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Forecasting Stocks with Multivariate Time Series Models.

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***ABSTRACT**: This work seeks to forecast stocks of the Nigerian banking sector using probability multivariate time series models. The study involved the stocks from six different banks that were found to be analytically interrelated. Stationarity of the six series were obtained by differencing. Model selection criteria were employed and the best fitted model was selected to be a vector autoregressive model of order 1. The model was subjected to diagnostic checks and was found to be adequate. Consequently, forecasts of stocks were generated for the next two years.*
***KEYWORDS:** Stationarity, VAR models, Stable process, White noise process and Cross correlation.*

I. INTRODUCTION

Most times, the issue of stock investment, stock market and stock trading is treated with less interest. Both the learned and the illiterate world quickly switch to other channels when stock and its related discuss are going on television. Most people find it difficult to believe that stock is another viable area to invest in especially at this period of economic doldrums. The Stock and shares represent ownership interest in a business while stock market is a branch of the capital market. The capital market is the "backbone" of any economy and is made up of the money market and the capital market. The money market (commercial banks) is concerned with the trading of short-term instruments like bank deposits, treasury bills and treasury certificates while the capital market involves the long-term instruments. The two markets complement one another and thereby leading to a robust and balanced development of the financial system. The capital market comprises markets and institutions that facilitate the issuance and secondary trading of long-term financial instruments. Meanwhile, the money market functions basically to provide short-term funds. The capital market provides funds to industries and governments to meet their long-term capital requirements such as financing of fixed investments like buildings, plants, machinery, bridges etc. The capital market plays key roles in stimulating industries thereby enhancing robust economic growth and development. One could imagine what the economy will be in the absence of a capital market. Definitely, industrial growth would be deterred as the money market is not designed to provide such funds. The presence of a secondary market such as the stock exchange is a vital aspect of the capital market. Therefore, the stock market is at the heart of capital market development in any country.

1.1 *Stock exchange*

A stock exchange is an arrangement (or place) where large and small investors alike buy and sell (through stock brokers) securities (shares and bonds) of companies and government agencies respectively. This arrangement could be through computers, telephone, fax, trading floor etc. The stock exchange provides the essential facilities for companies and government to raise money for business expansion and development projects through investors who own shares in corporations for the ultimate benefit of the economy. Stocks and shares represent ownership interest in a business. People invest in stock in other to share in the fortunes of companies. Some people buy stocks with the hope of seeing their capital grow; but keeping pace with inflation has always been the investor's primary objective.

Before investing in stock as well as any business, certain steps are necessary. The stock market is a financial game of winners and losers as is obtainable in any business. This necessitates why people understudy businesses to know its nitty-gritty before investing in them. If this is not well taken care of, the investor stands the risk of losing his investment while the opposite is the desired good news. The challenge now is how do investors identify viable stocks and guide it towards making profit? Is there a way to predict the stock market? An investor may see the price of a certain stock advancing and choose to invest in it without taking into cognizance the price movement and the likely movement in future. Being oblivious of the future can sometimes be dangerous and disastrous in business as it may cause a huge loss of investment. It is therefore pertinent that the prediction of the likelihood of the future stock trend is desirable. Time series stand tall in addressing the challenge.

For one to better understand stock prices on the stock exchange, reference on the past data is needed. Hence, the work of most researchers have been recorded and documented for the purpose of reference and historical reasons. In other that data or observations be made relevant in determination and prediction of the future, it becomes necessary that regard is made to time.

The body of techniques available for analyzing series of dependent observations is called time series (Box *et al*, 2008). Time series analysis investigates sequence of observations on a variable that have been measured at regularly recurring time points.

The analysis of time series is based on the assumption that successive values in the data file represent consecutive measurements taken at equal time intervals. There are two main goals of time series analysis which consists of identifying the nature of the phenomenon represented by the sequence of observations and forecasting (predicting future values of the time series variables). In data analysis, variables of interest can be univariate or multivariate. In the case of univariate data analysis, the response variable is influenced by only one factor while that of multivariate case is influenced by multiple factors. In some situations, however, analyzing time series using multivariate methods is reasonable because univariate analysis could be limiting. Multivariate time series analysis is employed when one wants to model and proffer explanation on the interaction and counter interaction among a group of time series variables. This work intends to study these interrelationships among variables and to build a multivariate time series model that can predict the future of stock values for six different banks in Nigeria.

II. LITERATURE REVIEW

Based on recent economic uncertainty, several discussions on the volatility of the stock market cannot be avoided. In describing the current market, Robert Engle, a finance professor at New York University stated, "We have no idea where things are going" (Merle, 2008). Many a times, investors in stock have lost their investments as a result of poor market analysis. Researchers over the years have researched on the possible methods that could enable investors in stock to manage their investments gainfully.

Abdulsalam *et al* (2011) used regression and a data mining technique to developed tools for exploiting essentially time series data in financial institutions. They built a prediction system that uses data mining technique in producing periodic forecasts of stock market prices. Their technique was a complement to proven numeric forecasting method using regression analysis. The financial information obtained from the daily activity summary (equities) was taken as input. Regression analysis was adopted as a data mining technique to describe the trends of stock market prices of the Nigerian stock exchange. Finally, predictions were made on the future stock market prices of three banks in Nigerian banking sector.

Campbell (2000) used multivariate system in modeling financial variables like stock returns. This multivariate system allows stocks in one variable to propagate to the others. Campbell (2000) used vector auto regression as a mechanism to link vector stationary time series together. It was discovered that price formation was impacted by certain frictions like trading costs, short sale restrictions and circuit breaker.

Amihud (2002) found that expected market illiquidity positively affected ex ante stock excess return over time. Additionally, stock returns were found to be negatively related over time to contemporaneous unexpected illiquidity and the illiquidity in turn affected small firm stocks strongly.

Quintana and West (2009) introduced new models for multiple time series. These new models were illustrated in an application to international currency exchange rate data. The models provided a tractable and sequential procedure for estimation of unknown covariance structure between series. They carried out a principal components analysis which enabled an easy model assessment.

Chordia *et al* (2003) explored liquidity movements in stock and treasury bond markets over a period of more than 1800 trading days. They found that a shock to quoted spreads in one market affected the spreads in other markets and the return volatility was an important drive of liquidity. Innovations to stock and bond market liquidity and volatility was proved to be significantly correlated. The correlation results confirmed that the common factors drive liquidity and volatility in the markets play an important role in forecasting stock and bond liquidity.

Lendasse *et al* (2000) developed a method to predict non-linear tools. This method was able to find non-linear relationships in artificial and real-world financial series. The method used several information as input to compress the model to a state vector of limited size. This facilitated the subsequent regression and the generalization ability of the forecasting algorithm of fitting a non-linear regression on the reduced vector. An improved result was obtained when the method was compared to linear and non-linear models that such compression was not used.

