MODELLING PASSENGERS TRAFFIC STATUS OF OBONG VICTOR ATTAH INTERNATIONAL AIRPORT, UYO, NIGERIA

ISSN: 2141 – 3290
www.wojast.com

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ABSTRACT

This paper investigates existence of causation between the arrivals and departures of airline data at Obong Victor Attah International Airport based on monthly data recorded from January 2010 to December 2018 using bivariate analysis. Vector Autoregressive Distributed Lag Models (VARDLM) have been developed using the existing Vector Regression Models (VRM) and Vector Autoregressive Lag Models (VARLM). The VARDLM, obtained as a combination of the VRM and the VARLM, is used to establish existence of causality between present and previous time arrivals, and also with the departures; that is, arrivals of airline passengers at a specific time depends on the departures at the same time, and vice versa. This existence of causation follows from the findings: that long period of departures contribute positively to present arrival and vice versa, and that there exists a strong correlation between the arrivals and departures which account for the significant contribution of the arrivals to departures (and departures to arrivals) at the same time period.

INTRODUCTION

Research on arrivals and departures of airline passengers is of great interest to many researchers. Afolayan *et al* (2012) investigated the trend and dynamics of rates of arrivals and departures of airline passengers at international airports in Nigeria with interest on the movements of passengers between geographical zones in relation to seasons. The researcher observed periodical variation in patronage which peaks between September to December during the Christian and Islamic festivities and pilgrimages. Mobalaji and Wilfred (2011) adopted queuing theory to analyse take-off times, arrival times, and time between arrivals and times spent in Nigerian airports. Their finding showed that some Nigeria airports are underutilised. Nuhu and Anosike (2015) also applied queuing models to analyse passengers queue at Namdi Azikiwe International Airport. The result indicated tremendous population growth at the airport. Ubogu (2013) examined the determinant factors that air travellers consider for the choice of an airport. Source of data was primary through the use of questionnaire, with passengers as respondents. His study was anchored on the availability of aircraft, low fare charges, access time to the airport, previous usage of the airport, location of the airport in the region, minimum waiting time at airport, frequency of flight at the airport, availability of parking space, the nature of airport services available. Correlation matrix was adopted to examine inter-correlations amongst variable factors. Similarly Olukayode *et al (*2016) used descriptive statistics and Pearson Moment Product correlation to evaluate airport traffic systems in Nigeria while Nisansala and Mudunkotuwa (2015) carried out multivariate co-integration analysis of air passenger movement in Srilanka. The purpose of the analysis was to test causality between air passenger movement and economy. The analysis was carried out with passenger arrivals, departures, exchange rate and GDP as variables. Various econometric tests were carried out. The analysis revealed causality amongst variables. Usoro and Omekara (2008) used trivariate time series models to analyse internally generated revenue of a local government area in Akwa Ibom State. The analysis indicated the contribution of feed-forward and feedback parameters of the response and predictor vectors. Usoro (2018) carried out time series analysis of Nigerian GDP. Bilinear and ARIMA models were used to fit the data. Bilnear outperformed the ordinary linear ARIMA models. Gujarati and Porter (2009) used VAR model to test causality between two macroeconomic variables. The variables included Money Supply and Gross Domestic Product. Bilateral causality was established between the variables. Emeka and Aham (2016) applied autoregressive distributed lag cointegration technique to investigate long-run relationship among certain economic variables. Also to mention on the use of lagged variables includes Godfrey (1978) and Irefin and Yaaba (2011). Irefin and Yaaba investigated on income, monetary policy rate, imports and exchange rate. Omotor (2010) investigated on the relationship between inflation and stock market returns using autoregressive distributed lag model with evidence from Nigeria. Others on ARDL models include Kalu et al (2015, Segun *et al* (2017), Nwachukwu et al (2016) and Egbuwalo and Abere (2018). Douglas *et al* (1998) applied VAR models to panel data. Akpansung and Babalola (2011) adopted VAR models in investigating banking sector credit and economic growth in Nigeria. Croes and Vanegas (2008) carried out cointegration and causality tests to investigate the relationship among tourism development, economic expansion and poverty reduction in Nicaragua. The research investigation revealed a long-run stable relationship among the three variables. Akpan and Friday (2012) applied Multivariate Error Correction Model to investigate causal relationship between electricity consumption, carbon emission and economic growth in Nigeria. The results indicated unidirectional causality from economic growth to carbon emission and no causality between electricity consumption and economic growth in either way.

