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VECTOR AUTOREGRESSIVE MODELING OF SERVICE DELIVERY TOWARDS BOOSTING THE INTERNALLY GENERATED REVENUE IN KWARA STATE, NIGERIA.

ABDULLAHI, GATTA ABDULGANIY, ADEWARA, ADEDAYO AMOS AND GATTA NUSIRAT FUNMILAYO

Department of Statistics, University of Ilorin. Ilorin. Kwara State. Nigeria.
dangattaabdul@yahoo.com, aaadewara@gmail.com and nusiratfunmilayo@rocketmail.com

ABSTRACT

Subjective method of forecasting has a great consequence on double taxation, rise in inflation rate and uneven distribution of income, budget deficit etc. Therefore, it's important to look into such situation and provide the need to reduce the reliance of State Government on the Federal Allocation through provision of reliable estimates of internally generated revenue so as to provide realistic budget expenditures for the coming year and provides or sets standard performances for the system. The aim of this research work is to forecast for the future demand in services of Permit, C of O, R of O, and Valuation and consider how well one or more of these helps in predicting the other. Vector Autoregressive model has been designed to examine the relationship that exist between set of variables and helps as well in forecasting for the future occurrence of such events/variables. Based on the results of this research work, it was found that ***C of O*** *is the only variable that can be treated as endogenous variable given* ***Permit*** *and* ***Valuation*** *and finally forecast was made which shows the highest and minimum values for the* ***Permit***, ***C of O***, ***R of O*** *and* ***Valuation*** *with 960 & 54, 74 & 0, 86 & 0 and 41 & 0 at Jan 2017 and Oct 2015, April 2016 and Sept 2015, Oct 2016 and Dec 2013, Feb 2014 and Oct 2015 respectively, Government should use the forecasts as a set target for each parastatal for revenue derive and eliminate redundancy in the workforce, this will make the revenue projection more service deriving, reduced the inflation rate, eliminate double taxation and budget deficit for a fixed service cost and propose efficient Recurrent Expenditure/Expenses.*

Keywords: Certificate of Occupancy, Right of Occupancy, Permit, Valuation

INTRODUCTION

Vector auto-regression (VAR) constitutes a special case of the more general class of ARMA models. In essence, a VAR model is a fairly unrestricted (flexible) approximation to the reduced form of a wide variety of dynamic econometric models. VAR models can be specified in a number of ways.

$$\mathbf{Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_p Y_{t-p} + \varepsilon_t;}$$

$\mathbf{t = 1, \ldots, T,}$ where $Y_t = \{Y_{1t}, Y_{2t}, \ldots, Y_{nt})$, p is the lag length, Π_i is an (n×n) matrix of coefficients, t is the time period and n denotes the numbers of endogenous variables.

According to Christopher (1980), VAR model is a multivariate autoregressive model where each variable is regressed on its past values and the past values of the other variables in the system. Model building in VAR models then depends on the selection of the appropriate variables (based on theory). The specification of the dynamic structure proceeds based on testing for the appropriate lag length using the sample data. He argues that one of the critical contributions of the VAR approach is that it can serve to define the "battleground" of empirical debates about multiple time series data. It does this by providing a model of the dynamic and empirical regularities of a set of related time series. VAR would have **p** equations (in case we have **p** variables), one for each variable. Each variable would be regressed on its past values and the past values of the other variable. The resulting

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residuals (after checking for serial correlation) would be exogenous shock or innovation. One could look at the responses of each equation to see how these "surprises" in each variable affect the observed system. After accounting for these dynamics, one could engage in inferences about the Granger causal relationships between the variables and try to determine the endogenous structure and dynamics of the series.

He developed the approach of vector autoregressive systems (VAR) as an alternative to the traditional simultaneous equations system approach. Starting from the autoregressive representation of weakly stationary processes, all included variables are assumed to be jointly endogenous. Thus, in a VAR of order p (VAR(p)), each component of the vector **x** depends linearly on its own lagged values up to **p** periods as well as on the lagged values of all other variables up to order **p**. Therefore, our starting point is the reduced form of the econometric model. With such a model we can find out whether a specific Granger causal relation exists in the system. However, it has to be mentioned that the number of variables that can jointly be analyzed in such a system is quite small; at least in the usual econometric applications, this is limited by the number of observations which are available. Nevertheless, vector autoregressive systems play a crucial role in modern approaches to analyze economic time series.

The different equations of this system can be estimated using Ordinary Least Square (OLS). This leads to consistent estimates of the parameters with the same efficiency as a Generalized Least Squares Estimator. To estimate the system, the order **p** i.e. the maximal lag of the system, has to be determined. In order to fix **p**, any of the following information criteria can be used; the Final Prediction Error (FPE), the Akaike Criterion (AIC), the Schwarz Criterion (SC) and the Hannan-Quinn Criterion (HQ).

The VAR methodology has been applied to a vast range of empirical topic, including monetary and fiscal policy analysis and short-term economic forecasting. Also in the fields of regional science and spatial economics the scope of issue that could be addressed by means of properly identified structural VARs appears to be wide and includes: the analysis of the regional propagation of demand shocks via trade linkages; the assessment of long-run spatial spillover effects from local public expenditure to private sector performance; and the study of dynamic knowledge externalities linking patterning activity in the business sector to academic research in nearby areas. However, despite the fact that the VAR approach provides a potentially useful analytical tool allowing for the joint modeling of dynamic interdependencies within a group of connected areas, until lately it has received little attention in the applied spatial economics literature.

