An Appropriate Non Linear Regression Model for Assessing Community Policing and Violent Crimes Reduction

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Abstract: **An appropriate non-linear regression of the relationship between a response variable and the predictor variables was considered using Probit, Logit and Poisson Log-linear regression. The study focused on analysis of crime rate before and after engagement of Onelga Security Peace Advisory Committee (OSPAC) in Ogba, Ndoni, Egbema Local Government Area (ONELGA) of Rivers State using 220 questionnaires administered to households in twenty-five communities in the LGA by convenience sampling method. Descriptive statistics, ranks, percentage analysis and non-linear regression techniques were methods of analysis used. Microsoft Excel, SPSS 23 and Minitab 18 statistical Software were used. The Akaike Information Criterion (AIC) was used to compare the models. The results showed that Probit and Logit regression models identified the covariates of killing and rape cases as the major crime before engagement of OSPAC since both coefficients have significant effect at 5%. No independent variables have significant effects on response variables after the engagement of OSPAC, except the constant coefficient [β_0] which implies violent crime reduction in the community. It was concluded that the Logit regression model is more suitable for modelling response variable on the covariates and community policing intervention has an impact on violent crime reduction.**

Keywords: **Non-Linear Regression, Covariates, generalized linear model, Akaike Information Criterion, community policing intervention.**

I. INTRODUCTION

Budgetary allocation to security in Nigeria has been on the increase in recent times. Despite the increase, violent crimes have been on the rise. For example, within the first ten weeks of 2018, 1,351 people lost their lives in violent deaths across Nigeria (Ndujihe and Udochukwu, 2018). Yet, Security received a total of N1.283 Trillion (Odunsi, 2018) representing 14.07% of the nation's financial appropriation for the year. Beyond the budgetary allocations, 2015 statistics on the numerical strength of Nigeria's security personnel shows that the nation maintains a security force of about 371,800 police officers, 181,000 military personnel out of which 124,000 are active while 57,000 are reserved. There are also, men of other security outfits. Notwithstanding these huge human and financial provisions for security, the graph of violent crimes in Nigeria continued to show an upward trend.

The year 2015 marked the birth of a bitter chapter in the history of the people of Ogba/Egbema/Ndoni Local Government Area (ONELGA) of Rivers State, a narrative that would, in the years after, almost become synonymous with the area. It represented the peak of violent confrontation between rival cult groups that claimed many innocent lives. According to Partnerships Initiatives in the Niger Delta (2015), the year 2015 stands out as the most violent in Rivers State since the 2009 Presidential Amnesty program of the Federal Government of Nigeria. That year accounted for the highest number of reported fatalities in the past six years. Violence perpetrated by suspected cultists constituted a significant bulk of those incidents. The same report, which presented a crime report on Local Government basis, confirmed that ONELGA experienced the highest level of violent crimes within the period with over one hundred and twenty (120) people killed as a result of cult activities. These suggest that the traditional security architecture of the country in general, and ONELGA in particular are not sufficient to combat crime in the area. The uncontrolled surge in violent crimes and the seeming inability of the regular security outfit to rise up to the challenge informed the call for community policing.

In 2016, the ONELGA Security, Peace and Advisory Council (OSPAC), a Community policing outfit was established by the Local Government Administration. (Baron, 2019).

While it may be argued that the outfit has made strides in combating violent crimes in the area, the efficacy of community policing within our climes, considering the susceptibility of our institutions to political manipulation, is still a subject of intense debate among scholars, policy makers and the general public.

