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VECTOR AUTOREGRESSIVE ANALYSIS OF NEWLY-REGISTERED VEHICLES IN LAGOS STATE, NIGERIA

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ABSTRACT

Good transportation plays an essential role in the socio-economic development of any community or nation. This study examines the time series analysis of newly registered vehicles in Lagos State. Data was collected on different types of vehicles like saloon cars, ominibuses, minibuses, tractors, lorries, vans e.t.c. from 56 stations of the Motor Vehicle Administration Agency of Lagos State. Vector Autoregressive (VAR) Time series Model was fitted with the aid of R (R i386. 3.6.1) statistical software package. Descriptive Statistics showing the mean, standard deviation, and variance were obtained. Unit root Augmented Dickey Fuller (ADF) test for the entire series shows that the series is stationary. Time plots some of the vehicles show a positive trend like (saloon cars, van, lorry, minibus, ominibus), while those of tanker, tipper, trailer and tractor show a very sharp decrease in its series over the years. Forecast values were obtained on all the variables for 12 succeeding months. These reveal that it was only saloon cars and omnibus that show increase in their registration for the 12 months while tanker, van, tractor, lorry, trailer, minibus, and tipper show a decrease in new registration.

INTRODUCTION

Transportation, which is frequently referred to as the "wheel of development" is a catalyst that makes it easier to access additional services and opportunities because of the role it frequently plays as a gateway to other development sectors. Onokala (1994a) investigated the stages of transportation in Nigeria before the colonial era, there exist trade routes of tracts and waterways which served as important means of communication and transportation. There is no denying that a region with effective transportation infrastructure frequently has a higher chance of drawing nation builders. There needs to be a solid transportation system in place for economic development. The movement of people, goods, and levels of geographical accessibility are at the heart of the interaction between transportation systems and socio-economic transformations. Hence, economic prospects are evident in any community grow where transportation infrastructures are easily accessible.

In the modern era, a major component of economic development in Nigeria is the transportation infrastructure. Early in the 20th century, commerce shifted from waterways to railways, and then to the network of roads, while after the Second World War, air transportation was established. The modifications are done in accordance with Nigeria's economic progress, regional trade patterns, and commodity flow patterns.

Lagos State has a history of transportation sector development, much like many other developing cities throughout the world. The State's high population density is one of the key issues noted. A few data highlight the extreme pressure facing public transit. According to a 1989 survey by the Lagos Metropolitan Area Transport Authority, 2015, about 7.6 million journeys each day, of which 6 million, or 80%, were made using public transportation on the road. Lagos metropolitan has one of the lowest ratios of roads to population in the West African sub region, at 2.2km per 10,000 people. An average car travels from Lagos mainland and island with an average speed of 15Kph to 50 Kph. Hence, there exists little fluctuation in the day-to-day distribution of traffic volume. It is not surprising that the state's consumption of petroleum products represents around 40% of the national amount. Walking accounts for 40% of all trips in metropolitan Lagos, with the demand for journeys in the Lagos megacity region estimated at 22 million per day across all modes (including walking). By 2032, the daily demand for journeys will be roughly 40 million per day due to the significant rise in population and standard of life. The modes of transport include walking, use of Molue, BRT buses, Danfos, Private cars, Taxis, Tricycles, Okada, Trains and Ferries.

METHODOLOGY

The extension of the univariate autoregression analysis is the multivariate Vector Autoregression (VAR). It involves a vector of time-series variables, Y_{t+1}, usually represented as a linear function of $Y_t,\ldots,Y_{t-p+1}$, with deterministic terms (trends or an intercept). According to Watson (1994), this is an interesting feature that arises in VARs and not in univariate autoregressions, specifically, it might be that the time-series are cointegrated (that is, the individual series are nonstationary in the sense that they are integrated, but linear combinations of the series are integrated or order zero).
Multivariate time-series analyses usually involve a large number of unknown parameters, a problem which is greatly aggravated when nonlinearities are introduced. Practically, the extension of univariate nonlinear models to the multivariate setting is straightforward. But, due to the fact that relatively little amount of time-series observations available to economic forecasters, it is not very clear how best to apply nonlinear multivariate models in the area.