In Akwa Ibom Airport, passenger flights commenced operations in December 2, 2009, with two routes (Uyo to Abuja and Lagos). The airport is 24 kilometres southeast of Uyo and 16 Kilometres northwest of the river port of Oron. Currently, the airport is not a busy one because passengers are within the shores of Akwa Ibom State. The numbers of arrivals and departures are not competing with some long standing airports in Nigeria, such as Port Harcourt, Lagos, Abuja, Kano Airports, and others in terms of influx of air travellers. In Akwa Ibom International Airport, airlines may sometimes schedule two flights in a day, but circumstantially end up in offering one flight. This may be accounted for by low turn-out of airline travellers prior to scheduled time of every flight. Sometimes, airline operators renege in their operational policy due to certain challenges. These are evident in incessant reschedule of flights on the pretext of logistic reasons, therefore, contributing to inconsistency and lack of reliability in the services of airline operators. These occur regardless of the fact that there are always variations between the expected and actual numbers of arrivals and departures as may be recorded by each airline. This paper presumes that there is causation between the arrivals and departures. The causation is assumed because the modes of operations of airlines affect both the arrivals and departures. This causation between the arrivals and departures depends on the time period between the departure and arrival of each airline passenger at every airport.

The time differential between the departure and arrival of an airline passenger at an airport may be daily, weekly, monthly, quarterly or yearly and is dependent upon the circumstance and event of each airline traveller. That means, an airline traveller who is not a resident of Akwa Ibom State and arrives Ibom Airport may possibly schedule his departure date within a month, and also same with an airline passenger who is resident in Akwa Ibom and travels from the airport to arrive on schedule, except in rare cases of flight cancellations or reschedules due to operational challenges of airline operators and/or un-forgone circumstance of the traveller. This strongly points to existence of correlation between the arrivals and departures. Analytically, what constitutes the difference between the arrivals and departures in air travelling is not the number, but the time difference, which may be daily, weekly, monthly, quarterly, yearly, etc.

Sequel to this development, this paper considers time series analysis of the arrivals and departures of airline travellers at Ibom International Airport. It is also of interest in this paper to consider causality between the arrivals and departure as may be explained by feed-forward and feedback contributions in the time series models.

A simple Autoregressive Distributed Lag ADL (1,1) Model, (Johnston and Dinardo, 1997) is:

$$y_t = m + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \epsilon_t \quad (1)$$

Where, y_t is the dependent time series variable, x_t is the independent time variable, m is the constant term and ϵ_t is the error term. From the model, the regressors include lagged values of the dependent variable y_t, current and lagged values of the independent variable x_t and error term ϵ_t. The ADL (p,q), is of the form

$$y_t = m + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \beta_0 x_t + \beta_1 x_{t-1} + \cdots + \beta_q x_{t-q} + \epsilon_t \quad (2)$$

Vector Autoregressive Models (VARM) are models in which every variable is regressed as a function of the distributed lags of both the dependent and independent variables. Gujarati and Porter (2009) defined VAR Models for Canadian money and interest rate as

$$M_t = \alpha + \sum_{j=1}^{k} \beta_j M_{t-j} + \sum_{j=1}^{k} \gamma_j R_{t-j} + u_{1t} \quad (3a)$$

$$R_t = \alpha' + \sum_{j=1}^{k} \theta_j M_{t-j} + \sum_{j=1}^{k} \varphi_j R_{t-j} + u_{2t} \quad (3b)$$

Where M_t represents money and R_t represents interest rate. The above VAR model established relationship between Canadian money and interest rate. The results of the analyses indicated causality between money and interest rate. Another set of models considered in this paper are models of multi-variables without lags. Given a multiple regression model by Gujarati and Porter (2009) as

$$X_1 = b_1 + b_2 X_2 + b_3 X_3 + \cdots + b_k X_k + \epsilon \quad (4)$$

where X_1 is the regressand, $X_2, X_3, \ldots, X_k$ are the regressors, with parameters $b_2, b_3, \ldots, b_k$ respectively, ϵ is the error associated with the model. Model "4" is called a multiple regression model. If each of the variables is time dependent such that every variable is expressed as a linear function of other time variables, the expansion of model "4" produces the following models;

$$X_{1t} = c_1 + \alpha_{0.12} X_{2t} + \alpha_{0.13} X_{3t} + \cdots + \alpha_{0.1k} X_{kt} + \epsilon_{1t} \quad (5)$$

$$X_{2t} = c_2 + \alpha_{0.21} X_{1t} + \alpha_{0.23} X_{3t} + \cdots + \alpha_{0.2k} X_{kt} + \epsilon_{2t} \quad (6)$$

$$X_{nt} = c_n + \alpha_{0.n1} X_{1t} + \alpha_{0.n2} X_{3t} + \cdots + \alpha_{0.nk} X_{kt} + \epsilon_{nt} \quad (7)$$

Models (5), (6) and (7) are Vector Regression Models (VRM). It is called Vector Regressive Models because the models preclude lagged parameters of all the predictor variables. In this paper, the Vector Regression (VR) and Vector Autoregressive Lag (VARL) Models are combined to form Vector Autoregressive Distributed Lag Models (VARDLM). The models are considered for the analysis and modelling of the bivariate airline passenger data.