The primacy of security to the attainment of socio economic well-being of individuals and societies in general is no longer a subject of debate. The feeling of safety among citizens is an important factor in the achievement of development of the society. This is because it provides the needed freedom for individuals to freely go about their daily businesses without fear of molestation. Also, the feeling of assured security of lives and properties promotes investors' confidence in a system. This confidence is necessary for the enhancement of

the country's Foreign Direct Investment (FDI) profile and by extension, productivity and wealth accumulation [Ndujihe, Usman and Ojelu, 2020; Enyiche, 2017; Kpae and Adishi, 2017; Eke, 2014]. These directly impact the quality of life because an increase in employment opportunities raises the level of citizens' disposable income as well as their propensity to save and invest for greater wealth creation. This breaks the vicious cycle of poverty and further improves the bond of loyalty between the citizens and their government. (Jhingan, 2008). According to Sahara Reporters (January 2, 2018) cult violence increased very significantly in the Niger Delta in 2014, particularly in Rivers State, where the violence spread to virtually all the Local Government areas of the state. The report further revealed that the cult violence took the form of criminal, militant, communal, and/or political undertones, depending on the situation.

The Rivers state axis of the East-West road, a major access road linking the Eastern and the Western parts of the country has become notorious for the menace of kidnappings. Travelling on that route has become a major nightmare for commuters and business people alike (Premium Times: July 12, 2019). Ogba Egbema Ndoni Local Government Area, within this period, experienced the highest incidence of violent crimes in the form of cult clashes, leading to unwarranted loss of lives (Sahara Reporters: January 2, 2018). The almost daily experience of gruesome murder and sometimes beheading of victims and the apparent helplessness of the traditional security formations in the area necessitated the calls for alternative arrangement. This agitation led to the adoption of a community policing arrangement and the establishment of the OSPAC. Nearly four years into the operations of OSPAC, there appears to be mixed reactions on the effectiveness of community policing in combating violent crimes in our communities. Though there were reports of positive contributions of community policing in reducing violent crimes, there is no detailed research on nexus between the two in Rivers state. Hence, using the OSPAC community policing outfit, this work seeks to analyze the effectiveness of community policing in combating and reducing violent crimes (killing, kidnapping, rape and robbery incidents) in our communities using ONELGA as case study. The work seeks to answer the question: 'to what extent is community policing a panacea to the growing incidence of violent crimes in our society? It also, intends to determine the nonlinear regression model (e.g. Probit, Logit and Poisson Log-linear regression models) most appropriate for modelling violent crime reduction.

The significance of this work lies in the fact that it interrogated the contending views of the relationship between community policing and the reduction of violent crimes in our communities. Also, it will serve as a guide for government in determining the rate of violent crimes reduction in the state. By exploring the non-traditional approach to violent crime reduction in our communities, this work further expands the frontiers of the discussion on Nigeria's security issues. The empirical data generated by this study provides Nigerian policy makers with both policy options and insights on the need to make effective community policing a key component of their policy considerations in the nation's quest to drastically reduce violent crimes.

II. REVIEWED WORKS ON NON LINEAR REGRESSION AND VIOLENT CRIMES

A characteristic of the Poisson distribution is that its mean is equal to its variance. In certain circumstances, the observed variance is greater than the mean. This is known as over dispersion and indicates that the model is inappropriate. Over dispersion is not just any excess variation in the conditional distribution of count data, it could be due to omitted variable (relevant explanatory variable or dependent variable). Works on Poisson-based Regression Analysis of crime rates and over dispersion include Ijomah *et al.* (2018); Berk and MacDonald (2008); Richard and John, (2008); Berk (2003); Osgood (2000); Paternoster and Brame (1997); Cameron and Trivedi (1990); Pregibon (1981). Poisson regression can be used in studies in which the dependent variable describes the number of occurrences of some rare event such as suicide (Moksony and Hegedus, 2014). Antolos (2002) used a Nonlinear regression model to investigate the factors associated with burglary activity in Daytona Beach, Florida.

Logistic regression analysis applies maximum likelihood estimation after transforming the dependent variable into logit variable (White, 2013; Garson, 2004). A Logit variable is the natural log of the odds of the outcome occurring or not. Through this process the logistic regression estimates the probability of the occurrence of the event. However, logistics regression can also be used for categorical dependent variables with more than two classes. This is called Multinomial Logistic regressions (Bird *et al*., 2018). Logistics regression model was accepted to be the best model for assessing crime cases in Adamawa State as the result of the analysis showed that all possible two-way interactions between crimes, year of occurrence and gender was most appropriate for accessing crime cases in the State (Akinrefon, *et al.*, 2016).