VECTOR AUTOREGRESSIVE (VAR) MODEL

The complexity and versatility of the relationship between economic factors make the use of simultaneous systems of equations necessary. Moreover, the difficulties usually experienced in the determination of the independent and dependent variables, which are natural consequences of the relationship between economic parameters, have a significant effect on the consistency of the analysis. Hence, some constraints are usually required on the structural model in order to overcome the problem of determination in solving simultaneous systems of equations, (Adrian and Darnell 1990). VAR model which was introduced by Sims (1980) usually help in providing solution to this problem. The definitive technical reference for VAR models is provided by Lutkepohl (1991), and further studies of VAR techniques carried out by Watson (1994) and Lutkepohl (1999) as well as Waggoner and Zha (1999). According to Keating (1990), VAR models are usually preferred in terms of time series due to the fact that dynamic relationships can be ascribed to the structural model with no restrictions. The model was equally examined by Sims and Watson (1990). Stock and Watson (2001) also applied the VAR model in data description, structural inference, and policy analysis and forecasting and highlighted the major differences between the reduced-form, structural and recursive VARs. The model is quite different from the systems of simultaneous equations due to the fact it does not require internal-external distinction of variables from any economic theory. Moreover, VAR model helps to determine the one-way relationship between variables and also in showing linkages between variables in terms of lags (Kearney and Monadjemi 1990). VAR models Forecasts are usually flexible due to the fact that they can be made conditional on the potential future paths of defined variables in the model. Also, apart from data description and forecasting, VAR model is also an important tool for policy analysis and structural inference. The presence of lagged values of the dependent variables in the model also makes it possible to achieve strong predictions for the future (Kumar *et al.* 1995). More so, they are used for Multivariate Time Series.
The nature of the model is such that every variable is a linear function of past lags of itself as well as past lags of all other variables. For instance, given three different time series variables, xt,1, xt,2, and xt,3, the vector autoregressive model of order 1, VAR(1), is such that:

$$x_{t,1}=\alpha_1+\phi_{11}x_{t-1,1}+\phi_{12}x_{t-1,2}+\phi_{13}x_{t-1,3}+w_{t,1}$$

$$x_{t,2}=\alpha_2+\phi_{21}x_{t-1,1}+\phi_{22}x_{t-1,2}+\phi_{23}x_{t-1,3}+w_{t,2}$$

$$x_{t,3}=\alpha_3+\phi_{31}x_{t-1,1}+\phi_{32}x_{t-1,2}+\phi_{33}x_{t-1,3}+w_{t,3} \quad (1)$$

Each variable in (1) is a linear function of the lag 1 values for all variables in the set.

In general, having a VAR model of order p, the first p lags of each variable in the system are used as regression predictors for each variable. In terms of forecasting values of economic variables over short-term horizon, the model has also proven successful (Watson, 1994).

STATIONARY VECTOR AUTOREGRESSIVE PROCESSES

A VAR model is usually employed when each variable in the system depends on its own lags, and also on the lags of other variables. An example of a simple VAR model is given in (2):

$$x_{1t} = \varphi_{11}x_{1,t-1} + \varphi_{12}x_{2,t-2} + \epsilon_{1t}$$

$$x_{2t} = \varphi_{21}x_{2,t-1} + \varphi_{22}x_{2,t-2} + \epsilon_{2t} \quad (2)$$

where $E(\epsilon_{1t}\epsilon_{2t}) = \sigma_{22}\ for\ t = s\ and\ 0\ fot\ t \neq s.$ We could rewrite it as

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varphi_{11} & \varphi_{12} \\ 0 & \varphi_{21} \end{bmatrix}\begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \varphi_{22} \end{bmatrix}\begin{bmatrix} x_{1,t-2} \\ x_{2,t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \quad (3)$$

Or; $X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \epsilon_t$

and *$E(\epsilon_t)$=0, $E(\epsilon_t\epsilon_s)$=0 for s$\neq$ t and*

$$E(\epsilon_t \epsilon'_t) = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

It shows clearly that the vector-valued random variable X_t is VAR process of order 2. In general, a VAR process of order p, with white noise is given by;

$$x_t = \Phi_1 x_{t-1} + \Phi 2 x_{t-2} + \ldots + \epsilon_t \quad (4)$$
$$= \sum_{j=1}^{p} \Phi_j\, x_{t-j} + \epsilon_t$$

Using the lag operator,

$$\Phi(L)x_t = \epsilon_t \quad (5)$$

where $\Phi(L) = I_k - \Phi_1 L - \cdots - \Phi_p L^p$

The error term follows a vector white noise, i.e. $E(\epsilon_t) = 0$,

$$E(\epsilon_t\epsilon_s') = \begin{cases} \Omega\ for\ t = s \\ 0\ otherwise \end{cases}$$

Given Ω a $_{(k\ x\ k)}$ symmetric positive definite matrix.
Recall that, for a scaler AR(p) process,

$$\varphi(L)x_t = \epsilon_t$$

The results are such that {x_t} is covariance stationary if and only if all the roots in (6), lies outside the unit circle.

$$1 - \varphi_1 z - \varphi_2 z^2 - \cdots - \varphi_p z^p = 0 \quad (6)$$

Similarly, for VAR(p) process to be stationary, the unit roots in (7), all lies in the unit circle.

