The Dynamic Relationship Between Accidents, Drivers' Licensing and Automobile Registrations; A Vector Autoregression Perspective

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Authors' contributions

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Abstract

Aims/ Objectives: The paper seeks to investigate the dynamic relationship between drivers licensing, vehicle registration, motorbike registration and accidents.
Study Design: Cross-sectional study.
Place and Duration of Study: The secondary data was collated on a monthly basis on Accidents, Driver license, Motor Registration and Vehicle Registration that spanned 9 years from January 2010 to December 2018 from the Upper East Regional Office of the Drivers Vehicle and License Authority.

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Methodology: The data was analyzed using vector autoregression model to establish the dynamic relationship between the variables. The R and Eviews softwares were used in the analysis.

Results: The findings revealed that in the short-run and long-run neither Driver license, Vehicle Registration, Motor Registration none Accidents cannot influence much on each other but experienced their own shock. Findings further ascertain that Accidents can granger cause vehicle registration to change but the remaining variable have no much influence on accidents.Although, accidents can granger cause vehicle registration to change, the remaining variables had no influence on accidents. The finding finally concluded that ARCH-LM test indicated that there was no ARCH effect present in the series implying that the Vector Autoregression model was appropriate to establish the dynamic relationship between the variables.

1 Introduction

The motorcycles are Northern Ghana's most common means of transportation. Motorcycles are required by law to be licensed with a number plate before they're placed on the roads. It is done first, to know the number of motorcycles in the region; second, to get some revenue for the state and last, to be able to locate the owners in the case of an accident or robbery. However, there are still some motorcycles on our highways, without number plates. Users of such motorcycles are also required to possess a rider's license. An individuals riding skills is checked before a license is issued to ensure that such a rider can use the motorcycle safely on the road without causing accident or nuisance to other riders and road users.

Road traffic accidents and fatalities are a growing public health problem worldwide, according to Agnihotri and Joshi [1]. Collaborations to assess how poorly maintained vehicles contribute to traffic collisions and to evaluate the impact of safety measures [2]. Banthia et al. [3] also reported that road traffic accidents are a major cause of death and disability worldwide, with a large number occurring in developing nations. Motorcyclists are found to be about three times more likely to be involved in a collision than car drivers, and 16 times more likely to die [4]. The driver also absorbs both the kinetic and compressive energy arising from the collision in a motorcycle accident [5]. Murray et al. [6] identifies some barriers that hinder the safety of fleet in Australia.

Road traffic accidents are a significant but ignored global public health problem, requiring concerted efforts to prevent them effectively and sustainably. According to the Peden et al. [7], highway transport is the most complicated and the most hazardous of all the networks that people have to deal with on a daily basis. Worldwide, the number of people killed in road traffic accidents is estimated at approximately 1.2 million per year, while the number injured may be as high as 50 million [7]. The disaster behind such numbers often receives less media coverage than other less common, but more extreme forms of disasters. The total number of road fatalities and injuries worldwide is predicted to rise by about 65% between 2000 and 2020 [8], and fatalities in low and middle-income countries are projected to increase by as much as 80%. This calls for greater efforts and new measures to tackle the danger.

What is the condition of motorcycle registration and injuries in a developing country Ghana and a region like that of the Upper East of Ghana? It is the topic the researcher discusses in this work. Studies in some parts of the world (e.g. Ghana and Indonesia) have shown that road traffic

accidents are the leading cause of road death and injury, and that the majority of road traffic deaths and injuries occurred in rural areas on roads [9],[10].

Road accidents in the year 2009 were about 12,299 with a total of 2,237 casualties and 6,242 sustaining serious injuries [11]. The level of road trauma imposes huge economic costs, representing between 1 and 3 percent of GDP in most countries with about 70 percent of these accident related deaths occurring in developing countries [12].

The Bolgatanga Municipal Health Administration [13] reported that road traffic incidents in the area have regularly appeared in the top ten causes of hospital admissions and attendance since 2006. The report of the preceding year [14] carried the same indication. In Africa, it has been estimated that in 1990 59,000 people lost their lives in road traffic accidents, and by 2020 this number would be 144,000, a rise of about 144 percent [15]. This paper seek to examine the dynamic relationship between Accidents, motorcycle registration and vehicle registration in the Upper East region of Ghana.

2 Materials and Methods

The study made used of secondary data spanning over the period 2009 to 2016. Data was sourced from the Upper East Regional Driver and Vehicle License Authority in Bolgatanga, Ghana. As in most time series studies, we first checked for stationarity of the data.The ADF and PP unit root test was conducted to check for stationary of the data. The study employed Vector Autoregression model (VAR). According to James H. Stock and Mark W. Watson [16], a univariate autoregression is a single-equation, single-variable linear model in which the current value of a variable is explained by its own lagged values. A VAR is an n-equation, n-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining $n-1$ variables.

Also, the lag length (p) associated with the minimum from a set of values of AIC, SBIC and HQIC is selected as the correct lag length (p) for the VAR model. The Granger causality test to determine the dynamic relationship that exist among the variables was conducted. Variance decomposition as well as impulse response function was employed to determine the shock transmissions among the variables. The ARCH-LM test, correlogram of the residuals and serial correlation test was conducted to assess the fitness and adequacy of the VAR model. Stata and Eviews softwares were employed as the statistical tool for the analyses of the data.

