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Inference on Reported Vehicular Fatal Accidents in Nigeria Using a Bayesian Model

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ABSTRACT

The study introduced a special case of the Poisson-Generalized Gamma empirical Bayes model to survey states in Nigeria with a higher risk of fatal accidents. Monte Carlo error and stationary dynamic trace plots were used to validate model convergence and accuracy of the posterior estimates. The main results included the disease mappings that revealed Ebonyi had the highest risk of road vehicular fatal accidents in Nigeria with a relative risk estimate of 1.4120 while Abuja had the lowest risk with a relative risk estimate 0.5711. In terms of geopolitical region, the risk of road vehicular fatal accident is highest in South-South region with a relative risk estimate of 1.1850 while North-Central had the lowest risk with a relative risk estimate of 0.7846. The study is to aid planned government programs to ameliorate vehicular road carnage in Nigeria.

1. Introduction

The alarming rate of road vehicular accidents in Nigeria is becoming worrisome to individuals and government alike. According to the WHO (2018), accidents caused an estimated 1.35 million deaths worldwide. Further, as noted in the WHO (2018) report, road accident is one of the leading causes of death in the world. The risk of dying by road accident injury is highest in the African region with 26.6 traffic deaths per 100,000 people and lowest in the European region with 9.3 traffic deaths per 100,000 people. Nigeria statistics is succinctly put at 20.5 traffic deaths per 100,000 people and 615.4 traffic deaths per 100,000 motor vehicles, with a total fatality of 46,475 between 2013 and 2019 (NBS, 2019). These figures placed Nigeria among the highest in the rate of road accidents in the world and traffic deaths per inhabitants.

According to WHO (2018), the Nigeria figures are relatively very high compared with the United States' 12.4 traffic deaths per 100,000 populations, 14.2 traffic deaths per 100,000 motor vehicles, with the United Kingdom's 3.1 deaths per 100,000 people, 5.7 traffic deaths per 100,000 motor vehicles and with the China's 18.2 traffic deaths per 100,000 populations, 104.5 traffic deaths per 100,000 motor vehicles. As highlighted in NBS (2019), the vehicle population in Nigeria is put at 11,826,033, and the Nigeria's vehicle per population ratio is put at 0.06. The road is a primary means of commuting in Nigeria. According to NBS (2019), the current vehicular density in Nigeria is put at 60 vehicles every 1km, which poses a major challenge to road traffic. As discussed in Uchenna *et al.* (2019), Afolabi and Gbadamosi (2017), Oyenuga *et al.* (2016), Ohakwe *et al.* (2011), the causes of road accidents in Nigeria are diverse but linked to road conditions, vehicle conditions and driving habits which include over-speeding, drink-driving and overloading.

In this study, a special case of Poisson-Generalized Gamma (PGG) empirical Bayes model is proposed to investigate states in Nigeria with a higher risk of fatal accidents. The empirical Bayes (EB) model was considered appropriate because the accident data are from thirty-seven (37) independent but similar studies which EB method has the capacity to handle (Mbata *et al.,* 2018; Okafor and Mbata, 2012). EB analysis can also remove the random variability within and across studies, usually present in data from small population counts (Böhning *et al*., 2000; Raudenbush and Bryk, 1985). The following scholars have also employed EB model to study accident data in terms of estimation, prediction and trend pattern; Lee *et al.* (2019), Soro and Wayoro (2017), Fawcett *et al.* (2017), and Vogelesang (1997). The study was motivated because of the growing number of fatal vehicular crashes on Nigerian roads. Also, the need to identify the hotspot states towards curbing vehicular crashes on Nigerian roads. The remainder of the paper is structured as follows: the special case of PGG EB model is presented in Section 2, Section 3 deals with the data application and results, discussions of results was done in Section 4 and Section 5 highlighted the Summary and conclusion.

