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Hidden Markov Model with Switching Autoregression: A Study of Political Violent Deaths in Nigeria

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Abstract

In recent time, research on violent death has been rare with little attention drawn to its spread nature. This study extensively explores the dynamic nature of violent death as a stochastic process using monthly Nigeria Watch dataset on violent death count caused by political issues in Nigeria from June 2006 to March 2021 (n=178).

The methodology adopted for the study is Hidden Markov Model with Switching Autoregression (HMMSA), a dynamic non-linear model associated with time series that switches back and forth between distinct states called regimes which are hidden to the observer with an autoregressive structure.

Result showed that political violent death counts possessed statistically significant positive trend corresponding to an appropriate AR of order 2, and are non-normally and unevenly distributed on monthly basis. The observational hidden states and their transition probabilities from one state to the other accordingly under the Gaussian mixture and the grand transition probabilities of violent deaths count due to political issues were estimated to be $[P_{11} = 0.6010,\ P_{22} = 0.8674,\ P_{12} = 0.3990\ and\ P_{21} = 0.1326]$; The regime switching equations were estimated to be statistically significant at p value < 0.01. Other estimations include the conditional and regime-based residuals, filtered and smoothed probability, death counts regime classification plots, the predictive plots for best regime's model identification and parameter interval estimation.

Violent deaths attributed to political issue have been identified as those which are non-linear in nature due to the traits established from the findings. To monitor the dimension of spread of the underlying death count, regime 2 equation is best suited since it is superimposed with the actual differenced series.

This study therefore recommends further research which would allow for the building of sentry system for violence detection using Artificial Intelligence (AI) or Machine Learning (ML).

Keywords: Markov Model, autoregression, violent death, politics, firearm.

1.0 Introduction

Nigeria, the giant of Africa is a country located in the West known to be heterogeneous in nature due to the diversity in tribes and culture. It is of interest to note that diversity itself does not by default leads to high level of violence. Hence, tensions can be managed through responsive, inclusive, and broad-based political institution alongside social and economic institutions. Sudden increase in violent conflicts in Nigeria is due to strong central government; popular agitation for decentralized structure; dissatisfaction with the resource allocation; communal conflicts and demands by some identified groups for greater self-determination among others (Eliagwu, 2005). Burchard S. M. (2019) envisages that democracy comes at a price as a result; violence is encountered during most elections.

According to Ukah (2015), the manner governance is directed can either be reason for mitigating or reducing as well as curbing violence. Schmit (1968) posited that violence, particularly political violence, represents a disturbance to the political equilibrium system. According to Gurr (1970:2), political violence refers to all collective attacks within a political community against the political regime, its actors including competing political groups as well as incumbents – or its policies. Political violence is associated with thuggery, which is an act characterized by rudeness, hooliganism, touting, intimidation and harassment. It is a behaviour that disturbs peace, harmony and co-existence among groups. Political thuggery is an illegitimate and violent means of seeking political power with a view to subverting national opinion for parochial ends through self-imposition.

2.0 Literature Review

The applications of the statistical technique Hidden Markov Model developed by Baum and Petrie, 2006 cut across several disciplines. At initial time it was proposed by Baum L. E. to study the dynamics of speech recognition. Notwithstanding, the technique has been incorporated into the following fields statistical mechanic, information theory, signal processing, gesture recognition, handwriting, pattern recognition, chemistry, physics, thermodynamic, cryptanalysis, time series analysis, computational finance and so on. For time series prediction, HMM are used (Sipos, 2016). The essence of the technique is to generate a data sequence that is not directly observable though other set of data that depends on the sequence are directly observed.

Victor and Ukachi (2020) applied Hidden Markov Models for sentiment analysis. Their research was carried out in the field of sentiment analysis and it was done in relation to a research paper on semantic representation and the use of probabilistic graphical models for the determination and evaluation of sentiment in textual data. Their review presented grounds for future works that seek to develop methods for semantic text representations implemented in probabilistic graphical models (Hidden Markov Models) or that through a combination scheme allow for superior classification performance.

Another application of HMM was carried out by Zhao and Ohsawa (2018) where the higher dimension of HMM called 2dHMM was implemented. This HMM form helps provide the ability to model sentiment analysis in the higher dimension. This helps to capture event where the sentiment of a user concerning a product is influenced by the observation of the last two reviews or top –rated review by the user. And this will enable the modeling of dependencies between the last two comments and a top-rated review and the words of a user to perform sentiment classification.

Other forms of HMM utilizations cut across HMM with constructed hidden states and transition patterns of words in sentimental sentences. To creating unigrams to get the SIGs (similar syntactic sentimental information Groups), the Gaussian Mixture Models were adopted. To perform emotional classification the self-adaptive HMM was used (Liu et al, 2015).

Also Wei and Yongxin (2016), used the HMM to evaluate network public sentiment analysis of Chinese text by the adoption of convectional strategy.

Notwithstanding, the Poisson hidden Markov models for time series is also an area of concerned in literature. The work of Roberta, Giovanna and Luigi in 2017 is an emblem of the poisson application and integration with HMM for time series of over-dispersed insurance count (in non-life insurance).

3.0 Data and Methods

Data for the study

The data for this study is public violent deaths data in Nigeria. It is secondary form of data source obtained from Nigeria Watch database from June, 2006 to March, 2021. It is centered on the number of violent deaths recorded over time by the reporting agencies mentioned above. The data is collected on daily basis and for the purpose of this study the data was aggregated to monthly dataset. It therefore composed of 178 observable death counts.

Methods

The analysis of non-linear phenomena, such as regime shifts, can follow diversified strategies. In time series analysis there are several forms of smoothing. Smoothing is used for discovering some peculiar and intrinsic traits/features of the underlying series.

In this study we used a self-exciting regime model called Hidden Markov Model with Switching Autoregression (HMMSA) to fit a non-linear model (whose states are hidden or latent in nature) to monthly violent deaths series by considering a one month ahead prediction.

To achieve this, there would be need to explore the dynamics of the underlying violent death count via exploratory data analysis in form of trend analysis, tests of stationarity and normality.