2.1 Autoregressive (AR) model

Vector Autoregression (VAR) is a generalized reduced form which helps in detecting the statistical relationship among variables in a particular system. It allows all the variables in the system to interact with themselves and with each other, without having to impose a theoretical structure on the estimates. It provides additional method that help in analyzing the impact of a given variable on itself and on all other variables using Impulse Response Functions (IRFs) and Variance Error Decompositions (VED). An AR(p) is given by

$$y_t = \Sigma_{r=1}^{p} \alpha_r y_{t-1} + z_t \qquad (2.1)$$

$$\implies \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + z_t$$

where $\{\alpha_r\}_1^p$ are fixed constants and $\{z_t\}$ is purely white noise. Using the backward-shift operator, equation 2.1 is rewritten as

$$(1 - \alpha_1 B - \alpha_2 B^2 - \cdots - \alpha_P B^p)y_p = z_t$$

$$(B)y_t = z_t \qquad (2.2)$$

From equation 2.2

$$y_t = \alpha(B)^{-1} z_t$$

$$y_t = (1 - \alpha_1 B - \alpha_2 B - \cdots - \alpha_P B^P)^{-1} z_t \tag{2.3}$$

From Equation 2.3,

- $E(y_t) = 0$ since z_t is a random process.
- $Var(y_t)$ is finite provided $\Sigma_{i=1}^{\infty} \alpha(B)_i$ converges (a condition for stationarity).
- Equivalently, the stationarity condition is that the values of B to $\alpha(B) = 0$ must be greater than one.

The simplest form of an AR model is the first order denoted AR (1) and defined as $y_t = \alpha y_{t-1} + z_t$ It is stationary provide $|\alpha| < 1$.

2.2 Causality test

Granger causality test [17], is the frequently used test for exploring the causality among variables included in a VAR analysis. The primary purpose for fitting a VAR model and the interest of researchers is to establish the causality between the variables. When causality is detected, care must be taken in the interpretation. We say that variable y granger-causes variable x if variable y helps in the prediction of the variable x. According to Lütkepohl [18], the test for non-zero correlation between the error processes of the cause and eect variables is carried out in the process. The vector of endogenous variables y_t is usually, split into two sub-vectors $y_{1t}(k_1 \times 1)$ and y_{2t}, $k = k_1 + k_2$. Thus, the $VAR(p)$ is written as

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \sum_{i=1}^{p} \begin{bmatrix} \Pi_{11,i} & \Pi_{12,i} \\ \Pi_{21,i} & \Pi_{22,i} \end{bmatrix} \begin{bmatrix} y_{1,t-i} \\ y_{2,t-i} \end{bmatrix} + Cd_t + \begin{bmatrix} \varepsilon_{1,t-i} \\ \varepsilon_{2,t-i} \end{bmatrix} \tag{2.4}$$

The following hypothesis is then tested; $H_0 : \Pi_{21,i} = 0$ for $i = 1, 2, , p$ (that is y_{1t} does not Granger-cause y_{2t}. $H_1 : \Pi_{21,i} 0$ for $i = 1, 2, , p$. The test statistic is distributed as $F(PK_1 K_2 - n^*)$ where n* is the total number of parameters in the model in equation (2).

2.3 Impulse Response Function (IRF)

In Beenstock and Felsenstein [19], the Impulse Response Function (IRF) is used to determine how each endogenous variable responds over time to a shock in its own value and in every other variable. Again, any VAR can be modelled as a triangular moving average process.

$$y_t = + \theta_0 \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} \tag{2.5}$$

From this equation we can observe changes in y_t given a change in the residual. Plotting the IRF maps out the cyclic created in all variables given a shock in one variable.

$$\frac{\partial y_i, t+s}{\partial \mu_i, t} = \frac{\partial y_i, t}{\partial \mu_i, t-s} = \theta_{ij}^s i, j = 1, 2, \cdots n, s > 0 \tag{2.6}$$

It is common to draw bootstrapped confidence interval around IRF.

2.4 Forecast Error Variance Decomposition (FEVD)

If the innovation which actually drive the system can be identify, a further tool used to interpret VAR model is forecast error variance decompositions. It is given as

$$W_{jk,h} = \frac{\sum_{i=0}^{h-1} (e_i \theta_i e_k)^2}{\sum_{i=0}^{h-1} e_i \theta_i \sum_{i=0}^{h-1} \theta_i e_k} \tag{2.7}$$

Which denotes the kth column of I_k by e_k, the proportion of the h-step forecast error variance of the variable k [18].