Larsen (2010) developed a stock price prediction model. He used a novel two layer reasoning approach that employed domain knowledge from technical analysis in the first layer of reasoning. This process guided a second layer of reasoning based on machine learning. The model was supplemented by a money management strategy that used the historical success of predictions made by the model to determine the amount of capital to invest on future predictions. When the method was tested based on a number of portfolio simulations with trade signals generated, the model successfully outperformed the Oslo Benchmark Index (OSEBX).

Lee *et al* (2000) used the Auto-Regressive Integrated Moving Average (ARIMA) model to examine the impact of German hyperinflation in the 1920s stock returns. The result of the study showed that the hyperinflation in Germany in early 1920s co-integrates with stock returns. The fundamental relationship between stock returns and the expected inflation was highly positive. They concluded that common stocks appear to be a hedge against inflation during this period.

Ibrahim and Agbaje (2013) exploited the analytical technique of Auto regressive Distributed Lag (ARDL) bound test and examined the long-run relationship and dynamic interactions between Stock Returns and Inflations in Nigeria using monthly Data of all Shares Price Index. The results showed that there exist a long run relationship between stock returns and inflation.

Ajayi and Mougoue (1996) investigated the short-and long- run relationship between stock prices and exchange rates in eight advanced economies. Of interest, were the results on short-run effects in the U.S. and U.K. markets. They found that an increase in stock prices caused the currency to depreciate for both the U.S. and the U.K.. Ajayi and Mougoue (1996) explained that a rising stock market is an indicator of an expanding economy, which goes together with higher inflation expectations. They added that foreign investors perceive higher inflation negatively and because of this, the demand for the currency drops and depreciates.

Owing to the above reviews, multivariate time series models are very crucial in modeling and identifying the joint structure on which decisions could depend. The time varying techniques possess the properties of providing an insight into the multivariate structure of several interrelated series. The intent of this work is to identify the correlation structure of stock series of six Banks in Nigeria and possibly build a multivariate time series model for the prediction of future stocks.

III. METHODOLOGY

3.1 *Stationarity*

A time series is said to be stationary if its statistical properties remain constant through time. These properties are mean, variance etc. A non stationary series Z_t can be made stationary by differencing. The differenced series is given as

$$z_t = Z_t - Z_{t-1} = \nabla Z_t \qquad (1)$$

3.2 *Backward shift Operator*

The Backward shift Operator B is defined by

$$B^m Z_t = Z_{t-m} \qquad (2)$$

3.3 *The Backward Difference Operator*

The backward difference operator,∇ , is define by

$$\nabla = 1 - B \qquad (3)$$

3.4 *Cross Correlation*

Given two time series variables X_t and Y_t, the cross correlation for $lag\ k$ is given as

$$r(xy) = \frac{C_{xy}}{S_x S_y} \qquad (4)$$

where,

$$c_{xy} = \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \bar{x})\,(y_{t+k} - \bar{y}) \quad k = 0,\ 1,2\ \ldots \quad ;$$

$\bar{x}$ and $\bar{y}$ are the sample means of x_t and y_t, s_x and s_y are the sample standard deviations respectively.

3.5 *White Noise Process*

A white noise process $\underline{a_t} = (a_{1t}, \ldots, a_{kt})'$ is a continuous random vector satisfying

$$E(a_t) = 0,\ E(a_t\ a_t{}') = \Sigma_a \text{ and } E(a_t a_s') = 0 \text{ for } s \neq t. \qquad (5)$$

$\Sigma_a =$ covariance matrix which is assume to be non singular if not otherwise stated.

3.6 *Vector Autoregressive (VAR) Model*

The vector autoregressive (VAR) model gives an approach in modeling dynamics among a set of time dependent variables. It is an independent reduced form of dynamic model which entails constructing equation that makes each endogenous variable a function of their own past values as well as past values of all other endogenous variables. The basic p-lag Vector autoregressive VAR(p) model has the form.

$$z_t = c + \Phi_1 z_{t-1} + \Phi_2 z_{t-2} + \cdots + \Phi_p z_{t-p} + \mathrm{a}_t \quad ;\ t = 0, \pm 1, \pm 2, \ldots \qquad (6)$$

where

$z_t = (z_{1t}, \ldots, z_{kt})'$ is a $(k \times 1)$ vector of time series variable,

Φ_i are fixed $(k \times k)$ coefficient matrices,

$c = (c_1, \ldots, c_k)'$ is a fixed $(k \times 1)$ vector of intercept terms

$a_t = (a_{1t}, \ldots, a_{kt})'$ is an $(k \times 1)$ white noise process

The model can be expressed explicitly in matrix form:

$$\begin{pmatrix} z_{1t} \\ z_{2t} \\ \cdot \\ \cdot \\ z_{kt} \end{pmatrix} =$$

$$\begin{pmatrix} \phi_{11}^1 & \phi_{12}^1 & \cdot & \cdot & \phi_{1k}^1 \\ \phi_{21}^1 & \phi_{22}^1 & \cdot & \cdot & \phi_{2k}^1 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \phi_{k1}^1 & \phi_{k2}^1 & \cdot & \cdot & \phi_{kk}^1 \end{pmatrix} \begin{pmatrix} z_{1t-1} \\ z_{2t-1} \\ \cdot \\ \cdot \\ z_{kt-1} \end{pmatrix} + \begin{pmatrix} \phi_{11}^2 & \phi_{12}^2 & \cdot & \cdot & \phi_{1k}^2 \\ \phi_{21}^2 & \phi_{22}^2 & \cdot & \cdot & \phi_{2k}^2 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \phi_{k1}^2 & \phi_{k2}^2 & \cdot & \cdot & \phi_{kk}^2 \end{pmatrix} \begin{pmatrix} z_{1t-2} \\ z_{2t-2} \\ \cdot \\ \cdot \\ z_{kt-2} \end{pmatrix}$$

$$+ \cdots + \begin{pmatrix} \phi_{11}^p & \phi_{12}^p & \cdot & \cdot & \phi_{1k}^p \\ \phi_{21}^p & \phi_{22}^p & \cdot & \cdot & \phi_{2k}^p \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \phi_{k1}^p & \phi_{k2}^p & \cdot & \cdot & \phi_{kk}^p \end{pmatrix} \begin{pmatrix} z_{1t-p} \\ z_{2t-p} \\ \cdot \\ \cdot \\ z_{kt-p} \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ \cdot \\ \cdot \\ a_{kt} \end{pmatrix} \quad (7)$$

3.7 *Stable VAR (p) Processes*

The process (6) is stable if the roots of the auxiliary equation lie outside the unit circle. That is if

$$\det\left(I_n - \Phi_1 z - \cdots - \Phi_p z^p\right) \neq 0 \text{ for } |z| \leq 1. \quad (8)$$

A stable VAR(p) process $z_t, t = 0, \pm 1, \pm 2, ...$, is stationary.