METHODOLOGY

Statistical Method

This begins with the time plots of recorded arrivals and departures of airline passengers.

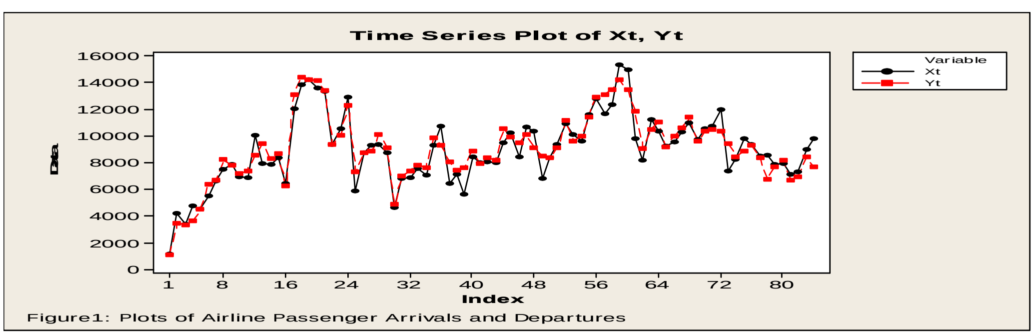

Figure1: Plots of Airline Passenger Arrivals and Departures

PRELIMINARY INVESTIGATION

The bivariate plots in Figure1 and basic statistics in Table1 provide preliminary investigation on the arrival and departure data. The statistical measures in table1 explain similarities and relationship between the two sets of data. This relationship presumes causation between the arrivals and departures of airline data.

Table1: Descriptive Statistics

Description	X_t(Arrivals)	Y_t(Departures)
No. of observations	84	84
Mean	8973	9080
Median	8872	8986
SE Mean	284	279
ST. DEV	2599	2554
Coeff. of Variation	28.97	28.13
Pearson Correlation of X_t and Y_t	0.946	

GENERALISED VECTOR AUTOREGRESSIVE DISTRIBUTED LAG MODELS

The generalised vector autoregressive distributed lag model used for simulations and analyses is given by the vector equation below:

$$\begin{pmatrix} X_{1t} \\ X_{2t} \\ \cdot \\ \cdot \\ \cdot \\ X_{nt} \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \\ \cdot \\ \cdot \\ \cdot \\ C_n \end{pmatrix} + \begin{pmatrix} \alpha_{1,11} & \alpha_{2,11} & \cdot & \cdot & \cdot & \alpha_{p,11} \\ \alpha_{1,21} & \alpha_{2,21} & \cdot & \cdot & \cdot & \alpha_{p,21} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{1,n1} & \alpha_{2,n1} & \cdot & \cdot & \cdot & \alpha_{p,n1} \end{pmatrix} \begin{pmatrix} X_{1t-1} \\ X_{1t-2} \\ \cdot \\ \cdot \\ \cdot \\ X_{1t-p} \end{pmatrix}$$

$$+ \begin{pmatrix} \alpha_{1,12} & \alpha_{2,12} & \cdot & \cdot & \cdot & \alpha_{p,12} \\ \alpha_{1,22} & \alpha_{2,22} & \cdot & \cdot & \cdot & \alpha_{p,22} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{1,n2} & \alpha_{2,n2} & \cdot & \cdot & \cdot & \alpha_{p,n2} \end{pmatrix} \begin{pmatrix} X_{2t-1} \\ X_{2t-2} \\ \cdot \\ \cdot \\ \cdot \\ X_{2t-p} \end{pmatrix} + \cdots$$

$$+ \begin{pmatrix} \alpha_{1,1n} & \alpha_{2,1n} & \cdot & \cdot & \cdot & \alpha_{p,1n} \\ \alpha_{1,2n} & \alpha_{2,2n} & \cdot & \cdot & \cdot & \alpha_{p,2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{1,nn} & \alpha_{2,nn} & \cdot & \cdot & \cdot & \alpha_{p,nn} \end{pmatrix} \begin{pmatrix} X_{nt-1} \\ X_{nt-2} \\ \cdot \\ \cdot \\ \cdot \\ X_{nt-p} \end{pmatrix}$$

