Foreign Private Investment and Economic Growth in Nigeria: A Cointegrated VAR and Granger causality analysis

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This research uses a cointegration VAR model to study the contemporaneous long-run dynamics of the impact of Foreign Private Investment (FPI), Interest Rate (INR) and Inflation rate (IFR) on Growth Domestic Products (GDP) in Nigeria for the period January 1970 to December 2009. The Unit Root Test suggests that all the variables are integrated of order 1. The VAR model was appropriately identified using AIC information criteria and the VECM model has exactly one cointegration relation. The study further investigates the causal relationship using the Granger causality analysis of VECM which indicates a uni-directional causality relationship between GDP and FDI at 5% which is in line with other studies. The result of Granger causality analysis also shows that some of the variables are Ganger causal of one another; the null hypothesis of non-Granger causality is rejected at 5% level of significance for these variables.

Keywords: Cointegration, VAR, Granger Causality, FPI, Economic Growth

JEL Classification: G32, G24

1.0 Introduction

The use of Vector Autoregressive Models (VAR) and Vector Error Correction Models (VECM) for analyzing dynamic relationships among financial variables has become common in the literature, Granger (1981), Engle and Granger (1987), MacDonald and Power (1995) and Barnhill, et al. (2000). The popularity of these models has been associated with the realization that relationships among financial variables are so complex that traditional time-series models have failed to fully capture.

Engle and Granger (1987) noted that, for cointegrated systems, the VAR in first differences will be miss-specified and the VAR in levels will ignore important constraints on the coefficient matrices. Although these constraints may be satisfied asymptotically, efficiency gains and improvements in forecasts are likely to result from their imposition. Hence, Engle and Granger (1987) suggested that if a time-series system under study includes integrated variables of order 1 and satisfy the conditions of cointegration relations, then this system will be more appropriately specified as a vector error-correction model (VECM) rather than a VAR. Comparisons of forecasting performance of VECMs versus VARs for cointegrated systems are reported in Engle and Yoo (1987) and Lesage (1990). The results of these studies indicate that the VECM is a more appropriate specification in terms of smaller long-term forecast errors, when the variables satisfy cointegration conditions.

Subsequently, Ahn and Reinsel (1990) and Johansen (1991) have proposed various algorithms for the estimation of cointegrating vectors in full-order VECM models, which contain all non-

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zero entries in the coefficient matrices. There are many examples of the use of full order VECM models in the analysis of short-term dynamics and long-term cointegrating relationships Reinsel and Ahn (1992), Johansen(1992, 1995).

Problems can arise in relation to the use of full-order VECM models, as such models assume nonzero elements in all their coefficient matrices. As the number of elements to be estimated in these possibly over-parameterized models grows with the square of the number of variables, the degrees of freedom is heavily reduced.

2.0 Materials and Method

Data used in this paper are annual figures covering the period 1970 – 2009 and variables of the study are FPI, GDP, INF and INT. This is obtained from the Central Bank of Nigeria (CBN)statistical bulletin. The theoretical model, which also serves as a basic frame work of our statistical analysis, is the Vector Autoregressive model of order p. VAR models are built based on the economic variables that are assumed to be stationary. However, many time series variables especially economic variables that occur in practice are non-stationary. Regressing two or more non- stationary variables may produce a spurious result.

As suggested by Box and Jenkins (1976), differencing such variables may make them stationary. Most economic variables are stationary in the first difference. However, differencing removes some long run information (Johansen, 1990). Engle and Granger (1987) introduced the concept of cointegration. Two or more non stationary series are cointegrated if their linear combination is stationary. Thus, the procedures for determining the order of integration as well as the cointegration rank are presented. Thereafter, causality analysis is carried out using Granger Causality approach. Finally, impulse response and forecast variance decomposition are discussed.