3.8 *Autocovariances of a Stable VAR(p) Process*

Subtracting the mean μ from the $VAR(p)$ gives

$$z_t - \mu = \phi_1(z_{t-1} - \mu) + \cdots + \phi_p\left(z_{t-p} - \mu\right) + a_t \, , \quad (9)$$

Post multiplying both sides by $(z_{t-l} - \mu)'$ and taking expectation, we have for $l = 0$ using $\Gamma_z(i) = \Gamma_z(-i)'$

$$\begin{aligned} \Gamma_z(0) &= \phi_1(z_{t-1} - \mu) + \cdots + \phi_p\left(z_{t-p} - \mu\right) + \Sigma_a \\ &= \phi_1 \Gamma_z(1)' + \cdots + \phi_p \Gamma_z(p)' + \Sigma_a \end{aligned} \quad (10)$$

If $h > 0$

$$\Gamma_z(l) = \phi_1 \Gamma_z(l-1) + \cdots + \phi_p \Gamma_z(l-p) \quad (11)$$

From these equations, the autocovariance functions Γ_z(l) for $l \geq p$ can be obtained if $\phi_1, ..., \phi_p$ and Γ_z(p − 1,…,Γl0 are known.

3.9 *Autocorrelation of a Stable VAR(p) Process*

The autocorrelations of a stable VAR (p) process are obtained from the matrix

$$R_z(l) = D^{-1} \Gamma_z(l) D^{-1} \quad (12)$$

Where, D is a diagonal matrix with the standard deviation of the component of z_t on the main diagonal. Thus,

$$D^{-1} = \begin{bmatrix} \frac{1}{\sqrt{\gamma_{11}(0)}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{\sqrt{\gamma_{kk}(0)}} \end{bmatrix} \quad (13)$$

and the correlation between $z_{i,t}$ and $z_{j,t-l}$ is

$$\rho_{ij}(l) = \frac{\gamma_{ij}(l)}{\sqrt{\gamma_{ii}(0)}\sqrt{\gamma_{jj}(0)}} \quad (14)$$

which is just the $ij -$ th element of $R_z(l)$.

3.10 *VAR Order Selection*

The three selection criteria that will be used to determine the order p of the VAR process are:

(i) *Akaike Information Criterion* (AIC) given as

$$\begin{aligned} AIC(p) &= In\left|\tilde{\Sigma}_\varepsilon(p)\right| + \frac{2}{N}(\text{number of estimated parameter}) \\ &= In\left|\tilde{\Sigma}_a(p)\right| + \frac{2pk^2}{N} \end{aligned}$$

(ii) *Hannan-Quin Criterion* (HQC) given as

$$\begin{aligned} HQC(p) &= In\left|\tilde{\Sigma}_a(p)\right| + \frac{2Ink}{N}(freely\ estimated\ parameters) \\ &= In\left|\tilde{\Sigma}_a(p)\right| + \frac{2InN}{N} pn^2 \end{aligned}$$

(iii) *Bayesian Information Criterion* (BIC) given as

$$BIC(p) = In\left|\tilde{\Sigma}_a(p)\right| + \frac{InN}{N}(freely\ estimated\ parameters)$$

$$= In\left|\widetilde{\Sigma}_a(p)\right| + \frac{2InN}{N}pk^2$$

where p is the VAR order,
$\widetilde{\Sigma}_a$ is the estimate of white noise covariance matrix Σ_ε
k is the number of time series components of the vector time series
N is the sample size.
In all the criteria above, each estimate is chosen so as to minimize the value of the criterion.

IV. DIAGNOSTIC CHECKS

There is always a need to diagnose a model after being fitted to a data. This is primarily done to examine whether the model is adequate or not. A general way of achieving this is to examine the behaviour of the residuals matrices. Under the assumption of model adequacy, the residuals are expected to follow a white noise process. According to Lutkepohl (2005); if $\rho_{uv}(i)$ is the true correlation coefficients corresponding to the $r_{uv}(i)$, then we have the following hypothesis test at 5% level to check whether or not a given multivariate series follows a white noise process or not. The hypothesis states:

$$H_0 : \rho_{uv}(i) = 0 \quad \text{versus} \quad H_1 : \rho_{uv}(i) \neq 0$$

Decision: Reject H_0 if $\left|r_{uv,i}\right| > \frac{2}{\sqrt{N}}$

To test for H_0 , the autocorrelations of the residuals are computed and their absolute values are compared with $\frac{2}{\sqrt{N}}$. If these absolute values are all less than $\frac{2}{\sqrt{N}}$; it is concluded that the multivariate model is adequately fitted.

V. FORECASTING

Suppose the fitted model in (6) is found to be adequate, then it can used to generate forecasts. The forecasts are generated by obtaining the estimates:

$$\widehat{z_t} = \hat{c} + \widehat{\Phi_1} z_{t-1} + \widehat{\Phi_2} z_{t-2} + \cdots + \widehat{\Phi_p} z_{t-p} \qquad ; \ t = 0, \pm 1, \pm 2, \ldots$$

Given the forecast origin t, the forecasts so obtained are the minimum mean square error forecasts (Lutkepohl, 2005**).**

VI. DATA ANALYSIS AND RESULTS

The multivariate data used for this work are the monthly recorded stocks from first Bank (Z_{1t}), Access Bank (Z_{2t}), UBA (Z_{3t}), Union Bank (Z_{4t}), GTB (Z_{5t}) and Wema Bank (Z_{6t}). Thus, the multivariate time series can be represented as the random vector $Z_t = (Z_{1t}, Z_{2t}, Z_{3t}, Z_{4t}, Z_{5t}, Z_{6t})$. The data which spans between 1999 to 2015 displayed in table 2 of appendix E. The R-software was used in the analysis.

6.1 *Time Series Plot*

The time series plot of the six time series data are displayed as multiple graphs in figure 1 below.

