Analysis of Cancer Incidence Using Count Regression Models

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Abstract- Cancer has become a major cause of morbidity and mortality in Adamawa, Nigeria and the world at large. Despite the threat cancer poses to the world, less attentions is giving to the menace compared to the other public health issues such as corona Virus that the world stood up and fought it. Research was conducted on 1,168 registered cancer patients in Adamawa state, Nigeria. Systematic random sampling was used to extract demographic information such as age, sex, marital status, level of education, occupation, date of first diagnoses. Data were analyzed using percentages, mean and modified negative binomial regression Model that was used which was later compared to the based model Poisson and the classical negative binomial model. It was discovered that the modified negative binomial regression model significantly outperformed both the based and classical model. It was further discovered that 92% of the confirmed cases survived the treatment with only 8% of the mortality recorded from the confirmed cases. 35% mortality were recorded from the 112 (65%) of the pending cases that were yet to be confirmed. This mortality which seems to be high in patients with pending cases were due to the lost in follow up from the patients. Surgery was discovered to be the best method for the treatment of cancer followed by the combinations of treatments. Lastly, it was discovered that Age influence the expected log count of the topography of cancer outcome of treatment by -0.1173, Sex influence the expected log count of the topographer of cancer treatment outcome by -0.2598, Educational status influence expected log count of the outcome of the treatment by 0.0369, Treatment type influence the expected log count of the topography of the outcome of the treatment of cancer by -0.0416. In conclusion, the risk factors to successful treatment of cancer in Adamawa includes the in ability to dictate cancer on time, lack of follow up with the treatment from the patients, treatment type and age of the patients as well the sex.

I. INTRODUCTION

Cancer is described by the World Health Organization (2021), as a generic term for a large group of diseases that can touch any part of the body. Other terms used are malignant tumors and neoplasms. One defining feature of cancer is the rapid development of abnormal cells that grow beyond their usual boundaries and which can invade adjoining parts of the body and spread to other organs; the later process is referred to as metastasis which are the primary source of death from cancer.

According Fatimah Abdulkareem (2009), there are 24.6 million people living with cancer globally, 12.5% of all deaths are attributed to cancer. She reiterated that the actual cancer burden in Nigeria is unknown due to lack of statistics or under reporting of such incidence which could be due to inadequate diagnostic facilities, limited access to care, inadequate technical manpower and infrastructure as well as quality cancer data systems, all these contribute to inaccurate data on cancer burden. However, she reported increase in cancer incidence and the age standardized incidence rates (ASR) for all cancer as 81.6% per 100,000 for males and 115.1% per 100,000 for females with 65.9% and 34.1% in females and males from Ibadan respectively. From Kano, out of 1001 cancers registered for period 1995-2004, male cancers accounted for 50.3% and 49.7% in females.

Anorlu *et al.* (2010), revealed that out of the 2200 patients admitted between 2002 and 2007 into the gynecology ward of the Lagos state university teaching hospital, 104 deaths were recorded and 83 (88.3%) of these deaths were attributed to cancer.

In addition, Elima Jedy Agba *et al.* (2012), discovered that the commonest cancer in Nigeria in 2009 to 2010 were cervical and breast cancer among women and prostate cancer among men. He further revealed that

there was significant increase in the incidence of breast cancer compared to historical records while the incidence of cervical cancer was stable. The mean age of diagnosis for cancer in men in Ibadan was 51.1 (20.1) Years and in Abuja 49.9 (19.0) years while in women, the mean age of the diagnosis (SD) for all cancers in Ibadan was 49.1(16.2) and 45.4(15.6) in Abuja. The age standardized incidence rates for all invasive cancers from the Ibadan cancer register (IBCR) was 66.4 per 100,000 men and 130.6 per 100,000 women while that of Abuja cancer register (ABCR) 58.3% per 100,000 for men and 138.6 per 100,000 for women.