In a multi-country set-up, cross-section interactions were most recently dealt with by Pesaran et al (2004), who introduced the Global VAR specification, where information on trade shares across countries is utilized to specify the channels of transmission of national disturbances across the world economy. Carlino and Defina (1995) provide straightforward implementation of the original Sims' approach, by fitting a VAR model involving a single endogenous variable (GNP) to the six regions in the US. In this case the limited number of areas (6 regions) and short lag order of the model allows the authors to estimate an unrestricted reduced form VAR specification. They are also among the first to employ impulse response analysis based on VAR estimation to measure the strength of spatial spillover effects across regions. However, the identification of structural shocks hinges on the assumption of no contemporaneous spillover effects, a hypothesis that can be overly restrictive in many empirical settings.

Space-time impulse response analysis is also dealt with by Giacinto (2006), who implements a VAR approach based on an underlying univariate STARMA (Space-Time ARMA) specification. Prior information on spatial contiguity is utilized both to place reasonable restriction on VAR coefficients matrices and to identify structural impulse responses. Lesage and Pan (1995) introduced information on spatial c**ontiguity** to specify the prior distribution of VAR coefficients in a Bayesian univariate regional VAR analysis. Canova and Ciccarelli (2006) have recently proposed a multi-country panel VAR specification that allows for cross-sectional interdependence in a general framework, in solving the incidental parameter

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problem by imposing standard (i.e. non spatial) prior distributional assumptions.

Christopher (1980) stated that; "if there is true simultaneity among a set of variables, they should all be treated on an equal footing; there should not be any prior distinction between endogenous and exogenous variables". Christopher (1972; 1980) pioneered the VAR methodology, building on the idea of dynamic decomposition of the variable in the system. He rejected the use of standard simultaneous equation models for three reasons:

*Identification restrictions on parameters used in SEQ (simultaneous equation) models are typically not based on theory and thus may lead to incorrect conclusions about the structure of the models and the estimates.
*SEQ models are often based on tenuous assumptions about the exogeneity and endogeneity of the variables. Because the true lag lengths of the variables are not known a prior, identification is then based on possibly specious assumptions about exogeneity. The formal identification of a dynamic simultaneous equation model requires that the exact true lag length to be known for each variable; otherwise, identification assumptions may not hold (Hatanaka, 1975)
*If the variables in the model are themselves policy projections, additional identification problems will be present because of temporal restrictions. This is the rational expectations critique: models are typically treated as though ceteris paribus claims will be true. In fact, they are not, and then we need to be able to assess the probabilistic implications of different paths of the variables.

Meyler et al (1998) outlined autoregressive integrated moving average (ARIMA) time series models for forecasting inflation. They considered two alternative approaches to the issue of identifying ARIMA model-the Box Jenkins approach and the objective penalty function methods. The emphasis is on forecast performance, which suggests that ARIMA forecast has outperformed.

Parallel investigation which is done by Kenny et al (1998) focused on the development of multiple time series models for forecasting inflation. The Bayesian approach to the estimation of vector autoregressive (VAR) model is employed. This allows the estimated models combine the evidence in the data with any prior information, which may also be available. A large selection of inflation indicators is assessed as potential candidates for inclusion in a VAR. The results confirm the significant improvement in forecasting performance, which can be obtained by the use of Bayesian techniques.

Leheyda (2005) studied the determinants of inflation in Ukraine through applying co-integration analysis and error correction modeling. A simple theoretical framework of inflation for a small open economy is being derived. The analysis is based upon three hypotheses: excess money supply, foreign inflation and cost-push inflation. Upon testing for the existence of the long-run co-integration relationships using Johansen procedure for the sectoral VARs, a structural inflation function as an equilibrium error correction model was established. The long-run money demand, purchasing power parity and mark-up relationships where found, which may govern prices in the long-run. In the short-run, inflation, money supply, wages, exchange rate and real output as well as some exogenous shocks influence inflation dynamics.

Vizek and Broz (2007) analyze inflation in Croatia in the period 1995-2006 using the co-integration approach. They find out that mark-up and excess money is the most significant variables for explaining the short-run behaviour of inflation. Furthermore, output gap, nominal effective exchange rate, import prices, interest rates and narrow money are also found to be important in the influence on inflation.

Dejan (2007) made factor forecasts for the overall inflation and the subcomponents (energy inflation, industrial goods inflation, services inflation, processed food and non-processed food inflation) for Slovenia. The forecasts of the factor model are compared to autoregressive (AR) and vector autoregressive (VAR) models in times of the Root mean squared error (RMSE). In attrition, the factors were identified so as to give interpretation to the forecasts. Results show

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that the factor model is significantly better than the AR benchmark forecasts and is not worse from the VAR forecasts for all subcomponents and the headline inflation, which render it a good tool for forecasting inflation in Slovenia.

Christopher (1980), therefore, proposed method for addressing the tenuous identification problems of the SEQ approach is to focus on the dynamic specification of the reduced form model. This is in contrast to the SEQ approach, which focuses on the identification choices in the model specification. Sims' approach is to ensure that the modelling approach to multiple time series provides a complete characterization of the dynamics of several series. This is done using a multivariate autoregressive model to account for the dynamics of all the variables. Building multivariate time series models, according to the VAR methodology, does not depend on a single theory. Instead, a multiple theories can be compared explicitly and evaluated (using hypothesis testing) without the identification assumptions that would be made in the specification of alternative simultaneous equation models. Because the variables in the VAR model do not segment a prior into endogenous and exogenous variables, we are less likely to violate the model specification and incorrectly induce simultaneity biases by incorrectly specifying a variable as exogenous when it is really endogenous.