The probit model estimates the probability that a value will fall into one of two possible binary outcomes. It is designed to estimate linear relationship between variables and it uses cumulative distribution function of the standard normal distribution to define f (•). The function will take any number and rescale it to fall between 0 and 1 (https://en.wikipedia.org › wiki ›). The Probit model uses observations, both those at the limit and those above the limit, to estimate a regression line. This technique is preferred over any alternative techniques that estimate a line only with observations above limit (McDonald and Moffit, 1980). The Probit Model is also called censor regression model.

Logit regression forms a best fitting equation or function using the maximum likelihood method, which maximizes the probability of classifying the observed data into the appropriate category given the regression coefficients. In this

study, we compared model and parameter estimates of Probit, logit and Poisson log-linear regression analysis with a view to determining which of the regression models fitted the data set considered. The fact that there has not been a detailed study of the community policing efforts in ONELGA, with reference to the operations of the OSPAC made it difficult to categorically make a case for community policing on the basis of statistical facts and figures. This is the gap this work intends to fill using the best fit Regression Models.

III. METHODS

This research focused on the before and after engagement of OSPAC in Omoku, Ndoni and Egbema Local Government Area (ONELGA) of Rivers State. ONELGA is a wide geographic area with very many households as a result, using probability sampling methods to draw the samples would be very time consuming and expensive hence, convenience sampling method was adopted for this research given the fact that every part of the Local Government Area had similar experiences regarding the violent crimes and community policing methods adopted. Households were selected in different parts of the LGA in no particular order and questionnaires administered to adult members of the household who accepted to participate in the study. A total of two hundred and twenty (220) questionnaires were administered to the households identified but only two hundred (200) of the questionnaires were returned (representing 90.9% return rate). However, during data cleaning, 15 questionnaires were discarded because of incomplete information that were vital. Thus, data for this research were extracted from 185 questionnaires. Microsoft Excel, SPSS 23 and Minitab 18 statistical Software were used for the analysis. Nonlinear regression models such as Probit regression model, Logit regression model and Generalized Linear Model (also called Poisson log-linear model) were the methods considered.

3.1 Model Specification

This class of models (Probit, Logit and Poisson log-linear regression models) are defined as follows:

Probit regression model:

$$\Pr obit(p) = \beta_0 + X'\beta \qquad (1)$$

Logit regression model:

$$Log\left(\frac{p}{1-p}\right) = \beta_0 + X'\beta \qquad (2)$$

and Poisson regression model:

$$\mu_i = \mu(X_i, \beta) = X_i'\beta \qquad (3)$$

where,

p is the probability of a success, X is vector of predictor variables and β is a vector of unknown coefficients associated with the predictors for Logistic regression model. For Poisson regression model; $\mu(X, \beta)$ to denote the function that relates the mean response μ_i to X_i, the values of the predictor variables for case *i* and β, the values of the regression coefficients.

However, the link function $g(p)$ can be expressed as

Logit: $$g(p) = Log\left(\frac{p}{1-p}\right) \qquad (4)$$

and the odds of success are

$$Odd\ ratio = \exp(\beta_i) \qquad (5)$$

Note: Equations (1), (2) and (3) are terms of multiple logistic regression model with more than one covariate, the probability event is

$$\Pr obit(p) = \beta_0 + X_1\beta_1 + X_2\beta_2 + \ldots + X_k\beta_k \quad (6)$$

Logit regression model:

$$Log\left(\frac{p}{1-p}\right) = \beta_0 + X_1\beta_1 + X_2\beta_2 + \ldots + X_k\beta_k \qquad (7)$$

and Poisson log-linear regression model:

$$\mu_i = \mu(X_i, \beta) = X_i'\beta = \beta_9 + X_1\beta_1 + X_2\beta_2 + \ldots + X_k\beta_k \quad (8)$$

We have β_0 = constant, β_i = coefficients, k is number of independent variables and X_i is the i^{th} predictors.