According Olakanmi Ralph *et al.* (2014) in his research on cancer mortality pattern in Lagos University Teaching Hospital revealed that cancer account for 24.0% of total deaths recorded in the Lagos State University Teaching Hospital Lagos Nigeria between 2000 to 2013 period. Putting the yearly cancer mortality rate ranged between 11.9% and 42.1%, with 450 males and 986 females' deaths, given the ratio as 1:2.2. He further observed that 1436 cancer related deaths were recorded during the study out of the 5979 total diagnosed cancer cases.

Olakanmi Ralph Akinde *et al.* (2015) observed that 70% of the total mortality due to cancer occurred in low and middle income countries. A total of 1436 (4.74%) cancer deaths were recorded from 30287 total deaths. He further stated that mortality due to cancer stood at 99,249 and 156,290 between 2000 and 2004 in Egypt and South Africa respectively.

Saibu G. Morounke *et al.* (2017) in his research on epidemiology and incidence of common cancers in Nigeria, observed that out of 4209 cancer cases extracted from the Nigeria National System of Cancer Registries (2016), 25.9% were males while 74.1% were females which was recorded in Lagos, the second rank after Lagos was Enugu Center with the total cancer cases of 3282 in which 40% were male and 60% were female. Edo and Anambra were the next rank after Enugu with 2230 and 2024 cases respectively. He further observed that the least cancer were recorded in Bayelsa and Kogi with 140 and 187 cancer cases respectively. Iyiola R. O *et al.* (2017), in his research on modelling cancer risk factors for vital topographies in the south western states of Nigeria, revealed that age, marital status, age at first menstruation, use of birth control pill, consumption of high fat diet, alcohol, obesity and having multiple sex partners were all significant factors for breast cancer. For cervical cancer significant risk factors include Age at first menstruation, and consumption of high fat diet while for colon cancer, the significant risk factors were Age, marital status, educational status and place of residence.

According to the World Health Organization (WHO 2018) health emergency team lead in Nigeria, Clement Peter, 41,000 Nigerians were killed by cancer in 2018, out of an estimated 166,000 cases recorded in the country. He further explained that 14 million new cases and 8.2 million mortalities were recorded in 2012 while 18.1 million new cases and 9.6 million deaths were recorded in 2018 globally.

The cancer burden in Africa is projected to multiply itself twice from 1,055,172 new cases in 2018 to 2,123,245 cancer cases by 2040.

WHO (2018) identified the most prevalent types of cancer in Nigeria as breast cancer, cervical cancer, and prostate cancer. In addition to the previous ones mentioned are blood cancers, lungs, colon, stomach, liver and kidney cancer.

Sarada Ghosh *et al.* (2019), revealed that when gender is giving, the estimated rate Colon and Rectum cancer is 4.75 times Kidney and Renal cancer which was more among females.

Meanwhile, the World Health Organization (WHO 2020) fact sheet revealed that out of the total Nigerian population of 200,963,603, a total cancer cases of 115,950 and 70,327 cancer deaths were recorded in 2018.

1.1 Materials and Methods

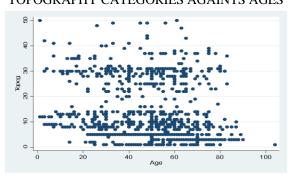
This is a population-based cancer registries where by 1,168 cancer records were used for the purpose of this research. Demographic information were extracted using systematic random sampling. Count models such as Poisson regression model, classical negative

binomial regression, and modified negative binomial regression (Winkelmann 2008), were fitted and compared.

The classical negative binomial regression was modified by adding a nonnegative multiplicative random effect which is used to model the individual heterogeneity such as early dictation of cancer, accessibility to the hospital and the family history of cancer were multiplied and added to the model. Data was analyzed using STATA version 15.

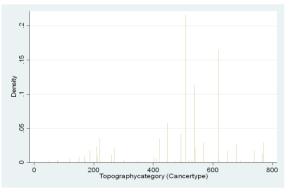
1.3 Results:

FIGURE 1: SCATTER PLOT OF THE TOPOGRAPHY CATEGORIES AGAINTS AGES



The above graph is the scatter plots of cancer topography which consisted of different cancer types registered.