2. Methodology

The proposed EB model is a special case of Poisson-Generalized Gamma model (PGG) introduced by Mbata *et al.* (2018). The model is built on Bayes' Theorem and has the form of Equation (1) (Gelman *et al.*, 2004):

$$p(\tilde{\theta}|y,\emptyset) = \frac{l(\theta|y)\,p(\theta|\emptyset)}{\int_\theta l(\theta|y)\,p(\theta|\emptyset)d\theta} \propto l(\theta|y)\,p(\theta|\emptyset) \quad (1)$$

Where, $\int_\theta l(\theta|y)\,p(\theta|\emptyset)d\theta$ is the unconditional marginal distribution whose inverse is the constant of proportionality (c). The quantity c is a normalizing constant to ensure that the posterior distribution $p(\tilde{\theta}|y,\emptyset)$ is a proper density. $\emptyset$ represents the hyperparameters of the prior distribution $(p(\theta|\emptyset))$ usually estimated from the observed data (y). It implies that: (i) $p(\tilde{\theta}|y,\emptyset)$ are the posterior distributions of the parameters θ given (y) and hyperparameters $(\emptyset)$ in the model after observing the data. (ii) $l(\theta|y)$ is the likelihood function of the probability distribution with respect to θ, which reflects the relationship between the data and the parameter(s). (iii) $p(\theta|\emptyset)$ is the prior distribution of the parameter θ given the hyperparameters $(\emptyset)$, which reflects the initial information on the parameter(s). Generally, a Bayesian model consists of a likelihood distribution and a prior distribution. The inference about the parameter of interest is based on the posterior distribution using MCMC sampling technique (Gelman *et al.*, 2004).

Therefore, the PGG EB model is a conjugate Poisson-Generalized Gamma model where the Poisson distribution represents the observed data likelihood and the Generalized Gamma (GG) distribution is used as the prior distribution of the Poisson parameter. As discussed in Vogelesang (1997), Hauer (1995), the Poisson distribution has become a standard for analysing accident data. However, the choice of prior for appropriate modelling differs and depends on the nature of the study. Thus, under PGG conjugacy, as highlighted in Mbata *et al.* (2018), the posterior density distribution is obtained as Equation (2):

$$P(\tilde{\theta}_i|Y_i;\, \alpha,\beta,\lambda) = \frac{\lambda\beta^{\alpha\lambda}}{\Gamma(\alpha)}\theta^{Y+\,\alpha\lambda-1}e^{-\left(E\theta\,+(\beta\theta)^\lambda\right)},\ \alpha,\beta,\lambda,\theta > 0. \quad (2)$$

A proper posterior density distribution is obtained as

$$p(\tilde{\theta}_i|Y_i,\alpha,\beta,\lambda) = \frac{\lambda\beta^{Y+\,\alpha\lambda}}{\Gamma\left(\alpha+\frac{Y}{\lambda}\right)}\theta^{Y+\,\alpha\lambda-1}e^{-(\beta\theta)^\lambda}.\ \ \alpha,\beta,\lambda,\theta > 0. \quad (3)$$

The PGG relative risk estimator, variance (Var) and standard deviation (SD) are obtained as

$$\hat{\tilde{\theta}}_i^{PGG} = \frac{\Gamma\left(\alpha+\frac{Y_i+1}{\lambda}\right)}{\beta\,\Gamma\left(\alpha+\frac{Y_i}{\lambda}\right)}. \quad (4)$$

$$Var\left(\hat{\tilde{\theta}}_i^{PGG}\right) = \frac{\Gamma\left(\alpha+\frac{Y_i}{\lambda}\right)\Gamma\left(\alpha+\frac{Y_i+2}{\lambda}\right) - \Gamma^2\left(\alpha+\frac{Y_i+1}{\lambda}\right)}{\beta^2\,\Gamma^2\left(\alpha+\frac{Y_i}{\lambda}\right)}. \quad (5)$$

$$SD\left(\hat{\tilde{\theta}}_i^{PGG}\right) = \sqrt{Var\left(\hat{\tilde{\theta}}_i^{PGG}\right)} \quad (6)$$

Where $\boldsymbol{Y_i}$ be the observed number of fatal vehicular crashes in State $i\ (i = 1,\ \ldots, K)$**,** $\boldsymbol{E_i}$ be the expected number of fatal vehicular crashes in State $i\ (i = 1,\ \ldots, K)$**,** $\boldsymbol{N_i}$ be the total number of road vehicular crashes in State $i\ (i = 1,\ \ldots, K)$**,** $\boldsymbol{\theta_i}$ be the maximum likelihood estimate of relative risk of fatality in State $i\ (i = 1,\ \ldots, K)$**,** $\boldsymbol{\tilde{\theta}_i}$ be the Posterior estimates of relative risk of fatality in State $i\ (i = 1,\ \ldots, K)$**.** Hence, $\boldsymbol{E_i} = \boldsymbol{N_i}\boldsymbol{\bar{r}} = \boldsymbol{N_i}\left(\frac{\sum_{i=1}^k \boldsymbol{Y_i}}{\sum_{i=1}^k \boldsymbol{N_i}}\right)$ while estimated $\boldsymbol{\theta_i}$ is $\boldsymbol{\theta}_i = \frac{\boldsymbol{Y_i}}{\boldsymbol{E_i}}$ $(thus\ \boldsymbol{Y}_i = \boldsymbol{E_i}\boldsymbol{\theta_i})$. $\boldsymbol{\bar{r}}$ is the overall road accident crashes risk in the entire States. The full derivation of PGG EB model and proof of some of its properties are found in Mbata *et al.* (2018).