3 Results and Discussion

In this section of the study, we deal with the analysis of the data, discussion and interpretation of the results obtained from the study. The section is presented into preliminary analysis, further analysis and discussion of the results.
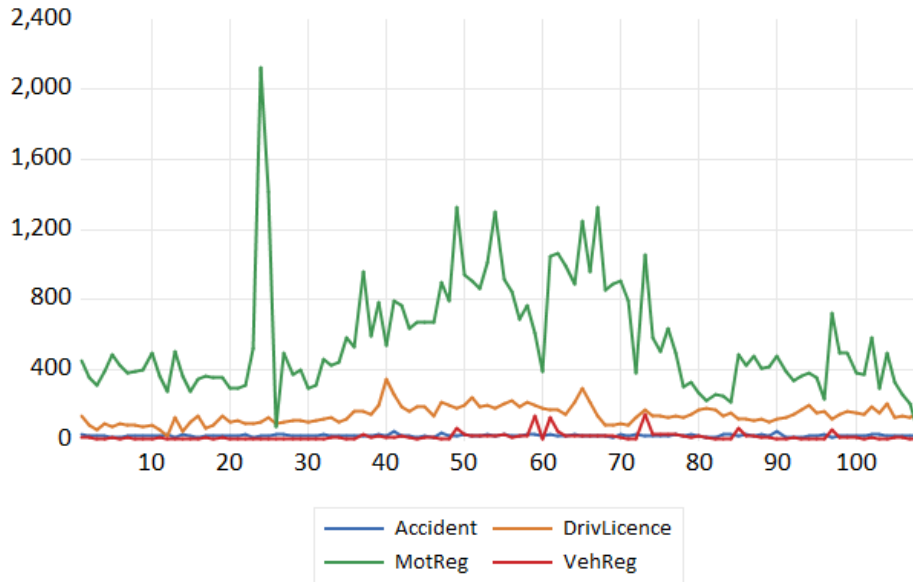

Fig. 1. Time series plot of accidents, motor registration, vehicle registration and driver license

In order to achieved the first objective of the study, the Fig. 1 reveals the pattern of the Accidents, Driver License, Motor Registration and Vehicle Registration of the time series plot of the data. All the four variables were plotted on single graph and the graph displayed some level of stationarity in the data as all series fluctuated about a fixed point. There was no exhibition of any pattern of trend and the presence of seasonality was not observed in all the four variables. Accidents fluctuated above Driver License, Motor Registration and Vehicle Registration and relatively exhibiting higher variability.

3.1 Stationary test

To investigate whether the four time series data are stationary or not, the ADF and PP unit root was employed. Table 1 is the presentation of Accidents, Driver License, Motor Registration and Vehicle Registration. The trend component was absent when the test was conducted. All the series were stationary at 5% level of significance. This meant that the data was good for fitting the VAR model.

3.2 VAR models and lag selection

The VAR model order assumed to increase with the sample size and that is $h \sim p(T)^{1/3}$, where T is size of the time series in Lütkepohl and Saikkonen [20]. The conclusion they made was that VAR(p) are fitted to data such that h goes to infinity with sample size. We considered VAR models

from lag 1 to lag 8. VAR model at lag 2 was chosen by FPE, AIC, SC, HQ whiles VAR model at lag 1 was chosen by HQ. VAR model at lag 8 was chosen by LR criteria as displayed in Table 2. The Lag 1, lag 2 and lag 8 are useful for predicting accidents whiles its lag 3, lag 4, lag 6 and lag 7 are not. Lag selection criterion has advised us to take lag 2 in the VAR model to be optimum lags. It is clearly shown that lag 2 is appropriate to estimate VAR model based on FPE, AIC, SC, HQ and HQ.

Table 1. Stationary test

Method	Statistic	Probability	Cross-section	Observations
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.8122	0.0000	4	427
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-Stat	-11.2019	0.0000	4	427
ADF - Fisher Chi-square	121.889	0.0000	4	427
PP - Fisher Chi-square	163.448	0.0000	4	428

Table 2. VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2036.654	NA	6.24e+12	40.81308	40.91728	40.85525
1	-1977.885	111.6607	2.65e+12	39.95770	40.47874	40.16857*
2	-1969.831	14.65851	3.11e+12*	40.11662*	41.05448*	40.49619*
3	-1962.775	12.27765	3.74e+12	40.29550	41.65018	40.84376
4	-1957.351	9.003376	4.65e+12	40.50702	42.27854	41.22399
5	-1950.527	10.78177	5.66e+12	40.69054	42.87889	41.57621
6	-1939.586	16.41240	6.38e+12	40.79171	43.39688	41.84607
7	-1932.157	10.54818	7.76e+12	40.96315	43.98514	42.18620
8	-1910.664	28.80091*	7.19e+12	40.85328	44.29211	42.24504

Table 3 represent the parameters estimates of the VAR model. Some of the coefficients of the VAR models are found not to be significant and this suggests that further analysis be conducted to ascertain whether or not the coefficients are indeed not significant. A Wald test was thus conducted on the perceived insignificant VAR models coefficients. It surprisingly turned out that the overall probability value was significant suggesting that the coefficients cannot be rejected and should rather be retained.

Table 4 shows clearly the four VAR models estimated. Also in that table is the Durbin-Watson Statistic for each of the four VAR models which are all less than 4, indicating that all the four VAR models are free from serial correlation.

3.3   Stability condition of the VAR model

The Table 5 indicates the stability condition of VAR (8) model. The results shows that all the roots are inside the unit circle since the modulus of the roots are all less than 1. This means that the VAR (8) stability condition is achieved. This confirms that Accidents, Driver License, Motor Registration and Vehicle Registration are stationary as stated in the earlier tests.