FIGURE 2: HISTOGRAM REPRESENTATION OF THE TOPOGRAPHY OF CANCER



Looking at the above histogram, it is evidence that the data is approximately normal by having the highest observation at the nearly middle of the observations. Although the observations are relatively skewed to the right.

TABLE 1: Model Selection Criteria									
Model	AIC	BIC							
Poisson	14937.3	14962.62							
Regression									
Model									
Classical NB	7998.752	8069.634							
Regression									
Model									
Modified NB	7968.075	8044.02							
Regression									
Model									
Source: Extracted f	From STATA 15								

Source: Extracted from STATA 15

From the above table, it was observed that the modified negative binomial regression model has the least AIC and BIC compared to the existing Poisson regression model and classical negative binomial model which imply that the modified negative binomial regression model significantly outperformed the based model Poisson regression and the classical negative binomial regression model and is the best fit for modelling cancer which was highly significant.

 TABLE 2: Negative Binomial Regression Model

IADLL	2. 10cg		nonna	regies		Iouci
Topog.	Coe	Std.	Ζ	P >	[9	5%
of	f.	Err.		$ \mathbf{Z} $	Co	onf.
Outcom					Inte	erval]
e						
Age	-	0.00	-	0.00	-	-
	0.11	14	8.2	0	.01	.008
	73		1		45	9
Sex	-	.053	-	0.00	-	-
	.259	9	4.8	0	.36	.154
	8		2		55	1
Educati	.036	.021	1.6	0.00	.00	.079
onal	9	7	8	93	61	0
Status						
E	-	.078	-	0.00	-	0.00
	.442	8	5.6	0	.59	23
	2		1		68	
Treatm	-	.020	-	0.03	-	-
ent type	.041	0	2.4	8	.08	.002
	6		7		09	3
Const.	4.30	.204	21.	0.00	3.9	4.70
	23	6	03	0	01	3

Log likelihood = -3981.1901	
Chibar2(01) = 6641.02	LR
Chi2(5) = 118.87	
Pseudo $R2 = 0.0147$	Prob.
> Chibar2 = 0.000	

Source: Extracted from STATA 15

• Interpretation of the model:

From the above table of coefficient of the negative binomial regression, the dependent variable is topography of the outcome of the treatment of cancer which was regressed against the various independent variables age, sex, educational status, treatment type and the nonnegative multiplicative random effect (\in).

The Age had a coefficient -0.1173, which was statistically significant. It means that for every increase in age, the expected log count of the topography of the outcome decrease by -0.1173.

Likewise the sex had a coefficient of -0.2598 which was also statistically significant. It is interpreted as for every increase in sex, the expected log count of the topography of the outcome of cancer treatment is decrease by -0.2598.

In addition, educational status had the coefficient 0.0369, which means that for every increase in educational status, the expected log count of the topography of cancer increase by 0.0369.

The treatment type had the coefficient of -.0416 which is statistically significant indicates that for every increase in the treatment type, expected log count of the topography of the outcome of cancer treatment decreases by -0.0416

The modified negative binomial regression model $\lambda_i = \exp(x_i^T \beta)\epsilon_i$ can be fitted as follows:

Log (Topography of Outcome) = [(-0.1173) Age + (-.2598) Sex + (0.0369) Educational Status + (-0.0416) Treatment type] [-0.4422].