2.1. The Special Case of PGG EB Model: is obtained by putting $\beta = 1$ in Equation (3). Thus

$$p(\tilde{\theta}_i|Y_i,\alpha,1,\lambda) = \frac{\lambda}{\Gamma\left(\alpha+\frac{Y}{\lambda}\right)}\theta^{Y+\,\alpha\lambda-1}e^{-(\theta)^\lambda}.\ \ \alpha,\lambda,\theta > 0. \quad (7)$$

The relative risk estimator, variance (Var) and standard deviation (SD) are derived as

$$\hat{\tilde{\theta}}_i^{PGG} = \frac{\Gamma\left(\alpha+\frac{Y_i+1}{\lambda}\right)}{\Gamma\left(\alpha+\frac{Y_i}{\lambda}\right)}. \quad (8)$$

$$Var\left(\hat{\hat{\theta}}_i^{PGG}\right) = \frac{\Gamma\left(\alpha+\frac{Y_i}{\lambda}\right)\Gamma\left(\alpha+\frac{Y_i+2}{\lambda}\right) - \Gamma^2\left(\alpha+\frac{Y_i+1}{\lambda}\right)}{\Gamma^2\left(\alpha+\frac{Y_i}{\lambda}\right)}. \quad (9)$$

$$SD\left(\hat{\hat{\theta}}_i^{PGG}\right) = \sqrt{Var\left(\hat{\hat{\theta}}_i^{PGG}\right)} \quad (10)$$

To completely specify the posterior distribution model, the hyperparameter α of the prior distribution is estimated from the GG distribution using a method of moment estimation proposed by Huang and Hwang (2006). Given the pdf of GG distribution, when $\beta = 1$, as

$$p(\theta_i|\alpha,\lambda) = \frac{\lambda}{\Gamma(\alpha)}\theta^{\alpha\lambda-1}e^{-(\theta)^{\lambda}}, \theta > 0. \quad (11)$$

Thus, the rth Moment is expressed as

$$E(\theta^r) = \mu^r = \frac{\Gamma\left(\alpha+\frac{r}{\lambda}\right)}{\Gamma(\alpha)} \quad (12)$$

The mean and variance are expressed in Equation (13) and Equation. (15) as

$$\mu = \frac{\Gamma\left(\alpha+\frac{1}{\lambda}\right)}{\Gamma(\alpha)} \quad (13)$$

$$\mu^2 = \frac{1}{K}\frac{\Gamma\left(\alpha+\frac{2}{\lambda}\right)}{\Gamma(\alpha)} + \frac{(K-1)}{K}\frac{\Gamma^2\left(\alpha+\frac{1}{\lambda}\right)}{\Gamma^2(\alpha)} = \frac{\Gamma(\alpha)\,\Gamma\left(\alpha+\frac{2}{\lambda}\right)+(K-1)\Gamma^2\left(\alpha+\frac{1}{\lambda}\right)}{K\,\Gamma^2(\alpha)} \quad (14)$$

$$\sigma^2 = \frac{\Gamma(\alpha)\,\Gamma\left(\alpha+\frac{2}{\lambda}\right) - \Gamma^2\left(\alpha+\frac{1}{\lambda}\right)}{\Gamma^2(\alpha)} \quad (15)$$

Therefore, square of the coefficient of variation (CV) is obtained as

$$\frac{\sigma^2}{\mu^2} = \frac{K\,\Gamma(\alpha)\,\Gamma\left(\alpha+\frac{2}{\lambda}\right) - K\,\Gamma^2\left(\alpha+\frac{1}{\lambda}\right)}{\Gamma(\alpha)\,\Gamma\left(\alpha+\frac{2}{\lambda}\right) + (K-1)\Gamma^2\left(\alpha+\frac{1}{\lambda}\right)} \quad (16)$$