In this research, the response variable, Y denotes the probability distribution. The response is whether there is reduction in the rate of violent crimes before and after the engagement of OSPAC (Yes = 1, No = 0 and I don't know = 2) given the respondents' education qualification (Primary, Secondary, Technical, Tertiary = 1; No formal education = 0), Sex (Male = 1, Female = 0) and age. The predictors, X_i, i = 1, 2, … k (k = 4 for each model) are described as follows:

Rate of Killing before the engagement of OSPAC (X_1) 2015-2017

Rate of Kidnapping before the engagement of OSPAC (X_2) 2015-2017

Rate of Rape cases before the engagement of OSPAC (X_3) 2015-2017

Rate of Robbery incidents before the engagement of OSPAC (X_4) 2015-2017

In addition,

Rate of Killing after the engagement of OSPAC (X_1) 2018-2019

Rate of Kidnapping after the engagement of OSPAC (X_2) 2018-2019

Rate of Rape cases after the engagement of OSPAC (X_3) 2018-2019

Rate of Robbery incidents after the engagement of OSPAC (X_4) 2018-2019

For the Data Analysis, we used the goodness-of-fit tests, Wald test (Z^*- test). The decision is to reject the null hypothesis of an adequate fit if the p-value is less than the accepted α - level, for the test. Our interest is to investigate if (i) the respondents' education qualifications (primary, secondary, technical, tertiary = 1; No formal education = 0) on observed age range have effect on the two or more covariate variables before OSPAC intervention (2015-2017) and after OSPAC intervention (2018-2019) using Probit and Logit Analysis, (ii) the respondents' education qualifications (primary, secondary, technical, tertiary = 1; No formal education = 0) on observed sex (Male = 1, Female = 0) have effect on the two or more covariate variables before OSPAC intervention (2015-2017) and after OSPAC intervention (2018-2019) using Poisson log-linear model. Furthermore, we tested whether several $\beta_k = 0$ relate to the response variables. The following techniques were employed: Likelihood ratio test Statistic G_2, Odd ratio, Wald test (Z^*- test), Pearson Goodness-of-Fit (Chi-Squared) and Model selection criteria: Akaike Information criterion (AIC).

3.2 Likelihood ratio test Statistic G_2 and Odd Ratio

Whereas the Likelihood ratio test Statistic, G_2 was used to test whether a subset of the X variables in a multiple logistic regression model can be dropped (i. e., testing whether the associated regression coefficients $\beta_k = 0$). The Odd ratio was used to interpret the relationship between predictor and response. The odds ratio (q) can be any nonnegative number. The odds ratio = 1 serves as the baseline for comparison. q = 1 indicates no association between the response and predictor, q > 1 indicates the odds of success are higher for the reference level of the factor and q < 1 indicates the odds of success are less for the reference level of the factor. Values farther from 1 represent stronger degrees of association.

Illustration: The odds increase multiplicatively by e^{β_1} for every one-unit increase in X. The odds ratio is equivalent to exp(β_k). For example k=1, if β_1 is 0.75, the odd ratio is exp(0.75),

which is 2.11. This indicates that there is a 111% increase in the odds of success for every one-unit increase in X.

3.3 Wald test (Z^*- test)

A large-sample test of a regression parameter can be constructed based on the hypotheses, such that

$$H_0 : \beta_k = 0 \text{ against } H_1 : \beta_k \neq 0 \qquad (9)$$

an appropriate test statistic is:

$$Z^* = \frac{b_k}{S\{b_k\}} \quad k = 0,1,\ldots, p \qquad (10)$$

and the decision rule is:

$$If \left|Z^*\right| \leq z(1-\alpha/2), \; conclude \; \mathrm{H}_0, \text{ otherwise reject } \mathrm{H}_0$$

where Z is a standard normal random variable and $S\{b_k\}$ is the estimated approximate standard deviation of b_k obtained from Equation (1), (2) and (3).

3.4 Criteria for Model Selection

The Akaike Information Criterions (AIC) was used for the model selection. The general form of the AIC, calculated using residual sum of squares from regression is:

$$AIC = n \times In(RSS/n) + 2 \times p \qquad (11)$$

where n is the number of data points (observations); RSS is the residual sum of squares (MSE=RSS/n) and P is the number of parameter in the model.