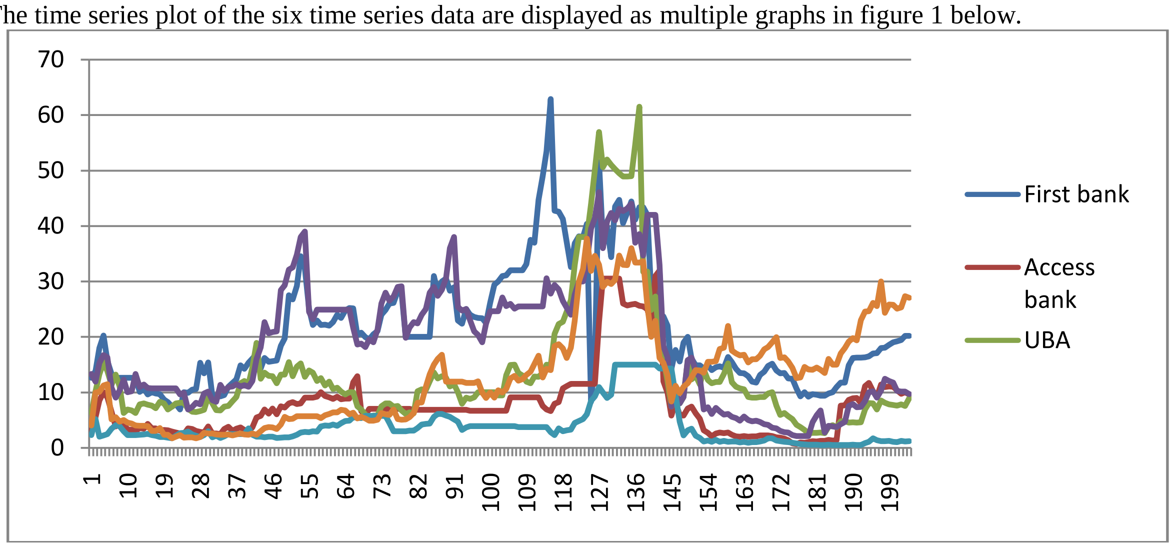


Figure 1 : Time series plot of the six raw series

It is quite clear from the above plots that none of the series is stationary. Differencing is therefore required to achieve stationary.

6.2 *Differenced Series Plots*

Using the first difference in equation (1), the plot of the differenced series is shown in figure 2 below.

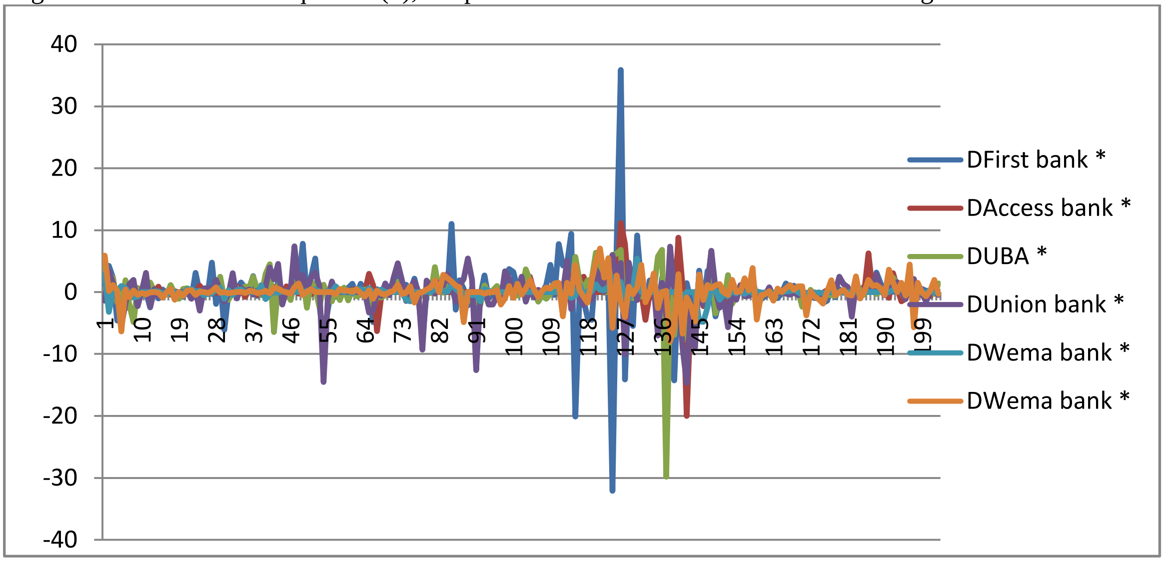


Figure 2 : Time series plot of the six differenced series

The plots in figure 2 clearly show that the six series are stationary and the multivariate technique can now be applied.

6.3 *The Raw data Correlation Matrix*

The correlation matrix of the six random variables $\left(Z_{t(Corr.)}\right)$ below shows that the variables are highly positively correlated. Hence, the multivariate technique can address the interrelationship amongst the variables.

$$Z_{t(Corr.)} = \begin{pmatrix} 1.000 & 0.655 & 0.636 & 0.801 & 0.055 & 0.750 \\ 0.655 & 1.000 & 0.800 & 0.740 & 0.803 & 0.605 \\ 0.636 & 0.800 & 1.000 & 0.704 & 0.718 & 0.649 \\ 0.801 & 0.740 & 0.704 & 1.000 & 0.691 & 0.789 \\ 0.556 & 0.803 & 0.718 & 0.691 & 1.000 & 0.806 \\ 0.750 & 0.605 & 0.649 & 0.789 & 0.806 & 1.000 \end{pmatrix}$$

6.4 *The Cross Correlations*

The cross correlation matrices at different lags (lags 1 – 5) are displayed in appendix A. The high values further confirm the interrelationship among the variables and the appropriateness of fitting multivariate model to the series.

6.5 *Model Selection*

The AIC, BIC and HQC at the different lags are displayed in table 1of appendix B. The three selection criteria attains minimum (the bolded values) at lag 1. Hence the selected model is $VAR(1)$.

6.6 *Model Presentation*

Using equation (7) in the methodology, the $VAR(1)$ model with significant parameters is presented in matrix form as shown:

$$\begin{pmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \\ z_{4t} \\ z_{5t} \\ z_{6t} \end{pmatrix} = \begin{pmatrix} 0.357 \\ 0.000 \\ 0.000 \\ 0.000 \\ -0.348 \\ 0.000 \end{pmatrix} + \begin{pmatrix} 0.718 & 0.000 & 0.000 & 0.000 & 0.000 & 0.058 \\ 0.000 & 0.882 & 0.000 & 0.000 & 0.000 & 0.301 \\ 0.000 & 0.000 & 0.940 & 0.000 & -0.041 & 0.169 \\ 0.000 & 0.000 & 0.000 & 0.998 & 0.000 & 0.000 \\ 0.000 & -0.119 & 0.017 & 0.106 & 0.842 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.975 \end{pmatrix} \begin{pmatrix} z_{1t-1} \\ z_{2t-1} \\ z_{3t-1} \\ z_{4t-1} \\ z_{5t-1} \\ z_{6t-1} \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \\ a_{5t} \\ a_{6t} \end{pmatrix} \tag{15}$$

This can be expressed explicitly as follows:

First Bank : $z_{1t} = 0.357 + 0.718z_{1t-1} + 0.058z_{6t-1} + a_{1t}$ (16)

Access Bank : $z_{2t} = 0.882z_{2t-1} + 0.301z_{6t-1} + a_{2t}$ (17)

UBA : $z_{3t} = 0.940z_{3t-1} - 0.041z_{5t-1} + 0.169z_{6t-1} + a_{3t}$ (18)

Union Bank : $z_{4t} = 0.998z_{4t-1} + a_{4t}$ (19)

Wema Bank : $z_{5t} = -0.348 - 0.119z_{2t-1} + 0.017z_{3t-1} + 0.106z_{4t-1} + 0.842z_{5t-1} + a_{5t}$ (20)

GTB : $z_{6t} = 0.975z_{6t-1} + a_{6t}$ (21)

VII. DIAGNOSTIC CHECKS

After obtaining the multivariate model (15), the next step is to ascertain whether the model is adequately fitted or not. The following diagnoses are carried out to this effect.