Outcome	Coef.	Std. Err	Z	P> Z	[95% Con	f. Interval]
Age	-0.0111	.0014	-7.80	0.0000	0139	0083
Sex						
Male	Ref					
Females	2745	0.0537	-5.11	0.0000	3797	1693
Educational						
Status						
No School	Ref					
Primary level	0.1145	.0958	1.19	.232	0733	.3025
Secondary level	.1732	.0654	2.65	0.008	.0451	.3013
Tertiary Level	.1292	.0719	1.50	0.072	01168	.2701
E	4329	.0785	-5.52	0.000	5868	2791
Treatment Type						
Traditional	.2167	.1516	1.43	0.153	0804	.5137
Surgery	.3586	.1113	3.22	0.001	.1404	.5767
Radiotherapy	.8545	.5153	1.66	0.097	1555	1.8644
Chemotherapy	0.0854	.1483	0.06	0.954	2821	.2992
Palliative Care	.2405	.3389	0.71	0.478	4237	.9046
Combination of	-0.0242	.1696	-0.14	0.887	-0.3565	0.3082
Treatment						

TABLE 3: Negative Binomial Regression Model Based on Categories of the Independent Variables.

Const.	3.5321	.2066	17.10	0.000	3.1273	3.9370				
/1nalpha	.3408	.0445			4281	2536				
Alpha	.7112	.03166			.6518	.7760				
Log likelihood =	-3969.0373	Chibar2(01) = 64	38.92	LR Chi2(13)	= 143.17					
Pseudo R2 =	= 0.0177	Prob > Chi2 = 0.0	00							
Source: Extracted from STATA										

Interpretation of the Negative Binomial Regression Model

Looking at the above table of the negative binomial regression model, the chibar2 value of 6438.92 is far from zero signify that the model is statistically significant. (Regina 2020).

Here we analyzed variables according to various categories as against the reference category.

The age had the negative binomial regression coefficient of -0.011 which indicates that for every unit increase in age, the expected log count of topography of outcome decreases by -0.011.

The variable sex had two categories, the females had a coefficient -0.2745 against the reference categories which is males. It indicate that for every increase in the number of females diagnosed with cancer, the expected log count of the topography of the outcome of the treatment decreases by -0.2745 as against the reference category males. (Regina 2020)

The categorical variable educational status has four categories which include no school attended, primary level of educate, secondary level of education and tertiary of education.

The primary level of the education had the coefficient of 0.1145 as against the reference category no school attended. This means that for every increase in the number of cancer patients diagnosed with primary level of education, the expected log count of the topography of the outcome of the treatment increases by 0.1145.

The secondary school level of education had the coefficient 0.1732 against the reference category no school attended at all level. This means that for every increase in the number of cancer patients with

secondary school level of education, the expected log count of the topography of the outcome of the treatment increases by 0.1732.

The tertiary level of education had a coefficient of 0.1292 against the reference category no school attended at all level which indicates that for every increase in the number of cancer patients with tertiary school level of education, the expected log count of the topography of the outcome of the treatment increases by 0.1292. (Regina 2020)

Meanwhile, the variable treatment type has five categories which are statistically significant.

The category of traditional treatment had the coefficient .2167 which indicates that for increase in the number of patients that apply traditional method of treatment, the expected log count of the topography of the outcome of the treatment increases by 0.2167

In addition, the category Surgery had the coefficient 0.3586, which indicates that for every increase in the number surgery performed on the cancer patients, the expected log count of the topography of the outcome of the treatment of cancer increases by 0.3586. (Regina 2020).

More so, the category of Radiotherapy had the coefficient of 0.8545 that indicates that every increase in the number of cancer patients that under goes radiotherapy, the expected log count of the topography of the outcome of the treatment of cancer patients increases by 0.8545.

Moreover, the chemotherapy with regression coefficient of 0.0854, means that for every increase in the number of cancer patients that received chemotherapy method of treatment, the expected log count of the topography of the outcome of the treatment increases by 0.0854.

Finally, the category Palliative care had the variable - 0.0242 which means that for every increase in the number of Patients that received palliative care method, the expected log count in the topography of the outcome of the treatment of cancer decreases by - 0.0242.

II. DISCUSSION

This research revealed that the participants consist of 42% males and 58% females, and the most common cancer that affects the populace of Adamawa state were breast cancer, prostate and cervix cancer. The above results indicates that no gender is exempted from the menace of cancer which cut across all categories.