To investigate the presence of trend in the series, the trend model of the series need to be established with violent deaths count depending on the time as presented in eqn. 1

$$\boldsymbol{y_t = \alpha + \beta t + \varepsilon_t} \qquad \mathbf{1}$$

Where y_t is violent death count, α is the intercept, β is the slope and ε_t is a white noise.

The associated trend is significance on the basis of t-Test if the p-value < 0.05.

The tests of stationarity for the violent death count are Augmented Dickey Fuller (ADF) and Philip Peron (PP) Test having the null hypothesis: Violent death count is non-stationary on the basis of trend stationarity for Hidden Markov Model with Switching Autoregression parameters estimation. This implies that for the parameters of the HMMSA to be estimated the trend component must be removed by de-trending or differencing the series.

The ADF test statistics is given as

$$\boldsymbol{t_{ADF} = \frac{\sum_{i=1}^{p} \hat{\phi}_i - 1}{s.e\left(\sum_{i=1}^{p} \hat{\phi}_i\right)} = \frac{\hat{\beta}}{s.e(\hat{\beta})}} \qquad \mathbf{2}$$

attributed to the model

$$\boldsymbol{\Delta y_t = \mu + \beta t + \varepsilon_t} \quad \textbf{3}$$

where $\hat{\beta}$ is the estimate of β in eqn.3 and $s.e(\hat{\beta})$ is the standard error of the estimate.

While that of the PP test is established on the null hypothesis $\rho = 1$attributed to the model

$$\boldsymbol{\Delta y_t = (\rho - 1)y_{t-1} + \varepsilon_t} \quad \textbf{4}$$

The Philip Perron test is based on the non-parametric adjustment to the t-test statistic and therefore becomes more reliable and consistent in relation to autocorrelation and heteroscedasticity in the disturbance process of the model (Phillips and Perron, 1988).

The tests of normality include the Shapiro-Wilks and Jarque-Bera Tests which both investigate the joint null hypothesis of skewness and kurtosis coefficients not significantly different from 0 and 3 respectively.

Hidden Markov Model with Switching Autoregression

The methodology to be adopted in this paper is Hidden Markov Model with Switching Autoregression which exists in the domain of state space (dynamic process) for process characteristics classification, transition probability generation and prediction.

The two basic assumptions underlying the framework include:

State process x_t which is hidden or latent and assumed to be Markovian.
The observations y_t are independent given the states x_t.

This therefore suggests that dependence among the observations is generated by states.

States: Regime Identification

Regime 1: Regular Violence state (Low variability)

Regime 2: Irregular Violence state (High variability)

Regime 1 has to do with the class of observable death counts with very low variability in fluctuation over a certain period of time tagged a regular occurrence state but not severe before a higher form of variability is encountered as a shock that changes the pattern of variability in higher fashion and thence, regime two (a non-regular but severe state of violent death) is encountered until a lower variation is encountered afterwards.

Filtering Probability

The associated probability of transition from a state to another is computed using the filtering probability defined as:

$$\mathbf{P}(\boldsymbol{X_t}|\boldsymbol{Y_t}) = \frac{\boldsymbol{P(Y_t|X_t)p(X_t|Y_{t-1})}}{\boldsymbol{P(Y_t|Y_{t-1})}} \quad 5$$

for

$$\mathrm{P}(\boldsymbol{Y_t}|\boldsymbol{Y_{t-1}}) = \int \boldsymbol{P}(\boldsymbol{Y_t}|\boldsymbol{X_t})\boldsymbol{P}(\boldsymbol{X_t}|\boldsymbol{Y_{t-1}})\boldsymbol{dX_t} \qquad 6$$

where y_t is the violent death count and x_t is the regime of interest.

Since there exist a 2 – regime possible state for this study, the underlying switching autoregression model becomes

$$\boldsymbol{Y_t = \beta_0^{(X_t)} + \beta_1^{(X_t)}Y_{t-1} + \beta_2^{(X_t)}Y_{t-2} + \epsilon_t} \qquad 7$$

or

it transformed form (A de-trended or differenced Series).

$$\boldsymbol{\Delta Y_t = \beta_0^{(X_t)} + \beta_1^{(X_t)}\Delta Y_{t-1} + \beta_2^{(X_t)}\Delta Y_{t-2} + \epsilon_t} \qquad 8$$

where $\beta_i^{(X_t)}$ is the ith parameter for the autoregressive switching process when in state X_t, Y_t does not only depend on the last 2 observations, but also on the current states and $\epsilon_t \sim i.i.dN(0,\Sigma)$ or any possible mixture.

In the regime specific form the hidden Markov Model with Switching Autoregression becomes

$$\boldsymbol{x_t} = \begin{cases} \boldsymbol{\phi_0^{(1)} + \sum_{j=1}^{p} \phi_j^{(1)} y_{t-j} + \sigma^{(1)} v_t}, & \boldsymbol{for\ x_t = 1} \\ \boldsymbol{\phi_0^{(2)} + \sum_{j=1}^{p} \phi_j^{(2)} y_{t-j} + \sigma^{(2)} v_t}, & \boldsymbol{for\ x_t = 2} \end{cases} \qquad 9$$

where x_t is a latent two state/regime Markov chain.

4.0 Result and Interpretation

Exploratory Data Analysis

This includes the time plot, autocorrelation function plot (ACF) and the partial autocorrelation function plot (PACF).