The above matrix equations reduces to

$$X_{1t} = c_1 + \sum_{i=1}^{p} \alpha_{i.11} X_{1t-i} + \sum_{i=0}^{p} \alpha_{i.12} X_{2t-i} + \sum_{i=0}^{p} \alpha_{i.13} X_{3t-i} + \cdots + \sum_{i=0}^{p} \alpha_{i.1n} X_{nt-i} + \epsilon_{1t} \quad (8)$$

$$X_{2t} = c_2 + \sum_{i=0}^{p} \alpha_{i.21} X_{1t-i} + \sum_{i=1}^{p} \alpha_{i.22} X_{2t-i} + \sum_{i=0}^{p} \alpha_{i.23} X_{3t-i} + \cdots + \sum_{i=0}^{p} \alpha_{i.2n} X_{nt-i} + \epsilon_{2t} \quad (9)$$

$$X_{nt} = c_n + \sum_{i=0}^{p} \alpha_{i.m1} X_{1t-i} + \sum_{i=0}^{p} \alpha_{i.m2} X_{2t-i} + \sum_{i=0}^{p} \alpha_{i.m3} X_{3t-i} + \cdots + \sum_{i=1}^{p} \alpha_{i.mn} X_{nt-i} + \epsilon_{nt} \quad (10)$$

where, X_{it} is a n x 1 vector matrix, $\alpha_{i.jk}$ (i =1,…, p, j=1,…,n, $k = 1,\dots,n; i.e\ m = n$) are matrices of coefficients, c is an n x 1 vector of constants. Models "1", "2" and "3" are called Generalised Vector Autoregressive Distributed Lag Models (GVADLM).

Notation

Given $Y_{it}, (i = 1,\dots,n)$ and $Z_{it}, (i = 1,\dots,n)$ as vector regression and Vector autoregressive processes respectively, with Y_{it} as linear combinations of constants, A_i non-lags predictor variables and residuals, and Z_{it} as linear combinations of constants B_i, the lags of response and predictor variables and residuals.

Proposition

Let Y_{it} and Z_{it} be defined as Vector Regression Models (VRM) and Vector Autoregressive Lag Models (VARLM) respectively. The sum of Y_{it} and Z_{it} produces X_{it} ($Y_{it} + Z_{it} = X_{it}$) defines Vector Autoregressive Distributed Lag Models (VARDLM).

Proof

It is required to prove that VRM + VARLM = VARDLM

Case1:

$$Y_{it} = A_i + \sum_{j=1}^{n} \alpha_{i.jk} Y_{kt} + U_{it}, j \neq k; \ \alpha_{i.jk} = 0\ (j = k) \qquad (*1)$$

Equation $(*1)$ can be written in the form

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \\ \cdot \\ \cdot \\ \cdot \\ Y_{nt} \end{pmatrix} = \begin{pmatrix} A_1 \\ A_2 \\ \cdot \\ \cdot \\ \cdot \\ A_n \end{pmatrix} + \begin{pmatrix} 0 & \alpha_{1,12} & \alpha_{1,13} & \cdot & \cdot & \cdot & \alpha_{1,1n} \\ \alpha_{2,21} & 0 & \alpha_{2,23} & \cdot & \cdot & \cdot & \alpha_{2,2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{n,n1} & \alpha_{n,n2} & \alpha_{n,n3} & \cdot & \cdot & \cdot & 0 \end{pmatrix} \begin{pmatrix} Y_{1t} \\ Y_{2t} \\ \cdot \\ \cdot \\ \cdot \\ Y_{nt} \end{pmatrix} + \begin{pmatrix} U_{1t} \\ U_{2t} \\ \cdot \\ \cdot \\ \cdot \\ U_{nt} \end{pmatrix} \qquad (*2)$$

Where $Y_{1t}, Y_{2t}, \dots, Y_{nt}$ are vector regression time variables, $A_1, A_2, \dots, A_n$ are constants, $\alpha_{i.jk}$ are regression coefficients, $U_{1t}, U_{2t}, \dots, U_{nt}$ are residuals.

Equation $(*2)$ represents Vector Regression Models (VRM)

Case2:

$$Z_{it} = B_i + \sum_{i=1}^{p}\sum_{j=1}^{n} \alpha_{i.jk} Z_{kt-i} + V_{it}, i = 1,\dots,p\ j = 1,\dots,n, k = 1,\dots,n\ (i.e\ m = n) \qquad (*3)$$