Christopher (1980) opined that VAR modelers also have a different conception of the interplay of data and models. The goal of a VAR model is to provide a probability model of the dynamics and correlations among the data. Thus, VAR models are considered best when based on a simple, unbiased specification that accounts for the uncertainty about the dynamics and the model. To do this, pre-test biases must be avoided (Pagan, 1978). Thus, unlike the "specification-estimate-test-respecify" logic of classical approaches, SEQ models, ARIMA models, VAR models employ few hypothesis tests to justify their specification. This leads to a less biased representation of the model and its dynamics rather than the false sense of precision that can accompany other modeling strategies. That is, once we have entered this cycle of specification testing, the resulting inferences are a function of the test procedure and are less certain than the reported test statistics and associated levels of significance or reported P values would lead us to believe.

According to Simkins (1995), VAR models tend to suffer from 'over-fitting' with too many free insignificant parameters. As a result, these models can provide poor out-of-sample forecasts, even though within-sample fitting is good. Instead of restricting some of the parameters in the usual way, Litterman (1986) imposed a prior distribution on the parameters, expressing the belief that many economic variables behave like a random walk. Engle and Granger (1987) concept of co-integration has raised various interesting questions regarding the forecasting ability of Error Correction Models (ECM) over unrestricted VAR. Shoesmith (1992; 1995), Tegene and Kuchler (1994), and Wang and Bessler (2004) provided empirical evidence to suggest that ECM outperforms VAR in levels, particularly over longer forecast horizons. Shoesmith (1995) and Villani (2001), also showed how Litterman's (1986) Bayes approach can improve forecasting with co-integrated VAR.

Stationary Vector Autoregressive Model

Let Yt= (y1t, y2t,...,ynt)T denote an ($n\times 1$) vector of time series variables. The basic p lag vector autoregressive (VAR (p)) model has the form

$$\mathbf{Y_t = c + \Pi_1\, Y_{t-1} + \Pi_2\, Y_{t-2} + \dots + \Pi_p Y_{t-p} + \varepsilon_t;}$$

$\mathbf{t = 1, \dots, T,}$ where c denotes an $n\times 1$ vector of constants and $\prod_j$ an $n\times n$ matrix of autoregressive coefficient for j=1,2,...,p. The $n\times 1$ vector ε_t is a vector generalization of white noise.

Unit Root Test

Before fitting a particular model to time series data, the series must be made stationary. Stationarity occurs in a time series when the mean and autocovariances of the series remains constant over the time series. Therefore, the stochastic process Y_t is said to be stationary if

E (Y_t) = μ, constant for all value of t

Augmented Dickey-Fuller (ADF) Test

The standard Augmented Dickey-Fuller test is conducted by estimating the above equation after subtracting Y_{t-1} from both side of the equation.

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$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \varepsilon_t$$

where $\alpha = \rho - 1$ and $\Delta Y_t = Y_t - Y_{t-1}$

Portmanteau Autocorrelation Test

The portmanteau test for residual autocorrelation checks the null hypothesis that all residual autocovariances are zero, that is,

$$H_0: E(\varepsilon_t \varepsilon_{t-i}') = 0 (i = 1,2, \dots)$$

Results from the data used

	PERMIT	C of O	R of O	VALUATION
Mean	372.1865	20.80163	24.01389	12.56699
Median	317.5661	20.80836	17.50000	12.70494
Maximum	2107	74	86	41
Minimum	58	0	0	0
Std. Dev.	314.1674	14.68590	18.64078	5.979959
Observations	72	72	72	72

Table 1: Descriptive results from the original data collected

Here, the descriptive statistics obtained on the permit, C of O, R of O, and valuation are presented respectively in the table above.