For a set of k variables, $y_t = (y_{1t}, ..., y_{kt})'$, a VAR (p) model captures their dynamic inter relationships given by

$$y_t = \delta + \psi D_t + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \varepsilon_t \qquad (1)$$

We can rewrite equation (1) as

$$\phi(L) y_t = \delta + \psi D_t + \varepsilon_t \qquad (2)$$

where $\phi(L) = 1 - \sum_{j=1}^{n} \phi_j L^j$, $y_t = (y_{1t}, y_{2t}, ..., y_{kt})'$ is a set of kth time series variables, δ is the constant term, D_t denote the regressors associated with deterministic terms, ψ is the seasonal dummy and structural break, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t} ..., \varepsilon_{kt})'$ is a vector of an unobserved zero means independent white noise process with time invariant positive definite covariance matrix $E(\varepsilon_t \varepsilon_t') = \sum_k$, and $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p$ is a matrix of a lag polynomial with k x k coefficient matrices ϕ_j, j= 1,2,...p . Equation (2) can be rewritten as:

$$(1-\phi_1 L-\phi_2 L^2-...-\phi_p L^p)y_t=\partial+\psi D_t+\varepsilon_t \tag{3}$$

where $\phi(L)=(1-\phi_1 L-\phi_2 L^2-...-\phi_p L^p)$ is the characteristics polynomial. Each entry in the k x k matrix is a polynomial in L of order p.

If there is a Cointegration relationship among the variables, the analysis of such process is easily done with a model called Vector Error Correction Model (VECM), which is given by:

$$\Delta y_t=\pi y_{t-1}+\Gamma_1\Delta y_{t-1}+...+\Gamma_{p-1}\Delta y_{t-p+1}+\partial+D_t\psi+\varepsilon_t \tag{4}$$

where π = -($\mathrm{I}_n-\phi_1-\phi_2-...-\phi_p$) and $\Gamma_j = \ -(\phi_{i+1}+...+\phi_p)^{'}$ for (i = 1,2,...,p-1). We obtain Equation (4) by subtracting Y_{t-1} from both sides and rearranging Equation (2). Since ΔY_t does not contains stochastic treads by our assumption that all variances should be I(1) , the mean term πX_{t-1} is the only one which includes I(1) variables. Hence,

πy_{t-1} must also be integrated of order 0, I (0). This contains the Γ_j, (j = 1, 2,…,1-p)

which are often referred to as the short-run dynamic or short-run parameters while πy_{t-1} is sometimes called the long-run part. The model in 4 is abbreviated as VECM (P-1). To distinguish the VECM from VAR model the latter is sometimes called the level version (Lutkepohl, 1991). If the VAR (p) has a unit root, that is; if $det\left(I_k-\phi_1 z-\phi_2 z^2-...-\phi_p z^p\right)=0$ for z =1, then the matrix π is singular.

Suppose it has rank r, that is, rank $(\pi)=r$. Then it is well known that π can be written as product of $\pi=\alpha\beta^{'}$, where α and β are k x k matrices with rank (α) = rank(β) = r. Pre-multiplying $\pi Y_{t-1}=\alpha\beta^{'}Y_{t-1}$ by $\left(\alpha^{'}\alpha\right)^{-1}\alpha^{'}$ shows that $\beta^{'}Y_{t-1}$ is I(0) and therefore contains the cointegrating relations. Hence, there are r = rank (π) linearly independent cointegrating relations among the components of Y_t. The matrices α and β are not unique so there are many possible β matrices which contain the cointegrating relations or linear transformations of them. Consequently, relations with economic content cannot be extracted purely from the observed time series. Some non-sample information is required to identify them uniquely.

Assuming that all the short run dynamics, constant terms and deterministic terms are equal to zero we have:

$$\Delta Y_t=\pi Y_{t_{-1}}+\varepsilon_t \tag{5}$$

Now, taking the expectation of equation 5 we have:

$$0=\mathrm{E}(\pi\mathrm{Y}_{t-1})+E(\varepsilon_t)$$
$$\Rightarrow 0=\pi Y_{t-1} \tag{6}$$

As a set of r equilibrium conditions which guide the evolution of Y_t overtime and $\alpha\beta'Y_{t-1}$ will contribute $\alpha_{11}\beta_1'Y_{t-1} + \alpha_{12}\beta_2'Y_{t-1} + \cdots + \alpha_{1r}\beta_r'Y_{t-1}$ to the explanation of ΔY_{1t}. The linear combinations of Y_t will have zero expected values and finite variances so that not only will zero be the expected value of these terms but will also be meaningful in that there will be a non – trivial probability of being “close” to it. In contrast, if the variances are to go to infinity as the sample size increases, then the expected value would become important as it occurs with non-stationary linear combination (Engle and Granger, 1987), and translates this into a requirement measures should be zero mean and stationary.