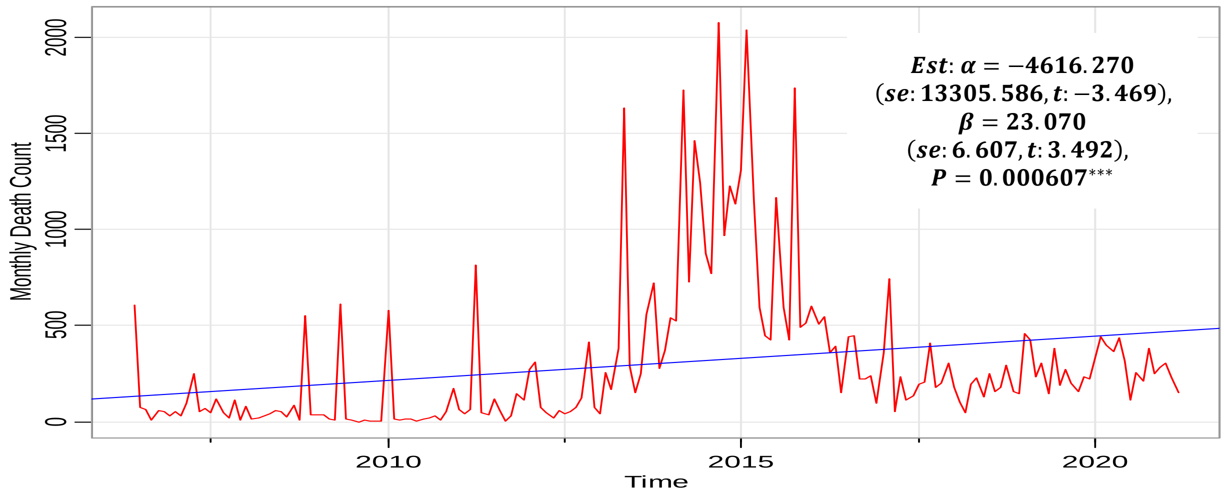

Figure 1a: Time plot of monthly violent deaths count due to political issues with estimated trend line.

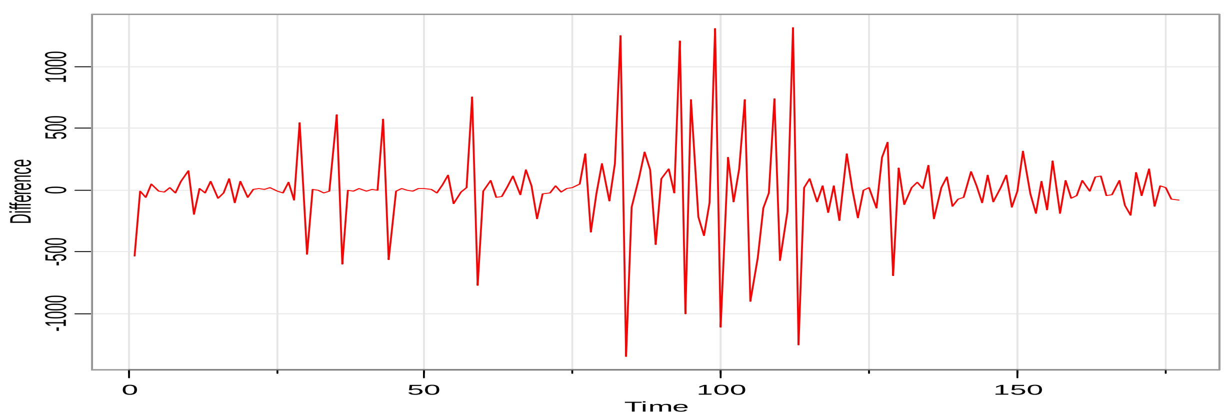

Figure 1b: Time plot of differenced monthly violent deaths count due to political issues.

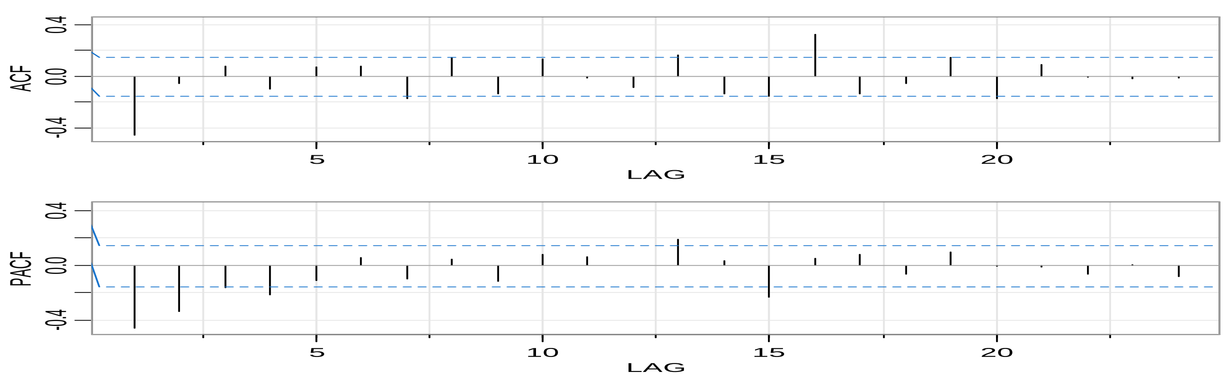

Figure 1c: Autocorrelation function (ACF) and partial autocorrelation function for the monthly violent deaths count attributed to political issues.

Figure 1a and 1b are diagrammatical representation of violent death count associated or attributed to political issue and the differenced monthly series respectively. The time plots suggest that the highest death count was reported around 2014. The occurrence of death occurred in an increasing but fluctuating between 2013 and 2016. Thereafter continue to swing between 0 and 500. From the trend estimation result, it is observed that for every one month step ahead the number of reported violent deaths would increase by approximately 24 victims and this imply a significance positive trend with p-value (0.0006) > 0.05 level of significance. The ACF and PACF plot suggests that AR(2) and MA(1) are corresponding orders of the Autoregressive and Moving average models in need of further analysis.

Test of Normality

Table 1: Normality Test for Public Violent Deaths in Nigeria from June, 2006 to March, 2021.

Shapiro-Wilks Test		Jarque-Bera Test		
Statistic(W)	**P-value**	**Statistic(χ^2)**	**df**	**P-value**
0.71407^{***}	$< 2.2 \times 10^{-16}$	460.47^{***}	2	$< 2.2 \times 10^{-16}$

Hypothesis: H_0: Violent death count related to political issues is normally distributed.