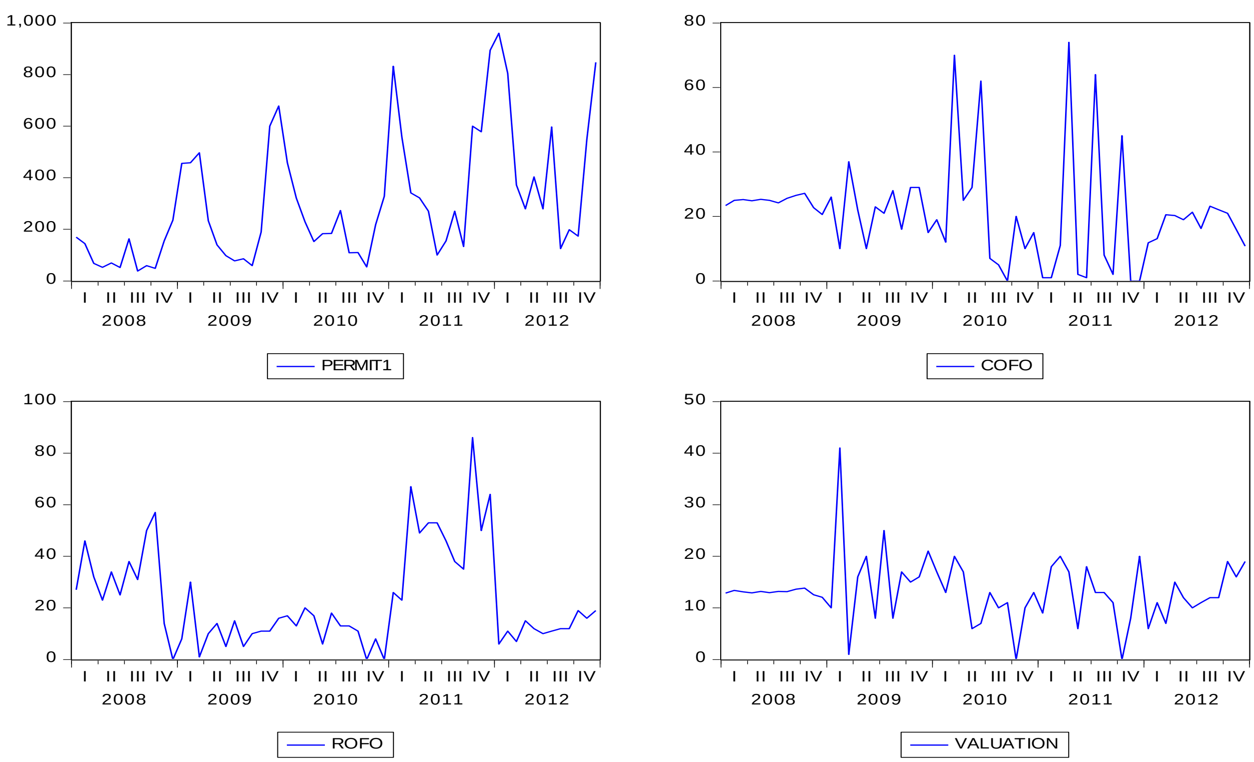

FIGURE1: Time Plot of the Original Series

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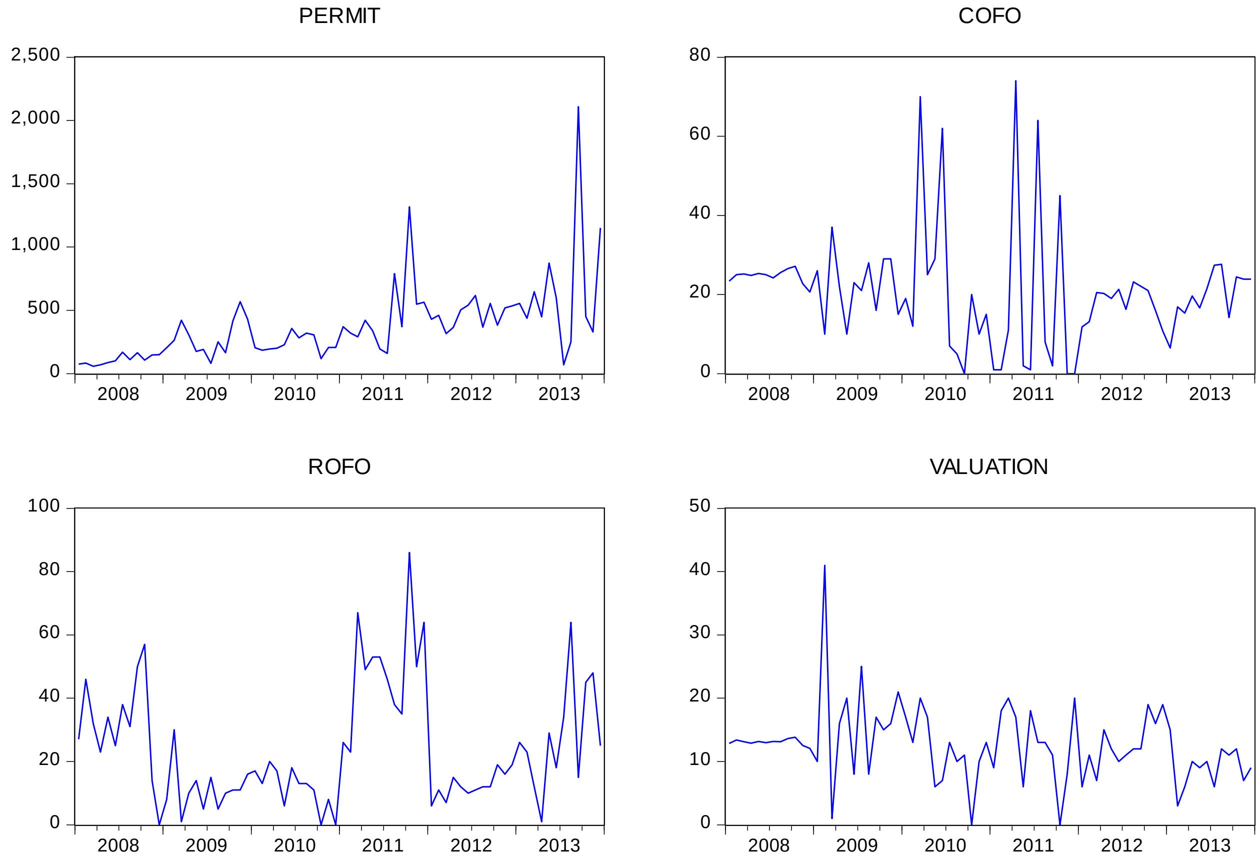

FIGURE 2: Time plot for the deseasonalized data of the Original Series

Unit properties of individual series

The stationarity of the series can be tested by using the Augmented Dickey-Fuller (ADF) test.

H_0: The series is non-stationary

H_1: The series is stationary

Table 2: Unit Root Tests Result (At Level)

SERIES	**LEVEL WITH INTERCEPT**	
	Test statistic	Prob.*
	ADF	ADF
Permit	-3.010104	0.0387
C of O	-3.723923	0.0057
R of O	-3.093159	0.0316
Valuation	-9.061094	< 0.001
Critical value (5%)	-2.904848	

The results of ADF test presented above using MacKinnon (1996) critical values indicate that the series in level contain unit root would be rejected for all the series because the respective p-values are less than the conventional significance level α = 0.05. Hence, the ADF test shows that all series are stationary in the levels.

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Estimating the VAR order

Specifying the lag length has strong implications for subsequent modeling choices. To determine the appropriate lag length for the VAR model, the Akaike Information Criteria (AIC), Schwarz Information Criteria (SC), Hannan-Quinn (HQ) Information Criteria were used.

Table 3: Lag Length Criteria

Lag	AIC	SC	HQ
0	37.60840	37.75439	37.66486
1	36.79330	**37.52324***	**37.07558***
2	36.83441	38.14830	37.34251
3	**36.78311***	38.68096	37.51703
4	37.14241	39.62420	38.10214
5	37.33624	40.40199	38.52179

Using SC and HQ, it can be concluded that the optimal lag length is 1 if we are to go by the principle of parsimony.