7.1 *Residual Autocorrelation Function*

As stated in section 4 of the methodology, the following hypothesis are applied:

$$H_0: \rho_{uv}(i) = 0 \text{ versus } H_1 : \rho_{uv}(i) \neq 0$$

In the series, we had $n = 204$

This gives the boundary condition for residual autocorrelation function to be

$$\frac{2}{\sqrt{204}} = 0.1400$$

and H_0 is rejected if $\left| r_{uv,i} \right| > \frac{2}{\sqrt{n}} = 0.1400.$

Comparing the values of autocorrelations in the residual correlation matrices at different lags (lags 1 – 3) in appendix A with $\left| r_{uv,i} \right|$, we find that none of the residual autocorrelations is greater than 0.1400. This means that the residuals follow a white noise process. In other words, the fitted model is adequate.

7.2 *Residual Plots*

The residual plots obtained by fitting the model (15) are plotted in appendix D. The plots show that all the six residual series: $a_{1t}, a_{2t}, a_{3t}, a_{4t}, a_{5t}, a_{6t}$ of the residual vector a_t resemble a white noise process which is part of the assumptions needed to be satisfied for model adequacy.

VIII. FORECASTS

Since the constructed model has satisfied the basic assumption of model adequacy, it can be used for generating forecasts. The forecasts for the years 2016 and 2017 generated by multivariate model are displayed in table 1 of appendix E.

IX. DISCUSSION AND CONCLUSION

Forecasting stocks is very important in the banking sector especially in the present day devastating economy in Nigeria. Since the gains and losses in stocks are highly probable, there is need to be guided by probability models that can predict the future stocks. Such models are time series models which could either be univariate or multivariate. Univariate models can only handle a series that is independent of any other series. However, many time series that arise in nature are interrelated. The interrelationship of such series can easily be revealed by the correlation structure exhibited by the series. The stocks of the different banks considered in this work were found to be highly correlated; and the applied multivariate methods took care of the correlation structure of the component series of the vector. Since the constructed multivariate model was found to be adequate, the generated forecasts are reliable. The forecasts can serve as a guide to banks that may wish to involve in stocks in 2017.

Appendix A: Raw Data Cross Correlations at different Lags

(i) Lag 1

$$\begin{pmatrix} 0.656 & & & & \\ 0.636 & 0.801 & & & \\ 0.802 & 0.742 & 0.704 & & \\ 0.556 & 0.805 & 0.718 & 0.690 & \\ 0.653 & 0.606 & 0.657 & 0.597 & 0.714 \end{pmatrix}$$

(ii) Lag 2

$$\begin{pmatrix} 0.656 & & & & \\ 0.636 & 0.803 & & & \\ 0.802 & 0.745 & 0.703 & & \\ 0.557 & 0.808 & 0.718 & 0.689 & \\ 0.657 & 0.608 & 0.666 & 0.506 & 0.524 \end{pmatrix}$$

(iii) Lag 3

$$\begin{pmatrix} 0.656 & & & & \\ 0.636 & 0.808 & & & \\ 0.803 & 0.752 & 0.702 & & \\ 0.557 & 0.810 & 0.717 & 0.689 & \\ 0.661 & 0.609 & 0.673 & 0.513 & 0.631 \end{pmatrix}$$

(iv) Lag 4

$$\begin{pmatrix} 0.658 & & & & \\ 0.636 & 0.808 & & & \\ 0.803 & 0.752 & 0.702 & & \\ 0.557 & 0.817 & 0.717 & 0.687 & \\ 0.769 & 0.610 & 0.688 & 0.526 & 0.549 \end{pmatrix}$$

(v) Lag 5

$$\begin{pmatrix} 0.658 & & & & \\ 0.636 & 0.808 & & & \\ 0.803 & 0.752 & 0.702 & & \\ 0.557 & 0.817 & 0.717 & 0.687 & \\ 0.669 & 0.610 & 0.688 & 0.526 & 0.549 \end{pmatrix}$$

Appendix B

Table 1: Values of the Selected Criteria with their Respective lags

SN	*p*	AIC	BIC	HQC	M(*p*)	*p - Value*
1	0	-8.9166	-8.9166	-8.9166	0	0
2	**1**	**-22.1034**	**-21.5179**	**-21.8666**	2484.5532	0
3	2	-21.9974	-20.8263	-21.5237	43.8279	0.1735
4	3	-21.8943	-20.1377	-21.1837	42.8496	0.2009
5	4	-21.7537	-19.4115	-20.8062	35.1302	0.5098
6	5	-21.6691	-18.7413	-20.4847	42.7995	0.2023
7	6	-21.4904	-17.9771	-20.0692	26.7579	0.8684
8	7	-21.322	-17.2232	-19.664	27.2192	0.8538
9	8	-21.2109	-16.5265	-19.316	34.2149	0.5537
10	9	-21.12358	-15.8659	-19.004	37.6525	0.3935
11	10	-21.0089	-15.1534	-18.6402	29.2669	0.7791
12	11	-20.9415	-14.5004	-18.3359	35.2615	0.5035
13	12	-21.0198	-13.993	-18.1774	50.6697	0.0533
14	13	-20.9061	-13.2939	-17.8268	26.6779	0.8709