IV. RESULTS

4.1 Descriptive Statistics of responses to questions in section A of the questionnaires

The results from the questionnaire responses of Section A, are summarized using percentage analysis of the demographic variables in Table 1.

Table 1: Demographic data of the respondents

Demographic variable	Sub Variables	Frequency	Percentage (%)
Age	20-30	54	29.2
	31-40	57	30.8
	41-50	31	16.8
	51-60	22	11.9
	61 and above	21	11.4
Sex	Male	85	45.9
	Female	100	54.1
Education	Primary	7	3.8
	Secondary	63	34.1
	Technical	34	18.4
	Tertiary	81	43.8
Employment Status	Employed	48	25.9

	Unemployed	63	34.1
	Self Employed	74	40.0
Duration of Stay	Less than 5 Years	19	10.2
	5-10 Years	30	16.2
	More than 10 Years	136	73.5

From Table 1 above it was observed that more of the respondents (30.8%) were in the 31 to 40 years' age interval. The respondents were made up of more females (54.1%) than males (45.9%). There were more respondents with tertiary educational qualifications (43.8%) and majority of the respondents are educated. Some of the respondents are self-employed (40%) while 34.1% are unemployed. Many of the respondents (73.5%) have lived in the community for more than 10 Years. This suggests that the respondents are from the community not visitors (community individuals).

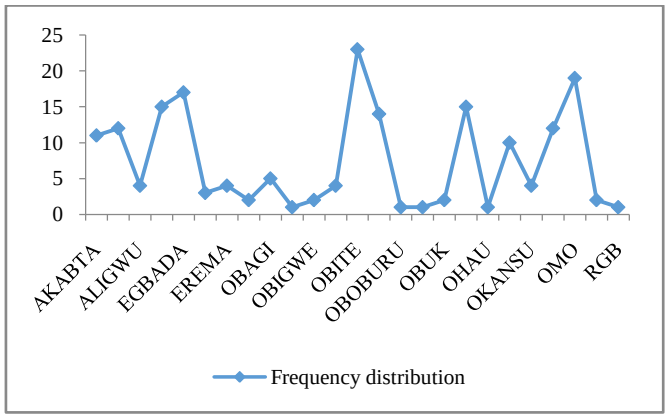

Figure 1: Distribution Plot of Respondents in the various Communities sampled

Figure 1 shows the respondents distribution by communities. Obite community had the highest respondents (12.4%), follow by Omo (10.2%), Egbada (9.2%) and Ede (8.1%), etc.

4.2 Descriptive Statistics of responses to questions in section B of the questionnaires

The results from Section B of the questionnaires are summarized in Table 2. Ranks and nonlinear regression models such as Probit regression model, Logit regression model and Poisson loglinear models of the demographic variables were built and analyzed, and the results summarized in Tables 3, 4, 5 and 6 below.

Table 2: Community Policing and Violent Crime Reduction

Community Policing and Violent Crime Reduction (OSPAC)	Yes (1)	No (0)	I Don't Know (2)	Rate	Rate Approximate
reduction of kidnapping	181 (97.8)	3 (1.6)	1 (1)	3.0	**3**
rise in farming activities	172 (93.0)	8 (4.3)	5 (2.7)	2.9	**3**
increase in school enrolment	178 (96.2)	5 (2.7)	2 (1.1)	3.0	**3**
business outfit resumed	178 (96.2)	4 (2.2)	3 (1.6)	2.9	**3**
increase in late evening transportation and inter-community movements	177 (95.7)	7 (3.8)	1 (0.5)	3.0	**3**
steady return of night life and evening business activities	174 (94.1)	4 (2.2)	7 (3.8)	2.9	**3**
people feel safer now	179 (96.8)	2 (1.1)	4 (1.1)	2.9	**3**
steady return of people	173 (93.5)	9 (4.9)	3 (1.6)	2.9	**3**
significant reduction in cult activities	178 (96.2)	2 (1.1)	5 (2.7)	2.9	**3**
significant reduction of rape case	90 (48.6)	83 (44.9)	12 (6.4)	2.4	2
reduction of armed robbery	88 (47.6)	11 (5.9)	86 (46.5)	2.0	2
happiness over introduction of OSPAC	89 (48.1)	11 (6.0)	85 (45.9)	2.0	2