[9], opined that when $\lambda = 1.0$ gives a Gamma distribution and when $\lambda = 2.0$ approximately gives a Generalized Normal distribution. To optimize λ, value 0.5 is assumed. Therefore, when $\lambda = 0.5$ in Equation (16), we have;

$$\frac{\sigma^2}{\mu^2} = \frac{K\,\Gamma(\alpha)\,\Gamma(\alpha+4) - K\,\Gamma^2(\alpha+2)}{\Gamma(\alpha)\,\Gamma(\alpha+4) + (K-1)\Gamma^2(\alpha+2)}.$$

Simplifying by completing the squares, we have;

$$\hat{\alpha} = \left[6\left(\frac{\mu^2}{\sigma^2} - \frac{1}{K}\right) + \left(\frac{1}{2} + \frac{2}{K} - \frac{2\mu^2}{\sigma^2}\right)^2\right]^{\frac{1}{2}} - \left(\frac{1}{2} + \frac{2}{K} - \frac{2\mu^2}{\sigma^2}\right) \quad (17)$$

According to Marshall (1991), μ and $\sigma^2$are estimated as

$$\hat{\mu} = \frac{\sum_{i=1}^{k}\theta_i E_i}{\sum_{i=1}^{k}E_i} \text{ and } \hat{\sigma}^2 = S^2 - \frac{\hat{\mu}}{\frac{1}{K}\sum_{i=1}^{k}E_i}, \text{ where } S^2 = \frac{\sum_{i=1}^{k}E_i\left(\hat{\theta}_i - \hat{\mu}\right)^2}{\sum_{i=1}^{k}E_i}.$$

Monte Carlo error (MCE) and stationary dynamic trace plots are carried out to evaluate the accuracy and convergence of posterior estimates of the EB model. MCE estimates the difference between the mean of the sampled values and the true posterior mean value. As a rule of thumb, the simulation is run until the Monte Carlo error is less than about 5% of the sample standard deviation (Brooks and Gelman, 1998). For good details of Bayes theorem, see Gelman *et al.* (2004).

3. Results

The special case of PGG EB model is applied to reported road vehicular fatal accidents in Nigeria by states. The data were sourced from the National Bureau of Statistics (2013, 2014, 2015, 2017, 2018 and 2019), and the Nigerian states by geo-political zone aggregated data with the estimated expected counts are presented in Table 1. However, the 2016 data was excluded due to inconsistency in reporting with other years. The investigation is carried out using MCMC sampling technique by OpenBUGS statistical software and the program codes are found in the appendix. The posterior results of the EB model are presented in Table 2. The diagnostic dynamic trace plots are presented in Figure 1 for the six geo-political zones, respectively. The relative risk of fatal accident mapping is presented in Figures 2 and 3, respectively.

Table 1: Nigerian States by Geo-Political Zone Aggregated Reported Road Vehicular Fatal Accidents (2013-2019)