$\alpha_{i.jk} \neq 0$. Equation $(*3)$ can be written in the form

$$\begin{pmatrix} Z_{1t} \\ Z_{2t} \\ \cdot \\ \cdot \\ \cdot \\ Z_{nt} \end{pmatrix} = \begin{pmatrix} B_1 \\ B_2 \\ \cdot \\ \cdot \\ \cdot \\ B_n \end{pmatrix} + \begin{pmatrix} \alpha_{1,11} & \alpha_{1,12} & \alpha_{1,13} & \cdot & \cdot & \cdot & \alpha_{1,1n} \\ \alpha_{1,21} & \alpha_{1,22} & \alpha_{1,23} & \cdot & \cdot & \cdot & \alpha_{1,2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{1,n1} & \alpha_{1,n2} & \alpha_{1,n3} & \cdot & \cdot & \cdot & \alpha_{1,nn} \end{pmatrix} \begin{pmatrix} Z_{1t-1} \\ Z_{2t-1} \\ \cdot \\ \cdot \\ \cdot \\ Z_{nt-1} \end{pmatrix} +$$

$$+ \begin{pmatrix} \alpha_{2,11} & \alpha_{2,12} & \alpha_{2,13} & \cdot & \cdot & \cdot & \alpha_{2,1n} \\ \alpha_{2,21} & \alpha_{2,22} & \alpha_{2,23} & \cdot & \cdot & \cdot & \alpha_{2,2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{2,n1} & \alpha_{2,n2} & \alpha_{2,n3} & \cdot & \cdot & \cdot & \alpha_{2,nn} \end{pmatrix} \begin{pmatrix} Z_{1t-2} \\ Z_{2t-2} \\ \cdot \\ \cdot \\ \cdot \\ Z_{nt-2} \end{pmatrix} + \cdots +$$

$$+ \begin{pmatrix} \alpha_{p,11} & \alpha_{p,12} & \alpha_{p,13} & \cdot & \cdot & \cdot & \alpha_{p,1n} \\ \alpha_{p,21} & \alpha_{p,22} & \alpha_{p,23} & \cdot & \cdot & \cdot & \alpha_{p,2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_{p,n1} & \alpha_{p,n2} & \alpha_{p,n3} & \cdot & \cdot & \cdot & \alpha_{p,nn} \end{pmatrix} \begin{pmatrix} Z_{1t-p} \\ Z_{2t-p} \\ \cdot \\ \cdot \\ \cdot \\ Z_{nt-p} \end{pmatrix} + \begin{pmatrix} V_{1t} \\ V_{2t} \\ \cdot \\ \cdot \\ \cdot \\ V_{nt} \end{pmatrix} \qquad (*4)$$

Where $Z_{1t}, Z_{2t}, \dots, Z_{nt}$ are vector autoregressive variables, $B_1, B_2, \dots, B_n$ are constants, $\alpha_{i.jk}$ are autoregressive coefficients, $V_{1t}, V_{2t}, \dots, V_{nt}$ are residuals.
Equation $(*4)$ represent Vector Autoregressive Lag Models (VARLM)
Let $X = Y + Z => X_{it} = Y_{it} + Z_{it}$, where $C_i = A_i + B_i$ *and* $\epsilon_{it} = U_{it} + V_{it}$. Therefore VRM + VARLM = VARDLM. This completes the proof of models (8), (9), and (10),.
The matrix of cross-covariance functions of n-dimensional vector series is

$$\begin{pmatrix} \gamma_{x_{(1t+r)},x_{(1t+s)}} & \gamma_{x_{(1t+r)},x_{(2t+s)}} & \gamma_{x_{(1t+r)},x_{(3t+s)}} & \cdots & \gamma_{x_{(1t+r)},x_{(nt+s)}} \\ \gamma_{x_{(2t+r)},x_{(1t+s)}} & \gamma_{x_{(2t+r)},x_{(2t+s)}} & \gamma_{x_{(2t+r)},x_{(3t+s)}} & \cdots & \gamma_{x_{(2t+r)},x_{(nt+s)}} \\ \gamma_{x_{(3t+r)},x_{(1t+s)}} & \gamma_{x_{(3t+r)},x_{(2t+s)}} & \gamma_{x_{(3t+r)},x_{(3t+s)}} & \cdots & \gamma_{x_{(3t+r)},x_{(nt+s)}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{x_{(mt+r)},x_{(1t+s)}} & \gamma_{x_{(mt+r)},x_{(2t+s)}} & \gamma_{x_{(mt+r)},x_{(3t+s)}} & \cdots & \gamma_{x_{(mt+r)},x_{(nt+s)}} \end{pmatrix}$$

The above square matrix is reduced to $\gamma_{x_{(jt+r)},x_{(kt+s)}}$
Cross-Correlation function matrix is

$$\rho_{x_{(jt+r)},x_{(kt+s)}} = \frac{\gamma_{x_{jt+r},x_{kt+s}}}{\sqrt{\gamma_{x_{jt}}\gamma_{x_{kt}}}} \tag{11}$$

Where, j=1,…,m, k=1,…,n, $r \neq s$, (Anthony, 2015).

CROSS-AUTOCORRELATION FUNCTIONS
Figure 2 shows cross-autocorrelation functions of the stationary X_{1t} and X_{2t} series. X_{1t} represents arrivals, while X_{2t} represents departures.