3.4   Model adequacy and diagnosis checks

To investigate a proper model for a given time series data, it is necessary to carry out the ACF and PACF analysis. The Fig. 2 is the presentation of model adequacy and diagnostic checks to measure how the variables in the time series are related to one another. The correlation plot of

vehicle registration against vehicle registration shows that all the spikes within the lower and the upper bounds are not significant except lag 12 which is significant.

Table 3. Coefficient estimates of the VAR model

Lags	Coefficient	Standard Error	t-Statistic	Probability
C(1)	-0.004019	0.103474	-0.038843	0.9690
C(2)	0.277849	0.099681	2.787371	0.0056
C(3)	-0.000114	0.009229	-0.012373	0.9901
C(4)	0.000611	0.009224	0.066200	0.9473
C(5)	0.073532	0.063963	1.149603	0.2510
C(6)	-0.004420	0.064084	-0.068975	0.9450
C(7)	0.716444	0.350787	2.042393	0.0418
C(8)	0.375384	0.356716	1.052332	0.2933
C(9)	-22.97540	12.84064	-1.789272	0.0744
C(10)	-1.540891	1.220653	-1.262350	0.2076
C(11)	1.509765	1.175912	1.283910	0.1999
C(12)	0.562614	0.108866	5.167938	0.0000
C(13)	-0.002127	0.108817	-0.019548	0.9844
C(14)	0.344525	0.754549	0.456598	0.6482
C(15)	0.587871	0.755984	0.777624	0.4373
C(16)	1.289716	4.138127	0.311667	0.7555
C(17)	2.803194	4.208073	0.666147	0.5057
C(18)	25.32319	151.4772	0.167175	0.8673
C(19)	0.011677	0.165216	0.070675	0.9437
C(20)	0.099903	0.159161	0.627684	0.5306
C(21)	0.000280	0.014735	0.018987	0.9849
C(22)	0.009099	0.014728	0.617796	0.5371
C(23)	0.655051	0.102129	6.413969	0.0000
C(24)	0.054990	0.102323	0.537415	0.5913
C(25)	0.579703	0.560099	1.035001	0.3013
C(26)	-0.504936	0.569567	-0.886526	0.3759
C(27)	32.64042	20.50258	1.592015	0.1122
C(28)	-0.001564	0.030136	-0.051898	0.9586
C(29)	-0.002897	0.029031	-0.099775	0.9206
C(30)	-0.000932	0.002688	-0.346803	0.7289
C(31)	0.003780	0.002686	1.407011	0.1602
C(32)	0.016942	0.018628	0.909469	0.3637
C(33)	-0.003899	0.018664	-0.208901	0.8346
C(34)	-0.121288	0.102162	-1.187206	0.2359
C(35)	0.000530	0.103889	0.005097	0.9959
C(36)	22.46711	3.739680	6.007762	0.0000
Determinant residual covariance 1.30E+12				

The residual plot of vehicle registration against motor registration shown that all the spikes are not significant except at lag 8 and lag 12 whiles the residuals plot of vehicle registration against driver license showed that all the lags are not significant except lag 9 which shows a significant spike. The ACF plot of vehicle registration against accidents shows that all the spikes within the lower bound and the upper bound are not significant. All the spikes are not significant except in the case of motor registration versus vehicle registration at lag 12, motor registration versus driver license at lag 9 and accidents versus accidents at lag 9. The overall assessment indicated that the model is deemed fit and can be use to forecast since there is no significant spikes at lag 1 throughout individual plot.

Table 4. The four estimated VAR models

Equation: VEHREG = C(1)*VEHREG(-1) + C(2)*VEHREG(-2) + C(3) *MOTREG(-1) + C(4)*MOTREG(-2) + C(5)*DRIVLICENCE(-1) + C(6) *DRIVLICENCE(-2) + C(7)*ACCIDENT(-1) + C(8)*ACCIDENT(-2) + C(9)			
R-squared	0.181156	Mean dependent var	17.02830
Adjusted R-squared	0.113622	S.D. dependent var	24.16785
S.E. of regression	22.75346	Sum squared resid	50218.82
Durbin-Watson stat	2.075255		
Equation: MOTREG = C(10)*VEHREG(-1) + C(11)*VEHREG(-2) + C(12) *MOTREG(-1) + C(13)*MOTREG(-2) + C(14)*DRIVLICENCE(-1) + C(15) *DRIVLICENCE(-2) + C(16)*ACCIDENT(-1) + C(17)*ACCIDENT(-2) + C(18)			
R-squared	0.386282	Mean dependent var	576.0755
Adjusted R-squared	0.335666	S.D. dependent var	329.3175
S.E. of regression	268.4157	Sum squared resid	6988559
Durbin-Watson stat	2.035799		
Equation: DRIVLICENCE = C(19)*VEHREG(-1) + C(20)*VEHREG(-2) + C(21)*MOTREG(-1) + C(22)*MOTREG(-2) + C(23)*DRIVLICENCE(-1)+ C(24)*DRIVLICENCE(-2) + C(25)*ACCIDENT(-1) + C(26)*ACCIDENT(-2) + C(27)			
R-squared	0.545037	Mean dependent var	142.1321
Adjusted R-squared	0.507514	S.D. dependent var	51.76928
S.E. of regression	36.33031	Sum squared resid	128029.5
Durbin-Watson stat	2.044931		
Equation: ACCIDENT = C(28)*VEHREG(-1) + C(29)*VEHREG(-2) + C(30) *MOTREG(-1) + C(31)*MOTREG(-2) + C(32)*DRIVLICENCE(-1) + C(33) *DRIVLICENCE(-2) + C(34)*ACCIDENT(-1) + C(35)*ACCIDENT(-2) + C(36)			
R-squared	0.052986	Mean dependent var	23.10377
Adjusted R-squared	-0.025118	S.D. dependent var	6.544979
S.E. of regression	6.626667	Sum squared resid	4259.534
Durbin-Watson stat	2.020677		