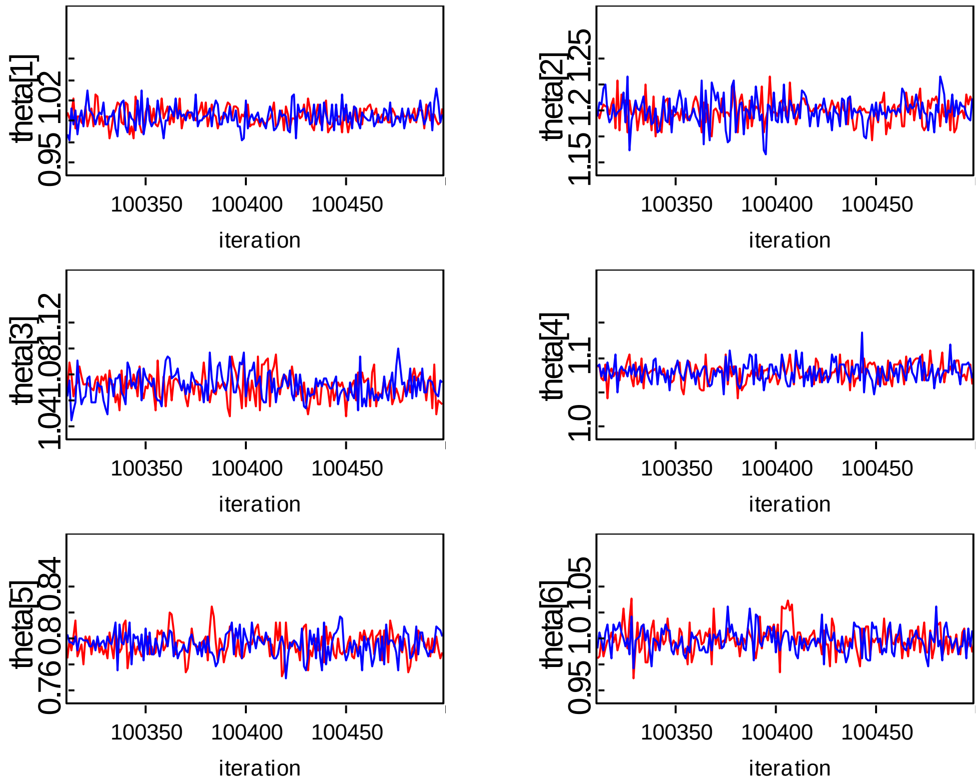
States	Total Number of Accidents (N)	Observed Number of Fatal Accidents (Y)	Expected Number of Fatal Accidents (E)
Abia	2526	750	1026.5819
Anambra	2855	1132	1160.2896
Ebonyi	4430	2505	1800.3793
Enugu	5554	1782	2257.1798
Imo	1405	569	571.0006
South-East (1)	**16770**	**6738**	**6815.4312**
Akwa-Ibom	1036	444	421.0368
Bayelsa	2831	1400	1150.5358
C/River	2357	1105	957.8993
Delta	1620	764	658.3780
Edo	2965	1224	1204.9943
Rivers	4997	2642	2030.8116
South-South (2)	**15806**	**7579**	**6423.6557**
Ekiti	833	274	338.5363
Lagos	9885	3033	4017.3249
Ogun	8784	4719	3569.8717
Ondo	3209	1374	1304.1574
Osun	3502	1769	1423.2344
Oyo	3110	1467	1263.9231
South-West (3)	**29323**	**12636**	**11917.0477**
Adamawa	1326	418	538.8946
Bauchi	2202	939	894.9064
Borno	1336	703	542.9586
Gombe	1857	724	754.6962
Taraba	2319	957	942.4559
Yobe	1568	784	637.2449
North-East (4)	**10608**	**4525**	**4311.1565**
Benue	2166	718	880.2757
FCT Abuja	7005	1588	2846.8751
Kogi	2156	816	876.2117
Kwara	1834	782	745.3489
Nassarawa	1984	546	806.3098
Niger	3463	1305	1407.3845
Plateau	2345	894	953.0224
North-Central (5)	**20953**	**6649**	**8515.4282**
Jigawa	1047	490	425.5072
Kaduna	3574	1388	1452.4956
Kano	4471	1822	1817.0419
Katsina	1924	726	781.9254
Kebbi	807	215	327.9698
Sokoto	1578	683	641.3089
Zamfara	1004	386	408.0318
North-West (6)	**14405**	**5710**	**5854.2807**
Nigeria	**107865**	**43837**	**43837.0000**

Source: National Bureau of Statistics (2013, 2014, 2015, 2017, 2018 and 2019).

Table 2: Nigerian States by Geo-Political Zone Relative Risk Estimates, Standard Deviation (SD), Monte Carlo Error (MCE) and Credible Interval of EB Model