Table 1 shows the test of normality for violent deaths attributed to Political issues reported in Nigeria from June, 2006 to March, 2021. Following from the results of Shapiro-Wilks and Jarque-Bera tests, it is sufficient on the basis of the computed p-values(< 0.05) level of significance to conclude that violent death as an unforeseen or unexpected occurrence is non-normally distributed. This result does not contradict pre-knowledge about the distribution of such events for they are unevenly distributed.

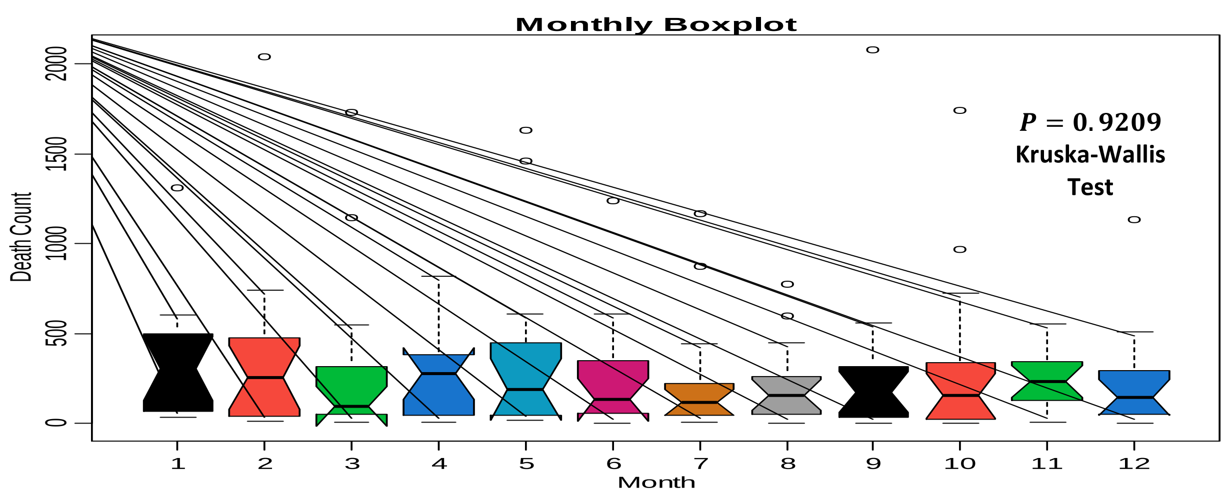

Figure 2: Monthly Boxplot of violent deaths count due to political issues underlying Kruskal-Wallis distribution-equality test.

The boxplot shows that violent death is most likely to occur in the month of February with the observed highest occurrence in October since majority of elections in Nigeria are scheduled for

February and sometimes extend to March and recently some take place in the late fourth quarter of the year. This result is therefore complementary. Form the test of equality of distribution, it is observed that the distribution is the same across the months of the year (see figure 2).

Test of Stationarity

Table 2: Stationarity Test for Death count attributed to all causes on the basis of the ADF and PP.

Augmented Dickey Test			Phillip Perrons Test		
DF Statistic	Lag Order	P-Value	DF(Z_α)	TLP	P-Value
-1.7333	5	0.6877	-79.927	4	< 0.01

Note: TLP = Truncated Lagged Parameter. DF = Dickey Fuller. "***" and "**" indicate significance at 1% and 5% respectively.

Table 2 gives the result of the test of stationarity of politics related violent death from June 2006 to May 2021. Results from the Augmented Dickey Fuller and Philip Perrons tests indicate that public violent death count is significant for stationarity. Hence, the series have no unit root considering a lag order of 5 under the ADF and 4 TLP under the PP testing procedure. This suggests that the series required no form of transformation before state estimation except differencing for a lower order less than 5.

Hidden Markov Models Estimation

Table 3: Hidden State and Transition Probability Estimation

Obs.	No. of Deaths	Estimated State	State 1	State 2		No. of Deaths	Estimated State	State 1	State 2
			Transition Probabilities					Transition Probabilities	
1	608	1	1.000000000	0.000000e+00	90	279	1	0.577355854	4.226441e-01
2	72	2	0.382790952	6.172090e-01	91	370	1	0.416582146	5.834179e-01
3	66	2	0.052930826	9.470692e-01	92	542	1	0.870403852	1.295961e-01
4	9	2	0.005798922	9.942011e-01	93	522	1	0.976784556	2.321544e-02
5	60	2	0.003357746	9.966423e-01	94	1728	1	1.000000000	2.173631e-27
6	51	2	0.003410615	9.965894e-01	95	727	1	0.999851475	1.485250e-04
7	32	2	0.003568494	9.964315e-01	96	1462	1	1.000000000	2.349324e-19
8	51	2	0.003410615	9.965894e-01	97	1241	1	1.000000000	9.192741e-14
9	28	2	0.003610303	9.963897e-01	98	875	1	0.999998838	1.161601e-06
10	97	2	0.003274986	9.967250e-01	99	774	1	0.999964476	3.552425e-05
11	252	2	0.005858087	9.941419e-01	100	2080	1	1.000000000	3.302044e-40
12	55	2	0.003385453	9.966145e-01	101	968	1	0.999999967	3.279660e-08
13	69	2	0.003318075	9.966819e-01	102	1229	1	1.000000000	1.733793e-13
14	45	2	0.003453484	9.965465e-01	103	1136	1	1.000000000	1.889482e-11
15	116	2	0.003313650	9.966864e-01	104	1308	1	1.000000000	2.353560e-15
16	46	2	0.003445905	9.965541e-01	105	2041	1	1.000000000	1.152768e-38
17	21	2	0.003691196	9.963088e-01	106	1143	1	1.000000000	1.346006e-11
18	114	2	0.003306963	9.966930e-01	107	596	1	0.995353140	4.646860e-03
19	11	2	0.003824867	9.961751e-01	108	448	1	0.918921181	8.107882e-02
20	78	2	0.003291152	9.967088e-01	109	426	1	0.888693949	1.113061e-01
21	16	2	0.003755273	9.962447e-01	110	1168	1	1.000000000	3.935025e-12
22	22	2	0.003679021	9.963210e-01	111	596	1	0.995353140	4.646860e-03
23	33	2	0.003558528	9.964415e-01	112	424	1	0.885617220	1.143828e-01
24	39	2	0.003502704	9.964973e-01	113	1739	1	1.000000000	9.425971e-28
25	56	2	0.003379582	9.966204e-01	114	489	1	0.958529938	4.147006e-02
26	50	2	0.003417328	9.965827e-01	115	511	1	0.972210533	2.778947e-02
27	23	2	0.003667055	9.963329e-01	116	603	1	0.996053762	3.946238e-03
28	88	2	0.003275823	9.967242e-01	117	510	1	0.971683593	2.831641e-02
29	8	2	0.003869379	9.961306e-01	118	546	1	0.986081407	1.391859e-02

