to estimate the possible deviation of the variance from the expected value under Poisson regression.

Therefore, using the negative binomial regression to model count data with a Poisson distribution has the consequence of generating more conservative estimates of standard errors and may modify parameter estimates (Hilbe, 2007).

The negative binomial probability density function below directly follows the derivation .

$$\frac{\Gamma(y+v)}{\Gamma(y+1)\Gamma(v)}\left(\frac{1}{1+\lambda/v}\right)^{v}\left(1-\frac{1}{1+\lambda/v}\right)^{y} \quad (3)$$

where:

- Γ is the gamma function.
- λ is the mean of the negative binomial distribution.
- v is the dispersion parameter.
- y is the dependent variable.

IV. RESULTS AND DISCUSSIONS

Table 1: Goodness of Fit for Poisson Model

	Value	df	Value/df
Deviance	11.746	990	.012
Scaled Deviance	11.746	990	
Pearson Chi-Square	11.260	990	.011
Scaled Pearson Chi-Square	11.260	990	
Log Likelihood[b]	-1151.352		
Akaike's Information Criterion (AIC)	2322.704		
Finite Sample Corrected AIC (AICC)	2322.926		

Bayesian Information Criterion (BIC)	2371.781
Consistent AIC (CAIC)	2381.781

In table 1. above The result shows that the value of the deviance is 0.12 and pearson chi square is 0.11 are both less than 1 which indicated underdispersion, hence has not violated any assumption. And Akaike's information criterion is less than the Bayesian information criterion.

Table 2: Omnibus Test for Poisson Regression Model

Likelihood Ratio Chi-Square	Df	Sig.
292.896	9	.000

The **Omnibus Test in** table 2 revealed that the likelihood ratio test of all the independent variables collectively improve the model over the intercept-only model. Having all the independent variables in this result with a p-value of .012 (i.e., p = .012), indicating a statistically significant overall model.

Table 3: Tests of Model Effects for Poisson Regression Model

Source	Type III Wald Chi-Square	Df	Sig.
(Intercept)	14.781	1	.000
Res	.036	1	.849
Age	`.103	1	.748
Geopoliticalzone	.265	1	.607
Education	.191	1	.662
Wealthindex	4.122	1	.042
Ethnicity	2.103	1	.147
Method	.357	1	.550
Sex	.034	1	.853
Religion	7.139	1	.008

In table 3 The **Tests of Model Effects** displays the statistical significance of each of the independent variables. Where wealth index and religion are 0.042 and 0.008 which are both less than 0.05 hence are most significant from the model effects.

Table 4: Goodness of Fit for Negative Binomial Model

	Value	df	Value/df
Deviance	4.284	990	.004
Scaled Deviance	4.284	990	
Pearson Chi-Square	3.943	990	.004
Scaled Pearson Chi-Square	3.943	990	
Log Likelihood[b]	-1638.770		

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Akaike's Information Criterion (AIC)	3297.540
Finite Sample Corrected AIC (AICC)	3297.762
Bayesian Information Criterion (BIC)	3346.617
Consistent AIC (CAIC)	3356.617

In table 4 the value/df of both the deviance and pearson chi-square is 0.04 which is less than 1 indicating underdispersion . And also Akaike's information criterion is less than the Bayesian information criterion.

Table 5: Omnibus Test for Negative Binomial Model

Likelihood Ratio Chi-Square	Df	Sig.
111.886	9	.000

The **Omnibus Test in** table 5 revealed that the likelihood ratio test of all the independent variables collectively improve the model over the intercept-only model. Having all the independent variables in this result with a p-value of .012 as in table 4.1 (i.e., p = .000), indicating a statistically significant overall model.

Table 6: Tests of Model Effects for Negative Binomial Model

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	5.414	1	.020
Res	.019	1	.891
Age	.084	1	.772
Geopoliticalzone	.174	1	.677
Education	.058	1	.809
Wealthindex	1.401	1	.237
Ethnicity	.603	1	.437
Method	.135	1	.714
Sex	.012	1	.914
Religion	2.675	1	.102

Table 6 shows The Tests of Model Effects displaying the statistical significance of each of the independent variables. the independent variables are all greater than 0.05 hence they are all statistically none significant. As compared to the test of model effects in table 4.3.

V. CONCLUSION:

From the analysis, Poisson regression model outperformed negative binomial regression based on information criteria selection, it is evident from this study that poisson regression model is an applicable tool for predicting women fertility decision in Nigeria. This will ease the yearning of policy makers and researchers on fertility decision for up to date planning. Also government and non-governmental organizations should take conscious effort at encouraging religious leaders to encourage fertility decision through the use of modern contraceptives, early girl child marriage prominent in the northern region should be discouraged while the girl child who becomes a future woman should be motivated and empowered to increase their wealth and economic status thereby curtailing excessive births. Both religion and wealth index among other predictors considered in this research study were statistically significant in the fertility decision making.

VI. RECOMMENDATIONS:

Based on the results obtained, the following are recommended;

i. Poisson regression model should be adopted in modeling and predicting women fertility in Nigeria.
ii. Religion and wealth index should be always considered as significant factors among others that contribute to the fertility decision making.

Areas of future research

The following are the areas for future study;

i. More variables that contribute to fertility decision making can be considered
ii. More models could also be compared with those considered in this study

Declaration of competing interest

The authors do declare that there is no conflict of interest.

REFERENCES

[1]. Caldwell, J., Caldwell, P., & McDonald, P. (2002). Policy Responses to Low Fertility and its Consequences: A Global Survey. Journal of Population Research, 19(1), 1-24
[2]. Del Boca, D., Locatelli, M., &Vuri, D. (2003). What Child Care Works Best? Evidence from Italy. WP Child.
[3]. Department of Statistics Malaysia. (2013). Population Projection Malaysia
[4]. Ermish, J. (1988). The Econometrics Analysis of Birth Rate Dynamics in Britain. The Journal of Human Resources, 23(4), 563-576.
[5]. Gardner, W., Mulvey, E. P., & Shaw, E. C. (1995). Regression analyses of counts and rates:
Poisson, overdispersed Poisson, and negative binomial models. Psychological Bulletin,
118(3), 392-404.
[6]. H.P. Upadhyay, K.R. Bhandari(2017.)Factors associated with children ever born: a case study of somadi village development committee of Palpa District, Nepal Adv. J. Soc. Sci., 1 (1), pp. 15-29
[7]. Macro, National.Population. Commission Nigerai, Nigeria demographic and health survey .(2018)
[8]. Hilbe, J. M. (2007). Negative Binomial Regression. Cambridge: Cambridge University Press.
[9]. Hoffman, J. P. (2004). Generalized linear models: an applied approach. Boston: Pearson Education, Inc.
[10]. Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). Applied linear statistical models. New York: McGraw.
[11]. Rohana Kamaruddin (2017). Journal of Management and Sustainability; Vol. 7, No. 3; 2017
[12]. Shapiro, D., & Mott, F. L. (1994).Long-Term Employment and Earnings of Women in Relation to Employment Behavior Surrounding the First Birth. The Journal of Human Resources,