Augmented Dickey-Fuller (ADF) Unit Root and the Dickey Fuller-Generalized Least Square (DF-GLS) tests are applied to test for level of integration and possible co-integration among the variables (Dickey and Fuller, 1979; Said and Dickey, 1984), and is given by the regression equation

$$\Delta Y_t = \mu_0 + \mu_1 t + \phi Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \varepsilon_t, \text{ t} = p+1 \ldots T \quad (7)$$

Where p lags of ΔY_{t-j} are added to remove serial correlation in the residuals.

Hypothesis:

H_0 : $\phi = 0$ (there is unit root in the series).

$H_1 : \phi < 0$ (the series are stationary)

The hypothesis is tested on the basis of t-statistic of the coefficient ϕ

Decision rule: Reject H_0 if test statistic is less than critical values, otherwise do not reject.

The ADF-GLS test is a variant of the Dickey Fuller test for unit root (for the case where the variable to be tested is assumed to have a non-zero mean or to exhibit a linear trend). The difference is that the de-meaning or de-trending of the variable is done using the GLS procedure suggested by Elliott et al. (1996). This gives a test of greater power than the standard Dickey-Fuller approach. Elliot et al (1996) optimized the power of the ADF Unit root test by detrending. If y_t is the series under investigation, the ADF –GLS Test is based on testing

$H_0 : \psi^* = 0$ against $H_1 : \psi^* \neq 0$ in the regression equation:

$$\Delta y_t^d = \psi^* y_{t-1}^d + \psi_1 \Delta y_{t-1}^d + \ldots + \psi_{p-1} \Delta y_{t-p+1}^d + u_t$$

where y_t^d is the detrended series. (8)

Decision rule: Reject H_0 if test statistics is less than critical values.

(See Haris and Sollis, 2004 for details).

2.1 Estimation of VECM

Estimation of VECMs of the form:

$$\Delta Z_t = \Phi(B)\Delta Z_{t-1} + \mu + \beta e_{t-1} + v_t \quad (9)$$

is discussed in many texts (see Banerjee et al. 1993; Hamilton, 1994; Johansen 1995), and routines are available in most econometric packages. Without going into unnecessary details, ML estimates are obtained in the following way: Consider (9) written as

$$\Delta Z_t = \mu + \sum_{i=1}^{m-1} \Phi_i \Delta Z_{t-1} + \beta\alpha^T Z_{t-1} + v_t \quad (10)$$

The first step is to estimate (10) under the restriction $\beta\alpha^T = 0$. As this is simply a *VAR* (m-1) in ΔZ_t. OLS estimation will yield the set of residuals $\hat{v}_t$, from which we calculate the sample covariance matrix

$$s_\alpha = T^{-1} \sum_{t=1}^{T} \hat{v}_t \hat{v}_t^T \quad (11)$$

The second step is to estimate the multivariate regression

$$Z_{t-1} = k + \sum_{i=1}^{m-1} \Xi_i \Delta Z_{t-1} u_t \quad (12)$$

and use the OLS residuals $\hat{u}_t$ to calculate the covariance matrices

$$s_{11} = T^{-1} \sum_{t=1}^{T} \hat{u}_i \hat{u}_t^T \quad (13)$$

and

$$S_{10} = T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{v}_t^T = s_{01} \quad (14)$$

2.2 Cointegration Rank Test

If r = n and A is unrestricted, the maximized log-likelihood is given by Banerjee *et al*. (1993) as:

$$\ln = K - \left(\frac{T}{2}\right) \sum_{i=1}^{n} \log\left(1-\lambda_i\right), \quad (15)$$

Where $K = -(T/2)\left(n\left(1+\log 2\pi\right) + \log\left|s_\infty\right|\right)$. For a given value of r < n, only the first r Eigen values should be positive, and the restricted log likelihood is

$$L(r) = K - (T/2)\sum_{i=1}^{r}\log\left(1-\lambda_i\right) \tag{16}$$

A likelihood ratio test of the hypothesis that there are r cointegration vectors against the alternative that there are n is thus given by

$$\eta_r = 2\left(L\left(n\right) - L\left(r\right)\right) = -T\sum_{i=r+1}^{n}\log\left(1-\lambda_i\right) \tag{17}$$