30	554	2	0.309873139	6.901269e-01	119	361	2	0.763756936	2.362431e-01
31	34	2	0.041348355	9.586516e-01	120	393	2	0.696728184	3.032718e-01
32	38	2	0.004082900	9.959171e-01	121	150	2	0.179902617	8.200974e-01
33	36	2	0.003529773	9.964702e-01	122	443	2	0.248531260	7.514687e-01
34	13	2	0.003796351	9.962036e-01	123	447	2	0.347342712	6.526573e-01
35	6	2	0.003900240	9.960998e-01	124	223	2	0.065140057	9.348599e-01
36	612	2	0.625961561	3.740384e-01	125	220	2	0.008881990	9.911180e-01
37	12	2	0.147238394	8.527616e-01	126	239	2	0.005347392	9.946526e-01
38	10	2	0.017633223	9.823668e-01	127	94	2	0.003273905	9.967261e-01
39	0	2	0.003998724	9.960013e-01	128	360	2	0.016799530	9.832005e-01
40	9	2	0.003854307	9.961457e-01	129	744	1	0.983533133	1.646687e-02
41	1	2	0.003981680	9.960183e-01	130	52	2	0.389621466	6.103785e-01
42	5	2	0.003916033	9.960840e-01	131	232	2	0.081210102	9.187899e-01
43	4	2	0.003932071	9.960679e-01	132	115	2	0.007855778	9.921442e-01
44	579	2	0.437152820	5.628472e-01	133	133	2	0.003396251	9.966037e-01
45	13	2	0.073931068	9.260689e-01	134	197	2	0.004199192	9.958008e-01
46	6	2	0.008360811	9.916392e-01	135	207	2	0.004415375	9.955846e-01
47	16	2	0.003755273	9.962447e-01	136	410	2	0.032493114	9.675069e-01
48	16	2	0.003755273	9.962447e-01	137	180	2	0.003896632	9.961034e-01
49	4	2	0.003932071	9.960679e-01	138	200	2	0.004260853	9.957391e-01
50	13	2	0.003796351	9.962036e-01	139	306	2	0.009291960	9.907080e-01
51	22	2	0.003679021	9.963210e-01	140	178	2	0.003865882	9.961341e-01
52	30	2	0.003589007	9.964110e-01	141	103	2	0.003281235	9.967188e-01
53	9	2	0.003854307	9.961457e-01	142	47	2	0.003438500	9.965615e-01
54	51	2	0.003410615	9.965894e-01	143	195	2	0.004159538	9.958405e-01
55	172	2	0.003779257	9.962207e-01	144	230	2	0.005042970	9.949570e-01
56	61	2	0.003352696	9.966473e-01	145	130	2	0.003378251	9.966217e-01
57	44	2	0.003461240	9.965388e-01	146	250	2	0.005773548	9.942265e-01
58	65	2	0.003334110	9.966659e-01	147	158	2	0.003607807	9.963922e-01
59	818	1	0.998416958	1.583042e-03	148	176	2	0.003836082	9.961639e-01
60	46	2	0.392540111	6.074599e-01	149	293	2	0.008215336	9.917847e-01
61	38	2	0.057866481	9.421335e-01	150	156	2	0.003586602	9.964134e-01
62	117	2	0.005483622	9.945164e-01	151	144	2	0.003475398	9.965246e-01
63	56	2	0.003379582	9.966204e-01	152	456	2	0.064782153	9.352178e-01
64	4	2	0.003932071	9.960679e-01	153	425	2	0.072876591	9.271234e-01
65	32	2	0.003568494	9.964315e-01	154	235	2	0.010976816	9.890232e-01
66	147	2	0.003500692	9.964993e-01	155	305	2	0.009201866	9.907981e-01
67	112	2	0.003300899	9.966991e-01	156	148	2	0.003509487	9.964905e-01
68	274	2	0.006957189	9.930428e-01	157	381	2	0.021886855	9.781131e-01
69	311	2	0.009762418	9.902376e-01	158	190	2	0.004065307	9.959347e-01
70	76	2	0.003296051	9.967039e-01	159	270	2	0.006731985	9.932680e-01
71	46	2	0.003445905	9.965541e-01	160	201	2	0.004282001	9.957180e-01
72	20	2	0.003703582	9.962964e-01	161	154	2	0.003566179	9.964338e-01
73	56	2	0.003379582	9.966204e-01	162	232	2	0.005107446	9.948926e-01
74	40	2	0.003494049	9.965060e-01	163	225	2	0.004889241	9.951108e-01
75	53	2	0.003397697	9.966023e-01	164	331	2	0.012028602	9.879714e-01
76	75	2	0.003298731	9.967013e-01	165	443	2	0.052936421	9.470636e-01
77	122	2	0.003337485	9.966625e-01	166	398	2	0.040859844	9.591402e-01
78	412	2	0.033431427	9.665686e-01	167	363	2	0.019972020	9.800280e-01
79	74	2	0.003301567	9.966984e-01	168	437	2	0.048307874	9.516921e-01
80	44	2	0.003461240	9.965388e-01	169	314	2	0.013724466	9.862755e-01
81	257	2	0.006079751	9.939202e-01	170	114	2	0.003306963	9.966930e-01
82	169	2	0.003739000	9.962610e-01	171	256	2	0.006034205	9.939658e-01
83	384	2	0.022764166	9.772358e-01	172	210	2	0.004486396	9.955136e-01
84	1632	1	1.000000000	4.701584e-22	173	380	2	0.021603786	9.783962e-01
85	286	2	0.592259222	4.077408e-01	174	248	2	0.005691270	9.943087e-01
86	151	2	0.122088097	8.779119e-01	175	285	2	0.007644728	9.923553e-01
87	251	2	0.021470459	9.785295e-01	176	306	2	0.009291960	9.907080e-01
88	558	1	0.328499539	6.715005e-01	177	232	2	0.005107446	9.948926e-01
89	723	1	0.997640507	2.359493e-03	178	153	2	0.003556257	9.964437e-01