States	$\hat{\theta}_i^{PGG}$	SD	MCE	5%SD	Lower Credible Limit	Upper Credible Limit
Ebonyi	1.4120*	0.0281	6.08E-05	0.0014	1.3580	1.4680
Imo	1.0630*	0.0432	9.48E-05	0.0022	0.9801	1.1490
Anambra	1.0080*	0.0295	6.38E-05	0.0015	0.9513	1.0670
Enugu	0.8063	0.0188	4.09E-05	0.0009	0.7697	0.8436
Abia	0.7676	0.0273	6.03E-05	0.0014	0.7151	0.8221
South-East 1	**0.9934**	**0.0121**	**2.51E-05**	**0.0006**	**0.9699**	**1.0170**
Rivers	1.3200*	0.0255	5.79E-05	0.0013	1.2700	1.3700
Bayelsa	1.2500*	0.0329	7.25E-05	0.0016	1.1860	1.3150
Delta	1.2180*	0.0430	9.40E-05	0.0021	1.1350	1.3030
C/River	1.1930*	0.0353	7.82E-05	0.0018	1.1250	1.2630
Akwa-Ibom	1.1440*	0.0522	1.18E-04	0.0026	1.0440	1.2490
Edo	1.0470*	0.0294	6.24E-05	0.0015	0.9904	1.1060
South-South 2	**1.1850***	**0.0135**	**2.99E-05**	**0.0007**	**1.1580**	**1.2110**
Ogun	1.3320*	0.0193	4.23E-05	0.0010	1.2950	1.3710
Osun	1.2690*	0.0298	6.86E-05	0.0015	1.2120	1.3280
Oyo	1.1910*	0.0307	6.70E-05	0.0015	1.1310	1.2510
Ondo	1.0830*	0.0288	6.35E-05	0.0014	1.0270	1.1400
Ekiti	0.9213	0.0522	1.19E-04	0.0026	0.8220	1.0260
Lagos	0.7645	0.0138	3.15E-05	0.0007	0.7377	0.7917
South-West 3	**1.0630***	**0.0094**	**2.13E-05**	**0.0005**	**1.0450**	**1.0820**
Borno	1.3640*	0.0501	1.11E-04	0.0025	1.2680	1.4640
Yobe	1.2900*	0.0451	1.07E-04	0.0023	1.2030	1.3800
Bauchi	1.0920*	0.0350	7.80E-05	0.0017	1.0240	1.1610
Taraba	1.0560*	0.0335	7.34E-05	0.0017	0.9910	1.1220
Gombe	1.0100*	0.0366	7.99E-05	0.0018	0.9389	1.0820
Adamawa	0.8460	0.0395	8.94E-05	0.0020	0.7701	0.9254
North-East 4	**1.0570***	**0.0157**	**3.50E-05**	**0.0008**	**1.0270**	**1.0880**
Kwara	1.1000*	0.0383	8.66E-05	0.0019	1.0260	1.1760
Plateau	0.9778	0.0320	7.20E-05	0.0016	0.9160	1.0410
Kogi	0.9745	0.0334	7.50E-05	0.0017	0.9102	1.0410
Niger	0.9542	0.0261	5.54E-05	0.0013	0.9037	1.0060
Benue	0.8587	0.0312	6.96E-05	0.0016	0.7987	0.9210
Nassarawa	0.7243	0.0300	6.68E-05	0.0015	0.6665	0.7842
FCT Abuja	0.5711	0.0142	3.18E-05	0.0007	0.5436	0.5993
North-Central 5	**0.7846**	**0.0095**	**2.13E-05**	**0.0005**	**0.7660**	**0.8034**
Jigawa	1.2400*	0.0539	1.21E-04	0.0027	1.1370	1.3480
Sokoto	1.1240*	0.0417	8.94E-05	0.0021	1.0440	1.2070
Zamfara	1.0390*	0.0505	1.15E-04	0.0025	0.9424	1.1400
Kano	1.0240*	0.0237	5.52E-05	0.0012	0.9779	1.0710
Kaduna	0.9818	0.0259	6.10E-05	0.0013	0.9317	1.0330
Katsina	0.9769	0.0353	7.77E-05	0.0018	0.9089	1.0470
Kebbi	0.7712	0.0486	1.09E-04	0.0024	0.6788	0.8693
North-West 6	**0.9808**	**0.0129**	**2.87E-05**	**0.0006**	**0.9557**	**1.0060**
Nigeria	**1.0000**					

Note: **Asterisk implies Relative Risk (RR) ≥ 1 (High Risk State). Non-asterisk implies Relative Risk (RR) < 1 (Low Risk State). SD (Standard Deviation), MCE (Monte Carlo error).*