This is known as the trace statistic, and testing proceeds in the sequence $\eta_1, \eta_2, ..., \eta_{n-1}$. A cointegrating rank of r is selected if the last significant statistic is η_{r-1}, which thereby rejects the hypothesis of n – r + 1 unit roots in A. The trace statistic measures the 'importance' of the adjustment coefficients β on the eigenvectors to be potentially omitted. An alternative test of the significance of the largest Eigen value is

$$\varsigma_r = -T\log(1-\lambda_{r+1}),\ \text{r = 1, 2, ... , n-1} \tag{18}$$

which is known as the maximal-Eigen value or λ–max statistic (Terence and Raphael, 2008)

Decision rule: Accept H_0: (there is no significant cointegration relationship) if t- statistic is greater than asymptotic critical - value or if the p – value is less than the level of significance, otherwise accept H_1: (there is significant cointegration relationship) if test statistic is less than the asymptotic critical values or if the p- value is greater than the level of significance. Testing sequence terminates if the null hypothesis cannot be rejected for the first time.

3.0 Empirical Results

Tables 1, 2 and 3 summarize the results of the unit root test. From the results all the variables are non-stationary at levels but stationary in the first difference since critical values are less than test statistics at the levels but critical values are greater than test statistics in the first difference for the ADF, ADF - GLS and KPSS tests leading to non-rejection of the null hypothesis at levels, but the null hypothesis is rejected at the first difference. Hence the series are integrated of order one I(1).

3.1 VAR Model Identification

We estimate the VAR model of GDP, IFR, FPI, and INR. With number of lags order of 3 based on information criteria, the values of AIC is given by VAR system, maximum lag order 3.

3.2 Johansen Cointegration Rank Test

We applied Johansen trace test and L max test in order to determine the cointegration rank of our variables because one of the condition to model with VECM is that there must be cointegration relationship. The results for the test are presented in Table 4.

Table1: The ADF Unit Root Test for Identification of Order of Integration of the Variables.

Level			First Difference	
Var	t -Stat Const	Const & Trend	Const	Const& trend
logIFR	-3.0607	-2.9377	-4.4830	-4.6192
LogGDP	-0.1642	-1.5888	-5.3123	-5.2309
LogFDI	-0.4164	-1.8626	-5.1281	-5.0567
logINR	-1.4420	-0.07861	-4.9007	-5.5052
Critical Val 5%	-2.93	-3.50	-2.93	-3.50
1%	-3.58	-4.15	-3.58	-4.15

Table 2: ADF- GLS Test for Identification of Order of Integration

Levels			First Difference	
VAR	Const	Const & Trend	Const	Const &Trend
logIFR	-2.3621	-3.3470	-6.5064	-6.5883
Log GDP	1.9815	-1.6052	-5.3816	-5.3475
Log FDI	1.11858	-1.8846	-5.0374	-5.1329
logINR	-1.1494	-1.1194	-4.8077	-5.4711
5%	-3.58	-3.19	-3.58	-3.19
1%	-2.91	-3.77	-2.91	-3.77

Table 3: KPSS Unit Root Test for Identification of Order of Integration

Levels			First Difference	
Var	Const	Const & Trend	Const	Const & Trend
logIFR	0.19369	0.1470	0.1476	0.0595
LogGDP	1.0911	0.1614	0.0913	0.0893
LogFDI	1.0802	0.1182	0.0628	0.0701
logINR	0.7434	0.2354	0.3751	0.1312
Crit. val. **5%**	0.574	0.146	0.463	0.146

Table 4: Johansen Test forCointegration Rank

Rank	Eigenvalue	Trace test p-value	Lmax test p-value
0	0.57922	58.311 [0.0032]	32.895 [0.0071]
1	0. 3084	25.417 [0.1515]	14.011 [0.3782]
2	0.2055	11.406 [0.1903]	8.7428 [0.3154]
3	0.06769	2.663 [0.1027]	2.6633 [0.1027]

From Table 4, the result of the cointegration rank is 1 based on the p-value since the first null hypothesis cannot be rejected at rank 1.