Table 3 gives the estimated states of the observable violent death count and their corresponding probabilities of transition from either states to another for the purpose of hidden Markov model estimation and classification.

Grand Hidden Markov Model Switching Autoregression Summary

Transition Probability and Model Fit Estimation

Table Error! No text of specified style in document.**: Estimated transition probability using the switching autoregression.**

Transition Probability			AIC	BIC	LogLik	Multiple R^2
State	1	2				
1	0.6010	0.1326	2326.125	2376.102	−1157.063	0.105
2	0.3990	0.8674				0.666

Political issue identified as one of the causes of violent death in Nigeria has accounted for 0.105 and 0.666 proportion of variation in the dynamics of politics related violent death count with respect to regime 1 and regime 2 respectively. The probability of the system being regular given its previous state as regular is 0.6010 and that of irregular given an irregular previous state is 0.8674. This suffices to say that regime 2 model is best suited predicting violent death attributed to political issues (see Table 4).

Hidden Markov Switching Autoregression Parameters Estimation (Regime Based)

Table 5: Switching autoregression parameter estimation

Regime	Coefficient	Estimate	Std. Error	t value	Prob.(>|t|)	
1	(Intercept)(S)	-10.2525	9.2966	-1.1028	0.270114	
	dpo_1(S)	-0.1644	0.0540	-3.0444	0.002331	**
	dpo_2(S)	-0.0232	0.0314	-0.7389	0.459968	
2	(Intercept)(S)	322.6050	100.1652	3.2207	0.001279	**
	dpo_1(S)	-1.1909	0.1537	-7.7482	9.326e-15	**
	dpo_2(S)	-1.3788	0.2657	-5.1893	2.111e-07	**

Table 5 shows the switching autoregressive parameter estimation results for the two possible regimes underlying the Politics related violent deaths count. Results show that considering an AR of order 2 as the basis of model estimation in the Hidden Markov Model with Switching associated with the PACF plot, all the parameters of the estimated regime 2 model were found be significant at 1% significance level indicated by ** as compared to regime 1 model with only one significant parameter.. Hence, regime 2 model is best suited for predictive analysis.

Table 6: Parameter Interval Estimation for Political Issues models

Variable	Regime	Lower	Estimation	Upper
Intercept	Regime 1	-27.26509	-10.37683	6.511432
	Regime 2	-66.29696	76.40207	219.101099
dpo_1	Regime 1	-0.3631454	-0.2312972	-0.0994489
	Regime 2	-1.0196453	-0.7441932	-0.4687410
dpo_2	Regime 1	-0.2000166	-0.1072658	-0.01451499
	Regime 2	-0.8122420	-0.4691271	-0.12601218

Table 6 presents the parameter interval estimation for deaths count on the basis of the estimated Hidden Markov Model with Switching Autoregression. The table shows the lower and the upper bound for the estimates which are represented by the column head: estimation. The results also indicate that differenced observable deaths count is negatively related to its first two lagged values.

Regimes Estimated Residuals, Filtered and Smoothed Probabilities plot

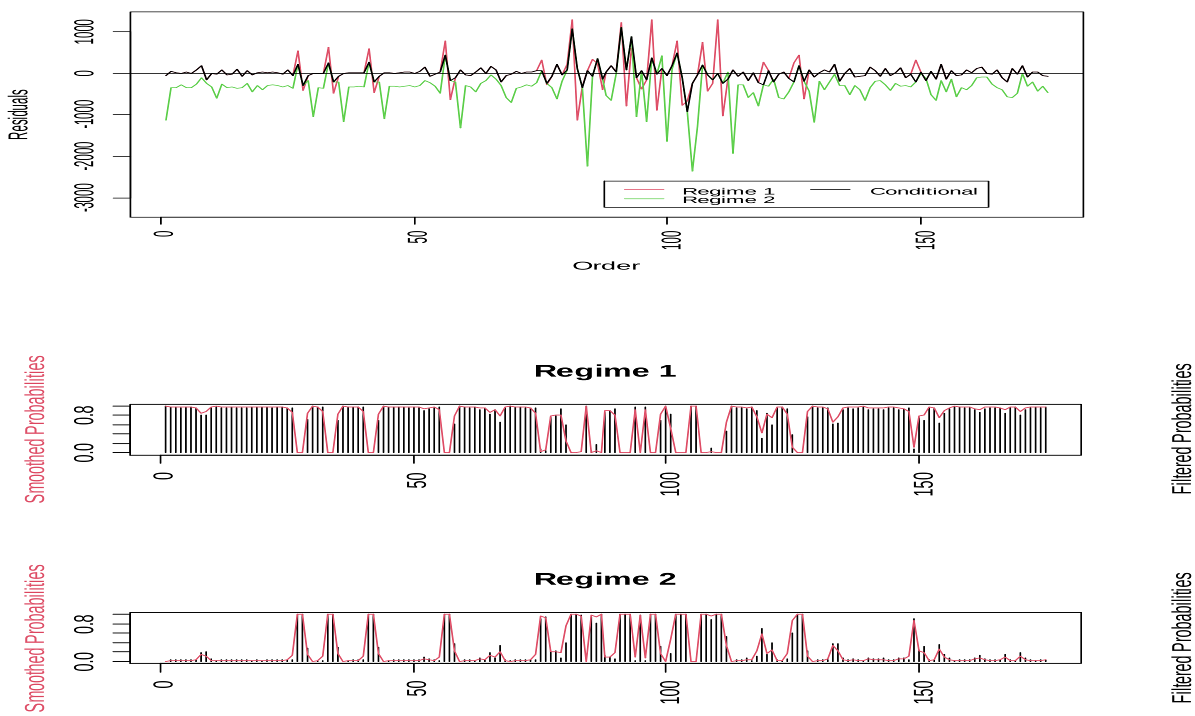

Figure 3: Regimes' estimated residuals, filtered and smoothed probabilities.