$$|1_k - \varphi_1 z - \varphi_2 z^2 - \cdots - \varphi_p z^p| = 0 \quad (7)$$

AUTOCOVARIANCE MATRIX FOR THE VAR PROCESS

For a covariance stationary k dimensional vector process {x_t}, let E(x_t) = μ, the autocovariance is defined by the following $k\ x\ k$ matrix

$$\Gamma(h) = E[(x_{t\ -\mu})(x_{t-h} - \mu)'] \quad (8)$$

When μ = 0, Γ(h) = E($x_t x'_{t-h}$) as a result of the lead-lag effect,

we may not have Γ(h) = Γ(−h), but Γ(h)′ = Γ(−h) as follows,

$$\Gamma(h) = E(x_{t+h}x'_{t+h-h}) = E(x_{t+h}x'_t),$$

taking transpose;

$$\Gamma(\mathrm{h})' = \mathrm{E}(x_t x'_{t+h}) = \Gamma(-\mathrm{h})$$

Similarly, when we have the scalar case, the autocovariance generating function of the process is defined as;

$$G_x(z) = \sum_{-\infty}^{\infty} \Gamma(\mathrm{h}) z^h \tag{9}$$

where z is again a complex scalar.

$$\Sigma = F\Sigma F' + Q$$

To solve for Σ, we use the Kronecker product, and let A, B, C be matrices whose dimensions are such that the product ABC exists. Then;

$$vec(ABC) = (C' \otimes A) \cdot vec(B) \tag{10}$$

where vec is the operator to stack each column of the k × k matrix into a k 2 -dimensional vector.

RESULTS AND FINDINGS

The yearly data span from 2000 to 2016 and was collected from Road Transport Statistics. The results obtained below the exploratory data analysis (EDA), time plot, and vector autoregression modeling of the newly-registered motor vehicles by type of vehicles was carried out.

EXPLORATORY DATA ANALYSIS (EDA)

Table 1 shows the summary of the descriptive statistics of the nine newly registered motor vehicles by type of vehicles. The summary report for the type of vehicles shows descriptive statistics like mean, variance, standard deviation, kurtosis, skewness, minimum, as well as maximum values. Figures 1- 9 show the time plots of each type of the newly registered vehicles over the years

Table 1: Summary of Statistics

	Saloon/ Station wagon/ Jeep	*Van, Pick-up*	*Lorry/Truck*	*Minibus*	*Omnibus*	*Tanker*	*Tractor*	*Trailer*	*Tipper*
Mean	162652.5	4559	7565.176	18110.29	695.235	60.11765	65.294	152.7059	513.294
Standard Error	18024.44	657.2358	1086.763	2022.773	138.907	14.52809	9.919	48.8436	98.932
Median	166207	5817	7881	19244	552	40	50	70	532
Standard Deviation	74316.67	2709.853	4480.838	8340.108	572.726	59.90084	40.900	201.3873	407.907
Sample Variance	5.52E+09	7343301	20077907	69557404	328015.1	3588.11	1672.846	40556.85	166388.5
Kurtosis	-1.12673	-1.51959	-1.53708	-0.6096	3.053443	1.257332	3.267	5.585914	-1.738
Skewness	-0.27862	-0.30194	-0.122	-0.090	1.693	1.318	1.604	2.282964	0.032
Range	236557	8412	13084	28775	2204	204	166	775	1095
Minimum	27729	341	494	3175	116	1	17	7	0
Maximum	264286	8753	13578	31950	2320	205	183	782	1095
Sum	2765092	77503	128608	307875	11819	1022	1110	2596	8726
Count	17	17	17	17	17	17	17	17	17

Time plot

Time plot shows the movement over time of a particular variable. Figures 1-9 show time plots of the type of vehicles from 2000 to 2016. In general, we observed fluctuations and inconsistent movement over the period of time.