Results of Cointegration Relations:

$$\hat{\beta} = \begin{pmatrix} 1.000 \\ -1.168 \\ -0.195 \\ 1.558 \end{pmatrix} \text{and } \hat{\alpha} = \begin{pmatrix} 0.111 \\ 0.299 \\ 0.227 \\ 0.054 \end{pmatrix} \quad (19)$$

The above results show that the cointegration relation with restricted constant is

$$ec_t^{ML} = GDP - 1.168FDI - 0.195IFR + 1.558INR$$
$$or$$
$$GDP = 1.168FDI + 0.195IFR \text{ - } 1.558INR \quad (20)$$

The equation above can be interpreted as follows: the coefficient of 1.168 value of foreign private investment in Nigeria (FPI) is the estimated output elasticity following that both Gross Domestic Product (GDP) and Foreign Direct Investment (FDI) appear in logarithms (Lutkepohl, 2005). A 1% GDP increase obtained in Nigeria will induce a similar 0.195% increase in inflation rate (IFR), and 1.558% decrease of interest rate (INR).

3.3 VECM Model Checking

The following tests on the residuals are applied to check for the adequacy of our VECM model (i) the Portmanteau LB test, (ii) Godfrey LM test for autocorrelation, (iii) Autoregressive conditional Heteroskedastic LM test for ARCH effect and (iv) Jarque-Bera test for Normality. The results are summarized in Tables 5 and 6:

Table 5 Results of VECM Test for Serial Correlation and ARCH Effect.

Residuals	P – values	Decisions
Portmanteau LB Test	0.9898	Accept H_0
Godfrey LM Test	0.0573	Accept H_0
ARCH LM Test	0.3098	Accept H_0

The results of Table 5 shows that the null hypothesis of no serial autocorrelation and conditional Heteroskedasticity will be accepted for portmanteau LB test, Godfrey LM and ARCH LM test since their p- values are greater than the significance values of 0.05 and 0.01 for the 5% and 1% significant levels.

Table 6: Results of VECMJarque– Bera and Shapiro - Wilk Test for Normality

Jarque-Bera Test			Shapiro-Wilk test	
Residuals	P- value	Decisions	P – Value	Decisions
U1t	0.0976	Reject H_0	0.0040	Reject H_0
U2t	0.0149	Reject H_0	0.0017	Rejected H_0
U3t	0.8449	Reject H_0	0.6133	Accept H_0
U4t	0.7518	Reject H_0	0.4408	Accept H_0

Table 6 shows that in Jarque-Bera test H_0 are rejected for all residuals which indicate that they are all normal. However in Shapiro-Wilk test H_0 for residuals are accepted for $U_3$and U_4 indicating that they are normal while U_1 and U_2 are not too far from normality and slight non-normality as documented by Juselius (2006) does not invalidate the test.

3.4 CUSUM and CUSUM – SQ Test for Stability

These two tests are applied to examine the stability of the long-run coefficient together with short run dynamics (Pearson and Pearson, 1997). CUSUM and CUSUM SQ test was proposed by Brown *et al*. (1975). The tests are applied on the residuals of all variables of VECM model (see the figure 2 below). If the plot of the CUSUM statistics stays within the critical bound of 95% level of significance, represented by a pair of straight lines drawn at 95% level of significance the null hypothesis is that all coefficients in the error correction model cannot be rejected. If any of the lines crosses, the null hypothesis of coefficient constancy at 95% level of significance will be rejected. A CUSUM-SQ test is based on the square recursive residuals, and a similar procedure is used to carry out this test.

Figures 1 and 2 are graphical representations of CUSUM and CUSUMSQ plots, respectively, which are applied to the error correction model selected by the adjusted R^2 criterion. CUSUM plots of the variables do not cross critical bounds which indicate no evidence of any significant instability. However, in CUSUMSQ plot of figure 2, three plots slightly cross the critical bound indicating slight instability of these variables.