Footnote: Rate approximate is significant if value is greater than (4+3+2+1)/4 = 2.5

Table 2 shows that the stated factors, after the engagement of OSPAC, are significant, except: (i) significant reduction of rape cases (ii) reduction of armed robbery and (iii) happiness over introduction of OSPAC.

4.3 Probit and Logit Regression Model

In Section 3.1, we considered four models to be built – Probit and Logit Regression models before and after engagement of OSPAC respectively. Table 3 gives a summary of results of the analysis of Probit and Logit models before the engagement of OSPAC. For the Probit model, Table 3 showed that cases of Killing (β_1) and Rape (β_3) were the major violent crimes before the engagement of OSPAC, since both coefficients have significant effects at 5%. However, the odds ratio suggests an approximate (at least one) violent crime for all the independent variables.

For the Logit model, Table 3 also showed that cases of Killing (β_1) and Rape (β_3) were the major violent crimes before the engagement of OSPAC, since both coefficients have significant effect at 10%. However, the odds ratio suggests an approximate (at least one) violent crime for all the independent variables except the constant coefficient of at least two violent crimes.

Table 3: Summary of results of the analysis of the Probit and Logit Models for 2015-2017

	PROBIT			LOGIT			
Predictor (2015-2017)	**Coefficients**	**P-values**	**Odds Ratio**	**Coefficients**	**P-values**	**Odds Ratio**	**Remark**
Constant (β_0)	0.453	0.375	1.573	0.769	0.222	2.158	β_1 and β_3 are sig. for both
Cases of Killing (β_1)	0.016	0.049**	1.017	0.025	0.077*	1.025	Models
Kidnap Cases (β_2)	-0.004	0.651	0.996	-0.006	0.667	0.994	
Rape Cases (β_3)	-0.018	0.042**	0.982	-0.028	0.057*	0.972	
Robbery incidents(β_4)	0.008	0.218	1.008	0.013	0.231	1.013	
MSE		54.991			54.951		LOGIT model is Slightly better than PROBIT, using AIC
AIC		751.325			**751.193**		
Pearson Goodness-of-Fit (Chi-Squared)		68.232 (0.697)			68.322 (0.694)		

Footnote: ***=sig. at 1%; **=sig. at 5%;*=sig. at 10%; the least AIC value is the best Model

Table 4 gives a summary of results of the analysis of Probit and Logit models after the engagement of OSPAC. In Table 4, the results of analysis of the Probit model showed no independent variables have significant effects on the response variable, except the constant coefficient [β_0], which represent other crimes not considered in the study, is significant after the engagement of OSPAC. It implies violent crime reduction in the community, since the p-value of the independent variables are greater than 5% [or p-value > 0.05] except the constant coefficient with p-value < 0.05. There was reduction in the rate of killing, kidnap, rape and robbery after the engagement of OSPAC.

For the Logit model, Table 4 showed similar results as the Probit model. It showed no independent variables have significant effects on the response variable, except the constant coefficient [β_0] which represents other crimes not considered in the study is significant at 1% after the engagement of OSPAC. It implies violent crime reduction in the community (p-value > 0.05) except the constant coefficient with p-value < 0.05. There was reduction in the rate of killing, kidnap, rape and robbery after the engagement of OSPAC.

Furthermore, Table 3 and 4 respectively, compared the Probit and Logit Analysis, using Mean Squared Error (MSE), AIC and Pearson Goodness-of-Fit (Chi-Squared). The AIC_p value (751.193) for the Logit regression model in Table 3 is smaller than that for the Probit regression model value (751.325). This suggests that the Logit regression model performed better than the Probit regression model. It also suggests that Logit regression model is the best model that fitted the count data well using AIC. However, both models performed well. Similarly, in Table 4, the Logit regression model fitted the count data well using AIC and as such is the best model.