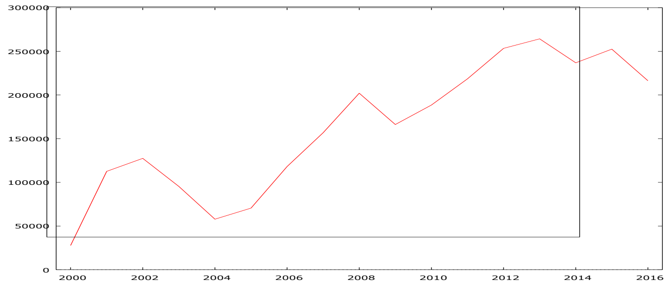

Fig 1: Time plot for Saloon

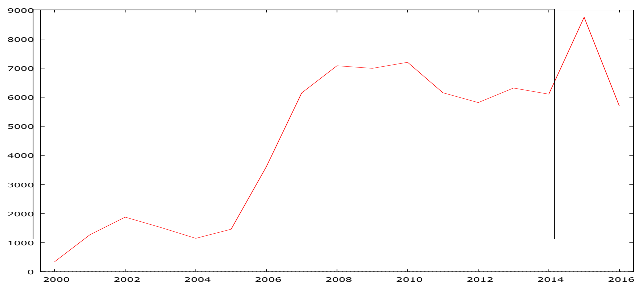

Fig 2: Time plot for Van

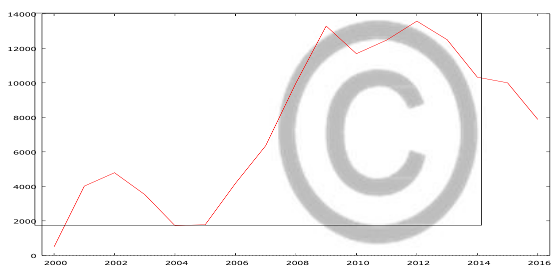

Fig 3: Time plot for Lorry

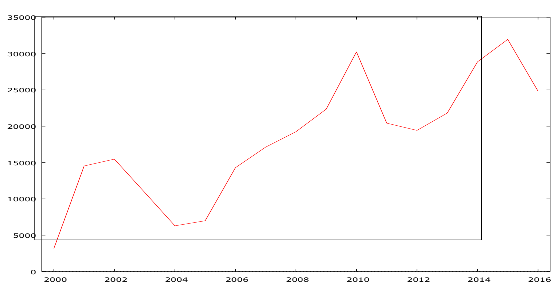

Fig 4: Time plot for Minibus

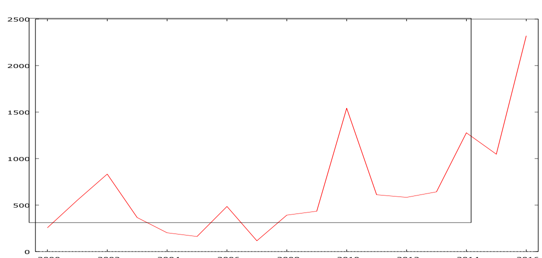

Fig 5: Time plot for Ominibus

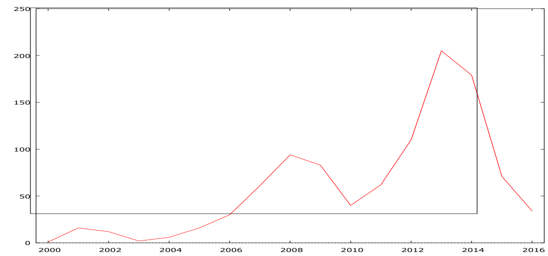

Fig 6: Time plot for Tanker

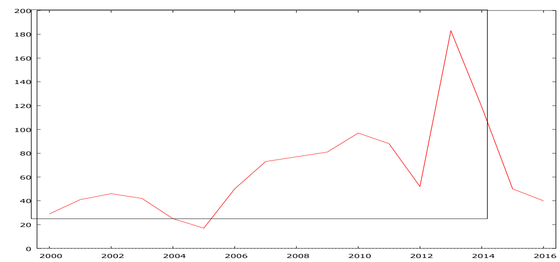

Fig 7: Time plot for Tractor

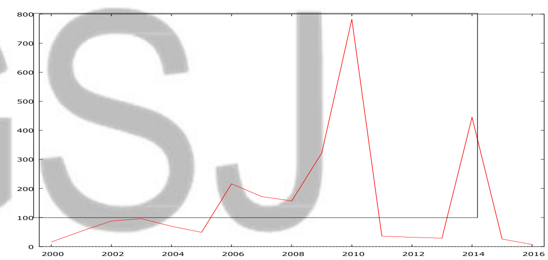

Fig 8: Time plot for Trailer

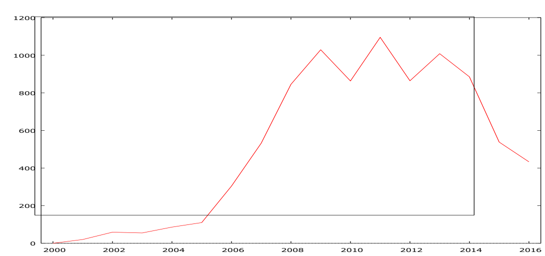

Fig 9: Time plot for Tipper

Unit root test

Usually, we check for the stationarity of each variable. In this study, we use both models of VAR in level and VAR in difference. It is because of the fact that many researchers usually use VAR model in difference but some researchers prefer the use of VAR in level regardless of the stationarity. Augmented Dickey-Fuller test statistic was carried out to test for the stationarity of the newly-registered motor vehicles series. Tables 1-10 show the unit root test with no drift and no trend, with drift and no trend and with drift and trend.