Table 5. VAR stability conditions

Root	Modulus
0.811723	0.811723
-0.526308	0.526308
0.519266	0.519266
0.464381	0.464381
0.141203 - 0.237046i	0.275915
0.141203 + 0.237046i	0.275915
-0.229555 - 0.083581i	0.244298
-0.229555 + 0.083581i	0.244298

3.5 ARCH-LM test

The ARCH-LM test was employed to test for constant variance assumption. The results for ARC-LM test is displayed in Table 6. We failed to reject the null hypothesis of no ARCH effects in the residuals since the p-value of the Chi-Square(1) test is 0.9451 and this implies that ARCH is not appropriate to be estimated but rather the VAR model provides an adequate representation of the accidents, driver license, motor registration and vehicle registration of the time series data since the model satisfies all the assumptions.

The LM statistic at various lag 1,2, and 3 with their corresponding probability values are also shown in Table 6. The probability at various lags are appears to be significant indicating that the VAR models are free from serial correlation. This implies that VAR model are adequate and can be used to forecast the future behaviour of the variables.
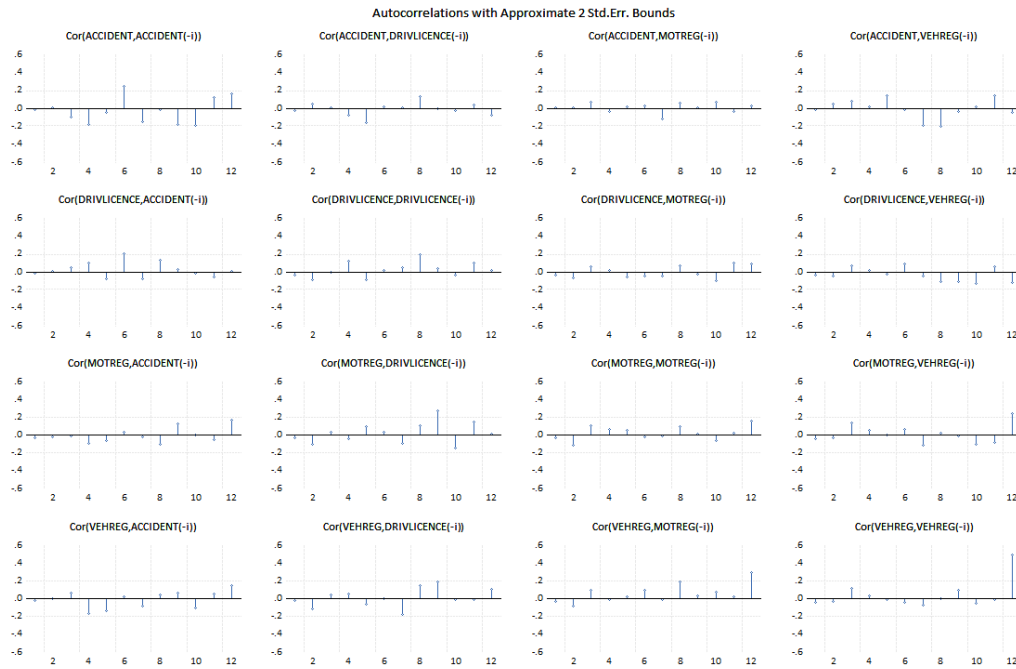

Fig. 2. Residual plot of ACF and PACF

Table 6. ARCH-LM test

F-statistic	0.004651	Prob. F(1,105)	0.9458
Obs*R-squared	0.004740	Prob. Chi-Square(1)	0.9451
LM			
Lags		LM-Stat	Prob
1		13.14813	0.6619
2		10.89854	0.8157
3		6.633902	0.9797

3.6 Causality test

From Table 7, we see relationship between accidents, driver license, motor registration and vehicle registration where almost all the probability values are greater than 0.05 meaning that driver license, motor registration and vehicle registration cannot granger cause accidents within the Upper East Region. Likewise, the relationship runs from accidents to vehicle registration with all probability value less than 0.05. Although, both accidents have greater influenced on vehicle registration but the remaining have no influence on accidents. This implies that for accidents to be reduced in our roads management of the road safety should enforce vehicle registration within the Upper East Region.