4.4 Probit Regression Model for the Combined 2015-2017 and 2018-2019

Similarly, a combined model for 2015-2017 and 2018-2019 was done, using Probit and Logit Analysis. It was used to estimate the independent variables parameters denoted as $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7 \; and \; \beta_8$ (Equation 8). The results are given in Table 5.

Table 5 confirmed the previous results of the Probit and Logit regression models respectively. However, cases of killing between 2015 and 2017 before the engagement of OSPAC is significant at 10%, while rape cases before the engagement of OSPAC is significant at 5%. Note that after the engagement of OSPAC, occurrences of violent crime between 2018 and 2019 is not significant (p-value > 0.05 for all the independent variables parameters).

Table 4: Summary of results of the analysis of the Probit and Logit Models for 2018-2019

	PROBIT			LOGIT			
Predictor (2015-2017)	**Coefficients**	**P-values**	**Odds Ratio**	**Coefficients**	**P-values**	**Odds Ratio**	**Remark**
Constant (β_0)	0.509	0.000***	1.664	0.824	0.001***	2.276	β_0 is sig. for both Model
Cases of Killing (β_1)	0.002	0.863	1.002	0.003	0.871	1.003	
Kidnap Cases (β_2)	0.007	0.491	1.007	0.010	0.522	1.010	
Rape Cases (β_3)	0.009	0.485	1.009	0.014	0.500	1.014	

Robbery incidents(β_4)	-0.012	0.458	0.998	-0.018	0.478	0.982	
MSE		56.337			56.377		LOGIT model is Slightly better than PROBIT, using AIC
AIC		755.997			755.932		
Pearson Goodness-of-Fit (Chi-Squared)		72.664 (0.555)			72.652 (0.555)		

Footnote: ***=sig. at 1%; **=sig. at 5%;*=sig. at 10%; the least AIC value is the best Model

Table 5: Combined Model Coefficients (parameters) Estimates, p-values and odds ratios, using Probit and Logit Analysis

	Predictor		**Probit Analysis**			**Logit Analysis**	
		Coefficients	**P-values**	**Odds Ratio**	**Coefficients**	**P-values**	**Odds Ratio**
Before OSPAC engagement	Constant (β_0)	0.497	0.226	1.644	0.892	0.225	2.440
	Cases of Killing 2015-2017 (β_1)	0.016	0.054*	1.016	0.025	0.077*	1.025
	Kidnap Cases 2015-2017 (β_2)	-0.006	0.536	0.994	-0.009	0.572	0.991
	Rape Cases 2015-2017 (β_3)	-0.020	0.037**	0.980	-0.032	0.048**	0.969
	Robbery incidents 2015-2017 (β_4)	0.013	0.109	1.013	0.021	0.119	1.021
After OSPAC engagement	Cases of Killing 2018-2019 (β_5)	-0.011	0.510	0.989	-0.019	0.498	0.981
	Kidnap Cases 2018-2019 (β_6)	0.013	0.356	1.013	0.020	0.370	1.020
	Rape Cases 2018-2019 (β_7)	0.007	0.614	1.007	0.011	0.612	1.011
	Robbery incidents 2018-2019 (β_8)	-0.010	0.567	0.990	-0.015	0.583	0.985
	MSE		594.00			594.00	
	AIC		1191.573			1191.573	
	Pearson Goodness-of-Fit (Chi-Squared)		66.003 (0.646)			66.238 (0.638)	

Footnote: ***=sig. at 1%; **=sig. at 5%;*=sig. at 10%.