3.6 Granger Causality Analysis

Here, the results for the analysis of causality are presented and the causality between the variables (if any) and the direction of the causality of the systems are determined using Granger Causality test. The results of the test are presented in table 7. The result estimate shows that at 5% most of the variables are Granger–not causal for GDP. However, there is unidirectional causality between FPI and GDP, and INR and GDP between INF and FPI. But there is bi-directional causality between FPI and INR.

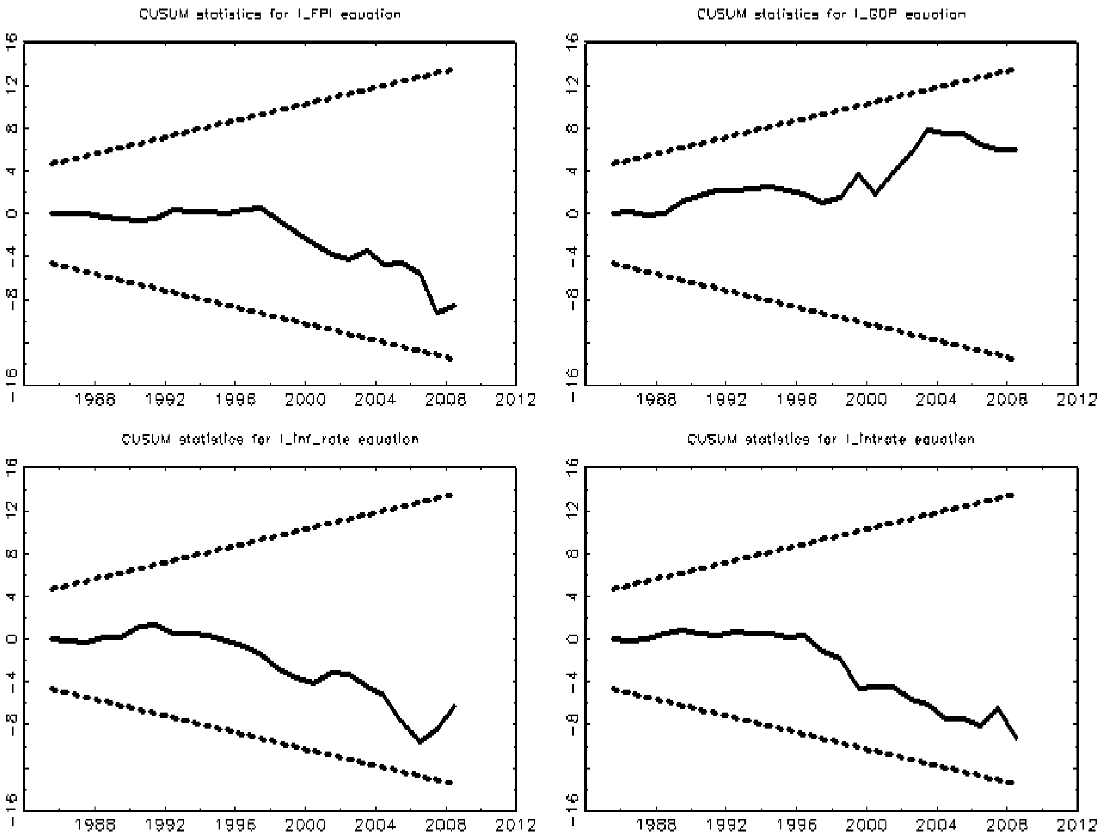

Figure 1: Plots of Residuals CUSUM

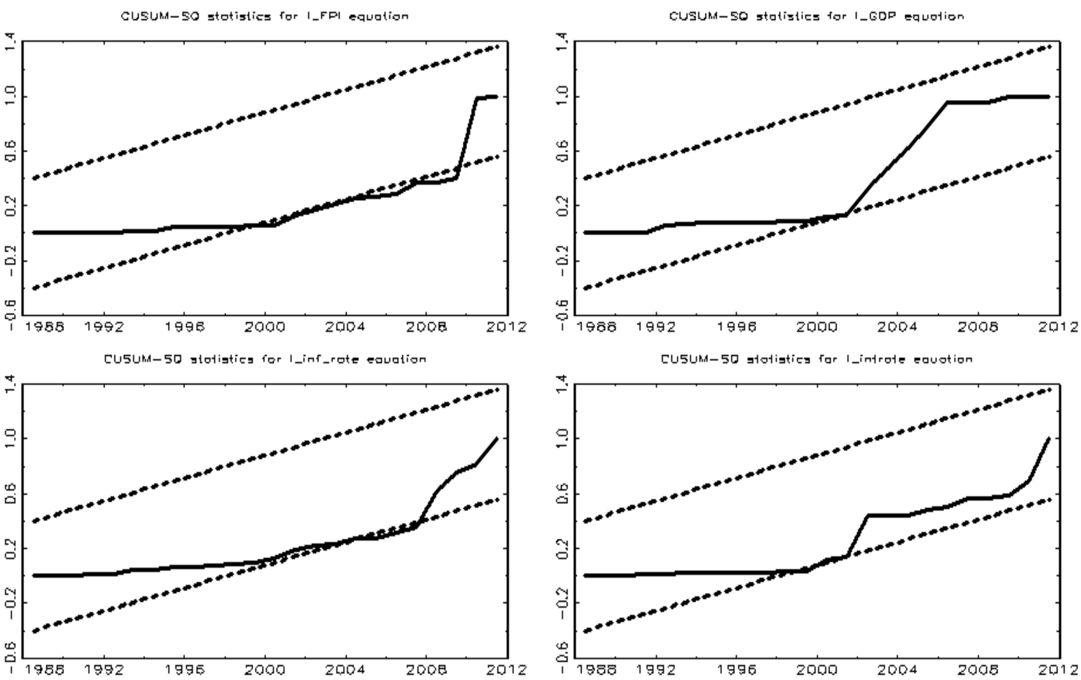

Fig.2. Plots of Residuals CUSUMSQ

Table 7: Results of Granger- Causality Analysis

Null hypothesis	F- stat	p – value	Decision rule
"GDP does not Granger – Cause FPI"	3.7001	0.0170	reject H_0 at 5%
"FPI does not Granger – Cause GDP"	2.1301	0.1071	do not reject H_0
"GDP does not Granger – Cause INR"	2.8787	0.0443	reject H_0
"INR does not Granger – Cause GDP"	4.0181	0.0118	reject H_0
"GDP does not Granger – Cause IFR"	1.8686	0.1459	do not reject H_0
"IFR does not Granger – Cause GDP"	0.8623	0.4663	do not reject H_0
"FPI does not Grander – Cause INR"	3.1550	0.0321	reject H_0
"INR does not Granger – Cause FPI"	2.2453	0.0935	do not reject H_0
"FPI does not Granger – Cause IFR"	0.7313	0.5378	do not reject H_0
"IFR does not Granger – Cause FPI"	2.1418	0.0336	reject H_0
"IFR does not Granger – Cause INR"	1.5539	0.2112	do not reject H_0
"INR does not Granger – Cause IFR"	0.6527	0.5847	do not reject H_0

4.0 Summary and Conclusion