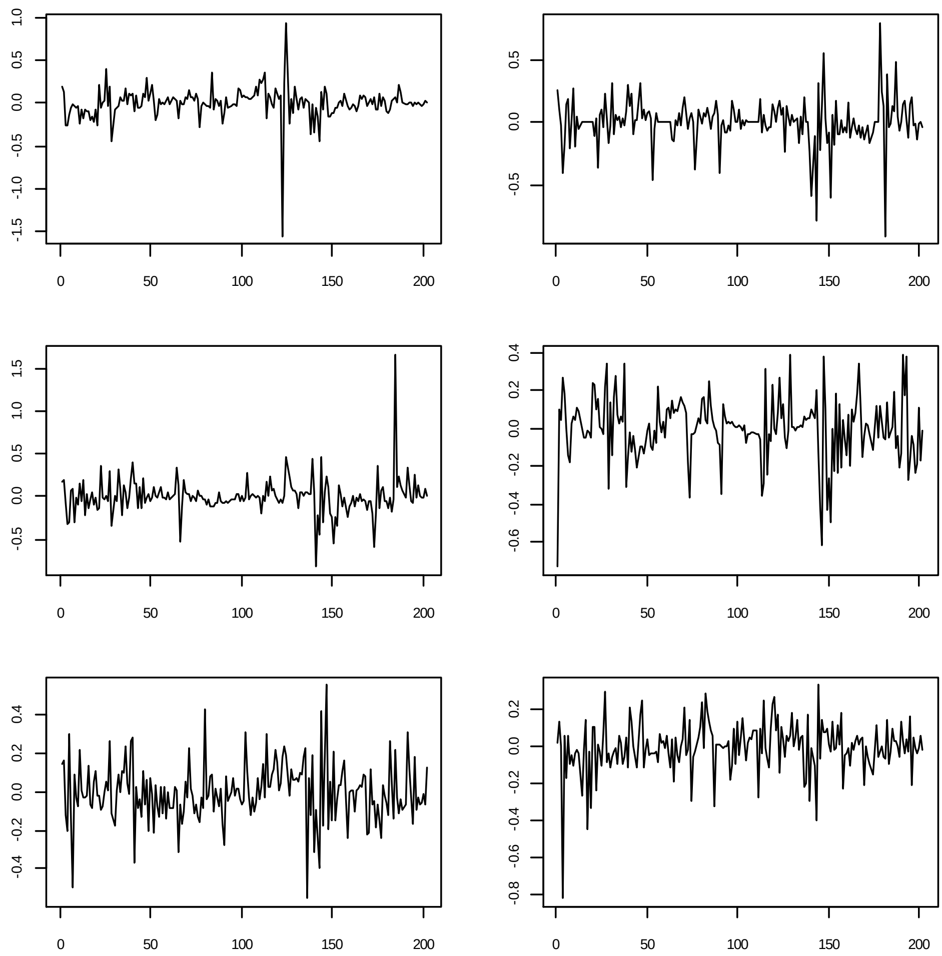
Appendix C: Residual Autocorrelation Matrices (lag 1-3) of the Fitted Model

$$R_1 = \begin{pmatrix} 0.001 & 0.010 & 0.051 & 0.013 & 0.091 & 0.082 \\ 0.020 & 0.023 & 0.050 & 0.111 & 0.078 & 0.001 \\ 0.022 & 0.130 & 0.072 & 0.071 & 0.101 & 0.020 \\ 0.010 & 0.003 & 0.006 & 0.067 & 0.004 & 0.005 \\ 0.041 & 0.021 & 0.016 & 0.002 & 0.007 & 0.000 \\ 0.110 & 0.035 & 0.091 & 0.077 & 0.084 & 0.003 \end{pmatrix}$$

$$R_2 = \begin{pmatrix} 0.011 & 0.022 & 0.121 & 0.066 & 0.011 & 0.055 \\ 0.033 & 0.033 & 0.112 & 0.044 & 0.018 & 0.123 \\ 0.012 & 0.111 & 0.033 & 0.024 & 0.034 & 0.097 \\ 0.042 & 0.071 & 0.011 & 0.069 & 0.114 & 0.016 \\ 0.041 & 0.072 & 0.010 & 0.011 & 0.023 & 0.022 \\ 0.012 & 0.005 & 0.022 & 0.054 & 0.111 & 0.005 \end{pmatrix}$$

$$R_3 = \begin{pmatrix} 0.021 & 0.011 & 0.023 & 0.033 & 0.111 & 0.071 \\ 0.055 & 0.056 & 0.022 & 0.015 & 0.000 & 0.022 \\ 0.038 & 0.122 & 0.051 & 0.021 & 0.051 & 0.077 \\ 0.011 & 0.055 & 0.015 & 0.069 & 0.011 & 0.062 \\ 0.011 & 0.022 & 0.052 & 0.032 & 0.072 & 0.011 \\ 0.021 & 0.072 & 0.033 & 0.045 & 0.023 & 0.014 \end{pmatrix}$$

Appendix D: Time Series Plots of the Residuals ($a_{1t}, a_{2t}, a_{3t}, a_{4t}, a_{5t}, a_{6t}$) Respectively



Appendix E

Table 1 : Forecasts of the Multivariate Model

Year	Month	First bank	Access bank	UBA	Union bank	Wema bank	GTB
2016	JAN	13.5	3.31	9.46	11.82	2.51	2.88
	FEB	13.86	3.02	11.13	11.44	2.77	2.72
	MAR	16.11	3.72	12.15	11.93	2.46	2.74
	APR	15.56	3.41	12.82	12.22	3.44	2.95
	MAY	16.35	4.17	14.12	12.01	3.16	2.44
	JUN	17.16	5.16	19.01	16.93	1.44	2.54
	JUL	13.62	5.23	13.51	18.56	2.89	4.31
	AUG	16.24	5.72	13.6	23.99	1.34	3.83
	SEP	15.74	7.34	12.96	20.87	2.11	3.98
	OCT	15.22	7.45	12.88	21.65	2.57	3.33
	NOV	15.33	7.23	11.6	21.74	1.56	4.01
	DEC	17.42	8.16	13.21	27.36	1.67	4.06
2017	JAN	21.22	6.13	11.32	27.01	5.44	13.11
	FEB	31.18	7.36	14.6	29.67	5.87	15.02
	MAR	27.13	5.23	12.33	27.89	6.47	16.72
	APR	29.21	6.45	13.72	29.22	6.23	16.18
	MAY	31.61	6.19	12.08	31.77	7.13	11.11
	JUN	28.71	6.26	12.16	39.56	5.17	12.01
	JUL	27.53	7.62	11.44	39.21	5.67	11.13
	AUG	20.15	6.77	10.55	26.33	4.99	11.24
	SEP	21.34	6.38	7.05	25.65	3.62	12.55
	OCT	23.66	6.92	9.77	25.34	3.82	11.19
	NOV	23.17	6.15	8.82	23.55	3.16	12.13
	DEC	23.01	6.78	9.35	21.44	3.37	11.22