VAR estimate

Having concluded that the variables are not co-integrated, since all the variables are *I(0)* we can proceed to estimate the VAR model. The VAR model has the following structure:

$\mathbf{Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_p Y_{t-p} + e_t;}$ $\mathbf{t = 1, \ldots, T}$ where $Y_t = \{Y_{1t}, Y_{2t}, \ldots, Y_{nt})$, p is the lag length, Π_i is an (n×n) matrix of coefficients, t is the time period and n denotes the numbers of endogenous variables.

The generalized form of the vector autoregressive (VAR) model for this research work can be specified as:

$$P_t = \varphi_P + \sum_{i=1}^{p} \alpha_i{}^P P_{t-i} + \sum_{i=1}^{p} \beta_i{}^P C_{t-i} + \sum_{i=1}^{p} \gamma_i{}^P R_{t-i} + \sum_{i=1}^{p} \delta_i{}^P V_{t-i} + \varepsilon_{Pt}$$

$$C_t = \varphi_C + \sum_{i=1}^{p} \alpha_i{}^C P_{t-i} + \sum_{i=1}^{p} \beta_i{}^C C_{t-i} + \sum_{i=1}^{p} \gamma_i{}^C R_{t-i} + \sum_{i=1}^{p} \delta_i{}^C V_{t-i} + \varepsilon_{Ct}$$

$$R_t = \varphi_R + \sum_{i=1}^{p} \alpha_i{}^R P_{t-i} + \sum_{i=1}^{p} \beta_i{}^R C_{t-i} + \sum_{i=1}^{p} \gamma_i{}^R R_{t-i} + \sum_{i=1}^{p} \delta_i{}^R V_{t-i} + \varepsilon_{Rt}$$

$$V_t = \varphi_V + \sum_{i=1}^{p} \alpha_i{}^V P_{t-i} + \sum_{i=1}^{p} \beta_i{}^V C_{t-i} + \sum_{i=1}^{p} \gamma_i{}^V R_{t-i} + \sum_{i=1}^{p} \delta_i{}^V V_{t-i} + \varepsilon_{Vt}$$

Since the optimal lag length is 1, the reduced form of the above model when p is 1 is;

$$P_t = \varphi_P + \alpha_i{}^P P_{t-1} + \beta_i{}^P C_{t-1} + \gamma_i{}^P R_{t-1} + \delta_i{}^P V_{t-1} + \varepsilon_{Pt}$$
$$C_t = \varphi_C + \alpha_i{}^C P_{t-1} + \beta_i{}^C C_{t-1} + \gamma_i{}^C R_{t-1} + \delta_i{}^C V_{t-1} + \varepsilon_{Ct}$$
$$R_t = \varphi_R + \alpha_i{}^R P_{t-1} + \beta_i{}^R C_{t-1} + \gamma_i{}^R R_{t-1} + \delta_i{}^R V_{t-1} + \varepsilon_{Rt}$$
$$V_t = \varphi_V + \alpha_i{}^V P_{t-1} + \beta_i{}^V C_{t-1} + \gamma_i{}^V R_{t-1} + \delta_i{}^V V_{t-1} + \varepsilon_{Vt}$$

Where P_t, C_t, R_t and V_t denote permit, C of O, R of O and Valuation at time t.

__**Estimates:**__

$$\hat{P}_t = 80.70065 + 0.704107P_{t-1} - 0.02032C_{t-1} - 0.008460R_{t-1} + 0.003257V_{t-1}$$
$$\hat{C}_t = 20.80729 - 0.517164P_{t-1} - 0.159731C_{t-1} - 0.096884R_{t-1} + 0.033675V_{t-1}$$

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$$\hat{R}_t = 20.66037 + 0.108205P_{t-1} + 0.042742C_{t-1} + 0.637653R_{t-1} - 0.042092V_{t-1}$$
$$\hat{V}_t = 14.51472 + 1.953810P_{t-1} + 0.644869C_{t-1} - 0.597618R_{t-1} - 0.148200V_{t-1}$$

Model diagnostics

In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be perform.

Test for Residual Autocorrelation

Portmanteau Q-statistic test for VAR model residual serial correlation is presented below. This test is used to test for the overall significance of the residual autocorrelations up to lag 2.

Hypothesis:

H_0: there is no residual autocorrelation (Q = 0)

Vs

H_1: there is residual autocorrelation (Not H_o)

Table 4: Test for residual autocorrelation

Lag	Q-stat	Test statistic.	Df
1	8.053020	NA*	8.191866
2	27.07048	0.5679	27.87661

Since p-value (0.5679) $>\alpha =$(0.05), we cannot reject H_0. Hence, we conclude that there is no residual autocorrelation at lag 2 and it is white noise.

Structural Analysis

Granger-Causality Test

Granger causality test is considered a useful technique for determining whether one time series is good for forecasting the other. The concept of granger causality test is explored when the coefficients of the lagged of the other variables is not zero. Table 5 presents results from the pair wise Granger-causality tests which were obtained with one lag for each variable.

Table 5:Pair-wise Granger-causality tests:

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
C of O does not Granger Cause PERMIT1	59	0.14732	0.7026
PERMIT1 does not Granger Cause C of O		5.37152	0.0241
R of O does not Granger Cause PERMIT1	59	0.01453	0.9045
PERMIT1 does not Granger Cause R of O		0.60225	0.4410
VALUATION does not Granger Cause PERMIT1	59	0.30676	0.5819
PERMIT1 does not Granger Cause VALUATION		0.54133	0.4650
R of O does not Granger Cause C of O	59	0.22302	0.6386
C of O does not Granger Cause R of O		0.12710	0.7228
VALUATION does not Granger Cause C of O	59	4.25749	0.0437
C of O does not Granger Cause VALUATION		0.14146	0.7083
VALUATION does not Granger Cause R of O	59	3.09543	0.0840
R of O does not Granger Cause VALUATION		0.77175	0.3834

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The result shows that only Valuation granger cause C of O but the reverse is not true. This implies that the relationship existing between valuation and C of O is unidirectional and that change in valuation corresponds to change in C of O at 5% rejection level.