The estimated residuals' plot based on regimes for visualizing violent deaths count attributed to political issues is shown by fig. 4.25. It is clearly observed that the estimated regime 1 residuals are relatively co-exhibit dimensional movement as the estimated conditional residuals. This therefore suggests that regime one has higher tendency of fitting violent deaths count underlying politics as a cause. It is worthwhile to note that the associated probabilities to observation estimated to be in regime on the basis of switching autoregression hidden Markov model are very high and highly concentrated as compared to those of regime 2 (see figure 3).

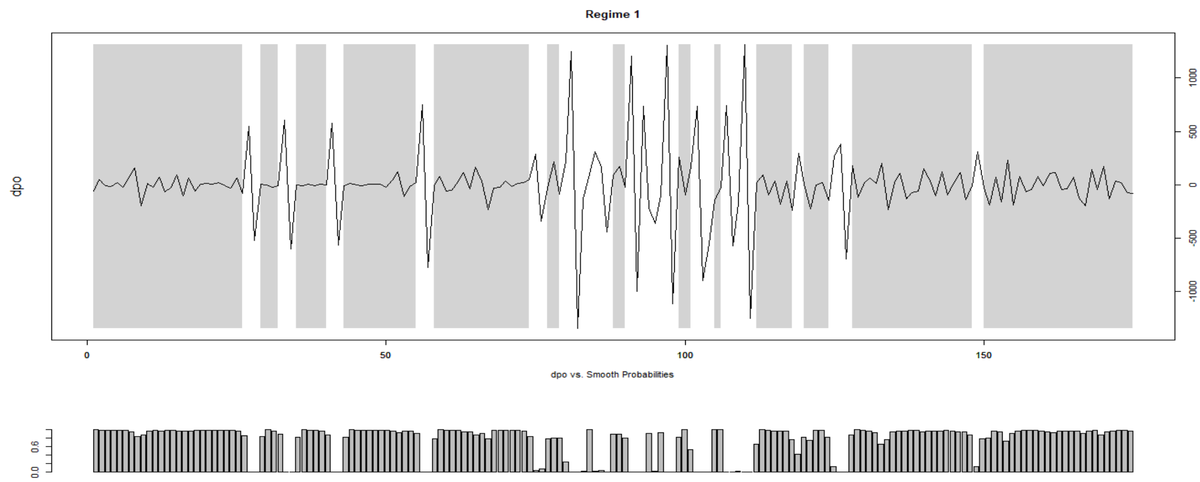

Figure 4a: Figure 4b: Regime Classification Plot of violent deaths count based on regime 1.

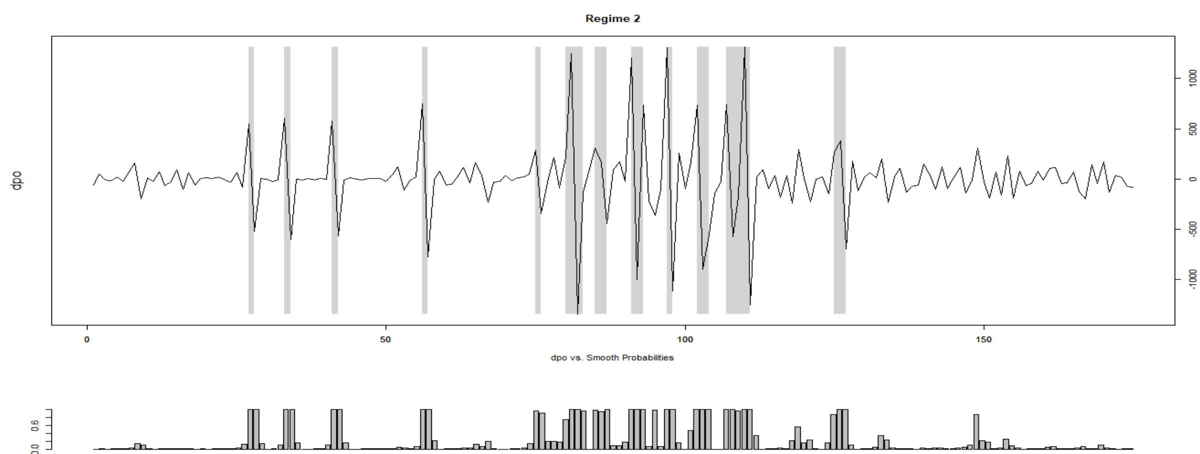

Figure 4b: Regime Classification Plot of violent deaths count based on regime 2.

Figure 4a,b reveal that over the period of study violent deaths count attributed to political issues have been more be classified by regime 1 suggesting a regular occurrence in the country. Hence, attention is expected to be drawn to this for assurance of citizens' safety for what has affected the economy in the past and present has every tendency to plaque the future of any economy, if adequate attentions are not drawn as and when due.

Predictive Analysis

The predictive analysis gives the diagrammatical representation of the ASHHM predictive plot which consists of the first differenced violent deaths series and its estimates (predicted).