Table 7. Pairwise granger causality tests

Null Hypothesis:	Obs	F-Statistic	Prob.
MOTREG does not Granger Cause VEHREG	106	0.20642	0.8138
VEHREG does not Granger Cause MOTREG		1.39233	0.2532
DRIVLICENCE does not Granger Cause VEHREG	106	2.19280	0.1169
VEHREG does not Granger Cause DRIVLICENCE		0.31788	0.7284
ACCIDENT does not Granger Cause VEHREG	106	3.43336	0.0361
VEHREG does not Granger Cause ACCIDENT		0.17968	0.8358
DRIVLICENCE does not Granger Cause MOTREG	106	1.41485	0.2477
MOTREG does not Granger Cause DRIVLICENCE		0.56021	0.5729
ACCIDENT does not Granger Cause MOTREG	106	0.40378	0.6689
MOTREG does not Granger Cause ACCIDENT		1.76989	0.1756
ACCIDENT does not Granger Cause DRIVLICENCE	106	1.11283	0.3326
DRIVLICENCE does not Granger Cause ACCIDENT		1.07875	0.3439

Table 8. Variance decomposition of accident

| Period	S.E.	VEHREG	MOTREG	DRIVER LICENSE	ACCIDENT
1	6.626667	0.979976	0.472442	1.298102	97.24948
2	6.697403	1.047139	0.480160	1.866069	96.60663
3	6.764106	1.184082	2.151723	1.905228	94.75897
4	6.780968	1.178417	2.554150	1.972826	94.29461
5	6.792404	1.225595	2.724286	2.064737	93.98538
6	6.798244	1.228906	2.787072	2.157371	93.82665
7	6.802420	1.241797	2.819823	2.225034	93.71335
8	6.805049	1.245130	2.838429	2.274654	93.64179
9	6.806841	1.249381	2.849504	2.308030	93.59308
10	6.808004	1.251253	2.856342	2.330955	93.56145

3.7 Impulse function

The impulse response function of VAR helps to interpret the dynamic relationship between variables of time series data. The impulse response among the accidents, driver license, motor registration and vehicle registration were explored. The Fig. 3 shows the interactions among accidents, driver license, motor registration and vehicle registration following a shock in the VAR model. The impulse response function must lie between 95% confidence interval. The two redline indicates the 95% confidence interval of lower and upper bound. Take for instance the impulse variable vehicle registration. In the first period, vehicle registration reacted positively to a shock in its own values followed by a zero response to second, third and fourth period. Motor registration reacted positive to a shock in vehicle registration in the first period followed by the decrease in movement to the third period and remain stable in the rest of the periods. Motor registration reacted positively to a shock in relation to its own self in the first period and decline gradually through the rest of the period. Driver license reacted zero in the first period to a shock in vehicle registration and maintained same response and stable movement through the rest of the period. Driver license reacted positively to a shock in motor registration from first period followed by a stable movement to the rest of the period. From the initial period, Driver license reacted positively to its own shock and then started declining in a stable movement to the final period.

Accidents had a zero reaction response to shock in vehicle registration from the first period through to the fifth period. Accidents reacted negatively in response to motor registration from the first

period and then increase from period three to period four. Thereafter, it remain stable throughout the rest of the period. Accidents reacted positively in response to driver license in the first period and then declined in the second period and thereafter remained on zero throughout the rest of the period. Accidents reacted positive response to its own shock at first and then it declined to a negative response at period two. Thereafter it increased in period three. However there was no response for the rest of the period. Details are shown in the Fig. 3.

Table 9. Forecast error variance evaluation

Variable	Inc.obs.	RMSE	MAE	MAPE	Theil
VEHREG	108	24.77672	16.31198	70.72873	0.471641
MOTREG	108	543.4784	437.7815	307.7484	0.675394
DRIVLICENCE	108	428.1352	425.4991	75.09557	0.595081
ACCIDENT	108	8.993223	6.950724	41.84171	0.220294
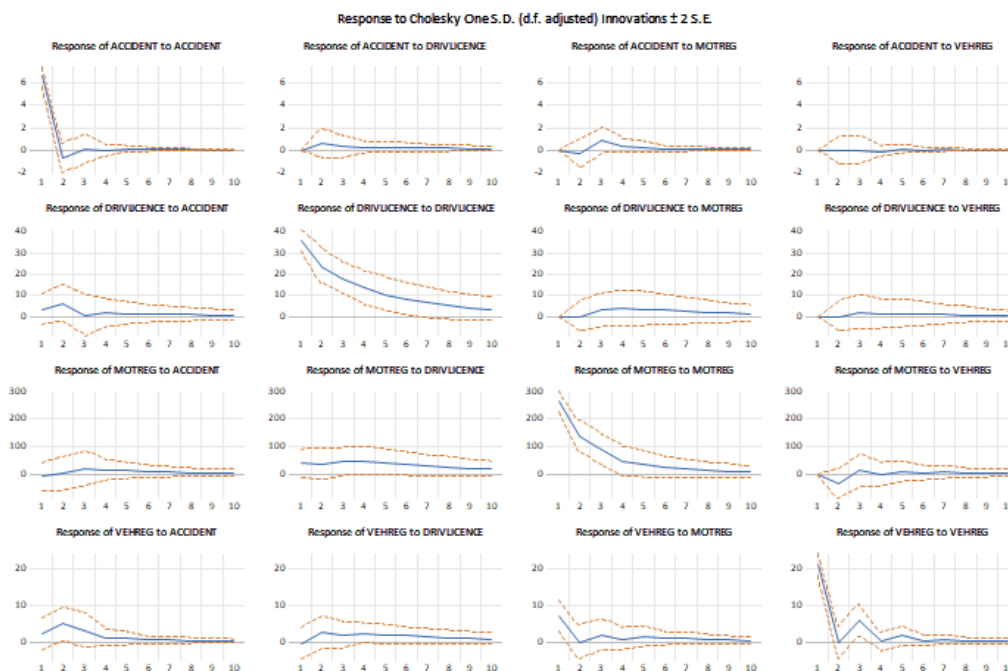
Fig. 3. Impulse Function