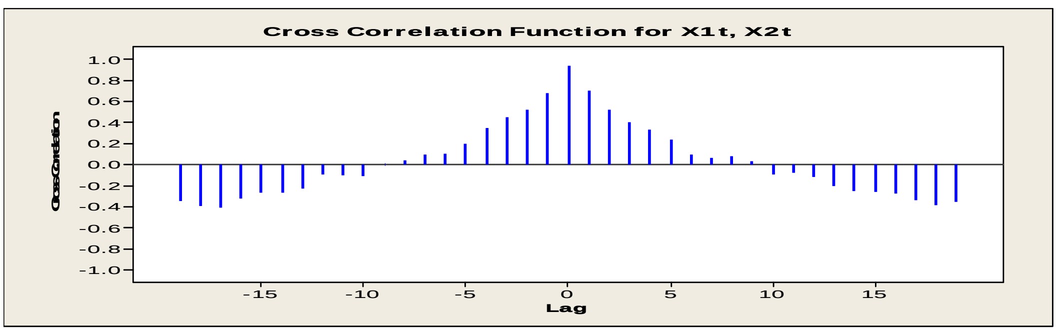

Figure 2: Cross-autocorrelation functions of X_{1t} and X_{2t}

The cross-autocorrelation functions and partial autocorrelation functions of the stationary series indicate that the series are characterised by autoregressive processes (Fig. 3). This explains the justification for VARDL models.

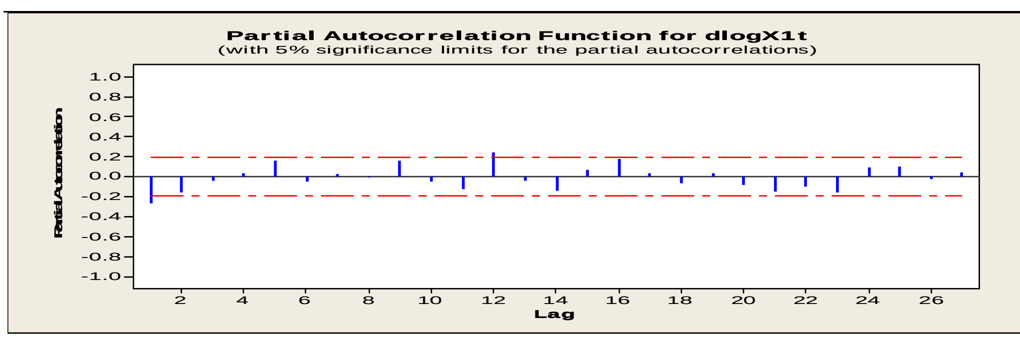

Figure 3: Partial autocorrelation functions of X_{1t}

The airline data are non-seasonal data. Besides, the distributions of Cross-ACF and PACF of the series do not exhibit seasonality to justify periodic lags.

Given the arrival and departure data X_{1t} and X_{2t} respectively, the Vector Autoregressive Distributed Lag Models for the X_{1t} and X_{2t} are

$$X_{1t} = \alpha_{0.12}X_{2t} + \alpha_{1.12}X_{2t-1} + \alpha_{2.12}X_{2t-2} + \cdots + \alpha_{p.12}X_{2t-p} + \alpha_{1.11}X_{1t-1} + \alpha_{2.11}X_{1t-2} + \cdots + \alpha_{p.11}X_{1t-p} + \epsilon_{1t} \quad (12)$$

$$X_{2t} = \alpha_{0.21}X_{1t} + \alpha_{1.21}X_{1t-1} + \alpha_{2.21}X_{1t-2} + \cdots + \alpha_{p.21}X_{1t-p} + \alpha_{1.22}X_{2t-1} + \alpha_{2.22}X_{2t-2} + \cdots + \alpha_{p.22}X_{2t-p} + \epsilon_{2t} \quad (13)$$

From model (12) , $\alpha_{0.12}$ is the feed-forward parameter of X_{2t} to X_{1t} at zero lag,
$\alpha_{1.12}, \alpha_{2.12}, \ldots, \alpha_{p.12}$ are feed-forward parameters of X_{2t} to X_{1t} at lags 1, 2, … , p respectively.
$\alpha_{1.11}, \alpha_{2.11}, \ldots, \alpha_{p.11}$ are feed-self parameters of X_{1t} to X_{1t} at lags 1, 2, … , p respectively.
From model (14), $\alpha_{0.21}$ is the feed-back parameter of X_{1t} to X_{2t} at zero lag,
$\alpha_{1.21}, \alpha_{2.21}, \ldots, \alpha_{p.21}$ are feed-back parameters of X_{1t} to X_{2t} at lags 1, 2, … , p respectively,
$\alpha_{1.22}, \alpha_{2.22}, \ldots, \alpha_{p.22}$ are feed-self parameters of X_{2t} to X_{2t} at lags 1, 2, … , p respectively.