92% of the confirmed cases survived the treatment with only 8% of the mortality recorded from the confirmed cases. 35% mortality were recorded from the 112 (65%) of the pending cases that were yet to be confirmed. This mortality which seems high were to be due to the lost in follow up from the patients.

Surgery was discovered to be the best method for the treatment of cancer followed by the combinations of other treatments.

Lastly, it was discovered that Age influence the expected log count of the topography of the cancer outcome of treatment by -0.1173, Sex influences the expected log count of the topographer of the outcome of the treatment of cancer by -0.2598, Educational status influences expected log count of the outcome of the treatment by 0.0369, Treatment type influences the expected log count of the topography of the outcome of the treatment of cancer by -0.0416.

CONCLUSION

Based on the research, we conclude that most of the cancer mortality in Adamawa state were found out to be from the patients that were lost in the follow up whose cancer status were not certified and later return to the facility at the late stage of the disease. It was also discovered that women were the most affected population in the state with the cases of breast and cervix cancer. The age group that were mostly affected by cancer menace are 56-60 followed by 46-50 cutting acrossed both youthful and aging age. Age, sex, treatment type were all risk factor to the successful outcome of the treatment of cancer in Adamawa state.

Lastly, Modified negative binomial regression outperformed both the Poisson regression model and classical negative binomial regression.

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APPENDIX

TABLE 8: Classical Negative Binomial Regression Model (STATA 15 Output)

. nbreg Topog Age Sex Educationstatus Treatmenttype, dispersion(mean)

Fitting Poisson model:

Iteration 0: log likelihood = -7463.6519 Iteration 1: log likelihood = -7463.6514

Fitting constant-only model:

0:	log	likelihood	=	-4053.067
1:	log	likelihood	=	-4040.6409
2:	log	likelihood	=	-4040.624
3:	log	likelihood	=	-4040.624
	0: 1: 2: 3:	1: log 2: log	1: log likelihood 2: log likelihood	1: log likelihood = 2: log likelihood =

Fitting full model:

Iteration	0:	log	likelihood	=	-4000.5834
Iteration	1:	log	likelihood	=	-3998.159
Iteration	2:	log	likelihood	=	-3998.1459
Iteration	3:	log	likelihood	=	-3998.1459

Negative binomial regression	Number of obs	=	1,168
	LR chi2(4)	=	84.96
Dispersion = mean	Prob > chi2	=	0.0000
Log likelihood = -3998.1459	Pseudo R2	=	0.0105

Topog	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
Age	0113848	.0014448	-7.88	0.000	0142165	0085531
Sex	2678758	.0545783	-4.91	0.000	3748474	1609043
Educationstatus	.0385149	.0220982	1.74	0.081	0047968	.0818266
Treatmenttype	0381673	.0201908	-1.89	0.059	0777406	.001406
_cons	3.466907	.139894	24.78	0.000	3.19272	3.741094
/lnalpha	2901617	.0439172			3762378	2040855
alpha	.7481426	.0328563			.6864391	.8153926

LR test of alpha=0: chibar2(01) = 6931.01 Prob >= chibar2 = 0.000

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Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
	1,168	-4040.624	-3998.146	6	8008.292	8038.67

Note: N=Obs used in calculating BIC; see [R] BIC note.		Note:	N=Obs	used	in	calculating	BIC;	see	[R]	BIC no	ote.
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TABLE 9: Modified Negative Binomial Regression Model

. . nbreg Topog Age i.Sex i.Educationstatus $\ensuremath{\mathfrak{C}}$ i.Treatmenttype, dispersion(mean)

Fitting Poisson model:

Iteration	0:	log	likelihood	=	-7188.5665
Iteration	1:	log	likelihood	=	-7188.4996
Iteration	2:	log	likelihood	=	-7188.4995

Fitting constant-only model:

Iteration	0:	log	likelihood	=	-4053.067
Iteration	1:	log	likelihood	=	-4040.6409
Iteration	2:	log	likelihood	=	-4040.624
Iteration	3:	log	likelihood	=	-4040.624

Fitting full model:

Iteration	0:	log	likelihood	=	-3975.0311
Iteration	1:	log	likelihood	=	-3969.1074
Iteration	2:	log	likelihood	=	-3969.0374
Iteration	3:	log	likelihood	=	-3969.0373

Negative binomial regression	Number of obs	=	1,168
	LR chi2(13)	=	143.17
Dispersion = mean	Prob > chi2	=	0.0000
Log likelihood = -3969.0373	Pseudo R2	=	0.0177

Topog	Coef.	Std. Err.	z	P> z	[95% Conf	. Interval]
Age	0111142	.0014252	-7.80	0.000	0139075	008321
Sex						
Females	2744602	.0536844	-5.11	0.000	3796797	1692407
Educationstatus						
Primary_level	.1145728	.0958769	1.19	0.232	0733424	.3024881
Secondary_level	.1732095	.0653738	2.65	0.008	.0450793	.3013398
Tartiary_level	.1292329	.0718992	1.80	0.072	0116869	.2701526
20	-1.092708	1.023932	-1.07	0.286	-3.099577	.9141614
e	432926	.0784964	-5.52	0.000	5867761	279076
Treatmenttype						
Traditional	.2166575	.1515517	1.43	0.153	0803784	.5136934
Surgery	.3585929	.1113194	3.22	0.001	.1404109	.5767748
Radiotherapy	.8544717	.5152996	1.66	0.097	155497	1.86444
Chemotherapy	.0085403	.148295	0.06	0.954	2821125	.2991932
Palliative_Care	.240484	.3388565	0.71	0.478	4236625	.9046305
Combinations_of_treatment	0241667	.1695694	-0.14	0.887	3565166	.3081832
_cons	3.532144	.2065535	17.10	0.000	3.127307	3.936982
/lnalpha	340845	.0445127			4280882	2536017
alpha	.7111692	.031656			.6517539	.7760008

LR test of alpha=0: <u>chibar2(01) = 6438.92</u> Prob >= chibar2 = 0.000

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Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
	1,168 -	4040.624	-3969.037	15	7968.075	8044.02

Note: N=Obs used in calculating BIC; see [R] BIC note.

TABLE 10 Poisson Regression Model (Based Model)

. poisson Topog Age Sex Educationstatus Treatmenttype

Iteration 0: log likelihood = -7463.6519 Iteration 1: log likelihood = -7463.6514

Poisson regression Log likelihood = -7463.6514				Number of o LR chi2(4) Prob > chi2 Pseudo R2	=	1,168 922.47 0.0000 0.0582
Topog	Coef.	Std. Err.	Z	₽> z	[95% Conf.	Interval]
Age Sex Educationstatus Treatmenttype _cons	0119599 3138504 .0315028 0361318 3.56899	.0004461 .0175831 .0062909 .0064324 .0430956	-26.81 -17.85 5.01 -5.62 82.82	0.000 0.000 0.000 0.000 0.000	0128343 3483126 .0191728 0487391 3.484525	0110855 2793882 .0438327 0235246 3.653456

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
	1,168	-7924.886	-7463.651	5	14937.3	14962.62

Note: N=Obs used in calculating BIC; see [R] BIC note.

TABLE 11: Poisson Regression Incidence Rate Table

. poisson, irr

Poisson regressio	on		L	umber of ob R chi2(4) rob > chi2	s = = =	1,168 922.47 0.0000
Log likelihood = -7463.6514			-	seudo R2	=	0.0582
Topog	IRR	Std. Err.	Z	₽> z	[95% Conf.	Interval]
Age	.9881113	.0004408	-26.81	0.000	.9872477	.9889757
Sex	.7306283	.0128467	-17.85	0.000	.7058782	.7562463
Educationstatus	1.032004	.0064922	5.01	0.000	1.019358	1.044808
Treatmenttype	.9645131	.0062041	-5.62	0.000	.9524296	.97675
_cons	35.48075	1.529063	82.82	0.000	32.60692	38.60787

Note: _cons estimates baseline incidence rate.