Table 2: Unit root test for Saloon Station wagon Jeep.

Type 1: no drift no trend		
Lag	ADF	P. value
0	0.446444431	0.763725016
1	0.064338729	0.653766541
2	0.3797448	0.744530878
Type 2: with drift no trend		
0	-1.828501535	0.392431879
1	-1.008918114	0.679683409
2	-0.905498826	0.715345232
Type 3: with drift and trend		
0	-2.070106736	0.527957306
1	-2.885913937	0.228758568
2	-3.176996739	0.122910277

Table 3: Unit root test for Van Pick up

Type 1: no drift no trend		
Lag	ADF	P. value
0	0.013208008	0.639052664
1	0.005487915	0.636831055
2	-0.118745714	0.60108037
Type 2: with drift no trend		
0	-1.643556289	0.459078815
1	-1.418901263	0.538309909
2	-1.362147352	0.557880223
Type 3: with drift and trend		
0	-1.481103659	0.763558536
1	-1.320521393	0.827791443
2	-2.043482045	0.538607182

Table 4: Unit root test for Lorry

Type 1: no drift no trend		
Lag	ADF	P. value
0	-0.037101217	0.624575189
1	-0.626933146	0.444448444
2	-0.400600773	0.519971001

Type 2: with drift no trend		
0	-1.672686444	0.448581462
1	-1.27700297	0.587240355
2	-1.279207873	0.586480044
Type 3: with drift and trend		
0	-0.59152477	0.96761897
1	-1.456073756	0.773570498
2	-0.981303747	0.924044887

Table 5: Unit root test for Minibus

Type 1: no drift no trend		
Lag	ADF	P. value
0	0.090366913	0.661256666
1	-0.123557192	0.599695772
2	0.501511161	0.779571557
Type 2: with drift no trend		
0	-1.996864653	0.331760485
1	-1.343826631	0.564197714
2	-0.88388338	0.722798834
Type 3: with drift and trend		
0	-2.751673306	0.277573343
1	-3.665376503	0.04533025
2	-2.871482467	0.234006376

Table 6: Unit root test for Omnibus

Type 1: no drift no trend		
Lag	ADF	P. value
0	0.127423258	0.671920362
1	0.817104365	0.870389745
2	0.652849532	0.823122167
Type 2: with drift no trend		
0	-1.187736968	0.618021735
1	-0.167186186	0.927407272
2	-0.122956438	0.933384265
Type 3: with drift and trend		
0	-2.305237202	0.439913745
1	-1.31085199	0.831659204
2	-1.933453522	0.582618591

Table 7: Unit root test for Tanker

Type 1: no drift no trend

Lag	ADF	P. value
0	-0.972630669	0.322077639
1	-1.542052079	0.120512538
2	0.577721007	0.801502448
Type 2: with drift no trend		
0	-1.636264122	0.461706623
1	-2.455901454	0.166341818
2	-0.717660986	0.780116901
Type 3: with drift and trend		
0	-1.449241419	0.776303433
1	-7.310142056	0.01
2	-4.366929659	0.010455942

Table 8: Unit root test for Tractor

Type 1: no drift no trend		
Lag	ADF	P. value
0	-1.085378873	0.28216677
1	-0.836921533	0.370116271
2	-0.369034625	0.529054784
Type 2: with drift no trend		
0	-2.454268087	0.166930419
1	-2.094385807	0.296617727
2	-1.441984895	0.530350036
Type 3: with drift and trend		
Lag	ADF	p.value
0	-2.626503716	0.323089558
1	-2.925969432	0.214192934
2	-2.508604365	0.365962049

Table 9: Unit root test for Trailer

Type 1: no drift no trend		
Lag	ADF	p.value
0	-2.426498878	0.018596197
1	-1.683499662	0.088071477
2	-1.097279248	0.277954248
Type 2: with drift no trend		
0	-3.510053314	0.018569524
1	-2.920620716	0.059911326
2	-2.321774811	0.214675744
Type 3: with drift and trend		
0	-3.357995783	0.083611697
1	-2.746868512	0.279320541
2	-2.137464631	0.501014148

Table 10: Unit root test for Tipper

Type 1: no drift no trend		
lag	ADF	p.value
0	-0.344773356	0.536036444
1	-0.464519583	0.501577098
2	-1.054285637	0.293173226
Type 2: with drift no trend		
0	-1.339210876	0.565789353
1	-1.419250173	0.538189595
2	-1.722735304	0.430545836
Type 3: with drift and trend		
0	-0.125705311	0.99
1	-0.096530438	0.99
2	-0.672214172	0.96111176

Note: in fact, p.value = 0.01 means p.value <= 0.01

Lag Length p

Lag length (p) was obtained by using different information criteria : AIC, HQ, SC, and so on. Lower values of these scores are better since these criteria penalize models that use more parameters.