Table 6: Poisson Log-linear Model Coefficients (parameters) Estimates, p-values and odds ratios for 2015-2017 and 2018-2019

	(2015 – 2017)				**(2018 – 2019)**			
Predictor	**Coefficients**	**P-values**	**Wald Chi-Square**	**Odds Ratio**	**Coefficients**	**P-values**	**Wald Chi-Square**	**Odds Ratio**
Constant (β_0)	0.816	**0.000*** **	12.563	2.261	0.877	**0.000*** **	122.632	2.404
Cases of Killing (β_1)	-7.17×10^{-5}	0.989	0.000	1.000	-0.004	0.345	0.891	0.996
Kidnap Cases (β_2)	-0.001	0.876	0.024	0.999	-0.004	0.523	0.407	0.996
Rape Cases (β_3)	0.006	**0.094***	2.813	1.006	0.003	0.679	0.172	1.003
Robbery incidents(β_4)	-0.007	**0.069***	3.307	0.993	-0.001	0.893	0.018	0.999
Deviance		54.178				55.182		
Scaled Deviance		54.178				55.182		
Pearson Chi-Squared		50.943				51.753		
Scaled Pearson Chi-Squared		50.943				51.753		
Log Likelihood[b]		-268.119				-268.621		
Akaike's Information Criterion (AIC)		546.238				547.242		
Finite Sample Corrected AIC (AICC)		546.573				547.578		
Bayesian Information Criterion (BIC)		562.339				563.344		
Consistent AIC (CAIC)		567.339				568.344		

Footnote: ***=sig. at 1%; **=sig. at 5%;*=sig. at 10%.

4.5 Generalized Linear (Poisson Log-linear) Models for 2015-2017 and 2018-2019

The generalized linear model (Poisson Log-linear model) was employed to determine if any other covariate (independent) variable is significant. Table 6 shows an addition variable is significant at 10% (Robbery incidents). Then, constant coefficient is significant at 1% and rape cases is significant at 10%. In addition, Table 6 also confirmed the previous Probit and Logit analysis results after the engagement of OSPAC.

V. DISCUSSION

This research used primary data set to determine an appropriate nonlinear regression model (Probit, Logit and Poisson Log-linear regression models) for assessing community policing and violent crimes reduction in ONELGA, Rivers State, Nigeria. The study focused on the analysis of crime rate before and after engagement of Onelga Security Peace Advisory Committee (OSPAC) in Ogba, Ndoni and Egbema Local Government Area (ONELGA) of Rivers State. The data were extracted from responses on the questionnaires administered to members of households in the study community. The data were presented in tabular form and analyzed using descriptive statistics, ranks and non-linear regression models (e.g. Probit regression model, Logit regression model and Generalized Linear Models or Poisson log-linear models).

The study found that after the engagement of OSPAC, violent crimes such as kidnapping, rape armed robbery and killing reduced considerably and normal life activities returned to the community. There was rise in farming activities, increase in school enrolments, business outfits resumed fully, night life returned gradually, cult activities reduced significantly and there was steady return of people to the community. These findings agree with Hanachor and Wordu (2021) which states that "This method of policing has helped most communities to identify and incisively address societal problems with full supports of government". It also agrees with the position of Atume (2017) on community policing.

Probit and Logit regression models showed that the major violent crimes identified in the study (e.g. Killing and rape Cases) before engagement of OSPAC were significantly reduced after engagement of OSPAC since none of the independent variables had significant effects on the response variable, except the constant coefficient [β_0] which represents other crime not considered in the study ($p > 0.05$ for both models).

The Generalized Linear Model (Poisson log-linear model) identified an addition variable, Robbery incidents, one of the violent crimes in the community before engagement of OSPAC as being significant at 10%. The constant coefficient is significant at 1% thus confirming the previous Probit and Logit analysis result of significant reduction in violent crime rate after the engagement of OSPAC. The covariates considered were not significant, except the constant coefficient [β_0].

VI. CONCLUSION

This research was conducted to identify an appropriate nonlinear regression model (e.g. Probit, Logit and Poisson Log-linear regression models) for assessing the impact of community policing on violent crime reduction using count data observations obtained from questionnaire responses. Using the AIC, logit regression model was identified to be more suitable for the observations considered.

It was therefore, concluded that the Logit regression model is more suitable for modelling response variable on the covariates. Secondly, community policing intervention has an impact on violent crime reduction.

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