ANALYSIS

Dynamic models with only significant parameter estimates are

$$X_{1t} = 0.928X_{2t} - 0.993X_{1t-1} - 0.923X_{1t-2} - 0.543X_{1t-3} - 0.318X_{1t-4} + 0.974X_{2t-1} + 0.791X_{2t-2} + 0.521X_{2t-3} + 0.318X_{2t-4} \quad (14)$$

$$X_{2t} = 0.664 + 0.615X_{1t-1} + 0.387X_{1t-2} - 0.694X_{2t-1} - 0.387X_{2t-2} \quad (15)$$

Table 2: Estimates of Parameters for model (14)

Predictor	Coeff.	SE. Coeff	T	P
X_{2t}	0.92837	0.06952	13.35	0.00
X_{1t-1}	-0.9929	0.09946	-9.98	0.00
X_{1t-2}	-0.9234	0.13250	-6.97	0.00
X_{1t-3}	-0.5432	0.13720	-3.96	0.00
X_{1t-4}	-0.3176	0.10090	-3.15	0.00
X_{2t-1}	0.9744	0.11810	8.25	0.00
X_{2t-2}	0.713	0.14902	5.30	0.00
X_{2t-3}	0.5208	0.14600	3.57	0.00
X_{1t-4}	0.3175	0.11340	2.80	0.00

Table 3: ANOVA estimates for model "14"

S.V	D.F	SS	MSS	F-ratio	P
Regression	9	0.753029	0.083670	36.97	0.00
Residual Error	94	0.212767	0.002263		
Total	103	0.965796			

Table 4: Estimates of Parameters for model (15)

Predictor	Coeff.	SE. Coeff	T	P
X_{1t}	0.66367	0.04610	14.40	0.00
X_{1t-1}	0.61503	0.07626	8.07	0.00
X_{1t-2}	0.38709	0.07238	5.35	0.00
X_{2t-1}	-0.69418	0.08999	-7.71	0.00
X_{2t-2}	-0.38747	0.08321	-4.66	0.00

Table 5: ANOVA estimates for model (15)

S.V	D.F	SS	MSS	F-ratio	P
Regression	5	0.416943	0.083389	47.19	0.00
Residual Error	100	0.176700	0.001767		
Total	105	0.593643			