Table 11: Selection and criteria level

$selection

AIC(n)	HQ(n)	SC(n)	FPE(n)
2	2	2	2

$criteria

	1	2
AIC(n)	-1.602616e+02	-Inf
HQ(n)	-1.603204e+02	-Inf
SC(n)	-1.547388e+02	-Inf
FPE(n)	8.698471e-67	0

From table 11, we could see that the highest obtainable criteria level is 1

The fitted VAR models and their respective parameter values are as follows.

Saloon = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3

where Saloon.l1=7.432013e-01, Van.l1=7.935663e+00, Lorry.l1=-8.676548e+00, Minibus.l1 = -6.522474e+00, Omnibus.l1=8.145928e+01, Tanker.l1=2.551953e+02, Tractor.l1=-7.027484e+02, Trailer.l1=2.236608e+01, Tipper.l1=1.553548e+02, const=9.666973e+04, sd1=1.050702e+04, sd2=-1.731484e+04, sd3=1.621820e+04.

Van = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=1.716068e-02, Van.l1=3.101962e-01, Lorry.l1=-4.922074e-01, Minibus.l1 = 5.587503e-02, Omnibus.l1=-3.171685e+00, Tanker.l1=1.876899e+01, Tractor.l1=-3.201190e+01, Trailer.l1=3.957000e+00, Tipper.l1=5.848877e+00, const=2.615178e+03, sd1=-1.661046e+03, sd2=-2.042747e+03, sd3=-1.158017e+03.

Lorry = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3 where Saloon.l1=5.721442e-02, Van.l1=-4.614615e-02, Lorry.l1=-6.027197e-01, Minibus.l1 = 1.542658e-02, Omnibus.l1=-2.794938e+00, Tanker.l1=-4.266456e+01, Tractor.l1=2.529578e+00, Trailer.l1=4.557908e+00, Tipper.l1=1.214531e+01, const=4.672027e+02, sd1=-1.275599e+03, sd2=1.038864e+03, sd3=6.671473e+02.

Minibus = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=-0.1362497, Van.l1=1.5657689, Lorry.l1=0.2747857, Minibus.l1 = 0.5371036, Omnibus.l1=3.0139764, Tanker.l1=130.5497539, Tractor.l1=-64.3271179, Trailer.l1=-13.7850276, Tipper.l1=6.9848662, const=15206.3930434, sd1=-2961.5729919, sd2=-2735.1798897, sd3=501.7782281.

Omnibus = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=-0.02144459, Van.l1=0.29777958, Lorry.l1=0.15590005, Minibus.l1 = 0.03576188, Omnibus.l1=1.57775363, Tanker.l1=11.98209872, Tractor.l1=-4.92010266, Trailer.l1=-2.89875277, Tipper.l1=-1.15104795, const=711.32586770, sd1=430.58963365, sd2=167.44211694, sd3=576.23751685.

Omnibus = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=0.001841068, Van.l1=0.017340478, Lorry.l1=0.002904533, Minibus.l1 = -0.020376444, Omnibus.l1=0.055594664, Tanker.l1=0.015250562, Tractor.l1=-0.069123237, Trailer.l1=0.178584939, Tipper.l1=-0.059055315, const=3.654025355, sd1=9.667957077, sd2=-6.750233718, sd3=17.618335094

Tractor = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=7.826456e-04, Van.l1=2.557420e-02, Lorry.l1=1.976976e-02, Minibus.l1 = -1.741782e-02, Omnibus.l1=4.058580e-02, Tanker.l1=2.639337e-01, Tractor.l1=-2.974469e-01, Trailer.l1=1.643274e-01, Tipper.l1=-2.097773e-01, const=4.870729e+01, sd1=-1.757357e+01, sd2-=2.452358e+01, sd3=7.559144e+00

Trailer = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=-6.895639e-03, Van.l1=8.392989e-02, Lorry.l1=9.730230e-02, Minibus.l1 = 9.538104e-03, Omnibus.l1=-3.487441e-01, Tanker.l1=1.918690e+00, Tractor.l1=1.842417e+00, Trailer.l1=-4.460801e-01, Tipper.l1=-5.625784e-01, const=3.092005e+02, sd1=-2.528011e+02, sd2=-2.137475e+02, sd3=-5.008338e+01