Table 2 : Stock Data of the Six Banks

Year	Month	First bank	Access bank	UBA	Union bank	Wema bank	GTB
1999	JAN	12.6	3	6.25	13.3	2.3	4.05
	FEB	13.8	5.5	10.2	11.9	5.19	9.95
	MAR	18	8.5	13.25	15.25	2	10.1
	APR	20.25	10	15.45	16.7	2.24	11.25
	MAY	15.65	9.1	13.8	16.3	2.47	11.45
	JUN	13.28	6.47	11.3	10.8	3.45	5.12
	JUL	12.6	3.83	13.2	9	4.07	5.55
	AUG	12.6	4.26	11.1	10.29	3.9	4.71
	SEP	12.6	4.35	6.25	12.28	3	5
	OCT	12.6	3.26	6.9	10	2.3	4.55
	NOV	12.6	3.26	6.7	10.2	2.3	4.4
	DEC	12.6	3	6.25	13.3	2.3	4.05
2000	JAN	10.1	3.51	7.8	10.93	2.32	4
	FEB	10.65	3.43	8	11.4	2.42	4
	MAR	9.6	4.3	7.75	10.74	2.53	3.9
	APR	10	3.45	7.55	10.7	2.3	3.05
	MAY	9.8	3.45	7.13	10.7	2.15	3.05
	JUN	9.7	3.05	8.24	10.7	1.95	3.6
	JUL	8.7	3.2	8	10.7	1.92	2.35
	AUG	8.2	3.1	6.9	10.67	1.83	2.35
	SEP	7.4	2.9	7.4	10.7	1.7	1.73
	OCT	7.89	2.7	8	10.7	2.16	2
	NOV	6.9	2.53	8.1	9.6	2.63	2.3
	DEC	10	2.41	8.08	9.9	2.7	1.85
2001	JAN	9.9	3.45	7	6.9	2.9	1.9
	FEB	10.5	3.35	6.5	7.35	2.4	1.9
	MAR	10.6	3.03	6.4	8.1	2.15	1.75
	APR	15.33	2.86	6.61	7.8	1.95	1.94
	MAY	13.4	2.7	6.8	9.78	2.28	2.71
	JUN	15.4	3.8	9.25	10.1	3	2.6
	JUL	9.3	2.55	8	8.55	1.91	2.6
	AUG	9.3	2.56	6.75	8.26	2.2	2.4
	SEP	9.25	2.41	6.72	11.3	1.75	2.35
	OCT	9.5	3.34	7.4	10.25	2.05	2.35
	NOV	11.01	3.75	7.5	10.9	2.48	2.4
	DEC	11.69	3	8.4	11.05	2.48	2.25
2002	JAN	12.3	3.43	9.12	11.45	2.48	2.45
	FEB	14.86	3.66	11.59	11.04	2.48	2.57
	MAR	14.21	3.18	12.03	11.29	2.48	2.4
	APR	15.34	3	11.5	11.01	3.48	2.35
	MAY	16.07	3.67	14.44	12.01	2.36	2.57
	JUN	16.96	5.46	18.9	16	1.98	2.35
	JUL	14.31	5.75	12.45	18.06	2	3.02
	AUG	16.18	6.89	13.5	22.63	1.9	3.6
	SEP	15.5	6.11	12.96	20.6	2	3.74
	OCT	15.62	7.06	12.88	20.85	2	3.68
	NOV	15.76	6.04	11.6	21	1.76	3.41
	DEC	18.4	7.45	13.2	28.4	1.82	4.2
2003	JAN	19.74	7.2	13.2	29.3	1.87	5.6
	FEB	27.52	8	15.44	32.1	1.9	5.17
	MAR	26.77	8.2	12.9	32.5	2.05	5.25
	APR	29.16	7.85	14.6	34.85	2.34	5.71
	MAY	34.56	8	15.2	38.01	2.77	5.7
	JUN	32.35	8.99	12.75	39	2.85	5.7
	JUL	25.1	9.04	13.9	24.49	2.8	5.7
	AUG	22.15	9	13.5	23.19	2.97	5.7
	SEP	22.95	9.2	12	24.91	2.91	5.7
	OCT	22.17	9.98	12.52	24.91	3.84	5.37
	NOV	22.19	9.3	11.2	24.91	4	5.9
	DEC	22	9.1	11.91	24.91	3.98	6.1
2004	JAN	22.65	8.77	10.55	24.91	4.19	6.38
	FEB	24	9.2	10.79	24.91	3.99	6.4
	MAR	23.44	8.72	10.1	24.91	4.41	6.87
	APR	24.75	8.85	9.6	24.91	4.85	6.72
	MAY	25.2	8.86	10	24.91	4.91	6.03
	JUN	25.15	11.79	10	21.62	5.51	6.34
	JUL	20.3	12.9	7.44	18.61	5.41	5.28
	AUG	20.75	6.61	6.87	18.75	5.37	5.57

	SEP	19.96	5.84	5.96	18.14	5.76	5.3
	OCT	19.57	6.98	5.43	19.54	5.76	4.9
	NOV	20.49	6.98	5.8	19	5.76	4.9
	DEC	21.05	6.98	5.79	21.33	5.76	5.1
2005	JAN	24	6.98	7.45	26	5.76	6.31
	FEB	24.83	6.98	8	27.94	5.76	6.03
	MAR	26	6.98	7.99	26.5	4.48	5.95
	APR	26.1	6.98	7.41	27.28	2.99	6.9
	MAY	28.26	6.98	7.51	29	2.98	5.21
	JUN	27.97	6.98	6.68	29.1	2.99	5.08
	JUL	19.96	6.98	6.08	19.8	3	5.11
	AUG	20	6.98	6.38	21.68	3.08	5.54
	SEP	20	6.83	6.19	22.65	3.1	6.3
	OCT	20	6.83	10.2	22.4	3.58	8.15
	NOV	20	6.83	10.5	23.95	4.21	8.18
	DEC	20	6.83	10.39	25.01	4.33	10.99
2006	JAN	20	6.83	11.99	27.97	4.37	13.25
	FEB	30.98	6.83	13.6	29	5.59	14.96
	MAR	28.1	6.83	12.49	27.39	6.12	16
	APR	29.99	6.83	12.9	28.45	6.08	16.8
	MAY	30.5	6.83	12.61	30.55	5.84	11.94
	JUN	28.3	6.83	11.05	35.99	5.6	11.94
	JUL	28.98	6.83	11.46	38	5.1	11.94
	AUG	22.95	6.83	10.01	25.37	4.7	11.94
	SEP	22.35	6.83	7.94	24.7	3.22	11.94
	OCT	25	6.83	9	25	3.7	11.69
	NOV	24	6.63	8.8	23	3.93	11.69
	DEC	23.6	6.63	9.05	21	3.93	11.69
2007	JAN	23.42	6.63	10	20.34	3.93	12
	FEB	23.35	6.63	10	19	3.93	10
	MAR	22.46	6.63	10	22.35	3.93	9
	APR	26.17	6.63	10	24.59	3.93	9.98
	MAY	29.4	6.63	10	24.59	3.93	9.06
	JUN	30	6.63	9.4	24.59	3.93	10.4
	JUL	30.99	6.63	9.4	27.1	3.93	10
	AUG	31.11	6.63	13.06	25.53	3.93	10.6
	SEP	32	9.1	14.93	25.96	3.93	12.53
	OCT	32	9.1	14.98	25.1	3.93	12.95
	NOV	32	9.1	13.44	25.48	3.74	12.11
	DEC	32	9.1	13	25.48	3.74	12.4
2008	JAN	33.12	9.1	11.9	25.48	3.74	13.12
	FEB	37.5	9.1	11.6	25.48	3.74	13.7
	MAR	37	9.1	12.81	25.48	3.74	15.09
	APR	44.74	9.1	12.75	25.48	3.74	16.61
	MAY	48.99	7.5	13.48	25.48	3.74	12.7
	JUN	53.5	6.9	14.99	30.55	3.74	14.23
	JUL	62.9	6.6	14.84	27.8	2.79	13.99
	AUG	42.77	7.93	20.5	29.35	2.28	18.34
	SEP	42.6	8.23	22.3	28.56	3.52	18.67
	OCT	41.23	10.7	22.7	26.46	3	17.9
	NOV	37.1	11.12	24.56	25.23	3.13	16.2
	DEC	32.59	11.51	26.62	24	3.25	18.06
2009	JAN	36.89	11.51	32.93	27.6	4.51	22.86
	FEB	38.11	11.51	37.99	29.94	4.86	29.9
	MAR	38	11.51	37.99	30	5.16	32.23
	APR	40.4	11.51	37.99	33.51	6.05	37.7
	MAY	8.3	11.51	43.96	39.49	8.45	31.9
	JUN	15.7	11.51	50.15	41.4	9.3	34.6
	JUL	51.54	22.68	56.95	46.09	10.95	33
	AUG	37.4	30.49	50.6	36	10	29
	SEP	39.91	30.49	52	40.78	8.98	29.89
	OCT	34.4	30.49	51	42.31	9.57	29.53
	NOV	43.51	30.49	50.25	41.01	15	30.25
	DEC	44.7	30.49	49.5	43.06	15	34.63
2010	JAN	40.5	26	48.9	42.7	15	33
	FEB	42.34	25.67	48.9	43.122	15	32.93
	MAR	44.45	25.8	48.99	44	15	35.96
	APR	41.11	25.94	54.7	36.98	15	33.4
	MAY	43.4	25.58	61.5	38.5	15	33.4
	JUN	43.4	25.48	31,71	34.63	15	33.6