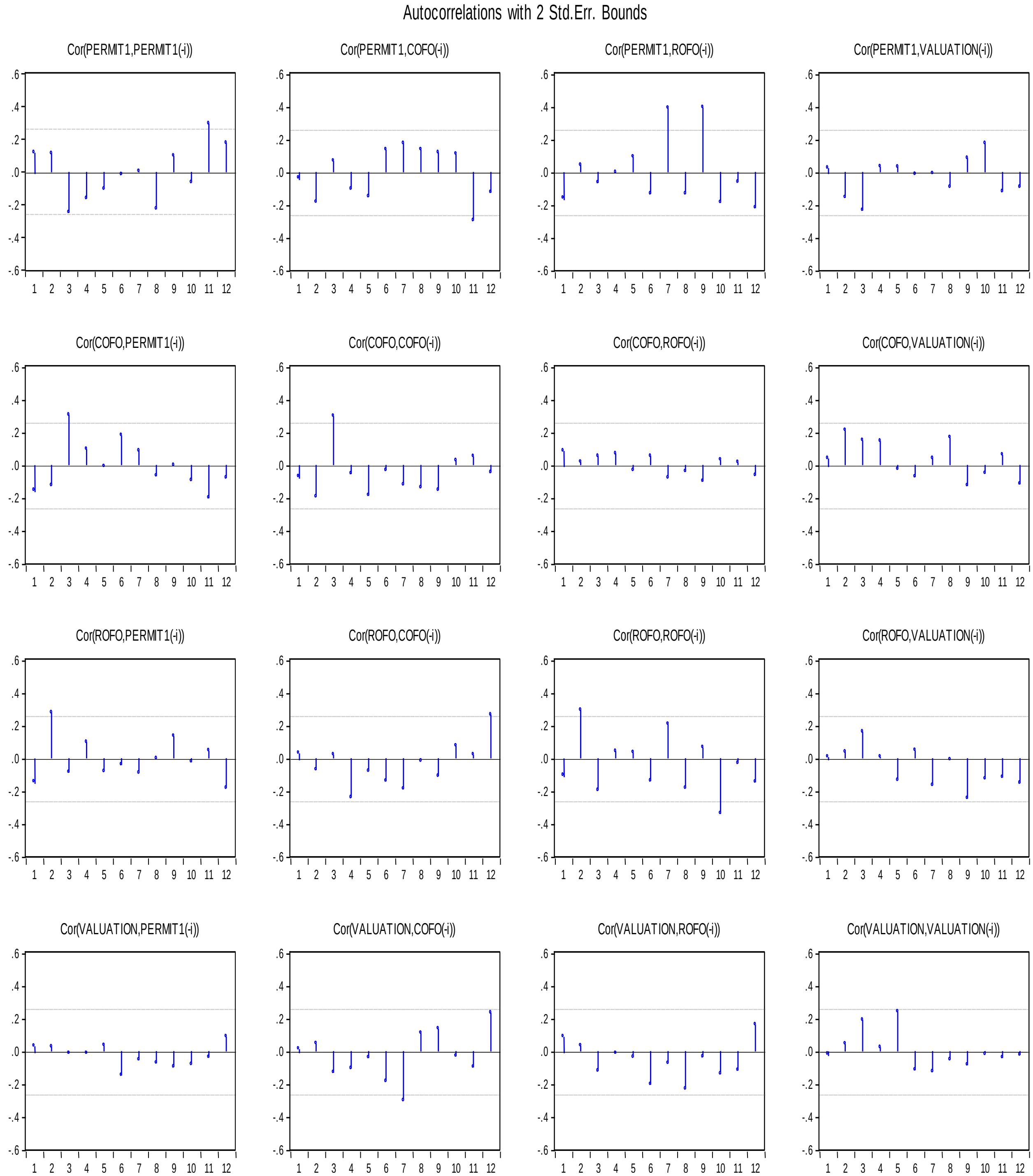

FIGURE 3: Auto-correlogram

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Forecasting

Plots of actual and forecasted values for the four variables

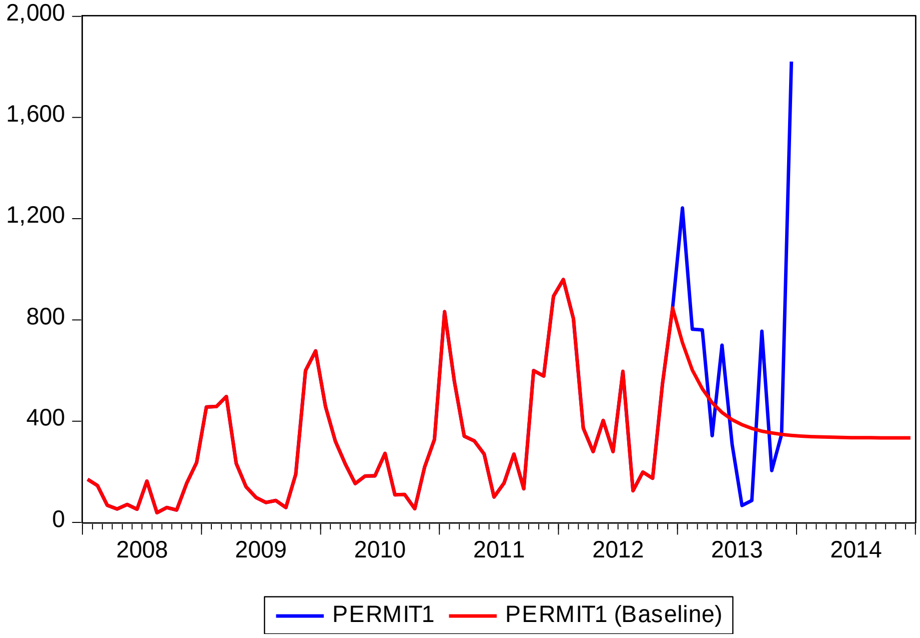

FIGURE 4 Permit Forecast

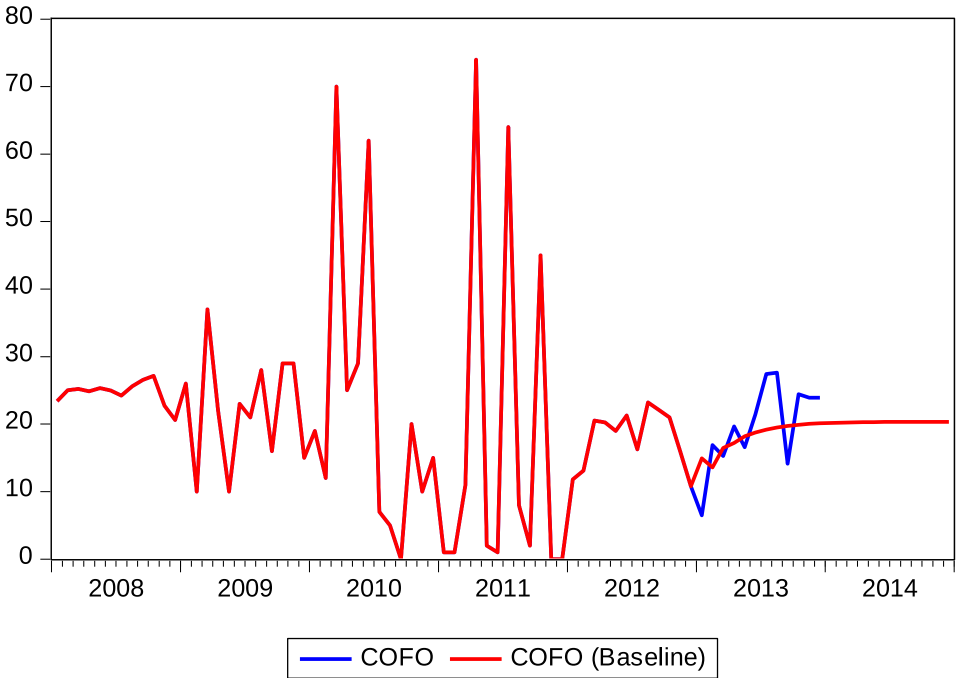

FIGURE 5: C of O Forecast

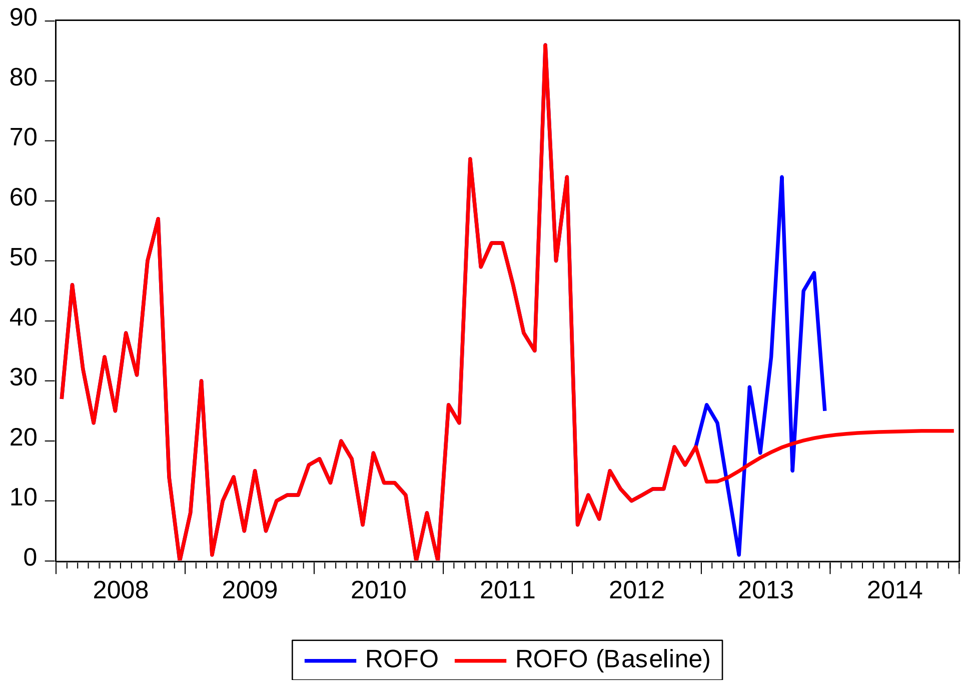

FIGURE 6: R of O Forecast

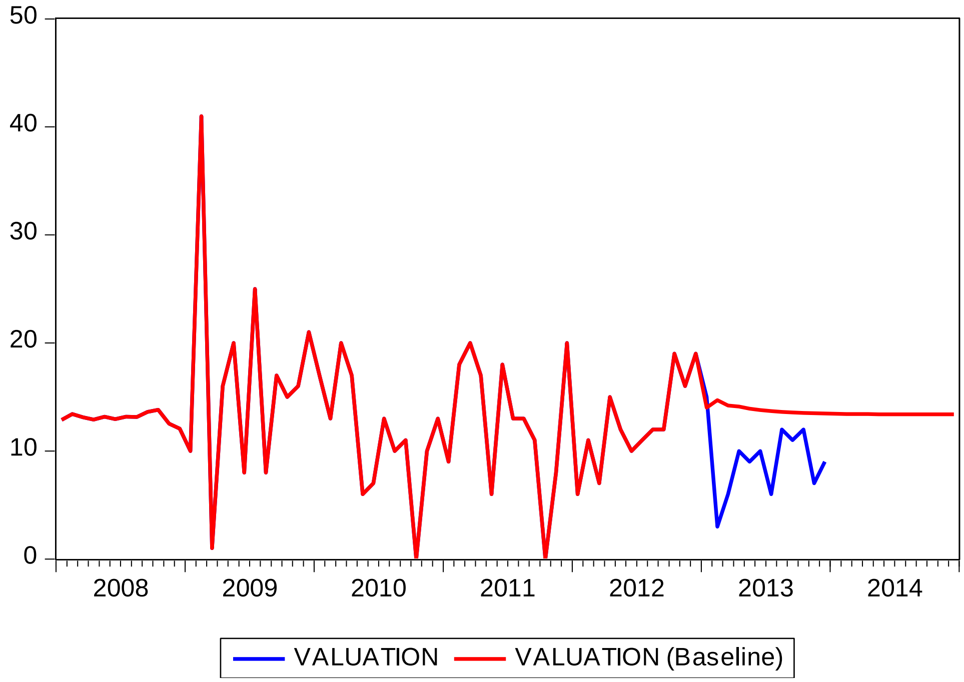

FIGURE 7: Valuation Forecast

Discussion of results

Table 1 is the descriptive statistics that presents the mean, median, maximum, minimum, standard deviation and observations of the permit, C of O, R of O, and valuation respectively. It was observed that among the above measures, **Permit** has the highest measures, followed by R of O, C of O and Valuation. Figure 1 present the natural pattern or behaviour of permit, C of O, R of O and Valuation each from 2008 to 2012, while figure 2 reveals the de-seasonalized data which implies that permit is more influenced by seasonal effect.

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Table 2 is the unit root test result, which reveals that the series is stationary at all level having rejected the null hypothesis. In Table 3. the optimum lag is obtained at lag 1, while