From the residuals impulse response function in Fig. 4, it is clearly shows that the upper diagonals and the lower diagonals are uncorrelated. This implies that the impulse response function actually reflects and explains the movement of the four variables in the study.

The variance decomposition of accident is shown in Table 8. In the short run, that is quarter 3, impulse or innovation or a shock to vehicle registration will account for 1.184% variation of the fluctuation in Accidents. A shock to motor registration can cause 2.152% fluctuation in accidents, impulse or innovation to driver license account for 1.905% variation of the fluctuation in accident. Also, a shock to accidents can cause 94.76% fluctuation in accidents (own shock). In the long-run, that is quarter 10, impulse or innovation or a shock to vehicle registration account 1.25% variation of the fluctuation in accident. Still in quarter 10, a shock to motor registration can cause 2.86%

fluctuation in accident. An impulse or innovation to driver license account for 2.33% variation of the fluctuation in accident, a shock to accidents can 93.56% fluctuation in accidents(own shock). This implies that both in the short and long-run vehicle registration and motor registration cannot contribute much to variation of the fluctuation in the accident.
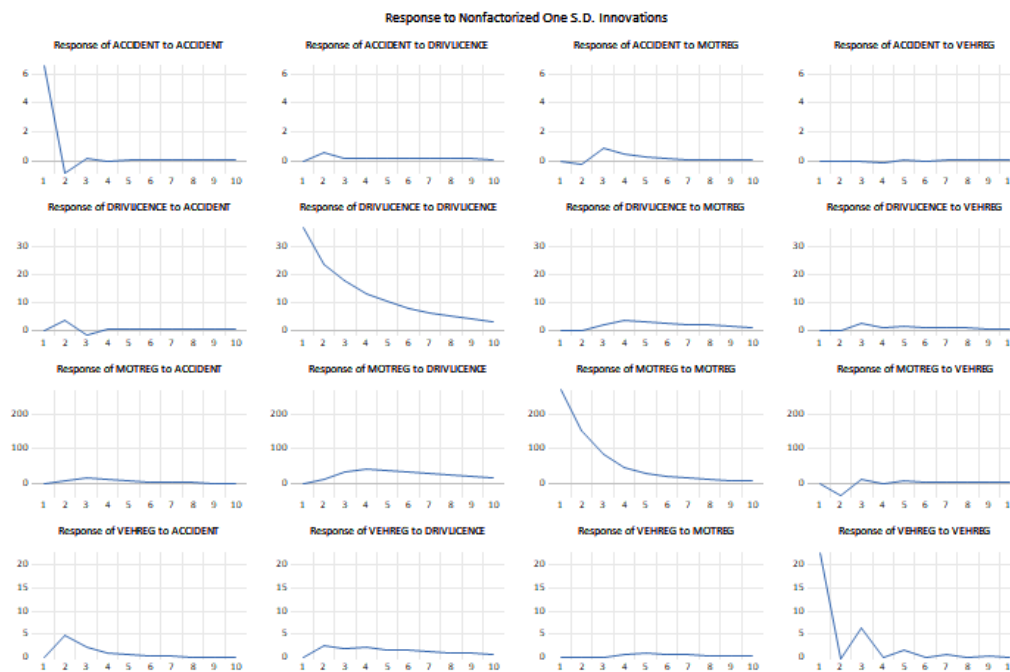

Fig. 4. Residual of the impulse function

It can be observed from Table 9 that the least variation among the four variables (Accidents, Motor Registration, Vehicle Registration and Driver license). The variable that has the minimum variation can be selected based on the minimum values of RMSE, MAPE, MAD, MSD and Theil. The maximum variation occurred in motor registration and this happened because the most popular means of transportation within the region is motorcycle. A careful inspection indicated that accidents within the region has the minimum variation and this implies that the accidents occurred at closed time interval.

4 Summary of the Findings

The findings in Fig. 1 revealed the pattern of the Accidents, Driver License, Motor Registration and Vehicle Registration of the time series plot of the data. All the four variables were plotted on single graph and the graph displayed some level of stationary in the data as all series fluctuate about a fixed point. There was no exhibition of any pattern of trend and the presence of seasonality was not observed in all the four variables. The relative accidents fluctuated above the Driver license, Motor Registration and Vehicle Registration and relatively exhibiting high variability.

To investigate whether the four time series data are stationary or not, the ADF and PP unit root was employed. The trend component was absence when the test was conducted. All the series were stationary at 5% level of significance. This means that the data was good for fitting VAR model.