For the prediction plots

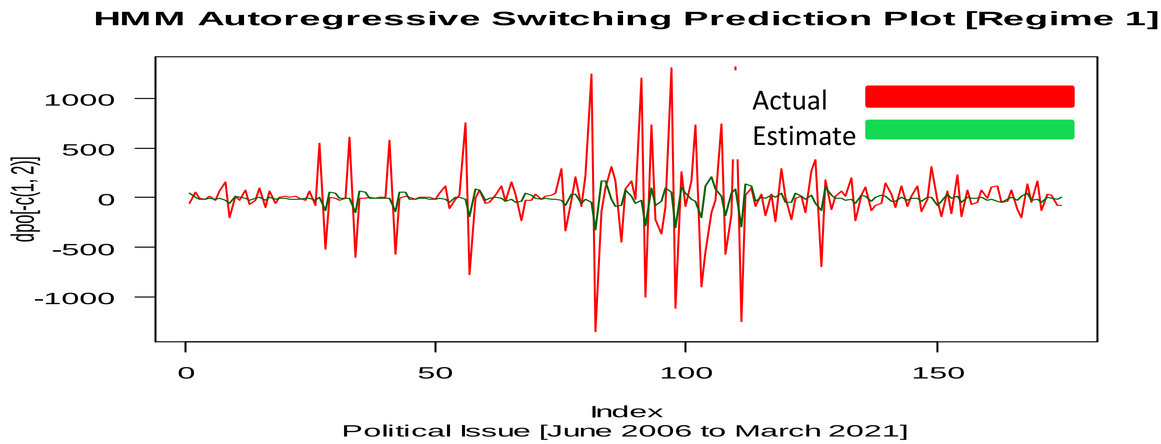

Figure 5a: Predictive Plot of violent deaths count attributed to regime 1 model.

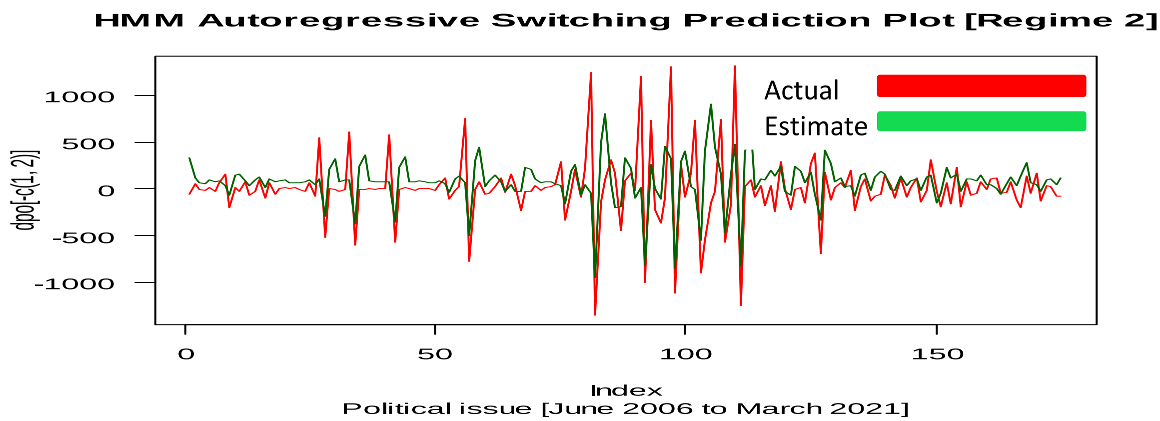

Figure 5b: Predictive Plot of violent deaths count attributed to regime 2 model.

Figure 5a,b give the predictive plot for violent death count attributed to political issue. Result shows that political issue could be better model with regime 2 due to its super-imposition on the actual death counts with almost the same fluctuation. This suggests that death count with respect to political issue is not just an illusion of regular but serious violence nature due to its peaks over the period of study. Hence, this helps draws the attention of the government and policy maker to ensure the rightful measures are in place for the safety of the citizens to be guaranteed before, during and after elections.

5.0 Discussion

Having carried out this research extensively on the basis of the underlying variable violent deaths count attributed to political issues, the following findings were discovered from the study. The time plot, trend analysis and ACF and PACF of violent deaths by causes established that the time plot for political issue suggests that the highest death count in this prospect was reported around 2014. From the trend estimation result, it is observed that for every one month step ahead the number of violent deaths to be reported would increase by approximately 24 victims and this imply a significance positive trend with p-value (0.0006) > 0.05 level of significance on the basis of statistical test of individual parameter significance. The assumed order of the (AR, MA) is (1, 2) respectively.

Following from the test of normality using the Shapiro-Wilks and Jarque-Bera procedure, the observable violent deaths count was found non-normally distributed due to its nature as pre-known to be unforeseen and unintentional. The distribution of violent death on monthly basis was estimated using the Kruskal-Wallis test to be equally. On the basis of stationarity test, violent deaths by causes were found to be stationary using the ADF test and PP testing procedure.

The Hidden States and transition probabilities for individual observable deaths count using the Kalmar filter were estimated using the Gaussian mixture. All the estimated states were found to be feasible underlying the aforementioned mixture. The grand transition matrices for the states were estimated for violent deaths dynamics and result shows that the probabilities of transition for political issues are $P_{11} = 0.6010,\ P_{22} = 0.8674,\ P_{12} = 0.3990\ and\ P_{21} = 0.1326$ indicating that indicate that violence in Nigeria has higher chance of remaining in the non-regular but severe state due to estimation. Considering the HMMSA result, regime 2 explains a larger proportion of the variations in violent death attributed to political issues. The parameters of the HMMSA were found to be statistically significant at 0.05 level of significance except the case of [Regime 1, 2nd differenced series], which renders regime 2 a better model for monitoring the dynamics of variation inherent in violent death count attributed to political issue.

6.0 Conclusion

Violence deaths in Nigeria attributed to political issues have been established from this research to be more of being an irregular occurrence since it occurs with low magnitude majority of time though very fatal. In the light of this study, result has proven to us that the occurrence of violent death is non-normal and therefore should be monitored closely since it is seen as nothing but a social and economic problem. Political issues are identified to be threats to the lives of citizens since violence attributed to them are very likely to claim the lives of people unexpectedly in Nigeria and depletion of the human population is relatively depletion of the economy.

7.0 References

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