Table 4 is the test for the presence of residual autocorrelation in the model, Since p-value (0.5679) $>\alpha =$(0.05), we do not reject H_0 and conclude that there is no autocorrelation at lag 2 and it is white noise.
Table 5 shows that the model having passed the unit root, the rejection of a null hypothesis implies that one variable is granger caused by the other, otherwise implies that one does not cause the other. Figures 3, 4, 5, 6 and 7 shows the forecast of Permit, C of O, R of O and Valuation while the entire forecast figures are depicted in the appendix.

C of O is the only variable that can be treated as endogenous variable given **Permit** and Valuation, since the long run relationship between **C of O** with valuation and **C of O** with Permit are significant. Thus, changes in the trend of demand of **Valuation** and **Permit** will in turn leads to changes in the demand of **C of O**.

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APPENDIX

Forecasted values

Month	Permit	C of O	R of O	Valuation
Jan-13	170	24	27	13
Feb-13	145	25	46	13
Mar-13	68	25	32	13
Apr-13	53	25	23	13
May-13	70	25	34	13
Jun-13	52	25	25	13
Jul-13	163	24	38	13
Aug-2013	38	26	31	13
Sep-13	59	27	50	14
Oct-13	49	27	57	14
Nov-13	155	23	14	13
Dec-13	236	21	0	12