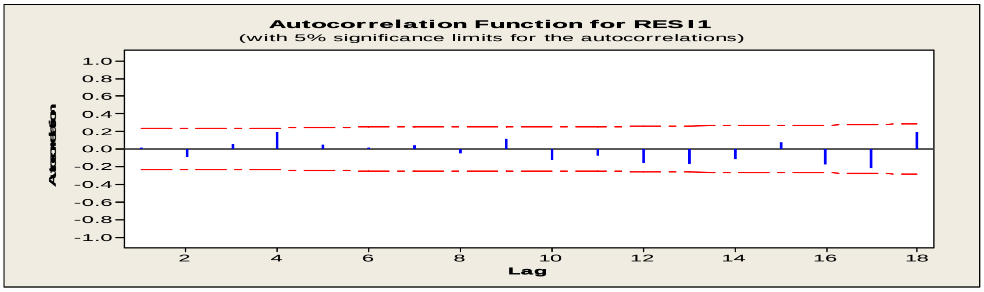

Figure 4: ACF of X_{1t} residual

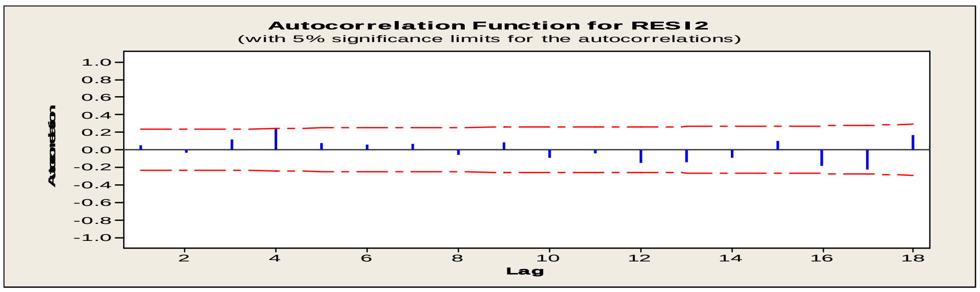

Figure 5: ACF of X_{2t} residual

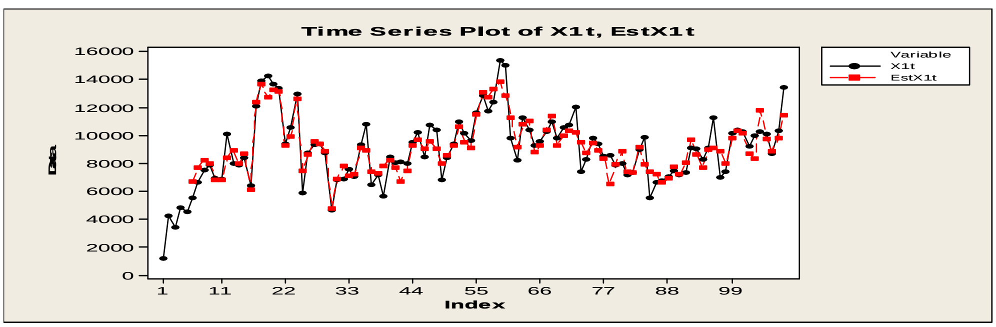

Figure 6: Plots of Actual and Estimates of Arrivals (X_{1t})

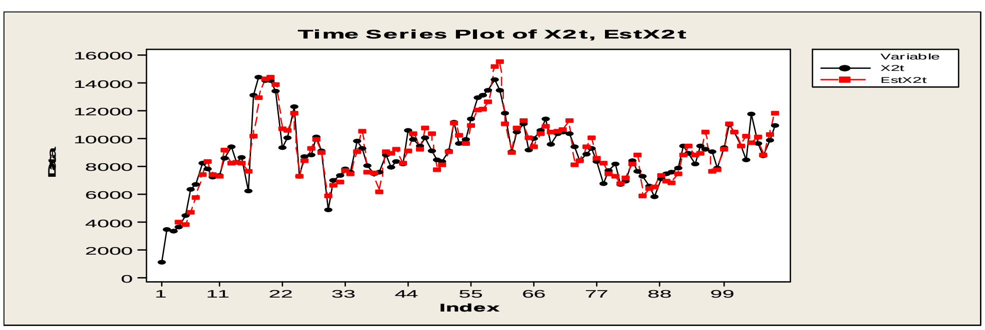

Figure 7: Plots of Actual and Estimates of Departures (X_{2t})

DISCUSSION

The generalised Vector Autoregressive Distributed Lag Models (GVARDLM) are models that establish dynamic relationship among associated variables. The models have both Vector Regression and Vector Autoregressive Lag components. The combination of the two models establishes the general VARDL models (8), (9) and (10). What differentiate the models from the existing VAR models is the introduction of VRM, which accounts for the zero lag component(s) in models (8), (9) and (10). These are clearly shown in the first matrix of parameters in subsection 3.3. From the matrices, each model includes zero lag of every independent variable in the relationship between the endogenous and exogenous variables. Models (12) and (13) are Vector Autoregressive Distributed Lag Models for $X_{1t}$and X_{2t}, representing the arrivals and departures of airline passengers at Ibom International Airport. VARDL models (12) and (13) deduced in this paper are bivariate, because empirical evidence are on two categories of data (arrivals and departures).

The distribution of PACF of the detrended series exhibits conspicuous spikes up to lag12. This increases the number of parameters in the models. In this paper, we reduce models (12) and (13) to models with significant parameter estimates. These are evident in models (14) and (15). Model (14) for X_{1t} shows the significant contribution of passenger departures at "t" time period to passenger arrivals at the same time period with 0.92837 parameter estimate. This implies that within one month interval, there is high dependent of arrivals on the departures. The difference could be in the number of days or weeks within a month, which defines a specific time period "t". The contributions of X_{1t-1},…, X_{1t-4} to X_{1t} as shown in model (14) describes long lagged negative relationship of arrivals between a specific and previous time periods. The positive parameter estimates of X_{2t-1} , … X_{2t-4}, explain long lagged positive contributions of X_{2t} to X_{1t}. Model (15) for X_{2t} has also brought to focus the fact that the departures at "t" time period depend on arrivals at the same time period. Also X_{1t-1} and X_{1t-2} contribute positively to X_{2t}, while X_{2t-1} and X_{1t-2} contribute negatively toX_{2t}. The parameter estimates in tables 2 and 4 revealed bidirectional causation between arrivals and departures. Analysis of Variances in tables 3 and 5 indicate overall fitness of the models to the sets of data. The time plots of the actual and estimates of arrivals and departures in figures 6 and 7 respectively show that actual and estimated values compete favourably.

CONCLUSION

The analysis clearly showcases the dependence of arrivals at a specific time period on the departures at the same time period and vice versa. For instance, if airline travellers depart Victor Attah International Airport on different flight schedules, there is likelihood that a maximum number of the travellers would have their different return schedules within the month. This accounts for the zero lag contribution of the departures to the arrivals at the same time period. In conclusion, the significant estimates of the parameters establish bidirectional causation between departures and arrivals at the same time period. In addition, there is a causation between present and previous time arrivals, and also applicable to departures.

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