	JUL	42	24.97	31.77	42	15	25.65
	AUG	27.7	22.21	24.82	42	15	20
	SEP	29.57	30.98	27.27	42	15	22.88
	OCT	22.26	31.95	19.26	33	14.29	16.17
	NOV	23.7	11.96	16	18.31	14.29	15.31
	DEC	22	9.86	12	16.31	14.29	13.09
2011	JAN	14.23	5.8	7.38	7.38	14.29	8.35
	FEB	17.65	8.14	10	10	9.51	11.18
	MAR	15.58	5.9	8	8	4.7	9.88
	APR	18.96	5.77	9.13	9.13	2.23	11.03
	MAY	19.99	7.05	15.79	15.79	3.15	11.64
	JUN	16.07	7.39	12.3	16.26	3.42	12.72
	JUL	14.85	6.2	13	13.73	2.17	14
	AUG	14.85	5.22	11.4	12.6	1.78	13.97
	SEP	14.3	3.13	14.12	6.91	1.16	13.52
	OCT	14.85	2.66	12.2	7.3	1.32	15.5
	NOV	14.01	2.02	11.63	6.05	1.1	15.5
	DEC	14.5	2.52	11.83	7.2	1.4	15.6
2012	JAN	14.7	2.7	11.86	6.55	1.08	17.81
	FEB	14.4	2.6	13.3	5.93	1.27	18.07
	MAR	16.39	2.7	15.2	6.05	1.05	21.98
	APR	15.42	2.3	11.8	5.55	1.15	17.54
	MAY	14.21	2.03	11	5.3	1.12	17.01
	JUN	13.5	1.97	10.7	4.85	0.99	16.66
	JUL	13.4	2.08	10.5	5.63	1.08	16.8
	AUG	12.9	1.94	9.13	4.95	0.89	15.4
	SEP	11.9	2	9.01	4.72	1.01	15.98
	OCT	11.74	2.01	9.02	4.87	1.03	15.98
	NOV	13.14	2.18	9.12	4.62	1.11	16.6
	DEC	13.73	2.18	9.15	4.2	1.29	17.76
2013	JAN	14.76	2.19	9.76	4.1	1.71	18.13
	FEB	15.17	2.11	9.99	3.61	1.72	19.05
	MAR	13.95	1.85	7.6	3.46	1.33	19.97
	APR	13.43	1.78	5.9	3.01	1.18	16.21
	MAY	13.48	1.6	6.25	2.77	1.08	16.3
	JUN	12.5	1.32	5.64	2.7	1	15.58
	JUL	12.44	0.73	5.15	2.28	0.89	14.4
	AUG	10.66	0.64	4.11	2.09	0.76	12.54
	SEP	9.26	0.95	3.69	2.09	0.68	12.67
	OCT	10.02	0.85	3.16	2.09	0.64	14.6
	NOV	9.2	1	2.55	2.09	0.55	14.1
	DEC	9.67	1.14	2.67	4.59	0.54	14.08
2014	JAN	9.56	1.1	2.67	5.87	0.54	14.45
	FEB	9.4	1.2	2.71	6.7	0.52	14.06
	MAR	9.4	1.2	2.61	2.71	0.5	13.49
	APR	9.78	1.4	3.74	3.95	0.54	16.02
	MAY	10.02	1.27	4.08	3.8	0.5	15
	JUN	10.92	1.32	3.66	3.73	0.5	15
	JUL	11.73	7.6	4.75	4.24	0.5	17
	AUG	11.74	7.62	4.83	4.65	0.51	18
	SEP	14.85	8.62	4.5	7.51	0.5	19.15
	OCT	16.21	8.9	4.58	7.84	0.54	19.8
	NOV	16.24	8.96	4.5	7.3	0.5	19.35
	DEC	16.28	8.05	4.56	7.35	0.5	23
2015	JAN	16.3	11.1	6.87	8.4	0.86	24.57
	FEB	16.48	11.7	8.06	10	1.08	24.6
	MAR	17	10.2	8	10.15	1.72	26.1
	APR	17.08	9.12	6.89	9	1.36	25.55
	MAY	18	11.37	8.52	10.3	1.2	29.99
	JUN	18.03	10.9	8.1	12.44	1.22	24.3
	JUL	18.55	11.06	7.82	12	1.25	25.8
	AUG	19.03	11	7.67	11.74	1.08	25.78
	SEP	19.2	10.35	7.55	10.25	1	25.1
	OCT	19.4	9.69	7.82	10.1	1.25	25.3
	NOV	20.2	10	7.51	10.1	1.14	27.3
	DEC	20.2	9.6	8.9	9.63	1.22	27.02

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