Figures 1: Dynamic Trace Plot of Posterior Convergence of the EB Model

Legend: Black = High Risk Area, White = Low Risk Area

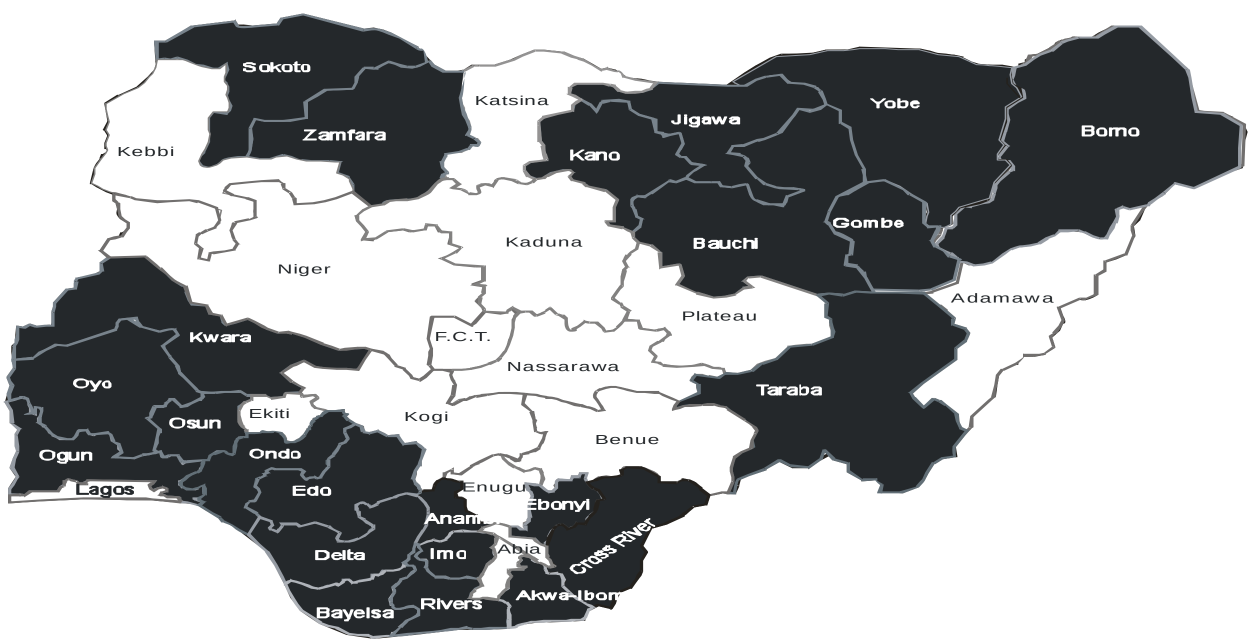


Figure 2: Nigeria States Relative Risk Estimates of Fatal Accident Incidence Mapping

Figure 3: Nigerian States by Geo-Political Zone Relative Risk Estimates of Fatal Accident Incidence Mapping

4. Discussion of Results

The Nigerian states by geo-political zone aggregated reported road vehicular fatal accidents between 2013 and 2019 are presented in Table 1 with the corresponding total number of accidents and estimated expected fatal road accidents. The results from Table 2 indicate that the estimates of relative risk (RR) of road vehicular fatal accidents by state in Nigeria range from 0.5711 (FCT Abuja, the lowest) to 1.4120 (Ebonyi state, the highest). This implies that the risk of having a road vehicular fatal accident is highest in Ebonyi State and lowest in FCT Abuja. Meanwhile, RR ≥ 1 implies higher risk while RR < 1 implies lower risk. Therefore, the relative risk estimates of twenty-three (23) states (Ebonyi, Borno, Ogun, Rivers, Yobe, Osun, Bayelsa, Jigawa, Delta, Cross-River, Oyo, Akwa-Ibom, Sokoto, Kwara, Bauchi, Ondo, Imo, Taraba, Edo, Zamfara, Kano, Gombe and Anambra) indicate higher risk of road vehicular fatal accidents. While fourteen (14) states, including FCT Abuja (Kaduna, Plateau, Katsina, Kogi, Niger, Ekiti, Benue, Adamawa, Enugu, Kebbi, Abia, Lagos, Nassarawa and FCT Abuja), indicate a lower risk of road vehicular fatal accidents. The relative risk of road vehicular fatal accident mappings are depicted in Figures 2 and 3, respectively.