In this study, we have presented an analysis of the cointegtation between the Foreign Private Investment (FPI) and Growth Domestic Product (GDP) with two other macroeconomic variables in Nigeria using data obtained from Central Bank of Nigeria Statistical Bulletin (2005) for the period of 1970 to 2005. In modeling Growth, these variables are chosen based of the fact that they are very important determinants of economic growth in Nigeria (Chette, 1998). The approach is important because developing countries in general, and Nigeria in particular is putting measures towards improving economic growth with emphasis on Foreign Direct Investment. The ADF, ADF – GLS and KPSS tests show that all the four variables are integrated of order one. VAR 3 and VECM 2 model were chosen based on Akaike criterion. The Johansen test shows that VECM 2 has a cointegration relationship with the rank of 1. Furthermore, the Granger Causality Analysis shows a unidirectional causality relationship between GDP and FPI which is in line with previous studies (Basu*et al.* 2003) and with two other macro-economic variables. The results support the theoretical contention and give strong support to the hypothesis that FPI inflows have impact on GDP.

In summary, our econometric estimates of the impact of FPI on GDP model for Nigeria suggest that there exists a long run relationship between FPI and GDP. Precisely, these findings suggest that the contribution of FPI to Nigerian economic growth is about 1.168% and all other variables have long run relationship with positive contribution in the growth model. However, interest rate has a negative contribution in the model.

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