Jan-14	456	26	8	10
Feb-14	458	10	30	41

Mar-14	497	37	1	1
Apr-14	233	22	10	16
May-14	140	10	14	20
Jun-14	98	23	5	8
Jul-14	78	21	15	25
Aug-2014	86	28	5	8
Sep-14	59	16	10	17
Oct-14	190	29	11	15
Nov-14	600	29	11	16
Dec-14	678	15	16	21
Jan-15	458	19	17	17
Feb-15	321	12	13	13
Mar-15	229	70	20	20
Apr-15	153	25	17	17
May-15	183	29	6	6
Jun-15	184	62	18	7
Jul-15	273	7	13	13
Aug-2015	109	5	13	10
Sep-15	110	0	11	11
Oct-15	54	20	0	0
Nov-15	218	10	8	10
Dec-15	328	15	0	13
Jan-16	832	1	26	9
Feb-16	557	1	23	18
Mar-16	341	11	67	20
Apr-16	322	74	49	17
May-16	270	2	53	6
Jun-16	100	1	53	18
Jul-16	155	64	46	13
Aug-2016	270	8	38	13
Sep-16	133	2	35	11
Oct-16	600	45	86	0
Nov-16	578	0	50	8
Dec-16	894	0	64	20
Jan-17	960	12	6	6

Feb-17	805	13	11	11
Mar-17	372	21	7	7
Apr-17	279	20	15	15
May-17	403	19	12	12
Jun-17	279	21	10	10
Jul-17	597	16	11	11
Aug-2017	125	23	12	12
Sep-17	199	22	12	12
Oct-17	174	21	19	19
Nov-17	548	16	16	16
Dec-17	847	11	19	19

Abbreviations and definitions used

IGR	**Internally Generated Revenue**
C of O	**Certificate of Occupancy**
R of O	**Right of Occupancy**
PERMIT	**Approval For Development of Land**
VALUATION	**Current Value as Land Appreciated**
MICRO-ECONOMICS	**Between individual business and society**
MACRO-ECONOMICS	**Between government business and a country**