Studying the geo-political zones, the results indicate for South-East region that Ebonyi (1.4120), Imo (1.0630) and Anambra (1.0080) states have higher risk of road vehicular fatal accidents while Enugu (0.8063) and Abia (0.7676) states have a lower risk of road vehicular fatal accidents. The entire South-East region has a lower risk of road vehicular fatal accidents, estimated at 0.9934. For South-South region, all the states, Rivers (1.3200), Bayelsa (1.2500), Delta (1.2180), Cross-River (1.1930), Akwa-Ibom (1.1440) and Edo (1.0470), are at higher risk of road vehicular fatal accidents, including the entire region at 1.1850. For South-West region, the risk of having a road vehicular fatal accident is higher in Ogun (1.3320), Osun (1.2690), Oyo (1.1910) and Ondo (1.0830) states than in Ekiti (0.9213) and Lagos (0.7645). The entire South-West region risk of a road vehicular fatal accident is higher at 1.0630.

For North-East region, the risk of a road vehicular fatal accident is higher in Borno (1.3640), Yobe (1.2900), Bauchi (1.0920), Taraba (1.0560) and Gombe (1.0100) states than in Adamawa state (0.8460) respectively. The risk of a road vehicular fatal accident is higher in the entire North-East region at 1.0570. For North-Central region, Kwara state (1.1000) has a higher risk of road vehicular fatal accident while Plateau state (0.9778), Kogi state (0.9745), Niger state (0.9542), Benue state (0.8587), Nassarawa state (0.7243) and FCT Abuja (0.5711) have a lower risk of road vehicular fatal accidents. The entire North-Central zone has a lower risk of road vehicular fatal accidents, estimated at 0.7846. Finally, for the North-West region, Jigawa (1.2400), Sokoto (1.1240), Zamfara (1.0390) and Kano (1.0240) states have a higher risk of road vehicular fatal accidents while Kaduna

(0.9818), Katsina (0.9769) and Kebbi (0.7712) states have a lower risk of road vehicular fatal accidents. The entire North-West result indicates a lower risk of road vehicular fatal accidents in the region, estimated at 0.9808.

The results indicated that there is the accuracy of the posterior estimates of the EB model since MCE<5%SD respectively. Consequently, the convergence of MCMC sampling as the chains overlap each other is shown in the stationary dynamic trace plots presented in Figure 1. Suggesting that the posterior estimates of the special case of PGG EB model is highly reliable.

5. Conclusion

The analyses have shown that South-East, North-Central and North-West regions have a lower risk of road vehicular fatal accidents while South-South, South-West and North-East regions have a higher risk of road vehicular fatal accidents. Therefore, it can be inferred that accidents in the South-East, North-Central and North-West are not usually fatal, though most major highways in the South-East are in poor condition, unlike in the North-Central and North-West regions where most highways are relatively in good condition. In addition, it was found that Ebonyi state has the highest risk of road vehicular fatal accidents in Nigeria because more than 50% of the crashes are fatal as a result of speed violation and poor condition of vehicles, as viewed by Ohakwe *et al.* (2011).

The high risk of road vehicular fatal accidents in the South-South and South-West can be attributed to high vehicular traffic density and over-speeding in most major highways in the regions, while North-East region is as a result of the poor condition of the major highways. Also, it can be deduced that the risk of road vehicular fatal accident in Lagos state and FCT Abuja is lower compared to Kano and Rivers states at higher risk of road vehicular fatal accident. Though Lagos state has a high vehicular density, the high traffic congestion in Lagos state and FCT Abuja alike is highly likely to reduce fatal crashes.

Finally, based on the results obtained in terms of geopolitical region, the risk of road vehicular fatal accident is highest in the South-South region with a relative risk estimate of 1.1850 while North-Central had the lowest risk of road vehicular fatal accidents with a relative risk estimate of 0.7846. Generally, the major highways in Nigeria are highly vulnerable to fatal accidents due to the deplorable condition of the roads. This has been previously highlighted in Atubi (2010). The study is highly likely to aid planned government programs towards ameliorating and curbing vehicular road carnage in Nigeria. The study recommends comprehensive rehabilitation and reconstruction of major highways in Nigeria. The study has added to the body of literature the use of a special case of PGG model in analyzing and mapping accident data.

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Appendix

```
#OpenBUGS DATA APPLICATION CODES

#PGG MODEL: alpha varies based on data estimate; beta is set at 1.0 while lambda is set at 0.5.

Model     {

   theta[i] ~ dggamma (alpha, beta, lambda)

   z[i] <- theta[i] * E[i]

   Y[i] ~ dpois(z[i])

}

alpha <- 0.104293664

beta <-  1.0000

lambda <- 0.5000

}
```