Tipper = Saloon.l1 + Van.l1 + Lorry.l1 + Minibus.l1 + Omnibus.l1 + Tanker.l1 + Tractor.l1 + Trailer.l1 + Tipper.l1 + const + sd1 + sd2 + sd3
where Saloon.l1=0.008913841, Van.l1=0.137920412, Lorry.l1=-0.019051378, Minibus.l1 = -0.077776221, Omnibus.l1=-0.088159596, Tanker.l1=-3.834842047, Tractor.l1=0.909017506, Trailer.l1=1.426419866, Tipper.l1=0.193445706, const = -76.645086833, sd1=-72.558757047, sd2=-2.967845447, sd3=132.295705374

Forecast for VAR in level

Using the VAR model in level, table 12 shows the forecast values obtained for the type of vehicles for the next twelve months, i.e. January to December.

Table 12: **Forecast values for the type of vehicles**

Fore cast	Saloon	Van	Lorry	Minibus	Omni bus	Tanker	Tractor	Trailer	Tipper
1	289646.84	-666.33	6604.83	20486.39	3108.79	108.27	72.67	-702.94	334.03
2	395555.04	-5652.08	1693.41	20169.99	3844.34	163.79	-4.15	-1443.79	-749.03
3	406406.29	-9921.13	-10878.54	12966.70	4333.20	225.59	24.90	-2375.12	-2120.59
4	348429.83	-19962.80	-28702.52	5449.34	6689.56	232.25	-54.25	-3164.36	-3732.94
5	382649.17	-33469.38	-48865.06	1598.24	9962.64	127.22	-255.34	-5070.00	-6383.78
6	461186.07	-55438.30	-80619.37	-11741.57	15804.83	10.78	-465.56	-7646.62	-10422.29

GSJ: Volume 11, Issue 7, July 2023
ISSN 2320-9186

7	600407.61	-92665.00	-129531.48	-49993.18	22549.04	52.29	-676.23	-12425.74	-15958.17
8	833953.38	-146704.05	-202404.78	-97686.79	32315.53	173.69	-1114.31	-19301.37	-24850.32
9	1093427.77	-220526.66	-313968.84	-153399.18	47070.98	282.69	-1636.20	-28864.48	-38306.73
10	1357483.19	-330882.07	-483936.99	-231573.35	70911.71	260.73	-2489.97	-42134.91	-58018.99
11	1823621.85	-496635.24	-730919.83	-360381.01	105227.40	93.19	-3941.48	-63371.77	-87235.71
12	2606986.24	-747780.19	-1095077.93	-559833.95	157658.94	-67.55	-6053.02	-95064.23	-130937.13