Table 3 represent the parameters estimates of the VAR model. The Lag 1, lag 2 and lag 8 were found to be useful for predicting accidents whiles its lag 3, lag 4, lag 6 and lag 7 were not. Lag selection criterion advised us to take lag 2 in the VAR model to be optimum lags. It clearly showed that lag 2 is appropriate to estimate VAR model based on FPE, AIC, SC, HQ and HQ. From Table 4, the Durbin-Watson Statistic for the four VAR models were all less than 4 indicating that all the four VAR models were free from serial correlation. Some of the coefficients of the VAR models were not significant and this suggested that further analysis be conducted to ascertain whether or not the coefficients are indeed not significant. Wald test was further conducted on perceived insignificant of the VAR models coefficients. It showed that the overall probability value was significant which indicated that the coefficients could not be rejected but rather retained. The results also showed that all the roots are inside the unit circle and the reason was that the modulus of the roots were less than 1. This means that the VAR (8) stability condition was achieved and hence suggested that the series (Accidents, Driver license, Motor Registration and Vehicle Registration) were stationary as stated in the ADF and PP test in Table 2. The ACF and PACF plot of vehicle registration against accidents shows that all the lags spikes within the lower bound and the upper bound were not significant. All the spikes of the lags were not significant except in the case of motor registration versus vehicle registration at lag 12, motor registration versus driver license at lag 9 and accidents versus accidents at lag 9. The overall assessment indicated that the model was fit and could be used to forecast since there was no significant spikes at lag 1 throughout individuals plot.

The ARCH-LM test was employed to test for constant variance assumption. The results for ARCH-LM test revealed that there was no ARCH effect in the series since the probability value of 0.9451 is greater than 0.05. This implies that ARCH is not appropriate to be estimated but rather that the VAR model provided an adequate representation of the series (accidents, driver license, motor registration and vehicle registration) since the constant variance assumption was satisfied. The LM statistic at various lag 1, 2, and 3 with their corresponding probability values are shown in Table 7. The probability values at various lags were greater than 0.05 indicating that the VAR models are free from serial correlation. This implies that VAR model are adequate and can use to forecast future behaviour of the variables.

It was found that although, accidents can granger cause vehicle registration change, the remaining variables have no influence on accidents. This implies that for accidents to be reduce in our roads management of the road safety should be enforced and vehicle registration within the region encouraged.

When the impulse variable was vehicle registration, it reacted positively to a shock in its own values in the first period, followed by a zero response in the second, third and fourth period. Motor registration reacted positively to a shock in vehicle registration in the first period followed by the decrease movement in the third period and remained stable in movement through the rest of the period. Motor registration reacted positively to a shock relative to its own shock in the first period and declined gradually to the rest of the period. Driver license reaction was zero in the first period to a shock in vehicle registration and maintained same positive stable movement to the rest of the period. Driver license reacted positively to a shock in motor registration from first the period followed by a stable movement through the rest of the periods. From the initial period, Driver license reacted positively to its own shock from first period and then started declining in a stable movement to the final period. Accidents had a zero reaction in response to a shock in vehicle registration from the first period and remained same throughout the fifth period. Accidents reacted negatively in response to motor registration from the first period and then increased from period three to period four and thereafter maintained a stable movement throughout the rest of the period. Accidents reaction was positive in response to driver license in the first period and then declined in second period thereafter its reaction was zero throughout the rest of the period. The reaction of accidents was positive in response to its own shock at the first period and then decline to negative

response at period two and thereafter increased in period three however there was no response for the rest of the period.

The residuals impulse response function in Fig. 4 indicated that the upper diagonals and the lower diagonals are uncorrelated. This implies that the impulse response function actually reflects and explained the movement of the four variables in the study. Table 8 revealed that in the short-run and long-run vehicle registration, driver license and motor registration cannot contribute much to variation of the fluctuation in the accidents but accidents experienced their own shock. The findings finally revealed that Accidents were having the minimum variation and motor registration obtained the maximum variation. This implies that the accidents occurred within the region at close time interval whiles the motor registration occurred at relatively wide time interval.

5   Conclusions

In conclusion we found that there was no exhibition of any pattern of trend and the presence of seasonality was not observed in all the four variables. All the four series were stationary at 5% level of significant. This was confirmed by stability test which showed that the roots were all found in the unit circle. Lag 2 was found to be appropriate to estimate VAR model based on FPE, AIC, SC, HQ and HQ This meant that the data was good for fitting the VAR model. The parameters of the model for the series were estimated and further analysis conducted to confirm the significance of the coefficients. An overall assessment of the the model through the model diagnostic test showed that the model was very fit to be used for forecasting purposes. In the short-run and long-run neither driver license, vehicle registration, motor registration nor accidents can influence much on each other but rather, they experience their own shock. Although, accidents can cause vehicle registration to change, the remaining variable had no influence on accidents. The finding further helps us conclude that there was no ARCH effect present in the series since the probability value 0.9451 is greater than 0.05 and this implies that the vector autoregression model was appropriate to establish the dynamic relationship between the variables. This implies that for accidents to be reduce in our roads, enforcement of compulsory vehicle registration in the region must be ensured.

Acknowledgement

Competing Interests

Authors have declared that no competing interests exist.

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