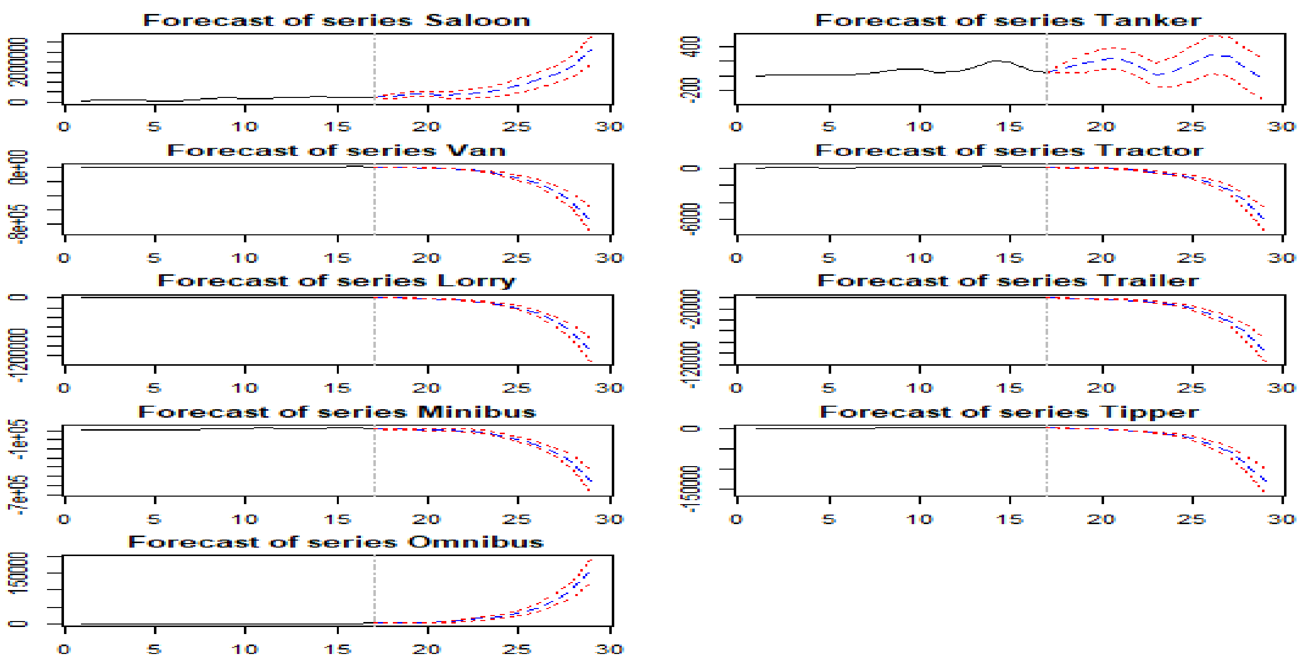

Fig 11: Forecast plot for the type of vehicles using VAR in level

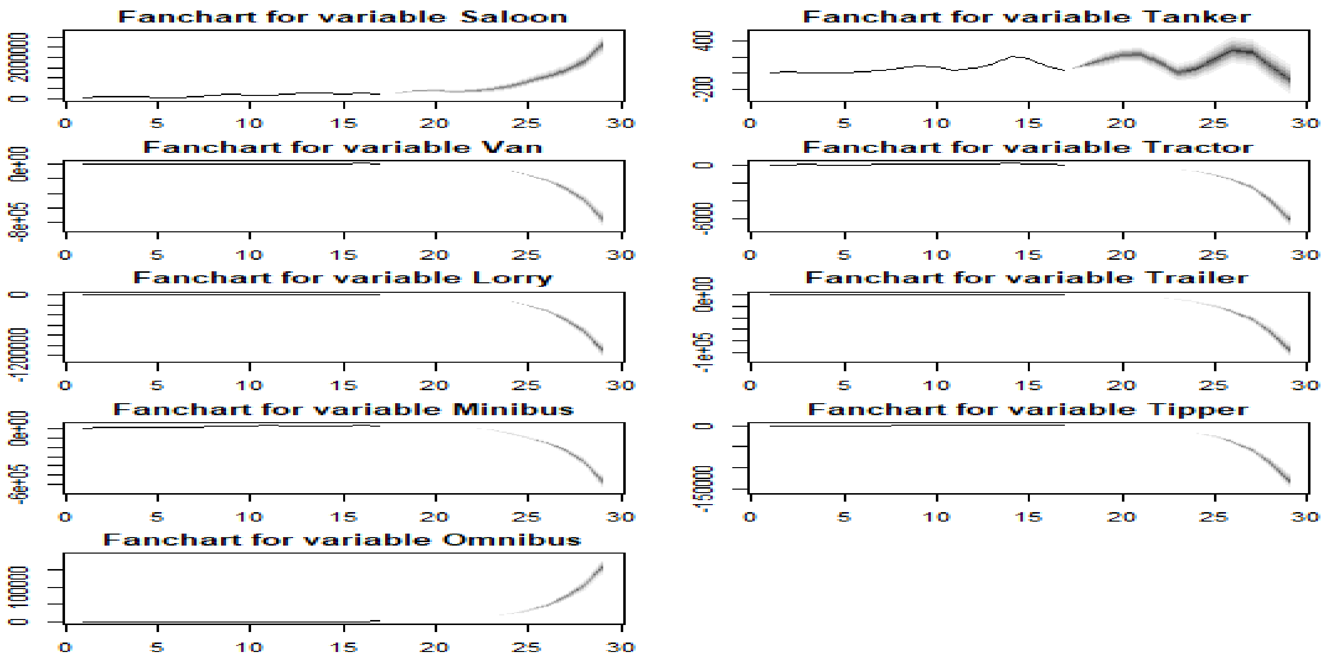

Fig 12: Fanchart for the type of vehicles using VAR in level

CONCLUSION

Recent sharp declines observed in the registration of some vehicles like van, tractor, lorry e.t.c are clear indications that many residents of the state are finding it difficult to purchase and newly register these set of vehicles. This in turn, will put pressure on the existing ones as Lagos populations increases and grows into a Mega city. The increase in registration of vehicles like saloon cars and ominbuses could be as a result of the fact that many the private vehicle owners like office workers and civil servants use saloon cars for commercial purposes before or after office hours. Many have to do this in order to get more income so as to meet up with the present economic situation in the country. Based on these findings, we would make the following recommendations to the government of Lagos State:

i. Government should ensure better economic, empowerment to boost vehicle purchasing power of citizens in the state.
ii. Road network should be improved to ensure less traffic delays for existing vehicles in the movement of goods and people from one part of the state to another.
iii. Traffic management bodies in the state should ensure enforcement of laws and orders to ensure better traffic situation.

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